Towards a Bayesian Approach in Criminology: A Case Study of Risk Assessment in Youth Justice

Hodges, Helen R.

Towards A Bayesian Approach in Criminology: A Case Study of Risk Assessment in Youth Justice

Main Body

(99,079 words with accompanying Technical Annex)

Helen Hodges

Submitted to Swansea University in fulfilment of the requirements for the Degree of Doctor of Philosophy

Swansea University

2018

Abstract

This research makes a significant and original contribution to emerging debates within criminology and the social sciences more broadly, concerning the academic merit of using Bayesian statistics to analyse complex social problems, such as crime, with a view to promoting progressive and evidence-based policy reform agendas. It uses the risk assessment process in youth justice as a case study to demonstrate the utility of adding Bayesian approaches in the standard analytical tool box used to investigate the aetiology of offending behaviours, particularly when dealing with relatively small data-sets.

The findings presented reinforce that it is possible using a Bayesian approach to 'do more with less' in terms of the number of cases analysed, and model the impact on the likelihood of further offending of individual characteristics, offending history, different types of offending and contact with the youth justice system. In considering the implications of its findings, the thesis considers how adopting a post-positivist stance - as called for by critics of the risk assessment process used within youth justice in England and Wales – enables new insights to be offered concerning the complex relationship between the framework of risk and protective factors and offending behaviours.

It is concluded that they are distinct advantages associated with the adoption of novel statistical techniques within criminology, especially at a time where there is an increased emphasis on making greater use of administrative data to develop robust evidence-based policy.

Contents

List of Tables

List of Figures

Abbreviations

APA	American Psychological Association
ASA	American Statistical Association
BF_{xx}	Bayes Factor, *Note: BF_{01} expresses the likelihood of H_0 relative to H_1 given the data whereas BF_{10} expresses the probability of the data given H_0, relative to H_1.*
DTO	Detention and Training Order
ESRC	Economic and Social Research Council
ETE	Education, Training and Employment
FTE	First-Time Entrant (into the Youth Justice System)
H_0	Null Hypothesis
H_1	Alternative Hypothesis
MCMC	Markov Chain Monte Carlo
NHST	Null Hypothesis Significance Testing
NHSTP	Null Hypothesis Significance Testing Procedures
PPV	Positive Predictive Value
RCT	Randomised Control Trial
RFR	Risk Factor Research
RNR	Risk, Needs and Responsiveness
SAC	Serious Acquisitive Crimes eg Burglary, Robbery, Vehicle Theft / Unauthorised Taking
VAP	Violence Against the Person
YJB	Youth Justice Board
YOS	Youth Offending Service
YOT	Youth Offending Team
YRD	Youth Restorative Disposal
YRO	Youth Rehabilitation Order

Additionally Section 5 of the accompanying Technical Annex provides an overview of terminology associated with hierarchical modelling and the associated diagnostic tests. This includes worked examples of the output, highlighting key features for those who are not familiar with undertaking analysis under a Bayesian framework.

1 The Rationale for Using Bayesian Approaches in Criminology

1.1 Introduction

In 2015, the journal *Basic and Applied Social Psychology* 'banned' null hypothesis significance testing including all vestiges of the procedure (p-values, t-values, F-values, statements about "significant" differences or lack thereof, and so on), suggesting that 'the journal would no longer publish papers containing p-values because the statistics were too often used to support lower-quality research' (Trafimow and Marks, cited in Woolston, 2015). Confidence intervals were also banned from the journal. Instead the editors indicated that they require strong descriptive statistics, including effect sizes. The presentation of frequency or distribution data is encouraged, where feasible. Such was the debate that this prompted that the American Statistical Association published a statement on p-values and statistical significance in March 2016. Their statement advocates that as an alternative, other approaches might be entertained, including confidence intervals and Bayesian methods, acknowledging that whilst these come with their own conceptual challenges, 'they may more directly address the size of an effect (and its associated uncertainty) or whether the hypothesis is correct' (Wasserstein and Lazar, 2016: 11).

The decision by the editors of the *Basic and Applied Social Psychology* (BASP) and subsequent statement from the American Statistical Association (ASA) raise the question as to whether it is time that criminology should similarly be looking beyond null hypothesis significance testing (NHST), especially given that Trafimow and Marks indicate that the motivation for their journal's ban is that it will liberate authors from 'the stultified structure of NHSTP thinking thereby eliminating an important obstacle to creative thinking' (2015: 2). This research therefore considers the extent to which creative thinking and innovation in criminology could be enhanced through the adoption of Bayesian methods.

In doing this, the arguments around why some believe that NHST and all its vestiges should be banned are summarised. Rather than replicate the various arguments that have been posited since the techniques came into common usage and adopt an anti-Frequentist stance, the view here is that in wishing to progress knowledge, the discipline should take advantage of all the tools in the toolbox. Hence, the emphasis within this research is upon how the discipline may benefit from the use of Bayesian methods. Chapter One therefore focuses upon introducing Bayesian approaches and outlines why criminological policy and practice would benefit from these in the context of the increasing concerns about the validity of NHST.

Research Aim and Objectives

Convention would have it that from the research objectives, specific research questions and hypothesis are then formulated which in turn are used to inform decisions about data and methods (de Vaus, 2001;

White, 2009). However, as Punch observes 'there are exceptions to this order of events, and it is not mandatory' (2006: 27). In this instance the overarching research aim is to **explore the utility for using Bayesian approaches within criminology through presentation of a case study focusing on risk assessment in the youth justice system in England and Wales.** Hence, this first chapter sets out the rationale for the adoption of new approaches within criminology, whilst Chapter Two provides context as to why the case study was chosen and how the development of risk assessment tools could benefit from a shift in the criminological gaze to reflect emerging technologies and techniques.

To achieve the research aim, it has been necessary to adopt a methods-led approach with data being purposefully selected to demonstrate the utility of conducting analysis under a Bayesian framework (details of which are described in Chapter Three). Methods-led approaches have been criticised for going against the logic of interconnectedness between method and research questions (Grix, 2002) with concern being raised about the construction and maintenance of 'mono-methods' which limit professional development (Gorard, 2002). However, since the emphasis here is on demonstrating how the application of novel statistical approaches can further knowledge, the approach adopted represents analysis-led rather than methods-led research which is more in keeping with Marx (1997) when he suggests that possible research questions may arise from the way in which new methods and theories might be applied to new settings. With this in mind, the following research objectives are identified:

- What can be learnt from approaches already used in other disciplines which could be applied to criminology and more specifically youth justice?
- How can the relationship between risk factors and (re)offending be explored using Bayesian approaches?
- What methodological challenges would need to be overcome?

The first of these objectives is addressed primarily through discussion within Chapter Two whilst the practical issues pertaining to the second objective are considered within Chapter Three. In keeping with the analysis-led approach, the research questions explored in the analysis chapters (Chapters Four to Seven) are located alongside the discussion of the dataset in Chapter Three, were developed to address common criticisms of the risk assessment tool used until recently in the youth justice system in England and Wales.

Notably ASSET and actuarial tools more generally have been criticised for being blunt tools which lack the sensitivity to be able to reflect the realities of real lives. Therefore, research questions have been designed to determine how gender, ethnicity and experience of care impact on the likelihood of further offending. These link into policy concerns around the over-representation of BAME and looked after children in the criminal justice system.

Young people who offend can live particularly chaotic lives. Therefore, there is also a desire to understand how responsive the risk assessment tool is to changes over time and whether these are affected by the 'event's such as breaching, returning to court and spending time in custody/ on remand. These issues which have not previously been considered as part of the evaluations of ASSET carried out on behalf of the Youth Justice Board (YJB) / Ministry of Justice. As it was anticipated that those with a prior history of offending would respond differently to those who are first-time entrants, research questions were also designed to explore the role played by the young person's criminal history on the likelihood of further offending behaviours. Table 1.1 summarises the research questions by theme.

Table 1.1: Summary of the Research Questions, by Chapter and Theme

Chapter and Theme		Research Questions
4	Risk Assessment Domains	What is the relationship between further offending, the 12 domains and time?
5	Dimensional Identity	What is the impact of gender and ethnicity on the likelihood of further offending?
		What is the impact of having experience of care on the likelihood of further offending over time?
6	Static Factors	What is the impact of the 'static' factors within ASSET in predicting further offending over time?
		Is it possible to extend the sensitivity of ASSET by extending any of the predictors?
7	System Contact	How is the likelihood of further offending affected by having experience of care and a previous offending history?
		What is the impact of coming into contact with facets of the youth justice system on the likelihood of further offending?

Cutting across the four analysis chapters, a further research question is posed which considers how well ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT. This final question provides a means of assessing the predictive accuracy of the various models constructed in response to the other questions posed and links back to concerns about the predictive accuracy of ASSET and actuarial tools more generally.

The analysis presented in Chapters Four to Seven utilises a range of common statistical techniques performed under the Bayesian framework in order to demonstrate how the relationship between risk factors and (re)offending can be explored. Chapter Four builds upon the work of Baker et al. (2003, 2005) and Wilson and Hinks (2011) by considering changes both in the total ASSET score and in the individual risk domain scores over time. A hierarchical model is constructed which mimics the features of ASSET with the ratings or 'scores' from 12 domains of risk being added together to allow the young person's perceived level of risk and hence the intensity of their contact with the YOT to be determined.

In subsequent chapters, this basic 'Dynamic' model is enhanced using time invariant predictors constructed to reflect aspects of dimensional identity, the four static factors and time varying 'events' which represent when the individual comes into contact with facets of the youth justice system. These include dichotomous, categorical and continuous predictors. Sadly, there was insufficient data to enable models to be simulated which would have enabled the impact of gender, ethnicity and age at first conviction to be explored over time. Whilst the it was also necessary to make compromises due to the size of the dataset, working with a comparatively small dataset also offered the opportunity to investigate the underlying data to understand what might be contributing to unexpected findings. As such the it has been possible to establish the utility of applying Bayesian approaches, by demonstrating their potential.

Although the analysis presented within the case study identifies some of the methodological challenges which would need to be overcome, many of these are associated with the size of the dataset. However, as highlighted in Chapter Eight, there are wider pedagogical and philosophical issues which the discipline will need to address if Bayesian approaches are to be used more widely. This research therefore represents an important key step in facilitating the paradigm shift required to enable this to happen.

The remainder of this chapter outlines the extent to which criminology as a discipline has engaged in the NHST debate, introduces Bayesian approaches and argues why now is an appropriate time to be considering their application.

1.2 Significance Testing and the Anti-NHST Debate

NHST represents an amalgamation of Fisher's significance testing and Neyman-Pearson's theory of hypothesis testing – something which has been frequently commented upon as part of anti-NHST arguments since they reflect different philosophical perspectives. Kruschke (2010a; 2010b; 2011; 2012) is just one of many who have been highly critical of NHST, emphasizing its inability to tell us what we want to know i.e. the probability of the hypothesis being true given the data. This, along with criticism that many researchers misinterpret the findings (see for example Nickerson, 2000 for a detailed discussion) have been key themes running throughout the anti-NHST literature.

The two most common misconceptions which cause confusion are '(a) that the size of the p-value indicates the strength of the relationship and (b) that statistical significance implies theoretical or practical significance' (Gliner et al., 2002: 84). To overcome these issues, the advice has been that there should be routine reporting of effect sizes in the form of confidence intervals (see for example Cohen, 1994; Gorard, 2014b) and improvements to the way in which statistics is taught to researchers (Gliner et al., 2002; Kalinowski et al., 2008). In the case of the former, this is now standard practice in most journals in keeping with the guidelines issued by the American Psychological Association (American Psychological Association, 2010), although this in itself is problematic since confidence intervals can also be readily misunderstood (Hoekstra et al., 2014) and do not have the properties at are often claimed on their behalf:

> 'Confidence interval theory was developed to solve a very constrained problem: how can one construct a procedure that produces intervals containing the true parameter a fixed proportion of the time? Claims that confidence intervals yield an index of precision, that the values within them are plausible, and that the confidence coefficient can be read as a measure of certainty that the interval contains the true value, are all fallacies and unjustified by confidence interval theory.'
>
> (Morey et al., 2015: 118)

The process of NHST has been scathingly referred to as being 'the null ritual' (Gigerenzer, 2004) arguing that the process is taught without statistical thinking and crucially without reference to concepts such as statistical power or effect size - a finding supported by Gliner et al. (2002) based on a review of how twelve key educational text books deal with the problems and common misconceptions. Cohen has similarly likened NHST to a ritual, but also alluded to a mechanised approach when he bemoaned the fact that 'after 4 decades of severe criticism, the ritual of null hypothesis significance testing – mechanical dichotomous decisions around a sacred .05 criterion – still persist' (1994: 997). Certainly, it would appear that where NHST is blindly followed without an understanding of the formal logic, in particular Modus Tollens associated with statistics, 'researchers are all too readily lulled into a false sense of science' (Lambdin, 2012: 71).

The problems of adopting this mechanised approach are further exacerbated by the ease with which analysis can now be undertaken in software such as SPSS, with students often being provided with instructions of how to carry out various statistical tests without having a good grasp of the underlying assumptions. For example, much of the data in the social sciences is not normally distributed, nor is it always drawn randomly from repeated samples, yet these characteristics underpin t-tests, chi-squared and many of the other tests which fall under the NHST umbrella. All too often students are told that if their sample is sufficiently large then they can assume normality, but how many actually check?

McShane and Gal (2016) suggest that whilst many researchers may be aware that statistical significance at the 0.05 level is a mere convention, what started as a rule of thumb has evolved into an ironclad principle that affects the interpretation of evidence. Thus, rote learning and recipe-like teaching / practice can be seen as treating 0.05 as a "magic number" upon which to make a dichotomous decision rather than evaluating evidence as a continuum. Where this happens, there is the potential for researchers to erroneously draw unwarranted conclusions because their evidence fails to attain statistical significance, rather than considering alternative explanations. Similarly, there is the potential for spurious findings – based on poor-quality data or lacking a plausible mechanism, to be published simply because they attained statistical significance.

Positivist Criminology and NHST

In his popular introductory text book, Newburn (2007) characterises criminology as being a strange beast, with origins in applied medico-legal science, psychiatry, a scientifically-orientated psychology and more recently sociology. As a discipline therefore, it is apt at borrowing from its neighbours. However, it could also be argued that it has picked up some questionable habits, some of which stem from the efforts of some criminologists to mimic scholars from the natural and physical sciences, who have sought to make the more discipline more scientific (DiCristina, 1997) and attempts to objectify the study of a social phenomenon.

To appreciate the oft contradictory and eclectic nature of criminology in the first half of the twentieth century, one only needs to look at the career of the criminological thinker Sutherland. He promoted a predominately sociological framework for criminology, pursuing a scientific, objective study of criminological phenomena through attempts to explain individual-level and macro-level differences in crime rates. Regarded as being hugely beneficial for the field of criminology, the imposition of sociological positivism (and hence a shift away from biogenic and psychiatric explanations of crime) brought about a tendency to focus on issues of cause and effect, empirical data, replication and public statement of research methods. Notably, Sutherland privileged empirical evidence over revealed truth whilst at the same time 'recognising and advancing a powerful initiative against the inherent biases of the "scientific" criminology of his time in terms of how crime was defined and what type of crime was studied' (Friedrichs, 2016: 4). However, as Laub and Sampson (1991) observe – drawing upon Gottfredson and Hirschi, Sutherland held doggedly to the interests of his own discipline, rather than being open to the interests of scientific explanation coming from other sources. In particular he promoted the influence of sociological variables such as peer group, culture and community. As a result, promotion of his theory of differential association came at the expense of a number of his contemporaries including the multiple-factor theory of crime advocated by the Gluecks – the latter now considered to be hugely influential in risk factor research.

Much maligned by Sutherland, and certainly not without their critics, the Gluecks' methodological approach with its emphasis on longitudinal and follow-up prediction studies, including where possible control groups for comparison studies; and the importance of triangulation through use of multiple sources in addition to official records exemplifies, at least on paper, qualities today associated with high quality quantitative research. Viewed through a contemporary lens, the flaws in each of their respective bodies of work are apparent, but what is significant is their pursuit of "scientific" approaches and the systematic collection of data to support their endeavours. In this respect, their legacy is unquestionable with elements of their respective methodological approaches now firmly embedded into contemporary criminological practice.

As the discipline has matured, it has become a more diverse and fragmented enterprise, with less of a sociological dominance (Friedrichs, 2016). Both classical and positivist traditions have contributed to its current form, shaping the development of theoretical approaches and the adoption of scientific principles. Whilst positivist assumptions have been much criticised, Bottoms asserts that:

> 'Whatever the defects of old-style positivism (and it has many), it has bequeathed to contemporary criminologists a fine tradition of careful observation of the natural and social worlds; of the scientist's duty to report his/her research data dispassionately, even if he/she finds them personally unwelcome; and of the careful search for causes and explanations'
>
> (Bottoms, 2008: 88)

Criminology's battle for recognition as a distinct scientific discipline coincided with the rise of statistical approaches championed by the likes of Fisher, Neyman and Pearson (see Salsburg, 2001), hence these form the bed rock of statistics within quantitative criminology. Indeed, NHST has been identified as being 'the engine that drives theory testing in criminology' (Barnes et al., 2017: 26). However, as criminology has moved further away from psychology and more towards sociology, so the relationship between theory and research has evolved, and crucially the nature of questions has changed.

The growing demand for more reliable evidence of cause and effect, along with a means to evaluate the effectiveness of interventions, has spurred the drive for experimental criminology which has encouraged the increased use of meta-analysis and randomised control trials in criminology. Hailed almost as a panacea by some, experimental criminology has been promoted as being able to:

> '...help make a world in which governments can refuse to waste money on ineffective criminal sanctions despite populist pressures; a world in which citizens can demand that government must test policies with well-controlled experiments before spending vast sums in the name of crime prevention.'
>
> (Sherman, 2009: 7)

Notably randomised control trials (RCTs) have for some time now been held up as being the 'gold standard' in criminology, being assigned a score of 5 on the Maryland Scientific Methods Scale (Farrington et al., 2002) and have been utilised by the Society of Evidence Based Policing and the College of Policing to contribute to the body of evidence on a range of policing methods - evidence from many of these experiments along with those from quasi-experiments is disseminated through the Global Policing Database and the What Works for Crime Reduction website. As Sampson (2010: 490) observes, 'claims for RCT superiority are not surprising given that experiments have long been cloaked in the mantle of science, especially the laboratory paradigm of randomisation (or investigator control over allocation to treatment)'. Criminologists have similarly turned to medicine and experimental methods to evaluate interventions using meta-analyses.

Such borrowing from our neighbours is seen as a way to increase the validity and robustness of research, a vital step if we are to see more evidence-based policy. However, in seeking to apply ideas from medicine to criminology, the dominance of positivist approaches has meant that empiricism and Frequentist approaches have been privileged as the route to the acquisition of criminological knowledge. The primary limitation of the positivist legacy is the belief that it is both possible and correct to understand notions such as offending behaviour by measuring variables and combining them in linear statistical analysis. But is it appropriate for use within a discipline where there is so much inherent complexity, unpredictability, context-dependence and multidimensionality?

The Anti-NHST Argument in Criminology

Whilst psychology has been particularly vocal in the anti-NHST argument, it has also been considered within criminology with Maltz's 1994 paper remaining perhaps one of the best known. He argues that criminologists should no longer make do with techniques which imply that there is a norm of behaviour to which we compare other's behaviour, and advocates for greater use of qualitative data including narrative accounts - a direction which has been taken successfully by some researchers. Bushway et al's 2006 paper is one of the few that has sought to quantify the extent of the problems arising from mis-application. They argue for promotion of more thoughtful application, 'to put NHST in its place: as a tool to facilitate the inferential process, not as the end game for quantitative research' (Bushway et al., 2006: 14). As part of this, the authors advise that size matters and hence greater attention should be placed on reporting effect sizes and statistical power.

A cursory glance at many criminological journals suggests that we are now seeing increased reporting of effect sizes, confidence intervals and meta-analysis, in part because of the American Psychological Association's (APA) guidelines around appropriate statistical practice. Whilst the guidelines provide the opportunity for many disciplines 'to become cumulative sciences of estimation that deal with quantifying uncertainty rather than simply making dichotomous accept-reject decisions on the basis of individual studies' (Fidler, 2010), the utility of NHST remains a concern especially when such research is used to inform policy and practice. Not only do we need to know the 'effect' size or strength of any pattern or finding that is being reported, but we also need to have an appreciation of the costs, benefits and possible dangers of using that finding in practice (Gorard, 2014a). The debate has prompted a call for more transparent methods and the need to eradicate 'black box' statistics. Only then can we get a sense of how trustworthy the findings are.

For research findings to be trustworthy, use of appropriate research designs and the meaningful operationalisation of variables have a fundamental role to play. Here is it perhaps more obvious where the problems lie. In medicine, variables are easy to define and can be measured with a high degree of precision, yet this is considerably more difficult when considering human behaviour. Thus, efforts to unpick for example, the causes of offending behaviour and identify appropriate treatments or interventions are inevitably limited by the inherent complexity and subjective understandings of the key concepts being measured. In the case of offending, all too often it is necessary to utilise proxy measures such as self-reported offending or police recorded crime, or to focus on restricted populations such as those in custody which introduces biases. This use of crude measurements means that there is insufficient sensitivity in initial conditions which then amplifies error in the conclusions drawn. In order to adhere to the assumptions of various statistical tests, it is often necessary to collapse groups, something which reduces the potential to draw out more sensitive measures of, in this case, offending by different sub-groups. Hence what looks like 'science' in criminology, with its sampling rules, methodological coherence, use of statistical tests and certainty of conclusions, is, in reality, a social construct of dubious, real-world validity (Salsburg, 2001).

The situation in criminology is further complicated by the reductionist simplicity of methods enshrined in positivist traditions which have privileged nomothetic methods. In the quest to identify stable, predictable, deterministic, replicable relationships with offending, risk factor research (RFR) – prominent in explaining youth offending - has sought to apply linear modelling techniques such as linear regression which suppose that incremental increases in predictor variables produce linear and proportional increases in effects / outcomes such as offending (Case and Haines, 2014). However, this is predilection compounds problems associated with the way in which key concepts have been operationalised and measurements made. Whilst various theories have been put forward to explain offending behaviour, the fact that such behaviours can be context specific means that there is a lack of research findings which explain why initiatives have worked in some geographical areas or with certain groups, but not others.

Is there a replication crisis in Criminology?

Replication is an essential component of the scientific process since it establishes stability and rules out the possibility that results are merely due to coincidence. As such replication enables claims to be substantiated and generalised to larger or different populations than used in the original study. Yet Farrington (2000) notes that pure replication in criminological research is rare and few replications studies are published in criminology – a situation which McNeeley and Warner (2015) have hypothesised may be due to the comparative youth of the discipline. This, they suggest, has resulted in a bias towards criminological research which examines new topics since these are perceived to be more interesting and therefore more worthy. Their review found that replication studies constituted just over 2 percent of articles published between 2006 and 2010 in leading criminological journals, compared to replication rates of between 3 and 10 percent in prestigious journals relating to other disciplines.

Lösel (2017) goes further suggesting there are many social factors in research that form obstacles against a culture of replication with the academic world reinforcing mass publication in criminology and other disciplines. This 'publish or perish' ethos means that researchers seem to avoid replications as they wish to be seen to demonstrate their own creativity. Large collaborative projects tend to be promoted by research foundations. However, these can make replication more difficult especially as time and resource issues can hinder replications of complex field experiments that require years of follow-up. In primary studies, it is argued that in studies with many variables, selective data analysis and reporting, and fishing for significance is a danger particularly in areas where there may be financial incentives. There is also a reluctance for scholars to share their own data with others despite policies to encourage open data access and greater transparency.

Whilst it is acknowledged that not all criminological studies should necessarily be expected to replicate, where general theories are being tested or evaluations of interventions undertaken then replication is important, especially where findings may then be applied to policy or practice, 'Replication of these types of research would allow practitioners to have more confidence in the original findings, lending credibility to the research process and making the integration of research results into policies and practice more attractive' (McNeeley and Warner, 2015: 582). However, where replication is not feasible, 'confirmatory meta-analyses can play an important role on the path towards more differentiated and replicated knowledge' (Lösel, 2017: 1). In this respect, there is the potential to learn from other disciplines e.g. clinical pharmacy, engineering and climate research where evaluations are undertaken of programme packages rather than focusing on specific components in isolation since factors often have a minor effect in isolation, but in combination, they may show a strong impact. Methodologically it is recognised that whilst this is more challenging, adopting such an approach facilitates understandings of the effects of combinations that may potentiate effectiveness or lead to negative side effects. Thus, from a realistic perspective, in promoting replication studies in criminology Lösel acknowledges that 'applied research in criminology often has an explanatory character' (2017: 14) and hence flexible strategies are required which are not limited by uniform and rigid guidelines.

Although Lösel believes that there is no need for using the term "crisis" within criminology, Barnes et al. (2017) have questioned how powerful the evidence is in criminology, suggesting that the discipline may be at risk of a replication crisis. They assert that the crisis in confidence which has struck scientific disciplines like psychology and neuroscience is intimately tied to the low levels of statistical power in many studies in these areas. Their analysis of effect sizes from 80 meta-analyses, covering more than 6,000 individual primary criminology studies published between 1995 and 2015 concluded that more than half of all studies were underpowered to detect the effect sizes that they observed. However, at least 25% of all criminology research was found to be very well powered. As a result, they conclude that 'studies in criminology have relatively high levels of statistical power and a relatively high PPV [Positive Predictive Value] compared to other areas of behavioural and social science' (Barnes et al., 2017: 24). However, they caution that this is *relative* to other behavioural science disciplines like psychology, neuroscience and behavioural genetics which are known to have alarmingly low statistical power and average PPV. Hence their estimated PPV of 0.4 to 0.8 (which suggests that a randomly selected study from a criminology journal would report that the null hypothesis was correctly rejected between 40% and 80% of the time) appears to be very favourable when compared with say Duncan and Keller's estimated

PPV of approximately 0.05 for candidate gene literature within behavioural genetics (2011, cited in Barnes et al., 2017).

Looking more widely across the social sciences, the replication crisis in psychology has prompted much debate about the reliability and robustness of published "scientific" experiments prompting Nature to survey 1,500 scientists as to their views on whether there is a replication crisis within their discipline and what factors could boost reproducibility (Baker, 2016). Of the 11 improvements suggested, nearly 90% ticked 'More robust experimental design', 'better statistics' and 'better mentoring'. Whilst the Nature article does not address what is meant by 'better statistics', the ASA statement suggests that Bayesian methods may address the problems associated with size effects and whether the hypothesis being tested is true. The following section therefore introduces Bayesian approaches as an alternative to NHST.

1.3 The Bayesian Way

The standard Frequentist interpretation of probability which many will have been taught at school describes long-run properties of repeated stochastic i.e. random events and associated standard statistical methods. Bayesian approaches offer alternative probabilistic methods which are essentially a 'subjective' interpretation of probability since they allow uncertainty or 'degree of belief' about any unknown but potentially observable quality to be expressed, whether or not it is one of a number of repeated experiments. In terms of the philosophical differences,

> 'Bayesians view observed data as permanently fixed, but unknown parameters are considered random quantities given distributions based on the current level of knowledge. Conversely, Frequentists view data as stochastic, coming from a never-ending stream created by exacting the same generating process, but parameters are quantities fixed by nature and never changing.'
>
> (Gill and Witko, 2013: 459)

The Bayesian starting point is therefore a belief or assumption - which could be informed by the results of previous research. In contrast Frequentist inference describes the behaviour of test statistics and confidence intervals under hypothetical repeated sampling from an underlying population using a battery of tests which fall under the umbrella of NHST.

Introducing Bayesian Approaches

At its most basic, Bayesian is a branch of probability that uses a subjective rather than objective or 'Frequentist' interpretation of uncertainty i.e. its starting point is a belief or an assumption rather than being based on relative frequencies, and it has the advantage that it can be updated as new information becomes available. It can also be applied to situations where an event cannot necessarily be repeated under identical conditions (as in the classical or Frequentist approach) and where the alternatives to the event cannot be reduced to a finite list of equally likely outcomes (as in the objective approach). Its subjective interpretation means it is considered to be more intuitive and hence more applicable in the real world.

Although it was independently discovered more than 250 years ago by Thomas Bayes (c. 1701-1761) and Pierre-Simon Laplace (1749-1827), it is this subjectivity - at a time when there was a growing conviction that modern science required objectivity and precision - which led to significant controversy and the theorem languishing in near obscurity until the dawn of the computer age. The increased computational power that became available in the 1980s and 1990s has led to the resurgence in the use of Bayes' rule (the theorem upon which Bayesian approaches are based). Notably the development of Markov Chain Monte Carlo or 'MCMC' methods in the 1990s made it easier to compute the mathematics required to model some of the more complex relationships that exist in real life data by enabling sequences of random samples to be obtained from probability distributions for which direct sampling is difficult. Together these developments have contributed to the proliferation of applications across a range of disciplines including medicine, psychology, physics, ecology, geology, artificial intelligence, economics and finance.

A key reason as to why Bayesian approaches have emerged as a powerful tool with a wide range of applications is that they provide a rigorous method for interpreting evidence in the context of previous experience or knowledge. As a result, one application which many will have benefited from without realising is Google's use of Bayesian techniques to classify spam and pornography and to find related words, phrases and documents within its search engine (McGrayne, 2011). Other examples deemed newsworthy are associated with cryptography – the breaking of the Enigma code is attributed to Alan Turing's use of Bayesian techniques (Good, 1979; Tarran, 2014; see also Simpson, 2010 in relation to the Japanese Naval 25 (JN 25) encryption); the hunt for missing ships and aircraft including the Malaysia Airlines Flight MH370 and Air France Flight 447 in 2011 (Flam, 2014a; Zahriyeh, 2014); establishing if the remains discovered in a Leicester car park really are those of Richard III (King et al., 2014b) and in the presentation of forensic data in legal cases (Blair and Rossmo, 2010; Fenton and Neil, 2013; Stone, 2013).

Bayes' Theorem

Bayesian statistical analysis relies on Bayes' Theorem (Equation 1.1) - an elegant formula which enables us to update *prior beliefs* about parameters and hypotheses in light of *data*, to yield *posterior beliefs*. Applying Bayes' rule transforms probabilities that look useful (but are often not), into probabilities that are useful. It does this by combining prior experience (in the form of a prior probability) with observed data (in the form of a likelihood) to enable us to interpret the data (in the form of a posterior probability). This process is known as *Bayesian Inference.* In the context of an experiment we are concerned with what is the probability that the proposed hypothesis is correct *(H)* given the data *(D)*. As can be seen from Equation (1.1), this would be written as $Pr(H|D)$. However, what is observed during an experiment is the data given the hypothesis being tested i.e. *Pr(D|H)* which is not what is required. In terms of interpreting the behaviour of test statistics using Frequentist techniques, this relies on using p-values and confidence intervals whilst Bayesian inference permits direct inferences to be made – see Equation (1.2). Hence the Bayesian probabilistic interpretation of statistical parameters is considered not only to be more intuitive, but since prior assumptions are stated, it is also more transparent.

Equation (1.1): Bayes' Theorem

$$\Pr(A|B) = \frac{\Pr(B|A)\,.\Pr(A)}{\Pr(B)}$$

where

- *A* and *B* are events and Pr(B) ≠ 0.
- *Pr*(*A*) and *Pr*(*B*) are the probabilities of observing *A* and *B* without regard to each other.
- *Pr*(*A*|*B*), a conditional probability, is the probability of observing event *A* given that *B* is true.
- *Pr*(*B*|*A*) is the probability of observing event *B* given that *A* is true.

This can be re-written in the context of observed data (D) and a hypothesis (H), where the interpretation is that the hypothesis is true.

$$\Pr(H|D) = \frac{\Pr(D|H)\,.\Pr(H)}{\Pr(D)}$$

where

Pr(H) is the prior probability

- *Pr(D)* is the marginal probability
- *Pr(H|D)* is the probability that the proposed hypothesis is true given some data that were actually observed. This is the posterior probability
- *Pr(D|H)* is the probability of observing the data given that the hypothesis is true. This is the likelihood.

Bayes Theorem can also be written as:

$$Posterior\ Probability = \frac{Likelihood\ x\ Prior\ Probability}{Evidence}$$

From this, the posterior probability is proportional to the prior probability time the likelihood.

Equation (1.2) – Bayes' Theorem for Two Hypotheses

Consider two hypotheses H_0 and H_1 which are 'mutually exhaustive and exclusive' i.e. one and only one is true. Before having access to any evidence, the respective prior probability of each hypothesis is *$Pr(H_0)$* and *$Pr(H_1)$*. Suppose that we have observed some data *D*, such as the results of a test and we know from past experience that the probability of observing y under each hypothesis is *$Pr(D|H_0)$* and *$Pr(D|H_1)$* respectively. These are the likelihoods.

By adapting Equation (1.1), we have the identity:

$$\Pr(H_0|D) = \frac{\Pr(D|H_0)\,.\Pr(D)}{\Pr(H_0)}$$

where $Pr(y) = Pr(D|H_0).Pr(H_0) + Pr(D|H_1).Pr(H_1)$ is the overall probability of D occurring

Now H_1 = 'not H_0' and so $Pr(H_0) = 1 – Pr(H_1)$ and $Pr(H_0|D) = 1 – Pr(H_1|D)$. In terms of odds rather than probabilities, Bayes' Theorem can be re-expressed as:

$$\frac{Pr(H_1|D)}{Pr(H_0|D)} = \frac{Pr(D|H_1)}{Pr(D|H_0)}\ x\ \frac{Pr(H_1)}{Pr(H_0)}$$

Now *$Pr(H_1) / Pr(H_0)$* is the 'prior odds', *$Pr(H_1|D) / Pr(H_0|D)$* is the 'posterior odds', and *$Pr(D|H_1) / Pr(D|H_0)$* is the ratio of the likelihoods. Hence

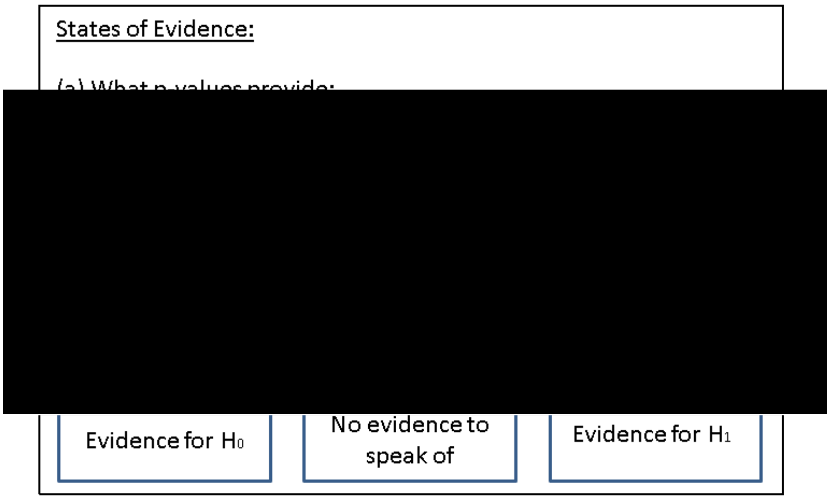
Posterior odds = likelihood ratio x prior odds

In the context of hypothesis testing, this can also be thought of as:

Posterior confidence = Bayes Factor x Prior confidence in H_1 rather than H_0

Under the Bayesian framework, the Bayes Factor provides a measure of the strength of the evidence for one theory verses another (e.g. H_1 verses H_0). This value is read directly hence a Bayes Factor of 5 suggests that the data are 5 times more likely under H_1 than H_0. Thus, if the Bayes Factor is about 1, the experiment was not sensitive. A value greater than 1 suggests that the data supports H_1 over the null whilst values less than 1 support H_0 over the theory being tested. As highlighted by Dienes and Mclatchie (2017), Bayes Factors have a distinct advantage over p-values in that they are able to provide a measure of strength of evidence, indicating the extent to which one's belief ought to change. Whereas p-values are interpreted as a dichotomous decision to retain or reject H_0 (Figure 1.1a), following the advice set out by Jeffreys that Bayes Factors of more than 3 are worth taking note of, it is possible to distinguish between evidence for the null hypothesis and insensitive data. Hence where the Bayes Factor is less than 1/3, this provides notable support for the null. Values between 1/3 and 3 suggest that there is no evidence to speak of. Those greater than 3, provide noticeable support for the theory (H_1) (Figure 1.1b).

Figure 1.1: Interpretation of Hypothesis Testing under (a) the Frequentist Framework and (b) the Bayesian Framework



Adapted from Dienes and Mclatchie (2017: 2)

Bayes' Theorem itself is utterly uncontroversial and adheres to the axioms of probability. It is important to reiterate this as many anti-Bayesian arguments have hinged upon creating controversy around the 'whimsical' choice of priors in the absence of genuine prior experience, branding them unscientific (Western, 1999).

Historically critics e.g. Efron (1986) expressed concern that there was also the potential for two researchers analysing the same data to have different prior beliefs and hence arrive at sets of different outcomes or posterior beliefs. However, this is now recognised as a key strength of Bayesian approaches since it enables subjectivity and context to be acknowledged. The result is that 'the prior distribution is explicitly specified and justified for a sceptical scientific audience' (Kruschke et al., 2012: 726). This transparency, which is sometimes lacking in Frequentist approaches, can also be extended by either conducting the analysis with more than one prior to demonstrate the invariant nature of the posterior distribution, or by using a noncommittal broad prior. A further advantage in relation to priors is that the probabilities for events are conditioned on the context, which includes the observer and all the observer's background knowledge and assumptions (Spiegelhalter et al., 2004). Through the choice of prior(s), this subjectivity can be treated with respect, in an open and transparent manner. This view is particularly relevant in the context of evaluations of criminological interventions where the viewpoints of sponsors, investigators, reviewers, politicians, policy makers and 'consumers' (e.g. institutional actors within the criminal justice system or those who engage specifically with victims / offenders) need to be taken into account (Carr, 2010). Consequently, a range of different priors may be utilised in the design, but potentially not reported as part of the results.

Bayesian Approaches as an Alternative to NHST: Transferability from Other Disciplines

One of the key methodological issues in the social sciences is that the way in which data is collected means that it does not always fit the criteria of being randomly selected cases and/or repeatable experiments – key features of traditional 'Frequentist' approaches. Yet these are the assumptions upon which NHST is based. In seeking to apply techniques - calculating standard errors, confidence intervals and performing significance tests (both explicitly and disguised within more complex statistical modelling) we risk 'errors, wasted opportunities, vanishing breakthroughs, and unwarranted conclusions' (Gorard, 2014b: 5). Doubt over the appropriateness of applying such tests to the types of data that we frequently come across within the social sciences generally has been the topic of much academic debate particularly in disciplines aligned to criminology such as the cognitive sciences (see for example Lambdin (2012), Gigerenzer and Marewski (2015)). With this in mind, the widespread adoption of alternative Bayesian approaches which are not dependent upon sample size, random sampling or repeated experiments have the potential to negate many of the abuses which have become unfortunately become so pervasive in social science research.

Successes in other disciplines, such as medicine, psychology and ecology suggest that it will be possible to transplant, with some minor adaptions, Bayesian approaches into criminology. Already Bayesian approaches have been used to explore different aspects of human behaviour and cognition including the assessment of risk for violent recidivism through multivariate Bayesian classification (Mokros et al., 2010); a Bayesian learning theory of deterrence among serious juvenile offenders (Anwar and Loughran, 2011) and the use of 'Bayesian Truth Serum' to consider the accuracy of survey responses in perceptual deterrence studies (Loughran et al., 2014). Although these come from psychology, it is easy to see how approaches could be replicated. Within criminology Bayesian quantile regression has been undertaken to analyse potential risk factors for the incidence of violent crime (Wang and Zhang, 2012) whilst Bayesian spatial techniques have been used by geographers and public health specialists to investigate journey to crime patterns for serial offenders (Levine and Lee, 2009; Levine and Block, 2011). Bayesian hierarchical models have been employed to look at arrest rates (Cohen et al., 1998) whilst Blattenberger et al. (2010) have compared three different types of Bayesian modelling techniques to explore the criminological, sociological and economic factors which predict parolees' return to prison. This latter example coming from academics based in economics.

Within public health literature examples can be found which also have a criminological slant including work estimating the prevalence of injecting drug users at a regional level (King et al., 2009; King et al., 2014a) utilising the small area techniques highlighted by Fienberg (2011) whilst geographers have contributed to understanding about the spatial relationship between alcohol outlets and violence (see for example, Zhu et al., 2006; Cunradi et al., 2012; Mair et al., 2013; Erickson et al., 2015; Fitterer and Nelson, 2015) and have begun to explore the potential for using Bayesian spatio-temporal modelling to look at localised crime trends (Law et al., 2014). These bodies of work utilise techniques which 'borrow' strength from other, typically neighbouring areas to refine the quality of the estimate.

Despite these examples, criminology is yet to embrace the advantages offered by employing Bayesian techniques. One of the few instances where a criminologist has applied Bayesian approaches to crime and criminal justice is the work by Berk et al. (1992a; 1992b) around policing domestic abuse in Colorado Spring. Now twenty-five years old, these papers rely on methods of evidence synthesis to consider the deterrent effects of arrest, a feature also utilised by Sullivan and Mieczkowski (2008) in their consideration of the utility of applying Bayesian approaches to synthesize the evidence from intervention studies.

Taking Stock and Looking Forward

The assertions from Barnes et al. (2017) come almost twenty years after the criminologist Bruce Western advocated to sociologists that 'Bayesian statistics offers practical methods for statistical inference that are rooted in the basic rules of probability theory. By using probability to describe uncertainty about parameters, the Bayesian approach converges with standard sociological understanding' (Western, 1999: 31). Much of this stems from the fact that despite mathematical advances, for a long time within the social sciences, Bayesian statistics was seen as a minority topic with Bayesian approaches often being dismissed despite a growing disquiet about the 'logic' of NHST and use of p-values, because of controversy over the use of subjectivism (see for example Stone, 2013: 119-128). This position is slowly changing and there are now several popular text books available which are aimed specifically at social scientists (see for example, Jackman, 2009; Kruschke, 2015; Kaplan, 2014).

Whilst criminology is not alone in its reliance on NHST, there are signs that other disciplines have begun to warm to the idea of using Bayesian approaches. In this respect, we cannot afford to be left behind. This is particularly true if we wish to (1) produce quantitatively informed research to inform policy and practice, and (2) make optimum use of the growing amount of administrative data that is collected at different stages of the criminal justice system. The discipline has previously demonstrated that it is adept at borrowing from its neighbours, with criminologists having shown their willingness to utilise techniques from other disciplines such as data visualization techniques including geospatial applications to consider crime trends (Chainey and Thompson, 2008; Chainey and Radcliffe, 2005) and data linkage to explore re-offending (Ministry of Justice, 2014a). As such they have demonstrated that they can be responsive to the challenge facing all social scientists to 'Import, Introspect and Innovate in order to better answer the questions of interest in the field' (Bushway and Weisburd, 2006: 1). However, in neglecting to explore the potential that Bayesian approaches may bring to criminology, then I believe we risk undermining the progress made thus far as a discipline in gaining credibility and legitimacy when it comes to informing policy decisions. It is therefore vital that criminologists continue to be both innovative and introspective in their analytical approaches, importing new and novel ideas where applicable from others.

1.4 From the New Penology to the Advent of Digital Criminology

The resurgence in the use of Bayes' rule in the 1980s and 1990s coincided not only with the dawn of the computer age, but also with the advent of actuarial justice - Feeley and Simon (1992; 1994) identified this emergence of new discourses, the formation of new objectives for the system and the deployment of new techniques as features of a 'new penology'. This shift marked a radically different orientation in the way in which crime was governed (known about and acted on), with 'the language of the new penology… anchored in the discourse of systems analysis and operations research. It conceives crime as systemic phenomenon and crime policy as a problem of actuarial risk management' (Simon and Feeley, 2003: 78). Since this time there have been significant advances in statistical application and the discipline has further evolved to meet the challenges and opportunities facing criminology in the age of Big Data. Notably, there have been advances in terms of computational power which has both increased the accessibility of the mathematics required to model some of the more complex relationships that exist in real life data and technological advances which have led to the digitalization of administrative data on a near universal scale.

The drive for efficiency and increasingly managerialist approaches adopted by the New Labour Government (1997-2010) under the auspices of risk (Turnbull and Spence, 2011; Brownlee, 1998) has resulted in the exponential growth of 'routine' data being collected. Within criminology, this includes data which enables an individual's progress through the criminal justice system to be monitored; provides details of both workflows and the workforce available to do this, along with the number of crimes recorded and convictions secured. The adoption of case management systems and the use of standardised tools for monitoring and risk assessment means that there is now a phenomenal amount of information about the criminal justice system available through government websites, from high level statistical trends to detailed (but typically anonymised) datasets. However, it is the data held by individual agencies that perhaps have the greatest potential to inform our understandings of the aetiology of crime and society's responses to offending behaviour since it is possible to link this individual level data to other sources including social survey data, victimisation and offending surveys, and administrative data around health, education, family life, employment and benefits. However, the utility of this data for contemporary criminology is only now starting to be appreciated, with the creation of the Administrative Data Research Network in 2013 making it easier for approved researchers who want to use government data for their social or economic research to access anonymised versions of datasets.

Across the social sciences, it has been suggested that there has been a digital turn, not just because of the increased digitalization of administrative data, but also the routine use of digital devices. Key developments such as the Internet and mobile technologies have created opportunities and challenges for criminologists, not least because of the emergence of new crime types which has in turn required legislative change and the employment of new, often technologically based responses. However, digital devices also enable researchers to collect, store and transmit numerical, textual, aural and visual signals. Thus, the digital turn has provided both the resources and sources of information for criminologists to analyse using emergent computational techniques from the organisational sciences and research rooted in artificial intelligence and expert systems. Such is the fundamental shift that this has promoted in the way in which research is now being undertaken in the social sciences and humanities has led commentators such as Kitchin (2014) to suggest that Big Data has created new epistemological approaches for making sense of the world and paradigm shifts.

Echoing developments in other social sciences and humanities, Smith et al. suggests that digital criminology 'concerns itself conceptually, methodologically and empirically with the task of understanding how digital devices/data are mediating experiences, impressions and processes of crime/crime control in familiar and strange ways' (2017: 263). Whilst Chan and Bennett Moses (2016) predict that the advent of 'Big Data' and machine learning algorithms will transform how criminologists work and think, I believe that in the context of seeking to predict future offending behaviour, we cannot overlook the complexity of human behaviour and social relations. As a result, whilst it may be appropriate in some areas of criminology to 'mine' data looking for new insights, caution needs to be applied before abandoning theory and prior understandings of recidivist behaviour in favour of a seemingly 'neutral' algorithms to aid criminal justice decision making. This is not to say that it may not be necessary to revise our views as a result of new evidence, but in a field where there is already concern about the creation of artefactual risk factors and an over-reliance upon correlations rather than causality (O'Mahony, 2009) enabling data to speak for itself, free from theory is too great a risk.

Much has been made of the potential for machine learning algorithms to generate *Minority Report* style models which would enable law enforcement to predict and punish crimes before they happen (see for example Mayer-Schibverger and Cukier, 2013). However, since these are still dependent upon the quality of the underlying data, if this has inherent biases then the resulting model will also have these biases (Issac and Dixon, 2017). For example, it has been demonstrated that the Correctional Offender Management Profiling for Alternative Sanctions (Compas) used by the a US court for risk assessment, is biased against black prisoners (Buranyi, 2017) whilst PredPol, a program used by predominately US police departments, but also Kent Police (O'Donoghue, 2016) to predict crime hotspots has been shown to get stuck in a feedback loop of over-policing in communities which are predominately black and/or brown (Lum and Isaac, 2016; Robinson and Koepke, 2016). This has implications for civil rights since equating locations with criminality amplifies problematic policing patterns (Shapiro, 2017: 458) Although there are instances where artificial intelligence has "successfully" predicted the outcomes of trials (see for example Johnson, 2016 in relation to verdicts at the European Court of Human Rights), there are calls for police agencies, software firms and the public to become more aware of the limitations of using machine learning techniques that rely on historical crime data since they risk fuelling a cycle of distorted enforcement (Robinson and Koepke, 2016).

O'Neil (2017) advocates, that data integrity checks are required so that we do not become overly reliant upon blindly applying algorithms which maintain the status quo. The distinct advantage of utilising Bayesian approaches with their ability to update models as new information becomes available, is that unlike machine learning, there is scope to incorporate both theory - through to the use of priors - and data from other sources (Berry, 2005). In the context of predicting offending behaviour this includes utilising narrative information held within an individual offender's case history and practitioner judgement (Deandrea et al., 2014), and accepting that there will be uncertainty within any model. Doing this enables the 'big picture' to be seen and helps counter concerns that relying upon administrative data to inform public policy provides only a perspective of crime viewed through the lens of the criminal justice system itself (McVie, 2016).

The stance taken by this research is that the advent of Big Data and digital criminology represents an opportunity for criminologists since it provides it offers the empirical flexibility to probe properly theorised lines of inquiry. Echoing the views of Langton and Bannister (2017), it is suggested that what Big Data does is enable criminologists to 'slice, dice and splice' datasets in multiple ways in order to advance the understanding of causal mechanisms.

Alongside the emergence of new data has come new techniques delivered through progress in computing and data science. This was apparent in the 1980s and 1990s when the increased computational power revolutionised the way in which researchers be it in the environment, economics, health, education or social sciences began to look at their data. Then it was necessary to respond to the curse of high-dimensionality' (McGrayne, 2011) with computers generating a multivariate revolution and spawning a plague of unknowns – the need to analyse more than more than one unknown at a time, and to calculate the relationship between multiple variables and ascertain their impact on each other. This proved to be a challenge for both Frequentist and Bayesian statisticians, but presented an opportunity to learn from those in business schools and theoretical economics who had been utilising Bayes' rule to aid decision making under extreme uncertainty and in the absence of sample data. The digital turn has similarly brought with it new techniques. Machine learning is possibly a step too far at this stage due to inherent biases in criminal justice data which currently limit its potential for predicting future offending behaviour, but this does not mean that as a discipline we should not seek to explore the possibilities that the advent of digital criminology affords us. It is therefore important that we continue to 'adapt the criminological gaze and imagination' so as not to 'impinge of the quality of the contribution [that] criminology can make to crime and justice processes' (Smith et al., 2017: 264). As part of the epistemological shift that Big Data and digital criminology has brought about, it is the contention of this research that now is an opportune time to expand the boundaries of contemporary criminological theory and research by exploring the utility of adopting Bayesian approaches within the discipline.

1.5 Doing More with Less: The Increased Use of Administrative Data

With increasing demands on an already stretched public purse, the focus has become one of doing more with less. As highlighted in the previous section, attention has turned to how to optimise the use of what has become a rich portfolio of data resources with the ESRC identifying as part of the Secondary Data Analysis Initiative that these are ripe for delivering high-quality and innovative research, generating knowledge exchange and policy and practitioner impact (Economic and Social Research Council, 2016). Whilst the volumes associated with 'Big Data' may address the issue of sample size, this emphasis on administrative data and re-using survey data is once again taking the discipline in a new direction and requires the researcher to adapt and learn new skills. It is therefore timely to once again be introspect and innovative, to look to import ideas and techniques from aligned disciplines such as public administration. If we are to do this then we need to bear in mind the observation from Gill and Witko (2013: 457) that public administration research 'generally uses data incompatible with standard Frequentist statistical thinking because they are usually population measures that can never be repeated as if in a standard experimental setting'.

Overcoming Methodological Challenges

The nature of the data utilised within criminology includes collections arising from the use of large-scale survey methods to capture snapshots of criminal activity and the victim experience of crime; the results of experiments and evaluations, and increasingly the systematic collation of data around criminal justice processes / outcomes. As budgets for research have been scaled back and the challenge of obtaining ethical approval for surveys with vulnerable people has intensified, fewer large-scale surveys are being conducted. The flip side of this is that there is increasing emphasis on using administrative data which is systematically collected for monitoring purposes to explore many of key policy issues.

Criminology's growing statistical evidence base is particularly amenable to the application of Bayesian approaches since administrative datasets often suffer from issues relating to collinearity – they typically contain large numbers of variables that can be causally related, with many also being non-stochastic i.e. the data is generated as a population rather than from a repeatable known probability process. Whilst there may be missing cases or missing values, under the Bayesian framework, these cases are considered to be a cause of bias rather than being a consequence of random sampling variation, an issue which can be addressed through judgement but not through significance testing. These characteristics create conceptual problems for traditional statistical inference:

> 'First, the data are not generated by probability sampling or random assignment. Second … an apparent population is the result of a data generation mechanism that produces only a single batch of data. In effect the machinery is turned off after a single batch is produced; the data generation mechanism cannot be expected to produce another dataset.'
>
> (Berk et al., 1995: 422)

In the quest for more reliable evidence of cause and effect along with a means to evaluate the effectiveness of interventions, experimental criminologists have promoted the use of randomisation as the 'best method for drawing causal inferences between treatment programmes and their outcomes' (Weisburd et al., 2007: 3). In exalting the virtues of techniques such as RTCs, it is inferred that non-randomised studies have less internal validity and that it is much more difficult to control for both measures and unmeasured factors or influences. However, it is worth noting that since Bayesian probability models are derived from subjective judgement, and hence do not require any underlying physical justification for a randomisation mechanism, the latter requirement is irrelevant. Thus, conducting experiments under the Bayesian framework negates issues around the power of the experiment and there is less emphasis upon achieving minimum sample sizes to detect effects. In this respect, Bayesian approaches are considered to be more efficient especially since sample size has become something of an obsession as researchers seek to demonstrate that their findings are empirically sound:

> 'a claim is commonly made that in some ways research in the social sciences is harder than in the natural sciences because the cases are more variable and less inherently predictable … In order to make believable claims, social science research would therefore need a larger number of cases than used in other area of investigation.'
>
> (Gorard, 2014a: 50)

Under the Bayesian framework with concerns about randomisation are negated, there is also more scope to undertake sub-group analysis it is possible to do this without being constrained by minimum sample sizes. This is particularly advantageous when looking at rare events since small datasets can be more effectively handled due to the incorporation of prior information in the estimation. That is not say that Bayesian approaches are perfect. Outside of criminology the difficulties of determining rates for different subgroups using both Frequentist and Bayesian approaches represents a challenge for statisticians wishing to demonstrate the effectiveness of interventions:

> 'Modern medical science is poorly equipped for identifying characteristics of patients who benefit from particular therapies, in large part because of the rigor of frequentist methods. In particular, the frequentist approach is not very good at discriminating subsets of patients who benefit, but many Bayesian methods are "too good" in the sense that they are overfitting. Perhaps a spirit of ecumenism in which Bayesians and frequentists learn from each other will be necessary to begin to crack this knotting but critically important problem.'
>
> (Berry, 2006: 429)

1.6 The Availability of Administrative Data

With the advent of the increased digitalisation, there has been growing recognition of the research potential of administrative data and its ability to inform policy and practice around a range of social, environmental, health and security issues. In 2012, the Cabinet Office published *The Open Data* White Paper which suggested that '…data is the 21st century's new raw material' (2012: 5). The richness of the largely untapped sources was further acknowledged by the Administrative Data Taskforce who subsequently published a series of recommendations to address the challenges which needed to be overcome if the UK is to become a world leader in research using de-identified administrative data. They found that:

> '… access to and use of such data for research purposes in the UK has been difficult, due mainly to the concerns that data holders have had about the possibility that information that identifies individuals could enter the public domain or because of legal restrictions they face on the uses to which such data can be put.'
>
> (Administrative Data Taskforce, 2012: iii)

A key driving force in moving this agenda forward has been that the data is relatively inexpensive to exploit, compared to the costs of establishing specially commissioned surveys additionally in using routinely collected data, it is perceived that it is more efficient since research findings can be generated quicker. This argument echoes the views held around secondary data analysis – that this is a 'relatively quick method of research as someone else has already been through the more time consuming job of collecting the data' (Rowlingson, 2004: 139). However, it is not without its limitations as:

> '… the available data do not always perfectly fit the secondary analysts' research question for a number of reasons. Perhaps the population is slightly different. Or perhaps the sample is not large enough to enable certain types of subgroup analysis. Or perhaps some key questions were not asked, or at least were not asked in exactly the way the secondary analyst would have liked.'
>
> (Rowlingson, 2004: 140)

In the context of British research, it is further acknowledged that we lag behind other jurisdictions (such as the Nordic countries) in our abilities to make optimum use of administrative data due to the lack of unique identifiers with which to routinely link data and the fact that we generally do not seek people's permission to do this (McVie, 2016). This limits our ability to make joined up public policy decision making.

As will be discussed in greater depth in Chapter Three, the administrative data being utilised for this research is drawn from the case management system at a local Youth Offending Team. As such the process of linking multiple sources of information has already been undertaken by members of the administrative staff and practitioners at the Youth Offending Team (YOT) who are familiar with the individuals referred to the service. Hence it has been possible to create a de-identified linked database containing the young person's risk assessment scores, key socio-demographic characteristics, offending and court records. Access to this data has been secured though the Western Bay YOT Manager who is also the Data Controller. A number of conditions were imposed to protect the individuals whom the data relates to and ensure adherence to both the principles of the Data Protection Act 1998 and also management of information advice set out in *Advice on Information Management in Youth Offending Teams* (Youth Justice Board, 2011). This includes making provision for the safe storage of any data considered to be personal or sensitive. In order to adhere with these requirements, data has been extracted from Childview – the case management system by the YOT's Information Officer. Working versions of the dataset have been prepared within the secure environment of the YOT office with all identifying information being stripped out and replaced by a unique research ID. The lookup for this has been retained on the YOT's server.

The Application of Bayesian Approaches to Administrative Data

Gill and Meier (2000) have previously argued that public administration researchers should embrace Bayesian approaches, an argument which has taken on renewed importance in recent years as the volumes of data collected for administrative purposes continue to grow exponentially. Their augments apply equally to criminology where examples can also be found of data representing 'apparent populations' (Berk et al., 1995) – collections which usually describe an entire set of objects of interest, providing details of fluid events. Such one-time events are often situational in time and circumstance and hence why they can never be replicated. That is, we cannot go back and re-survey and 'assume that no attitudes, experiences or administrative events have changed. Thus our datasets represent a fixed, unique look at the phenomenon of interest' (Gill and Witko, 2013). In this instance, since all young people who come into conflict with the law are referred to their local YOT, the administrative data available for this research consists of a rich series of datasets of the 'apparent population' rather than being a sample.

As part of their rationale as to why Bayesian approaches should be adopted in public administration research, Wagner and Gill (2005) highlight an issue which commonly occurs within administrative data which reinforces the need to consider adopting alternative approaches:

> 'Public administration research often suffers from issues relating to collinearity, since scholars regularly obtain datasets with a large number of variables that can be causally related …This can create difficulties in a linear model as collinear explanatory variables carry little independent information, and the least squares estimator does not then provide a means to distinguish one co-efficient from another.'
>
> (Wagner and Gill, 2005: 3)

Whereas, in medical epidemiology researchers are very aware that confounding variables, biases and weak measures can lead to the discovery of unreal risk factors, O'Mahony (2009) argues that there is a tendency within RFR to ignore the question of effect sizes as long as statistical significance has been established, and to avoid testing the causal potency of apparent risk factors. This, he maintains had promoted the production of artefactual risk factors.

A key benefit of utilising administrative data to advance understandings of causal mechanisms is that typically within case management systems, when new information is added, it is 'date stamped'. This enables temporal precedence to be established.

2 Introducing the Case Study

2.1 Context

In selecting risk assessment in the youth justice system in England and Wales as a case study, it is recognised that the quality of the evidence base that underpins this process has been widely criticised and hence this research also provides an opportunity to extend knowledge and understanding around the relationship between youth offending and the framework of risk and protective factors. This chapter therefore sets out the strengths and limitations of risk assessment processes. This is done with a particular emphasis upon conceptual and methodological criticisms since this is where there is greatest scope to advancement through the use of alternative probabilistic methods.

Responding to Calls for a Post-Positivist Approach

Drawing upon complexity theory, Case and Haines present an argument in which they posit that 'the crude and imprecise *measurement* of risk in youth justice processes has fed into insensitive *analyses* and produced invalid conclusions that risk factors exert a linear, proportionate and deterministic influence on offending behaviour by young people' (2014: 132). Since the validity of research outcomes and conclusions are inherently linked to the tools of measurement and analytical approach utilised in research, they assert that 'using an imprecise and insensitive measurement tool and plugging measurements uncritically into statistical analyses results in alchemy: crude, invalid and artefactual results and conclusions that are distanced from individual and social realities' (2014: 133). Goldson and Muncie whilst making their case for youth justice with integrity, similarly argue that 'the social world and the processes of youth justice formation are far more complex than oversimplified evidence-based and what works discourses often imply'. They make the charge that 'the positivist assumption that quasi-scientific laws and rational prediction are not only possible and desirable, but also essential, for modernising youth governance is flawed' (2006: 98).

These arguments advance the limitations summarised in Chapter One around the use of NHST, calling for post-positivist statistical analyses. Whilst Case and Haines (2014) do not provide any details of what this might look like, they advocate as promising approaches such techniques as Bayesian analysis and data visualisation.

Achievement of the research aim i.e. to demonstrate the utility of Bayesian approaches to risk assessment processes within youth justice, is not only in keeping with the ASA statement, but also with the suggestions made by Barnes et al. (2017) for criminology generally and those made by critics such as Case and Haines (2014) with respect to risk assessment within youth justice in England and Wales. Thus, the choice of case study demonstrates the motivation to additionally further knowledge and understanding through exploration of the relationship between reoffending and the paradigm of risk and protective factors:

> 'A different or broader methodological profile in a scientific field often leads to new and varied insights. Moreover, because any methodology or tool associated with probability and statistics is created rather than found, different and broader approaches can be formulated at any time if the will to do so exists'.
>
> (McKee and Miller, 2015: 473-474)

Transferability

In the context of the case study chosen, it is the successes in medicine that are the most encouraging with Bayesian statistics having now permeated all the major areas of medical statistics including clinical trials; epidemiology; meta-analysis and evidence synthesis; spatial modelling; longitudinal modelling; survival modelling; modular genetics and decision making in respect to new technologies. The quasi-medical nature of the risk factor prevention framework which underpins the risk assessment tool bodes well conceptually for the application such statistics to youth justice and criminology more generally.

Particularly in the context of analysing multiple risk factors, use of Bayesian inference in medicine has been used to demonstrate the strength of links between exposure and disease – a key diagnostic feature. As the medical profession have demonstrated, having the correct diagnosis means that an appropriate treatment plan can be developed which is tailored to the individual and their circumstances. In principle, this is what happens in youth justice as well. The problem is however, that in youth justice, 'the science is … not always as scientific as we would like and in fact substantial problems can exist with the method used to identify risk facts in that quantitative variables are, in fact, constructs of social phenomenon' (France, 2008: 4). In presenting subjective processes as objective and scientific, there is an oversimplification of the potentially complex and dynamic aspects of children's lives, experiences, perceptions and thoughts into readily quantifiable and targetable risk 'factors'. It is these issues along with those associated with the evidence base which are summarised in this Chapter.

The Rise of Risk Orientated Thinking

The development of a standard risk assessment tool for use with young people who have offended did not occur in isolation. Rather it reflects the growing momentum with which policy and practice has become increasingly focused on risk (Turnbull and Spence, 2011). Indeed Kemshall et al. (1997) suggested that 'risk assessment, risk management, the monitoring of risk and risk-taking itself were rapidly becoming the dominant *raison d'etre*' for personal social services including probation. Specifically, they observed that:

> 'Notions of risk are increasingly becoming embedded in organizational rationales and procedures for both the services and relationships with users and clients. Similarly,

> estimations about risk have become key in identifying priorities and making judgements about the quality of performance and what should the central focus of professional activities. Notions of risk have taken on a strategic significance for rationing services and holding professionals and others accountable in a changing political and economic context where potential need and demand is increasing but where there are insufficient resources.'
>
> (Kemshall et al., 1997: 214)

Twenty years later risk orientated thinking is now embedded in almost all aspects of mainstream criminology (Walklate and Mythen, 2011). For example:

- In the prison system the risk of re-offending has to be determined before decisions can be made about releasing offenders, particularly for those who commit serious violent and sex offences who may be subject to an indeterminate sentence (Robinson, 2002; Buchanan and Grounds, 2011).
- In the criminal justice system, the police need to weigh up the chances of suspects absconding / failing to attend court; potential further offending or hindering the investigation in some way e.g. interfering with witnesses or evidence, whilst on bail (Dhami, 2005; Ofili, 2014).
- Associated with fear of crime, there are often individual concerns about the likelihood of becoming a victim of crime which can impact on perceptions of personal safety and security. These are often out of kilter with reality (Gray et al., 2011).

Although some of these decisions are made essentially upon the basis of individual judgement calls, the criminal justice system has becoming increasingly reliant upon standardised actuarial risk assessment tools, not just when considering sentencing and release, but also to make decisions around assignment to treatment. Having moved on from the prediction tables and first-generation risk assessment tools which were predominately unstructured professional judgements of the probability of offending behaviour, many of the second and third-generation risk assessment tools which have emerged largely since the 1990s, are grounded in the statistical association between risk and repeat offending (Schwalbe, 2007). Whereas second-generation tools were limited to prediction and classification, third-generation tools are characterised by their predictive role in informing intervention planning in addition to their classification role. Reflecting their respective roles as well as emerging knowledge about predictor variables and 'What Works', the focus of their content differs – the development of second-generation tools emphasized the classification of risk of recidivism irrespective of their content. Hence, they tended to be dominated by static risk factors like offence history. Whilst the dual focus of third-generation tools has meant that they usually consist of an array of dynamic risk factors which it may be possible to change as a result of intervention.

Third-generation tools are also required to gather information about criminogenic needs and responsiveness. The so-called fourth generation-tools take this approach one stage further, actively gathering information to facilitate planning, case management, supervision and service delivery

(Vaswani and Merone, 2014). A major goal of the fourth-generation instruments is 'to strengthen adherence with the principles of effective treatment and to facilitate clinical supervision devoted to enhance public protection from recidivism crime' (Andrews et al., 2006: 8). Thus '[c]urrent risk assessment practices are promoted on the basis of being able to provide an objective, impartial and rational decision-making process, reduce reoffending and increase public protection' (Lewis, 2014: 122). However, as this chapter will highlight, they have their limitations. It is both the design features and limitations of these tools, specifically the standardised tool used until recently within the youth justice system in England and Wales, which make this an ideal case study to demonstrate the utility of applying Bayesian approaches.

The Political Motivation for Commissioning a Standardised Risk Assessment Tool

Risk now appears across a range of social domains, such as health, welfare, crime, national security and the environment. With this, the terms risk and youth have become synonymous – a view that has become progressively more pervasive in the media and within policy responses. Young people have increasingly been perceived as being either 'at risk' or as 'posing a risk' (Armstrong, 2004; 2006). They are seen 'both as a treasured resource and as endangered and dangerous – at risk from others, to themselves, and to the fabric of communities' (Sharland, 2005: 36-37).

The problem of youth was played out in the media throughout the 1990s and 2000s. Panics about joyriding, alcopops, Ecstasy, girl gangs and persistent offenders predominated in the 1990s, to be joined by 'hoodies', 'boy racers', 'mini-moto riders', 'happy slappers', 'video-gamers', 'under-age binge drinkers', and 'feral yobs' the following decade (Muncie, 2009). In fuelling public concern, the media helped to perpetuate the notion of children as evil, a view that then became enshrined in legislation.

As Sharland (2005) observes, politicians and policy makers have become concerned with how best to preventing young people from taking or being exposed to risk, from becoming socially excluded, deviant, unhealthy or unproductive. Care leavers, teenage parents, young homeless, addicts or those with mental health problems have been identified as being discrete populations of children at risk who have tended to require a more welfare orientated approach. Whilst policy has sought to control those seen as being troublesome rather than troubled, at risk of offending or simply being offensive. There has however, within the risk rhetoric, been a blurring of these distinctions, with Goldson (2000; 2002) suggesting that concerns for the former have been subsumed by the 'need' to control.

The Crime and Disorder Act, 1998 restructured the delivery of youth justice in England and Wales, redefining its key purpose as preventing re-offending. Central to this were two concerns: the risk that involvement in the criminal justice system poses to young people's future and the accepted wisdom that young people grow out of crime (Phoenix, 2009b). At a policy level, notions of young people's needs began to be interpreted almost exclusively as 'criminogenic need' or 'risk of re-offending' promoting 'risk', its assessment and management to begin to dominate the 'new youth justice' (Gray, 2005; Armstrong, 2004). Represented as being 'the most radical shake-up of youth justice in 30 years' by then Home Secretary, Jack Straw (quoted in Pitts, 2005: 8), the Act introduced:

> '… fully-funded multi-agency groupings dedicated to work with young people who offend; the youth offending teams (YOTs); and the creation of a centralised, governmental body, the Youth Justice Board for England and Wales, charged with the realisation of an accountable, youth justice system and with the power and reach to deal with the problem of justice by geography, address the inequitable distribution of resources, and to effect a thoroughgoing reform of custodial institutions for children and young people'.
>
> (Bateman and Pitts, 2005: xvi)

The various other measures introduced by the Act provided for earlier and more intensive intervention in the lives of children and young people (Brown, 2005). In a climate where it was considered desirable to identify at an early age those considered to be at risk of future anti-social and offending behaviour, the policy emphasis was very much on the management and control of troublesome young people (Armstrong, 2006). To do this, it became necessary to identify those factors that make someone 'at risk' and for the development of a consistent approach for the youth justice system in England and Wales towards risk assessment.

Requirements for the Standardised Tool

Keen to promote consistency of practice within the new multi-disciplinary YOT settings, and to encourage practitioners to target interventions at the factors identified as being most closely associated with offending by young people, the Youth Justice Board set out a specification (in December 1998) for the development of a standard assessment profile to be used by the newly created YOTs. According to Baker et al. (2003), the key requirements for the tool were that it should:

- identify the key factors contributing to offending by young people
- provide a prediction of reconviction
- help to identify young people who may present a risk of serious harm to others
- identify situations in which a young offender is vulnerable to being harmed
- identify issues where more in-depth assessment is required.

There was also an expectation that the profile would be a 'live' document that would inform plans for working with young people (in both community and custodial settings). As such, it would be used to measure change over time when reapplied during, or at the end of, interventions. In addition to assisting in the collection of aggregate data, the Youth Justice Board (YJB) stated that its most important function would be 'to help YOTs to assess the needs of young people and the degree of risk they pose and then to match intervention programmes to their assessed need' (Youth Justice Board, 2000 cited in Baker et al., 2003).

The tender to design and produce the new assessment profile for the YJB was won by The Centre for Criminological Research (University of Oxford). Supported by an advisory panel consisting of representatives from YOTs, the secure estate, the Department of Health, the Department for Education and Skills, the Drugs Prevention Advisory Service, the magistracy and the police, the Centre designed ASSET. A tool which they felt incorporated and reflected a wide range of perspectives on the risks and needs of young people who offend.

ASSET, has in various forms, been the standardised risk assessment tool used across the youth justice system since YOTs came into being in 2000. However, as will be described in later sections, it has been subject to much criticism from practitioners and academics. It is this criticism, especially that focusing upon its reliance upon RFR and the methodological limitations of the evidence base which make it a particularly attractive case study for demonstrating the utility of Bayesian approaches.

In making this choice, it is acknowledged that ASSET has now largely been replaced by ASSETPlus. This fourth-generation tool was designed in response to the growing criticism and to address concerns around ASSET's usefulness and validity in the context of broader developments across services for children and young people, and the justice system itself. Although work to develop ASSETPlus began in 2010, its rollout across the YOTs and the secure estate has been beset by problems. It first went operational in October 2015, with the first Welsh YOTs getting ASSETPlus the following month. However, the deployment did not occur in Western Bay YOT – the YOT from which the data has been drawn from for this research, until April 2016. Given the emphasis upon predicting re-offending – a measure which can take up to 18 months to calculate, the timing of this research means that it was necessary to take this into account when selecting which data to utilise (see Chapter Three for details of the data specification). The roll out of ASSETPlus across the various English and Welsh YOTs was completed at the end of August 2017 (Youth Justice Board, 2017a) having taken almost 2 years.

In order to understand the various criticisms made about ASSET, it is important to recognise that many of these are not unique to youth justice. Whilst predictions of future offending are now an integral part of the criminal justice decision making process with ideas being incorporated from other disciplines, there are a number of key methodological limitations associated with the use of actuarial tools which undermine the assumption that being able to predict future criminality will reduce crime: firstly, the predictive accuracy of risk assessment tools; secondly, their ability to predict individual rather than group behaviour; and thirdly, the problem of predicting different types of offending. These limitations are considered within the remainder of this chapter firstly in the context of tools developed predominately for use with adults, before focusing more specifically upon those developed for young people and the role of risk factor research as the evidence base underpinning tools such as ASSET.

2.2 Probabilistic Decision Making in the Criminal Justice System

Predictive Approaches

Farrington and Tarling (1985) identify the following applications of predictive methods in criminology:

- The prediction of rates e.g. crime and imprisonment rates
- Parole and the evaluation of penal treatments
- Selective Incapacitation
- Dangerousness
- Delinquency

Whilst this list was drawn up more than thirty years ago, it provides a convenient starting point for considering issues faced by the contemporary criminal justice system in England and Wales. In outlining the development of actuarial tools in different settings, the intention is to provide context for discussions later within this chapter around how the use of Bayesian approaches have the potential to address some of the limitations of the risk assessment tools developed in relation to youth offending.

While the development of mathematical models to predict crime and imprisonment rates in the event of significant population, policy or legislative changes, fall largely outside the scope of the 'new penology' (Feeley and Simon, 1992; 1994), the other examples given reflect the shift in the direction of criminal justice. Earlier discourses of clinical diagnosis and retributive judgement began to be replaced with 'an actuarial language of probabilistic calculations and statistical distributions applied to populations' (1992: 452). Notably the emphasis switches from reforming the individual offender to consider aggregated groups such as "high-rate offenders" and "career criminals". These groups, along with other categories were defined by actuarial classifications. As part of this evolution, it is argued that the criminal justice system has become more concerned with managerial process with its goal no longer being to eliminate crime, but the identification and management of unruly groups through systemic coordination. This has been achieved through the deployment of new techniques such as statistical applications for assessing risk and predicting dangerousness.

Parole and the Evaluation of Penal Treatments

Farrington and Tarling (1985) believe that the greatest impact on policy and practice as a result of using predictive methods has been with regard to parole prediction. Whilst they provide details of a number of pieces of research which have influenced practice in both the USA and UK, it is the Burgess-type prediction devices which formed 'the core of actuarial parole prediction' (Kemshall, 1998: 45) until fairly recently. Under these, individuals are given a score based on binary responses to a series of predictor variables depending on whether the parole violation rate for the individual was greater than or less than the average for persons in that category, Burgess' methodology, developed in the early part of the twentieth century and replicated in subsequent studies, takes the form of a composite predictor, presented as an experience table which divides the sample into different risk groups with different probabilities of offending. Underpinning this is the assumption that a composite variable will predict the criterion more accurately than a single predictor. An English prediction score was constructed during the 1970s using sixteen variables covering offender's previous criminal history (type of offense committed; number of previous convictions and prison sentences; interval at risk since the last conviction; age at first conviction) plus the offender's age, marital status, living arrangements and employment history.

Work on the development of an actuarial reconviction predictor started in the 1990s, with the statistical analysis of the criminal records of 13,711 offenders being used to create the first national reconviction predictor for use by the Probation Service in England and Wales. Widely used, this second-generation tool was similarly based on static factors (such as sex, age and previous criminal history) but since these factors could not be changed, it failed to address issues which would enable correctional agencies to assess need or to plan or evaluate supervision. Various initiatives were sought to fill this gap, with work on OASys (a fourth-generation risk assessment system, linking assessment and case management (Lewis, 2014)) beginning in 2001. By 2006, this had become the standard system used by Probation throughout England and Wales, aiming to 'produce an assessment of dangerousness or risk of harm in addition to a risk score for reconviction' (Raynor, 2016: 31).

Evaluations of different penal treatments in the UK context have typically been linked to the 'What Works' agenda. Measuring the difference in outcomes for those in treatment and controls, these have rarely considered the mechanism which has brought about the change in behaviours, attracting criticism from realist criminologists such as Pawson and Tilly (2000). As such when applied in different geographies and with different types of offenders, initiatives have often had limited success. Where evaluations are being undertake of different penal treatments, propensity scores are often used to match control and test groups as an alternative to random assignment.

Selective Incapacitation

Interest in methods relating to the assignment of a lengthy sentence or other freedom-restricting penalties to repeat offenders grew in response to concerns that rehabilitation as a penal aim was not being achieved by existing treatments. The research was primarily focused on estimating the number of crimes prevented by mandatory sentence of incarceration for certain categories of detected offenders and depended on having detailed knowledge about criminal careers. Examples include Greenwood's proposed method of predicting which offenders committed offences at high rates whilst they were in the community.

In considering 'incapacitation effects' i.e. those crimes prevented while offenders are incarcerated, Greenwood's proposals were based a US survey of incarcerated males, with seven binary variables being selected to make up an additive predictive scale:

1. 'Incarcerated more than half of the two-year period preceding the most recent arrest
2. A prior conviction for the crime type that is being predicted
3. Juvenile conviction up to age 16
4. Commitment to a state or federal juvenile facility
5. Heroin or barbiturate use in the two-year period preceding the current arrest
6. Heroin or barbiturate use as a juvenile
7. Employed less than half of the two-year period preceding the current arrest'

(Greenwood, 1982: xv-xvi)

By identifying high-rate offenders, selective incapacitation policies were intended to target the most prolific offenders and design sentencing policies to incarcerate them during their most crime-prone years. During the 1990s, the reach was extended with the passing of 'three strikes' rules firstly in a number of US states before being adopted in the UK.

Reflecting the nature of the types of offences which fall under the definition of being 'grave crimes', there are two areas where risk assessment tools have been developed in the context of dangerous offenders – those assessing the risk of violence and those for sexual offenders. These will often rely more upon clinical prediction, utilizing 'the knowledge base, experience and expertise of professionals to make sense of someone who has been violent, and may include the use of actuarial or otherwise structured assessment protocols to inform the overall decision making' (Milner and Myers, 2007: 29). In the UK contexts, the International Classification of Disease (ICD-10) rather than the Diagnostic and Statistical Manual of Mental Disorders – Fifth Edition (DSM-5) tends to be used to provide the formal diagnosis required within psychological assessments of offenders presented to criminal courts prior to sentencing.

Douglas et al. (2016) suggest that there are currently more than 200 structured tools available for assessing the risk of violence in forensic psychiatry and criminal justice settings. Actuarial instruments (as opposed to structured clinical judgement tools) include the *Violence Risk Assessment Guide (*VRAG) (Quinsey et al., 2006) for serious violence prediction and the *Static-99* (Phenix et al., 2016) which is used with sexual offenders. Widely accepted as the definitive resource in assessing psychopathic personality disorders, the *Hare Psychopathy Check List – Revised* (PCL–R) is also commonly used in research on criminal offenders and forensic psychiatric patients (Hare, 2003). Notably in the UK context, such risk assessment tools form part of a wider clinical assessment process with risk assessment tools being 'used to roughly classify individuals at the group level, and not to safely determine criminal prognosis in an individual case' (Fazel et al., 2012).

Criticism of risk assessment within psychiatric literature has focused on the possibility that, in deploying risk assessment tools to realise justice or public protection, mental health professionals may fail to fulfil their professional obligations to their patients (Douglas et al., 2016). There are also considerable concerns around the predictive accuracy of actuarial tools, particularly where linked to post-sentencing detention and parole decisions. Where the probability of dangerousness is incorrectly identified, this could lead to low risk offenders being placed on lengthy treatment programmes or subject to prolonged detention in custody. Conversely high-risk offenders may be released prematurely, and there is a high probability of further offending. The implications of false positives and false negatives can therefore be significant. Hence an important element of the use of actuarial tools is that the rationale behind the decision is defensible, adding a layer of transparency which was not always afforded when using non-structured processes.

In the context of sexual offending where offending is relatively rare (i.e. a low base rate), the possibility of false positives is greater (Tully et al., 2013) and there is wide variability associated complex and multifactorial nature of this type of crime (Borum, 1996; Neller and Petris, 2013). Evidence suggests that within the sex offender population, there are differences based on the nature of the offence committed e.g. contact and non-contact, child sexual abusers and rapists, and between highly deviant and low deviant men. However, Craig et al. (2003) highlight that little is known about the differences between late- and early-onset offenders and between those who successfully complete treatment and those who drop out or complete treatment with little or no evidence of cognitive shift. The difficulties in predicting such behaviour is further complicated by the fact that many sex offenders engage in criminal behaviour that is not limited to deviant sexual activity. Criticisms of existing tools include question marks over their appropriateness in assessing sexual offenders with intellectual disabilities, from minority ethnic groups (Tully et al., 2013) and female offenders (Abulafia et al., 2015).

Increasingly routine risk assessment protocols are required to address specific factors relating to dual diagnosis. Many individuals who enter and move through the criminal justice system are portrayed as being high risk as a result of having substance misuse issues and/or mental disorders. For the criminal justice system those individuals who experience serious substance misuse and mental disorders represent a significant challenge, often existing at the intersection with the health system (Rose, 2016). Not only does the multi-faceted nature of their risk necessitate a response from across multiple policy, legislative and organisational arenas, but the complexity of their lives and the rarity of the grave crimes committed by dangerous offenders poses a particular challenge for practitioners.

Delinquency

In 1950, the Gluecks developed a *Social Prediction Table for Delinquency* based on comparing 500 institutionalized boys and 500 unconvicted boys, matched on age, IQ, national origin and residence in underprivileged areas, against five factors. In determining a score for each boy, the percentage of those in his category who were 'delinquent' were summed to give a total which was subsequently used to discriminate between 'delinquents' and 'non-delinquents'. The Gleucks advocated that their prediction device should be used to identify potential 'delinquents' at the time of school entrance (age 6). However, inherent flaws in their work led to criminological prediction in general and in particular in predicting delinquency being discredited. Where work was undertaken to predict youth offending after the 1950s, it was limited to questionnaire-based approaches using multivariate methods within psychology (Farrington and Tarling, 1985).

There has since been a resurgence of interest in predicting youth offending associated with developments in adult contexts which has broadly followed the same generational pattern as outlined by Andrews et al. (2006). As such, the promise of contemporary risk assessment is dependent on their ability to accurately and reliably predict the classification of young offenders so that decisions can be made with levels and intensity of supervision as well as the nature of the treatment required. The principals of risk, need and responsiveness which underpin the tools state that:

> '…in order to constitute effective practice, the intensity of the intervention needs to be matched to the young person's level of risk , the intervention should address the specific needs that are contributing to the risk level and the intervention needs to be responsive to the young person's circumstances, cultural requirements, learning style and developmental stage.'
>
> (Vaswani and Merone, 2014: 2)

Without an accurate assessment which adheres to these principals there is a danger of unintended and unwanted consequences such as increasing the offending of low risk offenders. These concerns echo those made with regard to adult offenders but take on greater meaning for young people due to the net widening tendencies of the various pieces of legislation introduced by New Labour. Through the inter-connectiveness of their social exclusion agenda, risk factors emerged not just for crime but also social problems with marginalised and excluded communities being particularly targeted. Attempts to manage intractable social ills led to the blurring crime and social policies, and sanctions being introduced for anti-social behaviour (Kemshall, 2008a). As the strategy for tackling youth crime has evolved under subsequent Governments, there is also a risk that in times of austerity, that inappropriate decisions are made about individual risk and need which place pressure on limited services or resources.

Current risk assessment tools consist of a mixture of instruments which have been adapted from the adult arena and those developed specifically for use with under 18s. For example, the PCL-R has been adapted into the *Hare Psychopathy Checklist: Youth Version* (PCL:YV) for the assessment of psychopathic traits in male and female offenders aged 12 to 18. In contrast, ASSET was designed as a bespoke tool, drawing upon risk factor research. This has been the dominant paradigm for understanding and addressing youth offending for much of the last 20 years and is also a source of criticism. Notably whilst the pursuit of the risk factor prevention paradigm has proven to be attractive to politicians and others because it provides a framework for conceptualising the risk factors approach to researching the origins of youth offending and devising preventative strategies (and hence provides the basis for tools such as ASSET), it is quite distinct to the risk focused epistemological approach which is commonly found in medicine (Case and Haines, 2009).

2.3 Risk Factor Research: The Evidence Underpinning ASSET

Risk Factors for Youth Offending

Risk factor research utilises the concept of risk factors (Hale et al., 2005: 392-393), with Farrington and West's work with the Cambridge Institute of Criminology dominating the field. Their research, a longitudinal study of 411 working class boys from the age of eight in 1961 has been particularly influential in a UK context in shaping contemporary risk assessment tools. According to Farrington (1996), the major risk factors associated with youth crime are:

- *Prenatal and perinatal:* Early child-bearing increases the risks of such undesirable outcomes for children as low school attainment, antisocial behaviour, substance use and early sexual activity. An increased risk of offending among children of teenage mothers is associated with low income, poor housing, absent fathers and poor child-rearing methods.
- *Personality:* Impulsiveness, hyperactivity, restlessness and limited ability to concentrate are associated with low attainment in school and a poor ability to foresee the consequences of offending.
- *Intelligence and attainment:* Low intelligence and poor performance in school, although important statistical predictors of offending, are difficult to disentangle from each other. One plausible explanation of the link between low intelligence and crime is its association with a poor ability to manipulate abstract concepts and to appreciate the feelings of victims.
- *Parental supervision and discipline:* Harsh or erratic parental discipline and cold or rejecting parental attitudes have been linked to offending behaviours and are associated with children's lack of internal inhibitions against offending. Physical abuse by parents has been associated with an increased risk of the children themselves becoming violent offenders in later life.
- *Parental conflict and separation:* Living in a home affected by separation or divorce is more strongly related to offending behaviours than when the disruption has been caused by the death of one parent. However, it may not be a 'broken home' that creates an increased risk of offending so much as the parental conflict that led to the separation.
- *Socio-economic status:* Social and economic deprivation are important predictors of antisocial behaviour and crime, but low family income and poor housing are better measurements than the prestige of parents' occupations.
- *'Delinquent' friends:* 'Delinquents' tend to have 'delinquent' friends. But it is not certain whether membership of a 'delinquent' peer group leads to offending or whether 'delinquents' simply

gravitate towards each other's company (or both). Breaking up with 'delinquent' friends often coincides with desisting from crime.

- *School Influences:* The prevalence of offending by pupils varies widely between secondary schools. But it is not clear how far schools themselves have an effect on offending behaviours (for example, by paying insufficient attention to bullying or providing too much punishment and too little praise), or whether it is simply that troublesome children tend to go to high 'delinquency'-rate schools.
- *Community influences:* The risks of becoming criminally involved are higher for young people raised in disorganised inner-city areas, characterised by physical deterioration, overcrowded households, publicly-subsidised renting and high residential mobility. It is not clear, however, whether this is due to a direct influence on children, or whether environmental stress causes family adversities which in turn cause youth crime.

The reality however, is that as Brown highlights 'many thousands of factors may place young people 'at risk' of offending, including, at different ages, 'biological, individual, family, peer, school, neighbourhood, and situational factors' (2005: 100). However, this leads to problems as many children who are technically 'at risk' lead 'successful lives', thus there is also a need to understand factors which in many various combinations act in a protective way, mitigating risk.

The Methodological Limitations of RFR

Case and Haines (2009) provide a narrative of the origins and development of RFR, covering the role of key longitudinal and cross-sectional surveys have had in shaping our current understanding of the risk-reoffending relationship. In charting the chronological journey from the pioneering work of the Glueck's in the 1930s through to the current day, they consider the contributions made by different theoretical perspectives highlighting RFR's developmental origins; the role of ecological, pathways and integrated approaches of recent years, and the unfulfilled promise of the constructivist strand. Highlighting the significant underpinning of risk factor prevention paradigm (RFPP) provided by findings from the prospective longitudinal Cambridge Study in Delinquent Development, they lament that:

> 'Even the more complex contemporary explanatory models have struggled to break the development shackles put in place by the Gleucks and the Cambridge Study. It is difficult to pinpoint an example of RFR that has not taken the developmental influence of psychosocial risk factors as its theoretical starting point and utilised factorisation and statistical analysis of risk as its methodological basis.'
>
> (Case and Haines, 2009: 100-101)

Dividing their critique of influential studies into longitudinal and cross-sectional designs, means that Case and Haines are able to provide an appraisal of their respective strengths and weaknesses as well as comment more generically on issues that affect these types of studies. O'Mahony (2009: 110) extends the critique, highlighting 'how prominent proponents of the RFPP, like Farrington often appear to pay on perfunctory attention to the paradigm's inherent flaws and continue to oversell the approach or at least allow policy makers to do so'. Notably he points to a 'bizarre, oxymoronic admission' made by Farrington about how 'typically, prospective prediction (based on the RFPP) is poor, but retrospective prediction is good' to question why it is that ASSET – a tool which by definition is designed to predict the future, is underpinned by the findings from a prospective study.

Debates about prospective and respective studies aside, the key pertinent design feature is temporal sensitivity since being able to establish temporal precedence enables causality to be explored - whereas longitudinal designs track an individual over time, cross sectional designs are essentially snapshots although a time dimension can be added by having a repeated cross-sectional design and collecting data from different (but comparable) individuals. By default, cross sectional designs put the theory variables and their associations in static form whereas longitudinal designs enable change over to time to be measured and are able to consider dynamic measures. Potentially two important characteristics of change can be captured by the longitudinal designs: (1) within-person change across time, or trajectories, and (2) inter-individual changes that can either be predicted or used for prediction (Ployhart and Vandenberg, 2010).

Through the objectification of the social sciences, positivists have strived to establish a causal connection between aspects of the social world in a bid to explain human behaviour. The positivist school of criminology introduced the problem of causality into criminological thinking applying methods from the natural sciences. The result has been a focus on searching for the causes of criminal behaviour which has assumed that this behaviour is predictable and determined. Whilst some aspects of the theory have fallen out of favour, the legacy of others remains within RFR. Notably RFR has tended to rely on demonstrating causality through statistical relationships and as yet there has been little emphasis placed on explaining how risk is related to offending, or what processes link the two:

> 'Finding out who might be prone to offending is only a first tentative step in the process of answering much more crucial questions about how and why people actually come to offend. This easily made elision between correlate and cause characterizes both the RFPP and the risk-focused research literatures and generally serves to obscure rather than clarify the complex issue of causation'
>
> (O'Mahony, 2009: 102)

If we return to the rationale behind third- and fourth-generation risk assessment tools, it becomes clearer as to why conceptualisation, operationalization and time sensitivity are so important. With multiple functions, there becomes a need to have a greater understanding of *why* it is some young people come into conflict with the law and subsequently commit further offences; *why* certain interventions work for some and not for others, and *why* others may be more responsive to treatment. Without this 'risk is hidden beneath a plethora of correlations that in themselves tell us little about the socio-historical nature, meaning and significance of crime and its discourses in these time in which we are now living' (Armstrong, 2004: 113)

The Aetiological Focus

The basic principle of RFR is to identify those risk factors associated with offending and implement measures or interventions designed to counteract them. However, the developmental focus of RFR has meant that typically researchers have sought early childhood psychosocial factors that are statistically related with the onset of teenage offending. In doing this, RFR has tended to utilise broad (factorised) measures of risk factors, relating them statistically to broad categories of offending (i.e. a single offence of any type as counted as 'offending' and any three offences is taken to be 'serious offending'). As a result, studies of the risk factor-offending relationship for young people have been overly superficial, generalised and insensitive. It has also been suggested that there is a 'psycho-social bias' (France and Homel, 2006) which has resulted in 'an artificial restriction in the range of factors that have been explored' (Case and Haines, 2009: 22).

Pitts (2001) has been highly critical of the 'narrowing of the aetiological focus' relating to youth offending in the political discourse promoted during the 1990s by New Labour which he suggests has resulted in a 'strangely skewed criminological perspective'. This has manifested itself in the promotion of risk factors derived from the *Cambridge Study*, which have then been reduced in multiplicity from the original list to favour of an emphasis on parenting, schooling and peers. By the time of the *No More Excuses* White Paper in 1997, the key risk factors being promoted were being male, poor parental discipline, criminal parents and poor school performance - the central practice of the newly formed YOTs being to identify and respond to these identified risk factors.

Critiques relating to the robustness of the evidence base have been further compounded by New Labour's assertions about the 'What Works' and their commitment to 'modernization' and evidence-based policy formulation. Despite the promise that policy decisions should be based on sound decisions, it is notable that in *Misspent Youth '98* it is observed that 'few programmes for preventing offending by young people in England and Wales have been thoroughly evaluated' (para 81, Audit Commission, 1998: 59). This, they attribute to the information to undertake the evaluation being absent or incomplete, in part due to the lack of co-ordination between agencies and partly as a result of the low priority given to evaluating public spending by some of the agencies involved. There are hints of the managerialist approach to come in youth justice when it is asserted that 'without sound evaluation, it is impossible to judge whether investing in such options saves money overall – so all schemes should be properly costed and monitored' (para 82, Audit Commission, 1998: 59).

Moving forward, the YJB has professed a commitment to knowledge / evidence-based approaches to policy formulation and practice development. However, a number of critics including Case (2007), O'Mahony (2009) and Goldson (2010) have challenged the rhetoric, suggesting that the evidence (where is exists) has only been selectively used, often for political gain. Paylor suggests that 'the new focus on 'risk' is simply a device aimed at winning elections. Electoral anxiety is the motor force of the youth justice, as opposed to a considered and compassionate response to children in trouble' (2010: 31). The emphasis on what is considered to be 'modifiable' has meant that the wider socio-economic problems are disregarded, privileging the 'family' under the rhetoric of care and support rather than social harms such as poverty. Thus, by focusing on 'modifiable' risk factors, interventions are most likely to impact on those living in the most challenging material circumstances. (Jamieson, 2005; Bateman, 2011).

A key issue in trying to understand 'What Works' in terms of interventions is that having identified so called risk and protective factors, there remains little understanding about how these impact on an individual basis on offending behaviour. Despite attempts to simplify the relationship through the RFPP, characterising it as a 'linear risk paradigm' the reality is somewhat more complex (see Case and Haines, 2014). When attempts are made to assess how programmes underpinned by this paradigm work to reduce offending, the absence of a theory of change (Pawson and Tilly, 2000) results in ineffectual evaluation. Drawing on the work of Bateman and Pitts, Case asserts that:

> 'According to Bateman and Pitts (2005: 253), the RFPP 'relies on an account of the origins of offending based on a combination of correlation and speculations'. The blind faith of politicians and academics in this burgeoning body of technical evidence is fraught with danger. If the available evidence cannot tell us *how* risk/protective factors work, *how* these factors may precipitate youth offending or *how* programmes underpinned by them can reduce offending, subsequent research conclusions and 'evidence-based' policies and practices are built on sand.'
>
> (Case, 2007: 98)

Paraphrasing Pawson and Tilly (2000), Case arguments for the realistic evaluation of interventions, stressing that the RFPP as it stands does not inform the youth justice system since we do not know 'what kinds of risk factors have what kind of impact upon what kinds of people under what kinds of circumstances and why?' Case (2007: 98).

An Epidemiological Approach to Risk

In the context of medicine and public health, the RFPP model is used to identify 'risk factors' for physical illnesses and 'protective factors' which can mediate against these illnesses. Knowledge of the risk and protective factors are then used to formulate preventative interventions which are targeted at those considered to be 'at risk' or 'high risk' of developing the illness. The epidemiological nature of the RFPP model has made it attractive to policy makers, practitioners and researchers interested in youth offending with the use of RFR within youth justice policy and practice growing exponentially in recent years. As a result, all young people who come into contact with the youth justice system in England and Wales are assessed in terms of their risk level. Considered to be the jewel in the actuarialist crown, RFPP within youth offending is:

> 'A pragmatic crime prevision tool that uses risk assessment and survey to identify factors in the key domains of a young person's life (family, school, community and psycho-emotional) that statistically increase the likelihood of (official or self-reported) offending ('risk' factors) or decrease its likelihood ('protective' factors). Identified risk and protective factors are then used to inform 'evidence-led' interventions that aim to reduce risk and prevent offending.'
>
> (Case, 2007: 92)

However, many commentators have been critical of the lack of statistical rigour within the evidence base – notably that there has been a reliance on the analysis of associations or correlations rather than establishing causality (Goldson and Muncie, 2006; Goldson, 2010; Case and Haines, 2010). Additionally, its positivist origins have sought to reduce what is a highly complex area into a tool which is oversimplified, generalised and superficial.

O'Mahony provides a detailed epidemiological critique of RFPP which highlights that risk-factor researchers 'are often guilty of forgetting that the measures in criminological epidemiological research are inherently weak and far less reliable than those used in medical epidemiology, which is the model they emulate' (2009a: 103-104). This is further compounded by their tendency to fail to report effect sizes where statistical significance has been established and to avoid testing for 'the causal potency of apparent risk factors' (ibid). What are often produced therefore are artefactual risk factors – artefacts rather than facts, based on flawed theory and flawed (proxy) data. The failure of the field to ask:

> 'Is the association valid?; if valid, does it represent a causal effect?; if there is a causal inference, what elements in the experience or circumstance provides the risk and by what mechanism does it operate?; and does the risk operate in all people in all circumstances or is it contingent on either particular individual characteristics or a particular social context?'
>
> (Rutter, 2005 cited in O'Mahony, 2009: 105)

has resulted in a long list of 'risk' factors for both anti-social and offending behaviour which O'Mahony argues betray the field's lack of ability to synthesize or produce a coherent explanation for the development and maintenance of such behaviour.

Broadly speaking factors are considered to be either *static* i.e. circumstances or conditions that cannot be changed, such as age at first offence, or *dynamic* i.e. factors which have the potential to change. Dynamic factors are those which can potentially be changed such as friends or school performance. By assessing both static and dynamic factors, the intention is to assess not only level of risk, but also identity potential ways in which risk can be reduced. In this way, the young person's needs can be addressed, and appropriate decisions made about interventions.

2.4 ASSET: Design and Key Components

The Theoretical Basis

Whilst Farrington and West's Cambridge Study of Delinquent Development has dominated research into understanding and addressing youth crime, as Baker explains, when it came to designing ASSET, this was not the only source that was utilised:

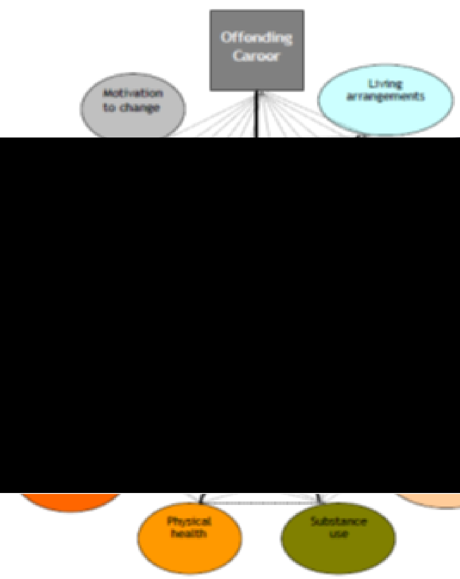
> 'This drew particularly on 'life course' or developmental perspectives (Sampson and Laub 1993, Loeber and le Blanc 1990) and the 'criminal career' paradigm (Blumstein et al 1998, Graham and Bowling 1995). Research into criminal careers has identified factors relating to the onset, persistence and desistance of offending and has shown that the factors contributing to one aspect of offending, such as onset, may differ from those which relate to persistence or desistance. The classification of risk factors used by Rutter, Giller and Hagell (1998) provided another useful framework. This distinguishes between 'individual characteristics' (such as hyperactivity or impulsivity), 'psychosocial features' (for example, poor parenting or school exclusion) and 'population-wide influences' (including the availability of drugs or weapons) that may contribute to offending behaviour. The aim in designing ASSET was to ensure that all of the key empirically based offending related risk factors were included.
>
> Whilst ASSET necessarily focuses on identifying factors contributing to offending behaviour, it also recognises the broad range of needs and problems experienced by this group of young people. Consequently, some items which might not contribute to the prediction of reconviction were included because of their value to practitioners in engaging and working with a young person. ASSET also acknowledges the insights of interactional theory which highlights the 'interactive and reciprocal causal influences that develop over time' (Thornberry 1997 p199). Problems in one part of a young person's life (e.g. education) may contribute to difficulties in another area (e.g. family relationships) which in turn affects other aspects of his/her behaviour and attitudes.'
>
> (Baker et al., 2003: 10-11)

The literature utilised reflects the implicit aetiology of the Crime and Disorder Act, 1998 in its emphasis on the development of offending and anti-social behaviour; risk factors at different ages and the effects of life events on the course of development. It also drew on the knowledge gained from the risk assessment processes which had been introduced into adult settings – the Offender Group Reconviction Scale (OGRS) had been used within probation from 1996 onwards, and elsewhere.

The inclusion of dynamic risk factors, or criminogenic needs plus the theoretical basis underpinning ASSET distinguishes it from earlier first-generation and second-generation tools that consisted mainly of clinical / professional judgements and risk instruments consisting mostly of static items (Andrews et al., 2006). Consisting of 13 inter-related sections dealing with factors such as 'family and personal relationships', lifestyle' and 'thinking behaviour' (Figure 2.1), ASSET was rolled out across the newly formed YOTs in 2000.

Figure 2.1: Components of the ASSET Core Profile

Nature of the Domains / Sections
Dynamic – living arrangements; family and personal relationships; education, training and employment; neighbourhood; lifestyle; substance use; physical health; emotional and [redacted] indicators of vulnerability; indicators of risk of serious harm to others and a brief 'What do you think?' self-assessment section for young people to complete.



Adapted from Baker et al. (2003: 99), Youth Justice Board (2010b: 17-20); Case and Haines (2015: 102)

Within each section or domain are a series of questions requiring yes, no or don't know responses along with a narrative 'evidence box' where further details of the problem or issues identified can be recorded. Practitioners are then asked to rate (using a 0-4 scale) the extent to which each of these sections is related to the likelihood of further offending by the young person. Examples are given within the guidance (Youth Justice Board, 2008a) as to how the ratings might be applied specifically in relation to each domain. Summaries are also provided in the Technical Annex. Generic descriptions can be found in Table 2.1. It is these rating which will form the basis of the hierarchical modelling described in Chapters Four to Seven.

Table 2.1: The Subjective Ratings Used within ASSET

Rating	Description
0	Not associated at all
1	Slight, occassional or only a limited indirect association
2	Moderate but definate association - could be direct or indirect link. May be related to some offending, but not all. Tends to become offending related when combined with other factors
3	Quite strongly related - normally a direct link, relevant to most types / occassions of his/her offending
4	Very strongly related - wil be clearly and directly related to any offending by the young person. Will be a dominant factor in any cluster of offending-related problems.

Adapted from Youth Justice Board (2008b: 4)

As highlighted in Figure 2.1, there are also a number of sections which do not require a numerical rating. These include sections on positive factors (intended to capture information about aspects of the young person's life which could be considered to be protective factors with respect to re-offending, to be strengthen as part of any intervention), vulnerability (any possibility of the young person being harmed) and an 'indicators' of serious harm. This latter section serves as a screen to identify cases which require a more detailed assessment of the likelihood of a young person causing serious harm to others. For the minority of cases in which some initial indicators of a risk of serious harm to others have been identified, the Risk of Serious Harm (ROSH) form can be utilised to provide the more in-depth assessment. Scores for a series of static factors were subsequently added to improve the predictive accuracy of the ASSET under the Scaled Approach, increasing the maximum potential ASSET score from 48 to 64. Details of the scores assigned can be found in Table 2.2.

To support the assessment process, a self-assessment form 'What do YOU think?' was also designed to provide the opportunity for young people to directly record their views regarding their circumstances as well as explanations for their offending behaviour. Whilst this does not contribute to the ASSET Score, it can provide practitioners which additional information to consider when making an assessment and determining the appropriateness of different types of interventions. The form is also intended to facilitate discussion. Practitioners are required to complete the core assessment document with every young person before any intervention is made. They also need to review and update the assessment at the end of any intervention.

Table 2.2: Static Risk Factors and the Scores Assigned to these in ASSET (Max = 16) Under the Scaled Approach

Static Factors	Scoring	Notes
Offence type	Motoring offences/ vehicle theft/ unauthorised taking = 4 Burglary (domestic and non-domestic) = 3 Other offence = 0	When determining the young person's score for this static factor category, YOTs will need to ensure that this is adhered to. The offence type refers to the current offence. Future offending episodes will not continue to count any previous burglary or motoring offences unless the new primary index offence is one of offences. If their current primary index offence is not one of these offences then they will score 0.
Age at first Reprimand/ Caution/Warning	10 to 12 = 4 13 to 17 = 2 No previous Reprimand/ Caution/Warning = 0	If the young person does not have previous reprimands/ cautions or a final warning they will score 0 in this category.
Age at first conviction	10 to 13 = 4 14 to 17 = 3 No previous convictions = 0	If the current conviction is their first conviction the young person will score a 0 for this category as the assessment is in relation to their current offence.
Number of previous convictions	4 or more = 4 1 to 3 = 3 No previous convictions = 0	YOTs should not count the current conviction to this score as the assessment is in relation to the current offence. All previous convictions will count even if there has been a significant gap in offending.

Adapted from Youth Justice Board (2010b: 18)

Is ASSET *really an Asset?*

Taken at face value, ASSET was seen as improving the quality of practice in assessment and planning. As previously highlighted, prior to its introduction the process of assessing risks and planning interventions was perceived to lack rigour and consistency. The introduction of ASSET heralded in a new era of actuarial justice, bringing a standardised approach to decision making within the youth justice system. However, before ASSET was even commissioned, commentators such as Haines and Drakeford (1998: 217) were cautioning 'the dangers of attempting unthinkingly to transfer actuarial methods into the field of human behaviour'. Drawing on Kemshall (1995, 1996), they highlight a number of caveats which they assert needed to be borne in mind when drawn into the risk assessment arena. Sadly, as time progressed, many of these concerns were to be realised:

- 'The danger of regarding risk assessment as a neutral, value-free technical operation. In fact it is an enterprise determined by the political and economic context within which it takes place. 'Risk' is not a shared or unproblematic concept which everyone might be expected to take a common view
- The danger represented by reliance on data which has the appearance of reliability and 'science', but which turns out on closer inspection to be far less rigorous
- The difficulty with which such methods encounter in encompassing qualitative as well as quantitative information
- The danger which arises from 'the potential for the concept of risk to be used as a mechanism of social regulation, justifying the extension of community surveillance and dis-proportionately affecting some groups of the population

- 'Play it safe' regulations which elicit cautious practice and which do not, in any case, guarantee risk-free practice
- 'Hindsight bias' which shapes practice on the basis of enquiries into disasters, rather than learning from successes
- The over-use of negative indicators by management'

(Haines and Drakeford, 1998: 217-218)

Although the YJB has previously been very positive about ASSET, commenting for example in 2002 that 'More than any other aspect of the reformed system, this tool, properly used is capable of preventing further offending' (cited in Baker, 2004: 72), as will be seen the tool has been subject to much criticism. However, for 15 years ASSET remained the standard risk assessment tool used across the youth justice system in England and Wales albeit in a modified form under the Scaled Approach.

The Movement towards the Scaled Approach

The Audit Commission's 2004 review of the youth justice reforms recommended that the YJB should make changes to the National Standards introduced in 2000 to reflect a risk-based approach and should make greater use of the assessment process to inform interventions. In doing this it used the term 'scaled approach' – the name which was later to be given to the new model:

> 'YOTs should make better use of ASSET to determine the amount as well as the nature of interventions with individuals using a scaled approach'
>
> (Audit Commission, 2004 cited in Monk, 2009)

Consultation on proposals for the new model, revisions to the National Standards and case management guidance began in November 2007, with more than 130 responses being received reflecting the growing disquiet about the suitability of ASSET in its original format. Amongst the key issues raised was 'how to make ASSET assessments as reliable and consistent as possible, given that they are the basis for the Scaled Approach' (Youth Justice Board, 2008c: 5).

At the time of the consultation, ASSET had been in operation for more than seven years with two evaluations of the validity and reliability of ASSET having been conducted (Baker et al., 2003; Baker et al., 2005). The first of these had included a 'thorough test of ASSET's predictive validity … to establish its credibility and relevance to YOT practice' (2003: 7). Analysis was presented which suggests that the ASSET rating score predicted reconviction with 67% accuracy – a rate comparable to that found for equivalent tools being used at the time with adult offenders, and considered to be particularly encouraging given the 'greater difficulties in predicting the future behaviour of young people who are often at an early stage in their criminal careers simply as a result of their age' (2003: 7). It further asserted that this level of predictive accuracy was maintained with respect to specific socio-demographic sub-cohorts e.g. females, ethnic minorities and younger age groups. The various recommendations made by the report including ways in which predictive reliability could be increased through the inclusion of static scores around offending history. This resulted in a revision to the original ASSET model.

The 're-launch' of ASSET in summer 2003 included revised versions to the 'What do YOU think?' self-assessment form, Final Warning ASSET, standardised Intervention Plan and explanatory notes. The Bail ASSET and ROSH forms were also revised in consultation with YOT staff. In the case of the latter, it was designed so that the risk classifications used would be the same as in OASys, the assessment tool used by prison and probation services with adult offenders (Baker et al., 2005).

All Change

The roll out of the Scaled Approach was timed to reflect the major youth justice provisions of the Criminal Justice and Immigration Act 2008 (CJIA 2008) including the new Youth Rehabilitation Order (YRO) which had been introduced to replace the then myriad of community sentencing options. The YRO required a more tailored and targeted approach to the proposals made in court reports, enabling sentencers to tailor sentences on the basis of individual risk and need, drawing on a menu of interventions to tackle offending behaviour. A key part of this was that community sentences could be returned to on multiple occasions.

According to David Monk (2009), Head of Practice at the YJB, the development of the Scaled Approach was informed by a number of factors including a review of evidence to develop the revised Key Elements of Effective Practice. This highlighted that interventions were more effective when:

- the level and intensity of intervention is matched to an assessment of the likelihood of reoffending
- it is focused on the risk factors associated with offending

He also highlights the role played by the growing interest in a risk-led approach with a risk-based pilot being run by the YJB in four YOTs between December 2007 and June 2007. This concluded that the approach was backed by frontline workers:

> 'There is very clear evidence that the practitioners in the pilot YOTs considered that adopting the risk-based approach had resulted in better outcomes for young people and these outcomes were measured in terms of better targeting and tailoring of interventions and more appropriate levels of contact,'
>
> (YJB, 2010 cited in Puffet, 2010a)

However, the authors of the report – Matrix Evidence, were critical of the fact that they had not been tasked by the YJB with gauging the success of the system in terms of reconviction rates or value for money. This they felt constrained them 'from making objective assessments of the different practices adopted by pilot YOTs and identifying which were the most effective' (Puffet, 2010a). Rather they were able to make a number of technical recommendations as to how the Scaled Approach should be rolled out nationally, which included the importance of accurate and consistent assessment with rigorous quality checks and that the YJB should implement a method of risk assessment based on the 'highest of any' system that is populated by scores for risk of re-offending and risk of serious harm have been adopted (see Youth Justice Board, 2010a: 113-116). Further recommendations were made which focused on the provision of guidance. Judging by the statistics which featured in the YJB's press release a prior to the launch, significant strides had been made to ensure that practitioners were trained and prepared for the changes, and that the IT systems were ready. Indeed '87% believed that they had had the right support from the YJB to get the Scaled Approach successfully up and running in line with the YRO' (Youth Justice Board, 2009a). This is a marked contrast to the situation at the time of ASSET's launch in 2000.

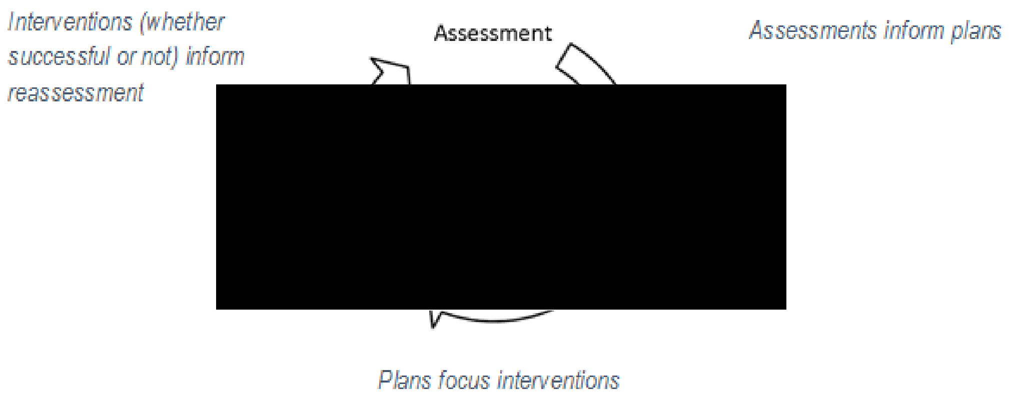
With a tiered framework of interventions in the adult sector, it was also acknowledged that there was an opportunity to gather learning from these along with the implementation of Onset – ASSET's sister referral and assessment framework, in 2007. This 'pre-crime screening tool' (Baker et al., 2005: 8) was intended to identify those 8-13 year olds who would benefit from early intervention, applying a tailored approach to the targeting of prevention services at those at highest risk of anti-social or offending behaviour.

The changes introduced under the Scaled Approach therefore did not bring about a change in the assessment tool, rather they changed the process of assessment and the way in ASSET scores would be used to determine the planning of interventions and nature / intensity of supervision. In implementing the Scaled Approach, there was the opportunity to harmonise practice:

> 'The basis of this 'new' model is the existing framework of 'Assessment, Planning, Interventions and Supervision (APIS). APIS forms the basis for youth justice practice and all elements of this have minimal National Standards for practitioners to adhere to in order to ensure fair, equitable and consistent practice across the system.'
>
> (Sutherland, 2009: 44)

Sutherland highlights that the thinking behind the introduction of an explicit risk-led approach was that there would be an intentional differentiation according to the assessed risks and needs of young people in terms of the interventions planned. By improving the practice of ASSET completion, writing of the pre-sentencing reports and intervention planning, it was intended that YOTs would be able to more effectively target their resources. Thus, the Scaled Approach made much more explicit the links between assessments, plans, interventions and reassessments (as per Figure 2.2) and was designed to inform the ongoing case management of children and young people subject to YOT interventions.

Figure 2.2: APIS Framework – The continuous cycle of (re)assessment, (re)formulation of sentence planning, and supervision approaches



Adapted from Sutherland (2009: 44-45)

How the Scaled Approach works

In aiming to ensure that interventions are tailored to the individual and based on an assessment of risk and needs, and that the intended outcomes are to reduce the likelihood of re-offending, practitioners were required to determine the appropriate level of YOT intervention based primarily on two factors:

- **Likelihood of reoffending** - To assess the likelihood of the young person reoffending, practitioners are required combine the scores from the 12 main sections of ASSET – Core Profile (which relate to dynamic factors affecting offending behaviour, using the ratings given in Table 2.1) and score four 'static' factors (Table 2.2), to arrive at a total score between 0 and 64.
- **Risk of serious harm** – A full ROSH form is completed if there is a 'Yes' response to any of the questions in the 'Indicators of serious harm to others' section of the ASSET – Core Profile.

Under the Scaled Approach practitioners were required to use the framework set out in Table 2.3 to determine the most suitable level of intervention for managing the young person. This then formed the basis of the proposal to the court or information for the panel. It is notable that it was felt necessary to revise the thresholds for the intervention levels as it was identified that too many young people were falling into the 'low' category. These changes were reflected in the second version of the post-consultation document released In February 2009 (Youth Justice Board, 2009b).

There was scope for practitioners to review the intervention level in the context of all other available information and consider whether there are any factors that indicate the intervention level may need to be amended e.g. where a young person had committed a particularly serious offence but was assessed by the YOT as low likelihood of reoffending or low risk of serious harm. Should the responsible officer decide to increase or decrease the initial intervention level then the decision needed to be defensible, discussed and agreed with a manager, with the reasons clearly recorded. The link between the intervention level and the intensity of supervision is summarised in Table 2.4.

Table 2.3: Determining Intervention Level

Child / Young Person's Profile	Intervention Level	Revisions Made
Low likelihood of reoffending (as indicated by ASSET score [dynamic and static factors] between 0 and 14 inclusive) AND Low risk of serious harm (as indicated by no risk of serious harm assessment being required, or low risk of serious harm assessment)	STANDARD	Originally proposed as being 'Low' with ASSET scores less than 25
Medium likelihood of reoffending (as indicated by ASSET score [dynamic and static factors] between 15 and 32 inclusive) OR Medium risk of serious harm (as indicated by risk of serious harm assessment)	ENHANCED	Originally proposed as being 'Medium' with ASSET scores between 25 and 41
High likelihood of reoffending (as indicated by ASSET score [dynamic and static factors] between 33 and 64 inclusive) OR High or very high risk of serious harm (as indicated by risk of serious harm assessment)	INTENSIVE	Originally proposed as being 'High' with ASSET scores of 42 or over

Adapted from Youth Justice Board (2008d) and Youth Justice Board (2009b)

Table 2.4: Statutory contacts for assessed intervention levels

Intervention Level	Minimum number of contacts per month for first three months of order	Minimum number of contacts per month for remainder of order
Standard	2	1
Enhanced	4	2
Intensive	12	4

Adapted from Youth Justice Board (2010b: 12)

Scaled Approach intervention levels were not affected by any identified issues around the vulnerability or welfare of the young person. However, as YOT practitioners have ongoing responsibilities for addressing safeguarding and welfare issues as part of wider social / children's services partnerships, then appropriate action could be taken to ensure that these considerations were reflected in the overall intervention plan and vulnerability plan where one was needed. If the child or young person was assessed as being particularly at risk of harm from themselves or others then the appropriate action could also be identified, with the potential to utilise multi-agency input. The final judgment was then used to inform the proposal made to the court or report to the youth offender panel.

Thus, the Scaled Approach provided a framework for assessment, proposals to courts and youth offender panels, interventions and review. As a model for interventions delivered by the YOT, it reflected the statutory aim of the youth justice system to prevent offending, including reoffending, by children and young people and was designed to help YOTs become more effective in delivering this requirement in their local communities. Prior to its launch, Monk (2009) had promoted the following anticipated benefits:

- More efficient and effective allocation of YOT resources
- Fewer young people in custody
- Strengthened case management across the youth justice system

- Improved practice in assessment quality, pre-sentence reports (PSRs) and intervention planning
- Tailored interventions based on the young person's risks and needs

The combination of these it was believed would reduce reoffending; reduce the risk of serious harm and would lead to increased public confidence in the youth justice system.

Is the Scaled Approach a Failed Approach?

Despite claims that all available evidence was utilised to inform the development of the Scaled Approach, the YJB has continued to face criticism about the approach not least for having the potential to lead to different levels of intervention for young people committing the same crime:

> 'if two young people commit the same offence but have different risk score, the higher risk one will be required to meet their YOT more often than the low-risk one, and more often than the current system'
>
> (Bateman quoted in Pemberton, 2009)

Just four months after its launch, questions were being raised about how sentence recommendations from the Criminal Justice and Immigration Act 2008 were being calculated and as part of a wider review of the future needs of the youth justice system, the YJB announced a review of the predictive validity of ASSET. The timing of the review was criticised with Nacro's Senior Policy Development Officer, Tim Bateman (quoted in Puffet, 2010b) asserting that 'If the YJB was considering a fundamental review of assessment policy it would have made sense to incorporate it into any plans they had to change the nature of intervention'. However, Monk defended the decision, saying that the review would be 'a long-term project and it would have been unrealistic to carry out prior to the introduction of the new sentencing system' (ibid).

The Review reported in December 2011 (Wilson and Hinks, 2011) by which time sponsorship of the YJB had moved to the Ministry of Justice. This found that ASSET was still a good predictor of proven re-offending among young people and that the findings were broadly in line with Baker et al's 2003 evaluation (based on a variant utilising scores from the 12 dynamic domains). It tested a number of models including a simulation of the Scaled Approach, different combinations of dynamic and static scores, and the Offender Group Reconviction Scale (OGRS 3) being used with adult offenders within OASys – use of the latter within youth justice had previously been advocated by Howard et al. (2009) and was considered to be an efficient and quick pre-screening tool since data could be extracted directly from the Police National Computer (PNC).

Wilson and Hink's key findings and recommendations were:

- ASSET 'dynamic plus OGRS 3' was found to be the best predictor of proven re-offending of those tested. Hence the predictive ability of ASSET could be improved by replacing the ASSET static component of the Scaled Approach with OGRS 3.
- Using OGRS 3 as a predictor of risk of re-offending was as good as using ASSET (both pre- and Scaled Approach), but it should not be used for Final Warnings as there was no information about criminal history to calculate a score.
- Of the 12 ASSET dynamic factors, 'lifestyle', 'substance use' and 'motivation to change' were highly statistically significant predictors of proven one-year re-offending. 'Living arrangements', 'family and personal relationships', and 'education, training and employment' were also statistically significant. The remaining six factors, although of less importance to predicting proven re-offending, are likely to still be relevant for understanding the needs experienced by young people. Hence in order to inform intervention planning, the information captured via the 12 domains is also required. This enables areas of need to be identified and addressed.
- Not all young people (72%) had an ASSET completed within 30 days prior to, or after, the index disposal – for most disposals, an ASSET assessment should be conducted 10-15 days prior to the order being made as the information gathered forms part of the PSR. This suggested that the timeliness and completeness of ASSETs requires further improvement to ensure that assessments are completed in line with National Standards.

As with the risk assessment tools used in adult settings, questions have also been raised about the predictive accuracy of the tools developed for predicting youth offending. However, issues are also raised about the integrity of the evidence base with Case and Haines arguing that:

> '… the risk assessment processes promoted by the Youth Justice Board and particularly the risk assessment instruments that underpin these processes, have been founded on the mis-appliance of research findings and have exacerbated the methodological over-simplification, indefinite and imputation that undermine RFR.'
>
> (Case and Haines, 2009: 256)

Through a detailed critique of the major studies contributing to the RFR paradigm, they highlight how factorisation and reductionism have over-simplified the context and operation of risk whilst the aggregation of findings has limited the potential to understand some of the complex relationships that exist within youth offending. In particular they question the value of homogenising 'offending' into *lifetime, active, general* and *serious*, and promotion of prevention as a dichotomy of risk. In reviewing the respective research designs and data collection methods utilised within these studies, Case and Haines are critical of their ability to determine causality and of a psychosocial bias which has tended to overlook socio-structural factors such as gender, class, poverty and societal access routes to opportunities.

2.5 The Actuarial Fallacy and Predictive Accuracy

There are significant methodological limitations with actuarial approaches resulting from the 'actuarial fallacy' – this relates to the fact that actuarial methods can only provide an estimate to the probability that an offender with a particular set of characteristics will be reconvicted within a defined period: it does not provide the means of making an accurate prediction for a specific individual. It is this feature which has also proven to be controversial in medical epidemiology despite its more precise and rigorous measurements (O'Mahony, 2009). In translating criminological risk-focused epidemiological research into a format that can be more readily understood by practitioners, much of the 'daunting detail and conceptual and statistical complexity' (2009: 100) has been over-simplified. Many of the key concepts are undefined with this ambiguity being identified as a methodological paradox by Case and Haines (2009). They highlight that although many of the conclusions of RFR are presented as if there is homogeneity, there remains uncertainty and disagreement in the field. With poorly-defined and partially understood concepts, it calls into question just how scientific the conclusions really are.

Methodological Issues Affecting Predictive Accuracy

The accuracy and utility of actuarial risk assessment tools has been subject to much debate amongst academics and practitioners. Gottfredson and Moriarty (2006), in a follow up to earlier work, highlight that many of the issues they had identified twenty years previously remained a problem. In providing their critique, they point to a number of issues which they assert are fundamental to the development and implementation of risk assessment tools which are often ignored including those that affect accuracy and the nature of the criterion variables chosen. In terms of statistical methods being used in criminological prediction studies, the approaches listed reflect advances made in applied mathematics and the increased computational power available for analysis e.g. 'cross-classification tables; multiple regression; multiple discriminant function analysis; multidimensional contingency table analysis; logit, probit and tobit analysis; a variety of clustering approaches; and neural networks' (Gottfredson and Moriarty, 2006: 183).

Despite these advances, Gottfredson and Moriarty express concern that all too often those developing prediction tools have failed to consider base rates. In the context of prediction tools, the consequence of having a base rate further from 0.5 is that it increases the likelihood of inaccurate prediction. This has the potential to introduce larger errors at the extremes i.e. for more frequent or infrequent events and hence could limit the usefulness of a tool for predicting for example, more serious offences which are committed less frequently by young people. A notable exception to this which comes from Harris and Rice – part of the team responsible for developing the VRAG tool and for promoting the use of receiver-operating characteristic (ROC) statistics as an index of predictive accuracy (Rice and Harris, 1995). They have examined base rates using Bayes Theorem to consider informative priors to actuarial violent risk assessment, concluding that 'what makes a base rate an informative prior partly depends on how much it differs from the selection rate, especially, in forensic clinical practice, how low it is' (Harris and Rice, 2013: 119). They do however, caution that 'more empirical work is required before Bayes' rule can be automatically applied to actuarial assessment norms' (Harris and Rice, 2013: 120).

In identifying the sample for constructing prediction tools, it is advocated that the sample must be representative of the population on which the device is intended to be used (this is not the same as the being representative of the population as a whole). This is done to ensure that appropriate base rates are used and also as a measure to minimise shrinkage of power. Cross-validation is typically undertaken therefore using construction and validation samples. Whilst this is now more common practice, this has not always been the case. Similarly, there are examples of experiments intended to identify predictor variables which were designed without control groups (see Case and Haines, 2009 for a critique of the research designs utilised in key surveys which underpin risk assessment in a UK context).

Perhaps most significantly, risk assessment devices are being used on populations for which they were not designed. This can be because the original research was not representative of the wider youth offender cohort or it because the predictive variables may prove to be more (or less) predictive for some defined populations when the composition of the population is different. Gottfredson and Moriarty (2006: 190) give the examples of 'race' noting that 'it may be predictive of criminal convictions in some large urban populations and not at all predictive in suburban or rural populations', and age. In the case of the latter they note that 'some items that are predictive during some age ranges may not be if other age ranges are considered.' They conclude with the following:

> 'Despite good and consistent advice to the contrary, policy makers continue to seek a panacea through 'risk assessment', typically by seeking to adopt a pre-packaged 'one-size-fits-all' risk assessment tool. And despite good and consistent advice to the contrary, basic methodological requirements of risk assessment development are frequently ignored.'
>
> (Gottfredson and Moriarty, 2006: 195)

The Predictive Accuracy of ASSET

As previously indicated, Baker et al. (2003) had reported that the original version of ASSET had a predictive validity of 67%. The measure used to determine this was the 'percentage correctly predicted' which is essentially a crude sum of the proportion of non-reconvicted low scorers (32.7%) and reconvicted high scorers (34.3%) and was used to enable comparisons to be made with equivalent models at that time in Probation (for example Raynor et al., 2000). The way in which the percentage correctly predicted is presented within the report serves to highlight the fact that 16.3% of low scorers went on to be reconvicted within 12 months whilst 16.7% of higher scorers had no proven reoffending during the following year (Table 2.5). As Smith (2006) highlights this is equivalent to 33% of young people for whom the outcomes of ASSET profiling have been neither valid nor reliable. When you consider that tossing a coin has a predictive accuracy of 50% does not give must confidence in using ASSET to justify the intensiveness of an intervention as became the case under the Scaled Approach.

Table 2.5: Plotting Percentage Correctly Predicted: ASSET (Original Version)

		Outcome	
		Non-Recidivists	Recidivists
Prediction	Low Risk	True Negative (32.7%)	False Negative (16.3%)
	High Risk	False Positive (16.7%)	True Positive (34.3%)

Notes: Based on Baker et al (2003) which reported on the original version of ASSET, considering re-offending after 12 months

More recently there has been a shift in the reporting effect sizes and hence predictive validity, with increasing use of area under the curve (AUC) – a form of receiver-operating characteristic (ROC) analysis to measure the predictive ability of both adult and juvenile risk assessment instruments (Baglivio and Jackowski, 2013). This approach has been shown to be robust to variation in base rates, selection ratios, and truncated distributions – common problems in risk assessment research (Rice and Harris, 1995; Gottfredson and Moriarty, 2006; Schwalbe, 2008). Although comparatively new to criminology, the AUC is the preferred method of predictive or diagnostic accuracy in forensic psychology and psychiatry (Rice and Harris, 2005), and has been used as a measure of effect size when reporting violent and sexual recidivism:

> 'The AUC statistic illustrates the probability that a score (eg on a risk assessment instrument) of a randomly selected case from one population (eg a youth who recidivates) will be higher than a randomly selected score from a second population (eg a youth who does not recidivate). An additional benefit is that the AUC is less affected by fluctuating or low base rates (eg historically low recidivism rates for females)'
>
> (Baglivio and Jackowski, 2013: 27)

Baker et al. (2005) suggest that for the original version of ASSET, the AUC for the construction sample was 0.719 at the 12-month stage and 0.731 at the 24-month stage. The AUC measure of predictive validity has since been utilised to assess ASSET as part of the YJB's review of assessment and intervention planning (Wilson and Hinks, 2011). They suggest that the AUC for ASSET pre-Scaled Approach i.e. based on a score out of 48, was 0.68 whilst for the simulated model intended to represent ASSET under the Scaled Approach was 0.70 (Table 2.6). Their report found that the simulated model was significantly different from the earlier version at a significance level of $p<0.001$.

Although the benchmarks for interpreting AUC values are arbitrary, generally the higher the AUC, the higher the predictive validity. Wilson and Hinks (2011) for example suggest that a model is generally considered 'moderate' if the AUC value is 0.64–0.70 and 'good' if 0.71 or above. This is broadly consistent with the benchmarks put forward by van der Put et al. (2014) i.e. that an AUC value greater than 0.70 is considered to be 'acceptable', whereas an AUC value of greater than 0.75 is considered to be high. To put the findings for ASSET into context, Schwalbe (2007) reports that the weighted average AUC for the third-generation juvenile risk assessment instruments included in his meta-analysis was 0.646 (95% Confidence Interval: 0.588 to 0.704) but ranged from 0.57 to 0.78. This average was calculated using twenty-one third generation tools including ASSET.

Table 2.6: The Predictive Accuracy of ASSET and ASSET under the Scaled Approach

	ASSET 'Dynamic (48)'	Simulated ASSET 'Static plus Dynamic (64)'
Description of Model	This model represents the pre-Scaled Approach practice of undertaking risk assessments and remanted the practice for Final Warning cases. It utilised a score out of 48 for the ASSET dynamic factors	This model was simulated to represent how assessments were undertaken for 'sentanced' cases under the Scaled Approach. It utilised a score out of 64 derived from both the statsic and dynamic ASSET factors
AUC	0.68	0.7
Standard Error (SE)	0.012	0.011
95% Confidence Intervals around the AUC	0.66 - 0.70	0.68 - 0.72
Interpretation of AUC	Moderate / Acceptable	Acceptable

Adapted from Wilson and Hinks (2011: 26)
Notes: Validation sample (n= 2,172), sentenced cases only.
Data was taken from the Juvenile Cohort Study. Since this took place before the introduction of the Scaled Approach, it was necessary to simulate scores for the static factors. Hence results referring to the 'simulated' ASSET can only be regarded as indicative. The Standard Error provides an estimate of the uncertainty about a calculated value (here the AUC). The smaller the Standard Error, the more confidence that the reported value is the 'true' value. AUCs of 0.5 are the practical minimum as these could have been obtained by randomly, while AUCs of 1 represent the hypothetical situation where in this instance, all proven re-offenders have higher scores than non-proven re-offenders.

Whilst Wilson and Hinks highlight the limitations of their methodological approach, they are at pains to stress the representativeness of the data they used and the importance of providing timely results to inform the YJB assessment review. In doing this they emphasize that the study 'did not intend to exhaust all the many possible options in designing a risk assessment tool and developing the 'best' possible predictor of youth re-offending' (Wilson and Hinks, 2011: 1). The number of cases used is however, significantly higher than those used in earlier reviews by Baker et al, thus negating some of the previous challenges made around the robustness of the analysis.

From a generic perspective, reliability relates to the need for significant result to be more than a one-off finding and therefore inherently repeatable. However, this can be dependent upon the stability with which measurements may be made. As Gottfredson and Moriarty observe, 'statistical validity is constrained by the reliability with which criterion and predictor measurements are made' and they argue that 'no risk assessment device can be better than the data from which it is constructed' (2006: 183).

2.6 Sensitivity: One Size Does Not Fit All

As a result of factorisation – which also has its origins in the positivist philosophy of science, it is argued that RFR has become a 'blunt tool' with which to 'carve out risk factors and 'at risk' populations' (Case and Haines, 2009: 19). In seeking to reduce information from a raft of different sources (e.g. surveys, behavioural rating scales, psychometric tests and official records along with qualitative risk data from interviews and observations), into subjective scores corresponding to broad 'risk' categories, risk assessment tools are insensitive not just to individual differences but also fundamental differences in terms of the nature and type of offending. Whilst the aggregation of variables and assumptions of homogeneity help to make risk assessment tools 'easy to understand and communicate, and … readily accepted by policy makers, practitioners and the general public' (Farrington, 2000: 7), this has come at the cost of sensitivity. This particularly has implications due to the multiple functions of fourth-generation tools where it could be argued that in order to respond to individual risk, need and responsiveness, then increased sensitivity is required. Only then can scant resources be appropriately targeted.

Dimensional Identity

If we are to consider how to address the insensitivity of many risk assessment instruments with respect to demographic characteristics it is necessary to consider the concept of dimensional identity (Schwalbe et al., 2006). The concept was developed in the person-centred research paradigm within developmental psychology and is said to exist when a measure such as recidivism in a risk assessment instrument is the same for all subpopulations within a sample. If empirical research demonstrates that the predictive validity of the risk assessment tool is greater for some groups than others, then it fails to possess dimensional identity. It is only when the dimensional identity exists that the generalizability of the risk assessment tool can be asserted.

Certainly, if disparities based on race/ethnicity and gender are to be reduced within the criminal justice system, then the predictive validity of risk assessment instruments should not differ across demographic groups. Although written in the context of the juvenile justice system in the United States and Canada, Schwalbe et al highlight that:

> 'Risk instruments are designed to reduce, racial, ethnic and gender disparities and biases by increasing the consistency of assessment through a structured process … Coupled with needs assessment, sentencing guidelines, and other reports, risk assessment is an important element of a larger strategy to reduce racial and gender disparities in the treatment of offenders by the juvenile justice system'
>
> (Schwalbe et al., 2006: 306)

Given the way in which ASSET is used within youth offending under the Scaled Approach, there is a need for the predictive validity of the instrument to hold across diverse groups both in terms of assessing the likelihood of further offending and the tiered risk classifications. Thus, a medium-risk classification should convey a similar meaning with respect to the probability of reoffending for both males and females, for different racial /ethnic groups, and for different ages of offenders.

However, as yet there are few examples of where AUC has been utilised to measure the predictive validity of juvenile risk assessment tools by demographic subgroup. Exceptions include Schwalbe (2006; 2007; 2008) who has undertaken meta-analyses of juvenile risk assessment instruments from the United States; Meyers and Schmidt (2008) who has focused specifically on a Canadian clinician-led violence risk assessment tool and Emeka and Sorensen (2009) using data from the USA. All have examined differences by gender with Meyers and Schmidt also looking at race/ethnicity. Whilst the findings from the first two sets of studies were found to be inconclusive – an issue which is attributed to small sample sizes, Emeka and Sorensen's analysis of data from the Texas Juvenile Probation Commission led to the construction of a risk assessment scale which showed marked gender differences for the respective AUCs despite coming from a pooled sample. It is findings such as these which reinforce the need to periodically review the predictive validity of risk assessment instruments and for innovations such as gender-specific instruments to be explored:

> 'Gender differences, when they appear, can open the window in the presence of gender biases in juvenile justice decision-making. By routinely testing for gender differences, risk assessment validation studies can expose gender biases that can become the focal point for ongoing research and policy interventions. In this way, risk assessment instruments, and the research that supports them, can serve to increase, rather than undermine, gender equality in the juvenile justice system.'
>
> (Schwalbe, 2008: 1379)

More recent work by a Dutch team using police data has also asked if there are any sex differences in risk factors for re-offending and in risk profiles (van der Put et al., 2014). Their work categorises the girls into four groups: a low risk group (containing 65% of the girls) and three high risk groups (girls with 'delinquent' parents, victims of abuse, and repeat offenders), and shows that each has a specific set of risk factors and hence implies the need for specific interventions. These findings sit within the context of the development of new risk assessment tools for the prediction of first-time offending (Assink et al., 2016) and general recidivism (van der Put, 2014).

The predictive validity of juvenile tools on the basis of race / ethnicity have been considered by Baglivio and Jackowski (2013) and by Rembert et al. (2014). In both cases, the work has been undertaken using US samples. In the case of the former, it was not possible to determine whether the differences found between gender and race/ethnicity were due to shortcomings of the instrument or to external factors in the criminal justice system itself, noting that different law enforcement practices all affect estimates of predictive risk assessment instruments. Rembert et al. (2014) excluded Whites from their sample on the basis that inclusion biases the predictability of minority group members. Their research found that the Los Angeles County Needs Assessment Instrument was a better predictor of re-arrest for Hispanics then African American juveniles. The findings suggest that:

> '…these offender differential prediction validations warrant more complex statistical techniques. In particular, they support the use of multilevel modelling over the traditional logistical regression, due to the former's ability to decipher the impact of exogenous community-level variables (eg neighbourhood disadvantage, vacant housing, public assistance, crime rates, and law enforcement surveillance) on the respective outcome measures.'
>
> (Rembert et al., 2014: 161-162)

How Good is ASSET at Correctly Predicting Re-Offending for Sub-Populations?

In the absence of any published studies which either state the AUC or provide sufficient information for the AUC statistic to be calculated in order to measure the predictive validity of ASSET on the basis of subgroups, it is necessary to fall back onto an alternative measure of predictive validity described in Section 2.6. Baker et al present tables which provide the 'percent correctly predicted' for females, young offenders (10-15 year olds) and ethnic minority offenders with respect to proven reoffending within 1 year (Baker et al., 2003) and 24 months (Baker et al., 2005). This crude rate based on the proportion of those with a 'high' score being reconvicted plus the proportion of those with a 'low' score not being reconvicted, it suggests that there is little difference between the respective sub-groups. For example, overall recidivism was correctly predicted for 67.1% of the cases from June/July 2000. Amongst females, 66.0% were correctly predicted compared to 67.3% for males despite there being significant differences in their respective recidivism base rates – 39.5% for females compared to 53.1% for males.

The subsequent evaluation undertaken by Wilson and Hinks (2011) using data from the Juvenile Cohort Study to examine how well ASSET under the Scaled Approach predicted reoffending over one year, found that ASSET accurately assigned higher scores to those who went on to reoffend. A finding that was repeated when the analysis for females, BAME groups and those aged 10-15:

- Females: the mean ASSET score for those who reoffended was 24.3 (out of a maximum of 64 i.e. static plus dynamic scores) compared to 16.9 for those who did not reoffend ($t(921) = -12.6$, $p<0.001$; Effect size eta squared = 0.15)
- BAME: mean score of 22.4 amongst those who reoffended compared to 15.4 for those who had not reoffended ($t(747) = -10.6$, $p<0.001$; Effect size eta squared = 0.13)
- Young People aged 10-15 years: 23.1 compared to 16.8 amongst those who had not reoffended ($t(3,2182) = -16.5$, $p<0.001$; Effect size eta squared = 0.11)

This evaluation also used logistic regression to examine how well each of the 12 dynamic factors predicted reoffending over 1 year. However, the results of this analysis are not broken down by sub-group. As the headline findings have a specific bearing upon the results of the modelling described in Chapters Five and Six, these will be +.

As previously highlighted a key issue which has previously limited the potential for further exploration of gender-specific assessment tools has been small sample sizes – in the case of Baker et al's follow up work there were 399 females compared to 1,834 males whilst Wilson and Hink's work, 18% of the sentenced sample were females (917 out of 5,107). Echoing the views of van der Put et al. (2014) and Emeka and Sorensen (2009), it may well be that because girls make up only a small percentage of youth offenders, the risk factors that are important to female offending have not been identified and incorporated into risk assessment tools. Instead female risk factors have been embedded within male risk factors within generic tools.

This is also the position with regards to ethnicity with the BAME cohort making up just 8.4% of the cases analysed by Baker et al. (2005) – equivalent to 189 of the 2,233 cases. Although the cohort for the Wilson and Hinks (2011) analysis was larger: Black/Black British young people made up 5.7% (290) whilst 4.4% were Mixed and 4.4% Asian/Asian British, the comparatively small number of cases has limited the analysis which could be undertaken using traditional statistical approaches, especially when looking to further segment to the cohort say to focus on non-White females or those who committed different offences.

Different Types of Offending

In terms of predicting different types of offences, as previously highlighted, tools have been developed specifically for the risk assessment of serious violent and sexual offenders for use in clinical settings. However, it is acknowledged that low base rates, and particularly in the context of sexual offending, the diverse nature of the offending can limit the utility of these tools - as Kemshall (2008b: 10) observes, 'if something doesn't happen very often it is difficult to predict if and when it might happen in the future, although the consequences of it happening could be very high.' Thus, it is particularly difficult to accurately predict 'grave crime' such as murder, with practitioners being tasked to make difficult decisions about risk of harm. Predicting such offending amongst young people is even harder due to the rarity of such offending amongst under 18s. As a result, where such tools exist for young people, these are typically modified versions of adult tools and tend to focus on the dangerousness of the offender.

Tools for predicting more general youth offending, typically do not differentiate between violent, acquisitive and other types of offending. Although under the Scaled Approach, it should be noted that those young people whose primary index offence was burglary or motoring offences were assigned scores of 3 and 4 respectively within the Offence Type section of the Static Factors (Table 2.2). The higher perceived risk associated with having committed these types of offences was a reflection of the fact that when the research was undertaken, those young people who had committed one or more of these offences were more likely to be reconvicted in the subsequent 12 months than those young people whose index offence was another offence type. When Wilson and Hinks (2011) subsequently sought to compare the predictive validity of different models using logistic regression techniques, they found that relative to those who have committed other offences, the odds ratio for proven re-offending where the young person had committed motoring offences (including vehicle theft and unauthorised taking) was 0.87 whilst that for burglary (domestic and non-domestic) was 1.20. However, neither were found to be significant predictors of reconvictions within the model designed to represent ASSET under the Scaled Approach i.e. including both static and dynamic factors.

Type of reoffending is considered within Wilson and Hink's evaluation of ASSET, since they look at accuracy in predicting the severity of proven re-offending both by considering (1) the most serious re-offence and (2) the most punitive criminal justice disposal within the one-year follow up period. Generally, is was found that young people with more serious re-offences had on average, higher ASSET scores than those committing non-serious offences. They also found that young people receiving custodial sentences for a re-offence typically had higher ASSET scores than those receiving less punitive disposals. Based on the young person's most serious re-offence:

- Those whose re-offence was categorised as being a serious violence and sexual offence i.e. offences resulting in death, grievous bodily harm and serious sexual offences had a mean score of 25.9 (out of a maximum of 64)
- Those committing serious acquisitive crime i.e. robbery, burglary, theft of or from a motor vehicle, had a mean score of 25.8

It is reported that ASSET was unable to differentiate between the types of serious re-offence. However, it was possible to differentiate between those who went on to commit serious re-offences, and those who went on to commit 'non-serious' re-offences. This latter group had a mean score of 22.1.

In terms of the seriousness of the disposal received for the re-offence, it was found that those receiving custodial sentences had statistically significantly higher mean ASSET scores than those receiving community and other penalties. However, ASSET was unable to differentiate between those receiving community penalties and those received lower level disposals. Wilson and Hinks suggest that this first finding may be due to the escalator policy whereby those with a more prolific criminal history (and hence who score higher on the ASSET static factors) have a higher chance of receiving a custodial sentence. Notably the static factors age at first Reprimand/ Caution / Warning and age at first conviction were found to be highly significant predictors of reconviction in the model designed to represent ASSET under the Scaled Approach.

The number of previous convictions was also shown to be a significant predictor where the young person had 1-3 prior convictions relative to those who had none. However, it was necessary to remove the predictor for 4 or more previous convictions from the model due to a high correlation with age at first conviction. Differences in mean scores between these groups were reported:

- Number of Proven Offences: the mean ASSET score for those who 1-3 re-offences was 21.2 (out of a maximum of 64 i.e. static plus dynamic scores) compared to 26.2 for those who had more than 3 offences during one year ($t(2560) = 12.9$, $p<0.001$; Effect size eta squared = .06)

Theoretically there is a basis for being able to understand the different trajectories for different types of offender and offence. For example, Owen and Cooper (2013) found from their analysis of the Police National Computer for all first-time entrants into the criminal justice system in 2001, that the type of debut offence committed was significant predictor of both chronic offending status and committing a further serious offence (i.e. robbery, serious violence or a sexual offence). Whilst their analysis excludes low-level offences which have resulted in no further action or a restorative sanction which is not recorded on PNC, it suggests that re-offending rates are higher for those who were first sanctioned at a young age with those aged 10-17 at their first offence being 4 times more likely than those aged 18-25 years and 11 times more likely than those aged over 25 years when committing their debut offence to become chronic offenders i.e. to have committed 15 or more re-offences during the 9 year follow up period from 2001. Those aged 10 to 17 at their debut offence were 2.5 times more likely to commit a serious re-offence compared with 18-25 year olds (23% and 9% respectively); and 7 times more likely than older adults (3%). Table 2.7 summarises the respective proportions who went onto be chronic and serious re-offenders, by debut offence.

Table 2.7: The Proportion of 10-17 year old Offenders who Became Chronic and Serious Re-Offenders, by Debut Offence Type and Gender

	Chronic Offenders		Serious Re-Offenders	
	Young Men	Young Women	Young Men	Young Women
[redacted]				
Motoring Offences	7	3	16	8

Source: Owen and Cooper (2013: Tables B6 and B7)

Taking into consideration gender and age at debut offence, Owen and Cooper (2013) found that those who committed robbery as their debut offence were 1.7 times more likely to become a chronic offender compared with all other offence types. Those who committed vehicle theft or burglary were 1.6 times and 1.5 times, respectively more likely than offenders who committed other debut offence types to become chronic offenders.

Overall 65% of those aged 10-17 at their first offence re-offended within the 9 years compared to 47% of 18-24 year olds and 26% of those aged 25+. Just over four-fifths (81%) of 10-17 year olds whose debut offence was robbery went on to commit further offences in the 9 year follow up period along with nearly three-quarters (74%) of those who had committed a vehicle theft and 73% of those who had committed a burglary. Seven out of 10 (71%) of those whose debut offence was a weapons offence had gone on to commit one or more further offences in the follow up period.

Owen and Cooper (2013) also found gender differences in terms of the proportions going on to commit serious re-offences. For example, 44% of young males whose debut offence had been robbery went on to commit a serious re-offence as did around a third of those who had committed a burglary or vehicle theft. This compares to just over a quarter of females who had been 10-17 years when first sanctioned for a robbery debut offence. Similar patterns can be observed for other debut offence types.

Evaluations of ASSET have tended to focus on one-year and two-year proven reoffending measures and have not followed young people who offend over longer periods. However, a number of typologies have been complied such as that from the Edinburgh Study which differentiate between early onset chronic, early onset desisters, later onset decliners and those with no convictions (McAra and McVie, 2010) which also point to different durations of criminal career. Ultimately it would be desirable to identify how effective risk assessment tools such as ASSET are in identifying where differences lie in terms of the perceived risks of reoffending associated with each of these groups.

2.7 Summary of Key Issues

The criminal justice system has become increasingly reliant upon standardised actuarial risk assessment tools which have become increasingly more reliable in terms of predicting further offending with each successive generation. Predictive risk assessment tools have been developed to facilitate decisions around parole and the evaluation of treatments. In the context of determining the extent to which an offender poses a risk to themselves or others, tools have also been designed specifically for use within forensic settings to assess dangerousness, particularly in the case of selective incapacitation, serious violent and sexual offending. In some cases, the tools have been modified specifically for use with juvenile offenders. However, within England and Wales, ASSET and its successor ASSET Plus have been developed specifically as a tool to assess the likelihood of youth re-offending.

Whilst this Chapter has highlighted a number of fundamental issues in relation to ASSET, it should be noted that a number of these have been addressed through the development of ASSET Plus. Notably the literature published by the YJB suggests that clarification has been provided around the definition of risk being used and there have been attempts to reflect emerging research, policy and practice to reduce the psychosocial bias. However, many of the issues raised by critics relate to the continued use of Frequentist approaches to develop actuarial risk assessment tools and the use of RFR as an evidence base. With risk assessment tools now such an integral part of the criminal justice decision making process, being promoted as being able to provide an objective, impartial and rational process which reduces reoffending and facilitates increased public protection, common sense suggests that actuarial tools will continue to evolve. This creates an opportunity to continue to develop the evidence base that underpins them so that it remains fit for purpose.

As Harcourt (writing in the context of profiling and policing) argues:

> 'The general public and most academics generally support the use of prediction in policing. To most, it is a matter of plain common sense. Why would we not use our best social science research and the most advanced statistical methods to improve the efficiency of police investigations, sentencing decisions, parole practices, treatment efforts, and general correctional procedures? Why not display our wealth of new knowledge to fight more effectively? It would be crazy not to take advantage of what we now know about the propensity to commit crime.'
>
> (Harcourt, 2007: 21)

The reducing numbers within the formal youth justice system mean that increasingly those referred to the YOT represent more complex cases whilst reviews such as those by Lord Laming around the over-representation of those with care experience in the youth justice (Prison Reform Trust, 2016) and David Lammy MP around BAME experiences in the criminal justice system (Lammy, 2017) highlight inequalities. In order to support these young people a greater understanding of the interaction between risks, needs and vulnerabilities is required. Exploring emerging and innovative statistical approaches to examine this relationship therefore enables this to be done, particularly since Bayesian approaches are better suited to working with smaller datasets.

In terms of new tools that have been developed elsewhere and for more specific forms of recidivism, these have sought to utilise innovative techniques such CHAID (van der Put, 2014; Assink et al., 2016) and logistical regression. Whilst these have enabled more sensitive analysis to be undertaken using these approaches are not without their limitations not least the need for large sample sizes. In other disciplines, the quest for more sophisticated tools continues with Liu et al. (2011) for example having compared the accuracy of logistic regression, classification and regression trees (CART) and neutral networks in the context of predicting violent re-offending on a sample of UK male prisoners. Also, within the context of forensic risk assessment, Harris and Rice (2013) have begun to explore the potential of utilising base rates for violent offending as informative priors within a Bayesian framework whilst Blattenberger et al. (2010) has compared different Bayesian models to predict return to prison.

The following chapters present the methodology employed for exploring the potential for utilising Bayesian approaches along with administrative data from the youth offending service to advance our understandings along with findings from a hierarchical model conducted under a Bayesian framework. In keeping with the analysis led approach outlined in Chapter One, Chapter Three considers the structure of ASSET and the potential that this affords as well as identifying what can be achieved using the dataset available for this research. This is structured so as to provide the rationale for each of the research questions which underpin the analysis undertaken in Chapters Four to Seven.

3 Methodology

3.1. The Potential Advantages of Viewing RFR through an Alternative Epistemological Lens

The Potential to Increase the Sensitivity

The adoption of Bayesian approaches in youth justice, particularly through their application to administrative datasets represents an opportunity to address some of the key criticisms of RFR. By starting afresh with a suitably large administrative dataset and adopting an alternative epistemological lens, there is the potential for new criterion to be identified which will enable analysis to be undertaken to explore:

- Whether there are differences on the basis of demographic characteristics and experience of being in care.
- Different features of a 'criminal' career. For example, being a first-time entrant (FTE), age at first offence and conviction, and hence the duration of their time within the youth justice system. Associated with this is consideration of the impact of coming into contact with different facets of the youth justice system namely court appearances, the nature of the disposal received, spending time in custody / on remand and breaching.
- More sensitive measures of reoffending based on offence type and the seriousness of that offence. This will be explored through the use of the YJB Offence Categories and Gravity Scores used within the Reoffending Spreadsheet.

Undertaking this work will enable the lack of sensitivity with regard to the risk factor-reoffending relationship to be addressed. Whilst Bayesian approaches are not constrained in the same way by minimum sample sizes as Frequentist approaches, the permutations of predictor variables and criterion which can be explored is limited by the information captured within the dataset and the time available in order to carry out the analysis. As a result, whilst it is possible to do more with less in terms of sample size, the absence of data and insufficient cases to form subgroups can still limit the analysis. However, it should be noted that when looking at rare events Bayesian approaches are privileged over Frequentist ones since small datasets can be more effectively handled due to the incorporation of prior information in the estimation.

Subgroup Analysis

Given the interest in developing more sensitive measures of reoffending and examining the impact of different features of a criminal career, the adoption of an approach which is appropriate for research involving a small number of observations and cases with non-stochastic data is desirable. Bayesian methods are advocated since they allow for estimates and predictions when there is insufficient data to fit the desired model using Frequentist methods. Notably small data sets that produce fragile statistical methods based on Frequentist approaches can be more effectively handled by the Bayesian approach because of the incorporation of prior information in the estimation.

Whilst Bayesian approaches are not constrained in the same way by minimum samples sizes as Frequentist approaches, the extent to which such analysis can be undertaken in relation to say demographic characteristics, particular interventions or sociographic / structural variables is still dependent upon there being sufficient cases within the dataset to form the subgroups. The permutations of predictor variables and criterion which can be explored are therefore limited by the information captured within the dataset and the time available in order to carry out the analysis.

In opting to utilise Bayesian approaches as is done in subsequent chapters, the intention is to highlight the need to consider using all the tools in the toolbox in order to attempt to unpick what is a highly complex and often dynamic issue.

Sequential Learning and Dynamic Risk

Due to the monitoring requirements of the YOT it is possible to build up a picture over time of individuals and those sharing key characteristics. Through examination of their case histories and ASSET records, it is possible to establish temporal precedence. Key advantages of adopting a Bayesian approach include the fact that models can be updated as new information becomes available; that Bayesian methods support sequential learning and hence can utilise historical information and the results of other research when setting the prior (Berry, 2005). The approach also lends itself to the triangulation of data from other sources through data synthesis (McMahon et al., 2006). Notably the Bayesian approach is ideal for assessing and conveying uncertainty (Berry, 2006) giving it a distinct advantage over Frequentist approaches when it comes utilising information collected via subjective rating scales.

This latter feature is particularly pertinent in the case of the ASSET scores. Although RFR's claims to be culture-free (O'Mahony, 2009), it is anticipated that there may be variations in the interpretation of risk and/or adherence to guidance set out in the National Standards, and the introduction of subjectivity due to practitioner's individual values. As a result, inter-rater agreement is something that could impact on the generalizability of research findings. Agreement analysis has been an active research area where Bayesian approaches have been employed. Calle-Alonso and Pérez Sánchez (2014) for example suggests a Monte Carlo-based Bayesian approach for measuring agreement in a qualitative scale rather than Cohen's Kappa.

Berry highlights 'Bayesian methods support sequential learning, allow for finding predictive distributions of future results and enable borrowing strength across studies' (2005: 296). Specifically, he notes that 'the Bayesian paradigm allows for using historical information and results of other trials, whether they involve the same drug, similar drugs or possibly the same drug but with different patient populations.' It is these qualities of Bayesian analysis make it ideal for exploring the complex relationship between risk and youth offending without completely dismissing existing research. Given RFR's heavy reliance on the findings from a single data source which have since been replicated in a multitude of studies, it would be pragmatic to revisit prior assumptions about risk factors and their relationship with youth offending. This can similarly be achieved using Bayesian analysis with highlighting that some statisticians and scientists are optimistic that Bayesian methods can improve the reliability of research by allowing scientists to crosscheck work done with the more traditional or "classical" approach.

Complexity

In the context of advancing the evidence base in youth justice, a further feature which offers potential for extending knowledge is a mechanism for triangulating data from a number of different sources. Whilst Bayesian inference with its use of prior probabilities that can be drawn from previous research offers a formal process for synthesizing data from multiple sources, Bayesian evidence synthesis allows for the inclusion of other pertinent information that would otherwise be excluded as well as the potential to extend models to accommodate more complex, but frequently occurring, scenarios. Unlike in a meta-analysis, multiple treatment comparisons can be made, something which is much more in keeping with the suite of interventions which can make up a young person's action plan. Although the analysis presented in Chapters Four to Seven does not include interventions, the sequential manner in which different variables are added to the models serves to illustrate the potential for this to be done in the future.

3.2. Introducing the Youth Offending Service Data

Strengths and Limitations

Within youth justice in England and Wales, the Youth Offending Service maintains records on each young person that it comes into contact with including their ASSET scores over time, journal records of supervision meetings and other contacts, and details of progress made in relation to the both their order and any specified requirements. Additional partnership data may also be held both informing their pre-sentencing report and providing a more detailed picture of their individual circumstances. Whilst the assessment and ongoing monitoring requirements have been oft criticised for being 'managerialist' (Brownlee, 1998; Pitts, 2001; Baker, 2005), the data captured represents a comprehensive picture of key aspects of the young lives of those who have come into conflict with the law.

In the case of the youth offending data utilised for this research, this is very rich since it incorporates information collected from a number of different sources including the young person, their parent/guardian, the police/courts, case workers along with other statutory and non-statutory agencies that may work or have contact with the individual during their order. However, this information has been collected for the purpose of monitoring the client rather than for research purposes. As a result, the data is structured for ease of looking at individual's records rather than extracting large volumes of records.

When the research was originally conceived, the aspiration was to also look at what evidence existed within the ASSET which could be utilised to consider the prevalence of speech language and communication needs or mental ill health - issues which have emerged as areas for both societal and policy concern since 2000 and have been incorporated into the ASSET Plus framework. Unfortunately, during the initial familiarisation training received, it became apparent that although individuals may have referrals for support / treatment, the outcome of these referrals is not recorded within their record – the information being considered to be health data. This is also the case for referrals for substance misuse. This was particularly disappointing given the Wales specific Youth Justice Key Performance Indicators around mental health, emotional health and wellbeing, and substance misuse which relate to the number of children identified as requiring assessment within 10 days of the screening date (Welsh Assembly Government and Youth Justice Board, 2009) and the identification of these as priorities in *Children and Young People First* (Welsh Government and Youth Justice Board, 2014).

In addition to this, it is important to note that whilst individual case workers may have opted to refer to their client's progress within case notes, there is no systematic mechanism via a designated field. To access this information would have required a manual trawl through each individual's record which was not feasible within the time available There is also no guarantee that the information would be included - in the case of speech, language and communication needs (SLCN), for example, these could potentially have been identified by the young person's school or another agency, and unless disclosed by the individual or their parent/guardian, the case worker may not be aware of their difficulties including where there was a formal diagnosis.

Selection Criteria

a) Geography

In recent years there have been a number of local changes at Swansea YOT including the merger of Swansea, Neath-Port Talbot and Bridgend to create The Western Bay Youth Justice & Early Intervention Service. At the point where the data collection process commenced, the three local authorities each had their own standalone case management system. Although these have since been merged, the timing for this happening was uncertain with the initial attempt to integrate the systems before the roll out of ASSETPlus failing. Hence for pragmatic reasons, the decision was made to focus on those young offenders resident in the City and County of Swansea. This area had the highest caseload of the three original local authorities and a member of the academic staff within the department was able to facilitate discussions with the data holder to secure permission to utilise the data.

To enable those referred to Swansea YOT to be identified should the merger of the three local authority datasets take place during the data collection period, a unique identifier was created for each individual within Childview. This identifier or 'ResearchID' replaced the Service Reference and was used to anonymise in all working versions of the data. Thus, any individual level information that left the YOT premises also had name and address data stripped out to protect the identify of those that the YOT had worked with. As an additional precaution, the lookup between the Service Reference and ResearchID has been retained on the YOT's server should it be necessary to check details of any individual's record.

In 2012, Swansea YOT changed its case management system from YOIS to Childview. The decision was made not to carry over case records relating to those:

- Where the client was aged 23 years or over or the client's last offence dated before 2007
- Pre-court cases prior to 2009 or where the client was aged over 18
- Blank cases

As a result, the data set in Childview does not represent a full historical record of all clients. Concern was also expressed by the data holder that the older records held in YOIS would not reflect contemporary recording practices. The decision was therefore made to utilise young people's records from their point of entry into the re-offending cohort onwards rather than including those pre-dating the 2012/13 financial year.

b) The Reoffending Cohort

As part of the YJB's Reducing Reoffending Programme, each local YOT was provided with a pre-populated PNC Reoffending Data Tool or 'Reoffending Spreadsheet'. At the point of starting this research, spreadsheets were available for 2012/13 and 2013/14. Table 3.1 summarises the fields that appear within these spreadsheets with a single row per young person:

Table 3.1: Fields in the Local YOT Reoffending Spreadsheets 2012/13 and 2013/14

Field	Notes
PNC ID	(Blank)
YOT	
Service Reference	Replaced by ResearchID
Age	
Gender	
Ethnicity	
Locality (blank)	(Blank)
LAC at Time of Disposal	(Blank)
No of Previous Disposals	(Blank)
No of Previous Custodial Outcomes	(Blank)
Original Offence	
Outcome	See Table 3.2 for further information
Outcome Type	
Outcome Tier	
Date of Outcome (or custody release date)	
Original Gravity Score	
ASSET Score	
ASSET Band	
Intervention Level (amend if requried)	
Reoffended (Y/N)	See Section 3.4 for futher information
Reoffending Gravity Score	
Seriousness of Further Offending	
Most Serious Further Offence	
Number of Further Offences	
Date of 1st Further Offence	
Time Entering Cohort to 1st Further Offence	In Months and Days
Time Entering Cohort to 1st Further Offence	In Decimalised Months
Reoffence Same Category?	
Custodial Establishment (Custody Cases Only)	(Blank)

The spreadsheets incorporate local YOT level performance data from the official Ministry of Justice PNC reoffending summary level performance data and have been designed so that YOTs can identify areas for improvement and targeting resources; reconciling and identifying gaps between the local and PNC data (in particular for 17-year olds and pre-courts); and comparing performance both over time and with different geographies (Youth Justice Board, 2017b)

c) *Identifying those with ASSET Core Profiles*

Swansea YOT operates a diversionary 'Bureau' model and as such their case management system includes details of both statutory and non-statutory ('Bureau') clients. The model is 'designed to divert young people out of the formal processes of the Youth Justice System', with Bureau clients being 'young people who have commit a low-level offence and who have not previously received a Reprimand, Final Warning or Youth Conditional Caution' (Haines et al., 2013: 169). There is not a designated field within the case management system to differentiate between the two. Bureau clients are generally risk assessed using the shorter version of the ASSET tool which was designed for those receiving Final Warnings. Whilst this is captures ratings across for each of the domain scores, there is no necessity to provide accompanying narrative. Given the wish to be able to drill down into the behaviours and circumstances that have promoted a change in the individual domain risk scores, only those individuals who have ASSET Core Profiles have been included in the model. Cross-referencing the ResearchID's of those with ASSET Core Profiles with the re-offending spreadsheet suggested an initial profile of the records which could be included in the model.

2012/13 Spreadsheet

This initially consisted of 148 records of which 146 could be matched to ResearchIDs.

Upon investigation, it was possible to identify that

- One of these relates to an individual with no assessments on the system. He was charged with a motoring offence and given a fine.
- There were 17 individuals who could initially not be matched to ResearchIDs. 16 of these individuals had service references (the YOT's unique ID) which had previously been identified as being anomalies. The remaining anomaly related to a test case which was subsequently be removed.

After removing duplicates (the majority of which had arisen from the service ref anomaly) the resulting spreadsheet consisted of 134 unique individuals.

These records were then matched against the results of a query designed to pull back details of the ASSET Core Profiles. This identified 63 individuals who were part of the 2012/13 cohort who had been subject to the full risk assessment process. Of these 28 did not reoffend, 35 did reoffend.

2013/14 Spreadsheet

This initially consisted of 265 records from across Western Bay YOT of which 132 could be matched to ResearchIDs and hence can be assumed to be Swansea Young Offenders.

Upon investigation, it was possible to identify that

- One of these was a test case which was subsequently removed
- There were 8 individuals who had service references which had previously been identified as being anomalies.

After removing duplicates (the majority of which had arisen from the service ref anomaly) the resulting spreadsheet consisted of 131 individuals.

These records were then matched against the results of a query designed to pull back details of ASSET Core Profiles. This identified 61 individuals who were part of the 2013/14 cohort who had been subject to the full risk assessment process. Of these 45 did not reoffend, 16 did reoffend.

For the purposes of the model, the following criterion were then applied to identify those records which fell within the period of interest:

- 2012/13 reoffending spreadsheet only: those ASSETs dated from the outcome date of their primary offence in 2012/13 to 31st March 2014 have been included.
- 2013/14 reoffending spreadsheet only: those ASSETs dated from the outcome date of their primary offence in 2013/14 to 31st March 2015 have been included.
- If the young person appeared on both reoffending spreadsheets, then the period of interest runs from the outcome of their first offence in 2012/13 until 31st March 2015.

d) Harmonising the Outcomes

During the period of interest, the possible outcomes or 'disposals' for young people changed as a result of the Legal Aid, Sentencing and Punishment of Offenders Act (LASPO), 2012. With effect from 8th April 2013, Reprimands and Final Warnings were replaced by Youth Cautions and Youth Conditional Cautions. However, these are not directly comparable. Penalty Notices for Disorder or 'PNDs', more commonly known as 'on the spot fines' could previously be given to 16 and 17 year olds having committed low level offences. As a result of LASPO, PNDs were no longer available for under 18s in 2013/14. Table 3.2 summarises the disposals by the outcome tiers used in the two reoffending spreadsheets.

Table 3.2: Outcomes and Outcome Tiers for Young People Pre- and Post-LASPO

2012/13 Outcome	Outcome Tier	2013/14 Outcome
Detention and Training Order	Custody	Detention and Training Order
Youth Rehabilitation Order	Community	Youth Rehabilitation Order
Referral Order	First Tier	Bind Over
		Compensation Order
		Conditional Discharge
Final Warning	Pre-Court	Youth Caution
Conditional Discharge	No Intervention	
Reprimand		
Fine		

Comparing Tables 3.3 and 3.4, confirms that many of those without ASSET Core Profiles originally had no intervention or were subject to pre-court disposals. There are however, a small number who have gone on to commit further offences with their ASSET Core Profiles relating to these offences rather than the primary offence. Generally speaking there is a positive association between the assessed risk of reoffending (as measured by ASSET) and the outcome tier, with those receiving custodial sentences more likely to pose a greater risk. Within two cohorts there are a small number who have no ASSET recorded.

Table 3.3: Outcome Tier by ASSET Band for all Unique Individuals, Swansea YOT, 2012/13 and 2013/14

		ASSET Band					Total
		No Intervention	No ASSET	1 to 14	15 to 25	26 to 48	
2012/13	No Intervention	49	-	-	-	-	**49**
	Pre-Court	-	3	29	9	2	**43**
	First Tier	-	2	13	9	3	**27**
	Community	-	1	2	3	4	**10**
	Custody	-	-	-	1	4	**5**
Total		**49**	**6**	**44**	**22**	**13**	**134**
2013/14	No Intervention	81	-	-	-	-	**81**
	Pre-Court	-	1	-	-	-	**1**
	First Tier	-	1	6	13	12	**32**
	Community	-	3	-	5	6	**14**
	Custody	-	-	-	1	2	**3**
Total		**81**	**5**	**6**	**19**	**20**	**131**

Source: Local figures for 2012/13 and 2013/14 taken from locally held versions of the YJB's Re-offending Spreadsheets and may differ from published figures. In 2013/14 data for Swansea was published as part of the figures for Western Bay YOT with individuals being identified as being from Swansea on the basis of their YOT Identifier.

Table 3.4: Outcome Tier and ASSET Bands for those with ASSET Core Profiles, Swansea YOT, 2012/13 and 2013/14

		ASSET Band					Total
		No Intervention	No ASSET	1 to 14	15 to 25	26 to 48	
2012/13	No Intervention	12	-	-	-	-	**12**
	Pre-Court	-	1	6	2	2	**11**
	First Tier	-	1	13	6	3	**23**
	Community	-	-	2	3	4	**9**
	Custody	-	-	-	1	4	**5**
Total		**12**	**2**	**21**	**12**	**13**	**59**
2013/14	No Intervention	14	-	-	-	-	**14**
	Pre-Court	-	-	-	-	-	**0**
	First Tier	-	1	6	14	11	**32**
	Community	-	1	-	5	6	**12**
	Custody	-	-	-	1	2	**3**
Total		**14**	**2**	**6**	**20**	**19**	**61**

Source: Local figures for 2012/13 and 2013/14 taken from locally held versions of the YJB's Re-offending Spreadsheets and may differ from published figures. In 2013/14 data for Swansea was published as part of the figures for Western Bay YOT with individuals being identified as being from Swansea on the basis of their YOT Identifier. The bands correspond to the pre-Scaled Approach risk levels of Low, Medium and High, and are a sum of the ratings given for the 12 dynamic domains.

e) Matching to ASSET Core Profiles

The following query was created to extract data from Childview relating to the ASSET Core Profiles:

Query 1 – ASSET Scores by Domain

Date specified on the basis of the assessment start date i.e. from 1st April 2012 to 31st March 2015.

The queried fields from Childview were:

- YOT Identifier (replaced by ResearchID)
- Birthdate
- Age
- Gender
- Ethnicity
- Start Date
- Stage
- Instance
- Care Order
- Eligible Child
- Relevant Child

For Calculating Static Scores

- Age at First Reprimand or Caution
- Age at First Conviction
- Number of Previous Convictions
- Number of Custodials
- Primary Offence

For Calculating Dynamic Scores

- Living Arrangements
- Family and Personal Circumstances
- Education, Training and Employment
- Neighbourhood
- Lifestyle
- Substance Use
- Physical Health
- Emotional and Mental Health
- Perception of Self and Others
- Thinking Behaviours
- Attitudes to Offending
- Motivation to Change

ASSET Score and Level of Intervention

- ASSET Static Score
- ASSET Dynamic Score
- Indicated Level of Intervention
- Adjusted Intervention Level
- Interim Level

Unfortunately, it was not possible to pull back all the fields when the query was run. It was therefore necessary to manually populate these fields by looking at the individual records on Childview. The problem largely affected the fields required to calculate the static score i.e. original offence including date, age at first Reprimand/ Caution/ Warning, age at first conviction and number of previous convictions. However, stage was also not pulled back – this field denoting the point in the referral process that the assessment related to i.e. Start / Review / End.

Where the fields required to calculate the static score were populated within Childview, inspection revealed that there were a lot of inconsistencies. For example, one practitioner might have identified that the young person was aged 15 at the time of their first conviction, the next identified them as being 13. Whilst these inconsistencies did not prevent Childview from calculating a static score and hence a total ASSET score, where practitioners had failed to specify which offence was the Scaled Approach Offence (typically the one for which they had received the main outcome, or the one with the highest gravity score), then the static score was shown as being incomplete on the system. With an incomplete static score, the total ASSET score generated is misleading.

Having identified this issue with the static score generated within Childview, it was decided to use the information in the young person's offending and court records to populate the relevant fields.

f) Creating an Enhanced Version of the Dataset

The data represented as Queries 2 and 3 below was downloaded from each identified individual's record having previously been entered into Childview by the YOT. The information was then manually added to create an enhanced version of the dataset. From the offence records it was possible to determine when further offences have been committed and when young people had been breached. The court records provided the dates for when the young person had attended court, regardless of the outcome of the proceedings.

Queries 2 and 3 – Individual's Offence and Court Records

No date criteria specified

<u>Offences</u>

- YOT Identifier (replaced by ResearchID)
- Offence Date
- Age (Years and Months)
- Offence
- Plea
- Outcome
- Seriousness (Gravity Score)

<u>Court Proceedings</u>

- YOT Identifier (replaced by ResearchID)
- Proceeding Date
- Age (Years and Months)
- Court Action
- Main Offence
- Main Outcome
- Term

Notably from the proceeding dates, it was possible to identify which offence had led to the young person's inclusion within the reoffending cohort for that particular year since the outcome date is used rather than the date that the offence was committed to mark the start of the one year follow up period. The exception to this is those who received a custodial sentence in which case the follow up period starts at the point when the young person has been released. Typically, young people sentenced to a detention and training order or 'DTO' serve half of their term with the remainder of the sentence being served under the supervision of their local YOT in the community.

Where a young person has been returned to the court following a breach, the outcome for the primary offence was over-written in the offence record. Within the court records, only the main offence is provided, hence it was not always clear when offences had been dealt with, with typically the main offence being the one with the highest seriousness score.

By cross referencing the start dates of the ASSET Core Profiles with the offending and court records it was possible to identify if in the period prior to date of the assessment, the young person had:

- **Breached** – shown as an offence on the individual's offence record. In keeping with the definition used to identify proven reoffending (Section 3.5), where the young person has breached, this is not treated as a further offence
- **Committed an offence** – based on the date committed, regardless of the outcome subsequently received. All young people are reflected as having committed an offence at Time 0, marking their entry into the cohort.
- **Attended court** – proceeding dates are reflected on the court record. Given the lag in cases coming before the court and the potential for cases being withdrawn and adjourned, no distinction is made between the nature of the proceedings. This includes where the young person has been placed on remand and when sentenced. More serious cases typically take less time to court and hence the order of court appearances does not necessarily correspond to the order in which offences were committed.
- **Spent time in custody / on remand** – this information is reflected in the court record as an outcome of the proceedings.

Particularly in the case of offending and attending court, there may be multiple occurrences in the period leading up to the ASSET being updated, therefore the flags created reflect simply that such an 'event' has occurred.

3.3. Ethical Considerations

The main areas in which ethical issues can arise relate to whether there is harm or risk to participants; if there is a lack of informed consent; whether deception is involved, if there has been any invasion of privacy and respecting confidentiality (Punch, 2006). In the context of using administrative data, as has been done here, the data are not collected for research, but by the Youth Offending Service during the course of their normal business with data subjects being compelled to provide information about their circumstances and offending behaviour. As such there is a lack of implicit research consent which places a greater emphasis upon safeguarding the data and reporting with integrity.

Unlike administrative data available through the Administrative Data Research Network (ADRN), the data utilised within this research has been drawn directly from a live client database. Therefore, data classified as both personal and sensitive under the Data Protection Act 1998 features within the database. Further to this, data subjects, by virtue of their age are considered to be vulnerable with many having complex lives. For this reason, procedures were put in place to de-identify records onsite with pseudo identifiers being created for research purposes – the ResearchID. The 'lookup' of matched IDs has been retained on the YOT server – a secure environment - along with copies of original queries and datasets created during the process of de-personalising the data. In this way, the integrity of the personal data has been retained.

As part of the assurances made to the YOT during the process of negotiating access to the data, it was necessary to agree on steps to minimise the risks of statistical disclosure. For this reason, as will be seen in Chapters Four to Seven, data has been aggregated with pseudonyms being used when discussing individual cases. In some cases, it has been necessary to 'blur' the details to prevent individuals, their victims or their families being identified. Where it has been necessary to do this, it has been flagged in the text.

Although there has been no direct contact with the data subjects, in order to seek clarification, especially in the context of understanding the offending histories of some of the young people, it has been necessary to speak to individual YOT workers about individual cases. This has been done on the understanding that all information disclosed is confidential. Due to the sensitive subject matter and the vulnerability of the young people whose records are held within the YOT client database, it was necessary to secure Disclosure and Barring Service clearance; to sign a Third Party Connection Agreement with the City & County of Swansea which includes a confidentiality agreement and Memorandum of Understanding about the use of their IT systems. Copies of the latter can be found in Appendix 2 of this volume along with a copy of the completed University's ethics form (Appendix 1).

3.4. Specific Features of the Data within Childview and ASSET

As would be expected from any administrative dataset, Childview contains individual level data stored in a number of different formats including subjective rating scales from the ASSET Core Profile, free text, dates and postcodes. The 'date stamping' of activity provides a means of establishing temporal ordering for example, highlighting where the timing of offences and court appearances, and changes in their risk scores over time.

Repeated Measures

Since repeated ASSET Core Profiles are completed for young people over the course of their time with the YOT, the series of assessments for each individual can be thought of as being longitudinal data. As such the data lends itself to analysis by way of a hierarchical or multilevel model. When using hierarchical models to analyse longitudinal data, Level 1 is generally associated with a single measurement in time and Level 2 refers to an individual subject. In this way the advantages associated with the flexibility and power of such models can be maximised. For example, Finch et al. advocate that modelling longitudinal data in a multilevel framework allows 'the simultaneous modeling of both intra-individual change (how an individual changes over time) and inter-individual change (difference in temporal change across individuals)' (2014: 99-100).

Individuals under the supervision of the YOT will typically have a 'Start' and 'Finish' ASSET. Depending upon the duration of their order, they may have further 'Review' ASSETs since the National Standards recommend that assessments are reviewed every three months or where there has been a significant change in the young person's circumstances. As such the data is unbalanced with individuals having differing numbers of assessments. Traditional techniques, such as repeated measures ANOVAs can only analyse balanced datasets whereas multilevel modelling can utilise available data from 'incomplete' observations. Additionally, repeated measures ANOVAs rely upon the assumption of sphericity (i.e. of equal variances of outcome variable differences). This assumption is unreasonable given that variability may change considerably over time. Thus, multilevel models, which do not require this assumption, offer greater flexibility by allowing information to be included in the model specification about the anticipated effects of time on error variation.

Multilevel models also allow for more complex data structures to be explored and can be considered to be a 'powerful and flexible extension to conventional regression frameworks … extending the linear model and the generalised linear model by incorporating levels directly into the model statement, thus accounting for aggregation present in the data' (Gill and Womack, 2013: 3). Through use of a nested data structure, it is therefore possible to avoid the unaccounted for heterogeneity and correlation which are common in conventional, flat modelling. This has made hierarchical linear models the main type of application in biological and medical sciences (Snijders and Bosker, 2012: 247). However, as Gill and

Womack (2013) observe, although hierarchical structures are common in social science data, they are commonly ignored by social science researchers.

Notably it is easy to incorporate both time-varying 'Level 1' predictors and time invariant 'Level 2' or individual level characteristics. In this way, temporal changes associated with both the domain scores and individual characteristics can be explored as per first research objective. This advances the work undertaken by Wilson and Hinks (2011: 10) who utilised 'Only one (Core/Final Warning) ASSET assessment per offender' when selecting cases to include in their evaluation of the predictive accuracy of the tool.

To demonstrate the utility of the hierarchical modelling approach - the name often given to multilevel models run under a Bayesian framework, the equivalent models have also been run under a Frequentist framework. The R packages identified to undertake the analysis – MCMCglmm (Hadfield, 2010) and lme4 (Bates et al., 2015), are very similar in terms of the way in which the model is specified, with both packages have been written specifically to enable generalised linear models to be fitted. The former uses Markov chain Monte Carlo techniques to fit models under a Bayesian framework. The latter is recommended by Li et al. (2011) as the most efficient package for logistic random effects regression models for binary or ordinal outcomes under a Frequentist approach, in terms of usability, flexibility and speed.

Finch et al. (2014) provides an introduction to the glmer function in lme4 and to MCMCglmm. However, vignettes are available for both packages. This research therefore also draws upon techniques outlined in MCMCglmm Course Notes (Hadfield, 2016), and tutorials provided by Wilson et al. (2010) and de Villemereuil (2012).

Data Structure

Within Childview, much of the data being utilised has been captured using structured forms. However, these are supported by reports from practitioners, the police / courts and other agencies which are held within free-text and journal fields. Whilst there is a desire to incorporate expert opinion as a distinct advantage of Bayesian approaches is that it is possible to incorporate both qualitative and quantitative data, the volume of information and way in which it is held, limits the extent to which this can be utilised. However, as will be seen in Chapter Five, being able to draw upon this detailed information, aids in the interpretation of findings.

As outlined in Section 3.2, Childview was designed to enable practitioners to monitor individual clients rather than for research purposes. Hence whilst data may be captured and is visible within the various 'pages' of Childview, it is not necessarily possible to query the underlying data to do bulk extracts. As a result, it is possible for example to bulk download dynamic ASSET score (with accompanying identifiers) whilst the offence and court records can only be downloaded for individual clients. Other fields e.g. the static scores appear to be 'locked down'. The situation was further complicated during the data collection period by the transition to an updated version of Childview which was intended as a transition database prior to the roll out of ASSET Plus. The local YOT has since migrated to Childview 3. Subtle changes in field names which occurred during this process meant that a number of the built-in queries ceased to work further reducing access to raw data from the original assessment tool. It is however, possible to view individual historic records for those young people who have committed further offending and have since been assessed using the new tool.

Subjective Rating Scales

Concerns around the subjective nature of the rating scales within ASSET, are lessened as a result of clients typically having a dedicated key worker for the duration of their order who is responsible for reviewing and updating their risk assessments. However, within the dataset are a proportion of individuals who have been subject to multiple orders and it has not always been possible to have this level of continuity. As part of the negotiations to secure access to the data, it was agreed that individual practitioners would not be scrutinised. Hence, this potential area for variation has not been explored. In this respect it is prudent to highlight that the guidance which accompanies the ASSET tools is very comprehensive and therefore it is unlikely that within a local YOT there would be much variation ratings assigned by in a given situation.

As was done by Wilson and Hinks (2011), it has been necessary to assume that the ASSETs were completed correctly by practitioners. Particularly in the case of the dynamic scores it is not possible to undertake any quality assurance checks or to see if ratings from previous assessments had simply been copied. Inconsistencies were however identified in the static scores when the information from the ASSET was compared to the offence and court information held within Childview. As a result, this information has been used rather than that entered by the practitioner at the time of the assessment.

Strictly speaking the domain scores are ordinal data. However, in keeping with the advice given by Gelman (2010), the ratings have been treated as being discrete (from 0 to 4).

Missing and Incomplete Data

The issue of missing and incomplete data is not a modern phenomenon, nor is it unique to Bayesian approaches. Indeed, George B Vold, when writing about the efficiency of prediction in criminology in 1949 observed:

> 'The most discouraging thing about the whole field of prediction is criminology is the continued unreliability and general worthlessness of much of the so-called 'information' in original records. Opinions, hearsay, and haphazardly recorded judgements still constitute the bulk of any parole file.'
>
> (Cited in Farrington and Tarling, 1985: 15)

Whilst the view is that the quality of the data captured within the YOT is much higher than this, it has been necessary to follow the approach taken by both Baker et al (2003, 2005) and Wilson and Hinks (2011) to exclude ASSET records which were less than 80% complete. The difficulty encountered, is that for ease, Childview (the case management system within the YOT) permitted ASSET scores to be pre-populated using data from the previous assessment. The idea being that where there was new evidence (and hence a change in score) then this section could be over-written, leaving the remainder unchanged.

A manual check of the number, completeness and dates of the ASSET Core Profiles resulted in a small number of individuals being excluded – largely because their ASSET Core Profiles were blanks, were duplicates (based on start date and domain scores) or pre-dated the individual's entry to the cohort. Across the two years, it was necessary to exclude a further 12 individuals who only had a single ASSET Core Profile within the relevant period thus limiting the amount that they could contribute to the model. This reduced the size of the reoffending cohort with ASSET Core Profiles to 88. Between then they had 544 ASSET Profiles.

Issues around missing data within published sources are also a problem within RFR, limiting particularly analysis of trends amongst BME young offenders. Notably in 2013/14, a system error led to 7% of young people included in the annual workload statistics were shown as having 'unknown' ethnicity (Youth Justice Board and Ministry of Justice, 2015b). However, perhaps more significantly it appears that the YOT has adopted a practice of recording clients as being of 'Any other White background' rather than 'White British' – potentially to reflect their national identify as being Welsh. Unfortunately, it is not possible to differentiate between these young people and those who say are of Eastern European heritage. This, plus the low numbers recorded as being from Asian, Black, Mixed or Other backgrounds (6/88, 7%) limits the amount of analysis that can be undertaken around ethnicity, particularly if cross-referenced by gender. (Table 3.5)

Table 3.5: Ethnicity and Gender Profile of Clients

Ethnicity Recorded		Male	Female	Total
White	White Birtish	16	3	19
	White Irish	1		1
	Any Other White Background	66	7	73
Black	Black Caribbean	1		1
Asian	Pakistani	1		1
	Any Other Asian Background	2		2
Mixed	White and Asian	1		1
	White and Black Caribbean	1		1
	Any Other Mixed / Multiple Background	1		1
Grand Total		90	10	100

Notes: Young people included in the YJB's 2012/13 and /or 2013/14 Reoffending Spreadsheet for whom there are ASSET Core Profiles.

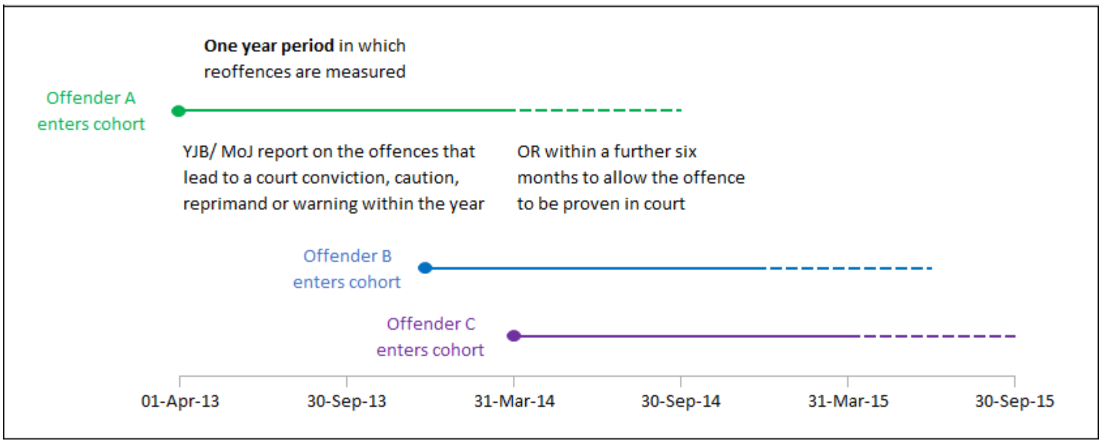
Snijders and Bosker (2012) note that it can be assumed that absent data are missing at random and the fact that there are missing does not in itself provide relevant information about the studied phenomena. However, it should be noted that MCMCglmm and lme4 do not handle missing data well and as a result it has been necessary to exclude a small number of records due to one or more domain score being missing.

3.5. Construct Validity: Re-Offending

Historically, there has been concerned raised around the measurement of crime as a social phenomenon, with many of the studies which have contributed to the RFR evidence base relying upon self-reported measures of offending. This has led to a body of literature which has sought to compare self-reported and 'official' measures. For example, West and Farrington (1977) have done this with the cohort from the Cambridge Study of Delinquent Development and more recently the self-reported 'delinquency' reported by those involved in the Edinburgh Study of Youth Transitions and Crime have been compared against the 'rich and detailed records that exist in Scotland about young people who have been in contact with the social work or children's hearing system' (Smith and McVie, 2003: 179). Comparisons have also been made elsewhere e.g. Sullivan and McGloin (2014) which additionally looks at the impact across gender and race/ethnicity.

In the context of this piece of work, ASSET is promoted as being an assessment tool for determining the risk of re-offending. However, the reality is that it is concerned with re-conviction. As such the concerns around using 'official data' are the most pertinent, with the potential for offending behaviour to occur which is does not come to the attention of the police / courts and hence may represent an under-representation of an individual's criminality. Following the Ministry of Justice *Consultation on Improvements to Ministry of Justice Statistics*, a proven offence is defined as any offence committed in a one year follow-up period that resulted in a court conviction, Caution, Reprimand or Final Warning in the one year follow-up or a further six month waiting period (to allow time for cases to progress through the courts) (Ministry of Justice, 2017a: 5). Although there has since been a move to a three-month cohort for re-offending (Ministry of Justice, 2017b), the data available to this research was based on a 12-month cohort. This is illustrated in Figure 3.1 for the 2013/14 performance year.

Figure 3.1: Proven Re-Offending: 2013/14 Cohort

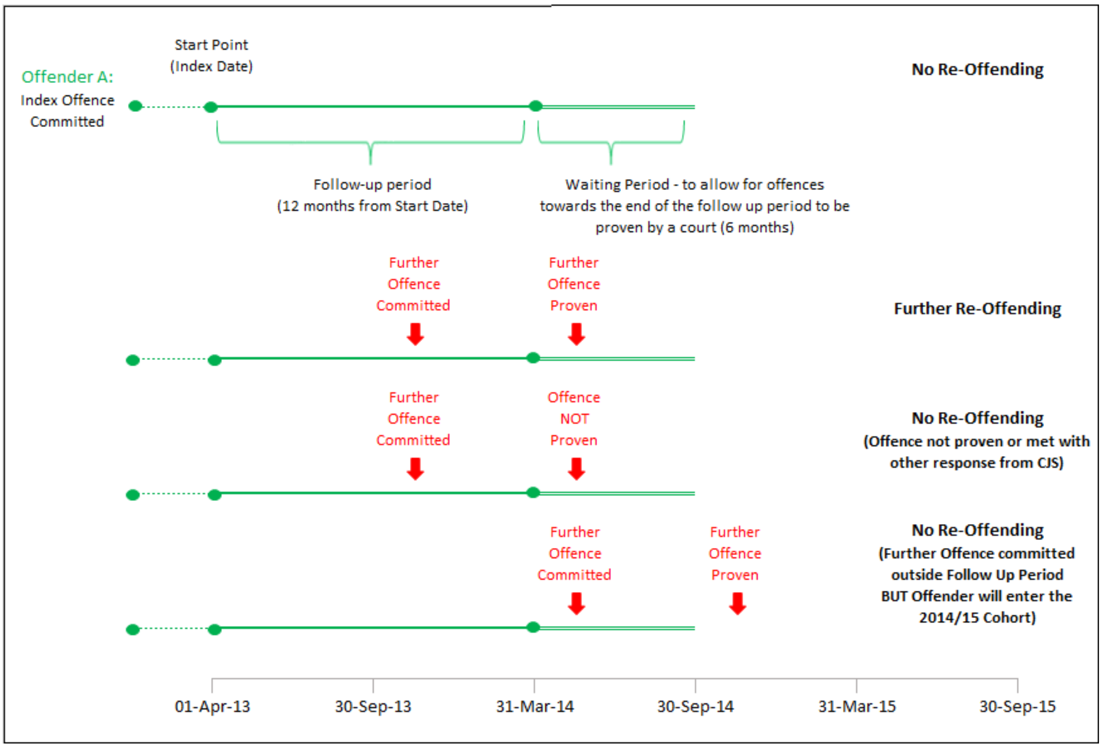


Adapted from Ministry of Justice, 2017

An offender enters the 2013/14 cohort if they are released from custody, received a non-custodial conviction at court or received an offence in the period April 2013 to March 2014. Potentially an offender can enter the cohort on 31st March 2014 and would still fall into scope. The need to wait for the 12-month follow up period plus up to six months for any further offending to be proven results in a lag in establishing whether or not the offender has re-offended. This is illustrated in Figure 3.2.

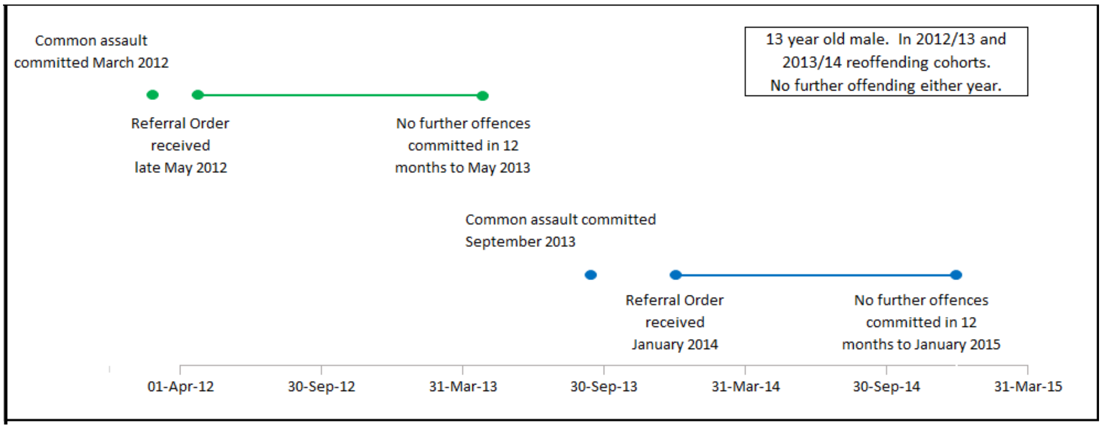
Due to the complexity of this administrative measure, the young person's reoffending status has been taken from the 'Reoffending Spreadsheet' since this was compiled utilising PNC records.

Figure 3.2: Re-Offending: A Worked Example Based on Offender A from the 2013/14 Cohort



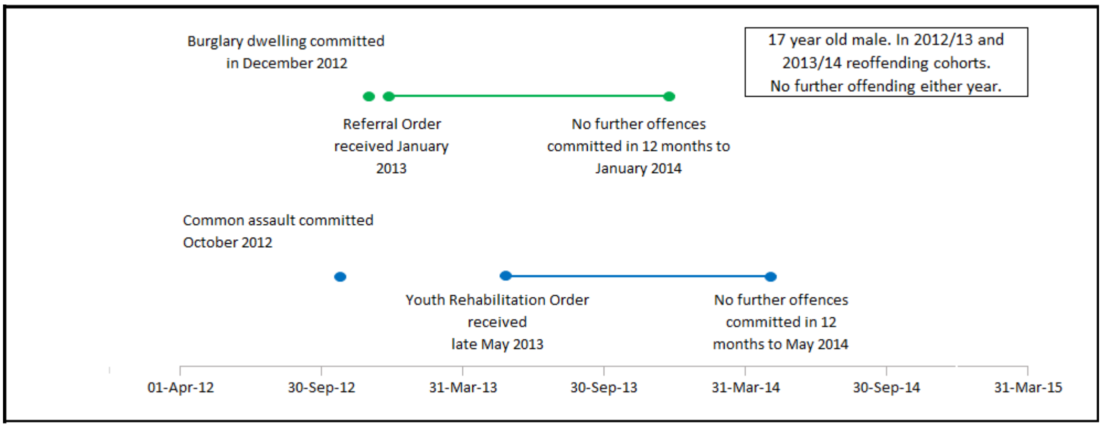
Analysis of the individual cases highlight that by virtue of their proven re-offending, there are 24 young people who feature in both the 2012/13 and 2013/14 cohorts. However, it is important to highlight that there are two young people who are shown as having not reoffended in both years. Figures 3.3 and 3.4 highlight how using the official Ministry of Justice measure of proven re-offending may not be as reliable as it initially seems. Whilst the utility of both self-reported and official measures of offending have been widely discussed elsewhere (see for example Farrington and Tarling (1985); Smith and McVie (2003)), the second case in particular illustrates that reliance upon the timing of the sentencing hearing to fulfil the criteria of further offending being proven and receiving a substantive outcome exposes a limitation of this measure. The first case demonstrates the importance of not just relying upon the domain risk scores – in this instance, the move would be reflected in the likelihood of reoffending scores relating to the young person's living arrangements and the family and personal relationships domains – but also having access to the supporting information which helped the practitioner come to their decision.

Figure 3.3: Case 1: A 13-year old Male Appearing in Both Cohorts



This individual has since gone on to commit further offences for which he has received substantive outcomes. However, there was a period of primary desistance which is understood to have coincided with a move to live with his father – his father being able to exert a stronger influence over his son's behaviour. The next period of offending began in February 2016.

Figure 3.4: Case 2: A 17-year old Male Appearing in Both Cohorts



In this second case, the earlier offence took longer to go to court than the more serious burglary dwelling. As a result, when sentenced for the common assault, he was also re-sentenced for the burglary. The referral order for the burglary placed him in the 2012/13 cohort whilst the youth rehabilitation order received for the common assault placed in him in the 2013/14 cohort. At the time of the second sentencing hearing, he was two weeks shy of his eighteenth birthday. No further offences have been committed since late 2012 hence he is reflected as having not reoffended in either year.

It should also be noted that the manual determination of proven reoffending is dependent upon the following criteria being taken into consideration:

> 'Offences are counted as proven re-offences if they meet all of the following criteria:
>
> - They are recordable. Not all offences are on the PNC and more recordable offences are entered than non-recordable offences. Analysis comparing offences proven at court with offences recorded on the PNC suggests the most common offences that are not recorded relates to motor vehicles, e.g. using a motor vehicle whilst uninsured against third party risks, speeding offences, keeping a vehicle on the highway without a driving licence or television licence evasion.
> - They were committed in England or Wales.
> - They are offences that were prosecuted by the police. PNC data are collected and input by the police and offences prosecuted by the police are likely to be recorded more comprehensively on the PNC than offences that are prosecuted by other organisations.
> - Offences are only counted if they are proven through caution, reprimands or final warnings (for juveniles) and court convictions. Offences that are not proven, or which meet with other responses from the Criminal Justice System, are not counted.
> - The offence is not a breach offence, i.e. breach of a court order, since we are only interested in new offences.'
>
> (Ministry of Justice, 2017a: 7-8)

Without access to PNC, it has been necessary to rely upon the information captured within Childview around the young person's offending and court appearances.

3.6. The Preferred Outcome Variable

As highlighted in the previous section, the 'official' measure of proven reoffending is somewhat artificial and is not without its limitations. In the context of the hierarchical modelling exercise, using re-offending which is measured at the individual level (Level 2) means that you no longer have a hierarchical structure i.e. time points nested within individuals. The preferred outcome variable is therefore further offending.

This measure has been added to the dataset to denote whether in the period prior to the assessment, the young person has committed one or more offences. As a result, at Time 0 (the initial assessment), every young person is reflected as having committed one or more offences. Details of further offences have then been added as a flag using information from the young person's offending records recorded within Childview. Since there is often a lag in cases going to court, the measure is not based on proven further offending. As indicated in Section 3.2, flags for breaches, court appearances and time spend in custody / on remand were added in a similar manner.

The rationale for including this measure is that regardless of the ultimate outcome, the arrest / charge is a reflection of the young person's offending behaviours and it is anticipated that this will be reflected in their risk score. The preferred outcome variable is therefore a binary measure. In the context of MCMCglmm, this means that the 'family' that the simulated model belongs to is ordinal whilst in lme4, the distribution is reflected as being binomial.

Research Question:

What does the modelling tell us about the relationship between further offending, the 12 domains and time?

3.7. Predictor Variables: Rationale for Inclusion

In wishing to achieve the research aims and objectives set out in Chapter Two, a Bayesian hierarchical modelling approach has been adopted which utilises administrative data from the young people's ASSET Core Profiles. The cohort has been identified using Swansea (and later Western Bay) YOT's pre-populated 2012/13 and 2013/14 reoffending spreadsheets, matched to ASSET Core Profiles.

In 2012/13, Swansea YOT had 134 clients in their Re-Offending Cohort after test cases and issues with erroneous YOT Identifiers were removed. As a result, the local figures used within this research differ from those published by the YJB and Ministry of Justice. The following year, 131 of the 273 of those on the newly formed Western Bay YOT's spreadsheet were Swansea clients. For consistency, analysis has been limited in the second year to just those known to Swansea. Once matched, their dynamic scores and additional individual level data held within Childview, the resulting dataset has been utilised to explore the role of:

- Individual, demographic characteristics
- Being looked after by the local authority
- The nature of the primary or index offence

In light of the inconsistencies around the way in which the static domains have been completed, proxy measures have also been developed to represent the young person's offending history and the impact of organisational measures reflecting specific facets of the youth justice system. This section therefore provides the rationale for the various predictor variables which will be used within the modelling. This is done by presenting analysis of both local data and national trends for proven reoffending to provide an indication of where differences might exist within the wider cohort.

Demographic Characteristics

Across the two re-offending spreadsheets, less than one in five of the young offenders is female – a figure which is slightly lower than the national proportion receiving substantive outcomes in 2012/13 and 2013/14 i.e. 19.3% and 18.6% respectively (Youth Justice Board and Ministry of Justice, 2015a: Tables 3.3 and 3.5) (Table 3.6).

Table 3.6: Demographic Profile, Swansea YOT, 2012/13 and 2013/14

		2012/13		2013/14	
		No	%	No	%
Gender	Male	109	81.3	108	82.4
	Female	25	18.7	23	17.6
Ethnicity	White	123	91.8	124	94.7
	Non-White	11	8.2	7	5.3
Age	10 years	0	0	0	0
(At the time of the primary offence)	11 years	0	0	0	0
	12 years	4	3	0	0
	13 years	6	4.5	3	2.3
	14 years	16	11.9	17	13
	15 years	32	23.9	31	23.7
	16 years	30	22.4	33	25.2
	17 years	46	34.3	47	35.9
All Persons		134	100	131	100

Source: Swansea YOT's Internal Re-offending Spreadsheet 2012/13 and Western Bay YOT's Internal Reoffending Spreadsheet 2013/14. 2013/14 Swansea figures identified on the basis of the individual's YOT Identifier.

In part reflecting the ethnic profile of Swansea at the time of the 2011 Census when 92.9% of Swansea's 10-17 year olds were identified as being White compared to the England and Wales average of 81.7% (Office of National Statistics, 2013), the numbers identifying as being non-White are low. In 2012/13, the breakdown was 4 Asians, 2 Mixed and 4 Unknown. The following year there were 2 Asians, 1 Black, 2 Mixed and 2 Unknown.

Nationally, 23.2% of those receiving substantive outcomes in 2012/13 were aged 10-14 years, falling slightly to 22.1% the following year (Youth Justice Board and Ministry of Justice, 2015a: Table 3.5). Locally, the proportion was lower – 19.4% in 2012/13 and 15.3% the following year, in part a reflection of the local diversionary practices which utilise the Youth Restorative Disposal (YRD) – a non-statutory disposal for young people committing a low-level offence (Haines et al., 2013). Introduced in 2008, this disposal is aimed at those who have not previously received a Reprimand, Final Warning or Youth Conditional Caution and is therefore more commonly given to younger offenders. As a non-statutory disposal YRDs are not considered to be a substantive outcome and hence those receiving it do not reach the threshold to appear on the YJB's reoffending spreadsheet.

At a headline level, 31.3% (42/134) of those in the 2012/13 cohort re-offended whilst the following year the proportion fell significantly to 20.6% (27/131) – the fall, in part linked to the local implementation of the Legal Aid, Sentencing and Punishment of Offenders Act, 2012 which provided for greater flexibility in the sentencing of young offenders. With increased use of diversionary activity, the local trend bucked that experienced nationally where the proven reoffending rate increased from 36.1% in the year ending March 2013 to 38.0% the following year (Youth Justice Board and Ministry of Justice, 2015a: Table 9.1).

Table 3.7: Proven Re-Offending, Local and National Rates, by Demographic Characteristics, 2012/13 and 2013/14

		2012/13		2013/14	
		Swansea YOT	England and Wales	Swansea YOT	England and Wales
Gender	Male	34.9% (38/109)	38.6%	23.6% (25/108)	40.4%
	Female	16.0% (4/25)	26.2%	8.0% (2/23)	28.4%
Ethnicity	White	30.9% (38/123)	36.0%	20.2% (25/124)	38.4%
	Non-White	36.4% (4/11)	Asian - 31.8% Black - 43.9% Other - 35.2%	28.6% (2/7)	Asian – 32.6% Black – 44.9% Other - 35.9%
Age	10-14 years	19.2% (5/26)	35.2%	10.0% (2/20)	38.9%
	15-17+ years	34.3% (37/108)	36.4%	22.5% (25/111)	37.8%
Overall		**31.3% (42/134)**	**36.1%**	**20.6% (27/131)**	**38.0%**

Notes: National figures taken from Youth Justice Board and Ministry of Justice (2015a: Tables 9.1, 9.2, 9.3 and 9.4) reflecting the years to end of March 2013 and March 2014 respectively. Local figures for 2012/13 and 2013/14 taken from locally held versions of the YJB's Re-offending Spreadsheets and may differ from published figures. In 2013/14 data for Swansea was published as part of the figures for Western Bay YOT with individuals being identified as being from Swansea on the basis of their YOT Identifier.

As can be seen, at both a local and national level, proven re-offending rates vary on the basis of gender, ethnicity and age (Table 3.7). However, the small numbers who have either identified as being Non-White or not had their ethnicity recorded in the local cohorts highlights how the rates may be susceptible to high variability due to the size of the cohorts, with proven reoffending rates being determined for aggregated groups even at a national level. This finding supports the rationale for including socio-demographic characteristics within the hierarchical model. Although, the low numbers suggest that may be necessary to set some of the variables up as being dichotomous e.g. White – Non-White.

As previously highlighted, by virtue of their offending behaviours, it is possible for some of those in the 2012/13 to also feature on the reoffending spreadsheet for the following year. In total there were 24 individuals who appeared on both spreadsheets. The demographic profile of 88 members of the combined cohort with ASSET Core Profiles is summarised in Table 3.8.

Table 3.8: Demographic Profiles of those with ASSET Core Profiles, Swansea YOT, 2012/13 and 2013/14

		2012/13 Only		2013/14 Only		Both		**Total**	
		No.	%	No.	%	No.	%	**No.**	**%**
Gender	Male	28	82.4	29	96.7	22	91.7	**79**	**89.8**
	Female	6	17.6	1	3.3	2	8.3	**9**	**10.2**
Ethnicity	White	30	88.2	29	96.7	23	95.8	**82**	**93.2**
	Non-White	4	11.8	1	3.3	1	4.2	**6**	**6.8**
Age	10 years	-	-	-	-	-	-	**-**	**-**
	11 years	-	-	-	-	-	-	**-**	**-**
	12 years	2	5.9	-	-	-	-	**2**	**2.2**
	13 years	-	-	1	3.3	2	8.3	**3**	**3.4**
	14 years	1	2.9	4	13.3	1	4.2	**6**	**6.7**
	15 years	8	23.5	8	26.7	9	37.5	**25**	**28.1**
	16 years	7	20.6	6	20	8	33.3	**21**	**23.6**
	17 years	16	47.1	11	36.7	4	16.7	**31**	**34.8**
All Persons		**34**		**30**		**24**		**88**	**100**

Notes: Age is at time committing the primary offence which led to entry to the cohort. Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14.

Of the 82 males in the cohort, 6 are identified as having a non-White background. However, all the females identified as being White. The youngest male appearing on the reoffending spreadsheet was 12 at the time of entering the cohort whilst the youngest female was 14. Overall, 85% (77/88) of the young people were aged 15 to 17 at the time of their primary offence. This included all 6 of those identifying as being from a non-White background.

Table 3.9 summarises the rates of further offending by gender and ethnicity for those in the reoffending cohort. Since this offending is not necessarily proven and may reflect multiple offences committed during the period between ASSET assessments, direct comparisons cannot be made with the published data.

Table 3.9:Rates of Further Offending Across the Two Years, by Gender and Ethnicity

	Comparator Groups		No.	Further Offences	% Committing Further Offences	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Gender	1	Male	79	39	49.4%	0.591	0.238
	2	Female	9	3	33.3%		
Ethnicity	1	White	82	41	50.0%	1.442	0.211
	2	Non-White	6	1	16.7%		
Total			**88**	**42**	**47.7%**		

Notes: Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1. This can be thought of as being the equivalent of a 2x2 chi-squared test. The two sets of Bayes Factors represent the results of (1) a two-sided alternative hypothesis that rates of further offending are equal (Null Hypothesis: Group 1 ≠ Group 2), and (2) a one-sided alternative hypothesis that the rates for Group 1 are larger than Group 2. Bayes Factors quantify the evidence for the alternative hypothesis relative to the null hypothesis and are interpreted using the categories suggested by Jeffreys (1961).

The rate for females (33.3%) is notably lower than that for males (49.4%) which is consistent with the national reoffending rates. There is moderate evidence to support the null-hypothesis that the rate for males is greater than that for female (BF_{10} = 0.238). Since the Bayes Factor is less than 1/3, this is can be interpreted as a significant result. National figures around the proven reoffending rate by ethnicity suggest that relative to those from a White ethnic background, the reoffending rates for those from an Asian or Other background are typically lower whilst those from a Black background have a higher reoffending rate (Youth Justice Board and Ministry of Justice, 2015a: Table 9.4) therefore a two-side hypothesis test was conducted to establish whether or not the apparent difference was statistically significant. This suggested that within this dataset, there is insufficient evidence for the alternative hypothesis that the reoffending rates are equal for both groups (BF_{10} = 1.442). For there to be substantial evidence against the null hypothesis, the Bayes Factor would need to be greater than 3. However, there is moderate evidence to suggest that the rate for the non-White group is significantly less than that for the White group (BF_{10} = 0.211) in the one-sided test.

Research Question:

What does the modelling tell us about the impact of gender and ethnicity on the likelihood of further offending over time?

Organisational Measure: Care Status

The young person's care history is recorded within the ASSET Core Profile, with fields populated by the practitioner to reflect whether the young person is, or ever has been:

- Accommodated by voluntary agreement with parents under section 20 of the Children Act 1989
- An 'eligible' or 'relevant' child

In the case of the former, if a young person who is accommodated under s20 goes into custody, he or she is no longer looked after by the local authority (although the authority may retain responsibility for providing a leaving care service). In such cases, it is necessary for the practitioner to update the ASSET after sentencing to reflect the change in status.

Eligible children are those young people still in care aged 16 and 17 who have been looked after for (a total of) at least 13 weeks from the age of 14. Relevant children are young people aged 16 or 17 who have already left care, and who were looked after for (a total of) at least 13 weeks from the age of 14, and have been looked after at some time while 16 or 17. The inclusion of these questions was intended to clarify whether a young person is entitled to the local authority's leaving care services under the provisions of the Children (Leaving Care) Act 2000. Where applicable, entitlement continues if he or she is remanded or sentenced to custody.

Given the concerns about the over-representation of looked after children in the youth and adult criminal justice systems, there is a desire to incorporate a measure within the final model. However, an initial examination of the data suggests 43 ASSET records (relating to 6 individuals) reflect that the young person was currently under a care order at the time of their assessment. There are an additional 4 records (1 individual) suggesting that the young person had previously been a looked after child. With just 7 young people having experience of being looked after based on this information, this limits the amount of analysis that can potentially be undertaken and the credibility of any findings. A further flag has therefore been created which reflects if (based on ASSET records) the child meets one or more of the following criteria:

- Previously or currently subject to a Care Order
- An Eligible child
- A Relevant child

In total, 25 of the 88 members of the cohort met these criteria, including 2 (out of the 7) females and 23 males. Just one young person with a non-White background had experience of being in care.

Of the cohort with experience of care, 18 have committed further offences since coming under the supervision of the YOT, equivalent to 72.0% compared to 38.1% (24/63) for those who have not met any of the criteria. There is very strong evidence in favour of the alternative hypothesis that the rate for those with experience of care having a higher likelihood of committing further offences (BF_{10} for the one-sided test = 33.97) (Table 3.10).

Table 3.10: Rates of Further Offending Across the Two Years, by Care Status

	Comparator Groups		No.	Further Offences	% Committing Further Offences	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Care Status	1	No Experience	63	24	38.1%	17.04	33.97
	2	Experience	25	18	72.0%		
Total			**88**	**42**	**47.7%**		

Notes: Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1.

Research Question:

What does the modelling tell us about the impact of having experience of care on the likelihood of further offending over time?

Offending History

Analysis of the offending history of the 88 individuals suggest that 33 (37.5%) were first time entrants at the time of entering the cohort i.e. the outcome received for their initial primary offences was their Reprimand, Final Warning, Caution or conviction based on data held on the Police National Computer (PNC). However, 11 of these had previously been in contact with the YOT having receive informal action or a Youth Restorative Disposal (YRD). Whilst for 19, the primary offence had been their first time of offending (or more correctly, being caught), there were also 3 who had previously been in trouble with the police. One of these was the young person whose offending was summarised in Figure 3.4. Another was dealt with informally for their primary offence (and receiving a Youth Caution) having committed an earlier, more serious offence which took 3 months to get to court. There, he received a referral order. The third had his case withdrawn when it got to court.

Published national figures suggest that as the number of previous offences increases, the proportion of offenders who reoffend increases, with the proven re-offending rate for those with no previous proven offences being 36.1% in 2013 compared to 49.1% for those who have. The equivalent figures in the year ending March 2014 were 38.0% for first time entrants (FTEs) and 51.3% for those already known to the youth justice system. As the number of previous offences increases as does the proven reoffending rate with three-quarters of those who have committed 11 or more previous offences having proven reoffending (Youth Justice Board and Ministry of Justice, 2015a: Table 9.6).

The local figures also suggest a difference in the proven re-offending rate, with 33.3% (11/33) of those identified as being an FTE at their time of entry the cohort went on to commit further offences compared with 57.4% (31/54) of those who had previously offended – the status of one individual is not known.

There is moderate evidence in favour of the null hypothesis that the rate of offending is higher amongst those who are not FTEs (BF_{10} for the one-sided test = 5.548) (Table 3.11).

Table 3.11:Rates of Further Offending Across the Two Years, by Offending History

	Comparator Groups		No.	Further Offences	% Committing Further Offences	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
FTE	1	FTE	33	11	33.3%	2.808	5.548
	2	Previous Offending	54	31	57.4%		
Age at First Offence	1	10 to 12	22	13	59.1%	0.623	0.136
	2	13 to 17	66	29	43.9%		
Age at First Conviction	1	10 to 13	11	7	63.6%	0.691	0.192
	2	14 to 17	77	35	45.5%		
Total			**87**	**42**	**48.3%**		

Notes: Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1.

Under the Scaled Approach, those who received their first Reprimand, Caution or Final Warning before the age of 13 were considered to be at a higher risk of re-offending than older children. The further offending rates have therefore been compared for the two age groups based on the proxy measure of age at first offence. This suggests that there is only anecdotal evidence to support the null hypothesis of there being a difference between the two groups (BF_{10} = 0.623). A similar trend was observed when the cohort was split on the basis of age at their first conviction – in this instance, those aged 10 to 13 were considered to be a higher risk then those aged 14 plus (BF_{10} = 0.691).

Despite these findings, the decision has been to retain these measures of the individual's offending history within the model. In terms of the gender profile, only one female received their first Reprimand/ Caution / Final Warning whilst in the younger age group, along with 21 (out of the 79) males. All the females were in the 14-17 year group when they received their first conviction, whilst 11 males were aged 10-13.

The Nature of the Primary Offence

The YJB's reoffending spreadsheets provide details of the main or primary offence. As such information is only provided about the offence which attracts the most severe sentencing outcome, or if there are two offences in the same case then the offence with the statutory maximum sentence is deemed to be the 'primary offence'. Other offences which are dealt with by that court case or cautioning occasion are ignored. This approach is consistent with that used in the publication of youth justice statistics (Youth Justice Board and Ministry of Justice, 2015c). However, it presents challenges not only during the preparation of the data for the modelling exercise but also when considering an approach to considering more sensitive measures of re-offending. Published national figures for the years being considered by this research suggest that the proven reoffending rate varies by index or primary offence suggesting that it may be a source of variation at an individual level (Figure 3.5). Inclusion of information about the nature of the primary offence also supports the aim of developing a more sensitive measure of reoffending.

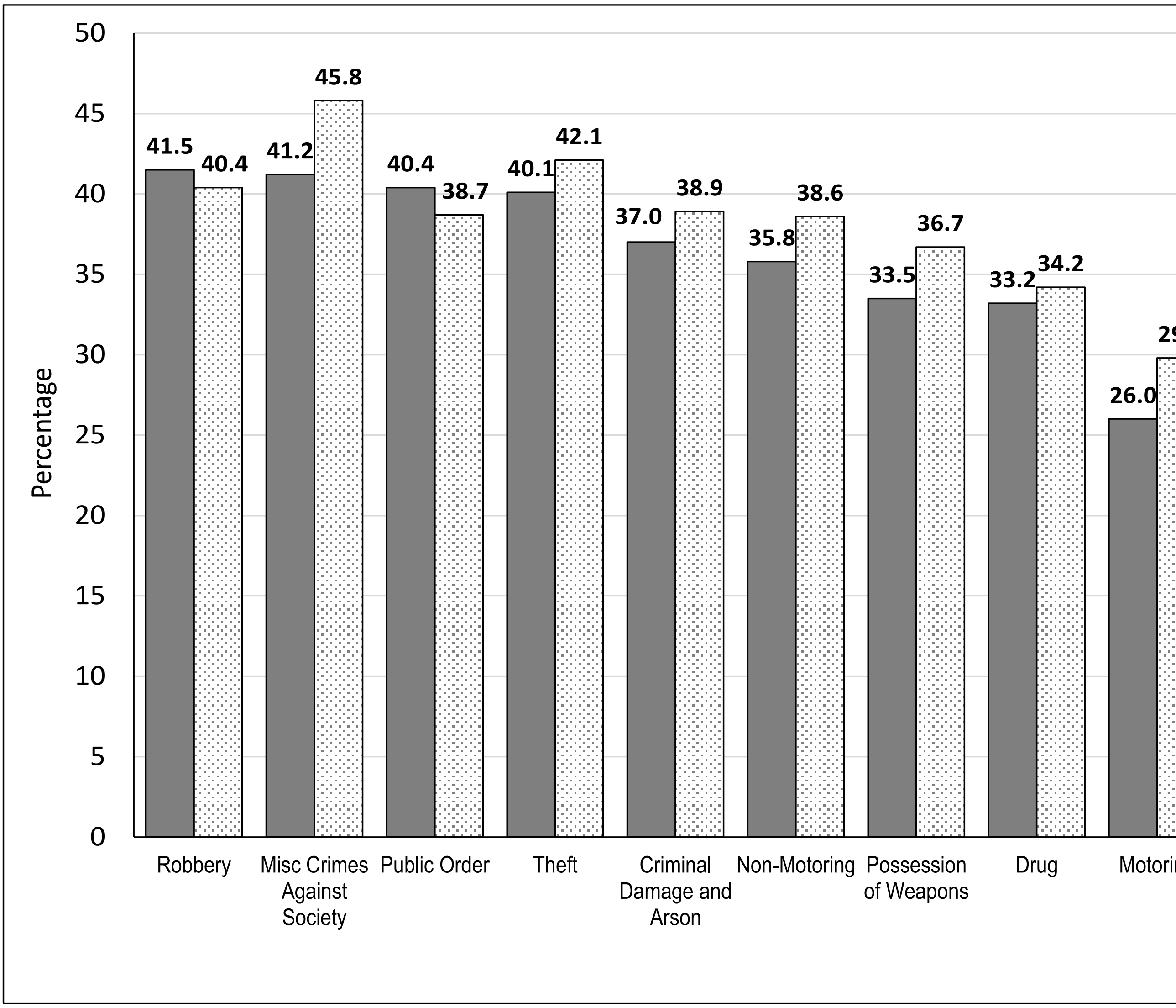
Table 3.12 provides a breakdown of the primary offences committed by those individuals in the reoffending cohort with ASSET Core Profiles along with the rate of reoffending and further offending for each category. The most commonly occurring primary offences are categorised as being violence against the person; theft and handling stolen goods; public order offences; drugs; criminal damage and motoring offences. The comparatively low numbers whose offending falls under some of the less commonly occurring principle offence categories may limit the analysis that can be undertaken. Notably across the two cohorts, there are no young people recorded as having their primary offence being death or injury by dangerous driving or arson.

Table 3.12:Primary Offence Category of Those with ASSET Core Profiles, with Re-Offending and Further Offending Rates

Primary Offence Category	Total	Re-Offended?		Further Offending?	
		Number	%	Number	%
Criminal Damage	12	6	50.0%	7	58.3%
Domestic Burglary	5	3	60.0%	3	60.0%
Drugs	8	5	62.5%	4	50.0%
Motoring Offences	4	1	25.0%	3	75.0%
Non Domestic Burglary	2	1	50.0%	1	50.0%
Other	1		0.0%		0.0%
Public Order	11	2	18.2%	3	27.3%
Racially Aggravated	1		0.0%		0.0%
Robbery	5	3	60.0%	3	60.0%
Sexual Offences	1		0.0%		0.0%
Theft And Handling Stolen Goods	10	3	30.0%	4	40.0%
Vehicle Theft / Unauthorised Taking	6	5	83.3%	5	83.3%
Violence Against The Person	22	8	36.4%	9	40.9%
Grand Total	**88**	**37**	**42.0%**	**42**	**47.7%**

Notes: Offence category of the primary offence upon entering the cohort. Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14.

Figure 3.5:National Proven Reoffending Data, by Index Offence, Years Ending March 2013 and 2014



Source: Youth Justice Board and Ministry of Justice (2015a: Table 9.5). The offence categories used here are based on the ONS crime classificatio in the reoffending spreadsheets.

The criteria set out which defines the Ministry of Justice's measure of reoffending (see Section 3.4) precludes any of the cohort having a breach as a primary offence since breaches typically result in the young person being re-sentenced rather than them receiving an additional substantive outcome. Where this has occurred, information about the original offence is given on the reoffending spreadsheet.

An alternative to using the offence category is to use the gravity scores of the primary offence (Table 3.13). Designed with eight levels, there are examples of offences scoring 2-6 within reoffending cohort. Reducing the number of groups to six as opposed to the populated offence categories, will incur less of penalty in any modelling and offers a means of making inferences about those offence categories for which there are no examples within the dataset.

Table 3.13:Gravity Score of the Primary Offence for Those with ASSET Core Profiles, with Re-Offending and Further Offending Rates

Gravity Score of the Primary Offence	Total	Re-Offended?		Further Offending?	
		Number	%	Number	%
2	31	13	41.9%	16	51.6%
3	31	12	38.7%	13	41.9%
4	9	4	44.4%	5	55.6%
5	4	2	50.0%	2	50.0%
6	13	6	46.2%	6	46.2%
Grand Total	**88**	**37**	**42.0%**	**42**	**47.7%**

Notes: Gravity score of primary offence upon entering the cohort. Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14.

Table 3.14:Primary Offence Category by YJB Gravity Score

Primary Offence Category	YJB Gravity Score					Total
	2	3	4	5	6	
Criminal Damage	11	1				12
Domestic Burglary					5	5
Drugs	8					8
Motoring Offences	3	1				4
Non Domestic Burglary			2			2
Other		1				1
Public Order	9	1		1		11
Racially Aggravated		1				1
Robbery					5	5
Sexual Offences			1			1
Theft And Handling Stolen Goods		10				10
Vehicle Theft / Unauthorised Taking		1	2	3		6
Violence Against The Person		15	4		3	22
Grand Total	**31**	**31**	**9**	**4**	**13**	**88**

Notes: Offence category and gravity score of the primary offence upon entering the cohort. Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14.

A further advantage is that using gravity scores offers a means of differentiating between the seriousness of the offence within an offence category (Table 3.14). For example, violence against the person offences account for almost one in four primary offence categories recorded (22/88). Of these,

- The majority have been identified as having a gravity score of 3 (68.2%). Violence against the person offences attracting a gravity score of 3 include: possession of an offensive weapon; threatening, abusive or insulting words / behaviour; assaulting a police officer and common assault.
- 18.2% had a gravity score of 4 – equivalent to assault occasioning bodily harm (ABH)
- No members of the cohort had been involved in firearms offences which have a gravity score of 5
- 13.6% had a gravity score of 6 – equivalent to grievous bodily harm (GBH)
- None of the cohort were recorded as being involved in more serious offending such as murder (8); manslaughter (8); abduction / kidnap (7); GBH or wounding with intent (7).

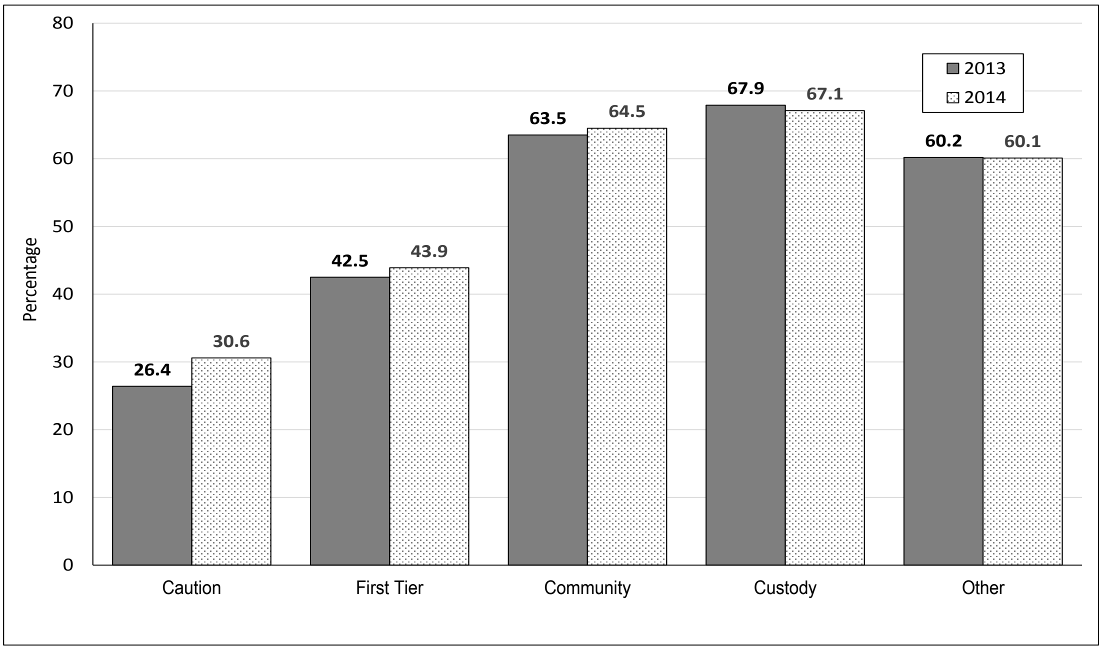
(It should be noted that the gravity scores utilised within this thesis are based on those published within the ASSET Guidance issued by the YJB (Youth Justice Board, 2008a: Appendix B). These have had various incarnations and differ from those used by the Police. A full list of offences by category and gravity score can be found in the Section 2 of the Technical Annex.)

Research Question:

What does the modelling tell us about the impact of the 'static' factors within ASSET in predicting further offending over time?

Inclusion of the outcome tier in the model is supported by the published reoffending figures by index disposal. Notably, at a national level, those receiving custodial sentences have a higher reoffending rate than those receiving pre-court disposals such as cautions (Figure 3.6).

Figure 3.6: National Proven Reoffending Data, by Index Disposal, Years Ending March 2013 and 2014



Source: Youth Justice Board and Ministry of Justice (2015a: Table 9.7).

However, in cross referencing the offences and outcomes in the reoffending spreadsheets with those recorded in the individual's offending and court records as held within Childview inconsistencies were found. It is likely that this is as a result of where young people have been returned to court to have their original sentence reviewed:

Individual (1) – committed a drugs offence (seriousness = 2) whilst on conditional bail and tag during the hearing relating to burglary dwelling offences. He was sentenced to an 8-month Detention and Training Order. The reoffending spreadsheet reflects his primary offence as being a drugs offence.

Individual (2) - Originally sentenced in 2011 to a 1-year conditional discharge for a drugs offence (seriousness = 2). However, he continued to offend and was referred back to the courts where he received a Youth Rehabilitation Order. Further restrictions were later added to this as he committed further offences before being sentenced to a 10-month Detention and Training Order. He is included on the reoffending spreadsheet as having received a custodial sentence for the 2011 drugs offence.

Without access to the original records in PNC, it has not been possible to establish the extent to which this has occurred across the dataset.

As previously highlighted, the timing of the research coincided with the changes in youth disposals coming about as a result of LASPO 2012. These changes were implemented between December 2012 and April 2013. To enable comparisons to be made across the period of interest it is therefore necessary to use outcome tiers as per Table 3.2. However, as can be seen from Table 3.15, as sentencing is dependent not just upon the seriousness of the offence, there is no direct correlation between the gravity score and the outcome tier of the disposal received for the primary offence.

Table 3.15: Outcome Tier of the Disposal Received for the Primary Offence, by YJB Gravity Score

Outcome Tier of the Primary Offence	YJB Gravity Score					Total
	2	3	4	5	6	
No intervention	5	5			1	11
Pre-Court	4	3	4	1		12
First-Tier	16	17	5	2	8	48
Community	4	6			2	12
Custody	2			1	2	5
Grand Total	**31**	**31**	**9**	**4**	**13**	**88**

Notes: Outcome tier of disposal received upon entering the cohort. Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14. For details of the disposals falling under each Outcome Tier see Table 3.2.

Initial analysis of the local re-offending rates by outcome tier suggests that they increase amongst those who have had court disposals, with the rate being highest amongst those sentenced to custodial sentences. The re-offending rates for those who were subject to no intervention or who received a pre-court disposal are notably a lot higher. It is important to note that since this research focuses upon those within the formal youth justice system. As such the ASSET Core Profiles for these individuals relate not to the primary offence, but to the assessment undertaken after their first further offence.

Given the comparatively small number of cases, particularly receiving community and custodial sentences, along with the concerns about the reliability of the outcomes recorded, the decision has been made not to investigate the role of outcome tier at this time. The information has however been retained within the dataset to assist in interpreting findings.

For completeness, the re-offending and further offending rates for each outcome tier of those cases included in the modelling exercise have been included (Table 3.16).

Table 3.16: Outcome Tier of the Disposal Received for the Primary Offence for Those with ASSET Core Profiles, with Re-Offending and Further Offending Rates

Outcome Tier of the Primary Offence	Total	Re-Offended?		Further Offending?	
		Number	%	Number	%
No intervention	11	8	72.7%	6	54.5%
Pre-Court	12	8	66.7%	8	66.7%
First-Tier	48	10	20.8%	16	33.3%
Community	12	7	58.3%	9	75.0%
Custodial	5	4	80.0%	3	60.0%
Grand Total	**88**	**37**	**42.0%**	**42**	**47.7%**

Notes: Outcome tier of disposal received upon entering the cohort. Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14.

Organisational Measures: Facets of the Youth Justice System

Cross-referencing court and offending records from Childview with the ASSET Core Profiles enabled 'flags' to be added to reflect whether or not in the period before the date of the assessment, the young person had:

- Breached (and this is recorded as an offence)
- Attended court
- Spent time in custody, including any time on remand

Breaches can be interpreted as a measure of non-compliance and can often result in the young person being returned to the court in order to have their order reviewed. Serious breaches can result in the young person becoming subject to a period in custody. Court appearances do not necessarily result in the young person being sentenced. The case may well be adjourned or even withdrawn. Depending upon the circumstances that have led to the young person appearing in court, they may be subject to further restrictions (including upon their liberty) with bail conditions potentially being applied including the young person placed on an Intensive Supervision and Support Programme (ISSP), tagged or remanded.

It was originally hypothesised that some young people would be motivated to stay out of any further trouble in the run up to their appearance in court and hence there would be decrease in their risk scores. However, there may be others who were anticipating for example a custodial sentence and the 'threat' of this loss of liberty may be sufficient for them to engage in further risky and offending behaviours believing that if they are going down then they might as well go down for everything. Increased risk scores were anticipated for this group.

It is recognised that some young people who have come into contact with the law live very chaotic and complex lives. Therefore, a period in custody can offer stability and an opportunity to engage in training, receive substance misuse treatment and participate in activities which address their thinking behaviours / attitudes towards offending. It is therefore anticipated that risk scores would go down, certainly in these domains. However, concerns about resettlement, the loss of liberty and having to face up to the consequences of their actions may have a detrimental effect on for example mental wellbeing.

Along with the domain scores, these predictors have the potential to change at the time of each assessment. Hence, they are included in the model as time-varying, 'Level 1' predictors.

Research Question:

What does the modelling tell us about the relationship between further offending and coming into contact with facets of the youth justice system?

3.8. Summary of Research Questions

Within this chapter, a number of research questions have been posed. These have been grouped within subsequent chapters:

Chapter and Theme		Research Questions
4	Risk Assessment Domains	What is the relationship between further offending, the 12 domains and time?
5	Dimensional Identity	What is the impact of gender and ethnicity on the likelihood of further offending?
		What is the impact of having experience of care on the likelihood of further offending over time?
6	Static Factors	What is the impact of the 'static' factors within ASSET in predicting further offending over time?
		Is it possible to extend the sensitivity of ASSET by extending any of the predictors?
7	System Contact	How is the likelihood of further offending affected by having experience of care and a previous offending history?
		What is the impact of coming into contact with facets of the youth justice system on the likelihood of further offending?

Chapter Four presents the development of the hierarchical model to reflect the ASSET Core Profile framework with its repeated measures. This enables the first research question to be explored. The basic dynamic model is then adapted to explore the impact of dimensional identify in Chapter Five and the impact of 'static' factors within ASSET in Chapter Six. Chapter Seven concentrates on whether having system contact increases the likelihood of further offending.

The nature of the measures used as proxies for the static factors in Chapter Six provide the greatest scope for considering whether it is possible to extend the sensitivity of ASSET through extending any of the predictors. Hence this research question is also explored within this chapter.

The second considered within Chapter Seven links back to the research questions posed in Chapter Five and Six which utilise the predictors around care and FTE status.

Cutting across the four chapters, a further question is posed which considers *How well ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT.* As highlighted in Chapter One, this final question provides a means of assessing the predictive accuracy of the various models constructed in response to the other questions posed.

4 Findings: Risk Assessment Domains

As highlighted in Chapter Two, the premise behind the APIS framework is the continuous cycle of (re)assessment, (re)formulation of sentence planning, and supervision approaches. As such the likelihood of reoffending determined by the ASSET Core Profile informs the action plan devised for the young person and determines the nature and level of interventions. The outcome of these interventions in reducing the likelihood of reoffending then inform the reassessment process (Figure 2.2). Having a continuous cycle means that a series of risk assessment scores are available for each young person which can then be analysed to explore the relationship between the twelve dynamic risk factors measures in ASSET and young offending behaviours. This has been done within this Chapter by focusing on the following research questions:

1. What is the relationship between further offending, the 12 domain scores and time?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

The first of these is addressed initially through consideration of the change in total ASSET scores and those relating to individual domains between assessments, building upon the approach taken by Baker et al (2005). Their analysis is then extended in section 4.2 through development of a hierarchical model representing the repeated assessment process undertaken using the ASSET core profile. The extent to which this model reflects the realities of a young person's change in circumstances during their time with the YOT is considered through presentation of three examples who for the purposes of this research will be referred to as Fred, David and Connor. Their scores will also be used in subsequent chapters to consider how models which reflect dimensional identity, the nature of criminal careers and system contact fit their changing circumstances.

As highlighted in Chapter Two, as part of the ASSET Core Profile, practitioners are required to provide a subjective rating of the young person's likelihood of reoffending based on a series of questions which are grouped under 12 domains:

- Living arrangements
- Family and personal relationships
- Education, training and employment (ETE)
- Neighbourhood
- Lifestyle
- Substance use
- Physical health
- Emotional and mental health
- Perception of self and others
- Thinking and behaviour
- Attitudes to behaviour
- Motivation to change

These represent the dynamic component of the overall ASSET score, with a maximum potential score of 48 (4 x 12). It is apparent from reviewing the linked reoffending spreadsheet and the ASSET Core Profile records that the score used for the ASSET banding / levels utilises only the dynamic score.

Guidance is available for practitioners (Youth Justice Board, 2008a) which includes further explanation of the evidence collecting questions and provides examples of ratings 1 or 2 and 3 or 4 for each domain. Table 4.1 provides a generic summary of the subjective ratings used. The distribution of domain scores can be found in Figure 4.1.

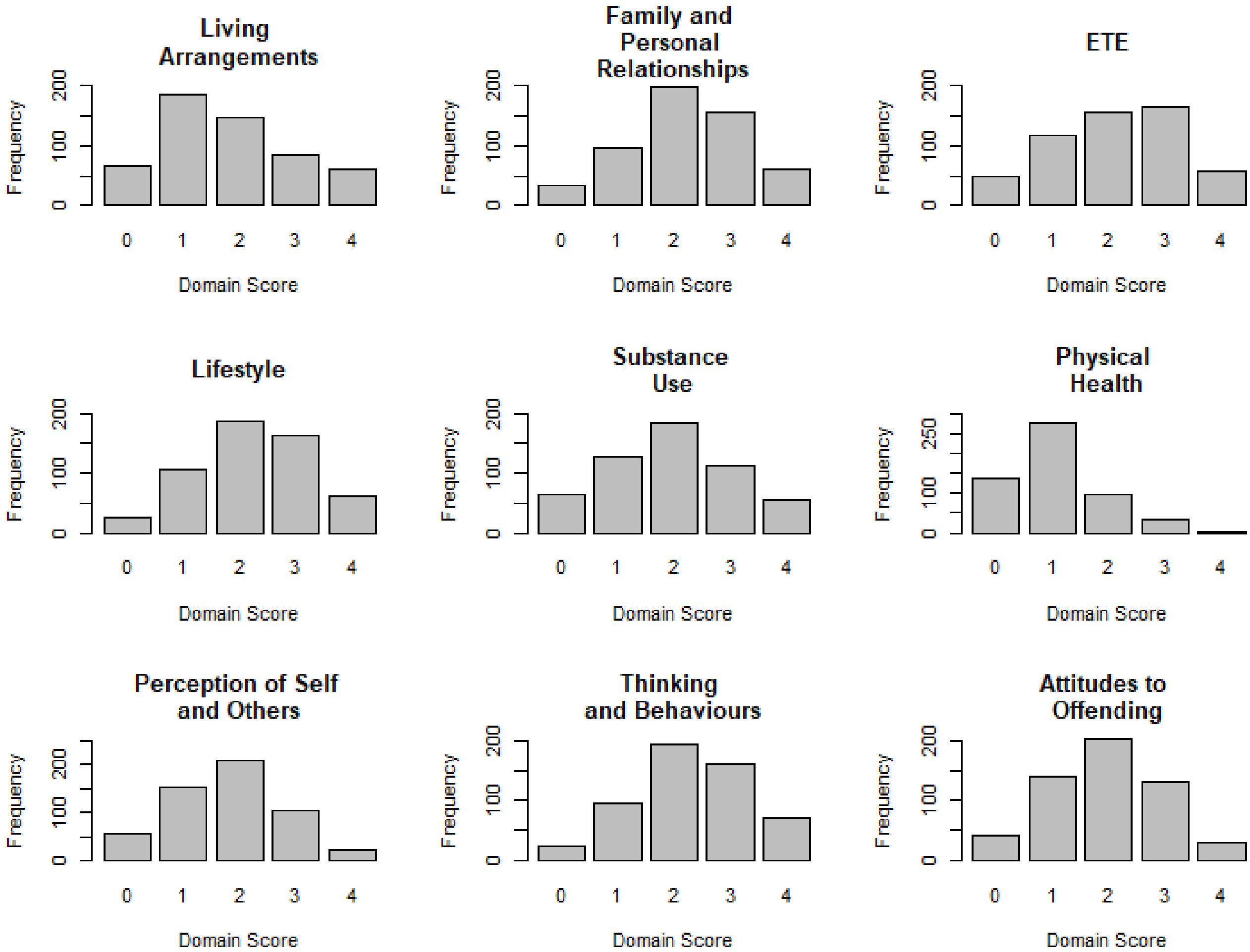
Table 4.1: Subjective Ratings Used in ASSET for the 12 Domains

Rating	Description
0	Not associated at all
1	Slight, occasional or only a limited indirect association
2	Moderate but definite association – could be direct or indirect link. May be related to some offending, but not all. Tends to become offending related when combined with other factors.
3	Quite strongly associated – normally a direct link, relevant to most types / occasions of his/her offending.
4	Very strongly associated – will be clearly and directly related to any offending by the young person. Will be a dominant factor in any cluster of offending-related problems.

Adapted from Youth Justice Board (2008b: 4)

A visual inspection the distributions of each of the domain scores (Figure 4.1) suggests that it is appropriate to assume that each set of measurements is independent and that each potential rating has an equal probability of being assigned. In this instance, the zero is meaningful therefore it has not been necessary to centre or standardise the domain scores.

Figure 4.1: Distribution of Domain Scores



Notes: n = 545 (All complete ASSETS), 87 Individuals

4.1 Changes over Time

Change in Domain Scores

Whilst previous reviews of ASSET have focused upon the validity and reliability in terms of predicting reconviction (Baker et al., 2003) and the link between ASSET and Intervention Plans (Baker et al., 2005), the second review also considered the effectiveness of the revised version of ASSET in measuring risk-related change. This component of the review explored the mean ASSET score change for community cases (n=607): measured once, between the first and second assessment. Their findings suggest that although some reductions were cancelled out by increases, seven of the 12 domains showed significant reductions. The most important of these were Thinking and Behaviour (mean score change = 0.20, $p<0.001$), Lifestyle (-0.15, $p<0.001$), ETE (-0.14, $p<0.001$) and Attitudes to Offending (-0.12, $p<0.001$). The changes in mean domain scores for Physical Health, Emotional and Mental Health, and Motivation to Change were not found to be significant whilst those for Perception of Self and Others, and Neighbourhood on average did not change (Baker et al., 2005: Table 3.8).

Change was also considered for custodial cases: measured at two points: on release, and after a period of post-release supervision. For this group (n=57), significant improvements were found between the first and third assessment in relation to 8 domain scores. As with community disposals, Thinking and Behaviour (-0.63, $p<0.01$), Lifestyle (-0.60, $p<0.001$) and Attitude to Offending (-0.54, $p<0.001$) were found to be more significant domains. The domains representing Motivation to Change, Perception of Self and Others, and Neighbourhood were found to not be significant whilst on average there was a marginal (but not significant) increase in the mean score for Physical Health (Baker et al., 2005: Table 3.12).

Repeating this exercise for the 87 individuals whose risk assessment scores form the basis of the case study suggests that whilst the mean domain scores at Time 0 are typically higher than those at Time 1 (with the exception of those for Emotional and Mental Health), there is no evidence to support this. Indeed, the Bayes Factors (BF_{01}) of 3 or more provide moderate evidence for the null hypothesis relative to the alternative hypothesis that the mean score at Time 0 is greater than the mean score at Time 1 whilst those which are less than 3 provide anecdotal evidence in factor of H_0 (Table 4.2).

Table 4.2:Changes in Dynamic ASSET Domain Scores between Initial and Second Assessments (All with ASSET Core Profiles Regardless of Disposal Received)

Domain	Mean Domain Score		Mean Score Change	BF_{01}	Error %
	Time 0	Time 1			
Living Arrangements	1.72	1.61	-0.11	3.399	~ 1.798e-6
Family and Personal Relationships	2.16	2.03	-0.13	2.991	~ 9.989e-6
ETE	2.00	1.91	-0.09	3.999	~ 3.151e-6
Neighbourhood	1.51	1.32	-0.19	1.838	~ 3.833e-5
Lifestyle	2.14	1.97	-0.17	1.983	~ 3.795e-5
Substance Use	1.66	1.56	-0.10	3.773	~ 1.067e-6
Physical Health	1.05	1.02	-0.02	5.383	~ 9.405e-6
Emotional and Mental Health	1.29	1.30	0.01	6.370	~ 5.635e-6
Perception of Self and Others	1.71	1.61	-0.10	3.223	~ 0.002
Thinking and Behaviour	2.22	2.09	-0.13	2.799	~ 1.556e-5
Attitude to Offending	1.72	1.69	-0.03	5.131	~ 9.582e-6
Motivation to Change	1.66	1.55	-0.11	3.394	~ 0.037

Notes: Of the 87 individuals, more than half (47) had received a first-tier disposal whilst 23 had received a pre-court disposal for the primary offence which lead to their inclusion in the reoffending cohort. Bayes Factors have been calculated for one-sided Bayesian Independent Sample T-Tests using JASP.

Having only 12 who received community disposals and 5 with custodial sentences, it is difficult to draw direct comparisons with the original research and it is also necessary to apply caution in interpreting these results due to the low number of cases involved overall. However, it is notable that the weakest evidence for no difference in mean score change is in relation to the Neighbourhood; Lifestyle; Family and Personal Relationships; and Thinking and Behaviour domains.

The general moderating trend that would be expected as a result of working with the YOT is more apparent when differences are considered between the mean domain scores at Time 0 and the individual's final ASSET (Table 4.3).

Table 4.3: Changes in ASSET Domain Scores between Initial and Final Assessments (All with ASSET Core Profiles Regardless of Disposal Received)

Domain	Mean Domain Score		Mean Score Change	BF_{01}	Error %
	Time 0	Final			
Living Arrangements	1.72	1.44	-0.28	1.007	~ 1.100e-6
Family and Personal Relationships	2.16	1.84	-0.32	1.970	~ 9.652e-5
ETE	2.00	1.77	-0.23	0.535	~ 3.842e-5
Neighbourhood	1.52	1.16	-0.36	3.737	~ 1.191e-4
Lifestyle	2.14	1.77	-0.37	3.560	~ 1.187e-4
Substance Use	1.66	1.52	-0.15	0.350	~ 1.383e-5
Physical Health	1.05	0.95	-0.09	0.298	~ 0.034
Emotional and Mental Health	1.29	1.30	0.01	0.159	~ 5.995e-6
Perception of Self and Others	1.71	1.43	-0.28	1.976	~ 9.682e-5
Thinking and Behaviour	2.22	1.82	-0.41	6.107	~ 1.458e-4
Attitude to Offending	1.72	1.55	-0.17	0.524	~ 3.840e-5
Motivation to Change	1.66	1.39	-0.27	1.058	~ 1.790e-5

Notes: The number of ASSETs completed per individual varies. For more details see Figure 4.2. Bayes Factors have been calculated for one-sided Bayesian Independent Sample T-Tests using JASP.

One-sided independent t-tests provide moderate evidence of a reduction in the mean domain scores for the Thinking and Behaviour, Neighbourhood and Lifestyle domains. However, it is important to note that not all young people experienced a net reduction in these domains during their time with the YOT, some saw increases, whilst others had the same rating at the beginning and end of their time with the YOT – although this is not to say that it did not vary. Certainly, when change in total ASSET Scores are considered, as in the next section, one in ten (10.6%) saw an increase of 7 or more between their initial and final assessments with those having the biggest increases subsequently being subject to custodial sentences reflecting the increased threat that they pose as a result of their escalating risky behaviour and/or offending.

Although it is important to stress the difference in the outcome variable being measured: Baker et al were concerned with the administrative measure of proven re-offending whereas this research has focused upon whether or not the young person has gone on to commit further offences, the findings were felt to be indicative of what might be expected in a time-varying ‘dynamic’ model. Indeed, as will be seen in section 4.2, the Lifestyle and Thinking and Behaviour domains were found to be significant predictors of further offending in Dynamic Model 1 (BDm1).

Change in Total ASSET Scores

Replicating the analysis that Baker et al. (2005) present in relation to the change in direction of total dynamic ASSET scores between assessments at Times 0 through to Time 10, it is possible to see why some of the apparently contradictory upward trajectories which are presented later in this chapter have occurred (Table 4.4), particularly when the cohort is segmented by whether or not the young person has committed a further offence in the intervening period.

Of the 84 young people with a complete set of domain scores at Time 0 and Time 1, nineteen had committed further offences before being re-assessed (at Time 1), equivalent to 22.6%. Whilst those who had not committed any offences saw an average reduction of 1.77 in their total ASSET score, the reduction was less for those who had offended (mean = -0.21).

14.1% (10 out of 71) of those assessed at both Time 1 and Time 2 had committed a further offence in the intervening period. On average their total ASSET scores increased by 2.20 whilst those who had not offended had a mean reduction of 0.69.

Table 4.4: Total ASSET Score Change by Direction, Between Successive Time Points
(All with ASSET Core Profiles Regardless of Disposal Received)

Difference in Total ASSET Score	Time 0 to 1		Time 1 to 2		Time 2 to 3		Time 3 to 4	
	No	%	No	%	No	%	No	%
Reduction of 7 or more	11	13.1%	6	8.5%	7	12.1%	8	17.0%
Reduction of 4 to 6	9	10.7%	5	7.0%	4	6.9%	3	6.4%
Reduction of 1 to 3	13	15.5%	8	11.3%	9	15.5%	14	29.8%
No Change	33	39.3%	28	39.4%	15	25.9%	10	21.3%
Increase of 1 to 3	11	13.1%	18	25.4%	8	13.8%	3	6.4%
Increase of 4 to 6	5	6.0%	2	2.8%	6	10.3%	3	6.4%
Increase of 7 or more	2	2.4%	4	5.6%	9	15.5%	6	12.8%
Total	84	100.0%	71	100.0%	58	100.0%	47	100.0%
Mean Score Change	-1.42		-0.28		0.62		-1.02	

Difference in Total ASSET Score	Time 5 to 6		Time 6 to 7		Time 7 to 8		Time 8 to 9	
	No	%	No	%	No	%	No	%
Reduction of 7 or more	3	9.7%	4	14.8%	2	8.3%	2	10.5%
Reduction of 4 to 6	2	6.5%	3	11.1%	0	0.0%	1	5.3%
Reduction of 1 to 3	7	22.6%	4	14.8%	2	8.3%	2	10.5%
No Change	8	25.8%	10	37.0%	12	50.0%	7	36.8%
Increase of 1 to 3	6	19.4%	3	11.1%	1	4.2%	6	31.6%
Increase of 4 to 6	3	9.7%	2	7.4%	2	8.3%	0	0.0%
Increase of 7 or more	2	6.5%	1	3.7%	3	12.5%	1	5.3%
Total	31	100.0%	27	100.0%	24	100.0%	19	100.0%
Mean Score Change	-0.10		-1.19		0.67		-0.42	

Notes: Mean change scores have only been calculated where there has been a complete set of domain scores. Hence the total number of cases does not matc

The situation between Times 2 and 3 is notable because there is very little difference between the mean ASSET scores of the two groups (Table 4.5). Although overall just over one in four (15 out of 58) did not experience a change in their total ASSET scores and 34.5% experienced a reduction in their scores, the change in the mean ASSET Score is influenced by a small proportion who had significant changes. For example, the maximum reduction experienced was -15, whilst there were three individuals whose score increased by more than 10 overall who had not committed any further offences. The circumstances of two of these young people form the basis of the case studies which are used in section 4.4 and subsequent chapters to consider how well the models reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT.

Table 4.5: Total ASSET Score Change by Direction, Between Time 2 and Time 3, by Whether or Not Further Offences Where Committed between ASSETs. (All with Complete ASSET Core Profiles Regardless of Disposal Received)

Difference in Total ASSET Score	Further Offending between Time 2 and Time 3				Overall	
	No	%	Yes	%	Number	%
Reduction of 7 or more	4	9.1%	3	21.4%	7	12.1%
Reduction of 4 to 6	4	9.1%	0	0.0%	4	6.9%
Reduction of 1 to 3	7	15.9%	2	14.3%	9	15.5%
No Change	13	29.5%	2	14.3%	15	25.9%
Increase of 1 to 3	6	13.6%	2	14.3%	8	13.8%
Increase of 4 to 6	2	4.5%	4	28.6%	6	10.3%
Increase of 7 or more	8	18.2%	1	7.1%	9	15.5%
Total	44	100.0%	14	100.0%	58	100.0%
Mean Score Change	0.61		0.64		0.62	

This negligible difference in the change in the total ASSET scores highlights that on average there is little to differentiate between those who had offended during the intervening period and those who had not. The nature of the modelling is such that differences in the average young person are reflected.

Between Times 3 and 4, 23.4% (11 out of 47) committed a further offence. Those who had not committed an offence prior to Time 4 experienced a mean decrease in their total ASSET score of 2.69 whilst those who had offended, typically saw their score increase by 4.45 – a differential of 7.15. However, it is important to note that more than half (53.2%) of those assessed at Times 3 and 4 saw a reduction in their total dynamic ASSET score. One of those who saw the greatest reduction in their score, forms the basis of the third case study discussed in section 4.4 and subsequent chapters.

Table 4.6: ASSET Score Change by Direction, Between Time 3 and Time 4, by Whether or Not Further Offences Where Committed between ASSETs. (All with Complete ASSET Core Profiles Regardless of Disposal Received)

Difference in Total ASSET Score	Further Offending between Time 3 and Time 4				Overall	
	No	%	Yes	%	Number	%
Reduction of 7 or more	8	22.2%	0	0.0%	8	17.0%
Reduction of 4 to 6	3	8.3%	0	0.0%	3	6.4%
Reduction of 1 to 3	12	33.3%	2	18.2%	14	29.8%
No Change	8	22.2%	2	18.2%	10	21.3%
Increase of 1 to 3	2	5.6%	1	9.1%	3	6.4%
Increase of 4 to 6	1	2.8%	2	18.2%	3	6.4%
Increase of 7 or more	2	5.6%	4	36.4%	6	12.8%
Total	36	100.0%	11	100.0%	47	100.0%
Mean Score Change	-2.69		4.45		-1.02	

The difference between the mean scores of those who have committed a further offence between Times 4 and 5 is not as great, but the nine who committed a further offence before Time 5 experienced a mean increase of 1.56 whilst the twenty-five who did not offend typically saw their total ASSET score reduce by an average of 0.36. After this time, the numbers whose ASSET scores contribute to the analysis falls to around a third or lower with the number who committed a further offence between measurement points falling to just three between Times 7 and 8. With such low numbers it is inappropriate to comment on the trends other than to highlight that the mean change in overall scores is negligible after Time 7 (Table 4.4).

If the data is segmented with respect to gender, ethnicity and age, then the differential between the mean changes in ASSET scores it is expected that at each time point to also vary. This was something which was explored by Baker et al. (2005), with the team finding that amongst those receiving community disposals there was no significant amount of change. They did however, find that those with higher initial ASSET scores recorded a larger score reduction between their initial and second assessment (equivalent to Times 0 and 1) than those with lower initial scores. This they suggested may have been as a result of either regression to the mean or a ‘ceiling effect’ caused by the fact that high scores cannot rise any further. Rather that replicate this approach with each of the individual characteristics, the remainder of this chapter describes the development of the hierarchical model which represents the way in which the ASSET Core Profile has been used in practice as a series of repeated assessments of an individual’s likelihood of reoffending. This basic model will then be enhanced in subsequent chapters to consider the potential impact of dimensional identity and experience of care (Chapter Five), different facets of the criminal career (Chapter Six) and system contact (Chapter Seven).

4.2 The Relationship between Further Offending and Domain Scores

Broadly speaking the independent variables being considered can be grouped into time varying and non-time varying. For example, the individual domain scores have the potential to be different at the time of measurement, whilst individual characteristics such as gender and ethnicity are 'fixed'. This section focuses specifically on the time-dependent domain score predictors which have been considered for the model representing the ASSET Core Profile.

From the Null Model to the 'Basic' Model

Finch et al. (2014: 88) suggest that 'to apply multilevel models to longitudinal data problems, time-varying predictors will appear at Level 1 because they are associated with specific measurements, whereas time-invariant predictors will appear at Level 2 or higher because they are associated with the individual (or higher data level) across all measurement conditions. Thus, the structure of the ASSET Core Profile data, with repeated measures being taken for each individual, can be thought of initially as a two-level model. The model will then be extended to consider individuals nested within higher level clusters based on their primary offence.

A random intercept model in which an individual's 'response' depends linearly on time, can be expressed as:

$$y_{ti} = \beta_0 + \beta_1 m_{ti} + \mu_{0t} + e_{ti} \tag{4.1}$$

Where y_{ti} is the dependent variable i.e. the likelihood of re-offending at occasion t (t = 1, … M) for individual i (i = 1, … n). m_{ti} is the occasion at which measurement t was taken on individual i. As such the subscript t refers to the Level 1 units and i to the individuals at Level 2.

The terms in Equation (4.1) are defined as follows:

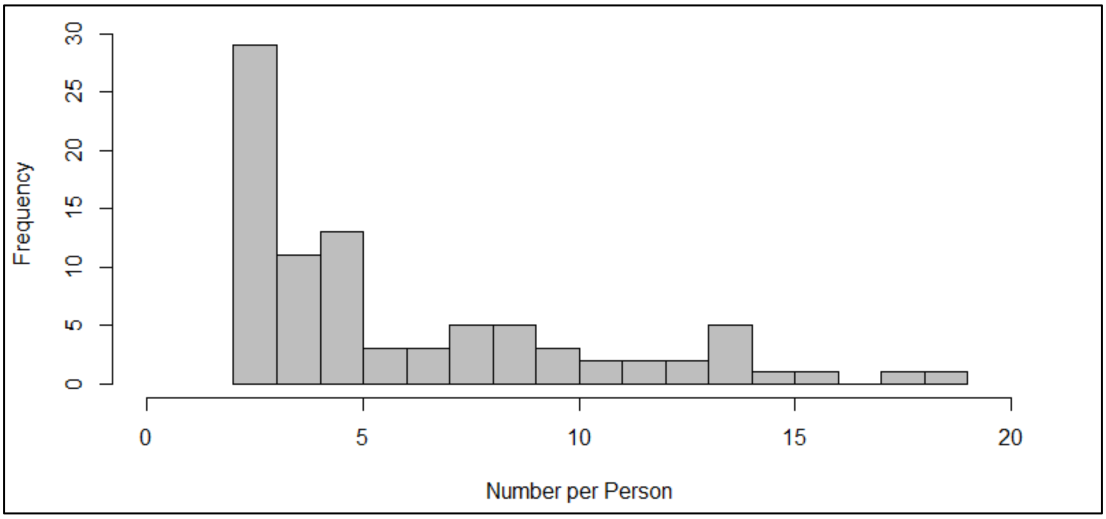
- β_0 is the overall intercept (averaged across individuals), interpreted as the expected value of y at m_{ti} = 0.
- β_1 is the slope of the regression of y on time, commonly referred to as the growth rate. In a random intercepts model, the growth rate of is assumed to be the same for all individuals.
- $\mu_{0t} \sim N(0, \sigma^2_{u_0})$ is an individual-specific random effect, capturing the effects on y of unmeasured individual characterises with values that are fixed over time. The intercept for individual i is $\beta_{0i} = \beta_0 + \mu_{0i}$, so μ_{0i} represents the difference between an individual's value on y (at any occasion) from the overall mean β_0. The variance of μ_{0i} ($\sigma^2_{u_0}$) is the between-individual variance in y after accounting for the linear effect of time.
- $e_{ti} \sim N(0, \sigma^2_e)$ is an occasion-specific (time varying) residual, capturing the effects on y of unmeasured time-varying characteristics. The variance of e_{ti} (σ^2_e) is the within-individual variance in y.

The time variable (measurement occasion) has been coded m_{ti} = 0, 1, ... M. As the first occasion is coded 0, time is said to be centred at the first occasion. Therefore, the model intercepts for all models can be interpreted as the expected likelihood of reoffending at m_{ti} = 0 i.e. at the time of their initial assessment.

The number of measurements per individual, m_{ti} can be anything, including one although for this model, those with only one record have been excluded. This number itself cannot be informative of the process being studied. However, larger numbers t_i give more information about intra-individual differences, and with larger average m_{ti} there is greater potential to fit models with a more complicated, and more precise random part.

The number of ASSET Core Profiles will depend upon the duration of a young person's order, the complexity of their personal circumstances and offending behaviours. In this instance 61% of the individuals had five or less records with the maximum being 19 (Figure 4.2). Since measurement occasions are not fixed, the data is considered to be unbalanced. This can be seen in Figure 4.3 where the trajectory of each individual's average domain scores is represented by a line. Moving from left to right, the chart becomes less congested as the number of young people in the cohort decreases over time.

Figure 4.2: Distribution of ASSET Core Profiles per Individual



Notes: Individuals have been identified as having multiple ASSET Core Profiles having met the criteria to be included on the YOT's Reoffending Spreadsheets 2012/13 and 2013/14.

To represent the ASSET Core Profile with its 12 domains, the random intercept model (4.1) can be extended. For ease, the domains are denoted as x_1 through to x_{12} respectively:

$$y_{ti} = \beta_0 + \beta_1 x_{1ti} + \beta_2 x_{2ti} + \beta_3 x_{3ti} + \beta_4 x_{4ti} + \beta_5 x_{5ti} + \beta_6 x_{6ti} + \beta_7 x_{7ti} + \beta_8 x_{8ti} + \beta_9 x_{9ti} + \beta_{10} x_{10ti} + \beta_{11} x_{11ti} + \beta_{12} x_{12ti} + \beta_{13} m_{ti} + \mu_{0t} + e_{ti} \quad (4.2)$$

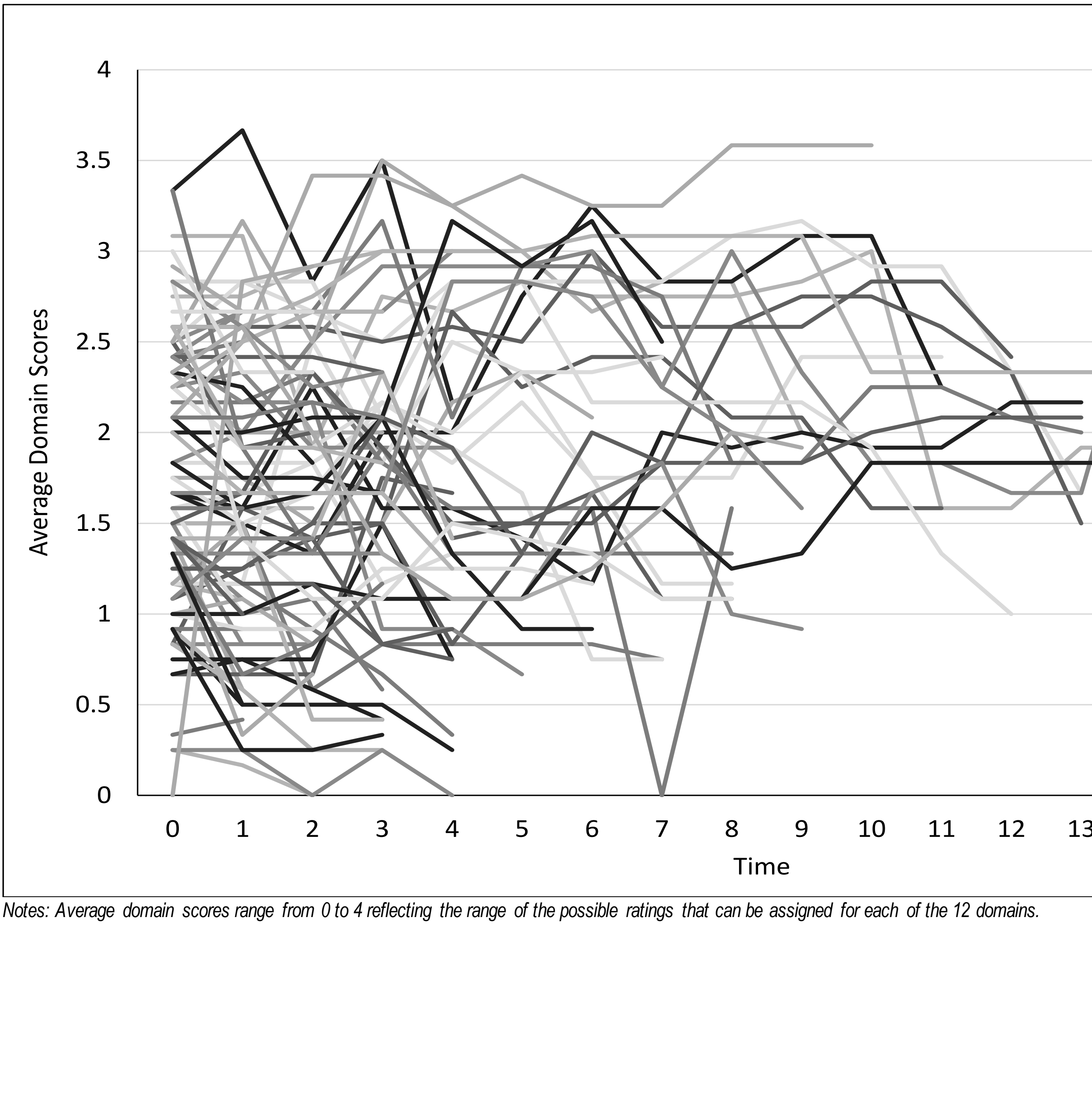
Since the dependent variable is dichotomous, with further offending being assigned the value of 1 and no further offending as 0, the multivariate logistical regression model (4.2) takes the form:

$$\Pr(y_{ti}= 1) = \text{logit}^{-1}(\boldsymbol{X}_{ti}\beta) \tag{4.3}$$

where $\boldsymbol{X}_{ti}$ is a matrix of predictors. Hence, the hierarchical logistic regression model which allows both the intercept and time-trend to vary by individual which involves all 12 domains plus time can be written as:

$$\Pr(y_{ti} = 1) = \text{logit}^{-1}(\beta_0 + \beta_1 x_{1ti} + \beta_2 x_{2ti} + \beta_3 x_{3ti} + \ldots. + \beta_{12} x_{12ti} + \beta_{13} m_{ti} + \mu_{0i} + \mu_{1i} m_{ti} + e_{ti}) \tag{4.4}$$

Figure 4.3: Average Domains Scores, by Individual



Notes: Average domain scores range from 0 to 4 reflecting the range of the possible ratings that can be assigned for each of the 12 domains.

Under this model, positive values of the slope indicate that the larger the value of the predictor, the greater the log odds of further offending. Through a transformation of the slope (by taking the natural log of the coefficient i.e. e^{β_n}), it is possible to obtain the odds of further offending as a function of the predictor(s). To aid interpretation of subsequent models, the standardised estimates of the coefficients with their 95% credible interval are presented alongside the unstandardised estimates.

It is this model (4.4) which is considered to be the 'basic' model which will be expanded upon in subsequent sections to explore the impact of:

- Dimensional identity (non-time varying, binary Level 2 predictors representing gender and ethnicity) and experience of care (a non-time varying, binary Level 2 predictor) (Chapter Five).
- Measures which represent aspects of the young person's criminal career (non-time varying, binary and continuous Level 2 predictors) and the nature of their primary offence (non-time varying, categorical and continuous Level 2 predictors) (Chapter Six)
- Organisational measures associated system contact. These include experience of care and with the young person's journey through the youth justice system such as court appearances, potential time in custody and non-compliance (time varying, binary, Level 1 predictors) (Chapter Seven).

the preparatory steps undertaken to get to the basic model are outlined below. Throughout, the goodness of fit is evaluated using the Deviance Information Criterion (Spiegelhalter et al., 2002). The Deviance Information Criterion (DIC) is a Bayesian information criterion that quantifies the information in the fitted model by measuring how well the model reduced uncertainty of future predictions. Adding more parameters often improves the fit of the model, but a penalty can be occurred as complexity increases. The DIC simultaneously accounts for model complexity (number of parameters) and model fit, by penalizing based on the number of (effective) parameters. It is calculated based on the sum of the effective number of parameters and the posterior mean of the deviance, with deviance defined as -2 times the log of likelihood function.

Although widely used in papers on applied Bayesian statistics, use of the DIC is not without its limitations (Spiegelhalter et al., 2014) including criticisms around its lack of consistency; not being based on a proper predictive criterion and having a weak theoretical justification. As a consequence, text books such as those by Kruschke (2013) and Gelman and Hill (2007) advocate the use of posterior predictive checks to evaluate absolute model fit. The Technical Annex therefore includes both the trace plots and posterior density plots for each of the dynamic models. As a further heuristic guide, models have also been run in the Frequentist paradigm using the lme4 package. However, it should be noted that warning messages around failure to converge are generated even with the Basic Model.

The sequential development of the models is described in subsequent sections so that evaluations can be made around the utility of including each predictor in the model. Under the Frequentist paradigm, ANOVAs have been used to compare the goodness of fit of each model relative to the version without the 'new' predictor. The output from these can be found in the Technical Annex alongside the R code and output from each stage of the modelling process.

Preparatory Models

a) The Empty or 'Null' Model

According to Robson and Pevalin (2016) the first step in multilevel modelling is to run a null or empty model (Bm0) with no covariates. A two-level model without independent predictors, the null model, can be expressed as:

$$\Pr(y_{ti} = 1) = \operatorname{logit}^{-1}(\beta_0 + \mu_i + e_{ti}) \tag{4.5}$$

Comparisons between this and the hierarchical logistic regression models which sequentially build up to the model representing the ASSET Core Assessment process with its 12 time-varying domains can be seen in Tables 4.7 to 4.12.

Table 4.7: Random Intercept Model for Further Offending

	Null Model						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
Individual (Intercept)	0.130	1.65E-04	0.049	1.139	1.000	1.051	Yes
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	-0.624	-0.789	-0.474	0.536	0.454	0.622	Yes

DIC	661.92

Source: Model Bm0, Technical Annex: p25-26

The model (BmT0 - summarised in Table 4.8), which allows each individual to deviate from the overall mean response by a person-specific constant that applies equally over time can be written as:

$$\Pr(y_{ti} = 1) = \operatorname{logit}^{-1}(\beta_0 + \beta_1 m_{ti} + \mu_{0i} + e_{ti}) \tag{4.6}$$

Where μ_{0i} represents the influence of individual i on his/her repeated observations. Comparing Tables 4.7 and 4.8, it is possible to see the impact of having likelihood of modelling Individual's assessments varying with time – under this model, the random individual-specific effect, μ_{0i} is estimated to be exp(0.039) = 1.040, with a 95% credible interval of 1.000 to 1.159. Notably, adding a single predictor (time) to the random intercepts model, adds to its complexity, increasing the DIC from 661.9 to 671.1.

Table 4.8: Random Intercept Model for Further Offending with Single Predictor

	Null Model, Random Intercept						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Individual (Intercept)	-0.044	-0.279	0.191	0.957	0.756	1.211	
Time	-0.159	-0.208	-0.108	0.853	0.812	0.898	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.039	2.06E-04	0.147	1.040	1.00	1.159	Yes

DIC	671.91

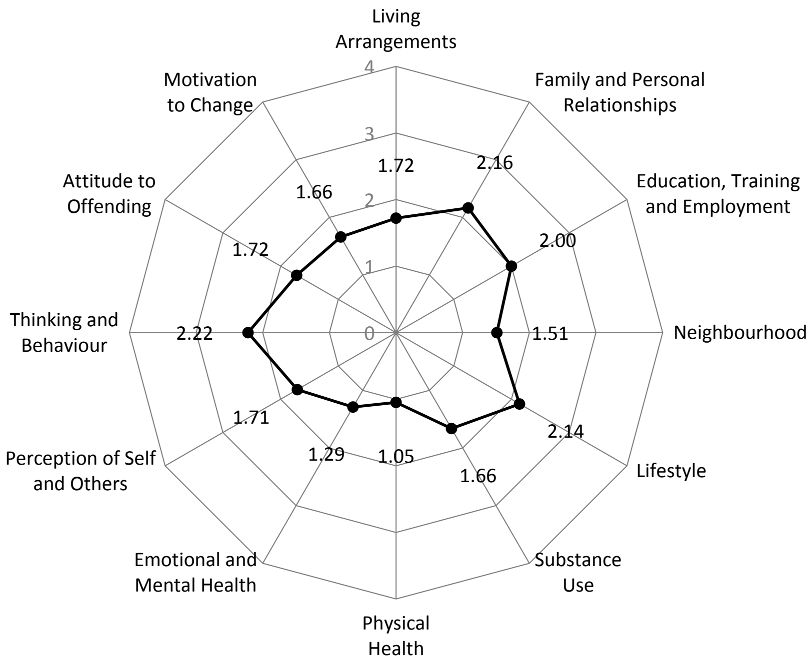
Source: Model BmT0, Technical Annex: p28-29

From these results, time appears to be negatively related to the likelihood of re-offending, suggesting that the likelihood decreases over time. This is what would be expected given the premise that as a result of working with the YOT, the young person's risk of further offending will reduce. Notably, this relationship is statistically significant with the range of estimates or 'credible interval' for the standardised coefficient being 1.000, 1.159. The odds of further offending as a function of time can be obtained through transformation ($e^{-0.159}$ = 0.853). Thus, for every additional assessment the young person is subject to, the estimated odds of them committing further offences are multiplied by 0.853. Since the unstandardised estimate of the credible interval does not include zero, this finding can be considered to be statistically significant.

b) Adding Time Varying Predictors to Represent the ASSET Domains

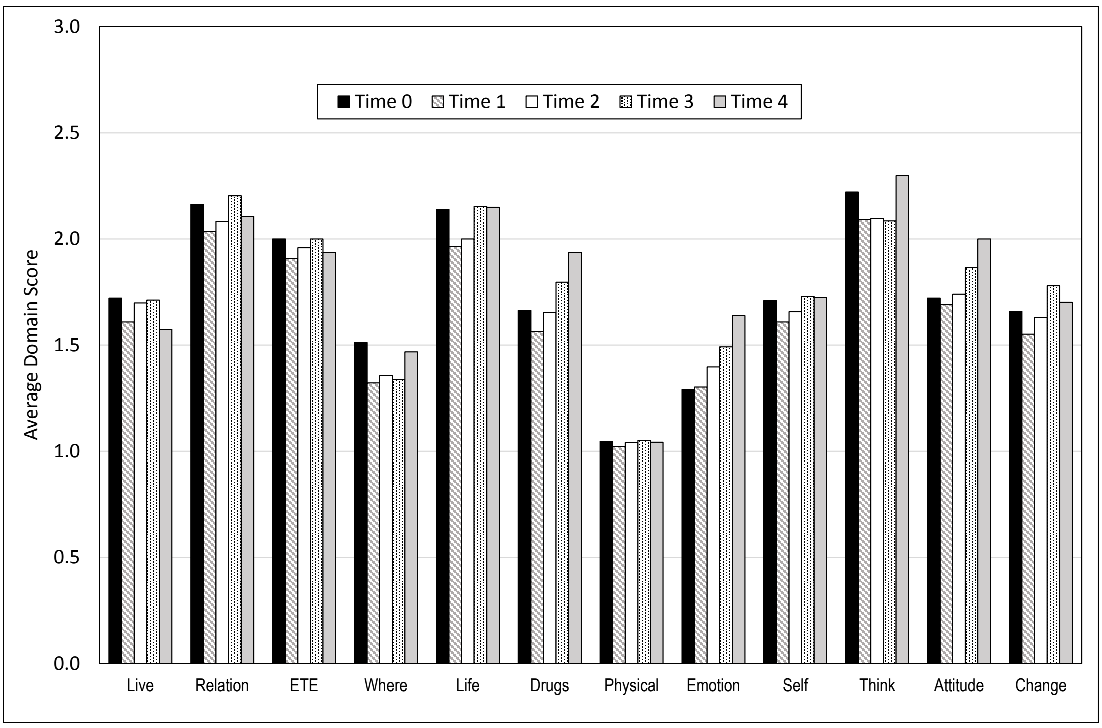
Although there is the potential for the individuals to have a rating of 0 to 4 for each domain, as highlighted in Figure 4.1, the majority receive rating of 1 or 2. Figure 4.4 summarises the mean scores for each domain at the time of the Individual's initial assessment (Time 0). In a small number of cases – where the primary index had been dealt with out of court, the young person's first ASSET Core Profile relates to their referral following their further offence.

Figure 4.4: Mean Domain Scores at Time 0



Ratings can vary depending upon how the Individual is progressing during their time with the YOT and in response to changes in their personal circumstances. Figure 4.5 summarises the mean scores for the first five measurement points, illustrating the time-varying nature of each these predictors.

Figure 4.5: Mean Domain Scores by Time



Notes: Time 0 = 87 individuals; Time 1 = 87 individuals; Time 2 = 73 individuals; Time 3 = 59 individuals; Time 4 = 47 individuals. The number of individuals having 5 or more assessments (Time > 4), is summarised in Figure 4.2.

Notably the mean scores for the 'substance misuse' (Drugs) and 'emotional and mental health' (Emotion) domains increase across the first five measurement occasions. Whilst this may in part be a reflection of the more complex lives of those remaining under the supervision of the YOT after Time 3, Wilson and Hinks (2011) report that practitioners found the' emotional and mental health' domain to be the most difficult to explore with young people, followed by 'family and personal relationships' (Relation) and 'perception of self and others' (Self). This, they suggest, may be a consequence of 'the limited skills of workers in this area' (2011: 55). As a result, it may take time for the practitioner to learn sufficient information about the young person to make an assessment of their risk level.

In the case of ratings for the substance misuse domain, this is perhaps more prone to a disclosure effect (Raynor et al., 2000) whereby the individual may be unwilling to disclose information which could be perceived as potentially getting them into further trouble. Notably, Wilson and Hinks highlight that there may be difficulties in exploring issues around substance use in the presence of a parent/guardian in the interview. Hence disclosure about the true nature and extent of a young person's substance use may only occur after the relationship has had a chance to develop with the practitioner leading to the upward trend in mean scores after Time 0.

Table 4.9: Random Intercept Model for Further Offending including ASSET Domains

	12 Domains + Time, Random Intercepts						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Individual (Intercept)	-0.894	-1.378	-0.425	0.409	0.252	0.654	Yes
Living Arrangements	0.009	-0.204	0.233	1.009	0.816	1.262	
Family and Personal Relationships	0.176	-0.062	0.422	1.193	0.940	1.526	
Education, Training and Employment	0.056	-0.151	0.261	1.058	0.860	1.299	
Neighbourhood	0.056	-0.127	0.238	1.058	0.880	1.269	
Lifestyle	0.075	-0.204	0.369	1.078	0.816	1.446	
Substance Use	0.119	-0.073	0.324	1.127	0.930	1.383	
Physical Health	-0.128	-0.360	0.104	0.880	0.697	1.109	
Emotional and Mental Health	-0.044	-0.252	0.164	0.957	0.777	1.178	
Perceptions of Self and Others	-0.026	-0.301	0.231	0.974	0.740	1.260	
Thinking and Behaviour	-0.006	-0.274	0.277	0.994	0.760	1.319	
Attitude to Offending	-0.050	-0.345	0.260	0.952	0.708	1.297	
Motivation to Change	0.163	-0.112	0.454	1.177	0.894	1.575	
Time	-0.188	-0.244	-0.133	0.828	0.784	0.875	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.040	1.80E-04	0.158	1.041	1.000	1.171	Yes

DIC	608.51

Source: Model BmT1, Technical Annex: p31-37

The random intercepts model including the 12 domains is summarised in Table 4.9. This reflects the mean score for each domain across all measurement occasions. Compared to the null model and the null + time model (Tables 4.7 and Table 4.8), the DIC is lower despite the increased complexity of the model suggesting that the addition of these predictors helps to reduce the amount of variance.

c) Varying the Slope to Allow Variation by Individual over Time (Adding Random Coefficients)

Notably the number of ASSET Core profiles varies by Individual (Figure 4.1) suggesting that time also needs to be included as a random coefficient. The model for further offending where both the intercept and time-trend vary by individual is written as:

$$\Pr(y_{ti} = 1) \; = \; \text{logit}^{-1}(\beta_0 + \; \beta_1 m_{ti} + \mu_{0i} + \mu_{1i} \; m_{ti} + e_{ti}) \qquad (4.7)$$

In this model, the fixed effects are represented as being β_0 and μ_{0i}, whilst the random effects are written as $\beta_1 m_{ti}$ and μ_{1i}. The term $\mu_{1i} m_{ti}$ represents the random coefficient, giving the difference between each Individual's coefficient from the overall population coefficient $\beta_1 m_{ti}$ where time is a predictor. The impact is to reduce the DIC to 487.64.

Table 4.10: Random Intercept and Varying Slope Models for Further Offending

	Null Model, Random Intercepts and Varying Slope						
	Unstandardised			Standardised			
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.134	2.31E-04	0.417	1.144	1.000	1.518	Yes
Time	1.122	0.3061	2.329	3.071	1.358	10.268	Yes
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	-0.123	-1.182	0.954	0.885	0.307	2.597	
Time	-0.139	-0.275	-0.017	0.870	0.759	0.983	Yes

DIC	487.64

Source: Model BmTV0, Technical Annex: p39-40

The estimate for the intercept – 0.134, is fixed with a 95% credible interval for the unstandardised coefficient of 0.000231 to 0.417. Since this interval does not contain 0, this is considered to be significant.

The slope for time indicates that the logit of the probability of further offending increases on average by 1.022 for every additional assessment. Exponentiating this value suggests that the odds of further offending increase by a multiplicative factor of 3.071 —that is, an increase of 307%—for every additional assessment. However, the credible interval suggests that this could range from 35.8% to 1026.8% highlighting the high amount of potential variability in this estimate.

d) The Basic Model

The Basic model (Bm1, summarised in Table 4.11) represents the repeated measurements from the ASSET Core Profile. Despite the increased complexity of the model, the DIC falls from 487.6 to 476.2. This also compares favourably to the DIC for the equivalent model without time as a random coefficient (Model BmT1, DIC = 608.5). Time is both significant as a fixed and random effect i.e. 0 is not in the interval. Notably, the posterior mean estimate for time as a fixed effect and its 95% credible interval are negative suggesting that in addition to the random effect of both time and individual, the probability of further offending decreases as time increases.

Table 4.11: The Basic Model: Random Intercept and Varying Slope Models for Further Offending including ASSET Domains

	12 Domains + Time, Random Intercepts and and Varying Slope						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Individual (Intercept)	-1.168	-2.379	0.129	0.311	0.093	1.138	
Living Arrangements	0.033	-0.216	0.293	1.033	0.806	1.340	
Family and Personal Relationships	0.275	-0.026	0.556	1.316	0.974	1.744	
Education, Training and Employment	0.094	-0.152	0.342	1.099	0.859	1.408	
Neighbourhood	0.044	-0.166	0.262	1.045	0.847	1.300	
Lifestyle	0.024	-0.316	0.371	1.024	0.729	1.450	
Substance Use	0.158	-0.087	0.388	1.172	0.917	1.473	
Physical Health	-0.114	-0.394	0.165	0.892	0.674	1.180	
Emotional and Mental Health	-0.003	-0.249	0.242	0.997	0.780	1.273	
Perceptions of Self and Others	-0.138	-0.443	0.182	0.871	0.642	1.200	
Thinking and Behaviour	-0.160	-0.508	0.157	0.853	0.602	1.170	
Attitude to Offending	0.043	-0.298	0.389	1.044	0.742	1.475	
Motivation to Change	0.231	-0.095	0.582	1.260	0.909	1.790	
Time	-0.153	-0.283	-0.018	0.858	0.753	0.982	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.101	1.99E-04	0.366	1.106	1.000	1.442	Yes
Time	1.267	0.338	2.605	3.550	1.403	13.531	Yes

DIC	476.20

Source: Model Bm1, Technical Annex: p42-47

Comparing this model with those summarised in Tables 4.7 and 4.8, demonstrates the utility of utilising a hierarchical modelling approach to analyse the data generated by the risk assessment process.

It is apparent from Table 4.11 that *time* is a significant fixed effect when included in the Basic Model alongside the 12 domains, with the negative coefficient suggesting that if the domain scores remain constant, the probability of further offending is expected to decrease. However, the significant random effects suggest that this trend will vary both by individual and time. In the dynamic equivalent of this Basic Model (Table 4.12), *time* is not a significant main fixed effect, but two of the domain predictors are when there is an interaction between these and time.

It should be noted that the coefficients presented in subsequent models have been generated through use of a simulated model. As a result, there can be some variability in the estimates for the fixed effects.

The Basic Dynamic Model

Under this model, there is the potential for each individual domain predictor to vary by time, reflecting the dynamic nature of the risk assessment framework. Full descriptions of each domain can be found in The ASSET Core Profile Guidance (Youth Justice Board, 2008a). Examples of ratings of 1, 2, 3 and 4 are given within this document to assist practitioners. Summaries can also be found in the Technical Annex.

Table 4.12: The Basic Dynamic Model Involving the 12 Domains

	Dynamic Model 1						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
(Intercept)	-1.099	-1.768	-0.483	0.333	0.171	0.617	
Time	-0.008	-0.109	0.088	0.992	0.897	1.092	
Living Arrangements (Live)	0.274	-0.473	1.000	1.316	0.623	2.719	
Family and Personal Relationships (Relation)	0.319	-0.697	1.331	1.376	0.498	3.783	
Education, Training and Employment (ETE)	-0.517	-1.306	0.274	0.596	0.271	1.315	
Neighbourhood (Where)	-0.254	-0.985	0.471	0.775	0.373	1.601	
Lifestyle (Life)	1.454	0.237	2.692	4.280	1.267	14.768	Yes
Substance Use (Drugs)	-0.320	-1.041	0.364	0.726	0.353	1.439	
Physical Health (Physical)	-0.586	-1.956	0.864	0.557	0.141	2.374	
Emotional and Mental Health (Emotion)	-0.381	-1.313	0.516	0.683	0.269	1.676	
Perceptions of Self and Others (Self)	1.000	-0.123	2.080	2.717	0.884	8.008	
Thinking and Behaviour (Think)	-1.109	-2.252	-0.096	0.330	0.105	0.908	Yes
Attitude to Offending (Attitude)	0.014	-1.142	1.116	1.014	0.319	3.053	
Motivation to Change (Change)	1.024	-0.156	2.238	2.785	0.855	9.372	
Time: Live	-0.041	-0.165	0.097	0.959	0.848	1.102	
Time: Relation	-0.063	-0.270	0.151	0.939	0.763	1.163	
Time: ETE	0.080	-0.077	0.219	1.083	0.926	1.245	
Time: Where	0.071	-0.050	0.193	1.074	0.951	1.213	
Time: Life	-0.204	-0.417	0.008	0.816	0.659	1.008	
Time: Drugs	0.089	-0.054	0.236	1.093	0.947	1.267	
Time: Physical	0.033	-0.174	0.235	1.033	0.840	1.265	
Time: Emotion	0.104	-0.082	0.301	1.110	0.921	1.352	
Time: Self	-0.265	-0.488	-0.040	0.767	0.614	0.961	Yes
Time: Think	0.288	0.051	0.533	1.334	1.052	1.704	Yes
Time: Attitude	0.068	-0.178	0.309	1.071	0.837	1.362	
Time: Change	-0.161	-0.412	0.080	0.851	0.662	1.083	
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.180	9.49E-10	0.697	1.197	1.000	2.007	Yes
Time	0.126	5.32E-10	0.514	1.134	1.000	1.672	Yes

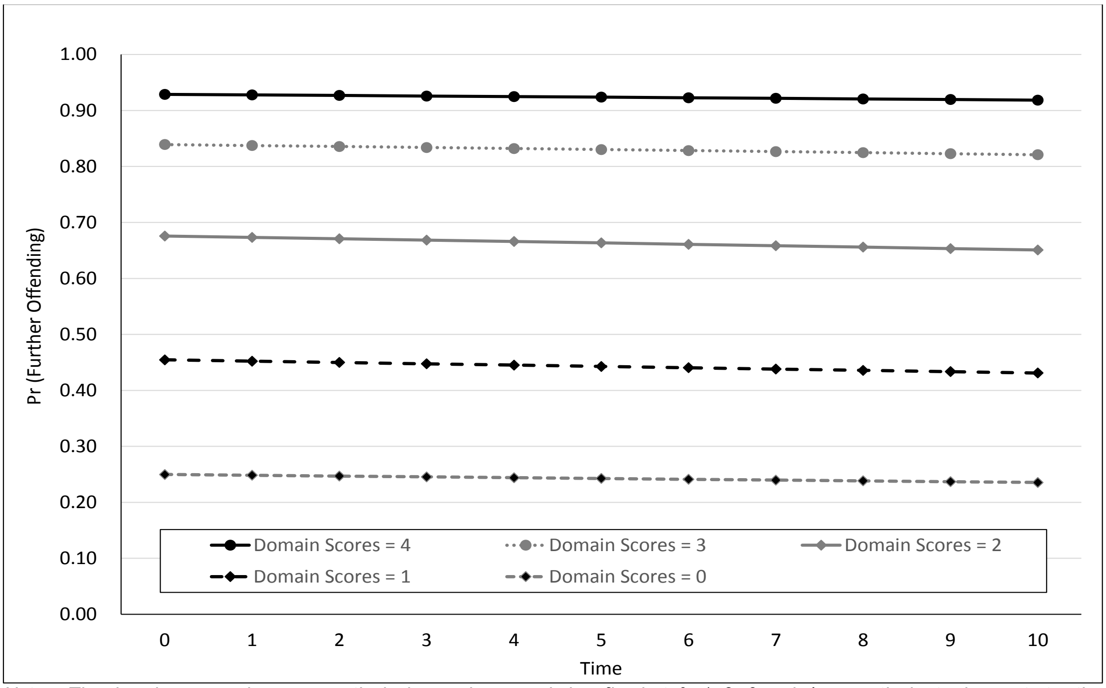
DIC	256.77

Source: Model BDm1, Technical Annex: p50-57

Under this model, the estimates for the fixed effect of the lifestyle and thinking and behaviour domains are flagged as being significant along with those for the interactions between time and perception of self, and time and thinking behaviours i.e. 0 is in the interval. These results suggest that the ratings for these two domains are statistically significantly related to further offending. The significant interactions suggest that how a young person' ratings for these domains change over time is also related to their likelihood of further offending.

The anticipation within the risk assessment framework is that domain scores will decrease over time as the young person works with the YOT. In Figure 4.6, the domain scores have been fixed at their initial values so that the estimated change in the probability of further offending from time 0 to time 10 can be seen. In doing this it is recognised that this is somewhat artificial, especially since individual young people can also have different scores in each of the 12 domains, reflecting their personal circumstances at a given time. The unbalanced nature of the data means that at later time points, there is less information for the model to draw upon and hence the domain scores of highly prolific and hence higher risk young people may have greater influence upon the model.

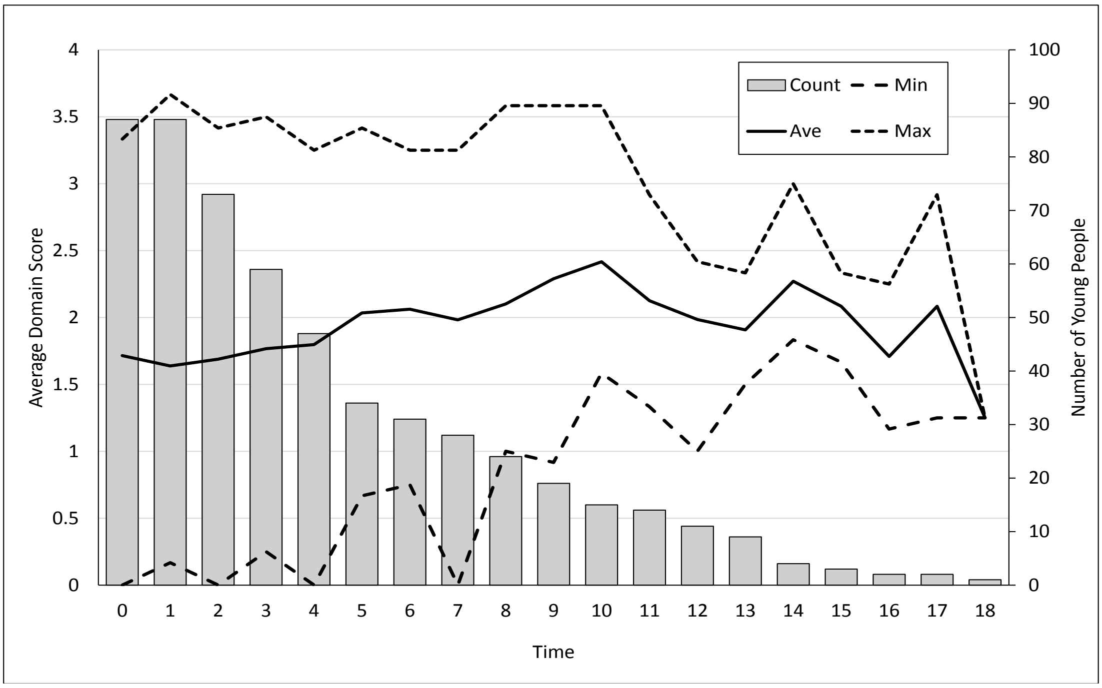
Figure 4.6: Changes in the Probability of Further Offending Over Time



Notes: The domain scores have respectively been shown as being fixed at 0, 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of further offending from time 0 to time 10. Estimates derived from Model BDm1.

Figure 4.7 summaries the number of young people with ASSETs at each time point along with the range of domain scores. To simplify the visual representation of the data from Figure 4.3, rather than presenting the Individual trajectories, these have been averaged. Hence the average mean score across the 12 domains has been presented along with the minimum and maximum. At time 18, these are all the same since they are based on the data from just one individual.

Figure 4.7: Summary of the Underlying Data for the Basic Dynamic Model (All Individuals)



Notes: Average domain scores range from 0 to 4 reflecting the range of the possible ratings that can be assigned for each of the 12 domains.

4.3 The role of the 12 domains in predicting further offending over time. How do these findings extend the existing evidence base?

The review of ASSET conducted by Wilson and Hinks (2011) considered the predictive validity of ASSET on proven re-offending over one year using a number of different measures:

- The accuracy of the total score (out of 64) in predicting the proportion of young people assessed using the Core ASSET Profile who re-offended within one year as well as the frequency and severity of re-offences and disposals. The results of this analysis were summarised in Section 2.6.
- A series of binary logistical regression models run to determine which of the 12 dynamic measures was the most predictive of re-offending.

In comparing different combinations of static and dynamic factors and the OGRS 3, this second exercise was undertaken using data relating to both Core Profile (sentenced) and Final Warning cases, with one assessment per person (n=7,621) rather than has been done here, using the repeated measures. Wilson and Hinks also used the administrative measure of proven re-offending rather than whether or not the young person had committing a further offence. As such it is not possible to draw direct comparisons using the 87 cases from Western Bay YOT. However, their results provide useful context when considering the findings presented in section 4.2.

Wilson and Hinks (2011) found that Lifestyle, Substance Use and Motivation to Change were highly significant predictors of proven one-year reoffending. Ratings in the Living Arrangements, Family and Personal Relationships and ETE domains were also statistically significant whilst those in the remaining six domains were felt to be relevant. From Dynamic Model 1 (BDm1), it is apparent that the Lifestyle domain is also a significant predictor of further offending along with Thinking and Behaviour. Notably, the interactions between *Thinking and Behaviour: Time*, and between *Perceptions of Self and Others: Time* were also found to be significant when no further predictors are included in the model.

Lifestyle

As can be seen from the description provided in the Technical Annex, the Lifestyle domain focuses upon the young person's friends and associates, what they do in their spare time and money issues. The positive coefficient for the Lifestyle domain as a main effect (BDm1, 1.454 [0.237, 2.692]) suggests that assuming all other predictors remain constant, an increase of 1 in the rating, increases the probability of further offending by a factor of 4.3 (exp(1.454)) with the credible interval suggesting that this could be between 1.3 and 14.8. The interaction between the domain and Time is not significant.

The fact that ratings for the Lifestyle domain were found to be significant predictors in both previous evaluations of ASSET and within this research fits with the literature. Indeed, as Warr (2012) highlights, few criminologists today would dispute the social nature of youth offending behaviours, with a number of major theories of 'delinquent' peer influence having been developed. In particular, it has been argued that criminal behaviour is learned from others in much the same way as all other forms of human behaviour is learnt. Whilst Sutherland's theory of differential association is commonly subscribed to in relation to peer influence, the causal mechanism and indeed the direction of this causation has been questioned. Drawing upon the sociological principle of homophily (people make friends with people who are similar to themselves), an argument can be made that people do not become 'delinquent' because they acquire 'delinquent' friends. They acquire 'delinquent' friends after they themselves have become 'delinquent'.

However, many criminologists maintain that the relation between 'delinquent' behaviour and 'delinquent' peers over time is likely to be bidirectional or sequential. Thornberry's *interactional theory of delinquency* combines aspects of both the socialisation and selection models – steming from the theory of differential association and social control theories respectively, asserting that 'associating with delinquent peers leads to increases in delinquency via the reinforcing environment by the peer network. In turn, engaging in delinquency leads to increases in associations with delinquent peers' (Thornberry et al., 1994: 74).

Jang (1999) has tested the developmental perspective of the *interactional theory of delinquency* which hypothesizes that the role of 'delinquent' beliefs varies developmentally, focusing on the age-varying effects of family, school, and 'delinquent' peers on offending behaviours for the crime-prone adolescent years i.e. between ages 11 and 20. Under this hypothesis Thornberry et al argued that although peers already have a significant impact on the adolescent's behaviour, during the early stages of adolescence (ages 11-13) parents still have a strong influence on their children. The impact of 'delinquent' peers on the adolescent's behaviour continues to grow as the locus of interaction and social influence shifts from the family to peer networks during middle adolescence (ages 15-16). In the final stages of adolescence, association with 'delinquent' peers still has a strong, primarily direct, influence on 'delinquent' behaviour, thought its effects are expected to be mediated by other factors e.g. 'delinquent' values and need to compete with activities such as employment, college, education and romantic relationships. Jang's analysis of five waves of the Rochester Youth Development Study using multilevel modelling supports the age-variance hypothesis, although he found that the impact of 'delinquent' peers on offending behaviours tended to peak earlier than hypothesised. A curvilinear pattern was observed which is understood to be the combination of developmental challenges and 'delinquent' activity, with developmental challenges reflecting the young person's struggle to adjust to their interim status (i.e. between child and adult status). Under this developmental perspective, problem behaviour including offending behaviour is seen as being a result of inadequate coping with the challenges of transition especially where they fail to find proper social support from their immediate surroundings.

Other features of the domain reflect participation in a broader range of reckless activities including those which place the young person and/or others at risk of physical injury (e.g. playing on railway lines, building sites or major roads, and racing cars around residential areas); activities done to impress others or to get a 'buzz'; and involving other in their offending. As the data collection process did not drill down to the responses to the 'Yes' / 'No' questions completed by the practitioners as part of the assessment process, it is not possible to ascertain the extent to which these are features of the young people's lives as Baker et al. (2003) did in their first published review of ASSET. However, it is notable that at Time 0, 73.9% (65 out of 87) where judged to be at significant risk of reoffending as a result of their Lifestyle with practitioners assigning ratings of 2 or more. This was one of the highest proportions with only the proportion deemed at significant risk because of their Thinking and Behaviours being higher (76.1%). The other domain with similar proportions considered to be at significant risk at Time 0 was Family and Personal Relationships (73.9%).

Thinking and Behaviours

The role of others in a young person's offending is complex, ranging from coercion, threats and manipulation through to committing offences to impress and gain in popularity. As such it is also reflected in the Thinking and Behaviour domain where the practitioner is asked to identify if the young person's actions are characterised by amongst other things, giving in easily to pressure from others and attempts to manipulate / control others.

The negative coefficient for the Thinking and Behaviour domain as a main effect (BDm1, -1.109 [-2.252, -0.096]) suggests that if the rating were to increase by 1 with no other changes, the probability of further offending would decrease by a factor of 0.33 (exp(-1.109)), although this could potentially be between 0.10 and 0.91. In addition to the main effect being significant, the interaction between this domain and Time is also significant with a positive coefficient (0.288 [0.051, 0.533]). Since the main effect for Time is not significant, it is difficult to draw firm conclusions about the net effect of these within the additive model. However, broadly speaking after Time 4, if all other domain scores remain the same then an increase in the rating for the Thinking and Behaviour domain increases the probability of further offending. The credible intervals for each of the coefficients represent the amount of uncertainty around these main effects and interactions involving them.

Notably Wilson and Hinks did not identify this domain as being a statistically significant predictor of reoffending although they note that along with Neighbourhood; Physical Health; Emotional and Mental Health; Perception of Self and Others; and Attitude to Offending, the Thinking and Behaviours domain was 'still likely to be relevant for understanding the needs in the experienced by young people' (2011: 29). In their interviews with practitioners, this domain was 'considered difficult to assess in the initial stages of the contact' (Wilson and Hinks, 2011: 55). This view is perhaps understandable given that the domain focuses on problematic patterns of thinking and types of behaviour in a range of different contexts e.g. at home, at school, with friends, in the neighbourhood, with staff and in relation to their offending. As such it is necessary to compile evidence from a number of different sources and to form a relationship with the young person. However, both practitioners and young people who have been assessed using ASSET have previously suggested that the Thinking and Behaviours and Lifestyle domains are clearly related with reoffending along with ETE and a lack of training / qualifications respectively, and in the case of young people, the neighbourhood (Youth Justice Board, 2005a) – a finding which is potentially linked to the perceived potential to be modified by practical and community-based prevention programmes.

Perception of Self and Others

This domain concentrates upon the young person's understanding of how they – and others – fit into the world around them. As such it considers whether the individual has an inappropriate level of self-esteem; a general mistrust of others; difficulties with self-identity and if they see themselves as an offender. In terms of their relationships with others, they may display discriminatory attitudes or have a lack of understanding for other people.

Individual Factors: Personality Traits, Attitudes, Beliefs and Offending

Using the groupings of risk and protective factors adopted by the YJB (Youth Justice Board, 2005b), it is apparent that a number of the traits which appear within the Thinking and Behaviour, and Perception of Self and Others domains can be considered to be individual or personal factors – the primary exception being aggression which is commonly considered to be a school factor due to its links to bullying behaviours although it can also be linked to family factors. These tend to focus upon personality traits, attitudes and beliefs:

- Hyperactivity and impulsivity
- Low intelligence and cognitive impairment
- Alienation and lack of social commitment
- Attitudes that condone offending and drug misuse
- Friends involved in crime and drug use

The association between various personality traits, attitudes and beliefs and offending during childhood and adolescence is well documented, featuring in the Gluecks' work undertaken in the 1920s and 1930s. Case and Haines for example highlight that in *500 Criminal Careers (1930),* the Gleucks identify 'dull or borderline intelligence, psychotic or psychopathic, neuropathic traits – extreme suggestibility, emotional instability, impulsiveness' (2009: 55) as personality / intelligence factors that were present in early childhood and early adolescence and related to later onset of recorded offending. In their follow up work *One Thousand Juvenile Delinquents (1934)*, the Gleucks identified 'sub-normal intelligence, marked emotional and personality handicaps' (Case and Haines, 2009: 57) as personality / intelligence factors which increased the risk of the young men coming before the courts as an official offender. Other factors were also identified within these studies under the domains of family, school, lifestyle and employment.

In their later study, *Unraveling Juvenile Delinquency (1950)*, the Gluecks identified strong associations between a range of biological, psychological and social risk factors measured in childhood and subsequent youth offending, notably:

> - *'Body type* – stocky, muscular mesomorphs
> - *Temperament* – restless, impulsive, extroverted, aggressive, destructive
> - *Attitude* – hostile, defiant, resentful, suspicious, stubborn, assertive, adventurous, not submissive to authority
> - *Psychological* – tending to think in concrete (rather than abstract) terms
> - *Family* – lack of parental discipline, poor supervision and low family cohesiveness.'
>
> (Case and Haines, 2009: 61-62)

Whilst the work of the Gleucks has been criticised for being overly simplistic, many of the subsequent longitudinal and cross-sectional risk factor research studies have investigated the association between personality traits, attitudes and beliefs, and subsequent offending behaviours. This includes the Cambridge Study in Delinquent Development and the Edinburgh Study of Youth Transitions and Crime which have been particularly influential in shaping policy and practice in England and Wales, and Scotland respectively.

Personality traits, attitudes and beliefs also form an integral part of the risk-needs-responsivity model of correctional assessment and rehabilitation (Andrews et al., 1990) which has been widely adopted within both the youth and wider justice system. The model (Table 4.13) comprises of the Central Eight split between the “Big Four” and the “Modest Four” – the former including a history of criminal behaviour, anti-social behaviour pattern, anti-social attitudes, values, beliefs and cognitive-emotional states, and anti-social associates. In the context of wishing to affect change, the risk-need-responsivity (RNR) model is particularly relevant with a number of international meta-analyses showing that if properly implemented, reductions in reoffending can be detected.

Although not without its detractors, the RNR model acknowledges the psychological nature of some risk factors which has led to the recognition that these are dynamic and modifiable. Hence the likelihood of further offending behaviour could be reduced by reducing the risk level associated with these factors. In matching services to the assessed risk level of the individual, focus can placed upon those attributes that are predictive of offending and ensure that they are targeted in the individual’s rehabilitation plan. In order to maximise the individual’s ability to benefit from a rehabilitative intervention, evaluations need to be tailored to the young person’s learning style, motivation, abilities and strengths with consideration also being made to their age, gender and ethnicity (Adler et al., 2016). As a result of the theoretical intercorrelations between these factors, some of the most effective intervention approaches are characterised by using a combination of skills training and cognitive behavioural intervention approaches, employing a multi-modal design with a broad range in interventions that address a number of offending related risks (Wilson, 2013).

Table 4.13: The Central Eight, Their Indicators and Associated Needs

Major Risk / Need Factor	Indicator	Dynamic Need
History of Anti Social Behaviour	**Early and continuing involvement in a number and variety of anti social acts in a variety of settings**	**Build non-criminal alternative behaviour in risky situations**
[redacted]		
School / Work	Poor Performance, low levels of satisfactions	Enhance performance, involvement, and rewards and satisfactions
Pro Social Recreation	Lack of involvement in Pro social hobbies and sports	Enhance involvement and rewards and satisfaction

Adapted from Andrews and Bonta (2010: Table 2.5). The "Big Four" are shown in bold.

Assuming that the principles of RNR are being adhered to within the YOT setting when planning interventions, then it follows that activities that counter the "Big Four" are going to be the most significant in promoting desistence. As such it is encouraging that research undertaken by the Ministry of Justice (Wilson, 2013) suggests that YOTs are better at addressing factors such as Lifestyle, Perception of Self and Others, Thinking and Behaviour, Attitudes to Offending and Motivation to Change, than others. However, it was acknowledged that there remained room for improvement in terms of aligning offending related risks and needs, aims in the intervention plan and subsequent provision. Wilson also identified that it was more challenging for the YOTs to directly address certain needs such as neighbourhood, living arrangements and family and personal relationships. Consequently, these were less likely to be targeted in intervention plans.

Given the transition to ASSET Plus which has happened since this inception of this research, there has been increasing emphasis upon promoting desistence. In particular McNeill (2009) highlights that desistence relates to age and maturing, to social ties or bonds, and to changing personal identities. However, for changes processes (like desistence) to occur, both practitioners and offenders need the motivation to change, capacity to be and to act differently and opportunities to do so, with all three being required for the change to occur. For some young people, the capacity to change is affected by non-criminogenic factors such as self-esteem, anxiety, victimisation issues and learning disabilities. Notably in the context of England and Wales, there has been a growing awareness of the high prevalence of neurodevelopmental disorders amongst those who offend (Hughes et al., 2012) which can hinder both treatment and the ability to actively engage in the youth justice process. Such individuals are more likely to struggle to engage and comply with requirements placed upon them. Speech, language and communication needs similarly may limit the young person's comprehension of diversionary / restorative justice processes and criminal proceedings (The Communication Trust, 2014; Youth Justice Board and Royal College of Speech and Language Therapists, 2015) meaning that they are more likely to enter the formal youth justice system. With increasing numbers now being diverted from the formal justice system, this begs the question as to whether those remaining represent more complex cases with more entrenched offending behaviours.

The YJB considered whether or not the cohort is becoming more complex as part of its three-year Reducing Reoffending Programme. In exploring this issue as part of their attempts to increase the sector's knowledge of reoffending and the drivers behind this, the YJB undertook analysis of ASSET data from over a six-year period, looking at changes in total ASSET scores and individual domain scores over time. Whilst this analysis was based on assessments rather than individual young people, it found that:

> 'For the year ending March 2016, the dynamic factors with the highest average ASSET scores are Lifestyle and Thinking Behaviour (indicating the strongest association with likelihood of further offending), with average scores of 1.89 and 2.23 respectively. The factors with the lowest values are Physical Health and Neighbourhood with scores of 0.31 and 1.01 respectively.
>
> While the scores or some factors dipped in the first years examined, they all increased over the whole period, indicating an average rise in the level of assessed risk/need that young people present. The factors showing the greatest percentage change in score over time are Perception of Self and Others (identity and self-esteem) and Emotional and Mental Health: between the year ending March 2010 and March 2016, these increased by 24% and 33% respectively.'
>
> (Youth Justice Board, 2016b: 7-8)

The report concluded that on average case complexity has been increasing over time with those in the higher risk score band falling at a lesser rate than those in the lower score bands, with proportionally now more assessments being in the higher band than in 2009/10. Notably the domains highlighted as having the highest average scores and greatest percentage change have also been highlighted in the findings from this research as having a significant role to play in a young person's likelihood of committing further offence. The exception to this is Emotional and Mental Health.

4.4 How well does the 'basic' model reflect the realities of young people's lives?

Andrews and Bonta (2007) suggest that third generation risk instruments are sensitive to changes in an offender's circumstances and hence should be able to provide practitioners with information as to what needs should be targeted in their interventions. They also assert that there is evidence that changes in the scores on some of these risk-need instruments are associated with changes in recidivism. Hence it would be expected that changes in risk scores would signal changes in the likelihood of the individual committing a new offence. In this way, such tools provide a means of monitoring the effectiveness, or ineffectiveness of programmes and supervision strategies, and of tailoring the nature of interventions to target accordingly. This section therefore considers the ability of the 'basic dynamic' model to reflect such changes. This has enabled the work of Wilson and Hinks (2011) who undertook a review of ASSET on behalf of the Ministry of Justice to be advanced.

In looking to explain the differences in the trajectories of the various probabilities of further of offending, three case studies are presented which illustrate the complexity of some of the young people's lives and how changes in their circumstances have impacted upon the ratings they have received at different time points. This work builds upon that of Baker et al. (2005) who in their review of ASSET had looked at early changes in the total dynamic score. Rather than fixing the domain scores as done in Figure 4.6, these reflect the realities of the young people's lives. To protect individual identities, pseudonyms have been used and some key identifying details have been omitted.

Table 4.14: Summary of Key Information for the Three Case Histories

	Fred	Connor	David
Gender	Male	Male	Male
Ethnicity	White	White	White
Experience of Care?	None	Yes	None
FTE Status Upon Entry to Cohort	FTE	Prior Offending History	Prior Offending History
Age at First Offence	14	14	10
Age at First Conviction	15	14	16
Primary Offence	Other (Criminal Damage)	SAC (Burglary Dwelling)	Other (Public Order)
Seriousness of Primary Offence	2	6	2
Breaches	None	0	1, 2
Court Appearances	0, 1, 2, 3, 4	0, 1	0, 1, 2, 4
Periods in Custody / On Remand	4	1, 2	None
Further Offending	None	1	None

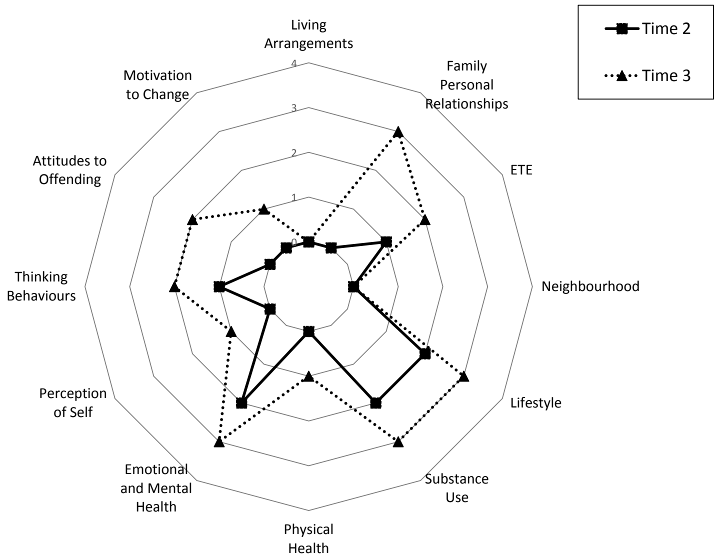
Notes: The information for breaches, court appearances, periods in custody / on remand and further offending relate to the measurement point after the event occurred.

Case Study "Fred"

As a 14-year old, Fred had been given a youth caution for criminal damage. However, with no proven offences during 2012/13 he does not appear on the reoffending spreadsheet for that year.

The following June he received a further youth caution after committing a theft offence. However, just over a month later Fred took a vehicle without consent and was given a 4-month Referral Order. A couple of months short of his 16th birthday (and whilst still on the Referral Order), Fred committed a burglary. This led to him being placed under Intensive Supervision and Surveillance Programme (ISSP) Bail and being tagged. As such he would have been mandated to engage in a structured programme of relevant activities including five core elements around offending behaviour; interpersonal skills; ETE; family support and restorative justice. In combining community-based surveillance with comprehensive and sustained focus on tackling the factors contributing to the young person's offending behaviour, the ISSP is the most rigorous, non-custodial intervention available to young people. In total there were seven court appearances over the following months before he was sentenced to a 10-month Detention and Training Order.

Figure 4.8: Case Study "Fred": Domain Scores at Time 2 and Time 3

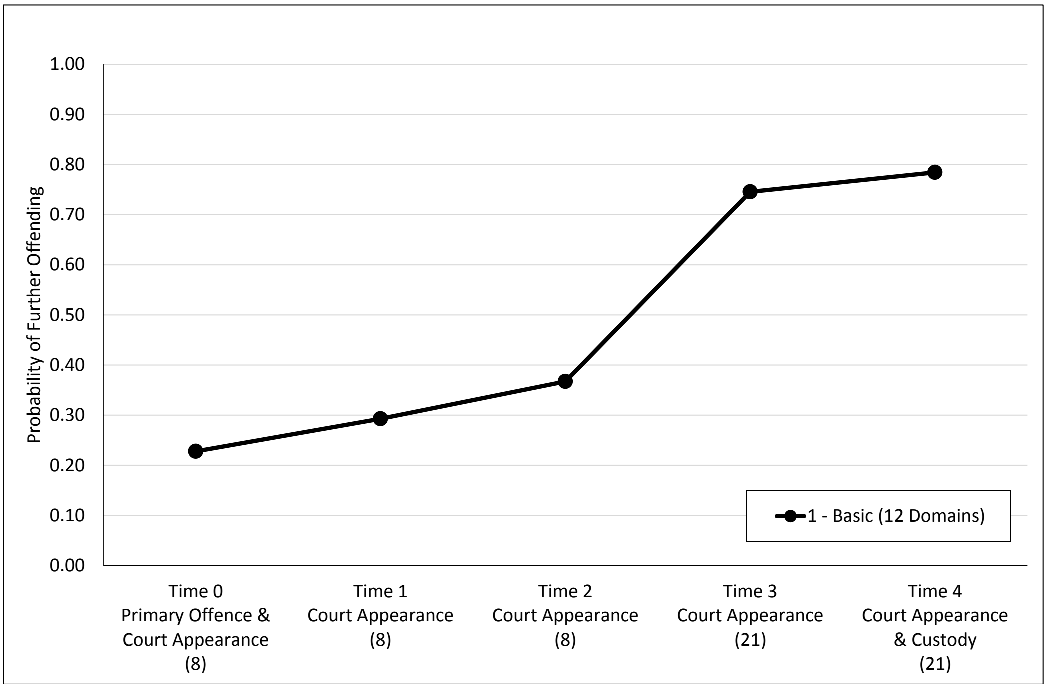


The interval between Time 2 and 3 relate to a 3-month period when Fred was on ISSP Bail and Tag, and he attended court four times - his sentencing took place a week after Time 3. During this time Fred's total dynamic ASSET score increases from 8 to 21 i.e. from low-medium to medium-high risk, but as can be seen from Figure 4.8, whilst there were no perceived differences in the level of risk associated with his living arrangements or the neighbourhood, his rating for the family and personal relationships domain increased from 0 to 3. The practitioner also judged that his lifestyle; substance use; and emotional and mental health were also quite strongly related to the likelihood of reoffending.

It is notable that Fred's rating for Attitudes to Offending increases from 0 to 2 suggesting that in the run up to his sentencing hearing he is displaying a lack of understanding about the impact of his offending; a reluctance to accept responsibility and potentially a denial of the seriousness of his behaviour (see description below). When coupled with the increase in the rating for the Family and Personal Relationships domain, this is indicative of a child whose parent(s) are not fully engaged in a supportive manner, perhaps as a response to the young person's increasingly problematic behaviour – evidenced by the increases in substance misuse and lifestyle ratings. In this case, accommodation records suggest that Fred was living at home with his mother and her partner, and he returns to this address after his time in custody. Since his living arrangements and the neighbourhood in which he lives are at no time considered to be associated with a risk of reoffending, it must be assumed that this is suitable, stable accommodation.

Figure 4.9 summarises the estimated probability of further offending based on the ASSET scores for Fred using the basic dynamic model based on just the 12 domains (BDm1) and the three models based on the domains, time and the various static factors discussed in the previous section. The increase in the domain scores between Times 2 and 3 summarised in Figure 4.8, is reflected in the upwards trend in the estimated probability of further offending based on coefficients from the basic dynamic model. Events and total ASSET scores are recorded along the x-axis. Although Fred did not commit any further offences, his increased scores led to him being in custody.

Figure 4.9: Estimated Probability of Further Offending Over Time: "Fred"



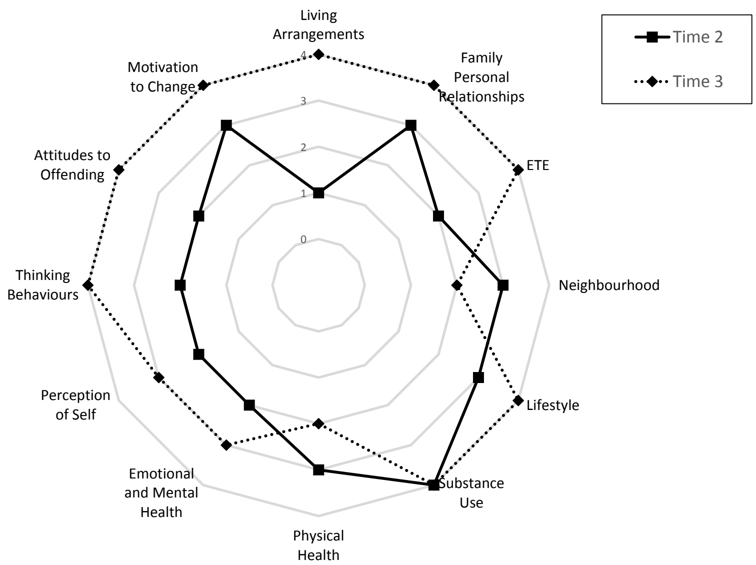
Case Study "Connor"

In contrast to Fred, "Connor" had already been identified as a prolific offender prior to joining the reoffending cohort in 2012/13. Having received a Final Warning for a non-domestic burglary in 2009 at the age of 14, Connor had been charged having committed further non-domestic burglaries on nine separate occasions including the offence which led to him being sentenced to his second Detention and Training Order (DTO). He had already been subject to a Referral Order which had been extended and Youth Rehabilitation Order as well as a couple of Conditional Discharges with offences including burglary non-dwelling, criminal damage and theft from the person.

His first DTO had been at the age of 16 following convictions for burglary non-dwelling; possession of Class C drugs and theft of a motor vehicle. Upon release, Connor had breached the terms of his licence and had been returned to custody to serve the remainder of his sentence. Two days after the end of his DTO, he was in court again – this time for an attempted burglary committed prior to his detention. He received conditional discharges for both this and at a subsequent hearing for vehicle interference. A month later he was fined for possession of cannabis. It was the attempted burglary com mitted in June 2012 which lead to Connor's inclusion on the reoffending spreadsheet. Having received a conditional discharge, he did not receive an intervention from the YOT.

During December 2012, Connor committed a theft - it was the theft that led to him being assessed using the Core ASSET Profile. Whilst on conditional bail for this he committed a common assault; two further non-domestic burglaries and been charged for being carried in an aggravated taken without owner's consent. As a result, he was remanded in custody in mid-January 2013 and was subsequently sentenced to an 8-month DTO. Connor's first three Core ASSET Profiles were conducted in January 2013 with Time 3 being post-release.

Figure 4.10: Case Study "Connor": Domain Scores at Time 2 and Time 3



As can be seen from Figure 4.10, Connor was judged to have a high risk of reoffending post-release, with a total dynamic ASSET score of 42 out of a maximum of 48. Notably the ratings for Neighbourhood and Physical Health reduced as a result of him being released from custody.

Connor's background is significantly more complex than Fred's, having been looked after for periods including spending around 3-months living in a residential care home whilst he was known to the YOT. He has also experienced the loss / bereavement of a close family member.

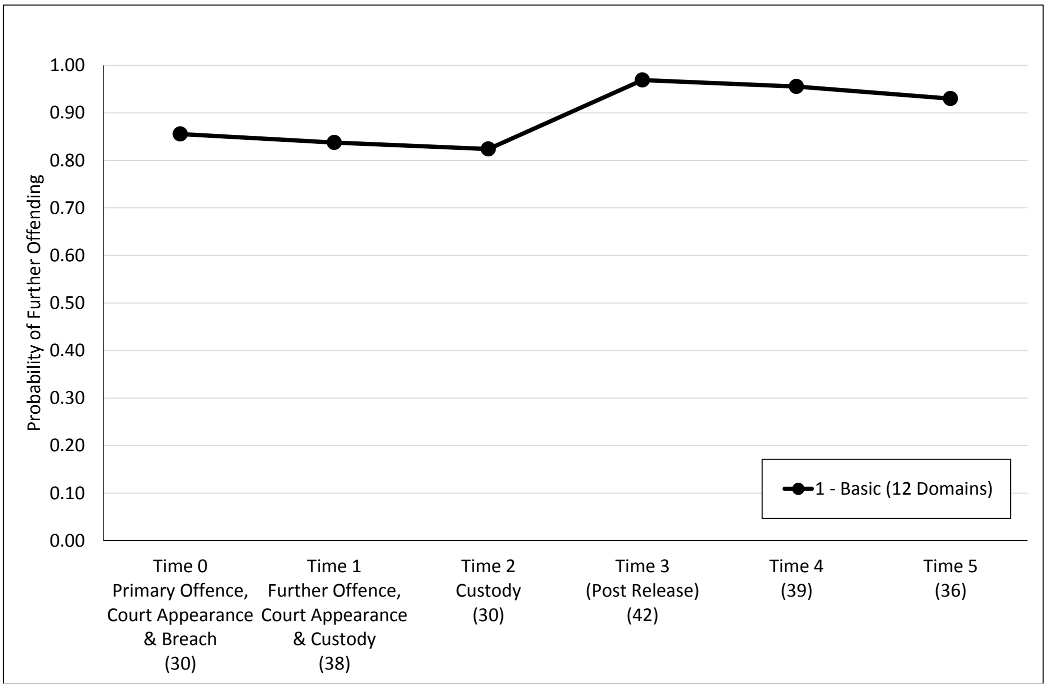
Connor has a diagnosis of ADHD and it has been identified within the case notes that he has significant issues with anger management. He is known to be violent although based on his offending and court records, with the exception of a charge of common assault when aged 17 which was subsequently dismissed, the incidences which attracted police attention occurred when he was aged 14. This included threatening, abusive or insulting words or behaviour (case dismissed) and two incidences of causing harassment, alarm or distress by threatening words or behaviour which occurred within a 3-week period – the latter resulting in him receiving a Youth Rehabilitation Order.

At different times, Connor has lived with different members of his family, with his accommodation records suggesting that he had been living with an Aunt prior to being taken into custody. Although upon release he appears to have moved into a bedsit under an independent tenancy. Notably from the time that he became known to the YOT in April 2009, it would appear that he has moved between six addresses described as being "at home", "family (immediate)" and "relatives" as well as being temporarily housed in a B&B and foster care prior to starting his custodial sentences at HMP Parc. In addition, therefore to a lack of stability in his living arrangements, it is likely that the combination of his ADHD, offending behaviours and drug use will have put a strain on relationships with family members hence the high ratings for these domains as well.

Figure 4.11 summarises the estimated trajectory for the probability of further offending using Connor's ASSET scores. Compared to Fred (who had an initial total ASSET score of 8 making him low-medium risk), Connor's was rated as being a high risk. Thus, his initial probability of further offending at Time 0 based on the basic dynamic model is notably higher and continues to be higher for the duration of his time under the supervision of the YOT.

Connor committed the common assault, non-domestic burglaries and vehicle interference at Time 1. Such was the perceived risk that he posed, he was remanded in custody. However, the basic dynamic model does not reflect this increase in the estimated probability of further offending at Time 1 despite the increase in his total ASSET score from 30 to 38.

Figure 4.11: Estimated Probability of Further Offending Over Time: "Connor"



Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with Connor having a total of 30 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that his primary offence (for the purposes of this exercise where the information has been taken from the reoffending spreadsheet) was a non-domestic burglary and as a result of his prior convictions.

Having fallen between Time 1 and 2, the model estimates that the probability of further offending increased following his release from custody – the changes in individual domain scores being shown in Figure 4.10. At Time 5 his estimated probability of further offending is higher than when he was initially assessed.

Sadly, without access to PNC it is not possible to ascertain whether Connor committed any further offences after this time. Having turned 18 whilst in custody (Time 2), he continued to be supervised by the YOT until the end of his order and would have been too old to have been included in the reoffending spreadsheet for 2013/14 had he committed any further offences after this time.

Case Study "David"

This final case study focuses on "David" who in contrast to Fred and Connor who were identified having experienced increases in their total dynamic ASSET score, saw a significant reduction in his score. David committed his first offence at age 10 and received his first conviction at age 16. However, after receiving a Reprimand for a common assault in 2006, there were no further offences until May 2012 when he committed two public order offences (Causing Harassment Alarm Distress by Threatening Words or Behaviour). Although his offending and court records suggest that he received a Referral Order (a First-Tier outcome) for these offences, he does not appear on the 2012/13 reoffending spreadsheet for Swansea YOT. Rather he appears within the 2013/14 cohort as a 17-year old having received a 12-month Youth Rehabilitation Order (YRO) for stealing a motor vehicle and being caught driving this without license or insurance.

David has been looked after for periods and it is identified that there are critical family and relationship issues. This includes a family history of both drug and alcohol use, and his case notes suggest that he been the victim of domestic violence, neglect, physical and emotional abuse. He is subject to a statement of education special needs and has both poor communication skills and literacy difficulties. There is also recorded that David is lacking some life skills and has mental health problems. He has some issue with anger management and significant issues with self-esteem. There are also some issues with identify / self-image and a critical lack of motivation around his offending behaviour.

David's accommodation records are particularly revealing since they suggest that despite having experienced significant disadvantage, he has managed to maintain a relationship with his mother although this has broken down at different points. After his initial assessment, there are three assessments made within a month, corresponding to when David appeared in court and was due to be sentenced for breaching his YRO. Time 3 relates to an assessment completed a week after the terms of his YRO were reviewed whilst Time 4 was completed 8 months later.

In the intervening period David's total score reduced by 16 overall with notable decreases in his ratings for the ETE; lifestyle; physical health; emotional and mental health and motivation to change domains (Figure 4.12). In part this reflects the greater stability in his life, having lived with his mother for approximately two and a half months at the time of the assessment. Prior to this he had periods where he was staying in B&B accommodation, had been homeless and spent time at a night shelter which had contributed to a deterioration in his physical health.

Figure 4.12: Case Study "David": Domain Scores at Time 3 and Time 4

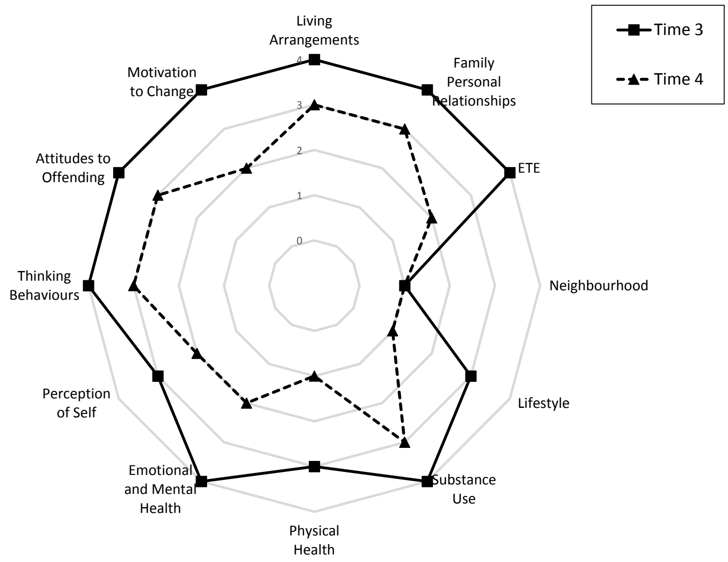
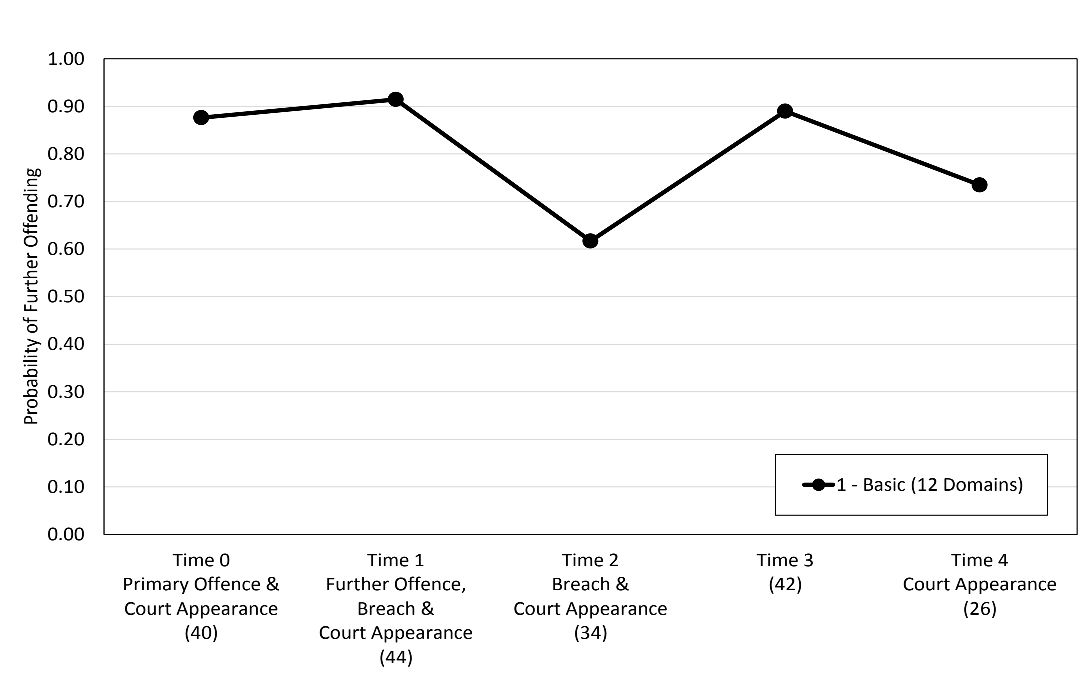


Figure 4.13 summarises the estimated trajectories for the probability of further offending using David's ASSET scores. Like Connor, David was also initially rated as being a high risk and he also committed a further offence before his assessment at Time 1.

Figure 4.13: Estimated Probability of Further Offending Over Time: "David"



Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with David having a total of 40 at Time 0, under the Scaled Approach he would have attracted additional scores since he was aged 10 at the time of his first Reprimand and as a result of his prior convictions.

The basis dynamic model suggests that there was an increase in the estimated probability of further offending which coincided with when the further offence was committed (at Time 1). There is then a fall (at Time 2) in his total ASSET scores followed by an increase, then a further fall. The two peaks in the trajectory correspond to where David had his highest ASSET scores and hence was considered by practitioners to have the highest likelihood of further offending. However, it is notable that the second peak (at Time 3) corresponds not to when he committed a further offence, but shortly after the terms of his YRO were reviewed.

4.5 Summary

The analysis presented in this chapter addresses the first research question *What is the relationship between further offending, the 12 domain scores and time?* By creating an additive multilevel model which represents the way in which scores from the risk assessment process are used over time, it has been possible to observe:

- That the assumption that a young person's probability of further offending will decrease over time as a result of working with the YOT is supported by the Basic Model (Bm1) where time is a significant fixed main effect with a negative coefficient.

- The progress that a young person makes through the YOT varies by individual and time, as evidenced by the significant random effects in Bm1.
- By allowing the individual domain scores to vary by time (the Basic Dynamic Model, BDm1), it is possible to identify which domains are the most significant as the young person progresses through their order. These findings support those previously identified in evaluations of ASSET (Baker et al, 2005, Wilson and Hinks, 2011) and more recent work by the YJB in relation to its Reducing Reoffending Programme (Youth Justice Board, 2016b), and anticipated, link back to the principals of RNR.

Alongside each of the preparatory models, the frequentist equivalent model has been run for comparison. As can be seen from the Technical Annex, running the frequentist version of the Basic Model (M1) resulted in warning signs about convergence (p48). Adding additional predictors and hence adding to the complexity of the basic model results in similar warnings. Whilst various online help pages like Stackflow suggest that these should not be taken too seriously, the fact that these are appearing prior to the dynamic model being constructed highlights the limitations of using frequentist approaches and the benefit of generating the models under a Bayesian framework.

Through consideration of the respective probabilities of further offending for Fred, Connor and David, it is possible to see that there some of the trends apparent in the trajectories which coincide with key events. For example, Fred's increasing ASSET scores let to him being detained, a trend that is apparent in Figure 4.9. Post-release, Connor's total ASSET score increased - a trend that was also reflected in the trajectory of his probability of further offending (Figure 4.11). David committed a further offence between Time 0 and Time 1. His ASSET score increased during this period and this is also reflected in the increased probability of further offending estimated by the BDm1 at this time.

The extent to which ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT (the second research question posed within this chapter) cannot be fully explored without considering individual differences; the impact of organisational factors such as having experience of care and as highlighted above understanding more about the impact of coming into contact with the different facets of the youth justice system. Hence, the data pertaining to Fred, Connor and David presented in this chapter will form a baseline against which subsequent models can be compared.

The findings in Chapters Five to Seven build upon this Basic Dynamic model by adding predictors to represent dimensional identity i.e. gender and ethnicity; the nature of criminal careers and different forms of system contact. These predictors have different characteristics and have been selected to demonstrate both the utility of the approach and its ability to handle different types of predictors, but also due to their theoretical role in understanding youth offending behaviours.

5 Findings: Dimensional Identity

Section 2.7 highlights concerns as to the insensitivity of many risk assessment instruments with respect to demographic characteristics. Building upon differences in the published proven reoffending and further offending rates determined for those within the reoffending cohort (summarised in Chapter Three), this Chapter focused upon the following research questions:

2. What is the impact of gender and ethnicity on the likelihood of further offending over time?
3. What is the impact of having experience of care on the likelihood of further offending over time?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

The predictors explored within this chapter are therefore:

- Gender – a dichotomous predictor (Male / Female)
- Ethnicity – a dichotomous predictor (White / Non-White)
- Care Experience – a dichotomous predictor reflecting whether or not the young person has had experience of care

Further individual level predictors relating to the age at first offence, age at first conviction, FTE status and the nature of the offence are considered in Chapter Six. Time-varying predictors reflecting events such as breaching, court appearances and spending time in custody / on remand are considered in Chapter Seven.

5.1 The role of gender and ethnicity

Description of the Data

It was apparent from the early analysis presented in Chapter Three to describe the reoffending cohort that there are low numbers of females and non-White young people within the dataset. Whilst this was to be expected, it is necessary to consider what can be achieved with such small sub-groups. Tables 5.1 and 5.2 summarise the Level 2 predictors for the six non-White young people and the nine females in the reoffending cohort respectively.

Table 5.1: Summary of Level 2 Predictors for the Nine Females in the Dataset

ID	Gender	Ethnicity	Care Experience?	FTE?	AgeFirst	AgeCon
1	Female	White	Yes	No	12	15
2	Female	White	No	No	13	14
3	Female	White	Yes	No	13	15
4	Female	White	No	No	14	14
5	Female	White	No	No	14	15
6	Female	White	No	Yes	14	16
7	Female	White	No	No	15	17
8	Female	White	No	No	15	17
9	Female	White	No	Not Known	17	17

Note: Since the FTE Status of the 9th Female is not known, it has been necessary to exclude her ASSETs from the modelling.

None of the females in the reoffending dataset are non-White, with two having experience of care. Just one was an FTE at the point of entry into the cohort although the absence of court and offending records within Childview for the ninth female means that it is not possible to establish whether or not they had a prior offending history. Their ages at the time of their first offence range from 12 to 17. However, the youngest age of conviction was 14. The low numbers of females with experience of care and who are FTEs respectively means there is insufficient data to enable reliable estimates to be simulated for the interactions between *Gender: Ethnicity, Gender: FTE and Gender: FTE: Care Experience*, particularly as further predictors are added to the model.

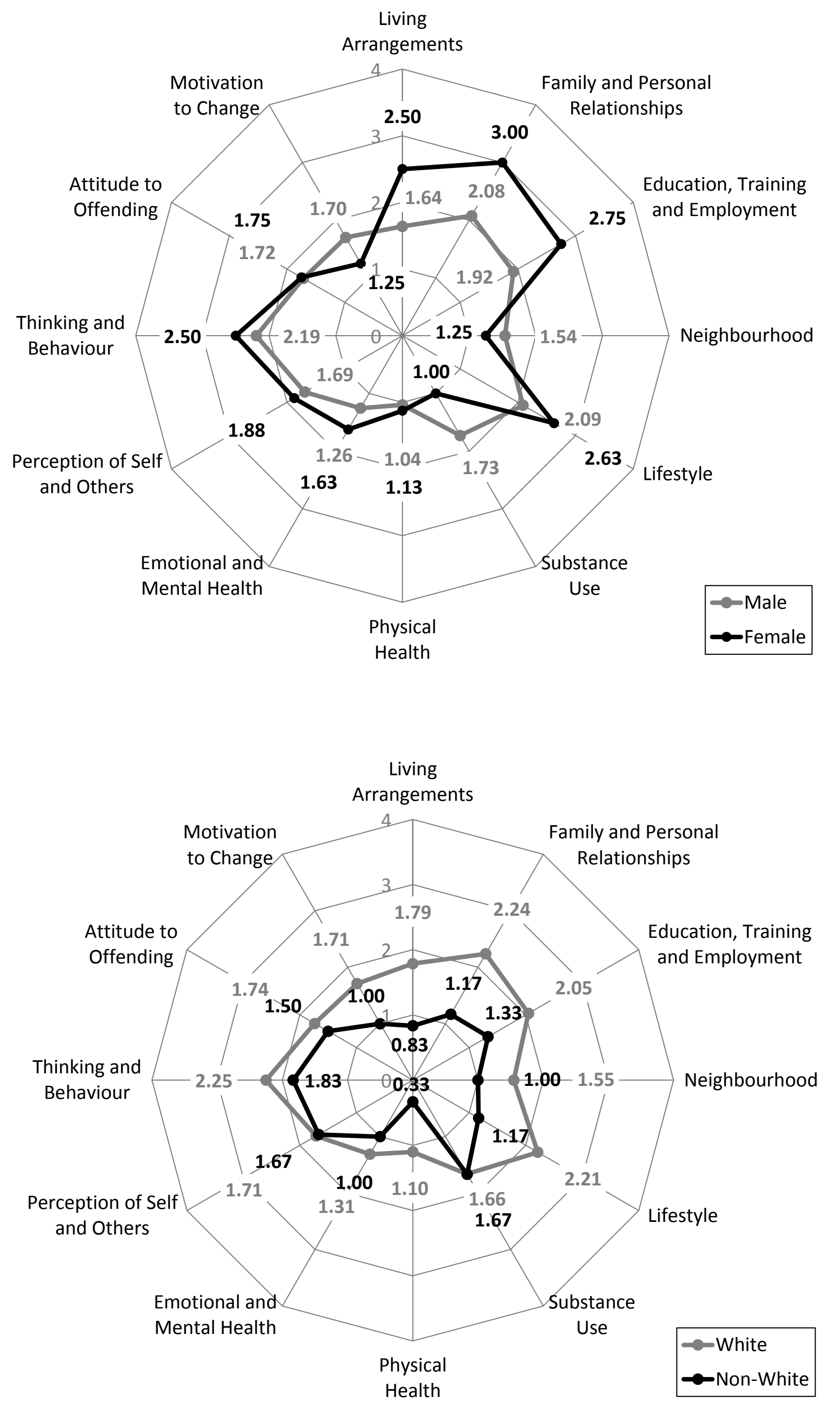
Table 5.2: Summary of Level 2 Predictors for the Six Non-White Young People in the Dataset

ID	Ethnicity	Gender	Care Experience?	FTE?	AgeFirst	AgeCon
1	Non-White	Male	Yes	No	10	10
2	Non-White	Male	No	No	12	13
3	Non-White	Male	No	No	13	14
4	Non-White	Male	No	Yes	15	16
5	Non-White	Male	No	No	15	17
6	Non-White	Male	No	Yes	16	16

As can be seen from Table 5.2, all the non-White young people are male; only one has experience of care whilst there are two who were FTEs at the time of entering the cohort. Their ages at the time of first offence and first conviction vary. The absence of females amongst this sub-group means that estimates cannot be simulated for the *Gender: Ethnicity* interaction term. The low numbers of non-Whites with experience of care and who are FTEs respectively also means there is very limited data which can be used to enable estimates to be simulated for the interactions between *Ethnicity: Care Experience*, and *Ethnicity: FTE* as further predictors are added to the model.

From Table 3.9, we know that the rate of further offending across the two years appears to be higher for males than females, and for Whites compared to non-Whites - given the size of the dataset, there is only moderate evidence to support this finding. However, it is born out in the published national data (for example Youth Justice Board and Ministry of Justice, 2015a). To understand why these differences occur, a number of factors are considered and hence in order to identify where there may be differences reflected within the model, the first step is to consider whether there are differences in their respective domain score profiles at Time 0 (Figure 5.1).

Figure 5.1: Domain Score Profile, by (a) Gender and (b) Ethnicity, at Time 0



Notes: Of the 87 individuals, 8 are female and 6 identify as being non-White. Time 0 represents the initial assessment undertaken.

One-sided Bayesian independent t-tests (Wagenmakers et al., 2017; Rouder et al., 2009) suggest that females (N=8) typically have higher ratings than males (N=79) at the time of their initial assessment for:

- Living arrangements ($BF_{10} = 3.268$ in favour of H_1: Males < Females, % error = $3.921e^{-5}$)
- Family and personal relationships ($BF_{10} = 3.616$, % error = $3.989e^{-5}$)

However, there is only anecdotal evidence to suggest that the following mean initial domain scores for males are higher than for females:

- Neighbourhood ($BF_{10} = 0.508$ in favour of H_1: Males > Females, % error = $1.056e^{-4}$)
- Substance Use ($BF_{10} = 1.433$, % error = $2.626e^{-4}$)
- Motivation to Change ($BF_{10} = 1.610$, % error = $3.060e^{-4}$)

Figure 5.1(b) suggests that the average initial ratings for those identifying as non-White (N=6) are typically higher than those for their White peers (N= 81) therefore the t-test considers the alternative hypothesis that the population mean for non-Whites is greater than that for Whites. The t-test suggests that there are differences in terms of ratings for:

- Living arrangements ($BF_{10} = 3.259$ in favour of H_1, % error = $3.613e^{-5}$)
- Family and personal relationships ($BF_{10} = 5.313$, % error = $2.123e^{-4}$)
- Lifestyle ($BF_{10} = 7.278$, % error = $2.719e^{-4}$)

Although the average initial domain scores for Substance Misuse (H_1: Non-Whites ≠ Whites, BF_{10} = 0.383) and Perception of Self and Others ($BF_{10} = 0.385$) appear to be very similar for both groups, there is only anecdotal evidence to support this. It is also important to note that since the non-White group consists of only 6 young people, the credible intervals for their respective mean domain scores are wide suggesting less certainty.

Adding Gender and Ethnicity to the Basic Model

Prior to running a dynamic model where the domain scores are allowed to vary over time, dummy variables for gender (referenced by males) and ethnicity (referenced by White) have been added to the Basic Model (summarised in Table 4.11). Running this less complex model which requires fewer iterations than the Basic Dynamic Model allows us to test if our assumptions appear to hold true i.e. that when all other factors are equal, males will have a higher further offending rate than females, and Whites have a higher further offending rates than their non-White peers.

Adding dummy variables for gender (referenced by males) and ethnicity (referenced by White) to the Basic Model, does not result in a marked reduction in the DIC for the respective models – the DIC for the Basic Model which did not involve any additional predictors was 476.20 whereas these are 476.52 and 475.19 for the versions involving gender (Model 1.1) and ethnicity (Model 1.2). There also does not appear to be any issues in relation to convergence when these models are run (Table 5.3).

To determine if all things being equal in terms of the other predictors in the specified model, there is a difference between the two groups, all the domain scores have been 'set' at 2. This has been chosen since it roughly corresponds to the mean scores overall. By summing the coefficients for the fixed effects, it is possible to determine the estimated probability of further offending at a given time e.g. Time 0. Doing this for each sub-group enables the odds of further offending to be compared. The Basic Models involving gender and ethnicity respectively suggest that:

- The odds of further offending amongst females are estimated to be exp(0.150) = 1.16 times the odds for male further offending (Model 1.1). [CI = 0.45, 3.03]
- The odds of further offending amongst those from White backgrounds is estimated to be 1/exp(-0.735) = 2.09 times higher than the odds for their non-White peers (Model 1.2) [CI = 0.76, 5.73]

The wide credible intervals for these is a consequence of the small numbers of females (8) and non-White (6) young people in the sample whilst the absence of any non-White females, means that it is not possible to explore the potential for any interaction between the two predictors. However, the additive model (Model 1.3) involving both predictors suggests that there is no notable penalty for adding both gender and ethnicity to the Basic Model.

The odds above reflect the impact of the respective demographic characteristics when all other predictors are equal. However, as highlighted in Figure 5.1, there appear to be different risk profiles at Time 0 for each of the demographic groups suggesting for example that there are marked differences in terms of average ratings for a number of domains which may be influenced by factors not reflected within the models.

Table 5.3: Random Intercepts and Varying Slope Models for Further Offending including ASSET Domains and Demographic Characteristics Unstandardised Coefficients

	Model 1.1				Model 1.2			
	Basic Model + Gender				**Basic Model + Ethnicity**			
	Unstandardised			Significant?	**Unstandardised**			Significant'
Fixed Effect:	Post.Mean	Lower CI	Upper CI		Post.Mean	Lower CI	Upper CI	
Intercept	-1.165	-2.385	0.089		-1.071	-2.295	0.209	
Gender (Male = Ref).	0.150	-0.798	1.107					
Ethnicity (White = Ref)					-0.735	-1.745	0.273	
Living Arrangements	0.033	-0.023	0.293		0.029	-0.231	0.285	
Family and Personal Relationships	0.271	-0.017	0.566		0.252	-0.039	0.544	
Education, Training and Employment	0.087	-0.167	0.329		0.081	-0.164	0.329	
Neighbourhood	0.046	-0.178	0.263		0.059	-0.162	0.278	
Lifestyle	0.021	-0.330	0.363		-0.022	-0.372	0.322	
Substance Use	0.163	-0.085	0.404		0.175	-0.058	0.417	
Physical Health	-0.117	-0.396	0.172		-0.146	-0.435	0.139	
Emotional and Mental Health	-0.001	-0.248	0.241		-3.58E-03	-0.247	0.239	
Perceptions of Self and Others	-0.144	-0.475	0.166		-0.114	-0.439	0.199	
Thinking and Behaviour	-0.164	-0.494	0.177		-0.129	-0.470	0.201	
Attitude to Offending	0.055	-0.289	0.412		0.056	-0.297	0.400	
Motivation to Change	0.241	-0.109	0.582		0.227	-0.108	0.568	
Time	-0.156	-0.290	-0.019	Yes	-0.156	-0.290	-0.025	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Significant?	Post.Mean	Lower CI	Upper CI	Significant'
Individual (Intercept)	0.117	1.46E-04	0.407	Yes	0.107	1.51E-04	0.377	Yes
Time	1.287	0.339	2.641	Yes	1.285	0.346	2.614	Yes
DIC	476.52				475.19			

Source: Models Bm1_d1 (Gender), Bm1_d1 (Ethnicity) and Bm1_d12 (Demographics), Technical Annex: p58-63 and p66-67.

5.2 Adaptations to the Model

The 'basic' hierarchical generalised linear model summarised in Table 4.12 has variables at two levels:

- Level 1 units are the measurement occasions (the ASSET Core Profiles) indexed by *t*
- Level 2 units are the individuals measured by *i*

Non-time varying characteristics such as gender and ethnicity represent additional Level 2 predicators to be added. The model proposed here therefore equates to:

$$\text{Level 1: Pr } (y_{ti} = 1) = \text{logit}^{-1}(\beta_0 + \beta_1 x_{1ti} + \beta_2 x_{2ti} + \beta_3 x_{3ti} + \ldots + \beta_{12} x_{12ti} + \beta_{13} m_{ti} + e_{ti})$$
$$\text{Level 2: Pr}(\beta_{hi}) = \text{logit}^{-1} (\gamma_{h0} + \gamma_{h1} z_{1i} + \gamma_{h2} z_{2i} + \gamma_{h3} z_{3i} + \mu_{hi})$$

Since this is an additive model – reflecting the way in which the ratings given for each of the 12 domains are added together to give a total ASSET score - the basic dynamic model (BDm1) is specified as a series of interactions between the individual domains and time. To add an additional Level 2 predictor, this is incorporated into each of the interactions as shown in BDmX_L2:

```
BDm1 <- MCMCglmm(FO.bin~live*time + relation*time + ete*time +
where*time + life*time + drugs*time + physical*time + emotion*time +
self*time + think*time + attitude*time + change*time, prior=priorD,
slice=TRUE, random=~time+Research.ID, data=dataD, family="ordinal",
nitt=100000, thin=25, burnin = 3000)

BDmX_L2 <- MCMCglmm(FO.bin ~ Level2*time*live + Level2*time*relation
+ Level2*time*ete + Level2*time*where + Level2*time*life +
Level2*time*drugs + Level2*time*physical + Level2*time*emotion +
Level2*time*self + Level2*time*think + Level2*time*attitude +
Level2*time*change, random=~time+Research.ID, data=data,
family="ordinal", prior=priorD, slice=TRUE, nitt=610000, thin=50,
burnin=3000)
```

By specifying the interactions in this way, when the resulting model is simulated, then all the terms are included individually in the model along with all the 2-way permutations and the 3-way interaction:

Description	Basic Dynamic Model (BDm1)	Dynamic model involving a Level 2 predictor (BDmX_L2)
Main Effects	12 x domains Time	12 x domains Time Level 2 predictor
2-way Interactions	Time x each of the 12 domains	Time x each of the 12 domains Level 2 predictor x Time Level 2 predictor x each of the 12 domains
3-way Interactions		Level 2 x Time x each of the 12 domains

Hence, the complexity of the model is significantly increased through inclusion of additional parameters. Examples of the output from these models can be found in the Technical Annex.

The Dynamic Models Involving Gender and Ethnicity

Extending the Basic Dynamic model as described in section 5.1, provides a sense of how the individual domains behave over time and if there are differences based on gender and the ethnicity of the young person. The resulting models are summarised in Tables 5.4 and 5.5 respectively. As there are no non-White females, no attempt has been made to stimulate a model involving an interaction between these two demographic predictors, thus extending Model 1.3.

Table 5.4: The Dynamic Model Involving Gender

	The Dynamic Model including Gender (BDm2_d1)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Intercept	-1.117	-2.745	0.538	0.327	0.064	1.713	
Gender (Male = Ref).	-4286.000	-7928.000	-153.000	0.000	0.000	0.000	Yes
Time	-0.220	-0.491	0.048	0.803	0.612	1.049	
Living Arrangements (Live)	-0.041	-0.515	0.418	0.960	0.598	1.519	
Family and Personal Relationships (Relation)	0.300	-0.159	0.822	1.350	0.853	2.276	
Education, Training and Employment (ETE)	-0.327	-0.740	0.044	0.721	0.477	1.045	
Neighbourhood (Where)	0.048	-0.349	0.434	1.049	0.705	1.543	
Lifestyle (Life)	0.039	-0.570	0.651	1.039	0.566	1.918	
Substance Use (Drugs)	0.338	-0.074	0.762	1.402	0.928	2.142	
Physical Health (Physical)	-0.733	-1.273	-0.236	0.481	0.280	0.790	Yes
Emotional and Mental Health (Emotion)	-0.126	-0.514	0.284	0.882	0.598	1.329	
Perceptions of Self and Others (Self)	0.048	-0.556	0.655	1.049	0.574	1.925	
Thinking and Behaviour (Think)	-0.080	-0.651	0.467	0.923	0.522	1.596	
Attitude to Offending (Attitude)	0.038	-0.533	0.619	1.039	0.587	1.856	
Motivation to Change (Change)	0.718	0.100	1.371	2.050	1.105	3.939	Yes
Gender: Time	1987.000	-102.000	3763.000	#NUM!	0.000	#NUM!	
Gender: Live	-428.100	-2063.000	542.000	0.000	0.000	2.44E+235	
Gender: Relation	574.300	-1086.000	2229.000	2.60E+249	0.000	#NUM!	
Gender: ETE	828.600	-1319.000	3225.000	#NUM!	0.000	#NUM!	
Gender: Where	1921.000	-69.530	3169.000	#NUM!	0.000	#NUM!	
Gender: Life	-3269.000	-7131.000	276.600	0.000	0.000	1.34E+120	
Gender: Drugs	736.900	-1511.000	2668.000	#NUM!	0.000	#NUM!	
Gender: Physical	1387.000	-128.000	3209.000	#NUM!	0.000	#NUM!	
Gender: Emotion	1584.000	-497.200	3372.000	#NUM!	0.000	#NUM!	
Gender: Self	-2575.000	-4725.000	181.400	0.000	0.000	6.04E+78	
Gender: Think	1307.000	-747.900	3240.000	#NUM!	0.000	#NUM!	
Gender: Attitude	1605.000	-47.730	3607.000	#NUM!	0.000	#NUM!	
Gender: Change	2017.000	-355.400	4101.000	#NUM!	0.000	#NUM!	
Time: Live	0.021	-0.077	0.112	1.021	0.926	1.118	
Time: Relation	-0.014	-0.127	0.099	0.986	0.881	1.104	
Time: ETE	0.104	0.019	0.198	1.110	1.019	1.218	Yes
Time: Where	0.009	-0.070	0.081	1.009	0.932	1.084	
Time: Life	0.002	-0.122	0.120	1.002	0.885	1.127	
Time: Drugs	-0.040	-0.130	0.039	0.960	0.878	1.039	
Time: Physical	0.151	0.026	0.264	1.163	1.026	1.303	Yes
Time: Emotion	0.038	-0.046	0.118	1.038	0.955	1.126	
Time: Self	-0.082	-0.198	0.046	0.921	0.821	1.047	
Time: Think	-0.011	-0.126	0.115	0.989	0.881	1.122	
Time: Attitude	0.007	-0.115	0.126	1.007	0.891	1.134	
Time: Change	-0.092	-0.214	0.039	0.912	0.808	1.039	

/continued

	The Dynamic Model including Gender (BDm2_d1)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
Gender: Time: Live	-183.100	-1051.000	206.800	0.000	0.000	6.49E+89	
Gender: Time: Relation	-410.400	-1144.000	320.000	0.000	0.000	9.42E+138	
Gender: Time: ETE	42.020	-953.900	1082.000	1.77E+18	0.000	#NUM!	
Gender: Time: Where	-580.200	-1372.000	150.400	0.000	0.000	2.08E+65	
Gender: Time: Life	979.400	-424.500	2278.000	#NUM!	0.000	#NUM!	
Gender: Time: Drugs	49.800	-373.700	410.900	4.24E+21	0.000	2.83E+178	
Gender: Time: Physical	-1193.000	-2069.000	-42.530	0.000	0.000	0.000	Yes
Gender: Time: Emotion	-768.100	-1842.000	658.200	0.000	0.000	7.12E+285	
Gender: Time: Self	1528.000	-244.000	3165.000	#NUM!	0.000	#NUM!	
Gender: Time: Think	-161.500	-469.800	188.400	0.000	0.000	6.62E+81	
Gender: Time: Attitude	-1308.000	-1979.000	-333.100	0.000	0.000	0.000	Yes
Gender: Time: Change	-1139.000	-2395.000	608.900	0.000	0.000	2.77E+264	
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.216	1.41E-07	0.611	1.241	1.000	1.842	Yes
Time	1.962	0.467	4.205	7.114	1.595	67.021	Yes

DIC	451.57

Source: Model BDm2_d1, Technical Annex: p70-82

The output from this model points to a number of issues. Notably there are a number of coefficients which when standardised are very large or cannot be calculated – reflected by **#NUM!** in Table 5.4. The trace plots for *Gender* as a main effect and a number of the interactions involving *Gender* and/or *Time* do not converge. A similar pattern can be seen with respect to the dynamic model involving ethnicity (Table 5.5).

Table 5.5: The Dynamic Model Involving Ethnicity

	The Dynamic Model including Ethnicity (BDm2_d2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
Intercept	-1.161	-2.883	0.480	0.313	0.056	1.617	
Ethnicity (White = Ref)	-709.400	-2192.000	319.400	0.000	0.000	5.17E+138	
Time	-0.178	-0.483	0.070	0.837	0.617	1.072	
Living Arrangements (Live)	-0.045	-0.488	0.418	0.956	0.614	1.518	
Family and Personal Relationships (Relation)	0.183	-0.310	0.703	1.201	0.733	2.019	
Education, Training and Employment (ETE)	-0.277	-0.656	0.129	0.758	0.519	1.138	
Neighbourhood (Where)	0.006	-0.400	0.381	1.006	0.670	1.464	
Lifestyle (Life)	0.059	-0.546	0.662	1.061	0.579	1.939	
Substance Use (Drugs)	0.373	-0.042	0.769	1.452	0.959	2.157	
Physical Health (Physical)	-0.583	-1.066	-0.094	0.558	0.344	0.911	Yes
Emotional and Mental Health (Emotion)	-0.197	-0.593	0.222	0.821	0.553	1.249	
Perceptions of Self and Others (Self)	0.366	-0.226	0.980	1.442	0.798	2.665	
Thinking and Behaviour (Think)	0.129	-0.425	0.751	1.138	0.654	2.118	
Attitude to Offending (Attitude)	0.048	-0.515	0.613	1.049	0.598	1.845	
Motivation to Change (Change)	0.264	-0.322	0.818	1.302	0.725	2.266	

/continued

	The Dynamic Model including Ethnicity (BDm2_d2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Ethnicity: Time	92.580	-245.100	494.200	1.61E+40	0.000	4.25E+214	
Ethnicity: Live	-2992.000	-6403.000	176.800	0.000	0.000	6.07E+76	
Ethnicity: Relation	302.700	-1924.000	2533.000	2.89E+131	0.000	#NUM!	
Ethnicity: ETE	1134.000	305.900	1902.000	#NUM!	7.09E+132	#NUM!	Yes
Ethnicity: Where	3182.000	1073.000	5074.000	#NUM!	#NUM!	#NUM!	Yes
Ethnicity: Life	1826.000	-3642.000	7020.000	#NUM!	0.000	#NUM!	
Ethnicity: Drugs	-4159.000	-7652.000	-536.600	0.000	0.000	0.000	
Ethnicity: Physical	2834.000	-523.000	6935.000	#NUM!	0.000	#NUM!	
Ethnicity: Emotion	211.400	-339.200	688.000	6.45E+91	0.000	6.23E+298	
Ethnicity: Self	2670.000	736.500	4807.000	#NUM!	#NUM!	#NUM!	Yes
Ethnicity: Think	-5015.000	-8640.000	-1847.000	0.000	0.000	0.000	
Ethnicity: Attitude	5100.000	1193.000	8550.000	#NUM!	#NUM!	#NUM!	Yes
Ethnicity: Change	-432.700	-2133.000	1198.000	0.000	0.000	#NUM!	
Time: Live	0.016	-0.083	0.110	1.016	0.920	1.116	
Time: Relation	0.004	-0.108	0.120	1.004	0.897	1.128	
Time: ETE	0.106	0.019	0.198	1.112	1.019	1.219	Yes
Time: Where	0.013	-0.063	0.086	1.013	0.939	1.090	
Time: Life	-0.020	-0.154	0.098	0.980	0.858	1.103	
Time: Drugs	-0.053	-0.148	0.027	0.948	0.862	1.028	
Time: Physical	0.144	0.025	0.263	1.155	1.026	1.301	Yes
Time: Emotion	0.051	-0.037	0.134	1.052	0.963	1.143	
Time: Self	-0.116	-0.235	0.006	0.890	0.791	1.006	
Time: Think	-0.043	-0.173	0.088	0.958	0.841	1.092	
Time: Attitude	-0.014	-0.141	0.109	0.986	0.868	1.115	
Time: Change	-0.016	-0.145	0.104	0.984	0.865	1.109	
Ethnicity: Time: Live	253.200	-255.000	811.200	9.19E+109	0.000	#NUM!	
Ethnicity: Time: Relation	-750.600	-2087.000	411.100	0.000	0.000	3.46E+178	
Ethnicity: Time: ETE	105.300	-212.600	423.600	5.39E+45	0.000	9.27E+183	
Ethnicity: Time: Where	286.000	-120.500	919.300	1.62E+124	0.000	#NUM!	
Ethnicity: Time: Life	333.200	-1106.000	1927.000	5.09E+144	0.000	#NUM!	
Ethnicity: Time: Drugs	-289.100	-924.400	432.000	0.000	0.000	4.12E+187	
Ethnicity: Time: Physical	-673.800	-1751.000	254.500	0.000	0.000	3.37E+110	
Ethnicity: Time: Emotion	676.200	171.900	1145.000	4.68E+293	4.52E+74	#NUM!	Yes
Ethnicity: Time: Self	-942.100	-1468.000	-251.900	0.000	0.000	0.000	Yes
Ethnicity: Time: Think	353.500	-15.060	867.600	3.34E+153	0.000	#NUM!	
Ethnicity: Time: Attitude	679.400	-138.400	1745.000	1.15E+295	0.000	#NUM!	
Ethnicity: Time: Change	-883.300	-1613.000	-212.700	0.000	0.000	0.000	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.211	1.04E-08	0.593	1.235	1.000	1.810	Yes
Time	2.158	0.494	4.716	8.654	1.639	111.720	Yes

DIC	453.19

Source: Model BDm2_d2, Technical Annex: p83-95

Reproducing Figure 4.7 with the data split by gender (Figures 5.6 and 5.7) highlights how from Time 10 there is only information about males upon which to base the model, with there being less than 2 girls from Time 5. As result, trends from this point on are dominated by a single female case. A similar trend can be seen in the case of ethnicity (Figures 5.8 and 5.9). Here there is just one non-White case whose domain scores are informing the model from Times 8 to 11. This contributes to the amount of uncertainty reflected in the wide credible intervals for some of the coefficients.

Figure 5.2: Summary of Average Domain Scores, by Gender (Males)

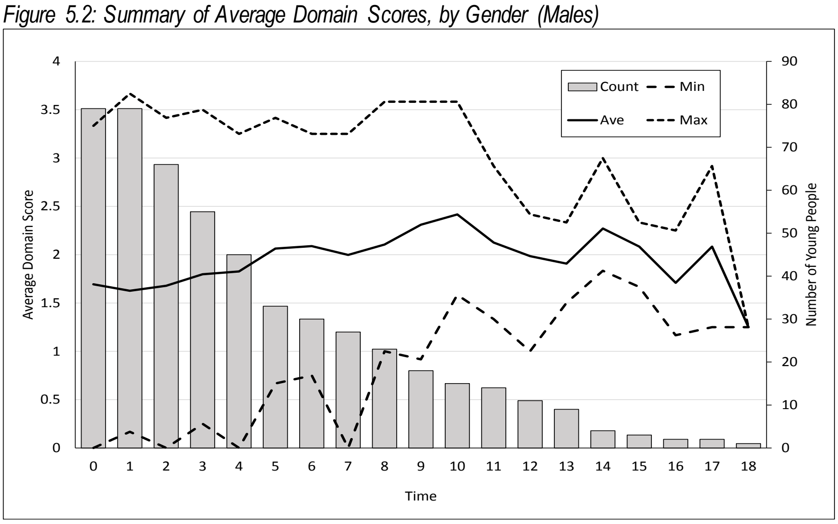


Figure 5.3: Summary of Average Domain Scores, by Genc

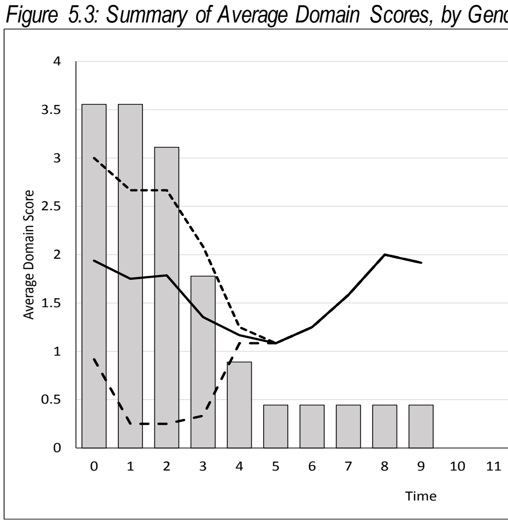


Figure 5.4: Summary of Average Domain Scores, by Ethnicity (White)

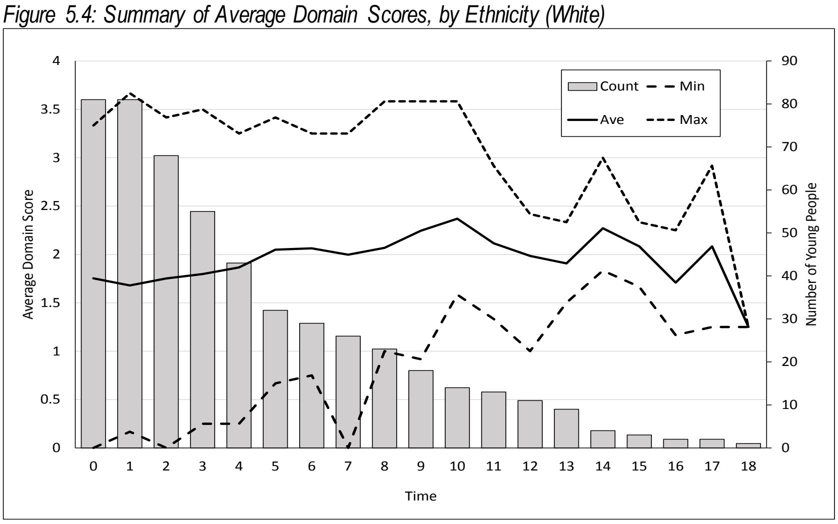
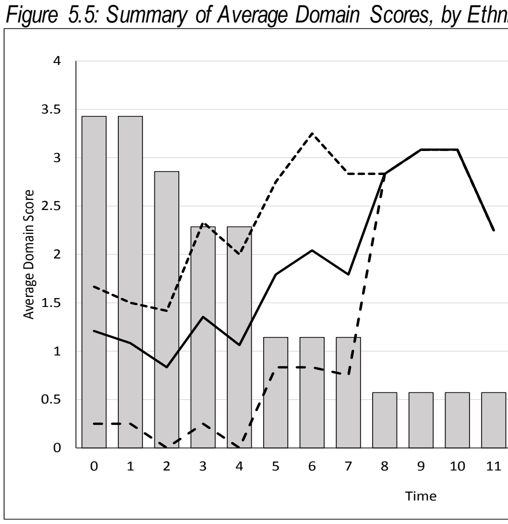


Figure 5.5: Summary of Average Domain Scores, by Ethni



Other potential explanations for the differences

Experience of Care

Table 3.10 suggests that there is very strong evidence to suggest that rates of further offending are higher amongst those who have experience of care than for those who have never being looked after (BF_{10} for the one-sided test = 33.97). Table 5.6 summarises the respective proportions who have experience of care, by gender and ethnicity.

Table 5.6: FTE Status, by Gender and Ethnicity

	Comparator Groups		No.	Care	% Care	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Gender	1	Male	79	23	29.1%	0.383	0.308
	2	Female	9	2	22.2%		
Ethnicity	1	White	82	24	29.3%	0.472	0.326
	2	Non-White	6	1	16.7%		
Total			**88**	**25**	**28.4%**		

Notes: Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1. The two sets of Bayes Factors represent the results of (1) a two-sided alternative hypothesis that the respective proportions of with experience of care are equal (Alternative Hypothesis: Group 1 ≠ Group 2), and (2) a one-sided alternative hypothesis that the rates for Group 1 are larger than Group 2. Bayes Factors quantify the evidence for the alternative hypothesis relative to the null hypothesis and are interpreted using the categories suggested by Jeffreys (1961).

There is anecdotal evidence to suggest from the two-sided test and moderate evidence from the one-sided test to suggest that the respective proportions with experience of care are the same when the reoffending cohort is segmented by gender and ethnicity respectively.

FTE Status

Table 3.11 suggests that there is moderate evidence to suggest that the rate of further offending is higher amongst those with a history of previous offending behaviour than those who are FTEs. Table 5.7 summarises the proportion of FTEs by gender and ethnicity respectively. Due to small numbers, the Bayes Factors for the two-sided tests are inconclusive.

Table 5.7: FTE Status, by Gender and Ethnicity

	Comparator Groups		No.	FTE	% FTE	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Gender	1	Male	79	32	40.5%	1.222	0.192
	2	Female	8	1	12.5%		
Ethnicity	1	White	81	31	38.3%	0.464	0.420
	2	Non-White	6	2	33.3%		
Total			**87**	**33**	**37.9%**		

Notes: Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1. The two sets of Bayes Factors represent the results of (1) a two-sided alternative hypothesis that the respective proportions of first-time entrants are equal (Alternative Hypothesis: Group 1 ≠ Group 2), and (2) a one-sided alternative hypothesis that the rates for Group 1 are larger than Group 2. Bayes Factors quantify the evidence for the alternative hypothesis relative to the null hypothesis and are interpreted using the categories suggested by Jeffreys (1961).

The one-sided test with respect to gender, the Bayes Factor of 0.192 suggests that the data are 5.2 times (1/0.192) more likely under the H_1. Hence there is moderate evidence to support the finding that males in the reoffending cohort are more likely to be FTEs than females. There is only anecdotal evidence of this with respect to ethnicity.

Nature of the Primary Offence

As can be seen from Table 5.8, the 18 young people whose index offence had been either a robbery, burglary or motoring offence i.e. a serious acquisitive crime, were all white males. The non-White males were equally split between those who had committed violence against the person offences and those whose primary offence fell into the 'other' category. Three-quarters of the females within the reoffending cohort had committed VAP offences.

Table 5.8: Type of Primary Offence, by Gender and Ethnicity

Sub-Group		Type of Primary Offence			Grand Total
		Other	SAC	VAP	
Gender	Female	2		6	8
	Male	46	18	15	79
Ethnicity	Non-White	3		3	6
	White	45	18	18	81
Grand Total		**48**	**18**	**21**	**87**

The low number of females and non-White young people makes it difficult to draw reliable conclusions about whether the differences observed in Figure 5.1 can be attributed to the nature of the primary offence or the seriousness of the offence (Table 5.9).

Table 5.9: YJB Gravity Score of the Primary Offence, by Gender and Ethnicity

Sub-Group		YJB Gravity Score					Total
		2	3	4	5	6	
Gender	Male	31	24	7	4	13	79
	Female		6	2			8
Ethnicity	White	29	28	9	4	11	81
	Non-White	2	2			2	6
Grand Total		**31**	**30**	**9**	**4**	**13**	**87**

On the basis of this analysis, the low number of cases for females and non-Whites make it difficult to establish the role that gender and ethnicity have when combined with other predictors when looking to create a dynamic model of the probability of further offending. However, it is possible to explore the role of having experience of care, being an FTE and the nature of the primary offence, with the latter being explored in Chapter Six.

5.3 The role of care experience

Description of the Data

Table 5.10 provides a breakdown of those who have never been looked after and those with experience of care, by gender and ethnicity. Whilst there are no non-White females in the reoffending cohort, two of the nine females have experience of care. Overall, there are 23 males with experience of care. One of these is non-White. As established in section 5.2, with such low numbers, it is difficult to reliably estimate the role of having experience of care by gender and ethnicity. However, it is useful to get a sense of the profile of the cohort by ethnic group as recorded in Childview.

Table 5.10: The Re-Offending Cohort, By Gender, Ethnicity and Experience of Care

Gender	Ethnicity		Care Experience		Total
			No	Yes	
Male	White	White - British	7	7	14
		White - Irish	1		1
		Any Other White Background	43	15	58
	Non-White	Black Caribbean		1	1
		Pakistani	1		1
		Any Other Asian Background	2		2
		White and Asian	1		1
		White and Black Caribbean	1		1
Male Total			56	23	79
Female	White	Any Other White Background	6		6
		White - British	1	2	3
Female Total			7	2	9
Grand Total			**63**	**25**	**88**

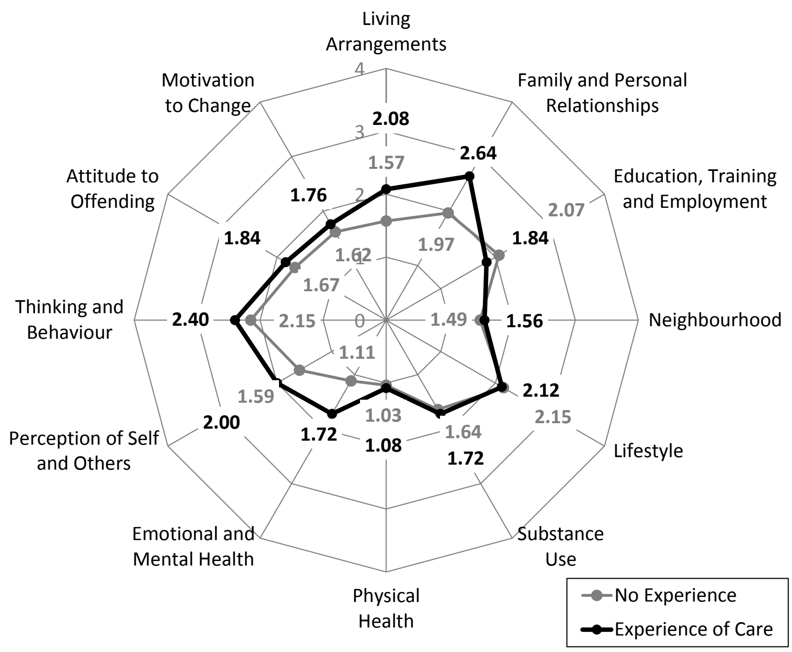
Notes: The FTE status of one female is unknown. It is therefore necessary to remove this case from subsequent analysis.

Of the 25 young people with experience of care:

- 7 were FTEs at the point of entering the reoffending cohort (28.0%). This compares to 41.3% of their peers without this experience.
- The average age of first offence was 13 – slightly younger than for those who have never been looked after (mean = 14 years). However, amongst both sub-groups, the youngest were aged 10. Amongst those who have never been looked after, roughly one in five (14/63) were aged 16 or 17 at the time of their first offence whereas the proportion amongst looked after children in the reoffending cohort was just 4% (1/25).
- Similar pattern is observed in terms of age of first conviction, with the average ages being 14 for those with experience of care compared to 15 for those who have never been looked after.

Lord Lamming's review of looked after children in the criminal justice system (Prison Reform Trust, 2016) presents evidence to suggest that whilst most children in care do not get in trouble with the law, looked after children in England are six times more likely than children in the general population to be convicted of a crime or receive an out of court disposal. The literature review which accompanies the Lamming Review (Staines, 2016), highlights ways in which the needs and vulnerabilities of children who have been looked after may be contributing to their over-representation in the criminal justice system. Some of these are apparent in the initial mean domain scores for those with and without experience of care at Time 0 (Figure 5.6).

Figure 5.6: Domain Score Profile, by Experience of Care, at Time 0



Notes: Of the 87 individuals, 25 have experience of care. Time 0 represents the initial assessment.

Those with experience of care (N= 25) typically have higher initial ratings for:

- Family and personal relationships (BF_{10} = 9.235e^{-4} in favour of H_1: No Experience > Experience of Care, % error = 3.494e^{-5})
- Emotion and Mental Health (BF_{10} = 4.332, % error = 6.155e^{-4})

There is moderate evidence to support the trend apparent in Figure 4.9 that there is no difference between the mean ratings for the two groups (H_1: No Experience ≠ Experience of Care) with respect to:

- ETE (, BF_{10} = 0.383)
- Neighbourhood (BF_{10} = 0.250)
- Lifestyle (BF_{10} = 0.245)
- Substance Use (BF_{10} = 0.252)
- Physical Health (BF_{10} = 0.252)

- Motivation to Change (BF_{10} = 0.250)

Additionally, there is anecdotal evidence in relation to Attitude to Offending (BF_{10} = 0.250) and Thinking and Behaviour (BF_{10} = 0.433).

Adding Experience of Care to the Basic Model

Adding a dummy variable for care experience (referenced by having experience) to the Basic Model, reduces the DIC from 476.20 to 473.48 (Tables 4.12 and 5.11). Inclusion of the additional predictor suggests that at Time 0:

- The odds of further offending amongst those with experience of care are estimated to be exp(0.50) = 1.649 times the odds for their peers without experience of care (Model 1.4). [CI = 1.016, 3.03]

The credible interval suggests that having experience of care is a significant predictor of further offending, equivalent to a 64.9% increase in the odds relative to their peers. Further to this, it highlights that the odds could be as much as three times higher.

Table 5.11: Random Intercepts and Varying Slope Models for Further Offending including ASSET Domains and Experience of Care

	Model 1.4: Basic Model + Care						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
Intercept	-1.232	-2.472	0.006	0.292	0.084	1.006	
Care Experience (None = Ref)	0.500	0.016	0.967	1.649	1.016	2.629	Yes
Living Arrangements	0.018	-0.222	0.282	1.018	0.801	1.326	
Family and Personal Relationships	0.217	-0.071	0.516	1.242	0.931	1.675	
Education, Training and Employment	0.139	-0.106	0.392	1.150	0.899	1.480	
Neighbourhood	0.010	-0.227	0.208	1.010	0.797	1.231	
Lifestyle	0.099	-0.248	0.460	1.104	0.781	1.584	
Substance Use	0.147	-0.092	0.385	1.159	0.912	1.469	
Physical Health	-0.088	-0.376	0.179	0.916	0.686	1.196	
Emotional and Mental Health	-0.042	-0.292	0.194	0.958	0.747	1.215	
Perceptions of Self and Others	-0.142	-0.448	0.164	0.867	0.639	1.179	
Thinking and Behaviour	-0.169	-0.528	0.146	0.845	0.590	1.158	
Attitude to Offending	-0.012	-0.360	0.328	0.988	0.698	1.388	
Motivation to Change	0.247	-0.102	0.583	1.281	0.903	1.791	
Time	-0.160	-0.304	-0.035	0.852	0.738	0.965	Yes
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.092	1.85E-04	0.348	1.096	1.000	1.416	Yes
Time	1.291	0.349	2.643	3.636	1.417	14.055	Yes

DIC	473.48

Source: Model Bm1_ch, Technical Annex: p96-97

The Dynamic Model Involving Experience of Care

Extending the Basic Dynamic model to involve experience of care (referenced by having never been looked after) results in a model which has no issues with convergence as can be seen from the trace plots in the Technical Annex.

Table 5.12: The Dynamic Model Involving Care Experience

	Dymanic Mode including Experience of Care (BDm2_ch)						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.501	-3.507	0.439	0.223	0.030	1.551	
Experience of Care (None = Ref)	1.462	-1.419	4.309	4.313	0.242	74.393	
Time	-0.335	-0.753	0.066	0.715	0.471	1.068	
Living Arrangements (Live)	-0.091	-0.729	0.552	0.913	0.482	1.737	
Family and Personal Relationships (Relation)	0.149	-0.547	0.883	1.161	0.579	2.419	
Education, Training and Employment (ETE)	-0.157	-0.668	0.324	0.855	0.512	1.382	
Neighbourhood (Where)	0.060	-0.501	0.608	1.062	0.606	1.838	
Lifestyle (Life)	0.611	-0.239	1.484	1.843	0.788	4.412	
Substance Use (Drugs)	0.125	-0.435	0.672	1.133	0.647	1.959	
Physical Health (Physical)	-0.082	-0.804	0.633	0.922	0.448	1.883	
Emotional and Mental Health (Emotion)	-0.405	-0.999	0.152	0.667	0.368	1.164	
Perceptions of Self and Others (Self)	-0.129	-0.920	0.680	0.879	0.399	1.974	
Thinking and Behaviour (Think)	0.095	-0.676	0.858	1.100	0.509	2.358	
Attitude to Offending (Attitude)	0.070	-0.750	0.871	1.073	0.472	2.389	
Motivation to Change (Change)	0.208	-0.519	0.960	1.231	0.595	2.611	
Care: Time	-0.075	-0.708	0.564	0.928	0.493	1.759	
Care: Live	0.453	-0.564	1.525	1.572	0.569	4.594	
Care: Relation	-0.046	-1.249	1.222	0.955	0.287	3.393	
Care: ETE	0.259	-0.753	1.274	1.296	0.471	3.574	
Care: Where	-0.311	-1.308	0.673	0.732	0.270	1.960	
Care: Life	-0.633	-2.109	0.826	0.531	0.121	2.283	
Care: Drugs	0.326	-0.614	1.267	1.385	0.541	3.551	
Care: Physical	-0.890	-2.115	0.365	0.411	0.121	1.441	
Care: Emotion	0.392	-0.649	1.400	1.480	0.523	4.056	
Care: Self	0.872	-0.559	2.304	2.391	0.572	10.012	
Care: Think	-0.841	-2.314	0.618	0.431	0.099	1.855	
Care: Attitude	-0.118	-1.420	1.272	0.889	0.242	3.569	
Care: Change	0.126	-1.393	1.521	1.134	0.248	4.576	
Time: Live	-0.035	-0.202	0.121	0.965	0.817	1.129	
Time: Relation	0.005	-0.175	0.183	1.005	0.840	1.201	
Time: ETE	0.057	-0.066	0.183	1.059	0.936	1.201	
Time: Where	-0.054	-0.191	0.077	0.948	0.826	1.080	
Time: Life	-0.005	-0.187	0.192	0.995	0.829	1.212	
Time: Drugs	0.036	-0.100	0.172	1.037	0.905	1.187	
Time: Physical	-0.042	-0.269	0.179	0.958	0.764	1.196	
Time: Emotion	0.053	-0.089	0.198	1.054	0.915	1.219	
Time: Self	0.072	-0.105	0.263	1.075	0.901	1.301	
Time: Think	-0.012	-0.207	0.180	0.988	0.813	1.197	
Time: Attitude	-0.095	-0.296	0.104	0.910	0.743	1.110	
Time: Change	0.027	-0.173	0.236	1.027	0.841	1.267	

/continued

	Dymanic Mode including Experience of Care (BDm2_ch)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Care: Time: Live	0.021	-0.199	0.249	1.021	0.820	1.282	
Care: Time: Relation	-2.07E-04	-0.283	0.278	1.000	0.753	1.321	
Care: Time: ETE	0.004	-0.199	0.216	1.004	0.820	1.241	
Care: Time: Where	0.178	-0.015	0.375	1.195	0.985	1.455	
Care: Time: Life	-0.083	-0.374	0.200	0.921	0.688	1.222	
Care: Time: Drugs	-0.072	-0.291	0.143	0.930	0.747	1.154	
Care: Time: Physical	0.242	-0.063	0.532	1.274	0.939	1.703	
Care: Time: Emotion	0.040	-0.195	0.279	1.041	0.823	1.322	
Care: Time: Self	-0.341	-0.644	-0.045	0.711	0.525	0.956	Yes
Care: Time: Think	0.085	-0.209	0.388	1.088	0.812	1.474	
Care: Time: Attitude	0.130	-0.174	0.443	1.139	0.840	1.558	
Care: Time: Change	-0.058	-0.354	0.248	0.944	0.702	1.281	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.520	9.93E-08	1.322	1.683	1.000	3.751	Yes
Time	2.188	0.435	4.774	8.917	1.544	118.392	Yes

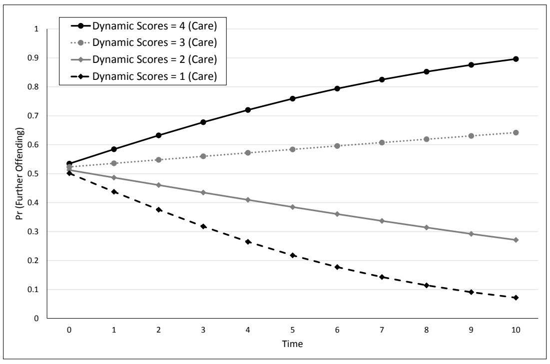
DIC	471.36

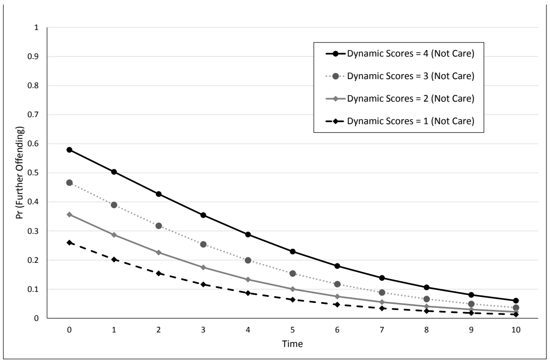
Source: Model BDm2_ch, Technical Annex: p100-112

The model has been used to consider the trajectory of the probability of further offending over time for those with experience of care relative to that for their peers who have never been looked after. In Figure 5.7, the domain scores have been fixed at their initial values so that changes can be seen in the estimated probability of further offending from time 0 to time 10. In the case of those who have never been looked after (Figure 5.7(a), n=63), there is a distinctive downwards curve which tends towards zero. The estimated probability of further offending at Time 0 is higher for those with higher initial domain scores which is in keeping with the subjective ratings – those with 3's and 4's are considered to have a higher likelihood of reoffending and hence are subject to more intensive supervision.

Figure 5.7: Changes in the Probability of Further Offending Over Time, by Care Experience

(a) Never Looked After *(b) With Experience of Care*



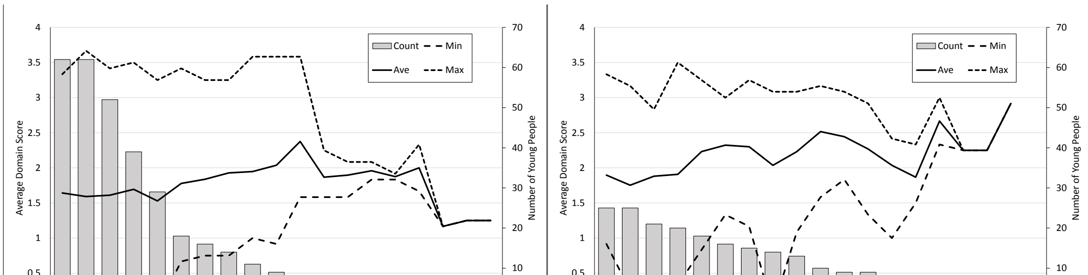


Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of further offending from time 0 to time 10. Estimates derived from Model BDm2_ch.

The trends apparent in Figure 5.7(b) are less clear and it is important that these are based on the repeated measurements of the 25 young people who have experience of care. As such there is the potential for the trend, particularly for the higher domain scores for these to have been unduly influenced by a very small number of cases, especially at later time points.

Figure 5.8: Summary of Average Domain Scores, by Care Experience

(b) Never Looked After *(b) With Experience of Care*



As can be seen from Figure 5.8, the mean domain score for those who have never been looked after has a net downward trend whereas for those with experience of care, there is a net upward trend. Notably after Time 14, there are only 2 or fewer cases relating to children with experience of care and to those who have never been looked after respectively. The domain scores from these cases determine the tail end of these trends.

5.4 The role of gender and ethnicity in the context of care experience

Although it is apparent from section 5.2 that there is insufficient data to support a dynamic model involving gender, ethnicity and experience of care, it is possible to add these three predictors to the Basic Model (described in Table 4.11). This provides an indication of how the odds of further offending are affected when these are allowed to interact. Unfortunately, due to the absence of any non-White females, it is not possible to simulate an estimate of the coefficient for the G*ender:Ethnicity* interaction – the model is rank deficient.

The basic model involving demographics and experience of care with interaction terms (Model 2) is summarised in Table 5.13. The addition of the interaction terms impacts on the amount of uncertainty which can be explained by the model with the DIC being lower for Model 2 than for Models 1.1, 1.2 and 1.3 respectively (summarised in Table 5.3) – 471.53 compared to around 476. This is despite the additional complexity.

Table 5.13: Model 2: The Basic Model plus Demographics and Experience of Care

	Model 2: Basic Model + Demographics + Care						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Intercept	-1.096	-2.413	0.230	0.334	0.090	1.259	
Gender (Male = Ref).	0.482	-0.577	1.557	1.620	0.562	4.746	
Ethnicity (White = Ref)	-1.349	-2.883	0.206	0.260	0.056	1.228	
Care Experience (None = Ref)	0.526	0.009	1.044	1.692	1.009	2.840	Yes
Living Arrangements	-0.005	-0.268	0.263	0.995	0.765	1.301	
Family and Personal Relationships	0.214	-0.091	0.514	1.238	0.913	1.672	
Education, Training and Employment	0.103	-0.153	0.369	1.109	0.858	1.446	
Neighbourhood	0.036	-0.186	0.268	1.036	0.830	1.308	
Lifestyle	0.033	-0.333	0.394	1.034	0.717	1.483	
Substance Use	0.189	-0.051	0.445	1.209	0.951	1.560	
Physical Health	-0.123	-0.411	0.182	0.884	0.663	1.200	
Emotional and Mental Health	-0.059	-0.303	0.193	0.943	0.739	1.213	
Perceptions of Self and Others	-0.158	-0.480	0.174	0.854	0.619	1.190	
Thinking and Behaviour	-0.147	-0.492	0.188	0.864	0.612	1.206	
Attitude to Offending	0.030	-0.341	0.390	1.031	0.711	1.477	
Motivation to Change	0.265	-0.086	0.614	1.303	0.918	1.849	
Time	-0.168	-0.314	-0.029	0.845	0.731	0.972	Yes
Gender:Care Experience	-1.715	-4.508	1.065	0.180	0.011	2.901	
Care Experience: Ethnicity	1.196	-0.890	3.308	3.308	0.411	27.318	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.120	1.87E-04	0.430	1.127	1.000	1.537	Yes
Time	1.462	0.401	3.037	4.315	1.493	20.843	Yes

DIC	471.53

Source: Model Bm1_d1.ch_d2.ch, renamed as Model 2, Technical Annex: p113-118

Both care experience and time are significant within Model 2, with the positive unstandardised coefficient suggesting a 'penalty' for having experience of care. The negative unstandardised coefficient for time suggests a moderating effect as time progresses, which is consistent with the premise that working with the YOT will reduce a young person's likelihood of further offending behaviours.

Using this model, it is possible to determine estimates for the probability of further offending at a given time point for different permutations of gender, ethnicity and care experience. These suggest that:

Compared to a male with no experience of care, at Time 0, the odds of further offending amongst

- males with experience of care are estimated to be 1.77 times higher
- females without experience of care, the odds are 1.65 times higher

However, for females who have never been looked after, the odds of further offending are 3.17 times higher than for those females who have experience of care. There is also a further notable gender difference amongst those who have experience of care, with the odds of further offending being 3.41 times higher amongst males than females.

Compared to a young person who is non-White with no experience of care, at Time 0, the odds of further offending amongst

- White young people with experience of care are estimated to be 1.14 times higher
- White young people without experience of care, the odds are 1.39 times higher
- Non-Whites with experience of care, the odds are 5.35 times higher

For White young people, the odds of further offending increase by a factor of 1.58 for those with care experience. Having experience of care also increases the odds for non-Whites, with those young people having experience of care having odds of further offending which are 3.86 times higher than for those who have never been a looked after child.

Model 2 can therefore be thought of as being:

$$\begin{aligned}\mathrm{Pr(Further\ Offending)} &\\ &= \mathrm{Logit}^{-1}\big(\mathrm{Intercept} + \beta_{\mathrm{Gender}}x_1 + \beta_{\mathrm{Ethnicity}}x_2 + \beta_{\mathrm{Care}}x_3 \\ &+ \beta_{\mathrm{Gender}}x_1\beta_{\mathrm{Care}}x_3 + \beta_{\mathrm{Ethnicity}}x_2\beta_{\mathrm{Care}}x_3 + [\mathrm{BASIC\ MODEL}]\big)\end{aligned}$$

Where

Gender (x_1) is coded as 0 for males and 1 for females

Ethnicity (x_2) is coded as 0 for Whites and 1 for non-Whites

Care (x_3) is coded as 0 for no experience, 1 for experience of care

Which becomes:

$$\begin{aligned}\mathrm{Pr(Further\ Offending)} &\\ &= \mathrm{Logit}^{-1}(-1.096 + 0.482x_1 - 1.349x_2 + 0.526x_3 - 1.715x_1x_3 \\ &+ 1.196x_2x_3 + [\mathrm{BASIC\ MODEL}])\end{aligned}$$

Hence for a White female with experience of care:

$$\begin{aligned}\mathrm{Pr(Further\ Offending)} &\\ &= \mathrm{Logit}^{-1}(-1.096 + 0.482(1) - 1.349(0) + 0.526(1) - 1.715(1)(1) \\ &+ 1.196(0)(1) + [\mathrm{BASIC\ MODEL}]) \\ &= \mathrm{Logit}^{-1}(-1.096 + 0.482(1) + 0.526(1) - 1.715(1) \\ &+ [\mathrm{BASIC\ MODEL}])\end{aligned}$$

From a methodological point of view, although it has not been possible to investigate the extent to which individual domains differ with respect to both gender and ethnicity over time, particularly in the context of care experience, it is possible to stimulate a model which represents a compromise. Table 5.14 builds on the dynamic model involving care (BDm2_ch, Table 5.12) by additionally including gender and ethnicity as main affects along with interactions between care experience and gender, care experience-ethnicity, gender-time, and ethnicity-time.

Table 5.14: The Dynamic Model involving Demographic Characteristics and Experience of Care

	The Dynamic Model including Demographics + Care (BDm 2)						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Intercept	-1.187	-3.288	1.019	0.305	0.037	2.770	
Gender (Male = Ref).	2.425	0.153	4.799	11.302	1.165	121.389	Yes
Care Experience (None = Ref)	1.631	-1.623	4.751	5.109	0.197	115.700	
Ethnicity (White = Ref)	-2.263	-4.420	-0.043	0.104	0.012	0.958	Yes
Time	-0.359	-0.801	0.067	0.698	0.449	1.069	
Living Arrangements (Live)	-0.298	-1.011	0.417	0.742	0.364	1.517	
Family and Personal Relationships (Relation)	0.159	-0.603	0.965	1.172	0.547	2.623	
Education, Training and Employment (ETE)	-0.349	-0.912	0.199	0.706	0.402	1.220	
Neighbourhood (Where)	0.105	-0.518	0.687	1.110	0.596	1.987	
Lifestyle (Life)	0.200	-0.731	1.209	1.222	0.482	3.350	
Substance Use (Drugs)	0.462	-0.195	1.070	1.587	0.823	2.915	
Physical Health (Physical)	-0.133	-0.880	0.663	0.876	0.415	1.941	
Emotional and Mental Health (Emotion)	-0.514	-1.133	0.109	0.598	0.322	1.115	
Perceptions of Self and Others (Self)	-0.140	-0.987	0.788	0.869	0.373	2.198	
Thinking and Behaviour (Think)	0.196	-0.591	1.043	1.216	0.554	2.838	
Attitude to Offending (Attitude)	0.240	-0.658	1.119	1.271	0.518	3.062	
Motivation to Change (Change)	0.436	-0.398	1.244	1.547	0.672	3.469	
Care Experience: Gender	-3.429	-7.727	0.575	0.032	0.000	1.778	
Care Experience: Ethnicity	0.216	-3.551	3.906	1.241	0.029	49.700	
Care Experience: Time	-0.115	-0.760	0.537	0.892	0.468	1.710	
Care Experience: Live	0.674	-0.544	1.783	1.962	0.580	5.948	
Care Experience: Relation	-0.133	-1.495	1.192	0.875	0.224	3.294	
Care Experience: ETE	0.388	-0.650	1.531	1.474	0.522	4.623	
Care Experience: Where	-0.354	-1.392	0.719	0.702	0.249	2.052	
Care Experience: Life	-0.183	-1.699	1.520	0.833	0.183	4.572	
Care Experience: Drugs	-0.036	-1.096	0.966	0.964	0.334	2.627	
Care Experience: Physical	-1.068	-2.521	0.193	0.344	0.080	1.213	
Care Experience: Emotion	0.522	-0.613	1.546	1.686	0.542	4.693	
Care Experience: Self	0.942	-0.544	2.572	2.564	0.580	13.092	
Care Experience: Think	-1.011	-2.562	0.561	0.364	0.077	1.752	
Care Experience: Attitude	-0.197	-1.613	1.262	0.822	0.199	3.532	
Care Experience: Change	-0.051	-1.584	1.581	0.950	0.205	4.860	

/continued

	The Dynamic Model including Demographics + Care (BDm 2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
Time: Gender	-0.528	-1.149	0.092	0.590	0.317	1.097	
Time: Ethnicity	0.210	-0.279	0.664	1.233	0.756	1.943	
Time: Live	0.004	-0.168	0.181	1.004	0.845	1.198	
Time: Relation	-0.011	-0.207	0.179	0.990	0.813	1.196	
Time: ETE	0.071	-0.059	0.205	1.074	0.943	1.227	
Time: Where	-0.068	-0.217	0.074	0.934	0.805	1.076	
Time: Life	0.050	-0.146	0.259	1.051	0.864	1.295	
Time: Drugs	0.000	-0.144	0.140	1.000	0.866	1.151	
Time: Physical	-0.030	-0.268	0.203	0.970	0.765	1.225	
Time: Emotion	0.082	-0.069	0.241	1.085	0.933	1.272	
Time: Self	0.094	-0.103	0.315	1.099	0.902	1.370	
Time: Think	-0.030	-0.235	0.175	0.970	0.790	1.192	
Time: Attitude	-0.114	-0.325	0.093	0.892	0.722	1.098	
Time: Change	-0.028	-0.252	0.185	0.972	0.777	1.203	
Care Experience: Time: Live	-0.020	-0.266	0.208	0.980	0.767	1.231	
Care Experience: Time: Relation	0.025	-0.267	0.331	1.026	0.766	1.392	
Care Experience: Time: ETE	0.002	-0.224	0.226	1.002	0.800	1.254	
Care Experience: Time: Where	0.202	-0.001	0.417	1.223	0.999	1.517	
Care Experience: Time: Life	-0.145	-0.470	0.149	0.865	0.625	1.160	
Care Experience: Time: Drugs	-0.033	-0.262	0.209	0.968	0.770	1.232	
Care Experience: Time: Physical	0.252	-0.047	0.574	1.286	0.954	1.776	
Care Experience: Time: Emotion	0.018	-0.219	0.273	1.018	0.803	1.314	
Care Experience: Time: Self	-0.381	-0.712	-0.054	0.683	0.491	0.947	Yes
Care Experience: Time: Think	0.121	-0.203	0.430	1.129	0.816	1.537	
Care Experience: Time: Attitude	0.124	-0.221	0.445	1.132	0.802	1.560	
Care Experience: Time: Change	-0.009	-0.332	0.304	0.991	0.717	1.355	
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.72	1.03E-05	1.67	2.049	1.000	5.317	Yes
Time	2.733	0.611	6.169	15.379	1.842	477.708	Yes

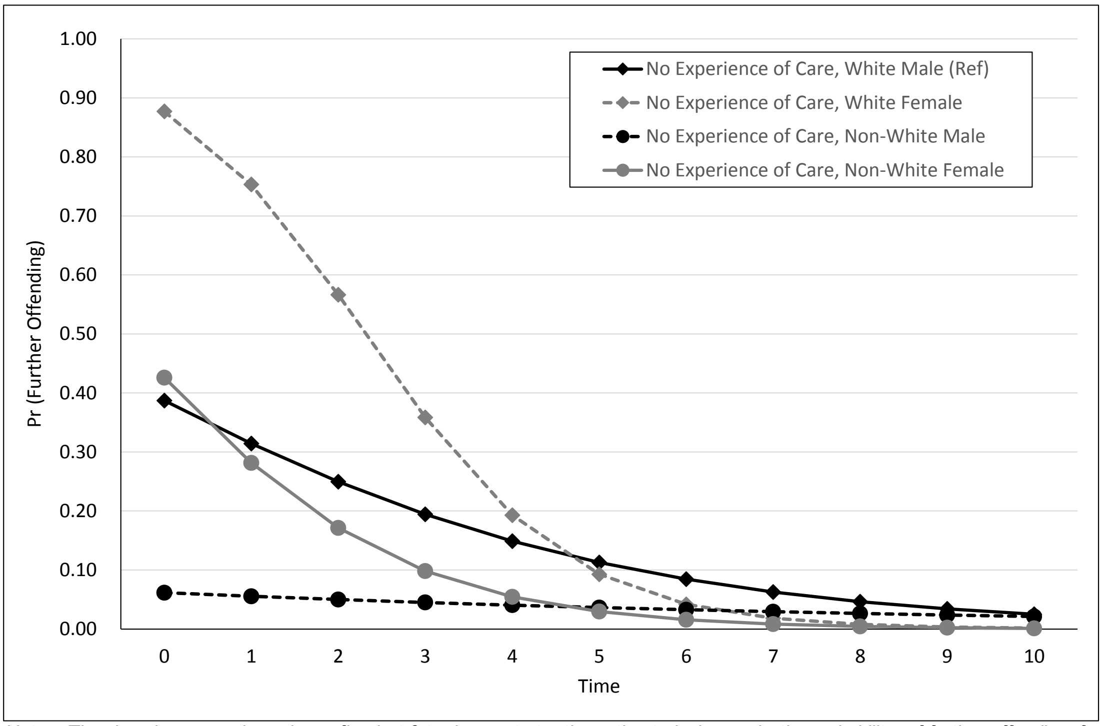
DIC	466.38

Source: Model BDm2, Technical Annex p121-134.

The model suggests that the main effects for gender and ethnicity are significant, with the estimate for gender being positive. So that the impact of this can be visualised, the probability of further offending has been calculated using the model with domain scores fixed at 2 so as to broadly represent the 'average' young person at the time of their initial assessment. As can be seen from Figure 5.9, the respective probabilities of further offending for females (males being the reference group for the Gender predictor), are higher generally higher until Time 4.

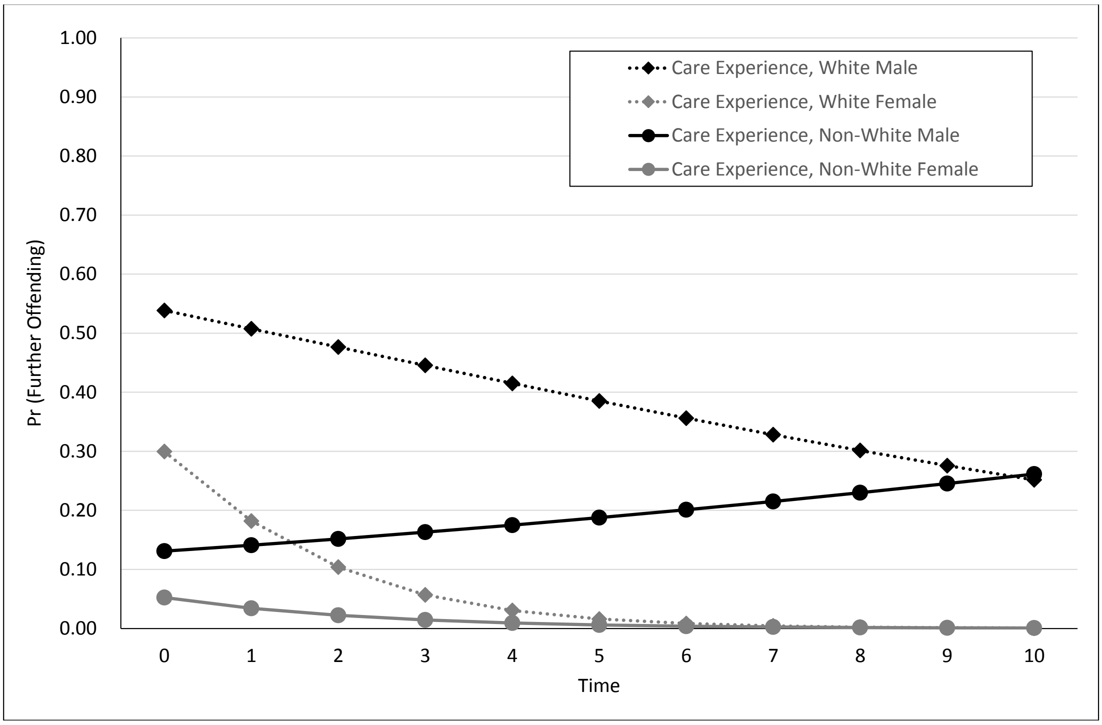
The estimate for ethnicity is negative, suggesting that those who are non-White have on average a lower probability of further offending than Whites (Figures 5.9 and 5.10). This finding is potentially linked not just to the small number of cases but also the net effect of having both Black and Asian young people within this group since national proven reoffending figures suggest that Black boys and girls are more likely to reoffend than Whites peers whilst Asian boys and girls are less likely to reoffend (Ministry of Justice, 2017c). This is also apparent in Figures 5.9 and 5.10. Estimates for non-Whites with and without experience of care have generated by the model due to the inclusion of the interaction term *Ethnicity: Care experience.*

Figure 5.9: Estimated Changes in the Probability of Further Offending for those with No Experience of Care, by Gender and Ethnicity



Notes: The domain scores have been fixed at 2 to demonstrate the estimated change in the probability of further offending for different sub-groups, from time 0 to time 10. Estimates derived from Model BDm2.

Figure 5.10: Estimated Changes in the Probability of Further Offending for those with Experience of Care, by Gender and Ethnicity



Notes: The domain scores have been fixed at 2 to demonstrate the estimated change in the probability of further offending for different sub-groups, from time 0 to time 10. Estimates derived from Model BDm2.

Care as a main effect is not significant. However, this is because the interactions between the 12 domains, ethnicity, gender and time help to explain some, but not all of the differences between those with experience of care and those who have never been looked after.

The low numbers of females and non-Whites in the reoffending cohort, means that there remains a high amount of uncertainty within the model – reflected by the DIC of 466.38 and the wide credible intervals for some of the main and interaction fixed effects. The estimated probability of further offending for these groups therefore also contain a high degree of uncertainty and especially at later time points, may prove to be unreliable.

The estimated trajectory of the reference group of White males with no experience of care (representing 58.0% of the cohort, 51/87), is shown on both Figures 5.9 and 5.10. Relative to this, the probability of further offending amongst White males (25% of the cohort) at each measurement occasion is estimated to be lower. Differences also exist for those with different risk scores. For example, at Time 0, the odds of a White male who has never been looked after committing further offences are estimated to be:

- 3 times higher than the odds of further offending for White males who have experience of care when their domain scores are fixed at 1.
- 1.9 times higher when domain scores are fixed at 2, as in Figure 5.9.
- 11% higher when domain scores are fixed at 3

The trend for the non-white male with experience of care is contrary to what would be expected. From Table 5.3, it is possible to see that this trend is based on data for just one individual who has exhibited more serious, sustained offending behaviours.

The trend for White females with experience of care also needs to be treated with caution as it is based upon data relating to just two young people. As both of these had comparatively low domain scores, particularly after Time 0, this casts doubt upon the reliability for estimated probabilities of further offending for higher domain scores. Looking across the females more generally, there were only three girls who committed further offences with these having higher average domain scores at the earlier measurement points than those who did not engage in any further offending. This was also the case for the non-White cohort.

Notably, it is possible to use the model to generate an estimated trajectory of the probability of offending for non-White females with experience of care despite there being no young people who share these characteristics within the dataset. Whilst looked after girls represent a very small proportion of the whole within the criminal justice system (Prison Reform Trust, 2016), it is inconceivable that nationally these would all be White.

5.5 How do these findings extend the evidence base?

Whilst there is a desire to extend what is known in terms of the young people with experience of care and particularly sub-groups within this cohort, there is insufficient data to reliably explore this with respect to gender and ethnicity. From BDm2, the positive coefficient for *Gender* as a main effect suggests that the non-reference group i.e. females have 'penalty' which if all other factors / scores in the model were equal would result in females having a higher initial probability of further offending. Since the coefficient for *Gender: Time* is not significant, it is not possible to be certain of the differences over time.

The negative coefficient for Ethnicity as a main effect suggests that the on average it is the reference group i.e. Whites who if all other factors / scores in the model were equal would have a 'penalty' which would result in non-Whites having a lower initial probability of further offending. However, the extent to which this is moderated over time is difficult to ascertain due to the coefficient for the interaction between *Ethnicity: Time* not being significant.

Both the dynamic model involving care (BDm2_ch) and the enhanced version which additionally incorporates gender and ethnicity (BDm2) resulted in significant coefficients for the interaction between *Care Experience: Time: Self*. This domain is one which Wilson and Hinks (2011) identified that practitioners had difficulty exploring with young people. Notably the coefficient for *Self* is not significant as a main effect suggesting that there are other factors which have not been included in the model which could account for this uncertainty. Potentially this could include gender and ethnicity, but there could also be additional explanatory factors which have not been included in these models.

As highlighted in section 4.3, the Perception of Self and Others domain concentrates upon the young person's understanding of how they – and others – fit into the world around them, including their levels of self-esteem; mistrust of others; difficulties with self-identify and if they see themselves as an offender – for a more detailed description see Section 1 of the Technical Annex. Baker et al. (2005) found differences in the ratings on the basis of gender and ethnicity which due to the small number of female and non-White cases within the dataset are not possible to explore in the context of this research. In particular their findings around self-identify and the general mistrust of others amongst BAME young people involved in the youth justice system are consistent with those found by David Lammy MP (Lammy, 2017) in his recent review of the over-representation of these groups. In the context of gender differences, Smith and McAra (2004) identified through their analysis of self-reported data that low self-esteem was more closely linked to delinquency in girls than boys. In terms of the factors that increased serious delinquency more in girls than in boys, these additionally included having a weak belief in conventional moral standards i.e. considering it acceptable to lie / steal / fight. Risk taking was found to be very strongly associated with delinquency for both sexes whilst impulsivity was found to be quite strongly associated.

Since the responses to the individual questions within the domain did not form part of the dataset created, it is not possible to ascertain where there are differences in the responses for different sub-groups of the cohort. It is however, possible to use BDm2 to consider the net impact of the probability of further offending should a young person with experience of care experience an increase in their rating for the Perception of Self and Others domain (whilst ratings in the other domains are not altered). Whilst the odds of further offending increase, the inclusion of time in the interaction acts as a moderating factor meaning that relative to a young person with experience of care who has not received the elevated rating, the 'gap' reduces:

- At Time 0, the odds of a typical young person with experience of care with an elevated rating for the Perception of Self and Others domain (i.e. with domain scores fixed at 2, reflecting the average rating for all young people in the dataset, and this domain increased to 3) is estimated to be 2.1 times more likely to commit further offences than their peer whose domain scores remained fixed at 2. By Time 2, the former is 1.2 times more likely to commit further offences than the young person with experience of care without the elevated rating.
- Amongst those without experience of care, at Time 0, the young person with the elevated rating is 1.1 times more likely to commit further offences.
- Relative to the typical young person with no experience of care, their peer who has been looked after with the elevated rating is estimated to be 4.5 times more like to commit further offences at Time 0, 2.8 times more likely at Time 5 and if still under the supervision of the YOT at Time 10, the odds of further offending are estimated to be 1.3 times higher.

More generally, the amount of uncertainty around the predictor for care experience and interactions involving this term can potentially be explained by the range of different reasons which can lead to a young person becoming looked after, the various legal status' that these young people can hold and the time which the child has been looked after. For example, a young person placed in care having previously been identified as being at significant risk of harm may be struggling to overcome these adverse childhood experiences whilst a child in a long-term stable placement may have formed strong relationships which have had a positive impact upon their perceptions of themselves and others. Similarly, a young person recently removed from the family home as a result of their offending behaviour may have a general distrust of others, especially those in authority.

Given the current policy emphasis, the role which experience of care plays in the likelihood of further offending, it will be revisited in Chapter Seven as part of the discussion of the impact of system contact.

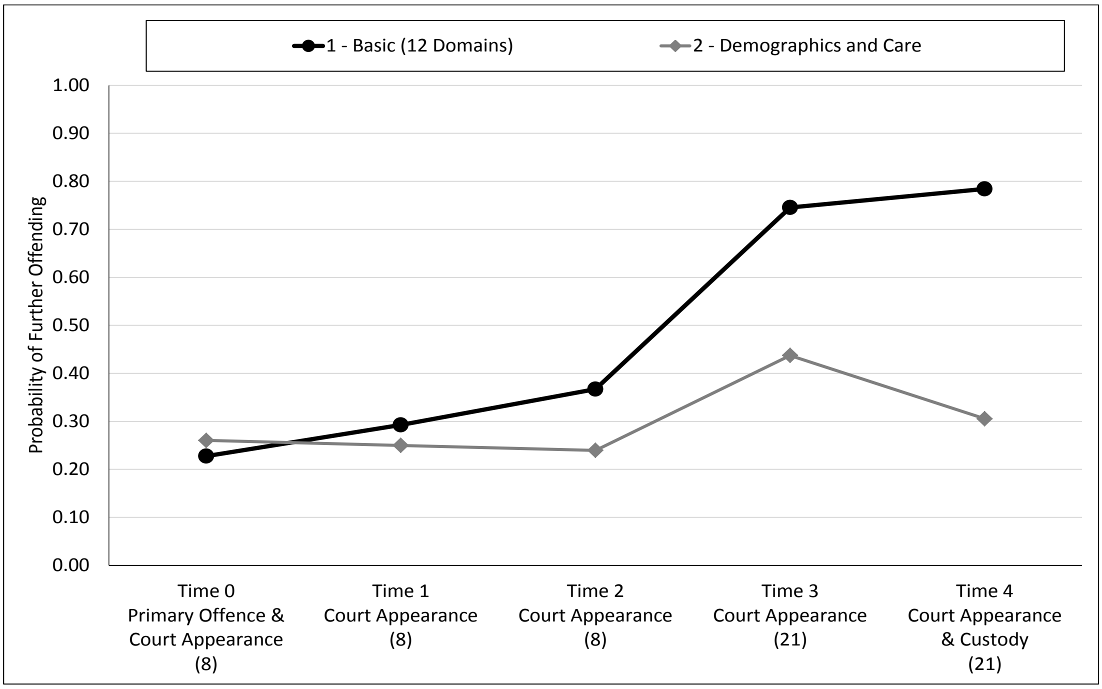
5.6 How does the model involving gender, ethnicity and care experience reflect the realities of real lives?

The following section returns to the examples of Fred, David and Connor, to consider how the estimates of their respective probabilities of further offending based on BDm2 compare with those generated by the Basic Dynamic Model (BDm1, summarised in Table 4.12).

Case Study "Fred"

"Fred" is a white male who has never been looked after. The trajectory of the probability of further offending based on BDm2 (in grey in Figure 5.11) suggests a slightly higher initial probability of further offending at Time 0 relative to that based on the Basic Dynamic Model (BDm1, in black). However, whilst the BDm1 shows an upwards trend which becomes steeper between Times 2 and 3 when his risk score increases to 21 – this was when he was on ISSP Bail and Tag, before flattening again towards Time 4, the model involving demographics and care has an initial decline before becoming steeper between Times 2 and 3. There is then a downward trend towards Time 4.

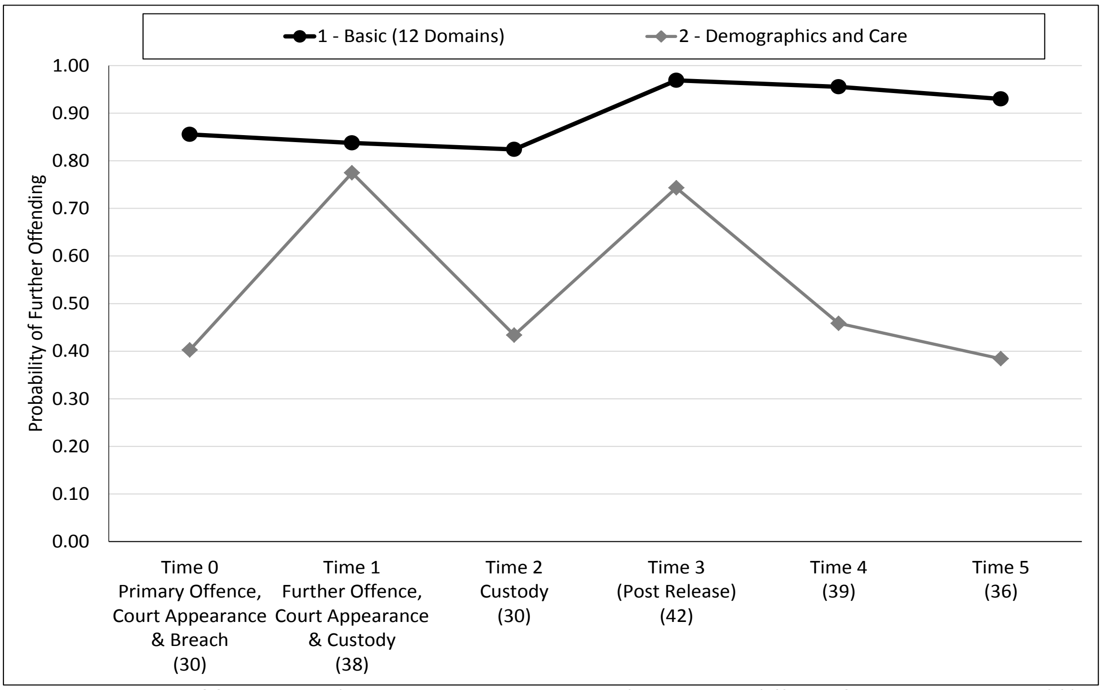
Figure 5.11: Comparisons of the Estimated Probability of Further Offending Over Time: "Fred"



Case Study "Connor"

"Connor" is also a white male. However, he does have experience of being looked after. He had been identified as a prolific offender prior to entering the 2012/13 reoffending cohort and this is reflected in his high-risk scores and the corresponding high probabilities of further offending in Figure 5.12. The effect of using BDm2 to generate the probability of Connor committing further offences is that it now reflects the increase in his total domain scores between Times 0 and 1 when he committed a further offence, the subsequent dip whilst he was in custody and then the increase post-release (at Time 3). BDm1 does not reflect this initial increase between Times 0 and 1, suggesting that actually his probability of further offending decreases during this time.

Figure 5.12: Comparisons of the Estimated Probability of Further Offending Over Time: "Connor"



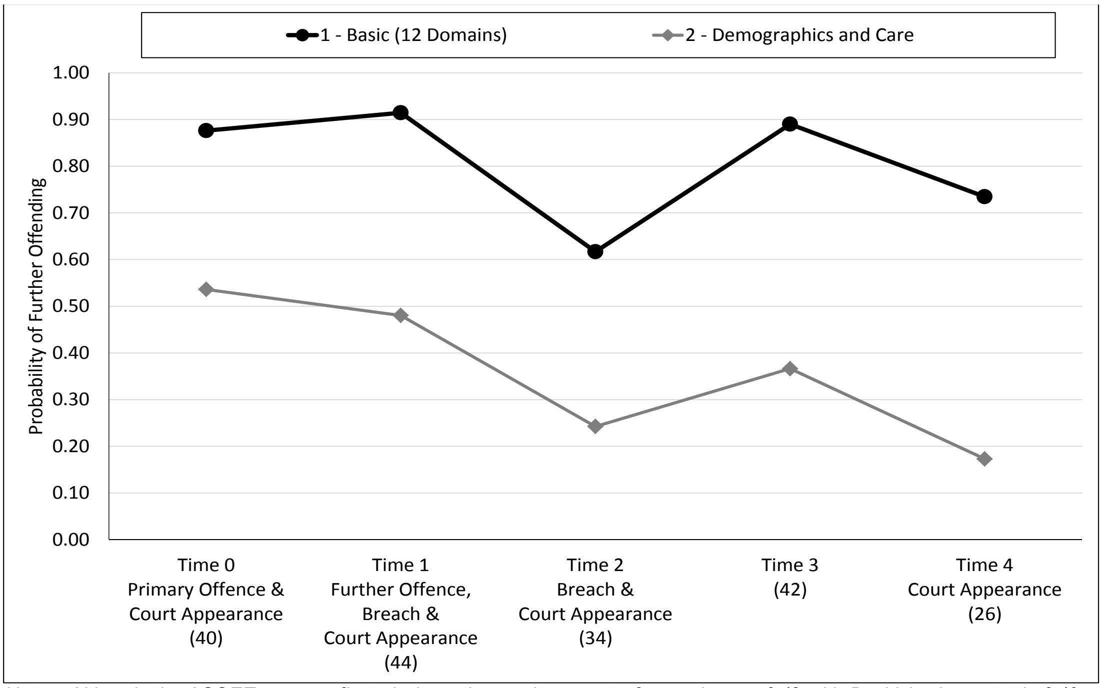
Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with Connor having a total of 30 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that his primary offence (for the purposes of this exercise where the information has been taken from the reoffending spreadsheet) was a non-domestic burglary and as a result of his prior convictions.

Case Study "David"

"David" is a white male who has never been looked after. The respective trajectories of the probability of David committing further offences whilst similar in shape, suggest quite a difference between the two models – at each measurement point, the probability of further offending is lower when based on BDm2.

Between Time 0 and Time 1, the Basic Dynamic Model suggests an increase in David's probability of further offending which corresponds to the increase in his ASSET score from 40 to 44. However, the trend suggests by estimates from BDm2 is downwards. This is despite the fact that David committed a further offence during this period. He also breached. Therefore, this is not what would be expected.

Figure 5.13: Comparisons of the Estimated Probability of Further Offending Over Time: "David"



Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with David having a total of 40 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that he was aged 10 at the time of his first Reprimand and as a result of his prior convictions.

Whilst it is not possible to measure the predictive accuracy of BDm2 relative to BDm1 which was constructed to represent the ASSET Core Profile, it would appear that including care and demographic characteristics has the potential to reduce the estimates of the probability of further offending for white males (reflecting the two reference groups for the Gender and Ethnicity predictors). However, it is notable that whilst the probability of further offending fell for David in the period when he committed a further offence whereas it increased for Connor suggests that further predictors may need to be incorporated into subsequent models to increase its sensitivity to changes over time.

5.7 Summary

The analysis presented in this chapter sought to address three research questions, with the final question being addressed as part of the previous section:

2. What is the impact of gender and ethnicity on the likelihood of further offending?
3. What is the impact of having experience of care on the likelihood of further offending?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

Sadly, there was insufficient data to fully explore the impact of gender and ethnicity on the likelihood of further offending over time. However, from their respective initial mean domain scores, there does appear to be significant differences in the profiles of males and females, and Whites compared to Non-Whites within the reoffending cohort. The extent to which this hold for those in the formal youth justice system in England and Wales more generally cannot be established, although it is in keeping with the findings of Schwalbe (2008), van der Put et al. (2014) and others who have explored the need for gender-specific instruments, and with work carried out using American samples which has considered whether there are differences on the basis of race/ethnicity.

Previous evaluations of ASSET have not considered potential differences on the basis of care status. However, the evidence presented as part of Lord Lamming's Review (Prison Reform Trust, 2016) highlights the over-representation of care experiences children within the youth justice system, pointing at the disadvantages that these children may face relative to their peers who have never been looked after. The models presented within this chapter represent a compromise as is not possible to fully differentiate between different sub-groups of the looked after children cohort e.g. on the basis of gender and/or ethnicity or their legal status. Despite this, when the estimated probabilities of further offending at different measurement points have been determined, it becomes apparent from the resulting charts that there are distinct differences in the estimated initial probability and the subsequent trajectory of change over time. Where it possible to access data from multiple YOTs and hence increase the size of the dataset, this is something I would be keen to explore further, especially given the current policy focus.

From a methodological point of view, what this chapter has demonstrated is the way in which the basic dynamic model can be extended to take into account additional predictors. Doing this increases the complexity of the model as highlighted in section 5.1 and is reflected in the increase in the DIC relative to the Basic Dynamic Model.

Subsequent chapters consider different types of predictors for example, in Chapter Six the predictor for the YJB Offence Category is categorical whilst that for the YJB Gravity Score is continuous. A key learning point from the analysis undertaken with respect to dimensional identity has been that although cohort has only been split into two groups - through the use of dichotomous predictors, the size of the dataset can still place limitations upon what can be explored. This is despite hierarchical modelling being promoted as being a more efficient approach. The small size of the non-reference groups has meant that at later measurement points, the model is informed by the data relating to just one individual, leading is potentially misleading trajectories of the estimated probability of further offending for some groups / fixed domain scores.

6 Findings: Static Factors

As described in Chapter Two, the ASSET Core Profile consists of two elements: the 12 domains or 'dynamic' factors, and four 'static' factors. The scoring for the static factors is summarised in Table 6.1, with a maximum potential score of 16 being assigned by practitioners to reflect the perceived additional risk posed by those with more established criminal careers, who were also committing more

Table 6.1: Scoring for the Static Risk Factors under the Scaled Approach

Static Factor	Scoring	
	Criteria	Score
Age at first reprimand, caution or warning	10 to 12	4
	13 to 17	2
	No previous reprimand, caution or warning	0
Age at first conviction	10 to 13	4
	14 to 17	3
	No previous convictions	0
Number of previous convictions	4 or more	4
	1 to 3	3
	No previous convictions	0
Offence Type	Motoring offences / vehicle theft / unauthorised taking	4
	Burglary (domestic and non-domestic)	3
	Other offence	0

Adapted from Youth Justice Board (2010b: 17)

This chapter considers the role that these static factors play with respect to the 12 dynamic risk factors, in predicting the likelihood of further offending. The following research questions are therefore considered:

4. What is the impact of the 'static' factors within ASSET in predicting further offending over time?
5. Is it possible to extend the sensitivity of ASSET by extending any of the predictors?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

The following non-time varying, Level 2 measures have therefore been added to the dataset to serve as a proxy for the static risk factors in ASSET:

- G_ageFirst – grouped aged at first offence. A dichotomous variable where the thresholds for the two groups reflect the scoring outlined in Table 6.1 i.e. young (10-12 years) and older (13-17 years)
- G_ageCon - grouped aged at first conviction. A dichotomous variable where the thresholds for the two groups reflect the scoring in ASSET i.e. young (10-13 years) and older (14-17 years)
- FTE – As it was not possible to check the number of previous convictions recorded on PNC, this dichotomous variable relies upon data held within Childview to determine whether the young person was a first-time entrant at the time of entering the cohort (Y/N)
- I_Cat2 - grouping of the offence categories used by the YJB in relation to the primary offence. Structured as a categorical predictor, this predictor has been constructed to differentiate between serious acquisitive crimes (SAC), violence against the person offences (VAP) and other offences.

In looking to establish if the sensitivity of ASSET can be extended, the following predictors are also considered:

- AgeFirst – age at first offence. Since the age of criminal responsibility is 10, this has been centred (by subtracting 10) to give a meaningful zero.
- AgeCon – age at first conviction. As with AgeFirst, this has also been centred (by subtracting 10) to give a meaningful zero.
- I_Seriousness2 – based upon the YJB Gravity Score of the primary offence, this enables the seriousness of the offence to be considered. Since the focus is on those in the formal youth justice system, this has been centred at 2 (reflecting the lowest gravity score of those in the reoffending cohort) to give a meaningful zero.

6.1 Description of the data

During the data collection process, it was identified that the static factors were not consistently completed and therefore it has been necessary to rely upon the information held within Childview in relation to the individual's offending and court appearances.

Table 6.2: The Reoffending Cohort by FTE Status, Grouped Age at First Offence, Grouped Age at First Conviction and Grouped YJB Offence Category

FTE Status	Grouped Age at First Offence	Grouped Age at First Conviction	Grouped YJB Offence Category			Total
			Other	SAC	VAP	
FTE	10 to 12 years	10 to 13 years	3		2	5
		14 to 17 years	10	3	1	14
	13 to 17 years	10 to 13 years	1	1		2
		14 to 17 years	16	7	10	33
FTE Total			30	11	13	54
Not FTE	10 to 12 years	10 to 13 years	1		1	2
		14 to 17 years			1	1
	13 to 17 years	10 to 13 years			2	2
		14 to 17 years	17	7	4	28
Previous Offending History Total			18	7	8	33
Grand Total			**48**	**18**	**21**	**87**

Notes: The individual whose FTE status is not known has been excluded from this summary.

Since some young people received a conviction on their first offence (rather than a Reprimand, Caution or Final Warning), then their age of first offence (AgeFirst) can be equal to their age at the time of their first conviction (AgeCon). This is more apparent when the reoffending cohort is segmented by age rather than grouped age at first offence and first conviction respectively.

Table 6.3: The Reoffending Cohort by FTE Status, Age at First Offence and Age at First Conviction

FTE Status	Age at First Offence	Age at First Conviction								Total
		10	11	12	13	14	15	16	17	
FTE	10									
	11									
	12			1	1		1			3
	13				2					2
	14					1	2	1	1	5
	15						7	4		11
	16							5	2	7
	17								5	5
FTE Total				1	3	1	10	10	8	33
Not FTE	10	1		1		2		2		6
	11			1		2	2			5
	12				2	2	4			8
	13				2	6	2		1	11
	14					5	4		3	12
	15						3	2	5	10
	16							1	1	2
	17									
Previous Offending History Total		1		2	4	17	15	5	10	54
Grand Total		**1**		**3**	**7**	**18**	**25**	**15**	**18**	**87**

Notes: The individual whose FTE status is not known has been excluded from this summary

Looking at the age that the FTEs received their first conviction, there appears to be conflicting information. In the main this is due to the way in which the predictor was set up, with the status upon entry to the reoffending cohort being used. Thus, young people who appeared on both the 2012/13 and 2013/14 reoffending spreadsheets were recorded on the basis of their status in 2012/13 - their inclusion the second year reflects the fact that they had gone on to commit further offences and hence in 2013/14. This status was carried forward into the second year rather than updating it to reflect that when the entered that cohort they had a previous offending history.

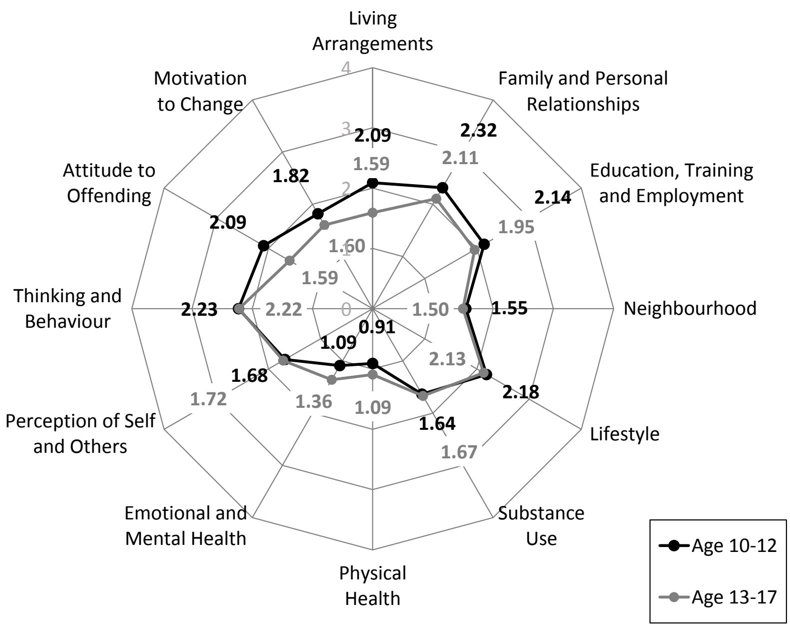
In the case of the FTEs who committed their first offence aged 12 and 14 but were not convicted until age 15 and 17 respectively, their initial offence was dealt with informally. The former appears in Table 6.2 as the FTE aged 10 to 12 years at time of first offence but aged 14 to 17 years at time of first conviction. A small number of FTE also had their birthday in the time that it took for the case to go to court accounting for the difference in ages.

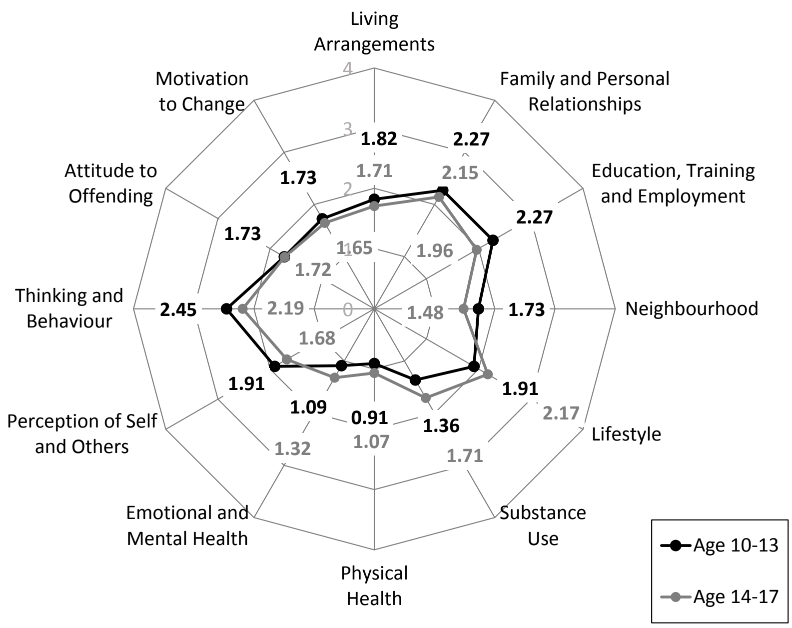
6.2 Initial Differences

Age at First Offence and Conviction

Under the Scaled Approach, the way in which the scores for the static factors relating to age were assigned is summarised in Table 6.1. The respective thresholds have been used to segment the reoffending cohort to explore differences in the domain scores at Time 0.

Figure 6.1: Domain Score Profile, by (a) Grouped Age at First Offence and (b) Grouped Age at First Conviction, at Time 0





Notes: Of the 87 individuals, 22 were aged 10-12 at the time of their first Offence. 11 were aged 10-13 at the time of their first conviction.

In the context of the grouped age at first offence, one-sided t-tests suggest that there no evidence to support the apparent differences in the mean domain scores at Time 0 between the younger and older sub-cohorts which can be seen in Figure 6.1(a). The exception to this is the Attitude to Offending domain where there is moderate evidence to suggest that on average, those aged 10-12 have higher ratings (BF_{10} = 4.046, % error = 3.405e^{-4}). There is also anecdotal evidence that this is also the case for the living arrangements domain (BF_{10} = 1.842, % error = 1.028e^{-4}). The equivalent two-sided tests in relation to the age at first conviction suggest that there is anecdotal evidence in favour of H_0 that there is no difference between the mean scores for each of the domains for each of the age groups. This is broadly consistent with the trends in Figure 6.1(b). However, this may in part be due to the small number of cases in the young age group - there are only 11 cases as opposed to 76 who received their first conviction after the age of 14.

Table 6.4: Random Intercepts and Varying Slope Models for Further Offending including ASSET Domains and the Two Age Related Static Factors

	Model 1.5: Basic Model + Grouped Age at First Offence				**Model 1.6: Basic Mo… Grouped Age at First C…**		
	Unstandardised			Significant?	**Unstandardised**		
Fixed Effect:	Post.Mean	Lower CI	Upper CI		Post.Mean	Lower CI	Upper…
Intercept	-1.090	-2.518	0.249		-0.888	-2.461	0.5…
Grouped Age at First Offence (Ref = 13-17 years)	-0.147	-0.620	0.363				
Grouped Age at First Conviction (Ref = 14-17 years)					-0.323	-0.946	0.3…
Living Arrangements	0.023	-0.254	0.291		0.034	-0.235	0.2…
Family and Personal Relationships	0.278	-0.030	0.574		0.276	-0.046	0.5…
Education, Training and Employment	0.074	-0.172	0.332		0.088	-0.151	0.3…
Neighbourhood	0.054	-0.169	0.278		0.036	-0.192	0.2…
Lifestyle	0.042	-0.311	0.386		0.041	-0.323	0.3…
Substance Use	0.173	-0.064	0.434		0.174	-0.062	0.4…
Physical Health	-0.123	-0.414	0.172		-0.111	-0.422	0.1…
Emotional and Mental Health	0.016	-0.230	0.265		0.000	-0.257	0.2…
Perceptions of Self and Others	-0.134	-0.480	0.186		-0.157	-0.496	0.1…
Thinking and Behaviour	-0.165	-0.527	0.148		-0.177	-0.506	0.1…
Attitude to Offending	0.024	-0.354	0.385		0.039	-0.331	0.3…
Motivation to Change	0.241	-0.105	0.574		0.242	-0.111	0.5…
Time	-0.163	-0.296	-0.014	Yes	-0.160	-0.312	-0.0…
Random Effect:	Post.Mean	Lower CI	Upper CI	Significant?	Post.Mean	Lower CI	Upper…
Individual (Intercept)	0.208	2.02E-07	0.566	Yes	0.190	1.79E-08	0.5…
Time	1.514	0.389	3.152	Yes	1.520	0.397	3.0…
DIC	473.29				473.17		

Source: Models Bm1G_cc2 (Grouped Age at First Offence) and Bm1G_cc3 (Grouped Age at First Conviction). Technical Annex: p135-136 and p139-140.

Inclusion of these predictors alongside the Basic Model does not reduce the DIC relative to the Basic Model despite the inclusion of an additional predictor (Models 1.5 and 1.6). Assuming all other things were equal, at Time 0:

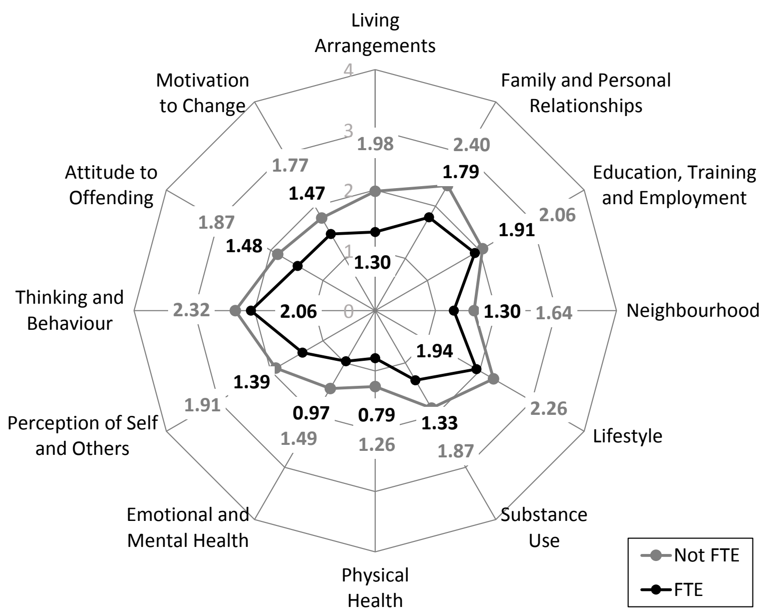
- The odds of further offending amongst those aged 10-12 years at the time of their first offence are estimated to be exp(-0.147) = 0.86 times the odds of who are older when they commit their first offence i.e. aged 13-17 years. [CI = 0.54, 1.44]
- The odds of further offending amongst those aged 10-13 at the time of their first conviction are estimated to be exp(-0.323) = 0.72 times the odds of those who are older i.e. aged 14-17 years when this occurs. [CI = 0.39, 1.38]

In each instance, the credible interval straddles one, suggesting that potentially there may be no difference between the odds of further offending amongst the two respective groups. This is not what would be expected given the theoretical underpinnings of the scoring of the static factors.

FTE Status

Whether or not the young person was a first-time entrant (FTE) at the time of entering the cohort has been determined from a combination of their offending and court records in Childview. Figure 6.2 segments the cohort on the basis of their FTE status, highlighting where there are differences in the mean domain scores at Time 0.

Figure 6.2: Domain Score Profiles, by FTE Status, at Time 0



Notes: Of the original 88 individuals, 33 are FTEs, there is also one individual whose status is unknown and hence has been excluded from these figures.

FTEs generally appear to have lower initial ratings for each of the 12 domains compared to their peers with history of previous offending. T-tests suggest that there is moderate evidence to support this difference in relation to:

- Living Arrangements (BF_{10} = 12.930 in favour of H_1: FTE < Prior, % error = 9.308e^{-5})
- Family and personal relationships (BF_{10} = 7.135, % error = 1.775e^{-4})
- Perception of Self and Others (BF_{10} = 6.884, % error = 0.001)

There is moderate evidence to suggest that there is no difference in the average initial domain scores for the two groups with respect to ETE (BF_{10} = 0.263 in favour of H_0: FTE = Prior, % error = 0.024).

A dummy variable for FTE Status (referenced by FTE) has been added to the Basic Model (Model 1.7, Table 6.5). The inclusion did not result in a marked reduction in the DIC.

Table 6.5: Random Intercepts and Varying Slope Models for Further Offending including ASSET Domains and FTE Status

	Model 1.7: Basic Model + FTE Status			
	Unstandardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	
Intercept	-1.212	-2.494	0.058	
First Time Entant (No = Ref).	0.083	-0.377	0.541	
Living Arrangements	0.036	-0.221	0.297	
Family and Personal Relationships	0.278	-0.016	0.570	
Education, Training and Employment	0.089	-0.159	0.333	
Neighbourhood	0.038	-0.184	0.252	
Lifestyle	0.031	-0.308	0.380	
Substance Use	0.159	-0.081	0.401	
Physical Health	-0.107	-0.395	0.177	
Emotional and Mental Health	-0.004	-0.249	0.279	
Perceptions of Self and Others	-0.132	-0.447	0.177	
Thinking and Behaviour	-0.155	-0.485	0.174	
Attitude to Offending	0.038	-0.316	0.379	
Motivation to Change	0.232	-0.102	0.577	
Time	-0.155	-0.294	-0.022	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.113	1.66E-04	0.403	Yes
Time	1.289	0.357	0.267	Yes
DIC	476.70			

Source: Models Bm1_cc1 (FTE Status). Technical Annex: p139-140

From the model it is estimated that at Time 0, with all other things being equal, the odds of further offending amongst FTEs are exp(0.083) = 1.09 times the odds for those with previous offending committing further offence. However, the credible interval of 0.69 to 1.72 suggest that it is plausible that the odds for further offending could be higher amongst non-FTEs which is what would be expected.

Offence Category

One of the original objectives for this piece of research was to explore the role of risk and protective factors for young people who have committed different types of offences. However, given the sample size, the reliability of using this as a measure needs to considered. Notably, as there is a desire to generate a model which considers offence category alongside other predictors, it has therefore been necessary to group the 13 YJB offence categories in order to reduce the amount of uncertainty around the simulated estimates. This is broadly in keeping with the static factor around offence type under the Scaled Approach (see Table 6.1). However, robbery offences have been grouped alongside domestic and non-domestic burglaries and theft of motor vehicles to form a 'Serious Acquisitive Crime' category. A breakdown of the cohort by offence category is provided in Table 6.6.

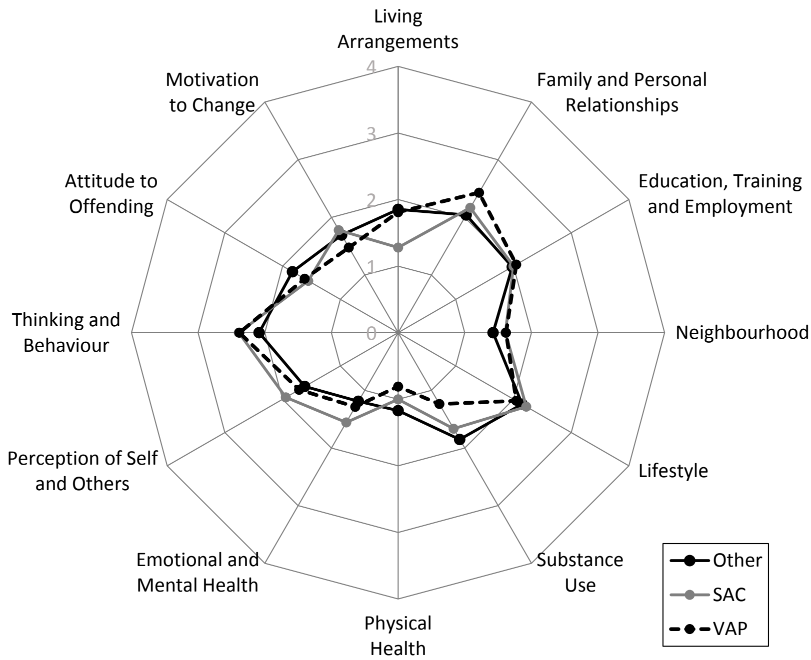
Table 6.6: The Re-Offending Cohort, by YJB Offence Category of Their Primary Offence

Type of Offence	YJB Offence Category	No.
Other	Criminal Damage	12
	Drugs	8
	Motoring Offences	4
	Other	1
	Public Order	11
	Racially Aggravated	1
	Sexual Offences	1
	Theft And Handling Stolen Goods	10
	Other Total	**48**
Serious Acquisitive Crimes (SAC)	Domestic Burglary	5
	Non Domestic Burglary	2
	Robbery	5
	Vehicle Theft / Unauthorised Taking	6
	Serious Acquisitive Crime Total	**18**
Violence Against the Person (VAP)		**21**
Grand Total		**87**

Notes: The individual whose FTE status is not known has been excluded from this summary

Grouping the YJB Offence Categories in this way means that 25.0% of the cohort entered having committed a violence against the person offence; one in five (20.5%) had committed a serious acquisitive crime whilst the remainder had committed offences which fell under 'Other'. Figure 6.3 compares the average initial domain scores for each sub-group.

Figure 6.3: Domain Score Profiles, by Grouped YJB Offence Category at Time 0



Notes: of the 87 individuals, 48 had committed an 'Other' offence; 18 had committed a serious acquisitive crime (SAC) whilst the remaining 21 had committed a violence against the person offence (VAP). Time 0 represents the initial assessment undertaken.

One-sided Bayesian independent t-tests suggests that those who have committed 'Other' offences have higher ratings than those who have committed VAP offences at the time of their initial assessment for:

- Substance misuse (BF_{10} = 2.444 in favour of H_1, % error =~0.008)
- Physical health (BF_{10} = 1.226, % error =~0.001)

There are also differences in the ratings for the living arrangements domain with these being higher for those committing other and violence against the person offences than for those who had committed a SAC offence:

- 'Other' offenders have higher ratings for the living arrangements domain than those committing SAC offences (BF_{10} = 1.688 in favour of H_1, % error =~9.055e^{-4})
- SAC offenders have lower initial ratings than those committing VAP offences (BF_{10} = 3.286 in favour of H_1, % error =~5.624e^{-4})
- There is moderate evidence to suggest that the ratings for Other offenders are not greater than those for VAP offenders (BF_{10} = 0.285 in favour of H_0, % error =~0.003)

There is no other evidence to support differences in the average domain scores between offenders committing the different types of offences at Time 0.

Table 6.7 compares the impact of incorporating both the Grouped and Ungrouped YJB Offence Category into the Basic Model. In Model 1.8 (Bm1_o1), the reference category is criminal damage whereas in Model 1.9 (Bm1G_o1), the categories are grouped with the reference category being 'Other Offence'. From Table 6.6, it is apparent that there are a number of YJB Offence Categories where there is only one case contributing information to the data e.g. the estimates for racially aggravated, sexual and other offences. There are also only two young people who entered the reoffending cohort having committed non-domestic burglaries. For this reason, it is felt that a potentially more accurate picture can be obtained by aggregating the YJB Offence Category as in Model 1.9.

Notably where the ungrouped predictor is used (Model 1.8), the substance misuse domain is significant, with the estimate suggesting that as the rating for this domain increases, it increases the probability of further offending. The certainty surrounding the estimate for this domain is lost when the YJB Offence Category is grouped.

Model 1.9 suggest that all other things being equal, the odds of further offending amongst those who committed a serious acquisitive crime are exp(0.162) = 1.8 times the odds of those who committed an 'Other Offence' [CI = 0.70, 2.17]. Those who committed a violence against the person offence have odds which are exp(0.234) = 1.3 times higher [CI = 0.70, 2.25].

Table 6.7: The Basic Model plus (a) YJB Offence Category and (b) Grouped YJB Offence Category

	Model 1.8: Basic Model + YJB Offence Category						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-0.783	-2.313	0.704	0.457	0.099	2.023	
YJB Offence Category (*Ref = Criminal Damage*)							
Drugs	-0.982	-2.063	0.123	0.374	0.127	1.131	
Motoring Offences	-0.307	-1.690	0.991	0.736	0.185	2.693	
Other	-0.744	-4.289	2.689	0.475	0.014	14.720	
Public Order	-0.870	-1.909	0.272	0.419	0.148	1.313	
Racially Aggravated	-1.457	-5.018	2.069	0.233	0.007	7.919	
Sexual Offences	-1.981	-4.987	0.947	0.138	0.007	2.577	
Theft And Handling Stolen Goods	-0.407	-1.466	0.623	0.666	0.231	1.865	
Domestic Burglary	-0.095	-1.183	1.088	0.909	0.306	2.967	
Non Domestic Burglary	0.044	-1.638	1.747	1.045	0.194	5.739	
Robbery	-0.960	-2.158	0.238	0.383	0.116	1.269	
Vehicle Theft / Unauthorised Taking	-0.216	-1.144	0.742	0.806	0.319	2.100	
Violence Against The Person	-0.221	-1.111	0.568	0.802	0.329	1.765	
Living Arrangements	0.097	-0.176	0.402	1.102	0.839	1.495	
Family and Personal Relationships	0.298	-0.020	0.620	1.347	0.980	1.859	
Education, Training and Employment	0.046	-0.217	0.316	1.047	0.805	1.372	
Neighbourhood	0.050	-0.201	0.295	1.052	0.818	1.344	
Lifestyle	-0.007	-0.386	0.376	0.993	0.680	1.457	
Substance Use	0.310	0.040	0.594	1.363	1.040	1.811	Yes
Physical Health	-0.181	-0.500	0.152	0.834	0.606	1.164	
Emotional and Mental Health	-0.020	-0.269	0.267	0.980	0.764	1.306	
Perceptions of Self and Others	-0.114	-0.459	0.226	0.892	0.632	1.254	
Thinking and Behaviour	-0.215	-0.571	0.177	0.806	0.565	1.193	
Attitude to Offending	0.038	-0.352	0.413	1.039	0.703	1.512	
Motivation to Change	0.220	-0.158	0.570	1.246	0.854	1.769	
Time	-0.183	-0.343	-0.042	0.833	0.710	0.959	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.275	2.94E-07	0.761	1.316	1.000	2.140	Yes
Time	1.660	0.439	3.541	5.259	1.551	34.501	Yes

DIC	474.54

	M
	Uns
Fixed Effect:	Post.Mean
(Intercept)	-1.297
Grouped YJB Offence Category (*Ref = Other*)	
Serious Acquisitive Crime	0.162
Violence Against The Person	0.234
Living Arrangements	0.052
Family and Personal Relationships	0.270
Education, Training and Employment	0.081
Neighbourhood	0.050
Lifestyle	0.036
Substance Use	0.183
Physical Health	-0.116
Emotional and Mental Health	0.015
Perceptions of Self and Others	-0.158
Thinking and Behaviour	-0.168
Attitude to Offending	0.039
Motivation to Change	0.234
Time	-0.165
Random Effect:	Post.Mean
Individual (Intercept)	0.220
Time	1.540

DIC	

Source: Models Bm1_o1 and Bm1G_o1, Technical Annex: p147-152

6.3 Developing Model 3

Since the four predictors are proxies for the static factors in ASSET, there is a theoretical rationale for including all four in the model for predicting the likelihood of further offending based on offending history.

Table 6.8: Model 3: The Basic Model plus Static Factors

	Model 3: Basic Model + Static Factors						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Intercept	-1.493	-3.529	0.300	0.225	0.029	1.350	
First Time Entant (No = Ref).	0.059	-3.748	4.159	1.060	0.024	64.035	
Grouped Age at First Offence (Ref = 13-17 years)	1.613	-0.405	3.776	5.019	0.667	43.639	
Grouped Age at First Conviction (Ref = 14-17 years)	0.405	-0.940	1.850	1.499	0.391	6.357	
Grouped YJB Offence Category (Ref = Other)							
Serious Aquisitive Crime (SAC)	0.084	-4.312	4.245	1.087	0.013	69.761	
Violence Against the Person (VAP)	0.701	-1.250	2.501	2.017	0.287	12.190	
Living Arrangements	0.047	-0.245	0.337	1.048	0.782	1.401	
Family and Personal Relationships	0.312	-0.038	0.637	1.366	0.963	1.891	
Education, Training and Employment	0.058	-0.223	0.324	1.060	0.800	1.382	
Neighbourhood	0.035	-0.221	0.277	1.035	0.802	1.320	
Lifestyle	-0.050	-0.421	0.351	0.951	0.656	1.421	
Substance Use	0.266	-0.017	0.540	1.305	0.983	1.716	
Physical Health	-0.141	-0.486	0.203	0.869	0.615	1.225	
Emotional and Mental Health	0.061	-0.212	0.332	1.063	0.809	1.394	
Perceptions of Self and Others	-0.201	-0.581	0.171	0.818	0.559	1.187	
Thinking and Behaviour	-0.154	-0.529	0.202	0.857	0.589	1.224	
Attitude to Offending	0.015	-0.366	0.426	1.015	0.693	1.531	
Motivation to Change	0.248	-0.134	0.605	1.282	0.874	1.831	
Time	-0.198	-0.347	-0.038	0.821	0.707	0.963	Yes
FTE: G_AgeFirst	-1.411	-7.863	5.147	0.244	0.000	171.846	
FTE: G_AgeCon	-0.310	-7.286	5.715	0.733	0.001	303.311	
FTE: SAC	1.131	-0.413	2.754	3.100	0.662	15.713	
FTE: VAP	-0.902	-6.732	4.788	0.406	0.001	120.039	
G_AgeFirst: G_AgeCon	-1.705	-4.131	0.447	0.182	0.016	1.564	
G_AgeFirst: SAC	-1.483	-3.074	0.071	0.227	0.046	1.073	
G_AgeFirst: VAP	0.394	-3.461	4.479	1.483	0.031	88.159	
G_AgeCon: SAC	0.819	-3.527	5.025	2.268	0.029	152.201	
G_AgeCon: VAP	-0.905	-5.341	3.252	0.404	0.005	25.842	
FTE: G_AgeFirst: G_AgeCon	1.518	-4.181	7.408	4.563	0.015	1649.488	
FTE: G_AgeFirst: VAP	0.849	-5.209	6.817	2.337	0.005	913.141	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.330	1.86E-08	0.902	1.390	1.00	2.464	Yes
Time	1.767	0.388	3.699	5.853	1.475	40.407	Yes

DIC	473.50

Source: Model Bm1G_cc123o1 (Model 3), Technical Annex: p155-156.

Although the model was specified to include all the potential 2-, 3- and 4-way combinations of the four predictors, it is notable that estimates have not been simulated for the following interactions:

FTE: G_ageFirst: SAC	G_ageFirst: G_ageCon: VAP
FTE: G_ageCon: SAC	FTE: G_ageCon: VAP
FTE: G_ageFirst: G_ageCon: SAC	FTE: G_ageFirst: G_ageCon: VAP
G_ageFirst: G_ageCon: SAC	

When compared to the underlying data (Table 6.2), only one of those who had committed a serious acquisitive crime had been aged 10-13 at the time of their first conviction. This young person had been an FTE at the time of joining the reoffending cohort. Whilst there were three young people who had committed serious acquisitive offences who had been aged 10-12 at the time of their first offence, these all had a history of prior offending at the time of entering the cohort. In terms of those who had committed violence against the person offences, there were none who had been FTEs aged 13-17 at the time of their first offence and aged 10-13 at the time of their first conviction. Hence the model being rank deficient with respect to interactions involving both G_ageCon and VAP and another predictor.

Table 6.8 additionally highlights the impact of the low numbers for different permutations of the predictors, with wide credible intervals for the estimates for the 2- and 3-way interactions which could be simulated. With insufficient data to support a model of this complexity, two options present themselves. The first is to remove the predictors for grouped age at first conviction since there are only 11 in the non-reference category. The second is to explore the whether it is appropriate to replace the YJB Offence Category with the predictor for YJB Gravity Score. In the case of the latter, this is still in keeping with the notion that those that have committed more serious offences pose a greater risk.

Removing Grouped Age of Conviction

Table 6.9 summarises the characteristics of the 11 individuals who were convicted of their first offence before the age of 14 i.e. those in the non-reference group of G_ageCon. As can be seen four of these were first time entrants at the time of entering the reoffending cohort. Of these, two were aged 13 at the time of their first offence which means that due to the different thresholds for the two age-related predictors employed within ASSET, they were in the older age group for G_ageFirst.

Table 6.9: Characteristics of those Convicted of Their First Offence Before Age 14

ID	FTE?	AgeFirst	AgeCon	YJB Offence Category	Grouped YJB Offence Category	YJB Gravity Score
1	No	10	10	Drugs	Other	2
2	No	11	12	Drugs	Other	2
3	Yes	12	12	Theft & Handling Stolen Goods	Other	3
4	No	10	12	Violence Against the Person	VAP	3
5	No	12	13	Public Order	Other	2
6	No	12	13	Violence Against the Person	VAP	3
7	Yes	12	13	Violence Against the Person	VAP	3
8	Yes	13	13	Violence Against the Person	VAP	3
9	Yes	13	13	Violence Against the Person	VAP	4
10	No	13	13	Criminal Damage	Other	3
11	No	13	13	Non Domestic Burglary	SAC	4

Just one of the younger group had committed a serious acquisitive crime. However, there was another boy who had committed a violence against the person offence with a gravity score of 4. In total, there were five who committed violence against the person offences. The remainder committed a variety of Other Offences. Table 6.10 summarises the underlying data with respect to the FTE Status, Grouped Age at First Offence and Grouped YJB Offence category. Notably there are no examples of where a young person with a previous offending history, having committed their first offence aged 10 to 13 years, had committed a serious acquisitive crime. The resulting model (Table 6.11) is therefore unable to simulate an estimate for the interaction between *FTE: G_ageFirst: SAC.* There is also a lot of uncertainty around some of the estimates where they are based on a low number of cases.

Table 6.10: The Reoffending Cohort by FTE Status, Grouped Age at First Offence and Grouped YJB Offence Category

FTE Status	Grouped Age at First Offence	Grouped YJB Offence Category			Total
		Other	SAC	VAP	
FTE	10 to 13 years	13	3	3	19
	14 to 17 years	17	8	10	35
FTE Total		30	11	13	54
Not FTE	10 to 13 years	1		2	3
	14 to 17 years	17	7	6	30
Not FTE Total		18	7	8	33
Grand Total		**48**	**18**	**21**	**87**

Notes: The individual whose FTE status is not known has been excluded from this summary.

Table 6.11 summarises a version of Model 3, with Grouped Age of First Conviction excluded.

Table 6.11: Model 3a: The Basic Model plus FTE Status, Grouped Age at First Offence and Grouped YJB Offence Category

	Model 3a: Basic Model + FTE Status, Grouped Age at First Offence and Grouped YJB Offence Category						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Intercept	-1.230	-2.729	0.214	0.292	0.065	1.239	
First Time Entant (No = Ref).	-0.224	-4.074	3.490	0.800	0.017	32.787	
Grouped Age at First Offence (Ref = 13-17 years)	0.159	-0.672	0.975	1.173	0.511	2.651	
Grouped YJB Offence Category (Ref = Other)							
Serious Aquisitive Crime (SAC)	0.970	-0.062	2.018	2.638	0.940	7.520	
Violence Against the Person (VAP)	0.383	-0.951	1.780	1.467	0.386	5.932	
Living Arrangements	0.050	-0.218	0.337	1.051	0.804	1.401	
Family and Personal Relationships	0.300	-0.041	0.618	1.350	0.960	1.855	
Education, Training and Employment	0.036	-0.232	0.296	1.037	0.793	1.344	
Neighbourhood	0.042	-0.206	0.283	1.043	0.814	1.327	
Lifestyle	-0.008	-0.383	0.372	0.992	0.682	1.451	
Substance Use	0.226	-0.036	0.510	1.254	0.965	1.665	
Physical Health	-0.097	-0.430	0.217	0.907	0.650	1.243	
Emotional and Mental Health	0.070	-0.182	0.342	1.072	0.833	1.408	
Perceptions of Self and Others	-0.198	-0.563	0.128	0.821	0.569	1.137	
Thinking and Behaviour	-0.157	-0.509	0.194	0.854	0.601	1.214	
Attitude to Offending	0.002	-0.401	0.364	1.002	0.669	1.439	
Motivation to Change	0.251	-0.103	0.593	1.286	0.902	1.809	
Time	-0.186	-0.343	-0.045	0.830	0.709	0.956	Yes
FTE: Grouped AgeFirst	-0.044	-4.176	3.610	0.957	0.015	36.972	
FTE: SAC	1.210	-0.272	2.622	3.355	0.762	13.761	
FTE: VAP	-0.948	-5.671	3.752	0.388	0.003	42.595	
Grouped Age First: SAC	-1.668	-3.165	-0.264	0.189	0.042	0.768	Yes
Grouped Age First: VAP	-0.369	-1.987	1.360	0.692	0.137	3.897	
FTE: Grouped AgeFirst: VAP	1.454	-3.566	6.248	4.282	0.028	517.235	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.267	3.30E-08	0.725	1.306	1.000	2.065	Yes
Time	1.658	0.421	3.306	5.249	1.523	27.276	Yes

DIC	473.13

Source: Model Bm1G_cc12o1 (Model 3a), Technical Annex: p160-161.

Considering the YJB Gravity Score rather than the Grouped YJB Offence Category

The YJB Gravity Score can be used to reflect the seriousness of the young person's primary offence. Table 3.14 summarised the profile of members of the re-offending cohort, showing that none of the re-offending cohort had committed an offence with a gravity score of 1, or with a gravity score of 7 or 8. Including this predictor, centred on 2 as an initial value, alongside the Basic Model results in a model with a DIC of 473.7 (Table 6.12).

Table 6.12: The Basic Model plus YJB Gravity Score

	Model 1.10: Basic Model + YJB Gravity Score						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.195	-2.565	0.303	0.303	0.077	1.354	
YJB Gravity Score (Ref = 2)	0.001	-0.161	0.163	1.001	0.852	1.177	
Living Arrangements	0.042	-0.213	0.319	1.043	0.808	1.375	
Family and Personal Relationships	0.277	-0.007	0.596	1.319	0.993	1.815	
Education, Training and Employment	0.074	-0.175	0.332	1.077	0.840	1.393	
Neighbourhood	0.047	-0.196	0.257	1.048	0.822	1.293	
Lifestyle	0.040	-0.317	0.404	1.041	0.728	1.498	
Substance Use	0.172	-0.081	0.408	1.188	0.922	1.504	
Physical Health	-0.132	-0.432	0.163	0.876	0.649	1.178	
Emotional and Mental Health	0.004	-0.248	0.251	1.004	0.780	1.285	
Perceptions of Self and Others	-0.137	-0.446	0.195	0.872	0.640	1.216	
Thinking and Behaviour	-0.157	-0.508	0.158	0.854	0.601	1.171	
Attitude to Offending	0.034	-0.328	0.386	1.035	0.721	1.471	
Motivation to Change	0.231	-0.113	0.586	1.260	0.893	1.796	
Time	-0.161	-0.307	-0.023	0.851	0.736	0.977	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.211	2.84E-11	0.573	1.235	1.000	1.773	Yes
Time	1.503	0.418	3.106	4.495	1.520	22.332	Yes

DIC	473.69

Source: Model Bm1_o2a, Technical Annex: p164-165.

Model 1.10 provides an estimate for the fixed effect of the seriousness of the primary offence. Assuming all other factors are equal, at Time 0, the odds of further offending increases by a multiplicative factor of exp(0.001) = 1.001 for each additional level of seriousness over a gravity score of 2 [CI = 0.85, 1.18]. As can be seen from Table 6.13, if the predictor for grouped age at first conviction is used to segment the cohort in addition to the other three predictors, there are a number of empty cells which would lead to the resulting model being rank deficient. Removing *G_ageCon* (Table 6.14) reduces the number of empty cells.

Table 6.13: The Reoffending Cohort by FTE Status, Grouped Age at First Offence, Grouped Age at First Conviction and YJB Gravity Score

FTE Status	Grouped Age at First Offence	Grouped Age at First Conviction	YJB Gravity Score					Total
			2	3	4	5	6	
FTE	10 to 12 years	10 to 13 years	3	2				5
		14 to 17 years	6	5	1	1	1	14
	13 to 17 years	10 to 13 years		1	1			2
		14 to 17 years	11	11	3	2	6	33
FTE Total			20	19	5	3	7	54
Not FTE	10 to 12 years	10 to 13 years		2				2
		14 to 17 years		1				1
	13 to 17 years	10 to 13 years		1	1			2
		14 to 17 years	11	7	3	1	6	28
Not FTE Total			11	11	4	1	6	33
Grand Total			**31**	**30**	**9**	**4**	**13**	**87**

Notes: The individual whose FTE status is not known has been excluded from this summary.

Table 6.14: The Reoffending Cohort by FTE Status, Grouped Age at First Offence and YJB Gravity Score

FTE Status	Grouped Age at First Offence	YJB Gravity Score					Total
		2	3	4	5	6	
FTE	10 to 12 years	9	7	1	1	1	19
	13 to 17 years	11	12	4	2	6	35
FTE Total		20	19	5	3	7	54
Not FTE	10 to 12 years		3				3
	13 to 17 years	11	8	4	1	6	30
Not FTE Total		11	11	4	1	6	33
Grand Total		**31**	**30**	**9**	**4**	**13**	**87**

Notes: The individual whose FTE status is not known has been excluded from this summary.

The three individuals with a prior offending history at the time of entering the re-offending cohort, who had been aged 10 to 12 years when they committed their first offence had all committed offences with a gravity score of 3. As can be seen from Table 6.10, one of these had been an 'Other' offence whereas two had committed violence against the person offences. In the resulting model (Table 6.15), an estimate for the interaction between grouped age at first offence and gravity score has not been simulated reflecting the lack of cases. However, a 3-way interaction involving all three predictors has been estimated reflecting the fact that it has been possible to determine some information about the likelihood of further offending amongst the younger age group and how this is affected by the seriousness of their primary offence.

Table 6.15: Model 3b: The Basic Model plus FTE Status, Grouped Age at First Offence and YJB Gravity Score

	Model 3b: Basic Model + FTE Status, Grouped Age at First Offence and YJB Gravity Score						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Intercept	-1.381	-2.831	0.141	0.251	0.059	1.152	
First Time Entant (No = Ref).	-0.998	-3.230	1.031	0.369	0.040	2.804	
Grouped Age at First Offence (Ref = 13-17 years)	0.326	-0.453	1.110	1.385	0.636	3.034	
YJB Gravity Score (0 = Gravity Score of 2)	0.334	0.017	0.647	1.396	1.017	1.910	Yes
Living Arrangements	0.037	-0.262	0.288	1.037	0.769	1.334	
Family and Personal Relationships	0.274	-0.035	0.580	1.315	0.965	1.787	
Education, Training and Employment	0.072	-0.179	0.327	1.074	0.836	1.387	
Neighbourhood	0.078	-0.140	0.322	1.082	0.869	1.380	
Lifestyle	0.028	-0.322	0.403	1.029	0.725	1.497	
Substance Use	0.164	-0.097	0.431	1.178	0.907	1.539	
Physical Health	-0.126	-0.432	0.187	0.882	0.650	1.205	
Emotional and Mental Health	0.038	-0.212	0.289	1.038	0.809	1.335	
Perceptions of Self and Others	-0.122	-0.461	0.217	0.885	0.631	1.243	
Thinking and Behaviour	-0.142	-0.497	0.197	0.868	0.609	1.217	
Attitude to Offending	-0.003	-0.364	0.358	0.997	0.695	1.430	
Motivation to Change	0.234	-0.127	0.572	1.264	0.880	1.772	
Time	-0.176	-0.322	-0.025	0.838	0.725	0.975	Yes
FTE: Grouped AgeFirst	1.029	-1.084	3.218	2.799	0.338	24.989	
FTE: Seriousness	0.152	-0.249	0.563	1.164	0.779	1.756	
FTE: Grouped AgeFirst: Seriousness	-0.529	-0.950	-0.115	0.589	0.387	0.892	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.191	2.84E-11	0.577	1.210	1.000	1.781	Yes
Time	1.579	0.386	3.404	4.850	1.471	30.084	Yes

DIC	471.65

Source: Model Bm1G_cc12o2a (Model 3b), Technical Annex: p168-169.

Of the two options for developing a combined model which reflects elements of the four static factors incorporated into ASSET, it is this third model which has the lower DIC (471.7 compared to 473.1 for model 3a). However, the difference is negligible, and both models have limitations as a result of the underlying data.

From the work previously undertaken with respect to gender and ethnicity, it has been concluded that there is insufficient data to pursue a dynamic model involving grouped age at first conviction. However, the following section considers the remaining 'static' predictors.

6.4 Dynamic Models

As highlighted in Figures 6.1, 6.2 and 6.3, there are differences in the domain score profiles on the basis of the age at which theyyoung person entered the youth justice system, whether or not the young person was an FTE at the time of entry to the reoffending cohort and the nature of their primaryoffence. In this section, these differences are explored to consider how they alter over time.

FTE Status

The dynamic model involving FTE status is summarised in Table 6.16. Those with a prior history of offending make up the reference group.

Table 6.16: The Dynamic Model Involving FTE Status

	Dynamic Basic Model including FTE Status (BDm3_cc1)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.542	-3.853	0.732	0.214	0.021	2.080	
First Time Entant (No = Ref) (FTE)	0.995	-1.668	3.660	2.705	0.189	38.879	
Time	-0.164	-0.523	0.204	0.849	0.593	1.227	
Living Arrangements (Live)	-0.047	-0.612	0.574	0.954	0.542	1.775	
Family and Personal Relationships (Relation)	0.640	-0.018	1.344	1.896	0.982	3.833	
Education, Training and Employment (ETE)	-0.301	-0.828	0.165	0.740	0.437	1.179	
Neighbourhood (Where)	0.198	-0.318	0.737	1.218	0.728	2.091	
Lifestyle (Life)	0.362	-0.511	1.333	1.437	0.600	3.791	
Substance Use (Drugs)	0.207	-0.277	0.767	1.230	0.758	2.154	
Physical Health (Physical)	-0.411	-1.063	0.239	0.663	0.345	1.271	
Emotional and Mental Health (Emotion)	0.006	-0.480	0.551	1.006	0.619	1.734	
Perceptions of Self and Others (Self)	-0.522	-1.364	0.316	0.594	0.256	1.372	
Thinking and Behaviour (Think)	-0.003	-0.774	0.814	0.997	0.461	2.258	
Attitude to Offending (Attitude)	0.449	-0.335	1.324	1.566	0.715	3.758	
Motivation to Change (Change)	-0.087	-0.907	0.714	0.917	0.404	2.041	
FTE: Time	-0.766	-1.532	-0.046	0.465	0.216	0.955	Yes
FTE: Live	1.099	-0.321	2.548	3.001	0.725	12.775	
FTE: Relation	-1.572	-3.080	-0.208	0.208	0.046	0.812	Yes
FTE: ETE	0.266	-0.948	1.585	1.305	0.388	4.880	
FTE: Where	-1.479	-2.678	-0.294	0.228	0.069	0.745	Yes
FTE: Life	0.992	-0.652	2.701	2.696	0.521	14.889	
FTE: Drugs	-0.697	-1.973	0.538	0.498	0.139	1.713	
FTE: Physical	-0.406	-1.766	1.016	0.666	0.171	2.762	
FTE: Emotion	-0.526	-1.691	0.548	0.591	0.184	1.730	
FTE: Self	2.392	0.904	3.930	10.937	2.468	50.930	Yes
FTE: Think	-0.484	-1.928	0.990	0.617	0.145	2.690	
FTE: Attitude	-1.249	-2.686	0.231	0.287	0.068	1.259	
FTE: Change	1.193	-0.399	2.734	3.298	0.671	15.392	
Time: Live	0.019	-0.105	0.151	1.019	0.901	1.163	
Time: Relation	-0.071	-0.221	0.081	0.931	0.802	1.084	
Time: ETE	0.053	-0.058	0.158	1.055	0.944	1.172	
Time: Where	-0.005	-0.112	0.097	0.995	0.894	1.102	
Time: Life	-0.007	-0.180	0.182	0.993	0.836	1.200	
Time: Drugs	-0.027	-0.138	0.090	0.974	0.871	1.094	
Time: Physical	0.115	-0.053	0.275	1.122	0.949	1.316	
Time: Emotion	0.008	-0.106	0.113	1.008	0.900	1.119	

/continued

	Dynamic Basic Model including FTE Status (BDm3_cc1)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Time: Self	0.084	-0.082	0.239	1.088	0.921	1.271	
Time: Think	-0.062	-0.245	0.113	0.940	0.783	1.120	
Time: Attitude	-0.101	-0.285	0.065	0.904	0.752	1.068	
Time: Change	0.047	-0.113	0.215	1.048	0.893	1.240	
FTE: Time: Live	-0.243	-0.594	0.105	0.784	0.552	1.111	
FTE: Time: Relation	0.381	0.024	0.751	1.463	1.024	2.119	Yes
FTE: Time: ETE	0.254	-0.123	0.611	1.289	0.884	1.843	
FTE: Time: Where	0.251	0.029	0.496	1.285	1.029	1.642	Yes
FTE: Time: Life	-0.441	-0.862	0.000	0.643	0.422	1.000	
FTE: Time: Drugs	0.260	-0.061	0.608	1.297	0.941	1.836	
FTE: Time: Physical	-0.048	-0.431	0.347	0.953	0.650	1.415	
FTE: Time: Emotion	0.157	-0.093	0.426	1.170	0.911	1.531	
FTE: Time: Self	-0.614	-0.971	-0.267	0.541	0.379	0.766	Yes
FTE: Time: Think	0.184	-0.143	0.532	1.203	0.866	1.702	
FTE: Time: Attitude	0.296	-0.077	0.714	1.345	0.926	2.043	
FTE: Time: Change	-0.227	-0.606	0.156	0.797	0.546	1.169	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.71	3.54E-10	1.74	2.039	1.000	5.703	Yes
Time	3.136	0.523	6.932	23.012	1.686	1024.541	Yes

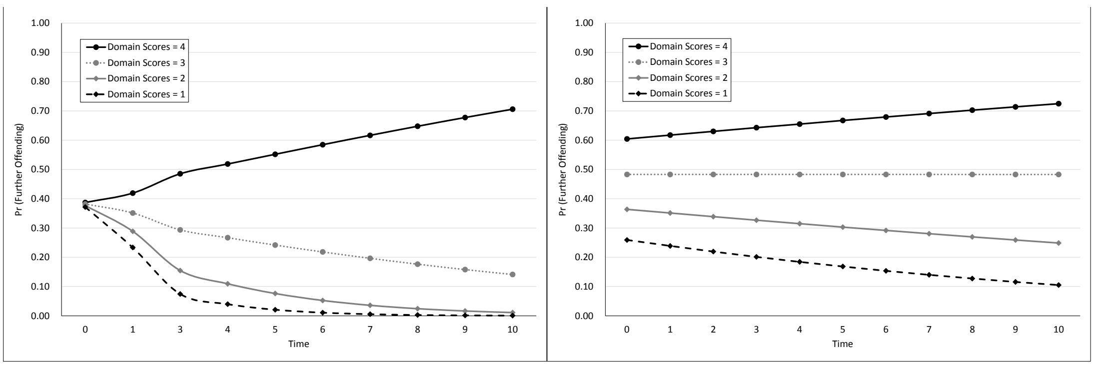
DIC	458.28

Source: Model BDm3_cc1, Technical Annex: p172-184.

The model has been used to consider the trajectory of the probability of further offending over time for FTEs and those with prior offending history (Figure 6.4). Whilst there remains considerable uncertainty within the model, notably the credible interval for the main effect of being an FTE, it is possible to see that amongst those with previous offending history, the initial probability of further offending is higher amongst those with higher domain scores. For both groups, the probability of further offending amongst those with very high domain scores increases over time. It is likely that this is associated with non-compliance leading to the young person being breached and having further court appearances. The impact of such contacts with youth justice processes is considered in Chapter Seven.

Figure 6.4: Changes in the Probability of Further offending Over Time, by FTE Status

(a) A First Time Entrant *(b) A Young Person with Previous Offending Behaviour*



Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of further offending from time 0 to time 10. Estimates derived from Model BDm3_cc1.

Grouped Age at First Offence

The dynamic model involving the grouped predictor for age at first offence is summarised in Table 6.17. This predictor uses the thresholds suggested by the scores assigned for the static factors to segment the cohort with those aged 10 to 12 being the reference group.

Table 6.17: The Dynamic Model Involving Grouped Age at First Offence

	Dynamic Basic Model including Grouped Age at First Offence (BDm3G_cc2)						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-3.285	-6.952	-0.407	0.037	0.001	0.666	Yes
Grouped Age First Offence (Age 10-12 = Ref)	2.340	-0.928	5.488	10.383	0.395	241.818	
Time	0.277	-0.421	0.963	1.320	0.656	2.620	
Living Arrangements (Live)	-0.367	-1.530	0.762	0.693	0.217	2.143	
Family and Personal Relationships (Relation)	1.479	0.071	2.905	4.387	1.074	18.271	Yes
Education, Training and Employment (ETE)	-0.419	-1.484	0.794	0.658	0.227	2.212	
Neighbourhood (Where)	0.165	-0.804	1.091	1.179	0.448	2.976	
Lifestyle (Life)	1.856	0.105	3.643	6.396	1.111	38.198	Yes
Substance Use (Drugs)	-0.055	-1.147	0.993	0.947	0.317	2.698	
Physical Health (Physical)	-0.947	-2.066	0.283	0.388	0.127	1.327	
Emotional and Mental Health (Emotion)	-0.559	-1.547	0.446	0.572	0.213	1.563	
Perceptions of Self and Others (Self)	-3.417	-5.411	-1.480	0.033	0.004	0.228	Yes
Thinking and Behaviour (Think)	0.622	-1.169	2.247	1.862	0.311	9.458	
Attitude to Offending (Attitude)	1.706	-0.163	3.783	5.505	0.849	43.951	
Motivation to Change (Change)	0.286	-1.359	1.917	1.331	0.257	6.802	
Grouped Age First Time	-0.559	-1.295	0.208	0.572	0.274	1.231	
Grouped Age First Live	0.484	-0.793	1.885	1.623	0.453	6.584	
Grouped Age First Relation	-1.584	-3.238	-0.048	0.205	0.039	0.953	Yes
Grouped Age First ETE	0.135	-1.095	1.307	1.144	0.334	3.697	
Grouped Age First Where	0.135	-1.095	1.307	1.144	0.334	3.697	
Grouped Age First Life	-1.624	-3.612	0.239	0.197	0.027	1.270	
Grouped Age First Drugs	0.342	-0.810	1.539	1.407	0.445	4.660	
Grouped Age First Physical	0.344	-0.976	1.694	1.410	0.377	5.442	
Grouped Age First Emotion	0.031	-1.057	1.244	1.031	0.348	3.469	
Grouped Age First Self	4.480	2.237	6.635	88.267	9.369	761.562	Yes
Grouped Age First Think	-0.594	-2.532	1.216	0.552	0.079	3.374	
Grouped Age First Attitude	-1.357	-3.479	0.703	0.258	0.031	2.020	
Grouped Age First Change	-0.448	-2.260	1.314	0.639	0.104	3.721	
Time: Live	-0.146	-0.410	0.145	0.864	0.664	1.156	
Time: Relation	-0.351	-0.718	-0.001	0.704	0.488	0.999	Yes
Time: ETE	0.158	-0.086	0.412	1.171	0.918	1.509	
Time: Where	-0.118	-0.315	0.096	0.888	0.730	1.101	
Time: Life	-0.419	-0.817	-0.016	0.658	0.442	0.984	Yes
Time: Drugs	0.229	-0.011	0.459	1.257	0.989	1.583	
Time: Physical	0.231	-0.068	0.541	1.260	0.934	1.718	
Time: Emotion	0.305	0.060	0.528	1.356	1.061	1.695	Yes
Time: Self	0.804	0.383	1.248	2.234	1.467	3.483	Yes
Time: Think	-0.186	-0.506	0.158	0.830	0.603	1.171	
Time: Attitude	-0.548	-0.911	-0.141	0.578	0.402	0.869	Yes
Time: Change	0.151	-0.166	0.526	1.162	0.847	1.692	

/continued

	Dynamic Basic Model including Grouped Age at First Offence (BDm3G_cc2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Grouped Age First Time: Live	0.191	-0.141	0.471	1.211	0.869	1.602	
Grouped Age First Time: Relation	0.413	0.018	0.794	1.512	1.019	2.212	Yes
Grouped Age First Time: ETE	-0.049	-0.323	0.233	0.952	0.724	1.262	
Grouped Age First Time: Where	0.142	-0.111	0.359	1.152	0.895	1.432	
Grouped Age First Time: Life	0.331	-0.148	0.740	1.392	0.862	2.096	
Grouped Age First Time: Drugs	-0.259	-0.525	0.015	0.772	0.592	1.016	
Grouped Age First Time: Physical	-0.128	-0.464	0.230	0.880	0.629	1.258	
Grouped Age First Time: Emotion	-0.171	-0.467	0.118	0.842	0.627	1.125	
Grouped Age First Time: Self	-1.064	-1.556	-0.594	0.345	0.211	0.552	Yes
Grouped Age First Time: Think	0.189	-0.209	0.533	1.209	0.811	1.704	
Grouped Age First Time: Attitude	0.425	0.010	0.870	1.529	1.010	2.386	Yes
Grouped Age First Time: Change	-0.094	-0.490	0.277	0.911	0.613	1.319	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.71	6.79E-06	1.70	2.041	1.000	5.496	Yes
Time	2.814	0.630	6.402	16.676	1.878	603.050	Yes

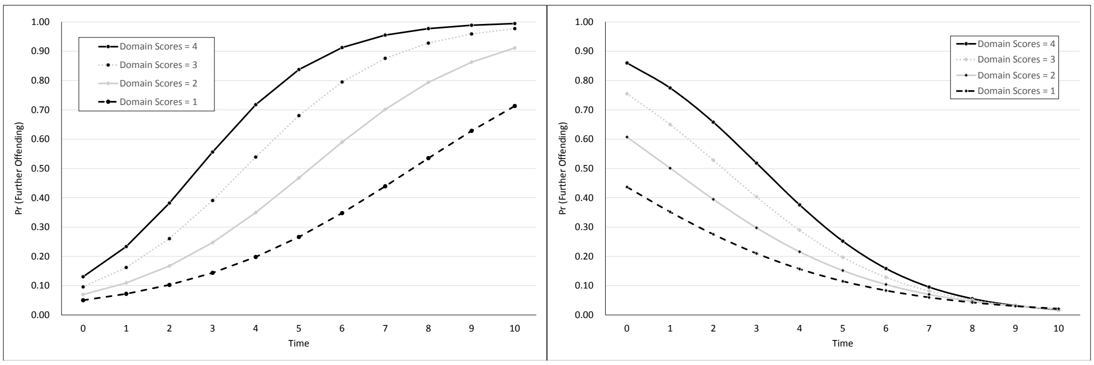
DIC	448.73

Source: Model BDm3G_cc2, Technical Annex: p185-197.

The model has been used to consider the trajectory of the probability of further offending over time for the younger and older groups based on their age at the time of their first offence (Figure 6.5). Notably, the trajectory for those aged 10-12 increases over time whereas that for those aged 13-17 decreases.

Figure 6.5: Changes in the Probability of Further Offending Over Time, by Grouped Age at First Offence

(a) Age 10-12 years *(b) Age 13-17 years*



Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of further offending from time 0 to time 10. Estimates derived from Model BDm3G_cc2.

This trend can be explained by looking at the mean domain scores for those aged 10-12 at the time of their first offence and how these change over time. As can be seen from Figure 6.6, the average domain score increases between Time 0 and Time 15 whereas the equivalent for the older group (Figure 6.7) is less pronounced and there is actually a net downward trend after Time 10.

Figure 6.6: Summary of Average Domain Scores, by Grouped Age at First Offence – Younger Group

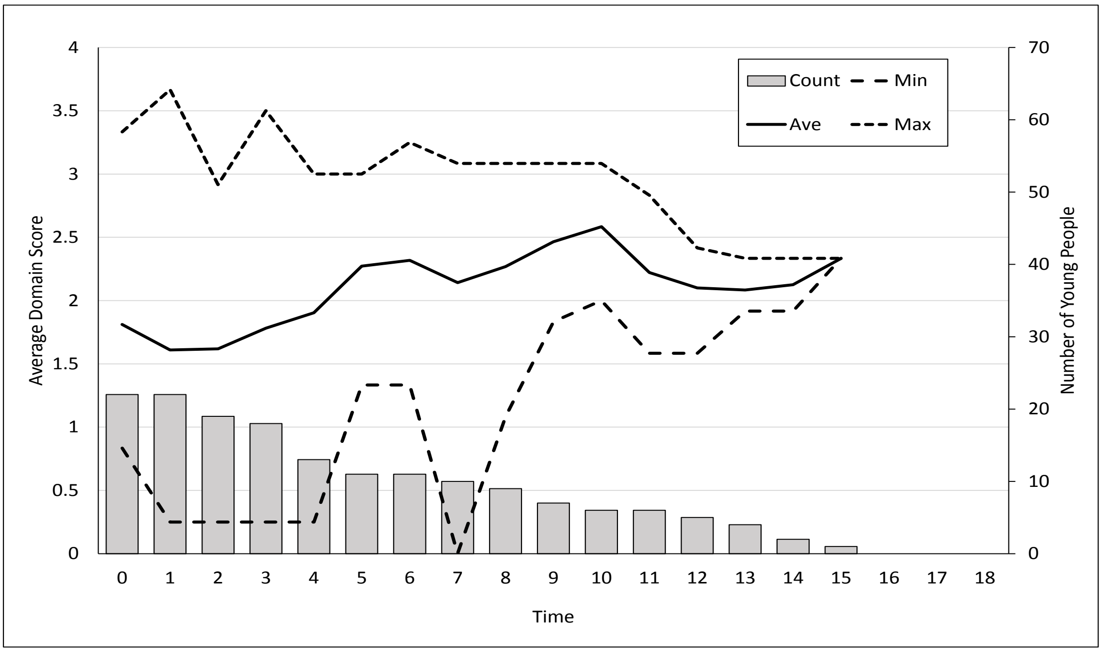
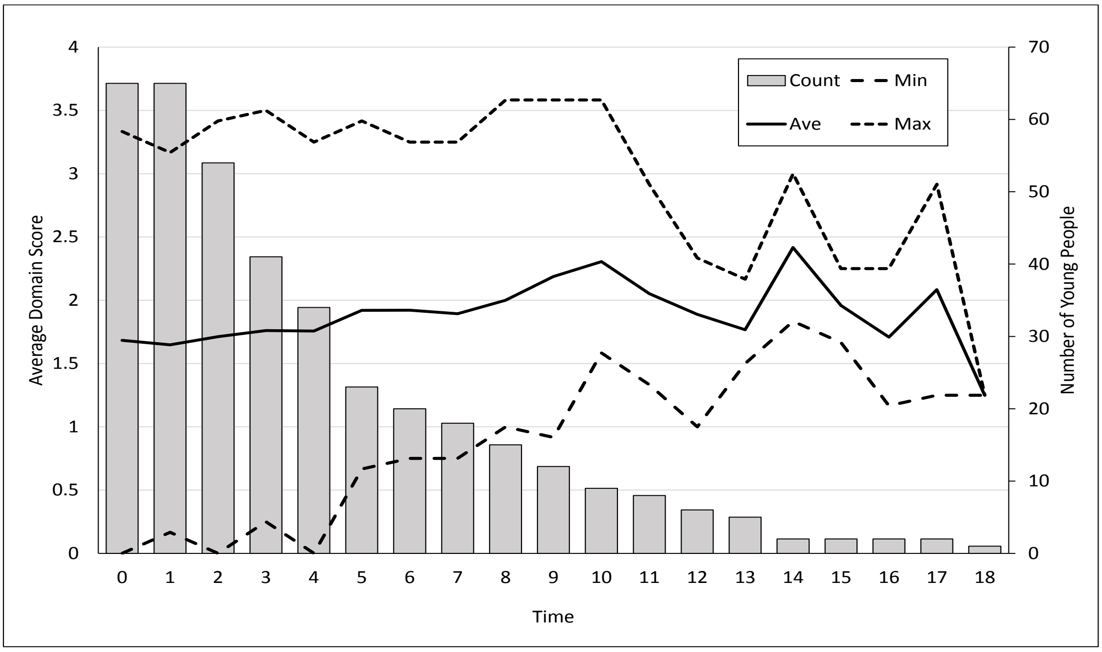


Figure 6.7: Summary of Average Domain Scores, by Grouped Age at First Offence – Older Group



From Time 14, both groups are informed by two or fewer cases. Within the younger group there was one individual who was assessed 16 times. In the older group, there was one individual who was assessed 19 times during the period of interest. This limits the reliability of models involving this predictor at later measurement points.

Offence Type: Grouped YJB Offence Category

The dynamic model involving the categorical predictor which reflects whether the young person had entered the cohort having committed a violent offence, a serious acquisitive crime (SAC) or an 'Other' offence is summarised in Table 6.18. In this model, 'Other' offences are the reference category.

Table 6.18: The Dynamic Model Involving Grouped YJB Offence Category

	Dynamic Basic Model including Grouped YJB Offence Category (BDm3G_o1)						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.743	-5.109	1.287	0.175	0.006	3.621	
Grouped YJB Offence Category (Ref = Other)							
Serious Acquisitive Crime (SAC)	1.924	-2.331	6.124	6.847	0.097	456.878	
Violence Against the Person (VAP)	-4.070	-10.078	1.331	0.017	0.000	3.785	
Time	-0.233	-0.830	0.284	0.792	0.436	1.329	
Living Arrangements (Live)	-0.165	-1.120	0.777	0.848	0.326	2.174	
Family and Personal Relationships (Relation)	0.058	-1.040	1.106	1.059	0.354	3.023	
Education, Training and Employment (ETE)	0.595	-0.182	1.355	1.813	0.834	3.877	
Neighbourhood (Where)	0.069	-0.743	0.837	1.071	0.476	2.310	
Lifestyle (Life)	-0.325	-1.832	1.123	0.723	0.160	3.075	
Substance Use (Drugs)	0.170	-0.691	1.064	1.185	0.501	2.899	
Physical Health (Physical)	-0.148	-1.086	0.760	0.862	0.337	2.138	
Emotional and Mental Health (Emotion)	-0.158	-0.908	0.652	0.854	0.403	1.919	
Perceptions of Self and Others (Self)	0.381	-0.912	1.582	1.463	0.402	4.866	
Thinking and Behaviour (Think)	-0.046	-1.145	0.970	0.955	0.318	2.637	
Attitude to Offending (Attitude)	-0.149	-1.454	1.053	0.861	0.234	2.865	
Motivation to Change (Change)	0.719	-0.531	1.899	2.053	0.588	6.678	
SAC: Time	-0.746	-1.623	0.182	0.474	0.197	1.199	
SAC: Live	0.522	-1.104	2.222	1.686	0.331	9.229	
SAC: Relation	0.777	-1.044	2.587	2.176	0.352	13.285	
SAC: ETE	-0.518	-2.148	1.168	0.596	0.117	3.215	
SAC: Where	0.897	-0.564	2.341	2.452	0.569	10.391	
SAC: Life	0.620	-1.804	2.928	1.859	0.165	18.687	
SAC: Drugs	0.381	-1.102	1.853	1.464	0.332	6.378	
SAC: Physical	-1.795	-3.842	0.215	0.166	0.021	1.240	
SAC: Emotion	0.045	-1.556	1.694	1.046	0.211	5.440	
SAC: Self	-1.012	-3.082	1.149	0.363	0.046	3.155	
SAC: Think	-0.253	-2.462	1.974	0.776	0.085	7.200	
SAC: Attitude	0.256	-1.893	2.418	1.292	0.151	11.223	
SAC: Change	-1.331	-4.312	1.750	0.264	0.013	5.754	
VAP: Time	0.829	-0.267	2.085	2.291	0.766	8.047	
VAP: Live	1.307	-1.290	3.652	3.694	0.275	38.552	
VAP: Relation	-0.996	-3.459	1.719	0.369	0.031	5.581	
VAP: ETE	-3.461	-5.758	-1.407	0.031	0.003	0.245	Yes
VAP: Where	-1.226	-3.084	0.684	0.293	0.046	1.981	
VAP: Life	3.032	0.437	5.904	20.728	1.548	366.635	Yes
VAP: Drugs	0.398	-1.540	2.112	1.489	0.214	8.264	
VAP: Physical	-0.865	-3.450	1.667	0.421	0.032	5.296	
VAP: Emotion	-0.458	-2.160	1.204	0.633	0.115	3.335	
VAP: Self	0.188	-2.047	2.613	1.207	0.129	13.639	
VAP: Think	2.361	-0.712	5.592	10.599	0.491	268.378	
VAP: Attitude	0.385	-2.933	3.469	1.469	0.053	32.119	
VAP: Change	0.769	-1.767	3.112	2.157	0.171	22.460	

/continued

	Dynamic Basic Model including Grouped YJB Offence Category (BDm3G_o1)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Time: Live	0.041	-0.159	0.243	1.042	0.853	1.275	
Time: Relation	0.155	-0.142	0.470	1.167	0.868	1.600	
Time: ETE	-0.155	-0.350	0.036	0.857	0.704	1.037	
Time: Where	0.030	-0.127	0.193	1.031	0.881	1.212	
Time: Life	0.079	-0.257	0.428	1.082	0.773	1.534	
Time: Drugs	0.058	-0.128	0.265	1.060	0.880	1.304	
Time: Physical	0.032	-0.215	0.300	1.033	0.806	1.350	
Time: Emotion	-0.094	-0.335	0.129	0.910	0.715	1.138	
Time: Self	-0.159	-0.418	0.101	0.853	0.658	1.107	
Time: Think	0.065	-0.212	0.328	1.068	0.809	1.388	
Time: Attitude	-0.076	-0.377	0.229	0.927	0.686	1.258	
Time: Change	-0.062	-0.339	0.216	0.940	0.712	1.241	
SAC: Time: Live	0.048	-0.300	0.404	1.049	0.741	1.498	
SAC: Time: Relation	-0.355	-0.793	0.063	0.701	0.452	1.065	
SAC: Time: ETE	0.260	-0.076	0.614	1.297	0.926	1.847	
SAC: Time: Where	-0.284	-0.564	0.022	0.753	0.569	1.022	
SAC: Time: Life	-0.114	-0.601	0.382	0.892	0.548	1.466	
SAC: Time: Drugs	-0.008	-0.359	0.300	0.992	0.699	1.350	
SAC: Time: Physical	0.134	-0.319	0.588	1.144	0.727	1.801	
SAC: Time: Emotion	0.315	-0.025	0.650	1.370	0.975	1.916	
SAC: Time: Self	0.357	-0.082	0.845	1.429	0.922	2.329	
SAC: Time: Think	-0.233	-0.749	0.267	0.792	0.473	1.306	
SAC: Time: Attitude	0.127	-0.372	0.636	1.135	0.690	1.888	
SAC: Time: Change	0.168	-0.378	0.764	1.183	0.685	2.147	
VAP: Time: Live	-0.221	-0.782	0.292	0.802	0.458	1.339	
VAP: Time: Relation	0.409	-0.222	1.120	1.506	0.801	3.065	
VAP: Time: ETE	0.994	0.410	1.611	2.703	1.507	5.008	Yes
VAP: Time: Where	0.446	0.010	0.930	1.562	1.010	2.536	Yes
VAP: Time: Life	-0.598	-1.197	-0.016	0.550	0.302	0.984	Yes
VAP: Time: Drugs	-0.241	-0.641	0.166	0.786	0.527	1.180	
VAP: Time: Physical	0.007	-0.701	0.761	1.007	0.496	2.141	
VAP: Time: Emotion	0.456	-0.018	0.978	1.577	0.982	2.660	
VAP: Time: Self	0.012	-0.494	0.497	1.012	0.610	1.643	
VAP: Time: Think	-0.752	-1.456	-0.122	0.472	0.233	0.885	Yes
VAP: Time: Attitude	-0.519	-1.396	0.234	0.595	0.248	1.263	
VAP: Time: Change	-0.307	-0.811	0.170	0.736	0.444	1.186	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	2.75	1.21E-05	6.12	15.643	1.000	453.956	Yes
Time	6.166	1.181	13.850	476.277	3.258	1.04E+06	Yes

DIC	442.99

Source: Model BDm3_o1, Technical Annex: p198-214.

Compared to where the Grouped YJB Offence Categories have been added to the Basic Model (Table 6.7), allowing the domain scores and the interactions upon these for the different offence types, to vary by time improves the DIC from 473.8 to 443.0. This suggests that despite the additional parameters, the dynamic model accounts for more of the uncertainty around the odds of further offending for the average young person. However, despite the trace plots suggesting that there has been convergence, the credible intervals for some of the main and interaction fixed effects are very wide including the estimates for SAC as a main effect and the interactions between VAP and the lifestyle and thinking behaviours domain scores. Figures 6.8 to 6.10 summarises the trajectories of the probability of further offending for each type of offence where the domain scores are fixed. The trend for other offences is notably different to that for serious acquisitive crimes and violence against the person offences.

At Time 1, for those with ratings of 2 across the domain scores, the probability of further offending is lowest amongst those who have committed violence against the person offences. The odds of further offending are estimated to be 1.2 times higher if they had committed a serious acquisitive crime, and 2.7 times higher if they had committed an 'Other' offence.

If similar comparisons are made at Time 6 (when the intersection between the trajectories occurs for violence against the person offences), the probability of a young person with domain scores of 2 committing further offences is lowest amongst those who have committed a serious acquisitive crime. Relative to this, the odds of further offending, are estimated to be 1.5 times higher if the young person's primary offence was either an 'Other' or a violence against the person offence.

Figures 6.11 to 6.13 summarise the average domain scores by primary offence. These do not offer an explanation as to why there is an intersection of the trajectories of the probabilities of further offending for the serious acquisitive crimes or the violence against the person offences.

Figure 6.8: Changes in the Probability of Further Offending Over Time - Serious Acquisitive Crimes

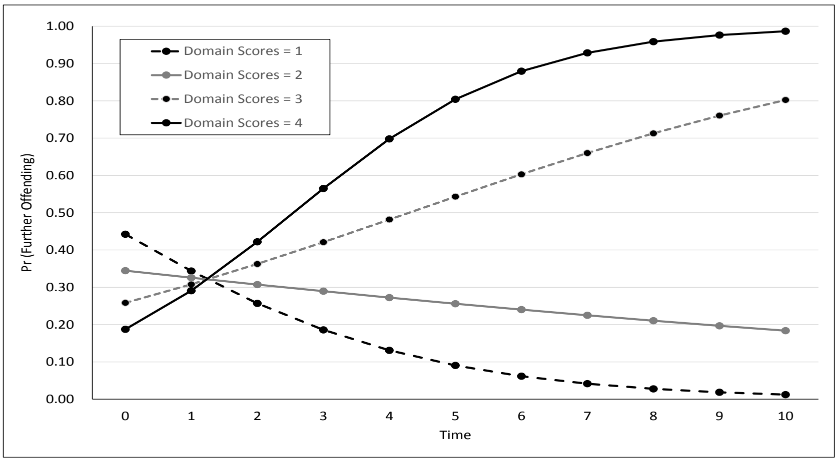


Figure 6.9: Changes in the Probability of Further Offending
Person

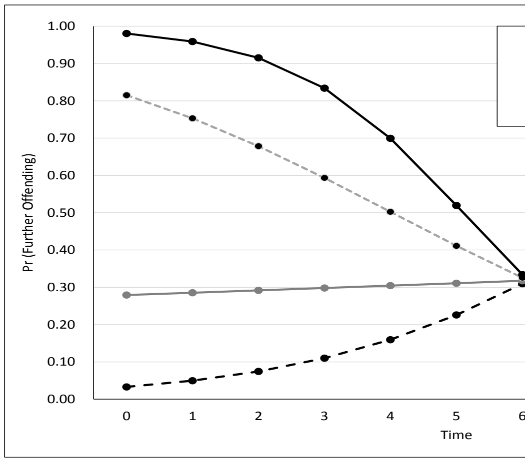
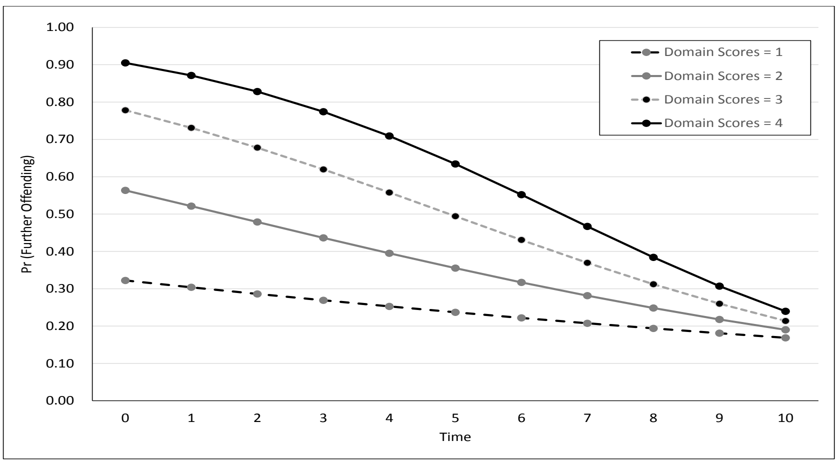


Figure 6.10: Changes in the Probability of Further Offending Over Time - Other Offences



Notes: The domain scores have respectively been shown as
the estimated change in the probability of further offending
derived from Model BDm3G_o1.

Figure 6.11: Summary of Average Domain Scores, by Primary Offence - Serious Acquisitive Crimes

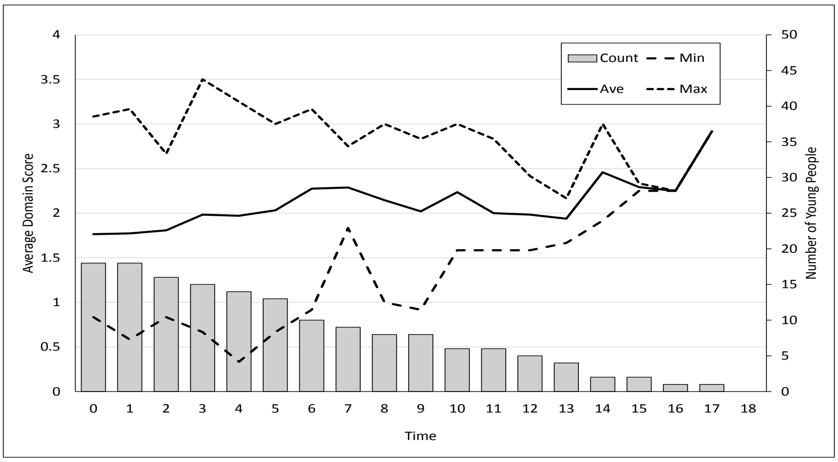


Figure 6.12: Summary of Average Domain Scores, by Prin Person

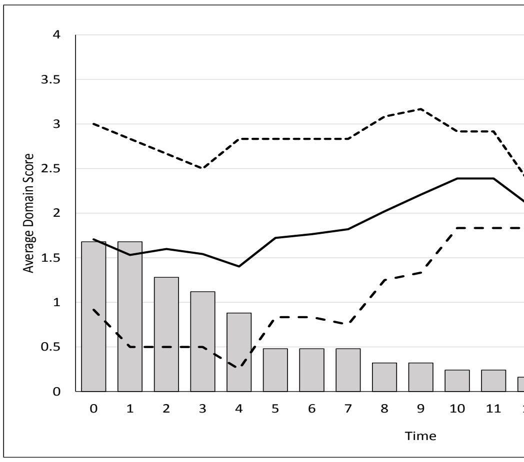
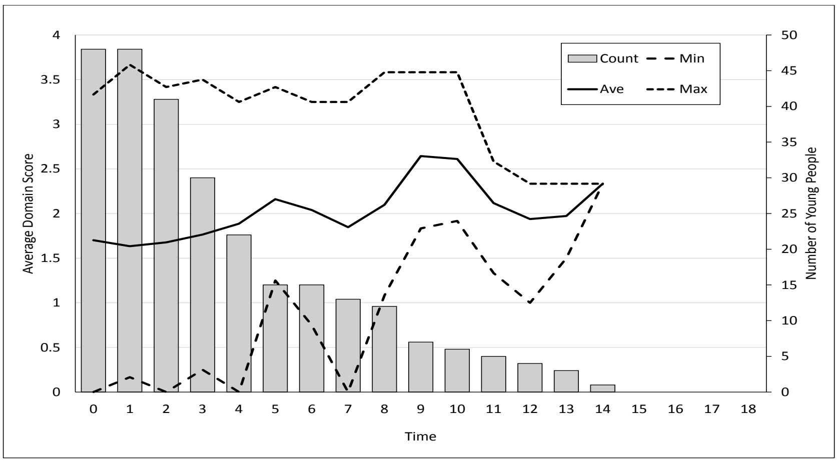


Figure 6.13: Summary of Average Domain Scores, by Primary Offence - Other Offences



The Seriousness of the Offence: YJB Gravity Score

Table 6.19: The Dynamic Model Involving YJB Gravity Scores

	Dynamic Basic Model including YJB Gravity Score (BDm3_o2a)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.306	-3.401	0.772	0.271	0.033	2.164	
YJB Gravity Score (Seriousness) (0 = Gravity Score of 2)	-0.143	-1.059	0.810	0.867	0.347	2.247	
Time	-0.145	-0.572	0.257	0.865	0.564	1.293	
Living Arrangements (Live)	-0.459	-1.156	0.190	0.632	0.315	1.210	
Family and Personal Relationships (Relation)	0.207	-0.552	0.960	1.230	0.576	2.613	
Education, Training and Employment (ETE)	-0.064	-0.664	0.487	0.938	0.515	1.628	
Neighbourhood (Where)	-0.091	-0.669	0.533	0.913	0.512	1.705	
Lifestyle (Life)	0.244	-0.633	1.211	1.276	0.531	3.357	
Substance Use (Drugs)	0.180	-0.423	0.787	1.197	0.655	2.197	
Physical Health (Physical)	-0.588	-1.282	0.120	0.556	0.278	1.128	
Emotional and Mental Health (Emotion)	-0.032	-0.630	0.526	0.969	0.532	1.693	
Perceptions of Self and Others (Self)	0.567	-0.288	1.476	1.764	0.750	4.376	
Thinking and Behaviour (Think)	-0.248	-0.984	0.556	0.780	0.374	1.743	
Attitude to Offending (Attitude)	-0.025	-0.895	0.835	0.976	0.409	2.305	
Motivation to Change (Change)	0.850	-0.077	1.783	2.339	0.926	5.949	
Seriousness: Time	-0.008	-0.245	0.232	0.992	0.783	1.262	
Seriousness: Live	0.285	-0.094	0.690	1.329	0.910	1.994	
Seriousness: Relation	0.015	-0.403	0.475	1.015	0.668	1.608	
Seriousness: ETE	-0.110	-0.495	0.246	0.896	0.610	1.279	
Seriousness: Where	0.145	-0.193	0.504	1.156	0.825	1.656	
Seriousness: Life	0.140	-0.406	0.729	1.150	0.667	2.072	
Seriousness: Drugs	0.064	-0.265	0.409	1.066	0.767	1.505	
Seriousness: Physical	-0.060	-0.521	0.393	0.942	0.594	1.481	
Seriousness: Emotion	-0.073	-0.434	0.328	0.930	0.648	1.388	
Seriousness: Self	-0.140	-0.589	0.340	0.869	0.555	1.405	
Seriousness: Think	0.112	-0.490	0.672	1.118	0.612	1.959	
Seriousness: Attitude	-0.019	-0.554	0.489	0.982	0.575	1.631	
Seriousness: Change	-0.339	-1.016	0.333	0.713	0.362	1.395	
Time: Live	0.079	-0.066	0.239	1.083	0.936	1.269	
Time: Relation	0.122	-0.093	0.332	1.130	0.911	1.394	
Time: ETE	0.022	-0.133	0.182	1.022	0.876	1.200	
Time: Where	0.094	-0.027	0.221	1.099	0.973	1.247	
Time: Life	-0.092	-0.312	0.124	0.912	0.732	1.132	
Time: Drugs	-0.026	-0.168	0.112	0.975	0.846	1.118	
Time: Physical	0.200	-0.002	0.399	1.221	0.998	1.491	
Time: Emotion	-0.110	-0.276	0.048	0.896	0.759	1.049	
Time: Self	-0.174	-0.361	0.014	0.840	0.697	1.014	
Time: Think	0.146	-0.036	0.329	1.157	0.964	1.389	
Time: Attitude	-0.031	-0.233	0.172	0.970	0.792	1.188	
Time: Change	-0.199	-0.408	0.004	0.819	0.665	1.004	
Seriousness: Time: Live	-0.014	-0.107	0.081	0.986	0.898	1.085	
Seriousness: Time: Relation	-0.104	-0.233	0.018	0.902	0.792	1.018	
Seriousness: Time: ETE	0.061	-0.045	0.163	1.062	0.956	1.177	
Seriousness: Time: Where	-0.087	-0.167	-0.006	0.917	0.846	0.994	Yes
Seriousness: Time: Life	0.028	-0.110	0.161	1.029	0.896	1.174	
Seriousness: Time: Drugs	-0.008	-0.092	0.067	0.992	0.912	1.069	

/continued

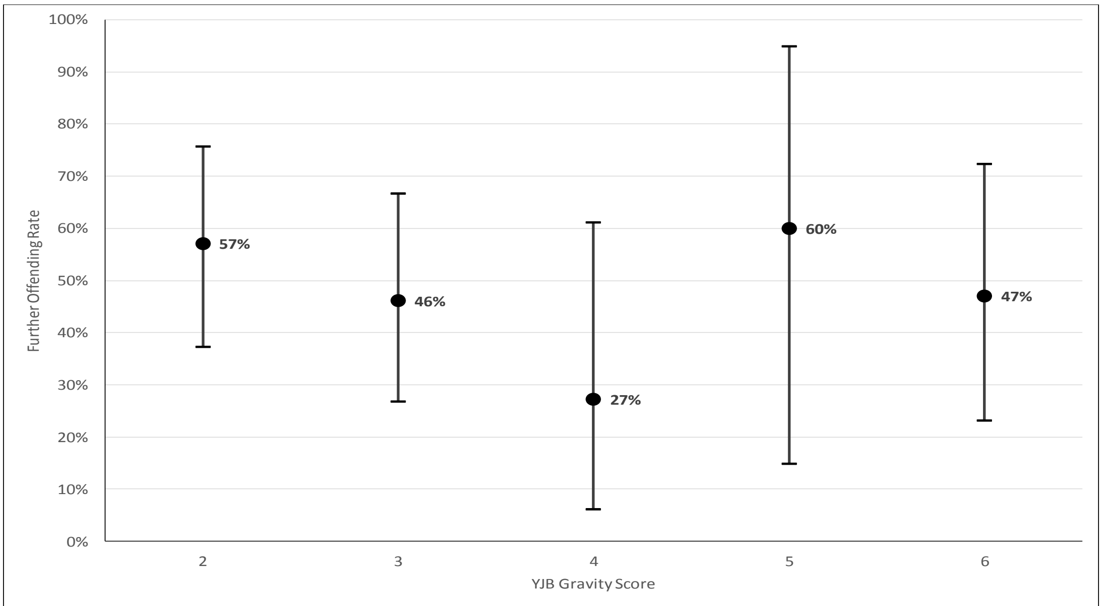
	Dynamic Basic Model including YJB Gravity Score (BDm3_o2a)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	
Seriousness: Time: Physical	-0.060	-0.181	0.055	0.942	0.834	1.057	
Seriousness: Time: Emotion	0.127	0.034	0.223	1.136	1.034	1.249	Yes
Seriousness: Time: Self	0.058	-0.054	0.162	1.060	0.948	1.176	
Seriousness: Time: Think	-0.131	-0.271	0.006	0.877	0.763	1.006	
Seriousness: Time: Attitude	0.026	-0.110	0.153	1.027	0.896	1.166	
Seriousness: Time: Change	0.096	-0.044	0.237	1.101	0.957	1.268	
Random Effect:	Post Mean	Lower CI	Upper CI	Post Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.335	6.61E-07	0.981	1.398	1.000	2.667	Yes
Time	2.614	0.568	5.735	13.654	1.765	309.513	Yes

DIC	472.66

Source: Model BDm3_o2a, Technical Annex: p215-227.

The model has been used to estimate the role that the seriousness of the primary offence has on the probability of further offending over time (Figure 6.14). As would be expected, those with higher domain scores have higher initial probabilities of further offending. However, it is those who have committed offences with lower gravity scores who are more likely to commit further offences – a trend that holds over time. This may well be linked to the type of offences that have a lower gravity score. For example, theft and handling stolen goods – a category which includes shoplifting; criminal damage and possession of drugs have low gravity scores. However, as can be seen from Figure 6.14, there is not a clear relationship between the proportion of further offending and YJB Gravity Score. This is also apparent in the national published figures (Figure 3.5).

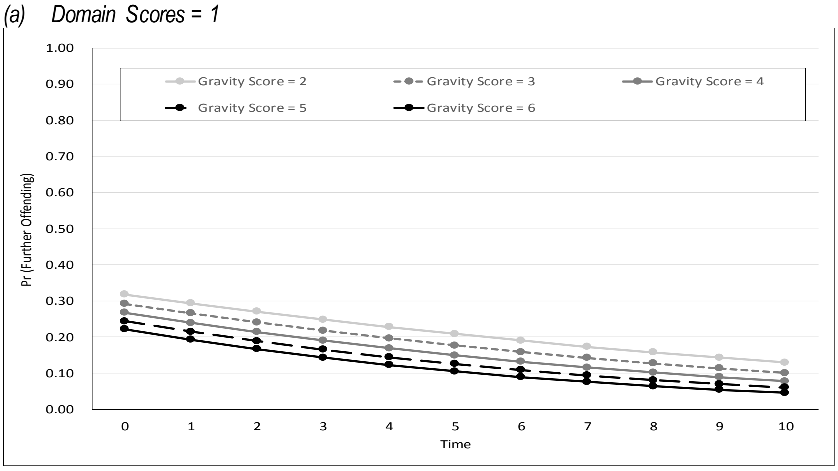
Figure 6.14: Rate of Further Offending, by YJB Gravity Score



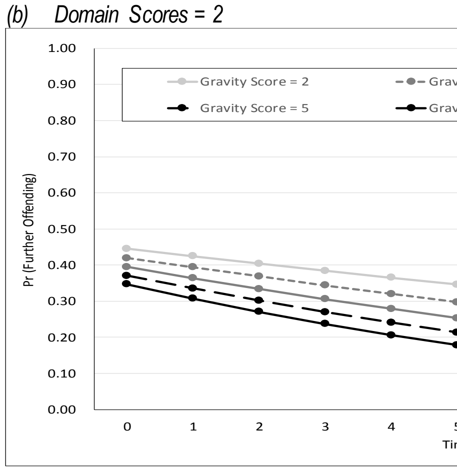
Note: 95% confidence intervals have been included to take into account the profile of the cohort by YJB Gravity Score. For example, there were 31 individuals whose primary offence had a gravity score of 2 and 30 with a gravity score of 3. This compares to 9 with a gravity score of 4; just 4 with a gravity score of 5 and 13 with a gravity score of 6.

Figure 6.15: Change in the Probability of Further Offending Over Time, by YJB Gravity Score

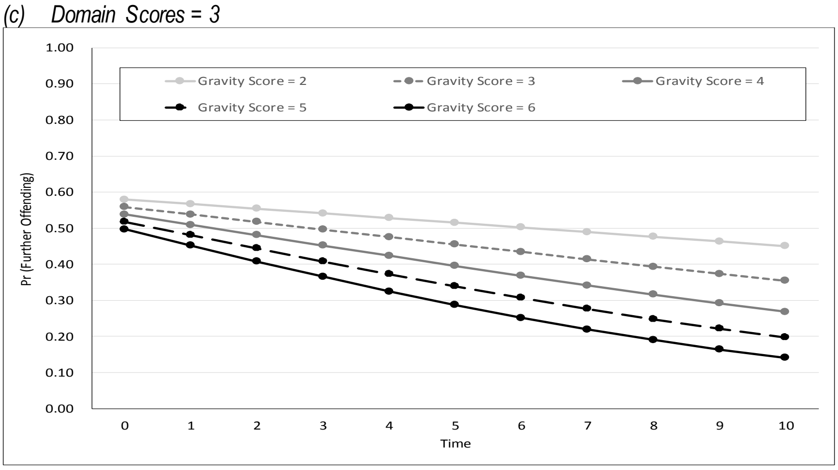
(a) Domain Scores = 1



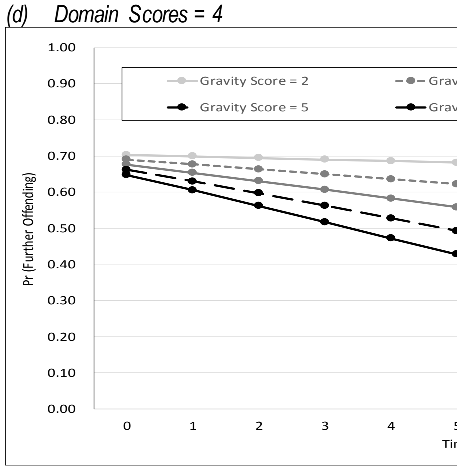
(b) Domain Scores = 2



(c) Domain Scores = 3



(d) Domain Scores = 4



6.5 A Combined Model Involving Offending History

Ideally, if there were sufficient data to support it, the combined model would involve measures reflecting all four of the static factors. However, it has been necessary to compromise. The following dynamic model therefore utilises:

- Grouped Age at First Offence – a dichotomous variable
- FTE Status – a dichotomous variable
- Seriousness of the Offence (I_Seriousness2) – a continuous variable

Version 1

From Model 3b (summarised in Table 6.15), it has been established that is possible to simulate estimates for the interactions between *FTE: G_ageFirst, FTE: I_Seriousness2*, and *G_ageFirst: I_Seriousness2*. This knowledge has been used to inform the specification of a combined model:

```
BDm3G_cc12o2a <- MCMCglmm(FO.bin~FTE*time*live + FTE*time*relation +
FTE*time*ete + FTE*time*where + FTE*time*life + FTE*time*drugs +
FTE*time*physical + FTE*time*emotion + FTE*time*self +
FTE*time*think + FTE*time*attitude + FTE*time*change +
G_ageFirst*time*live + G_ageFirst*time*relation +
G_ageFirst*time*ete + G_ageFirst*time*where + G_ageFirst*time*life +
G_ageFirst*time*drugs + G_ageFirst*time*physical +
G_ageFirst*time*emotion + G_ageFirst*time*self +
G_ageFirst*time*think + G_ageFirst*time*attitude +
G_ageFirst*time*change +
I_Seriousness2*time*live + I_Seriousness2*time*relation +
I_Seriousness2*time*ete + I_Seriousness2*time*where +
I_Seriousness2*time*life + I_Seriousness2*time*drugs +
I_Seriousness2*time*physical + I_Seriousness2*time*emotion +
I_Seriousness2*time*self + I_Seriousness2*time*think +
I_Seriousness2*time*attitude + I_Seriousness2*time*change +
FTE*G_ageFirst + FTE*I_Seriousness2 + G_ageFirst*I_Seriousness2,
random=~time+Research.ID,data=data3, family="ordinal", prior=priorD,
nitt=40000000, thin=10000, burnin=30000)
```

As can be seen from the resulting output (Technical Annex, p228-250), the Raftery-Lewis diagnostic suggests that the required number of iterations should be at least 48 million (rather than 56 million). However, in order to deal with the autocorrelation within the model, the thinning needs to be increased to 50,000. In order to achieve this level of thinning and achieve the minimum effective sample size, the number of iterations would need to be increased to 188 million. This is not feasible to run as it will take over a week.

The plots do not point to any significant issues, nor does the overall effective sample size of 3,997. However, closer inspection of the model summary highlights that the effective sample size for some of the estimates is notably lower. For example, the effective sample size for 'self' as a main effect is 599.7 whereas that for I_Seriousness2 is 531.8. Additionally, the effective sample size for some of the estimates for the interactions e.g. *FTE: Time* and *I_Seriousness: Relation* are even lower at 459.5 and 424.1 respectively. This reiterates the need to consider the autocorrelation not just of the random effects, but also the fixed effects in the model.

Whilst the DIC of 294.7 indicated the potential of this model, the wide credible intervals around many of the individual estimates suggest that it would not be possible to use this to determine the probability of further offending.

Version 2

In accepting that there is insufficient data to simulate models based on a series of all three measures, these have been considered in pairs. For example, the first of these involves a series of interaction between FTE, time and the 12 domains; G_ageFirst, time and the 12 domains; and an interaction between FTE and G_ageFirst:

```
BDm3G_cc12  <-  MCMCglmm(FO.bin~FTE*time*live  +  FTE*time*relation  +
FTE*time*ete + FTE*time*where + FTE*time*life + FTE*time*drugs +
FTE*time*physical + FTE*time*emotion + FTE*time*self +
FTE*time*think + FTE*time*attitude + FTE*time*change +
G_ageFirst*time*live + G_ageFirst*time*relation +
G_ageFirst*time*ete + G_ageFirst*time*where + G_ageFirst*time*life +
G_ageFirst*time*drugs + G_ageFirst*time*physical +
G_ageFirst*time*emotion + G_ageFirst*time*self +
G_ageFirst*time*think + G_ageFirst*time*attitude +
G_ageFirst*time*change + FTE*G_ageFirst,
random=~time+Research.ID,data=data3, family="ordinal", prior=priorD,
nitt=20000000, thin=5000, burnin=3000)
```

Equivalent models have also been run involving:

- FTE Status and YJB Gravity Score (BDm3_cc1o2a)
- Grouped Age at First Offence and YJB Gravity Score (BDm3G_cc2o2a)

The output from these models can be found in the Technical Annex on pages 251-302. Of the 3 models, it is BDm3G_cc12 i.e. the model specified above which has the lowest DIC.

Model	Static Factors in Model	DIC
BDm3G_cc12	FTE and Grouped Age at First Offence	391.2
BDm3_cc1o2a	FTE and YJB Gravity Score	432.8
BDm3G_cc2o2a	Grouped Age at First Offence and YJB Gravity Score	434.8

An examination of the output and plots from the dynamic model involving FTE and I_Seriousness2 (BDm3G_cc1o2a) suggests that there are no notable issues in terms of convergence or the effective sample sizes, that is the estimates for the number of independent samples (taking into account autocorrelations) generated by the MCMC run. Although, the effective sample size of 3,537 for the estimate for the interaction between FTE, Time and Drugs falls below 3,746, this is the only effective sample size to do this.

It was necessary to run the dynamic model involving G_ageFirst and I_Seriousness2 (BDm3G_cc2o2a) for slightly longer than for BDm3G_cc1o2a in order to meet the criteria for the various convergence diagnostics. Although an effective sample size of 4,997 was achieved by simulating a model with 5 million iterations, with a thinning of 1,000 and burn-in of 1000, the resulting output indicates that the effective sample size for the interaction between Neighbourhood (Where) and Time is the only one to fall below 3,746.

Version 3

Whilst acknowledging that this represents a compromise since there is insufficient data to support a more complex version, this model builds upon BDm3G_cc12 to include 2-way interactions between:

- I_Seriousness2 and Time
- G_ageFirst and I_Seriousness2
- FTE and I_Seriousness2

Whilst this model does not include any interactions between the 12 domains and I_Seriousness2, the inclusion of these interactions does enable some of the potential uncertainty around the seriousness of the primary offence to be explored. As a result, three out of the four proxies for the static factors are included.

To address the autocorrelation, it is necessary to set the thinning to 2,000 and increase the burn-in to 5,000. The resulting model requires at least 7,497,000 iterations (3,746 x 2,000 plus 5,000). To ensure that the sample size is sufficient, 8 million iterations were run. The output from the various convergence diagnostics can be found in the Technical Annex, pages 303-321. The model is summarised in Table 6.20 and for convenience, is renamed as BDm3.

Table 6.20: Dynamic Model 3

	Dynamic Basic Model including FTE Status and Grouped Age at First Offence with 2-way Interactions involving YJB Gravity Score (BDm3G_cc12_o2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-5.151	-11.164	0.570	0.006	0.000	1.769	
YJB Gravity Score (zero = 2) (Seriousness)	0.085	-1.265	1.478	1.089	0.282	4.384	
First Time Entant (No = Ref) (FTE)	-4.720	-14.578	4.547	0.009	0.000	94.371	
Grouped Age at First Offence (10-12 = Ref)	5.144	-1.234	11.585	171.444	0.291	1.07E+05	
Time	0.201	-0.725	1.139	1.223	0.484	3.125	
Living Arrangements (Live)	-0.674	-2.386	0.979	0.510	0.092	2.663	
Family and Personal Relationships (Relation)	2.671	0.384	4.840	14.454	1.468	126.427	Yes
Education, Training and Employment (ETE)	-1.092	-2.650	0.443	0.335	0.071	1.557	
Neighbourhood (Where)	0.480	-0.870	1.758	1.616	0.419	5.802	
Lifestyle (Life)	2.513	0.199	4.968	12.348	1.221	143.695	Yes
Substance Use (Drugs)	-0.447	-2.009	1.270	0.640	0.134	3.561	
Physical Health (Physical)	-1.160	-2.987	0.611	0.314	0.050	1.842	
Emotional and Mental Health (Emotion)	-0.472	-1.889	1.008	0.624	0.151	2.741	
Perceptions of Self and Others (Self)	-6.736	-10.171	-3.456	0.001	0.000	0.032	Yes
Thinking and Behaviour (Think)	1.840	-0.618	4.406	6.296	0.539	81.908	
Attitude to Offending (Attitude)	2.819	-0.321	6.040	16.757	0.725	419.973	
Motivation to Change (Change)	1.065	-1.535	3.995	2.901	0.215	54.335	
Seriousness: FTE	0.509	-0.709	1.936	1.664	0.492	6.931	
Seriousness: Grouped Age at First Offence	-0.673	-2.241	0.841	0.510	0.106	2.320	
Seriousness: Time	0.042	-0.080	0.161	1.042	0.923	1.175	
FTE: Grouped Age at First Offence	4.642	-4.263	13.741	103.803	0.014	9.29E+05	
FTE: Time	-1.046	-2.577	0.474	0.351	0.076	1.606	
FTE: Live	1.080	-1.841	4.083	2.944	0.159	59.300	
FTE: Relation	-0.025	-2.811	2.747	0.976	0.060	15.602	
FTE: ETE	1.228	-1.147	3.682	3.416	0.318	39.706	
FTE: Where	-4.412	-7.223	-1.939	0.012	0.001	0.144	Yes
FTE: Life	2.334	-1.050	5.869	10.316	0.350	353.918	
FTE: Drugs	-0.964	-3.505	1.834	0.382	0.030	6.261	
FTE: Physical	1.310	-1.556	4.124	3.707	0.211	61.798	
FTE: Emotion	-0.687	-2.927	1.532	0.503	0.054	4.628	
FTE: Self	2.151	-0.632	4.936	8.597	0.532	139.230	
FTE: Think	-2.604	-5.332	0.132	0.074	0.005	1.141	
FTE: Attitude	-3.706	-6.715	-1.076	0.025	0.001	0.341	Yes
FTE: Change	3.256	0.291	6.521	25.958	1.338	679.214	Yes
Grouped Age at First Offence: Time	-0.587	-1.873	0.828	0.556	0.154	2.289	
Grouped Age at First Offence: Live	1.274	-1.152	3.454	3.575	0.316	31.641	
Grouped Age at First Offence: Relation	-4.090	-7.298	-1.260	0.017	0.001	0.284	Yes
Grouped Age at First Offence: ETE	0.332	-1.547	2.373	1.394	0.213	10.735	
Grouped Age at First Offence: Where	1.478	-0.591	3.579	4.383	0.554	35.836	
Grouped Age at First Offence: Life	-2.416	-5.930	0.777	0.089	0.003	2.174	
Grouped Age at First Offence: Drugs	0.358	-1.860	2.531	1.430	0.156	12.566	
Grouped Age at First Offence: Physical	-1.260	-3.939	1.431	0.284	0.019	4.182	
Grouped Age at First Offence: Emotion	0.170	-1.771	2.323	1.186	0.170	10.202	
Grouped Age at First Offence: Self	8.071	4.001	12.025	3.20E+03	54.646	1.67E+05	Yes
Grouped Age at First Offence: Think	-0.318	-3.186	2.640	0.727	0.041	14.016	
Grouped Age at First Offence: Attitude	-0.362	-4.096	3.347	0.696	0.017	28.413	
Grouped Age at First Offence: Change	-3.297	-6.840	0.087	0.037	0.001	1.091	

/ continued

	Dynamic Basic Model including FTE Status and Grouped Age at First Offence with 2-way Interactions involving YJB Gravity Score (BDm3G_cc12_o2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Time: Live	-0.143	-0.517	0.258	0.867	0.596	1.294	
Time: Relation	-0.519	-1.013	-0.013	0.595	0.363	0.987	Yes
Time: ETE	0.208	-0.114	0.528	1.231	0.893	1.696	
Time: Where	-0.193	-0.461	0.085	0.824	0.631	1.089	
Time: Life	-0.528	-1.055	0.039	0.590	0.348	1.040	
Time: Drugs	0.340	0.020	0.701	1.405	1.021	2.015	Yes
Time: Physical	0.327	-0.118	0.756	1.387	0.888	2.130	
Time: Emotion	0.373	0.076	0.676	1.452	1.078	1.965	Yes
Time: Self	1.472	0.820	2.191	4.357	2.271	8.945	Yes
Time: Think	-0.366	-0.842	0.068	0.693	0.431	1.071	
Time: Attitude	-0.859	-1.421	-0.282	0.423	0.241	0.754	Yes
Time: Change	0.099	-0.413	0.605	1.105	0.661	1.830	
FTE: Time: Live	-0.593	-1.354	0.139	0.552	0.258	1.149	
FTE: Time: Relation	-0.083	-0.805	0.602	0.920	0.447	1.826	
FTE: Time: ETE	0.434	-0.227	1.116	1.544	0.797	3.052	
FTE: Time: Where	0.606	0.102	1.065	1.833	1.108	2.900	Yes
FTE: Time: Life	-0.526	-1.400	0.338	0.591	0.246	1.402	
FTE: Time: Drugs	0.695	0.066	1.285	2.004	1.068	3.615	Yes
FTE: Time: Physical	-0.920	-1.851	-0.108	0.398	0.157	0.897	Yes
FTE: Time: Emotion	0.498	-0.122	1.135	1.646	0.885	3.111	
FTE: Time: Self	-0.807	-1.497	-0.160	0.446	0.224	0.852	Yes
FTE: Time: Think	0.854	0.141	1.529	2.348	1.152	4.615	Yes
FTE: Time: Attitude	1.087	0.331	1.922	2.965	1.393	6.833	Yes
FTE: Time: Change	-0.987	-1.799	-0.236	0.373	0.165	0.789	Yes
Grouped Age at First Offence: Time: Live	0.325	-0.283	0.940	1.384	0.754	2.561	
Grouped Age at First Offence: Time: Relation	1.049	0.391	1.773	2.855	1.479	5.890	Yes
Grouped Age at First Offence: Time: ETE	-0.308	-0.807	0.198	0.735	0.446	1.219	
Grouped Age at First Offence: Time: Where	-0.004	-0.432	0.433	0.996	0.649	1.541	
Grouped Age at First Offence: Time: Life	0.358	-0.464	1.198	1.430	0.629	3.313	
Grouped Age at First Offence: Time: Drugs	-0.622	-1.204	-0.151	0.537	0.300	0.860	Yes
Grouped Age at First Offence: Time: Physical	0.554	-0.233	1.365	1.741	0.793	3.917	
Grouped Age at First Offence: Time: Emotion	-0.593	-1.183	-0.023	0.553	0.306	0.977	Yes
Grouped Age at First Offence: Time: Self	-1.562	-2.374	-0.739	0.210	0.093	0.478	Yes
Grouped Age at First Offence: Time: Think	-0.163	-0.820	0.494	0.850	0.440	1.639	
Grouped Age at First Offence: Time: Attitude	0.106	-0.695	0.908	1.112	0.499	2.479	
Grouped Age at First Offence: Time: Change	0.654	-0.129	1.402	1.923	0.879	4.064	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	7.37	1.133	15.09	1.59E+03	3.105	3.58E+06	Yes
Time	13.280	1.636	31.540	5.85E+05	5.135	4.98E+13	Yes

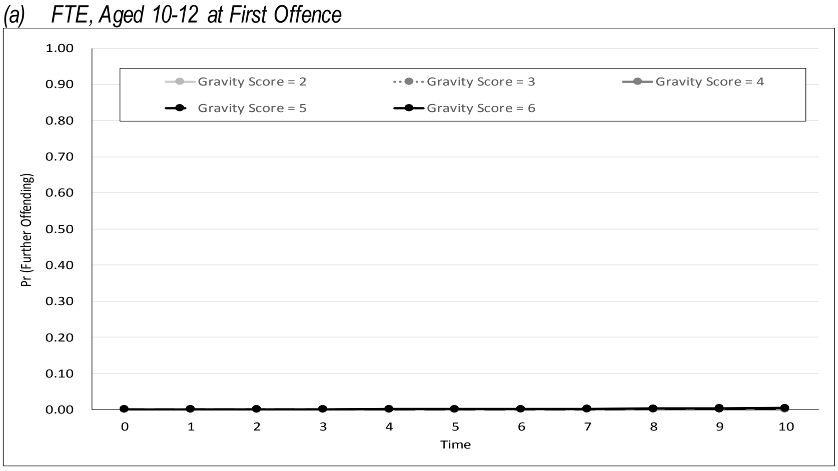
DIC	387.89

Source: Model BDm3G_cc12_o2, renamed as BDm3, Technical Annex: p303-321

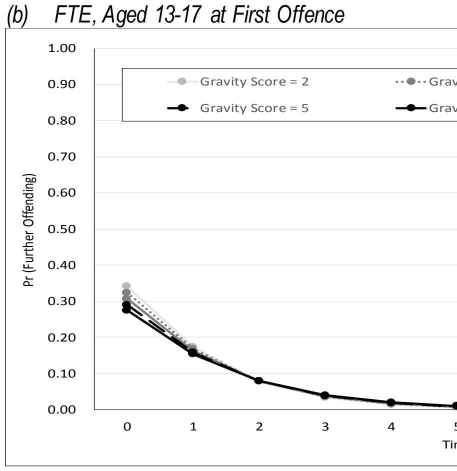
With a DIC of 387.9, this model appears to represent an improvement upon Model BDm3G_cc12. However, inclusion of I_Seriousness and the 2-way interactions involving Time, FTE and G_ageFirst does not appear to address the amount of uncertainty around the estimates for FTE and G_ageFirst both as main effects and the interaction between the two. The credible interval around the coefficient for the perception of self and others (Self) is also particularly wide as is the interval around the coefficient for the interaction *G_ageFirst: Self*. When the estimated probabilities of further offending are calculated, the implications of this become more apparent.

Figure 6.16: Change in the Probability of Further Offending Over Time, Dynamic Model 3

(a) FTE, Aged 10-12 at First Offence

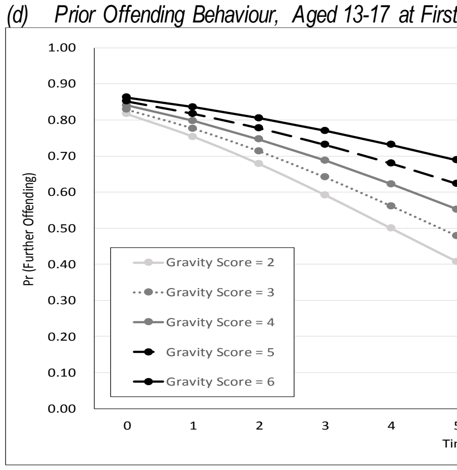


(b) FTE, Aged 13-17 at First Offence



(c) Prior Offending Behaviour, Aged 10-12 at First Offence

(d) Prior Offending Behaviour, Aged 13-17 at First



The very low probabilities of further offending amongst FTEs who were aged 10-12 at the time of their first offence (Figure 6.15(a)) are a reflection of the underlying data - there were just 3 cases within the dataset who shared these characteristics. None of these committed further offences hence the initial probability of further offending being zero, regardless of the seriousness of the primary offence.

Amongst FTEs who were aged 13-17 at the time of their first offence, the initial probability of further offending is higher amongst those who committed primary offences with a lower gravity score – a trend apparent in the dynamic model involving YJB Gravity Score, (BDm3_o2a, summarised in Table 6.19 and Figure 6.14). After Time 2, there is little difference in the downward trajectory of the estimates of probability for each YJB Gravity Score, approaching a probability of zero by Time 7. Amongst the 30 cases which shared these characteristics, the further offending rate was 36.7% (11/30).

Two-thirds (68%, 13/19) of those who had committed their first offence when aged 10-12 but had a history of prior offending at the time of entering the reoffending cohort was involved in further offending behaviour. Figure 6.15(c) summarises the estimates of the probability of further offending over time for this sub-group. Notably the initial probabilities of further offending are very low (as for FTEs aged 10-12, Figure 6.15(a)). However, the longer the individual is in contact with the youth justice system, the higher the estimated probability of further of further offending. Once more, the estimated probabilities of further offending are higher for lower gravity scores.

Just over half (51%, 18/35) of those with a prior offending history, who had been aged 13-17 at the time of their first offence committed further offences. What stands out in the summary of the estimated probabilities of further offending for this group is that at each measurement point, is that they are higher for the higher gravity scores. As time increases, the probabilities of further offending fall and hence this is quite different to the trend seen in Figure 6.15(c) for the younger group. The trend in Figure 6.15(d) is more in keeping with what would be expected if the premise that as a result of working with the YOT, the risk of further offending is mediated.

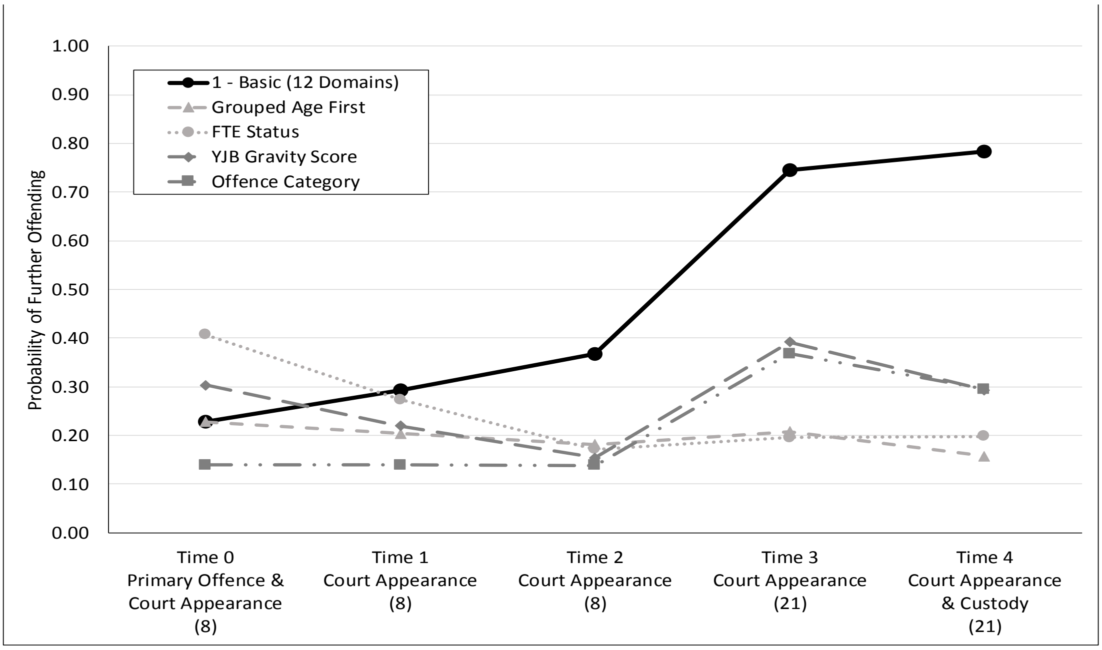
6.6 How do the models involving static factors reflect the realities of real lives?

The following section returns once more to the examples of Fred, David and Connor, to consider how the estimates of their respective probabilities of further offending based on (1) the individual dynamic models summarised in section 6.4, (2) the permutations considered under Version 2 and (3) the combined model involving the three static factors. In each instance these are compared to the estimates generated by the Basic Dynamic Model (BDm1, summarised in Table 4.12).

Case Study "Fred"

"Fred" is a white male who was an FTE at the time of entering the reoffending cohort. He committed his first offence aged 14, receiving his first conviction at age 15. The offence which led to his inclusion in the reoffending cohort was a criminal damage offence (Gravity Score = 2). This type of offence falls within the 'Other' offence category. Using this information along with the domain scores from each ASSET, the following estimates of probability of further offending have been calculated from the individual dynamic models:

Figure 6.17: Comparisons of the Estimated Probability of Further Offending Over Time – Individual Dynamic Models: "Fred"

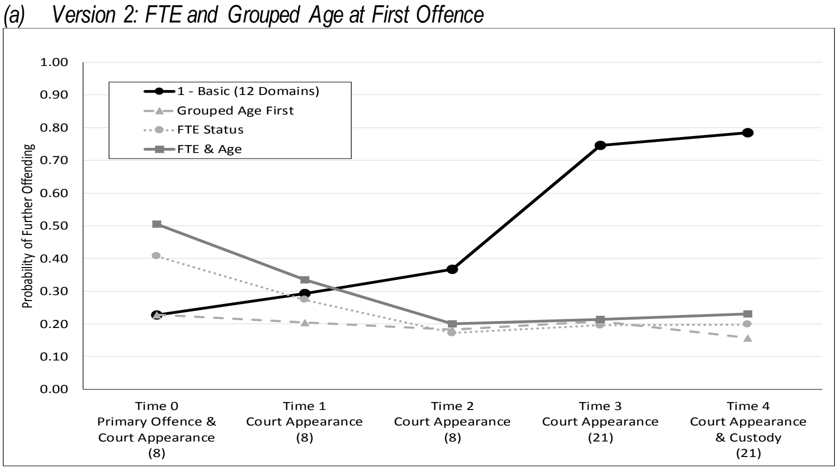


Source: BDm3_cc1 (FTE Status), BDm3G_cc2 (Grouped Age at First Offence), BDm3G_o1 (Grouped YJB Offence Category) and BDm3_o2a (YJB Gravity Score) along with BDm1.

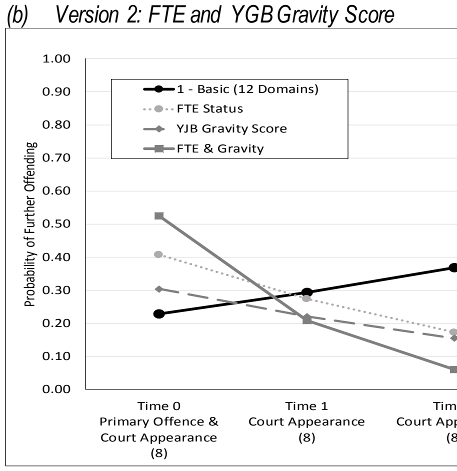
The four models result in quite different estimates for Fred's initial probability of further offending, one of which is the same as that resulting from the Basic Dynamic model based on the 12 domains. Those for FTE status and the YJB Gravity Score are higher. However, by Time 1, all are lower than the estimate from the Basic Dynamic Model. They fell again by Time 2.

Figure 6.18: Changes in the Probability of Further Offending Over Time: "Fred"

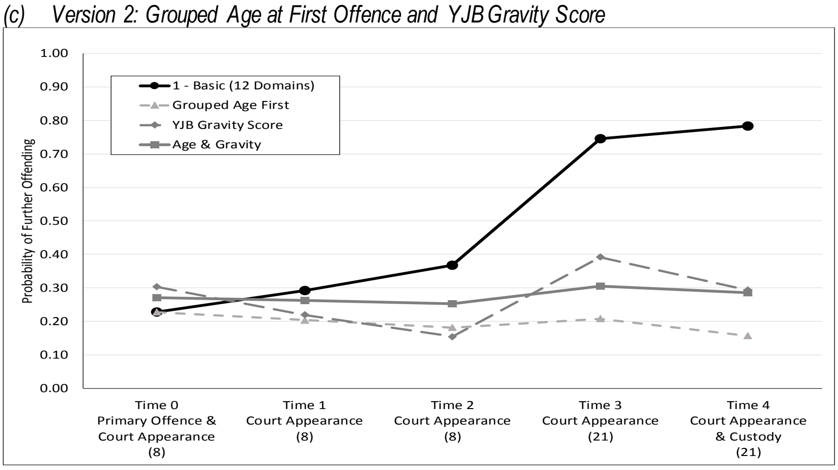
(a) Version 2: FTE and Grouped Age at First Offence



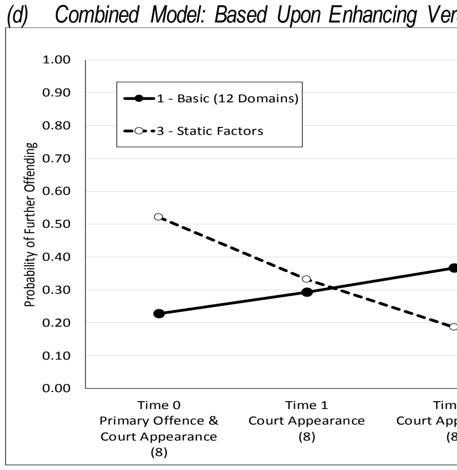
(b) Version 2: FTE and YGB Gravity Score



(c) Version 2: Grouped Age at First Offence and YJB Gravity Score



(d) Combined Model: Based Upon Enhancing Ver



Between Time 2 and Time 3, Fred was on ISSP Bail and Tag, and he attended court four times. His ASSET score increased from 8 to 21. This increase is reflected in the estimates based on the models involving the YJB Gravity Score and Offence Category, whereas the models involving Grouped Age at First Offence and FTE status do not. Fred was sentenced to custody a week after this assessment at Time 3. Hence during the intervening period, there was little opportunity for the individual domain scores to alter. However, whereas the Basic Dynamic Model suggests an increase in Fred's probability of further offending, the dynamic models involving YJB Gravity Score, Offence Category and Grouped Age at First Offence show a downward trend between Time 3 and Time 4.

Of the three models specified under Version 2, it is notable that those involving FTE status in combination with another static factor (summarised in Figures 6.16(a) and (b)) result in higher initial probabilities of further offending then the dynamic models based on the static factors individually.

The model involving both Grouped Age at First Offence and YJB Gravity Score (Figure 6.15(c)) reflects the increase in ASSET scores between Time 2 and 3 and corresponding increase in the probability of further offending that would be expected as a result of this, although not to the extent suggested by the Basic Dynamic Model. The other models do not show this.

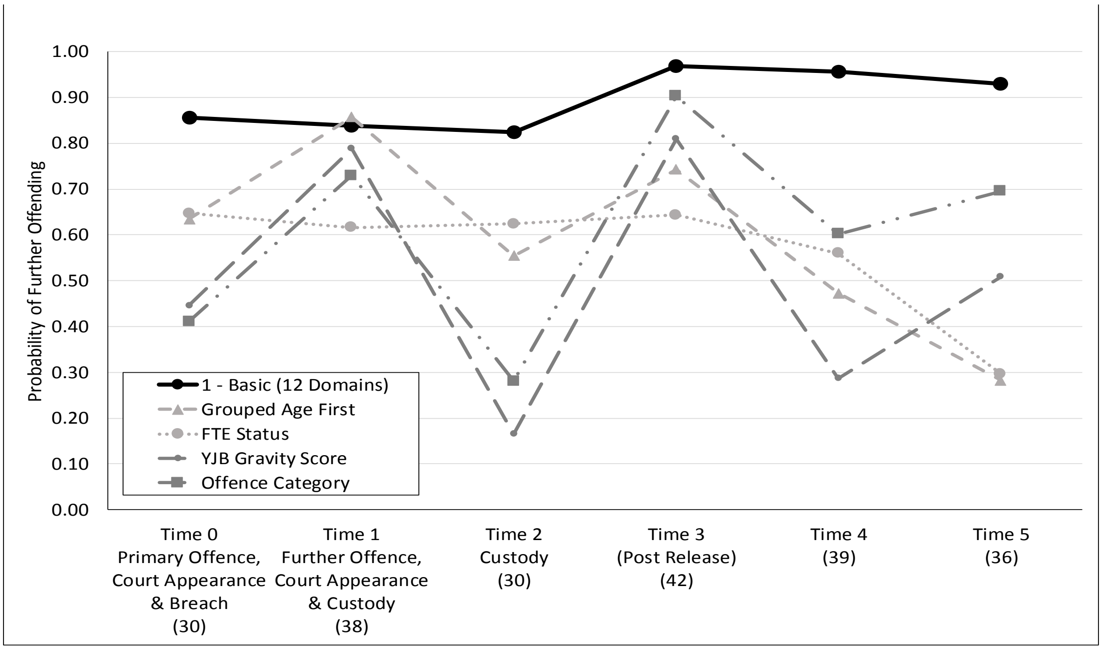
Given that the combined model (Figure 6.15(d)) is an enhanced version of that summarised in Figure 6.15(a), the trajectories for the estimated probabilities of further offending over time based upon Fred's domain scores are very similar.

Case Study "Connor"

"Connor" was also aged 14 at the time of his first offence. However, unlike Fred, he had been identified as a prolific offender prior to entering the 2012/13 reoffending. Connor's primary offence was a burglary (Gravity Score = 6), and therefore is categorised as a serious acquisitive crime. Using this information along with Connor's domain scores at each measurement point, it is possible to determine the estimated probabilities of further offending over time based on each model involving static factors. Figure 6.19 summarises the probabilities of further offending based on the individual dynamic static factors.

The initial probabilities arising from each individual dynamic model are lower than those suggested by the Basic Dynamic Model, with those simulated by the models involving FTE Status and YJB Gravity Score being the lowest. As time progresses, the estimated probabilities of further offending suggested by these two models is perhaps the most erratic.

Figure 6.19: Comparisons of the Estimated Probability of Further Offending Over Time – Individual Dynamic Models: "Connor"



Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with Connor having a total of 30 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that his primary offence (for the purposes of this exercise where the information has been taken from the reoffending spreadsheet) was a non-domestic burglary and as a result of his prior convictions.

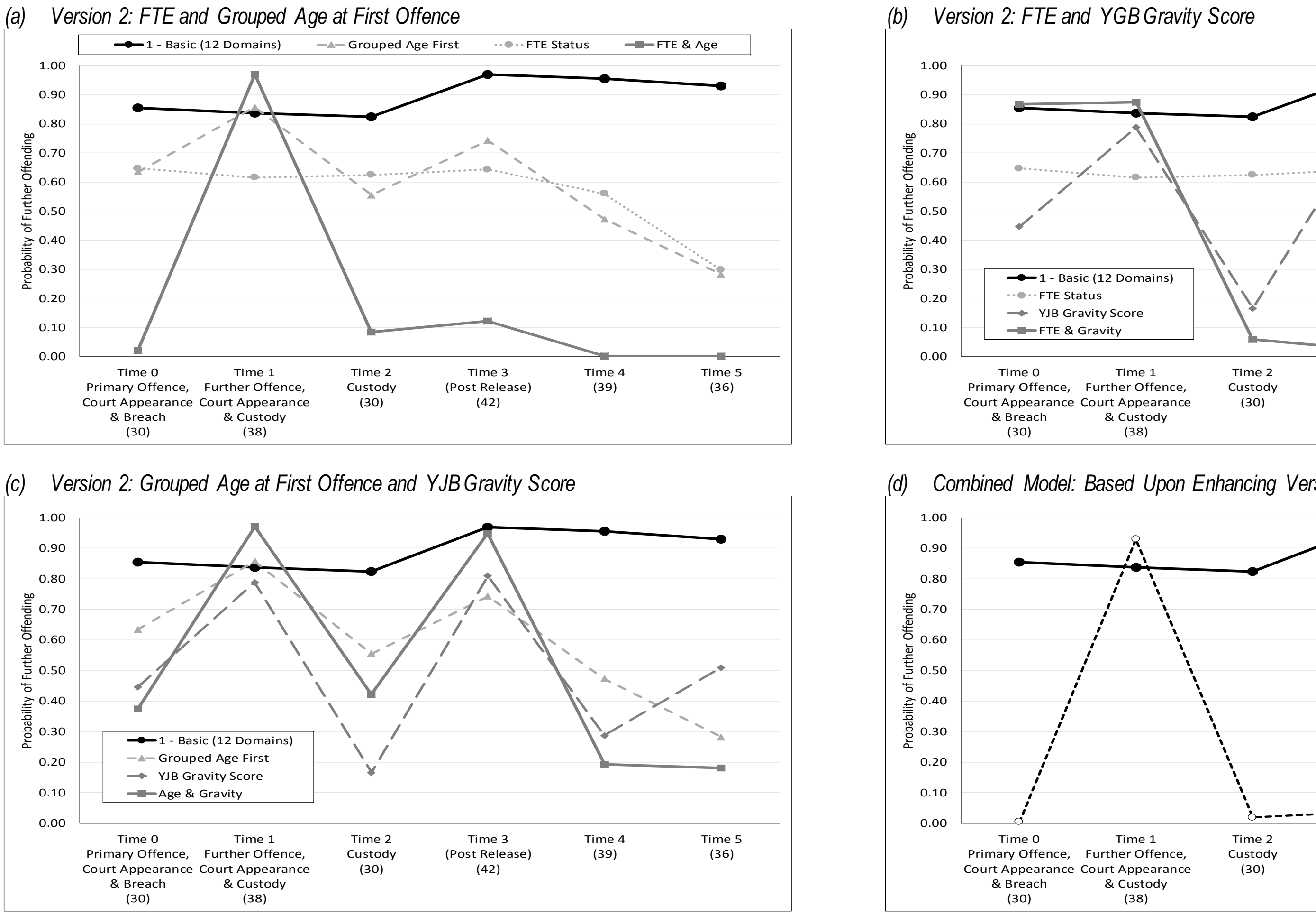
Connor committed a further offence prior to his assessment at Time 1. The estimated probabilities simulated by the individual dynamic models involving Grouped Age at First Offence, YJB Gravity Score and Offence Category increase – something which is not apparent with the Basic Dynamic model despite the increase in Connor's total ASSET scores (from 30 to 38).

The assessment undertaken at Time 2 coincided with when Connor was in custody. Once more the estimated probabilities of further offending based on the models involving Grouped Age at First Offence, YJB Gravity Score and Offence Category fell. Connor's total ASSET score at Time 2 was the same as that for Time 0. However, the estimated probabilities of further offending were lower, potentially an impact of the moderating effect of time.

Post release (Time 3) all the models, including the Basic Dynamic Model and that involving FTE Status suggest an increase in the risk of further offending. This is as hypothesised and will be explored further in Chapter Seven.

Of the individual models, it is the dynamic model involving FTE Status which potentially most closely follows the shape of that for the Basic Dynamic Model although the drop off between Times 3 and 5 is steeper and at each measurement point, the estimated probabilities of further offending are notably lower.

Figure 6.20: Changes in the Probability of Further Offending Over Time: "Connor"



When FTE Status is included alongside another static factor as in Figures 6.20(a) and (b), the resulting set of estimated probabilities are the furthest away from the shape of the Basic Dynamic Model and the individual dynamic models. Significantly the initial estimated probability for Connor simulated by the model involving both FTE Status and Grouped Age of First Offence (Figure 6.20(a)) is very low which does not fit with the level of perceived level of risk as determined by his key worker, with his non-compliance (the breach) or identified status as a prolific offender. Whilst the initial probability of further offending is higher in the other models generated in Version 2, these also does not appear to fit Connor's profile particularly well.

All three of the Version 2 models (Figures 6.20(a), (b) and (c)) suggest that Connor's probability of further offending at the time when he committed a further offence (Time 1) was approaching 1.0. This is also the case with the combined model (Figure 6.20(d)). Three of the four models involving two or more static factors suggest that whilst Connor was in custody (Time 2), his likelihood of further offending is close to zero despite his ASSET score being 30. This also seems unlikely raising further questions about the how well the various models reflect the realities of real lives.

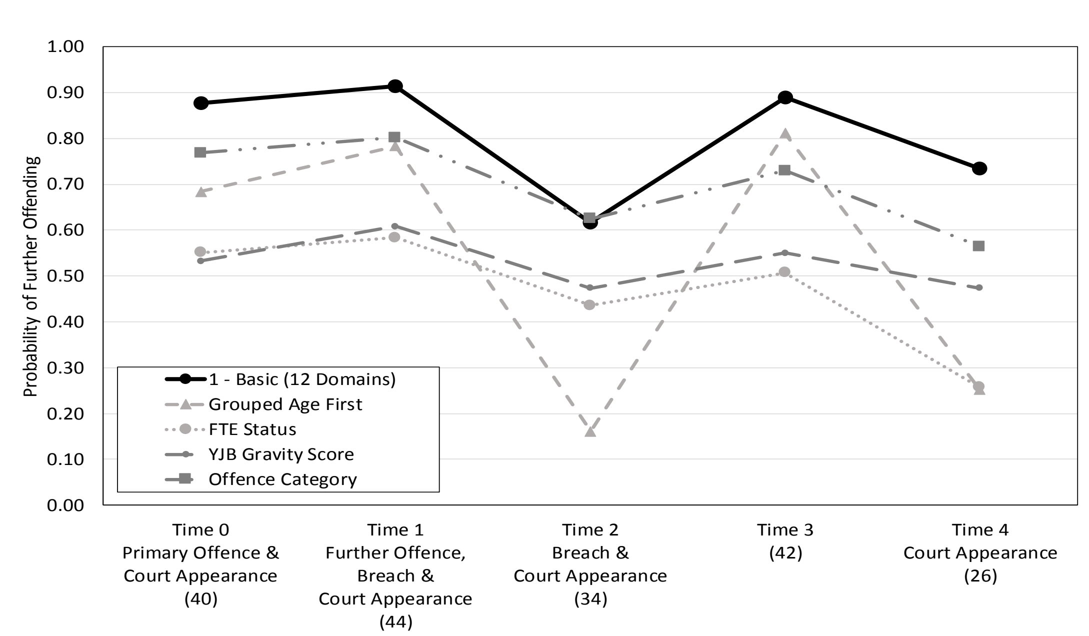
Particularly in the case of the combined model (Figure 6.20(d)), Connor's very low estimated probability of further offending post-release - when he was considered to have a high risk of further offending i.e. an ASSET score greater than 25 – additionally does not appear to be realistic. A similar trend is also apparent in the three models involving FTE Status (Figures 6.20(a), (b) and (d). However, it should be noted that despite the high score, Connor did not commit any further offences during the remainder of his time under the supervision of the YOT.

Case Study "David"

"David" has a history of prior offending behaviour, having committed his first offence at age 10. He became part of the reoffending cohort having committed a public order offence – an 'Other' offence with a Gravity Score of 2. The respective trajectories of the probability of David committing further offences based on the models involving the individual static factors have a similar shape with 'peaks' at Time 1 and Time 3 when David's ASSET scores were highest (Figure 6.21).

Of the three case studies, David has the highest initial ASSET score. Whilst the Basic Dynamic model did not suggest a significant difference in the initial probability of further offending between Connor (30, Figure 6.19) and David (40), an inspection of the individual dynamic models suggest that these all reflect David's higher ASSET score. Both David and Connor's sets of initial probabilities are also higher than those for Fred who had an opening ASSET score of 8 (Figure 6.17).

Figure 6.21: Comparisons of the Estimated Probability of Further Offending Over Time – Individual Dynamic Models: "David"



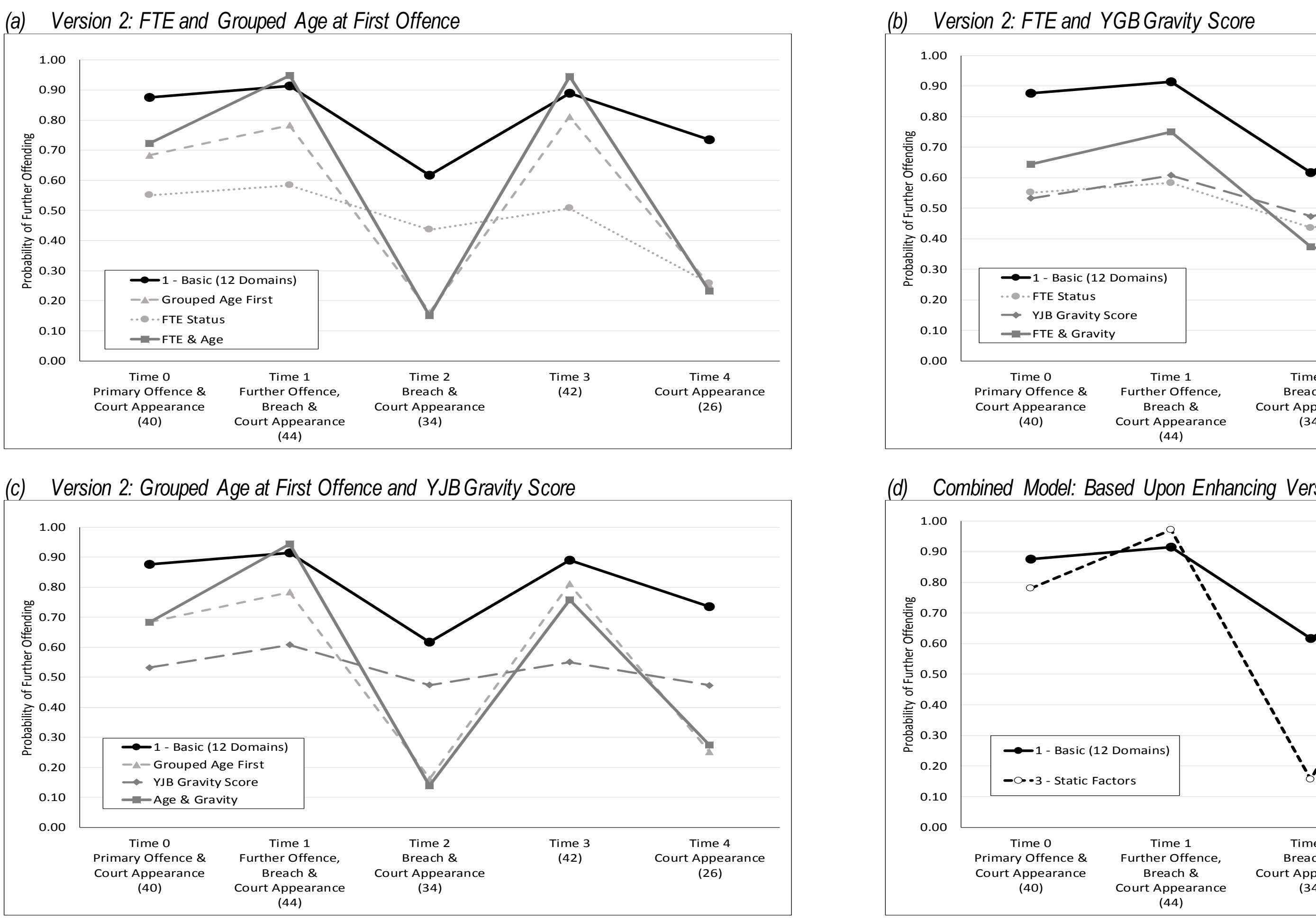
Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with David having a total of 40 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that he was aged 10 at the time of his first Reprimand and as a result of his prior convictions.

The models involving Grouped Age at First Offence and a further static factor suggest that David's probability of further offending was higher than that suggested by the Basic Dynamic model at Time 1. This corresponds to an increase in his ASSET score from 40 to 44, and when he committed a further offence, breached and consequently returned to court. Mirroring the trend apparent in the Basic Dynamic model, David's probability of further offending fell between Time 1 and 2. However, this decline is more pronounced in the models involving Grouped Age at First Offence (Figures 6.22(a) and (C)).

Notably the model involving FTE and YJB Gravity Score (Figure 6.22(b)) is the only one to not reflect an increase as a result of David's ASSET score then increasing to 42 at Time 3. The model involving both Grouped Age at First Offence and FTE Status suggests a probability of further offending which is approaching 1. However, whilst David's circumstances changed (as discussed in section 4.4), he did not commit a further offence, nor did he breach. During the following 8 months, David's ASSET score reduced to 26 with the probability of further offending also falling during this period. The court appearance at Time 4 for a breach of his YRO. However, this was withdrawn.

Given that the combined model has been constructed by enhancing the dynamic model involving Grouped Age at First Offence and FTE Status, it is not surprising that the estimated probabilities of offending over time are identical. Having centred the YJB Gravity Score at 2, this means that for David's public order offence (Gravity Score = 2), there is no additional 'penalty' for the seriousness of the offence.

Figure 6.22: Changes in the Probability of Further Offending Over Time: "David"



As with BDm2, it is not possible to measure the predictive accuracy of the combined dynamic model involving static factors. However, the observations made when utilising the ASSET scores of these three individuals does highlight some of its limitations. Notably, these arise from the amount of uncertainty surrounding the coefficients for FTE and Grouped Age at First Offence as main effects and the interaction between these two predictors.

6.7 Increasing the Sensitivity of the Model by Extending the Predictors

Whilst acknowledging that the combined model (BDm3) represents a compromise as there is not sufficient data to support a 'full' model involving proxies for all four of the static factors, this section considers the potential for increasing the sensitivity of the model by extending the predictors. This is done in the following ways:

- Treating the age-related predictors as continuous rather than dichotomous
- Revisiting the way in which the nature and severity of the offence is taken into account

Treating AgeFirst as a Continuous Predictor

Until now, age at first offence has been treated as being a dichotomous predictor, referenced by the younger age group. However, age can also be treated as being continuous, ranging from 10 – the age of criminal responsibility, and 17. Table 6.21 summarises the dynamic model involving the continuous predictor centred at age 10.

Table 6.21: The Dynamic Model Involving Age at First Offence

	Dynamic Basic Model including Age at First Offence (Bm3_cc2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-2.530	-5.688	0.408	0.080	0.003	1.504	
Age at First Offence (0 = 10 years)	0.297	-0.368	0.939	1.346	0.692	2.557	
Time	0.221	-0.397	0.807	1.247	0.672	2.242	
Living Arrangements (Live)	-0.109	-1.406	1.077	0.896	0.245	2.936	
Family and Personal Relationships (Relation)	1.607	0.207	3.022	4.985	1.229	20.528	Yes
Education, Training and Employment (ETE)	-0.409	-1.571	0.718	0.664	0.208	2.051	
Neighbourhood (Where)	0.252	-0.766	1.219	1.286	0.465	3.384	
Lifestyle (Life)	0.536	-1.115	2.142	1.710	0.328	8.516	
Substance Use (Drugs)	0.606	-0.579	1.692	1.834	0.561	5.432	
Physical Health (Physical)	-0.474	-1.602	0.703	0.623	0.201	2.019	
Emotional and Mental Health (Emotion)	-0.361	-1.405	0.673	0.697	0.245	1.960	
Perceptions of Self and Others (Self)	-2.082	-3.784	-0.323	0.125	0.023	0.724	Yes
Thinking and Behaviour (Think)	0.351	-1.242	1.997	1.421	0.289	7.370	
Attitude to Offending (Attitude)	0.445	-1.325	2.281	1.561	0.266	9.784	
Motivation to Change (Change)	0.170	-1.430	1.822	1.185	0.239	6.182	
Age at First Offence: Time	-0.140	-0.312	0.025	0.869	0.732	1.025	
Age at First Offence: Live	0.027	-0.289	0.366	1.027	0.749	1.442	
Age at First Offence: Relation	-0.364	-0.717	-0.012	0.695	0.488	0.988	Yes
Age at First Offence: ETE	0.021	-0.262	0.315	1.021	0.769	1.371	
Age at First Offence: Where	-0.046	-0.320	0.208	0.955	0.726	1.231	
Age at First Offence: Life	-0.052	-0.458	0.370	0.949	0.632	1.447	

/continued

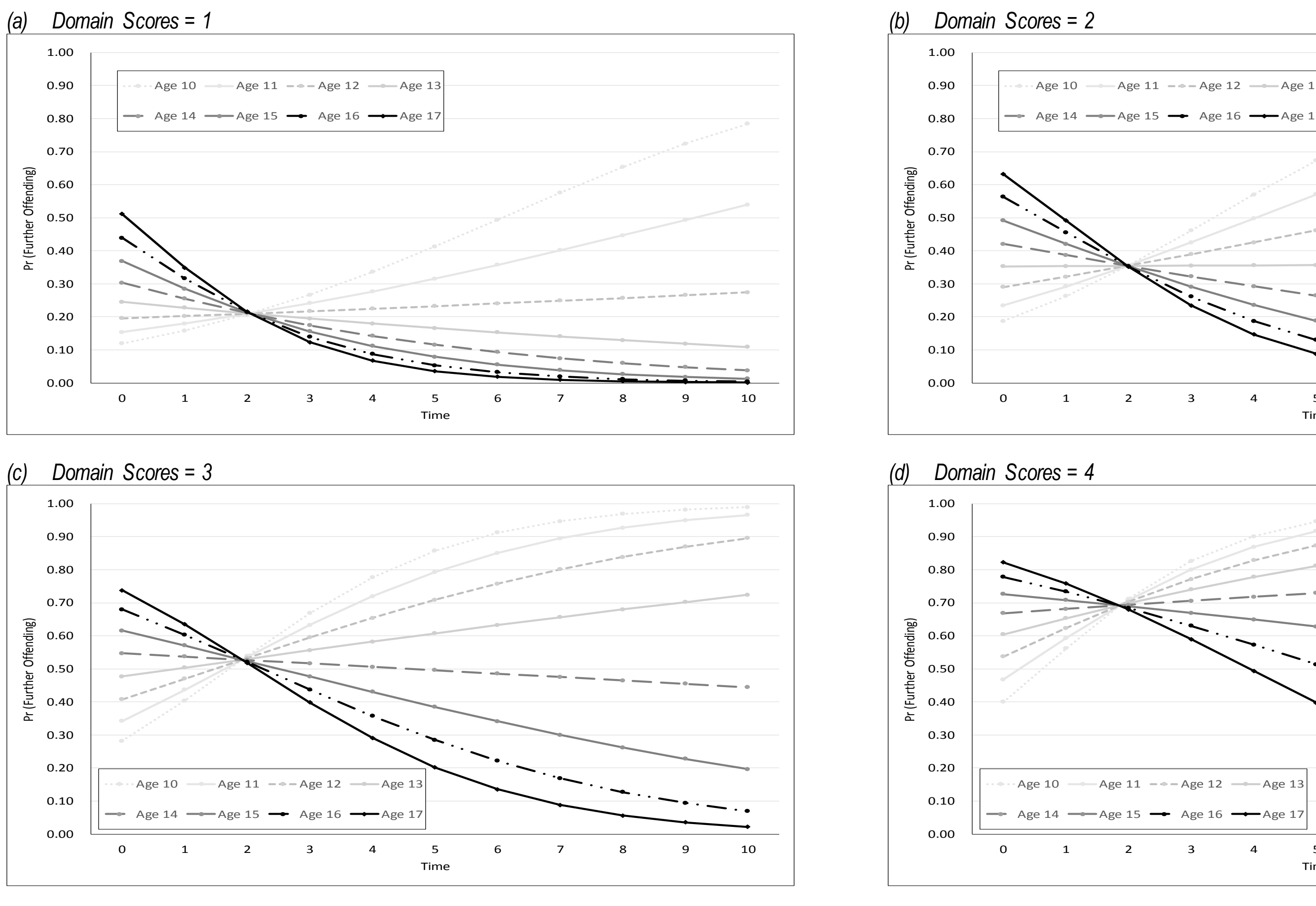
	Dynamic Basic Model including Age at First Offence (Bm3_cc2)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Age at First Offence: Drugs	-0.086	-0.376	0.196	0.918	0.687	1.216	
Age at First Offence: Physical	-0.047	-0.364	0.259	0.954	0.695	1.295	
Age at First Offence: Emotion	0.006	-0.265	0.292	1.006	0.767	1.339	
Age at First Offence: Self	0.666	0.238	1.116	1.947	1.268	3.053	Yes
Age at First Offence: Think	-0.123	-0.543	0.267	0.884	0.581	1.306	
Age at First Offence: Attitude	-0.020	-0.471	0.421	0.981	0.624	1.524	
Age at First Offence: Change	0.014	-0.448	0.451	1.014	0.639	1.570	
Time: Live	-0.075	-0.351	0.197	0.928	0.704	1.217	
Time: Relation	-0.361	-0.703	-0.020	0.697	0.495	0.980	Yes
Time: ETE	0.008	-0.254	0.270	1.008	0.776	1.310	
Time: Where	-0.043	-0.246	0.168	0.958	0.782	1.183	
Time: Life	0.014	-0.353	0.402	1.014	0.702	1.494	
Time: Drugs	-0.115	-0.381	0.117	0.892	0.683	1.124	
Time: Physical	0.233	-0.064	0.518	1.262	0.938	1.678	
Time: Emotion	0.115	-0.125	0.362	1.122	0.882	1.436	
Time: Self	0.515	0.153	0.903	1.673	1.165	2.467	Yes
Time: Think	-0.157	-0.482	0.170	0.855	0.618	1.185	
Time: Attitude	-0.096	-0.451	0.252	0.908	0.637	1.286	
Time: Change	0.071	-0.278	0.424	1.074	0.758	1.528	
Age at First Offence: Time: Live	0.031	-0.048	0.104	1.031	0.953	1.110	
Age at First Offence: Time: Relation	0.093	-0.002	0.181	1.098	0.998	1.199	
Age at First Offence: Time: ETE	0.032	-0.044	0.113	1.033	0.957	1.120	
Age at First Offence: Time: Where	0.019	-0.038	0.076	1.019	0.962	1.079	
Age at First Offence: Time: Life	-0.024	-0.130	0.086	0.977	0.878	1.090	
Age at First Offence: Time: Drugs	0.030	-0.045	0.105	1.031	0.956	1.111	
Age at First Offence: Time: Physical	-0.019	-0.102	0.065	0.981	0.903	1.067	
Age at First Offence: Time: Emotion	0.002	-0.073	0.076	1.002	0.930	1.079	
Age at First Offence: Time: Self	-0.183	-0.293	-0.083	0.833	0.746	0.920	Yes
Age at First Offence: Time: Think	0.040	-0.046	0.127	1.041	0.955	1.136	
Age at First Offence: Time: Attitude	-0.008	-0.109	0.092	0.992	0.896	1.096	
Age at First Offence: Time: Change	-0.016	-0.116	0.090	0.984	0.890	1.094	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.66	6.91E-07	1.53	1.938	1.000	4.609	Yes
Time	2.768	0.576	5.972	15.927	1.778	392.289	Yes

DIC	465.27

Source: Model BDm3_cc2, Technical Annex: p322-334.

As with previous dynamic models, the trajectory of the probability of further offending over time has been determined for each year from age 10 to 17. Figure 6.23 summarises these trajectories where the domain scores are fixed at 1, 2, 3 and 4 respectively. These charts suggest that that at Time 0, younger children have a lower probability of further offending than those who are older supporting the trend apparent in Figure 6.5.

Figure 6.23: Changes in the Probability of Further offending Over Time, by Age at First Offence

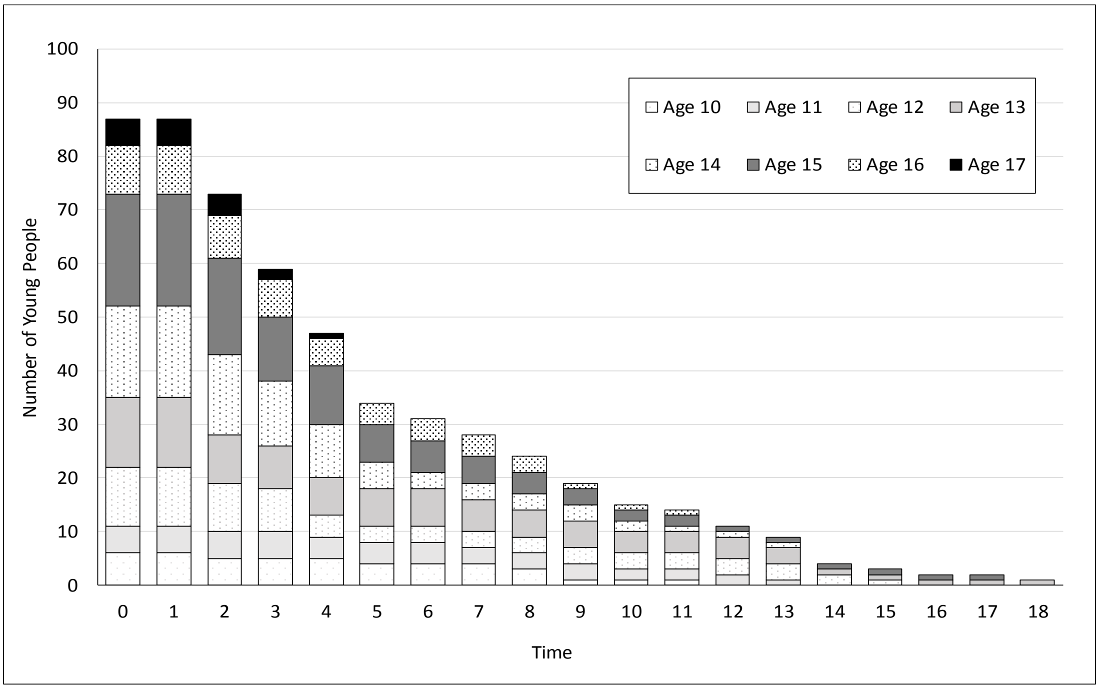


Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of fu
derived from Model BDm3_cc2.

For those under 12 who have lower domain scores, the probability of offending appears to increase, the longer they spend under the supervision of the YOT. This also appears to be the case for those aged 13 or 14 at the time of their first Offence who had higher domain scores. Particularly after Time 2, the number in remaining in the cohort whose ASSETs have been used to determine the fixed effects in the model fall. As a result, later estimates of the probability of further offending are less reliable.

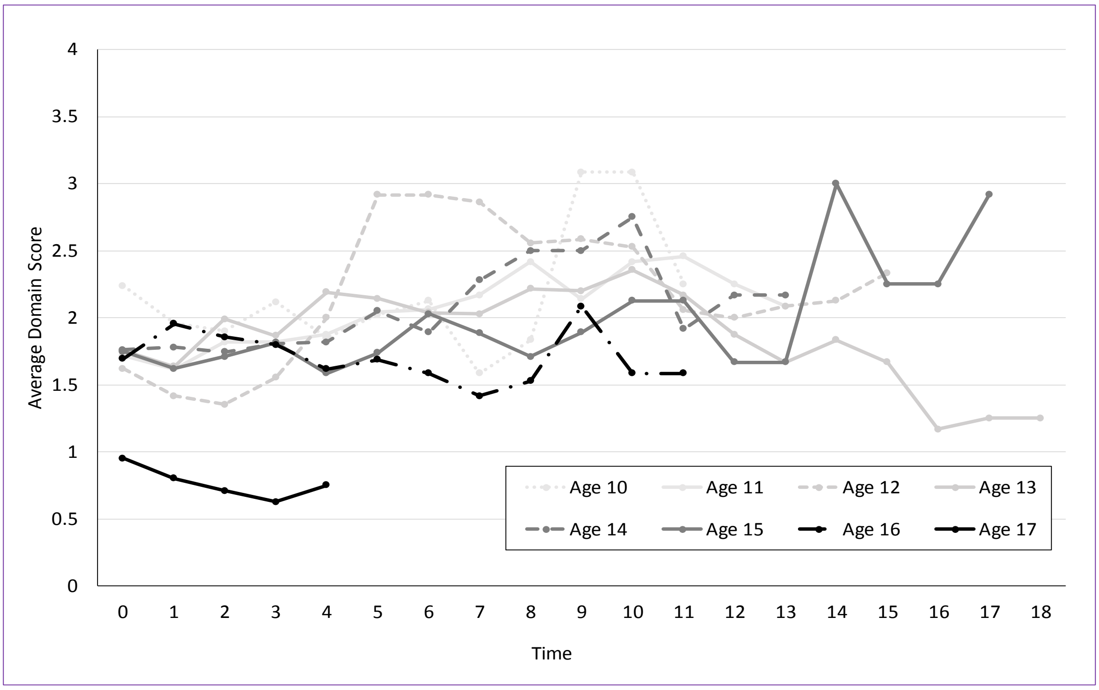
The probability of further offending for those aged 14 or over suggest a gradual downward trend, more like those seen in Figure 6.14 (the dynamic model involving YJB Gravity Scores). Despite those who are older at the time of their first offence having higher initial probabilities of further offending at Time 0, 17-year olds have a greater rate of decline than those aged 14. This trend can be observed where the domain scores are fixed at 1, 2 and 3. When the domain scores are fixed at 4, those aged 14 appear to have an upwards trajectory. It is likely that this apparent trend has resulted from the small number of cases that these estimates are based upon (Figure 6.24).

Figure 6.24: Summary of Average Domain Scores, by Age at First Offence (Trend in Cohort Size)



Notably there are only 5 young people whose first offence was at age 17. By Time 3, the number in the sub-group had fallen to 2 with one person having their final ASSET for Time 4. As a result, the amount that 17-year olds can contribute to the model is quite limited. Of the 9 young people aged 16 at the time of their first offence, there was just one person who was risk assessed after Time 8. Hence the mean domain score for 16-year olds at Times 9 to 11 is based on just one person (Figure 6.25).

Figure 6.25: Summary of Average Domain Scores, by Age at First Offence (Trend in Mean Scores)



At the other end of the age range, there were 6 young people who were aged 10 at the time of their first offence with one individual having 12 ASSETs (T=11). The last 3 observations for 10-year olds are based on just this individual. There were 5 young people whose first offence was at age 11. All but the last average domain score (at Time 11) is based on more than one ASSET.

Of the two dynamic models involving age at first offence, the one involving the grouped predictor has the lower DIC suggesting that it accounts for more uncertainty (448.73 compared to 465.27 for the continuous predictor). However, what is not clear is the extent to which the model with the continuous predictor is paying a penalty for having increased complexity. This is something that would only become apparent if there was more data with which to run the model.

Treating AgeCon as a Continuous Predictor

Theoretically it would also have been possible to treat the age at first conviction as a continuous predictor. However, as identified in Section 6.3, there are insufficient cases in the reoffending cohort to support a dynamic version of the model involving this predictor.

Further to this, Table 6.3 highlights that there would also be issues arising from multicollinearity between the two continuous age-related predictors should they be combined in the same model. Multicollinearity arises when there is a very high correlation between two or more predictor variables. Although overall the Pearson's correlation between the two age–related continuous predictors is 0.651 (CI = 0.502, 0.753, BF_{10} = 1.222e[9]), then the data is split on the basis of FTE Status, it suggests that the R_{Prior} = 0.554 (CI = 0.325, 0.760, BF_{10} = 1660) whilst R_{FTE} = 0.823 (CI = 0.642, 0.904, BF_{10} = 3.066e[6]). The consequence of multicollinearity is that 'the posterior distribution will say that a very large range of parameter variables are plausible, from tiny associations to massive ones, even if all the variables are in reality strongly associated with the outcome variable' (McElreath, 2016: 141-142).

Although overall the level of correlation is not that high, within this dataset, 63.6% (21/33) of the FTEs had been convicted of their first offence hence their age at first offence and age at first conviction was the same. Amongst those with a prior offending history the proportion was 14.8% (8/54), meaning that across the cohort the proportion was 33.3% with a further 28.7% having a 1-year difference (although this could be due to them having their birthday in the time between committing the offence and attending court).

The Raftery Lewis diagnostic suggests that to achieve convergence in a combined dynamic model involving the static factors where both age at first offence and age at first conviction are continuous, more than 150 million iterations would be required with a substantial burn-in. To address the autocorrelation within the model, it would be necessary to set the lag to at least 50,000. This is not feasible to run.

Nature and Seriousness of the Primary Offence

Table 6.22 summarises the profile of the cohort on the basis of the nature of their primary offence illustrating why it has been necessary to group the offence categories. As highlighted in Section 3.6, using a predictor based on the seriousness of the offence means that it is possible to differentiate between for example violence against the person offences which can vary in severity as well as potentially enabling inferences to be made about offences which fall under YJB Categories for which there are no cases within the dataset.

Table 6.22: The Re-Offending Cohort, by Grouped YJB Category and Seriousness of Primary Offence

Grouped YJB Offence Category	YJB Gravity Score					Total
	2	3	4	5	6	
Other	31	15	1	1		48
SAC		1	4	3	10	18
VAP		14	4		3	21
Grand Total	**31**	**30**	**9**	**4**	**13**	**87**

Notes: The individual whose FTE status is not known has been excluded from this summary.

Table 6.23: The Basic Model plus Grouped YJB Offence Category and Gravity Score

	Model 1.11: Basic Model + Grouped YJB Offence Category and YJB Gravity Score						
	Unstandardised			**Standardised**			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.229	-3.390	0.781	0.293	0.034	2.183	
Grouped YJB Offence Category (*Ref = Other*)							
Serious Acquisitive Crime	0.865	-1.911	3.481	2.376	0.148	32.493	
Violence Against The Person	1.313	-1.087	4.067	3.718	0.337	58.396	
YJB Gravity Score (Serious)	-0.015	-0.663	0.587	0.985	0.516	1.799	
Living Arrangements	0.047	-0.241	0.315	1.048	0.786	1.370	
Family and Personal Relationships	0.253	-0.055	0.575	1.288	0.947	1.778	
Education, Training and Employment	0.065	-0.194	0.340	1.067	0.824	1.404	
Neighbourhood	0.064	-0.190	0.288	1.066	0.827	1.333	
Lifestyle	0.049	-0.321	0.411	1.050	0.725	1.509	
Substance Use	0.207	-0.039	0.486	1.230	0.962	1.626	
Physical Health	-0.115	-0.422	0.192	0.891	0.656	1.212	
Emotional and Mental Health	0.022	-0.229	0.282	1.022	0.795	1.326	
Perceptions of Self and Others	-0.142	-0.496	0.178	0.868	0.609	1.195	
Thinking and Behaviour	-0.166	-0.521	0.174	0.847	0.594	1.190	
Attitude to Offending	0.029	-0.343	0.391	1.029	0.710	1.479	
Motivation to Change	0.213	-0.139	0.567	1.238	0.870	1.763	
Time	-0.177	-0.324	-0.025	0.838	0.723	0.975	Yes
Serious: SAC	-0.130	-0.910	0.623	0.878	0.402	1.864	
Serious: VAP	-0.316	-1.155	0.562	0.729	0.315	1.754	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.287	1.22E-07	0.720	1.332	1.000	2.055	Yes
Time	1.607	0.376	3.364	4.988	1.456	28.905	Yes

DIC	473.56

Source: Model Bm1G_o12a, Technical Annex: p335-336.

There is insufficient data to run a dynamic model involving both the type and seriousness of the primary offence. However, where these two predictors have been included alongside the basic model (Model 1.11), it suggests that all other things being equal, at Time 0:

- Relative to a young person with domain scores of 2 who has committed an 'Other' offence with a gravity score of 3, the odds of further offending are estimated to be 1.6 times higher if they had committed an equivalent serious acquisitive crime. The odds are 1.4 times higher if they commit an equivalent violence against the person offence.
- Comparing equivalent offences with a gravity score of 4, the odds of further offending are lowest if that offence is an 'Other' offence. Relative to this, the odds of further offending are estimated to be 1.4 times higher if the young person has committed a serious acquisitive crime but only 1.05 times higher if they committed a violent offence.

It is also possible to estimate the impact of committing a more serious offence within each offence type. Based once again upon equivalent young people with domain scores of 2, at Time 0:

- The odds of further offending are on average 1.02 times higher amongst those who committed an 'Other' offence with gravity score of 3, than for those who committed an equivalent offence with a gravity score of 4.
- Violence against the person: the odds of further offending appear to increase as the gravity score decreases. Relative to a VAP offence with a gravity score of 4, the odds of further offending are estimated to be 1.4 times higher amongst those who committed an offence with a gravity score of 3.
- Serious acquisitive crime: the odds of further offending appear to increase as the gravity score increases. Relative to a SAC offence with a gravity score of 3, the odds of further offending are estimated to be 1.16 times higher amongst those who committed an offence with a gravity score of 4.

Had there been sufficient data to support the model, it is anticipated that the trajectories of the probability of further offending as time progresses would be quite different. Published data suggests that amongst those who reoffend, the time to reoffence can differ significantly (Youth Justice Board and Ministry of Justice, 2016). As with reoffending rates, there is evidence to suggest that this varies by index offence, number of previous convictions and age (Owen and Cooper, 2013).

6.8 How do these findings extend the evidence base?

Static Factors

It is notable that in the individual dynamic and combined models involving FTE and Grouped Age at First Offence, there is a lot of uncertainty around the estimates for the static factors both as main effects and when in an interaction. In the combined model the estimated unstandardised coefficients are:

- FTE, -4.720 [-14.578, 4.547]. *In BDm3_cc1, the estimate is 0.995 [-1.668, 3.660]*
- G_ageFirst, 5.144 [-1.234, 11.585]. *In BDm3G_cc2, the estimate is 2.340 [-0.928, 5.488]*
- FTE:G_ageFirst, 4.642 [-4.263, 13.741]

This uncertainty is associated with the comparatively low number of cases, and particularly the fact that none of those who were FTEs aged 10-12 committed any further offences (Table 6.24). With just three individuals within this sub-group, there is little information, especially at later measurement points, which can be used to inform the estimates of the probability of further offending.

Table 6.24: The Reoffending Cohort by FTE Status and Grouped Age at First Offence, with Further Offending Rates

		Grouped Age at First Offence		Total
		10-12 years	13-17 years	
FTE Status	Prior Offending	68% (13/19)	51% (18/35)	57% (31/54)
	FTE	0% (0/3)	37% (11/30)	33% (11/33)
Total		59% (13/22)	45% (29/65)	48% (42/87)

The amount of uncertainty around the estimated coefficients suggests that the other predictors in the models i.e. time, the 12 domains and, in the case of the combined model, the YJB Gravity Score, do not adequately explain the amount of variation. Potential explanations include the role of gender, ethnicity and experience of care. However, there may be other factors which are not measured as part of the risk assessment process. As seen in Chapter Five, there was insufficient data within the reoffending cohort to explore these more fully.

The variable representing FTE status was constructed as a proxy measure for the number of previous convictions. Previous research by Wilson and Hinks (2011) identified that relative to having no previous convictions, having 1-3 convictions decreased the odds of proven reconviction by a factor of 0.44. However, it was not possible to calculate the odds ratio for those who had 4+ convictions due to a high correlation with age at first conviction. Given the practical difficulties in establishing the number of prior convictions from the offence and court records within Childview, the pragmatic decision was made to use a binary indicator to reflect the young person's status at the time of entering the reoffending cohort. For those appearing on both the 2012/13 and 2013/14 reoffending spreadsheets, their status was taken at the time of the primary offence in 2012/13. This leads to a small number of seemingly contradictory trends at an individual level.

The trajectory of the predicted probability of further offending for FTEs makes very little distinction at Time 0 on the basis of the domain scores (Figure 6.4(a)) – reflecting the difficulties in predicting further offending for those who have little previous contact with the youth justice system. In contrast practitioners will know more about those with a prior offending history. Having this knowledge enables the YOT to make a more informed judgement about the likelihood of re-offending based on the individual circumstances of the young person. For both groups the trajectory suggested for those who pose the greatest risk (reflected by fixing the domain scores at 4) is upwards which is contrary to what would be expected. However, the reality is that there are no young people who at any time were judged to have a total ASSET score of 48 although there are four who at different times had scores greater than or equal to 40, with the maximum total score being 44.

A notable feature of the underlying data is that due to the emphasis on those who are in the formal youth justice system and hence have been assessed using the Core ASSET Profile, many of those aged 10-12 at the time of their first offence already have a history of prior offending. Indeed, of the twenty-two young people within this younger group, just three were FTEs. Whilst two had had no previous contact with the YOT. They did however, commit a further offence within just a couple of weeks of the first and as a result were sentenced for both offences as the same time. Thus, differences in their age at the time of their first offence and conviction reflect only the time that the case took to get to court. However, the third young person had previously had informal action taken against him for an offence committed when aged 12 but was not convicted of an offence until he was aged 15. This meant that he was an FTE at the time of entering the cohort having not previously committed any proven offences. This scenario exposes a weakness in the construction of the predictor.

Under the Scaled Approach, those receiving their first reprimand, caution or warning aged 10-12 had 4 added to their total ASSET score. In translating this to also reflect the situation post-LASPO, I opted to use a wider definition whereby the age at first offence was used, drawing information from the offence and court records held within Childview. This meant that a small number who were known to the YOT as a result of having informal action taken against them or receiving a Youth Restorative Disposal – typically meaning that they had been subject to Swansea's Bureau proceedings, have similar inconsistencies in their age at first offence and FTE status. This had unintended implications in the analysis given the comparatively low numbers in the dataset especially at later measurement points.

From the basic model involving YJB Gravity Score (Bm1_o2a) it is unclear how the likelihood of further offending is affected by an increase in the seriousness of the primary offence, with the credible interval for the standardised coefficient straddling one. However, in the equivalent basic model which additionally involves FTE Status, Grouped Age at First Offence and interactions with seriousness, the role of YJB Gravity Score becomes more apparent. The significant positive coefficient (Bm1G_cc12o2a, 0.334 [0.017, 0.647]) suggests that increasing the seriousness of the offence, will increase the likelihood of further offending. Whilst it was not possible to simulate an estimate for the interaction for G_ageFirst: Seriousness, the model suggests that at Time 0, with all domain scores set at 2, the impact of increasing the YJB Gravity Score from 2 to 3 increases the probability of further offending:

- For those with a history of prior offending (the reference category for FTE Status), aged 10-12 at the time of their first offence from 0.502 to 0.585 i.e. the odds are increased by 16.5%
- For those with prior offending, aged 13-17 at the time of their first off offence the probability increased from 0.421 to 0.504 i.e. the odds increased by 19.6%
- For FTEs aged 10-12, having committed an offence with a YJB Gravity Score of 3 rather than 2, the likelihood of further offending increased from 0.271 to 0.499 i.e. the odds increased by 84.2%
- For FTEs aged 13-17, the impact of increasing the YJB Gravity Score was that their odds of further offending increased by 43.5% (from a probability of 0.212 at Time 0 to 0.304 if they had committed a primary offence with a gravity score of 3).

Whilst the figures presented to not represent the trend over time and are somewhat artificial in that they assume that of the domain scores are fixed at 2, they appear to support the rationale for diversionary activities which in the case of Swansea tend to be used with those who have committed low level offences, particularly where there is less evidence of a pattern of offending behaviour. By keeping these young people out of the formal youth justice system, it avoids the negative aspects of system contact, especially the stigma associated with labelling theory. Sadly, when this model was transformed into a dynamic model (BDm3, summarised in Table 6.20), there was insufficient data to support the additional complexity. As a result, it was not possible to explore this more fully.

The dynamic model involving Grouped YJB Offence Category (BDm3G_o1) was set up with Other offences as the reference category. It is notable that there is a lot of uncertainty around the estimate for SAC offences (1.924 [-2.331, 6.124]) and VAP offences (-4.070 [-10.078, 1.331]), with neither being significant. Where interactions occur, particularly between VAP and the individual domains, there is also a fair amount of uncertainty. For example, the positive significant interaction between *VAP: Life* (3.032 [0.437, 5.904]) and that between *VAP: Think* (2.361 [-0.712, 5.592]). There is more certainty when VAP and the individual domains interact with time, with those involving ETE and Where being positive whilst those involving Life and Think are negative. There is less certainty around the estimates for interactions involving SAC.

It is important to remember that the VAP offences, whilst largely less serious in nature e.g. Common Assault and Actual Bodily Harm (ABH), do include a small number of serious violent offences such as Grievous Bodily Harm (GBH) which attract a much higher Gravity Score. In contrast, the majority of Other offences are less serious in nature with Gravity Scores of 2 (65%, 31/48) and 3 (31%, 15/48). Without knowing the circumstances of the individual offences or events leading up to the assault, it is difficult in the case of the VAP offences to know if these acts of violence were one-off's or part of a prolonged pattern of aggressive behaviours. The implication being that those demonstrating aggressive behaviours being likely to be referred to interventions which are intended to help them to address their anger management issues, and potentially have recommendations within their order which limit who they can associate with. As a result, you would expect to see an improvement in their behaviour over time hence the negative estimate for the interaction between *VAP: Time: Life*. These types of interventions will also include work to help the young person understand the impact of their behaviour on others, and as a result, this would also be reflected in their scores within the Thinking and Behaviours domain.

Where aggressive and disruptive behaviour has involved in school settings, potentially directed at other pupils or staff, this can result in the young person being excluded. In keeping with the RNR approach placing the young person in alternative provision or arranging a place on a training course, typically has a moderating effect on their risk of further offending behaviour. Within the dynamic model (BDm3G_o1), this is reflected by the significant positive interaction between *VAP: Time: ETE* and the significant negative interaction between *VAP: ETE.* This is also consistent with the views of practitioners and those who have been assessed that ETE and a lack of training / qualifications are related to reoffending (Youth Justice Board, 2005a) which were raised in section 4.3. However, it also highlights that responses to youth crime need to be tailored according to the nature and seriousness of the offence committed. In this respect it is disappointing that there was insufficient data to develop a model which included both YJB Offence Category and YJB Gravity Score so that this could be explored further.

Domain Scores

In the context of this element of the research, it is notable the Lifestyle domain is significant in the dynamic model involving the grouped predictor for age at first offence (BDm3G_cc2, 1.856 [0.105, 3.643]) and the combined dynamic model for offending history where the model also includes the grouped predictor for age at first offence (BDm3, 2.636 [0.219, 5.213]). This finding does not hold where the predictor for age at first offence is continuous (BDm3_cc2, 0.536 [-1.115, 2.142]. The positive coefficients suggest that as the rating for Lifestyle increases by 1, then the probability of further offending increases. However, this is mediated by the interaction between *Time: Lifestyle* (BDm3G_cc2, -0.419 [-0.817, -0.016]) with the negative coefficient suggesting that as time progresses this impact decreases.

One of the features of this domain is that it reflects participation in a broader range of reckless activities including those which place the young person and/or others at risk of physical injury (e.g. playing on railway lines, building sites or major roads, and racing cars around residential areas); activities done to impress others or to get a 'buzz'; and involving other in their offending. As the data collection process did not drill down to the responses to the 'Yes' / 'No' questions completed by the practitioners as part of the assessment process, it is not possible to ascertain the extent to which these are features of the young people's lives as Baker et al. (2003) did in their first published review of ASSET. However, it is notable that at Time 0, 73.9% (65 out of 87) where judged to be at significant risk of reoffending as a result of their Lifestyle with practitioners assigning ratings of 2 or more. This was one of the highest proportions with only the proportion deemed at significant risk as a result of their Thinking and Behaviours being higher (76.1%). The other domain with similar proportions considered to be at significant risk at Time 0 was Family and Personal Relationships (73.9%).

Given that two of the four examples of high ratings given by the YJB for the Lifestyle domain (Youth Justice Board, 2008a: 10-11) relate to co-offending – a well-documented criminological phenomenon, it is notable that there is also evidence to suggest that the prevalence of co-offending also varies by age. Carrington (2015) for example, has explored the structure of age homophily in co-offending groups through consideration of the mean age differences. His results indicate a strong age homophily in the population which decreases with increasing age of co-offenders. However, the trend is structured within four aggregated age groups, the first three of which are bounded by the age of criminal responsibility and criminal majority in Canada i.e. between 12 and 18 years. Pertinent to this research is the finding that youth (12-17 year olds) were found to have the strongest and most narrowly defined age homophily, tending to co-offend with others who were within a year or so of their own age. Those aged 3 to 11 years were also found to exhibit strong age homophily, but their co-offending was less narrowly age-exclusive and more dispersed among members of their own aggregated age group, regardless of their specific age.

Kivivuori (2007) asserts that there is a distinct, but related type of offending: crime by proxy where the offender commits the crime *for* someone rather than *with* someone. In exploring whether or not shoplifting is a proxy crime and addressing fears in Finland that adolescents who were criminally culpable were coercing those younger than them to commit crimes as their proxies, Kivivuori draws upon historical accounts including some which are akin to Dickensian descriptions in Oliver Twist of Fagin like characters who entice youngsters into crime to suggest that there is a historical precedent for this type of offending. Although he found that these concerns had been exaggerated, Kivivuori found that 7.2% of respondents had shoplifted for someone else and that it appeared to be related to peer-group activities. Notably males who had acted as proxies were more often paid or threatened to steal whereas females shoplifted as proxies to increase their popularity.

Carrington (2015) also investigated the so called “Fagin” hypothesis that offenders below the age of criminal responsibility are particularly attractive as co-offenders for older offenders – a phenomenon which is specifically identified within the examples of higher ratings for Lifestyle. This was disconfirmed with children below 12 being found to be unlikely to co-offend with 12-17 year olds, and very unlikely to co-offend with adult offenders once the population age distribution was controlled for. Despite this finding, there is an established narrative, according to Lammy (2017), associated with gang activity whereby vulnerable young people are coerced into committing criminal acts by powerful adults. In particular drawing upon findings from police records and the National Crime Agency (2017), Lammy makes reference to many children and young adults from BAME backgrounds being drawn into the criminal justice system having been recruited by gang leaders to sell drugs or to carry weapons. Within this gang culture girls and young women who ‘become involved are targeted because they are vulnerable, potentially class A drug users; and they can often find themselves controlled through threats and intimidation’ (2017: 20).

The substance use domain focuses upon the types of substances used, when used and age at first use. It was found to be a highly statistically significant predictor of proven one-year reoffending in the logistical regression model based upon the 12 ‘dynamic’ domains and the significant at the 0.05 level in the simulated model representing ASSET under the Scaled Approach (Wilson and Hinks, 2011). In the case of the latter, Lifestyle and Motivation to Change were also found to be significant.

Whilst BDm3 is a compromise since there was insufficient data to incorporate all four static factors, it is notable that the estimates for substance misuse (Drugs) are significant when in interactions with Time.

This includes the 3-way interactions *G_ageFirst: Drugs: Time* and *FTE: Drugs: Time*, with the former being a significant negative coefficient whereas the latter is a significant positive coefficient. Given the respective reference categories for these two predictors, it suggests that those with a history of prior offending with substance misuse issues will see a greater 'penalty' over time than FTEs as will those aged 10-12 at the time of their first offence who have alcohol or drug problems. More generally, the significant positive coefficient for the interaction between *Time: Drugs* suggests that if the young person's substance misuse issues are not addressed, they will continue to be at a higher risk of further offending behaviour. For this reason, it is recognised in Welsh policy that:

> 'Having access to the right services at the right time, designed to minimise the impact of substance misuse, is essential. The relationship between crime, anti-social behaviour and impact on personal health is well understood and documented. Service access to those agencies set up and funded to provide help for young people who misuse drugs and alcohol should be based on an assessment of need. Referral pathways should be simple and understood by a range of professionals likely to encounter young people involved with the criminal justice system. This extends beyond YOTs and social workers. It should include schools based nurses and counsellors, youth and sports development workers, and teachers with pastoral care duties.'
>
> (Welsh Government and Youth Justice Board, 2014: 10)

This priority is also reflected in the devolved outcome indicators around access for those in the youth justice system to assessment and treatment for substance misuse need: In 2013/14, 90.4% of assessments were made within 5 working days of referral, which was a 3 percentage point increase compared to the previous year, whilst the proportion of young people with identified needs that started interventions within 10 working days was 96.6%. This was a 3.7 percentage point increase on the 92.9% in 2012/13 (Youth Justice Board and Ministry of Justice, 2015c).

The estimated coefficients for the Relationships with Family and Friends domain and Perception of Self and Others domain are significant main effects in BDm3 and the dynamic model involving Grouped Age at First offence. In the case of the latter, the large positive significant coefficient for the interaction between *G_ageFirst: Self* has a lot of uncertainty surrounding the estimate, highlighting just how much those aged 13-17 at the time of their first offence may be struggling with issues associated with self-esteem and self-identity. This includes potentially having adopted a criminal identify and displaying discriminatory attitudes towards others.

With so few cases in the dataset, it is not possible to explore whether there is a clearer pattern for those who have a history of prior offending or FTEs respectively. Similarly, it has not been possible to explore this in the context of the nature and / or seriousness of the primary offence. Had it been possible to do this, it would have provided additional information to inform the evidence base about criminal careers and the need for a tailored approach to interventions. However, it is apparent from Table 6.20, that having a history of prior offending explains a significant amount of uncertainty over time around variations in the Neighbourhood; Substance Misuse; Physical Health; Thinking and Behaviour; Attitude to Offending and Motivation to Change domains.

6.9 Summary

The analysis presented in this chapter sought to address three research questions, with the final question being addressed within section 6.6:

4. What is the impact of the 'static' factors within ASSET in predicting further offending over time?
5. Is it possible to extend the sensitivity of ASSET by extending any of the predictors?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

As in Chapter Five, the low number of cases within the reoffending cohort limits the construction of the combined model. Had there been sufficient cases, it would have been desirable to include all four static factors rather than make a compromise. There would also have been the potential to more fully explore how the sensitivity of the model could have been increased for example, by:

- treating the age-related predictors as a continuous rather than grouping them using the thresholds used in the Scaled Approach
- combining YJB Gravity Score and the Grouped YJB Offence Category;
- including gender, ethnicity and experience of care

It should be noted however, as highlighted in section 6.7, including continuous versions of age at first conviction alongside age at first offence introduces problems with collinearity. One alternative to get around this would be to consider age at the time of the primary offence and a measure that takes into account the time known to the YOT.

From a methodological point of view, whilst the potential for addressing the two research questions was limited by the low number of cases, in exploring the static factors, it has been possible to explore the use of different types of predictors. For example, the Grouped Age at First Offence was set up as a dummy variable whereas in treating age at first offence as a continuous variable meant that it became a multiplicative variable. The variable was also centred at 10 – the age of criminal responsibility. The DIC for the latter model was higher than that involving the dichotomous predictor (465 compared to 448), reflecting the increased complexity of the model. Comparing the resulting trajectories of the probability of further offending for the model involving the continuous predictor (Figure 6.23), it is possible to see features of both Figure 6.5(a) and (b). For those who were younger when then committed their first offence, the probability of further offending increases the longer the individual is in the formal youth justice system whereas that for the older group starts higher and then decreases.

The YJB Gravity Score is similarly a continuous predictor. In this case, the variable is centred at 2 reflecting the lowest score of primary offences committed by members of the reoffending cohort. Notably, none of the cohort committed very serious offences. However, it is possible to use the individual dynamic model and the combined model to estimate the probability of further offending for those who had committed offences attracting a gravity score of 7 or 8.

The predictor for Grouped YJB Offence Category is a categorical variable – in this case with three levels or 'factors'. The reference category was selected on the basis of the average initial scores, with those for SAC and VAP offences being higher than those for Other offences. If access could be secured to the national dataset, it would be worth exploring whether it would be possible to ungroup the categories. Based on published data, it is anticipated that there would be a very low number of individuals who had committed either serious sexual or serious violent offences including murder. The distinct advantage of using Bayesian approaches is that low incidence crime types can explored.

7 Findings: System Contact

This chapter concentrates on whether having system contact increases the likelihood of further offending. As such the following research questions are considered:

6. How is the likelihood of further offending affected by having experience of care and a previous offending history?
7. What is the impact of coming into contact with facets of the youth justice system on the likelihood of further offending?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

The first of these questions links back to the research questions posed in Chapter Five and Six which considered the predictors around care and FTE status. The additional predictors explored within this chapter are therefore:

- Breach - whether the young person has breached in the period before the ASSET
- Appear – whether the young person has had a court appearance (regardless of outcome) before the ASSET
- Custody - whether the young person has spent time in custody either on remand or as part of a custodial sentence before the ASSET

These time-varying Level 1 measures represent key features of the youth justice process and will be explored in Section 7.2.

7.1 Being known to the YOT and experience of care

Analysis in Chapter Six highlights that there are only three young people who were young FTEs i.e. who committed their first offence aged 10-12. As none of these went on to commit any further offences, it limits the extent to which FTE Status can be used as a predictor alongside grouped age at first offence – the implications of this can be seen in Figure 6.16(a).

Of the remaining predictors, grouped age at first offence providers the greatest opportunity for exploring the impact of being known to the YOT. Using their age at the time of their primary offence from the reoffending spreadsheet, it is possible to determine the difference between this and their age at the time of their first offence as recorded in their offence record in Childview. Within the reoffending cohort, the average difference was 1.9 years. However, amongst those in the younger group i.e. those at 10-12 at the time of their first offence, the average difference was 3.8 years (max = 7 years), whereas amongst the older group, the average difference was 1.2 years (max = 4 years). From this it can be inferred that those in the younger group have typically been in contact with the YOT for longer.

Whilst, ideally the impact of system contact on the probability of further offending would be modelled using FTE Status and Care Experience, as a compromise, *G_ageFirst* has been used to demonstrate the potential of using Bayesian approaches. The resulting dynamic model, renamed as Dynamic Model 4 (BDm4), is summarised in Table 7.1.

Table 7.1: Dynamic Model 4

	Dynamic Basic Model including Grouped Age at First Offence and Care Experience (BDm4G_cc2_ch)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-3.872	-8.998	0.955	0.021	0.000	2.599	
Grouped Age at First Offence (10-12 = Ref)	2.135	-2.230	6.925	8.455	0.108	1.02E+03	
Care Experience (No = Ref)	-0.228	-5.272	5.155	0.796	0.005	1.73E+02	
Time	0.057	-0.986	1.101	1.059	0.373	3.008	
Living Arrangements (Live)	-0.889	-2.551	0.638	0.411	0.078	1.892	
Family and Personal Relationships (Relation)	1.942	-0.205	3.994	6.969	0.815	54.287	
Education, Training and Employment (ETE)	-1.103	-2.870	0.388	0.332	0.057	1.474	
Neighbourhood (Where)	0.085	-1.248	1.379	1.089	0.287	3.970	
Lifestyle (Life)	3.334	1.002	5.708	28.041	2.723	3.01E+02	Yes
Substance Use (Drugs)	-0.852	-2.458	0.820	0.426	0.086	2.271	
Physical Health (Physical)	-0.654	-2.717	1.082	0.520	0.066	2.951	
Emotional and Mental Health (Emotion)	-1.227	-2.674	0.252	0.293	0.069	1.287	
Perceptions of Self and Others (Self)	-5.760	-8.833	-2.635	0.003	0.000	0.072	Yes
Thinking and Behaviour (Think)	1.798	-0.472	4.183	6.037	0.624	65.578	
Attitude to Offending (Attitude)	3.034	0.211	5.908	20.772	1.235	3.68E+02	Yes
Motivation to Change (Change)	0.467	-1.929	2.912	1.596	0.145	18.387	
Grouped Age at First Offence: Care Experience	2.550	-0.514	5.636	12.809	0.598	2.80E+02	
Grouped Age at First Offence: Time	-0.264	-1.195	0.726	0.768	0.303	2.066	
Grouped Age at First Offence: Live	0.632	-1.052	2.535	1.880	0.349	12.617	
Grouped Age at First Offence: Relation	-1.886	-4.096	0.330	0.152	0.017	1.391	
Grouped Age at First Offence: ETE	0.948	-0.688	2.782	2.580	0.502	16.148	
Grouped Age at First Offence: Where	-0.084	-1.549	1.334	0.919	0.213	3.797	
Grouped Age at First Offence: Life	-2.567	-5.160	0.006	0.077	0.006	1.006	
Grouped Age at First Offence: Drugs	1.200	-0.501	2.914	3.321	0.606	18.436	
Grouped Age at First Offence: Physical	0.655	-1.418	2.664	1.925	0.242	14.351	
Grouped Age at First Offence: Emotion	-0.205	-1.844	1.463	0.815	0.158	4.319	
Grouped Age at First Offence: Self	6.721	3.484	10.099	829.405	32.596	2.43E+04	Yes
Grouped Age at First Offence: Think	-1.034	-3.533	1.418	0.356	0.029	4.129	
Grouped Age at First Offence: Attitude	-2.351	-5.355	0.683	0.095	0.005	1.981	
Grouped Age at First Offence: Change	-1.600	-4.253	1.068	0.202	0.014	2.910	
Care Experience: Time	-0.074	-1.013	0.759	0.928	0.363	2.135	
Care Experience: Live	1.024	-0.689	2.681	2.786	0.502	14.597	
Care Experience: Relation	-0.406	-2.258	1.661	0.666	0.105	5.265	
Care Experience: ETE	0.053	-1.458	1.547	1.054	0.233	4.696	
Care Experience: Where	0.435	-0.985	1.843	1.545	0.373	6.314	
Care Experience: Life	-1.019	-3.178	1.298	0.361	0.042	3.660	
Care Experience: Drugs	0.140	-1.247	1.584	1.151	0.287	4.873	
Care Experience: Physical	-1.779	-3.694	0.284	0.169	0.025	1.329	
Care Experience: Emotion	1.582	-0.022	3.174	4.865	0.978	23.915	
Care Experience: Self	1.493	-0.856	3.922	4.450	0.425	50.495	
Care Experience: Think	-1.937	-4.050	0.118	0.144	0.017	1.125	
Care Experience: Attitude	-0.278	-2.230	1.611	0.758	0.108	5.007	
Care Experience: Change	0.460	-1.800	2.657	1.585	0.165	14.255	

/continued

	Dynamic Basic Model including Grouped Age at First Offence and Care Experience (BDm4G_cc2_ch)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Time: Live	-0.240	-0.624	0.127	0.787	0.536	1.136	
Time: Relation	-0.411	-0.863	0.057	0.663	0.422	1.059	
Time: ETE	0.185	-0.149	0.512	1.203	0.862	1.668	
Time: Where	-0.230	-0.505	0.078	0.794	0.604	1.081	
Time: Life	-0.622	-1.172	-0.101	0.537	0.310	0.904	Yes
Time: Drugs	0.480	0.117	0.838	1.616	1.124	2.311	Yes
Time: Physical	0.315	-0.228	0.821	1.370	0.796	2.273	
Time: Emotion	0.397	0.070	0.720	1.487	1.073	2.055	Yes
Time: Self	1.497	0.917	2.227	4.468	2.501	9.270	Yes
Time: Think	-0.437	-0.925	0.012	0.646	0.396	1.012	
Time: Attitude	-0.953	-1.519	-0.418	0.386	0.219	0.658	Yes
Time: Change	0.289	-0.281	0.807	1.334	0.755	2.242	
Grouped Age at First Offence: Time: Live	0.325	-0.115	0.784	1.383	0.891	2.190	
Grouped Age at First Offence: Time: Relation	0.375	-0.139	0.893	1.455	0.870	2.442	
Grouped Age at First Offence: Time: ETE	-0.217	-0.612	0.162	0.805	0.542	1.176	
Grouped Age at First Offence: Time: Where	0.137	-0.163	0.441	1.146	0.849	1.555	
Grouped Age at First Offence: Time: Life	0.491	-0.091	1.056	1.633	0.913	2.875	
Grouped Age at First Offence: Time: Drugs	-0.391	-0.773	-0.025	0.677	0.462	0.976	Yes
Grouped Age at First Offence: Time: Physical	-0.435	-0.979	0.040	0.647	0.376	1.041	
Grouped Age at First Offence: Time: Emotion	-0.160	-0.559	0.217	0.852	0.572	1.243	
Grouped Age at First Offence: Time: Self	-1.643	-2.358	-0.985	0.193	0.095	0.374	Yes
Grouped Age at First Offence: Time: Think	0.327	-0.181	0.830	1.387	0.834	2.293	
Grouped Age at First Offence: Time: Attitude	0.571	-0.067	1.216	1.769	0.935	3.375	
Grouped Age at First Offence: Time: Change	0.165	-0.408	0.740	1.179	0.665	2.096	
Care Experience: Time: Live	0.019	-0.373	0.442	1.020	0.688	1.556	
Care Experience: Time: Relation	0.009	-0.451	0.425	1.009	0.637	1.529	
Care Experience: Time: ETE	0.163	-0.144	0.498	1.177	0.866	1.645	
Care Experience: Time: Where	0.199	-0.110	0.469	1.220	0.896	1.598	
Care Experience: Time: Life	0.022	-0.430	0.435	1.022	0.650	1.544	
Care Experience: Time: Drugs	-0.170	-0.534	0.156	0.844	0.586	1.169	
Care Experience: Time: Physical	0.166	-0.301	0.617	1.180	0.740	1.854	
Care Experience: Time: Emotion	-0.155	-0.526	0.192	0.857	0.591	1.212	
Care Experience: Time: Self	-0.546	-1.019	-0.069	0.579	0.361	0.933	Yes
Care Experience: Time: Think	0.452	0.002	0.899	1.571	1.002	2.457	Yes
Care Experience: Time: Attitude	0.293	-0.196	0.801	1.341	0.822	2.229	
Care Experience: Time: Change	-0.390	-0.861	0.091	0.677	0.423	1.095	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	3.206	0.305	7.460	24.68	1.357	1.74E+03	Yes
Time	5.241	0.779	12.170	188.86	2.178	1.93E+05	Yes

DIC		425.90

Source: Model BDm4G_cc2_ch, renamed as BDm4, Technical Annex: p339-355.

Despite the additional complexity, including both grouped age at first offence and care experience in a dynamic model, reduces the DIC to 425.9. In comparison the dynamic model involving grouped age at first offence (BDm3G_cc2) has a DIC of 448.7 whilst that involving care experience has a DIC of 471.4. Using the model to estimate the probability of further offending over time results in the following sets of trajectories (Figure 7.1).

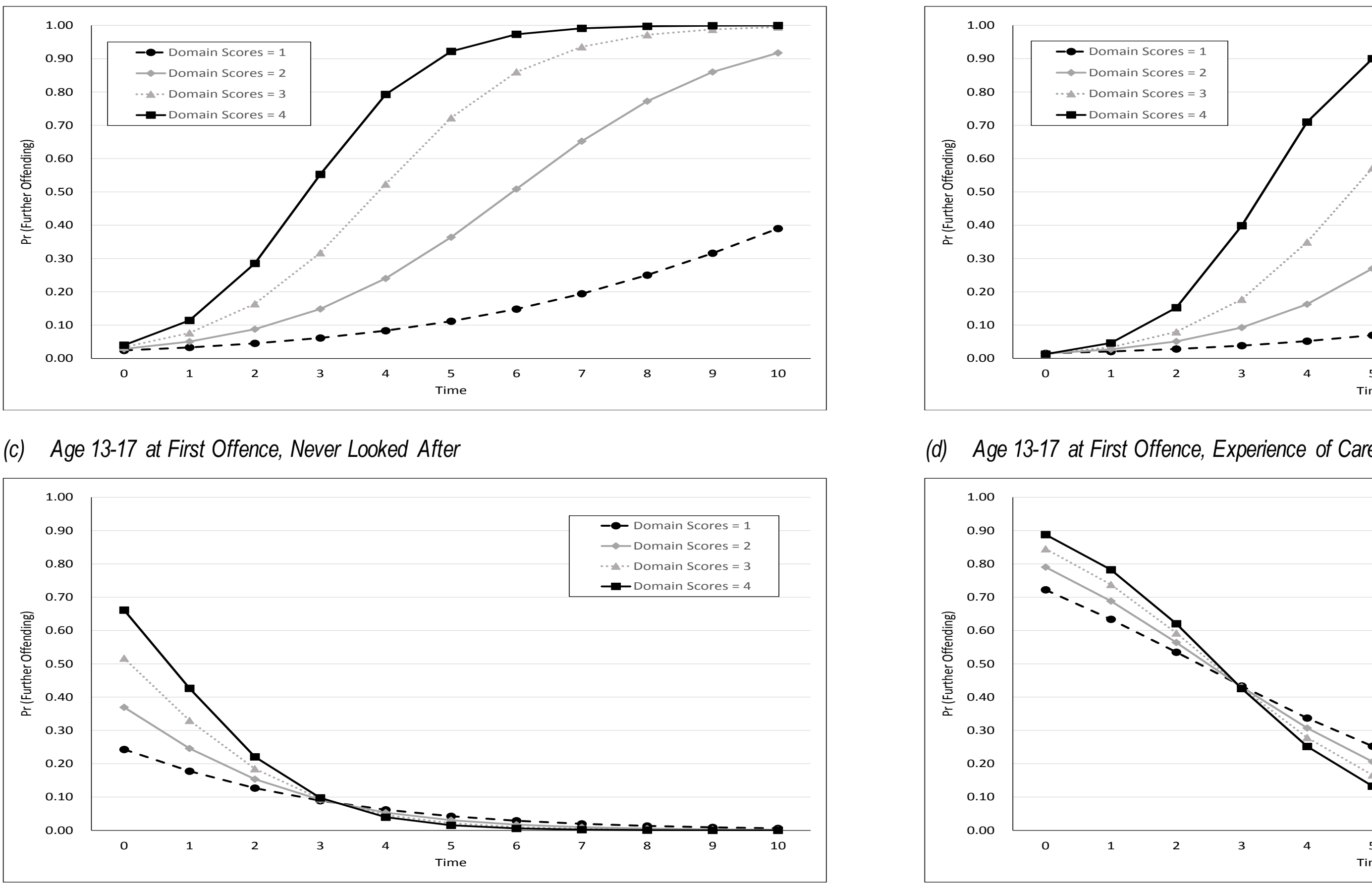
Figure 7.1: Changes in the Probability of Further Offending, Dynamic Model 4

(a) Age 10-12 at First Offence, Never Looked After

(b) Age 10-12 at First Offence, Experience of Care

(c) Age 13-17 at First Offence, Never Looked After

(d) Age 13-17 at First Offence, Experience of Care



Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of fu derived from Model BDm4.

Generally speaking, the initial estimated probability of further offending for those aged 10-12 at the time of their first offence are low. However, as can be seen from Figures 7.1(a) and (b), their estimated probability of further offending increases at later measurement points. This is broadly consistent with the trend observed as a result of estimates derived from the dynamic model involving grouped age of first offence (BDm3G_cc2, Figure 6.5). When the respective trajectories are compared for those in the younger group who have experience of care and those who have never been looked after, it is apparent that with the exception of when the domain scores were fixed at 1, the estimated probability of further offending is higher at each time point for those who have never been looked after. This is contrary to what would be expected but may well reflect the low numbers – there are only 8 young people who committed their first offence aged 10-12 who have experience of care.

In contrast, Figures 7.1(c) and (d) have a downward trajectory with the probability of further offending decreasing at later measurement points. The trend suggests that for those aged 13-17 at the time of their first offence, their estimated probability of further offending decreases the longer they are in contact with the YOT. However, it is notable that the initial probabilities of further offending are higher for those who have experience of care. This is apparent when the domain scores are fixed at 1, 2, 3 and 4 respectively. This difference is also apparent at all later measurement points, with the estimates for the probability of further offending taking longer to tend towards zero.

Notably when the further offending rates are compared for the four different groups, there is no evidence to suggest that amongst those who first offended aged 10-12, there is only anecdotal evidence to suggest that the rates are different on the basis of having experience of care relative to those who have never been looked after (BF_{10} = 0.882 for the two-sided test). However, there is strong evidence to support the rate within the older group being higher amongst those with experience of care (BF_{10} = 16.48). Table 7.2 summarises the respective rates.

Table 7.2: Further Offending by Experience of Care and Grouped Age at First Offence

		Grouped Age at First Offence		Total
		10-12 years	13-17 years	
Care Status	Never Looked After	50% (7/14)	34.7% (17/49)	38.1% (24/63)
	Experience of Care	75% (6/8)	70.6% (12/17)	72.0% (18/25)
Total		59.1% (13/22)	43.9% (29/66)	47.7% (42/88)

From Table 7.1, it is clear that the perception of self and others domain has a key role to play. It has previously been discussed a number of times, but in this particular context, the lack of uncertainty around the estimates is indicative of the issues around self-identity which may be faced by those who have had prolonged contact with the youth justice system, having committed their first offence at a young age and/or being a looked after child. Notably the guidance relating to this domain makes specific reference to the following common factors that may contribute to a poor or confused sense of self-identity:

- 'A lack of knowledge of personal and family history (eg a young person subject to a care order who has little knowledge about his/her birth family);
- Experience of discrimination;
- A feeling of cultural/social isolation;
- A very unstable or highly dysfunctional family background.'

(Youth Justice Board, 2008a: 16)

There may also be issues associated with having a mistrust of others and perceptions of having a criminal identity which could also be factors associated with having prolonged exposure to 'The System' and the impact of labelling. Having potentially established a criminal identity, the young person may well feel that further offending behaviour is inevitable hence the significance of the attitudes to offending domain both as a main effect and in the interaction with time. With this there is an increased likelihood of 'falling in with the wrong crowd' and participation in reckless activities including substance misuse. This pattern can similarly be seen within the model with the lifestyle domain being significant as a main effect and in the interaction with time. In the case of substance use, if this is seen as being highly associated with their likelihood of reoffending, attracting higher ratings, then this will need to be addressed. The negative significant estimate for *G_ageFirst: Time: Drugs* suggests that time has less of a mediating effect if the young person was aged 10-12 at the time of their first offence.

Having Experience of Being Looked After

Looked after children and Care Leavers have long been over-represented in the criminal justice system, and as such there is a growing body of research which investigates the relationship between involvement in the care system and negative outcomes for children. Notably Staines (2016) produced a systematic review and narrative synthesis of the international literature to accompany Lord Laming's review of looked after children in the criminal justice system. Given the comprehensive nature of this review, the intention is not to reproduce the findings here.

As highlighted in Section 4.3, there were significant difference in the initial mean ratings for the Family and Personal Relationships and Emotional and Mental Wellbeing domains. This is consistent with the findings summarised by Staines which suggests that looked after children have significantly worse emotional, psychological and behavioural health, and to experience difficulties in interpersonal relationships. However, whilst research suggests that looked after children are at greater risk of having poor educational attainment and having fewer employment / training opportunities; of living in more deprived areas; having poorer physical health including being involved in substance misuse, in this study, there was moderate evidence to suggest the average initial scores for looked after children in the reoffending cohort are not that dissimilar to those for their peers in these domains. It is perhaps the absence of these differences that have contributed to the lack of significant coefficients in the Dynamic Model involving Care (BDm2_ch). The only significant coefficient in the model was for the *Care Experience: Time: Self* interaction (BDm2_ch, -0.341 [-0.644,-0.045]).

Blades et al. (2011) identified a number of inconsistencies as a result of speaking with young people with relevant experiences which are pertinent to this research. For example, some children with a history of offending said they had offended prior to going into care, citing peer pressure as the most common reason, although other reasons given included difficulties controlling anger, a lack of money, being bored and living in a high crime area. However, there were also children who felt that being in care was the primary reason for their offending behaviour, or at least being in the care system increased the likelihood of offending. A small number believed that being in care had no real affect, or even reduced their chances of offending.

To attempt to unpick this further, it would be necessary to take into account the individual experiences and pathways before and after entering care. It is known for example that there are links between adverse family experiences and proven offending, with maltreatment and going into care as a teenager potentially having a stronger association with youth offending than maltreatment or care only being experienced in early childhood (Forty and Sturrock, 2017). The type and instability of the placement can also have a bearing with those in residential care homes not only being criminalised at excessively high rates (Howard League for Penal Reform, 2017) but may also not be receiving an equivalent level of parental-type support when they come before the court (Sentencing Council, 2017).

Having Experience of the Youth Justice System

Analysis by the Ministry of Justice (Sutherland et al., 2017) suggest that the characteristics of FTEs have changed over time in a way that was consistent with increasing numbers of young people who commit first time low-level offences being diverted from the formal youth justice system. Compared to those entering the system in 2003/04, FTEs in 2012/13 (which coincidently is within the period of interest for this research) were, on average:

- More likely to be older (aged 15 to 17 years)
- Less likely to be female
- Less likely to be White
- More likely to have committed a more serious offence

In investigating possible explanations for these changes, it was observed that 2009 onwards, 'a new 'class' of FTEs emerged who were older, black, violent and female (although the majority in this group were still male) and/or who had committed a violent offence' (Sutherland et al., 2017: 16). This group were more likely to have received court outcomes. As the profile of FTEs changed, the probability of proven reoffending within a year increased.

Since the young people's whose risk assessment score were utilised for this research were all in the formal youth justice system, comparisons cannot be made with the typology described by Sutherland et al. However, there are notable differences in the profiles of FTEs and those with a prior history of offending: Of the 33 FTEs within the cohort, all but one was male. 69.7% (23/33) were aged 15-17, 30.3% (10/33) were aged 12-14, with none of the FTEs being aged 10 or 11. Two identified as being non-White. Their average total ASSET score was 18.0 (out of 48) at Time 0.

In contrast, 87.0% (47/54) of the young people with a prior history of offending at the time of entering the cohort were male. The majority (77.8%, 42/54) had been aged 10-14 at the time of their first offence with 11 of these being aged under 12. Four young people were identified as being non-White. There are no significant differences in terms of the nature of the primary offence or its severity as determined by the YJB Offence Categories and Gravity Scores respectively. However, the disposals received for the primary offence do have a different profile, with none of the FTEs having received community or custodial sentences. Their average total ASSET score at Time 0 was 22.8. Since this score is across the 12 dynamic domains, it does not take into account their prior offending history or the nature of their primary offence i.e. the static factors.

As highlighted in Chapter Six, FTEs typically had lower initial ratings for Family and Personal Relationships, Emotional and Mental Health, and Perception of Self and Others. The estimated coefficients for these domains were also are main effects in the Dynamic Model 3 (BDm3) whilst in the dynamic model involving FTE Status (BDm3_cc1), these were significant when in interactions with FTE. Interactions terms involving Neighbourhood were also significant in the FTE dynamic model.

These domains link to findings from the Cambridge Study which suggest that protective factors, particularly those from high risk backgrounds include:

> '…having a resilient temperament; a warm and affectionate relationship with at least one parent; parents who provide effective supervision, pro-social beliefs and consistent supervision; and parents who maintain a strong interest in their children's education.'
>
> (Farrington, 2002: 427)

Conversely, family variables such as a parental rejection, erratic and harsh discipline, marital conflict and weak emotional attachment to parents have been consistently identified as being significant predictors of anti-social behaviours such as drug use and offending behaviour (Haines and Case, 2005) whilst resilience is key to how a young person coming into contact with different facets of the youth justice system copes. In particular those whose offending behaviour has contributed to a deterioration of the relationship that they have with their family / carers are likely to struggle without appropriate support. For those young people passed between members of the extended family / placements, this can be particularly distressing adding to feelings of shame, rejection and self-worth which in turn can affect their emotional wellbeing and mental health.

When the initial domain scores for FTEs and those with a prior offending history are segmented according to whether or not they went on to commit further offences (Table 7.3), this highlights distinct differences between the two groups which were not as evident in the modelling as would perhaps have been expected.

Table 7.3: Initial Average Domain Scores by FTE Status and Whether or Not Further Offending Occurred

Domain	FTE			Prior Offending		
	No Further Offending (N = 22)	Further Offending (N=11)	Bayes Factor 10 (H1: Group 0 < Group 1)	No Further Offending (N = 22)	Further Offending (N=31)	Bayes Factor 10 (H1: Group 0 < Group 1)
Living Arrangements	1.182	1.545	0.879	1.591	2.258	3.124
Family and Personal Relationships	1.727	1.909	0.478	2.045	2.645	3.378
ETE	1.682	2.364	2.467	1.773	2.258	1.014
Neighbourhood	1.045	1.818	3.369	1.455	1.774	0.727
Lifestyle	1.727	2.364	1.801	1.864	2.548	8.794
Substance Use	1.091	1.818	2.119	1.455	2.161	4.067
Physical Health	0.591	1.182	2.095	1.000	1.355	0.946
Emotional and Mental Health	0.909	1.091	0.506	1.273	1.645	0.768
Percpetion of Self and Others	1.091	2.000	9.148	1.682	2.065	1.507
Thinking Behaviour	1.773	2.636	5.830	2.045	2.516	1.982
Attitudes to Offending	1.227	2.000	4.519	1.682	2.000	0.917
Motivation to Change	1.143	2.091	10.243	1.545	1.935	1.005

Notes: One-sided Bayesian independent t-tests have been conducted using JASP version 0.8.5 (JASP Team, 2017b). Bayes Factors quantify the evidence for the alternative hypothesis relative to the null hypothesis and are interpreted using the categories suggested by Jeffreys (1961).

Whilst those who committed further offences typically had higher initial domain scores than their peers who did not, amongst FTEs there are significant differences in the average scores for Motivation to Change (BF_{10} = 10.2), Perception of Self and Others (BF_{10} = 9.1), Thinking Behaviours (BF_{10} = 5.8) and Attitudes to Offending (BF_{10} = 4.5). In the case of Motivation to Change, there is strong evidence to support this difference amongst FTEs whilst for the other domains, there is only moderate evidence. Notably it is this domain which considers whether the young person displays an appropriate understanding of the problematic aspects of his/her own behaviour; an understanding of the consequences for him/herself of further offending; has identified clear reasons or incentives for him/her to avoid further offending or shows real evidence of wanting to stop offending. The other domain for which there is comparatively strong evidence relates to the perception of self and others. As discussed in Sections 4.2 and 5.5, this domain is concerned with the young person's understanding of how they – and others – fit into the world around them and is very much concerned with the formation of an offender identity.

Amongst those with a prior history of offending, there are significant differences in the initial domain scores for Lifestyle (BF_{10} = 8.8) and Substance Use (BF_{10} = 4.1) when the group is segmented on the basis of whether they went on to commit further offences. Whilst both domains had proved to be significant in published evaluations of ASSET, the basic dynamic model (BDm1, Table 4.11) did not suggest any significant coefficients either for Substance Use as a main effect or in an interaction. Of the various models presented in Chapter Six, it is only the Combined Dynamic Model for Offending History (BDm3) which include significant coefficients for this domain. Due to the compromises it was necessary to make in the combined model – see Section 6.5, it is difficult to interpret the relationship between FTE status, substance misuse and grouped age at first offence. However, as Haines and Case (2005) highlight in relation to their research involving Swansea YOT, there are significant overlaps in the risk and protective factors related to offending behaviours and drug misuse, with the wider literature prompting the inclusion of the availability of drugs in the neighbourhood and parental substance misuse within the ASSET framework.

A possible explanation as to why substance misuse is not significant in the Dynamic Model involving in Demographics and Care (BDm2) is that whilst the characteristics of the neighbourhoods in which young people live play a role in influencing the offending and drug using behaviour, these have been found to be relatively weak in comparison to individual characteristics such as personality and gender (McVie and Norris, 2006). In this instance the low number of females potentially contributed to this effect not becoming observed in the models involving gender.

Recognising the impact that substance misuse can have on the physical health, attitudes, problematic behaviours and poor decision making, substance misuse workers are embedded within YOTs with treatment representing an important element of the rehabilitation process – hence its identification within the Central Eight (Table 4.13). Sadly, those with more entrenched offending behaviours typically also have more entrenched substance misuse problems and their chaotic lifestyles can lead to non-compliance and hence being sucked further into the youth justice system.

7.2 Youth Justice Processes

Concern has grown in the last twenty years over the stigmatising, labelling and criminogenic effects that formal system processing has on young people (Haines et al., 2013). Notably, research suggests that processing youth people through the justice system increases the likelihood that they will offend again and re-enter the system (McAra and McVie, 2007; 2015; Petrosino et al., 2010) hence both local and jurisdictional initiatives to increase diversionary activity. Whilst Swansea was operating a diversionary model during the period of interest for this research which sought 'to mediate national policy prescriptions and to develop a local response to the excessive criminalisation of young people' (Haines et al., 2013: 171), the young people whose Core ASSETS were utilised for this research were processed through the formal youth justice system. Consequently, rates of system contact are higher than for the wider youth offending cohort.

Much of the quantitative work on system contact focuses upon individual's contact with the police, policing practices such as stop and search, and the impact of arrests. However, there is also research which considers whether or not contact with the youth justice system increases the likelihood of later offending. This work builds upon a long pedigree of criminological theory including theories of anomie, labelling and symbolic interactionism, with criminology having recently rediscovered social identify, and particularly the idea that criminal justice institutions can create and shape the objective and subjective identities of those that they police, sentence or incarcerate (Bradford et al., 2014). Notably Bradford et al suggest that fair process, legitimacy and compliance are linked by social identify with those who perceive that they have been treated fairly by police and other agencies, having their respect for that organisation enhanced, strengthening legitimacy as a result. In contrast, unfair treatment signals to people that they do not belong, undermining both identification and the legitimacy of the criminal justice system. Hence the nature of the encounters that young people have with the system have the potential not just to shape individual's perceptions of themselves, but also their sense of self-worth.

McAra and McVie suggest that there is a group of 'usual suspects' who the police may be unfairly targeting. Whilst it is the volume and seriousness of offending which is what first brings a young person to the attention of the police, having been 'identified as a troublemaker, `this *status* appears to suck young people into a spiral of amplified contact, *regardless* of whether they continue to be involved in serious levels of offending (according to their self-reports)' (2005: 9). Hence the adversarial nature of their contacts with the police, can result in certain categories of young people becoming permanent suspects rather than suspects for a particular offence. This, argue McAra and McVie, has the effect of recycling these young people whilst other serious offenders escape the tutelage of the formal system altogether. Importantly, selection effects at each stage of the youth justice process mean that the deeper the usual suspects penetrate the youth justice system, the more this is associated with *inhibited* desistence from offending (McAra and McVie, 2007).

Conventional thinking suggests that unfair (and thus labelling) system contact promotes 'delinquent' identities which in turn makes people more likely to act like one. Since people's social identities can also be shaped by encounters with other authority figures and are subject to alteration throughout people's lives, this suggests that they are potentially amenable to positive change when treated in a sensitive and principled manner. Hence the relationship between the young person and their practitioner is integral if entrenched negative perceptions of self-worth are to be countered. However, McAra and McVie (2007) suggest that once ascribed, young people find it hard to shrug off labels, creating a self-fulfilling prophecy which may be damaging to the young person in the long term. Notably they observe that:

> … youngsters are powerless to alter the majority of the factors that propel them further and further into the system at age 15 (including family structure, social deprivation, gender, and being known to the police and Reporter in earlier years). The only real certainty for such children is that the master status of troubled/troublesome youngster results in amplified levels of intervention.

(McAra and McVie, 2007: 338)

The findings from the Edinburgh Study in particular highlight the negative consequences of system contact, providing the theoretical context for exploring the relationship between not just FTE status, but also contact with different facets of the youth justice system. Since these can occur at any time during the young person's time under the supervision with the YOT, the predictors are time variant.

Adding dummy variables for breaches (referenced by breached) and custody (referenced by having spent time in custody or on remand) to the Basic Model, does not result in a marked reduction in the DIC for the respective models. However, as can be seen from Table 7.4, the inclusion of the dummy variable reflecting court appearances (referenced by appearance, regardless of outcome) reduced the DIC from 476.2 to 429.6 thus reducing the amount of uncertainty in the model.

The individual inclusion of the additional criminal justice related predictors suggests:

- The odds of further offending following a breach is estimated to be exp(0.190) = 1.21 times the odds for those who have not breached (Model 1.12). [CI = 0.67, 2.16]
- The odds of further offending following a court appearance is estimated to be exp(1.659) = 5.25 times the odds for those who have not had to attend court (Model 1.13) [CI = 3.34, 8.26]
- The odds of further offending following time in custody decreases, with the odds for those who have not spend time in custody between ASSETS, being estimated to be 1/exp(-0.528) = 1.70 times the odds for those who have spent time in custody (Model 1.14) [CI = 0.88, 3.33]

The credible interval for court appearance is a significant predictor of further offending, equivalent to a 525% increase in the odds relative to those who have not needed to attend court in the period between assessments.

Table 7.4: Random Intercepts and Varying Slope Models for Further Offending including ASSET Domains and Youth Justice System Process Predic Unstandardised Coefficients

	Model 1.12: Basic Model + Breach				Model 1.13: Basic Model + Court Appearance (Y/N)			
	Unstandardised			Significant?	Unstandardised			Significant'
Fixed Effect:	Post.Mean	Lower CI	Upper CI		Post.Mean	Lower CI	Upper CI	
Intercept	-1.143	-2.387	0.071		-1.833	-2.925	-0.720	Yes
Breach (Compliance = Ref)	0.190	-0.397	0.772					
Court Appearance (None = Ref)					1.659	1.206	2.112	Yes
Period in Custody (None=Ref)								
Living Arrangements	0.031	-0.230	0.289		0.022	-0.244	0.289	
Family and Personal Relationships	0.267	-0.034	0.547		0.271	-0.016	0.573	
Education, Training and Employment	0.094	-0.158	0.336		0.045	-0.204	0.289	
Neighbourhood	0.046	-0.173	0.264		0.050	-0.173	0.268	
Lifestyle	0.007	-0.342	0.354		-0.123	-0.471	0.233	
Substance Use	0.158	-0.079	0.396		0.103	-0.135	0.346	
Physical Health	-0.112	-0.392	0.168		0.010	-0.275	0.303	
Emotional and Mental Health	0.006	-0.241	0.245		0.014	-0.230	0.264	
Perceptions of Self and Others	-0.144	-0.460	0.166		-0.216	-0.554	0.101	
Thinking and Behaviour	-0.156	-0.489	0.168		-0.156	-0.488	0.188	
Attitude to Offending	0.041	-0.303	0.387		0.032	-0.323	0.386	
Motivation to Change	0.236	-0.108	0.575		0.282	-0.078	0.626	
Time	-0.154	-0.291	-0.024	Yes	-0.125	-0.244	-0.010	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Significant?	Post.Mean	Lower CI	Upper CI	Significant'
Individual (Intercept)	0.10	1.63E-04	0.37	Yes	0.03	1.47E-04	0.15	Yes
Time	1.26	0.34	2.61	Yes	0.82	0.16	1.72	Yes
DIC	476.73				429.55			

Source: Models Bm1_cj1 (Breach), Bm1_cj2 (Court Appearance) and Bm1_cj3 (Custody), Technical Annex: p356-365.

Table 7.4 summarises the various permutations considered in relation to enhancing the Basic Model through inclusion of the three time-varying predictors, and the resulting impact on the DIC. In terms of the impact of the individual predictors at a given point in time, the dummy variable representing whether or not the young person has had a court appearance (regardless of the outcome), had the greatest impact. In contrast, the inclusion of predictors to represent breaches and time in custody / on remand does not result in a decrease in the DIC relative to that for the Basic Model. However, there is a theoretical rationale for including these ultimately within a dynamic model involving predictors reflecting dimensional identify and static factors which is responsive to having contact with facets of the youth justice system.

The Dynamic Models for Individual Youth Justice Processes or 'Events'

a) Breaches

Across the dataset, 42% of the cohort have breached with the average number of breaches amongst this group being 1.8. The most common time to breach was before their initial assessment although there is a 'spike' at Time 5 when almost a quarter of those remaining in the cohort breached (Figure 7.2). Taking into account the reductions in the size of the cohort at successive measurement points, it is apparent that the proportion who breached progressively decreases to Time, 4. After this time there is not no clear trend.

Figure 7.2: Number and Percentage of the Cohort Who Breached, by Time

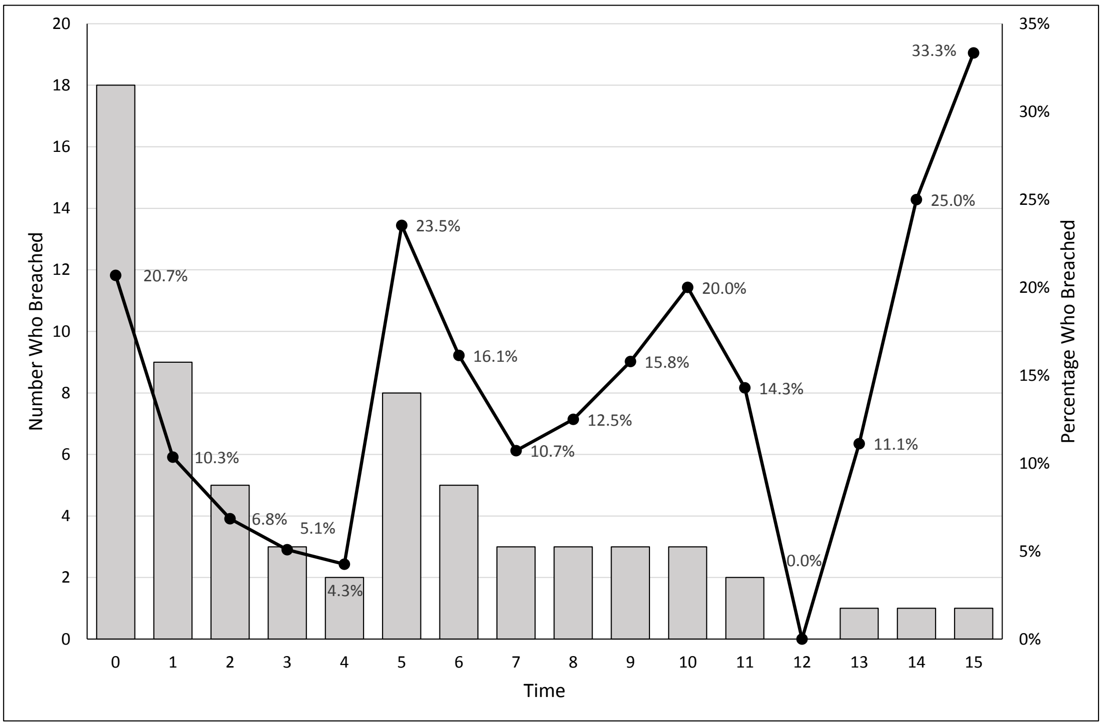


Table 7.5: The Dynamic Model Involving Breaches (BDm5_B)

	Dymanic Model 5: Breaches						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.093	-2.931	0.834	0.335	0.053	2.304	
Breach (None = Ref)	14.801	5.234	24.736	2.68E+06	187.600	5.53E+10	Yes
Time	-0.298	-0.613	0.016	0.742	0.542	1.017	
Living Arrangements (Live)	0.058	-0.453	0.594	1.060	0.636	1.811	
Family and Personal Relationships (Relation)	0.125	-0.454	0.691	1.133	0.635	1.995	
Education, Training and Employment (ETE)	-0.244	-0.686	0.175	0.783	0.503	1.191	
Neighbourhood (Where)	0.082	-0.361	0.621	1.085	0.697	1.861	
Lifestyle (Life)	0.257	-0.447	0.955	1.293	0.639	2.599	
Substance Use (Drugs)	0.319	-0.116	0.806	1.376	0.891	2.239	
Physical Health (Physical)	-0.730	-1.312	-0.166	0.482	0.269	0.847	Yes
Emotional and Mental Health (Emotion)	-0.353	-0.844	0.141	0.703	0.430	1.152	
Perceptions of Self and Others (Self)	0.270	-0.371	0.932	1.310	0.690	2.539	
Thinking and Behaviour (Think)	0.071	-0.528	0.750	1.074	0.590	2.118	
Attitude to Offending (Attitude)	0.140	-0.477	0.826	1.150	0.620	2.284	
Motivation to Change (Change)	0.387	-0.299	1.020	1.473	0.742	2.773	
Breach: Time	-6.005	-9.873	-2.506	0.002	0.000	0.082	Yes
Breach: Live	-10.356	-15.968	-4.401	0.000	0.000	0.012	Yes
Breach: Relation	15.299	7.367	23.776	4.41E+06	1582.266	2.12E+10	Yes
Breach: ETE	-10.431	-16.322	-5.105	0.000	0.000	0.006	Yes
Breach: Where	-0.794	-2.869	1.165	0.452	0.057	3.205	
Breach: Life	4.784	-0.908	10.398	119.611	0.403	3.28E+04	
Breach: Drugs	-3.051	-6.599	0.049	0.047	0.001	1.050	
Breach: Physical	4.932	1.218	9.213	138.666	3.381	1.00E+04	Yes
Breach: Emotion	7.798	3.609	12.234	2436.834	36.934	2.06E+05	Yes
Breach: Self	6.533	1.589	11.397	687.764	4.898	8.90E+04	Yes
Breach: Think	-19.325	-29.823	-7.734	0.000	0.000	0.000	Yes
Breach: Attitude	-4.251	-9.508	0.888	0.014	0.000	2.431	
Breach: Change	10.737	4.120	17.669	4.60E+04	61.561	4.71E+07	Yes
Time: Live	-0.004	-0.113	0.112	0.996	0.893	1.119	
Time: Relation	0.028	-0.112	0.164	1.028	0.894	1.179	
Time: ETE	0.089	-0.019	0.198	1.093	0.982	1.219	
Time: Where	0.015	-0.076	0.112	1.015	0.927	1.118	
Time: Life	-0.057	-0.205	0.094	0.945	0.815	1.098	
Time: Drugs	-0.021	-0.120	0.087	0.980	0.887	1.091	
Time: Physical	0.152	0.020	0.291	1.164	1.020	1.338	Yes
Time: Emotion	0.119	0.003	0.233	1.126	1.003	1.263	Yes
Time: Self	-0.096	-0.229	0.037	0.908	0.795	1.038	
Time: Think	-0.046	-0.191	0.090	0.955	0.827	1.094	
Time: Attitude	-0.052	-0.212	0.109	0.949	0.809	1.115	
Time: Change	-0.035	-0.192	0.105	0.966	0.825	1.110	

/ continued

	Dymanic Model 5: Breaches						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Breach: Time: Live	1.101	0.092	2.151	3.009	1.096	8.592	Yes
Breach: Time: Relation	-0.704	-2.249	0.774	0.494	0.106	2.168	
Breach: Time: ETE	2.291	0.897	3.973	9.887	2.451	53.166	Yes
Breach: Time: Where	-1.073	-1.858	-0.243	0.342	0.156	0.784	Yes
Breach: Time: Life	1.490	-0.087	3.071	4.439	0.917	21.569	
Breach: Time: Drugs	1.378	0.642	2.218	3.965	1.900	9.185	Yes
Breach: Time: Physical	-1.865	-3.357	-0.635	0.155	0.035	0.530	Yes
Breach: Time: Emotion	-2.807	-4.447	-1.452	0.060	0.012	0.234	Yes
Breach: Time: Self	-1.365	-2.244	-0.504	0.255	0.106	0.604	Yes
Breach: Time: Think	2.389	0.681	4.157	10.907	1.975	63.890	Yes
Breach: Time: Attitude	1.433	0.347	2.469	4.189	1.414	11.814	Yes
Breach: Time: Change	-3.626	-5.677	-1.558	0.027	0.003	0.211	Yes
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.583	2.89E-05	1.315	1.791	1.000	3.725	Yes
Time	2.273	0.452	4.976	9.708	1.571	144.894	Yes

DIC	449.91

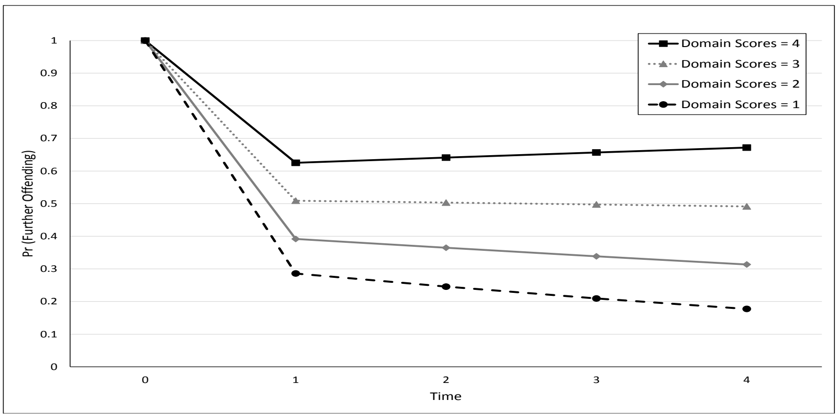
Source: Model BDm5_B, Technical Annex: p368-380.

The model can be used to estimate the impact of breaching at any given time on the probability of further offending (Figure 7.2). However, as can be seen from Table 7.5, there is a considerable amount of uncertainty relating to some of the estimates – evident in the wide credible intervals for estimates of the 2-way interactions between breaching and the individual domain scores, and by issues with the convergence for many of the 3-way interactions (see Technical Annex: p368-380). Whilst at Time 0 and Time 1, the impact of breaching is for the probability of further of offending to be close to 1, the shape of the trend at Time 2 (where the domain scores have been fixed at 4 - Figure 7.3(c)) is a reflection of this uncertainty as there is insufficient data to accurately estimate the probability of further offending at later measurement points amongst those with higher ratings. The fall in predicted probability reflected following a breach at Time 3 (Figures 7.3(d)) is contrary to what would be expected and is likely a result of the low number of cases upon which the model is based upon. This suggests that the model's ability to predict the probability of further offending as time progresses is potentially poor.

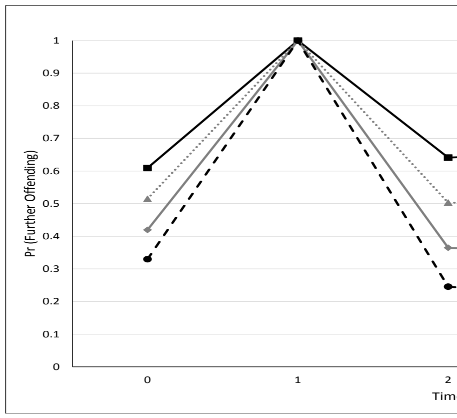
As with previous charts showing how the probability of further offending changes over time, fixing the domain scores provides a somewhat artificial impression of perceived levels of risk as typically the circumstances which lead to the breach will also have been reflected in increases in individual domain scores. Hence there would not be a return to the previous trajectory.

Figure 7.3: Changes in the Probability of Further Offending in Response to a Breach at Different Time Points

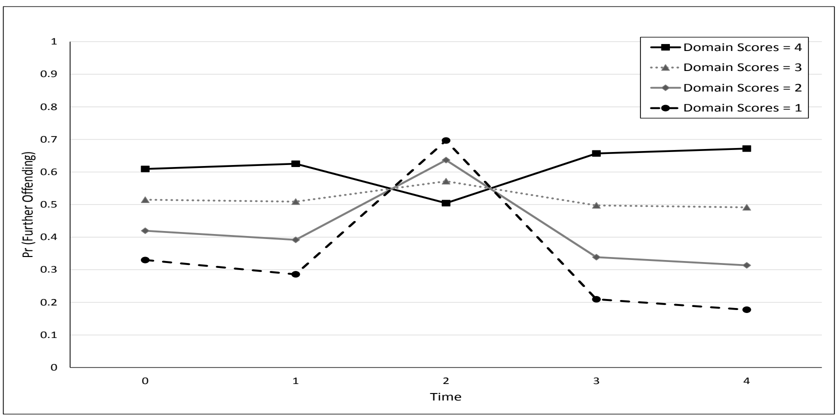
(a) Time = 0



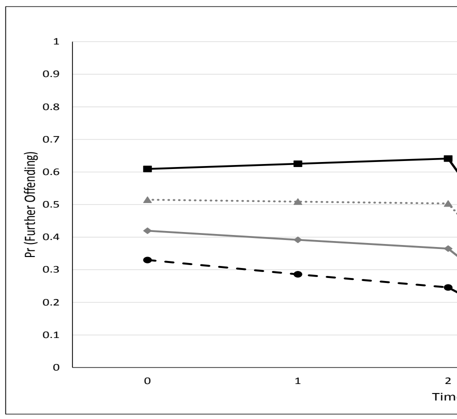
(b) Time = 1



(c) Time = 2



(d) Time = 3



Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of fu derived from Model BDm5_B.

It would also be anticipated that there would differences on the basis of individual characteristics and their criminal history. Table 7.6 summarises the breach rate for different sub-groups. Whilst the approach here mirrors that used in Chapter Three with respect to further offending i.e. that a flag has been created indicating whether or not the young person breached at any time whilst under the supervision of the YOT, regardless of when or how many times they were breached, it gives an indication of where there are differences.

Table 7.6: Breach rates, by sub-groups

	Comparator Groups		No.	Breached	% Breaching	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Gender	1	Male	79	35	44.3%	0.824	0.196
	2	Female	9	2	22.2%		
Ethnicity	1	White	82	36	43.9%	0.955	0.229
	2	Non-White	6	1	16.7%		
Care Status	1	No Experience	63	21	33.3%	8.235	16.38
	2	Experience	25	16	64.0%		
Age at First Offence	1	10 to 12	22	15	68.2%	16.15	0.094
	2	13 to 17	66	22	33.3%		
Age at First Conviction	1	10 to 13	11	5	45.5%	0.388	0.290
	2	14 to 17	77	32	41.6%		
FTE *	1	FTE	33	10	30.3%	1.315	0.095
	2	Previous Offending	54	27	50.0%		
Total			**88**	**37**	**42.0%**		

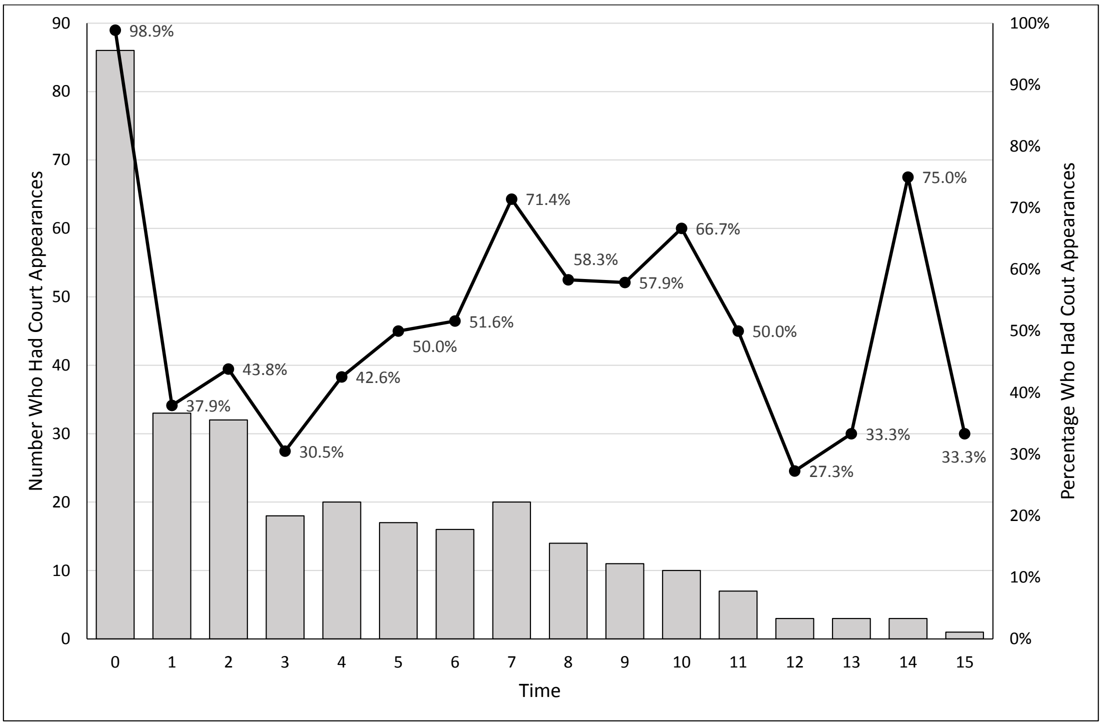
Notes: The individual whose FTE status is not known has been excluded from this summary. Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1 and are interpreted using the categories suggested by Jeffreys (1961).

With a BF_{10} of 16.38 for the one-sided test, there is strong evidence that those with experience of care have a higher breach rate than their peers in the formal youth justice system without this experience. Similarly, the two-sided suggest with respect to grouped age at first offence points provides strong evidence to suggest that rates for the two groups are different. When the appropriate one-sided test is run, it confirms that there is very strong evidence in favour of the breach rate being higher for those who committed their first offence aged 10-12 (BF_{10} = 32.21 that Group 1 < Group 2).

b) Court Appearances

All those young people whose ASSET Core Profiles have been considered as part of this research received court disposals and were within the formal youth justice system. As a result, court appearances after the time of the initial assessment are considered. Almost two-thirds of the cohort (65%) have additional court appearances, with the average being 3.6 appearances. This includes occasions when the case has been adjourned, they have been bailed, remanded or sentenced, or the case dismissed/withdrawn. The number of young people attending court decreases over time along with the size of the cohort subject to ASSET assessments decreases. Figure 7.4 includes a trend line reflects the proportion of the cohort at each measurement occasion who had attended court.

Figure 7.4: Number and Percentage of the Cohort Who had Court Appearances, by Time



As with breaches, a dynamic model – summarised in Table 7.7, has been simulated to enable the impact of court appearances on the probability of further offending to be estimated (Figure 7.5). However, with the higher numbers who have had court appearances, there is less uncertainty within the model. The only significant estimate is that for the fixed effect of the interaction between the court appearance and time. Since the estimate of the fixed effect is negative, this suggests that at later measurement occasions, the effect of court appearances have less of an impact on the probability of further offending although over time, the domain scores also change as a result of appearing in court. Although these changes help to account for some of the uncertainty around the impact of attending court, there remains some unaccounted-for uncertainty hence the wide credible interval for this main effect.

Table 7.7: The Dynamic Model Involving Court Appearances (BDm5_A)

	Dymanic Model 5: Court Appearances						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-5.053	-7.815	-2.257	0.006	0.000	0.105	
Court Appearance (None = Ref)	5.710	2.913	8.884	301.795	18.416	7218.360	Yes
Time	0.410	-0.133	0.977	1.506	0.875	2.657	
Living Arrangements (Live)	-0.066	-1.035	1.023	0.936	0.355	2.782	
Family and Personal Relationships (Relation)	1.349	0.127	2.514	3.854	1.135	12.352	
Education, Training and Employment (ETE)	-0.510	-1.380	0.420	0.601	0.252	1.521	
Neighbourhood (Where)	0.719	-0.228	1.657	2.053	0.796	5.243	
Lifestyle (Life)	-0.106	-1.453	1.173	0.899	0.234	3.230	
Substance Use (Drugs)	0.896	-0.060	1.808	2.451	0.942	6.096	
Physical Health (Physical)	-1.017	-2.169	0.008	0.362	0.114	1.008	
Emotional and Mental Health (Emotion)	0.133	-0.803	0.989	1.142	0.448	2.689	
Perceptions of Self and Others (Self)	0.157	-1.156	1.484	1.170	0.315	4.409	
Thinking and Behaviour (Think)	0.091	-1.153	1.382	1.095	0.316	3.984	
Attitude to Offending (Attitude)	0.122	-1.078	1.424	1.129	0.340	4.154	
Motivation to Change (Change)	-0.216	-1.721	1.221	0.806	0.179	3.390	
Appear: Live	0.053	-1.075	1.263	1.054	0.341	3.535	
Appear: Relation	-1.045	-2.364	0.303	0.352	0.094	1.353	
Appear: ETE	0.330	-0.662	1.337	1.391	0.516	3.808	
Appear: Where	-0.795	-1.854	0.227	0.452	0.157	1.254	
Appear: Life	0.107	-1.362	1.656	1.113	0.256	5.238	
Appear: Drugs	-0.789	-1.797	0.247	0.454	0.166	1.280	
Appear: Physical	0.802	-0.438	2.019	2.229	0.645	7.532	
Appear: Emotion	-0.185	-1.265	0.800	0.831	0.282	2.227	
Appear: Self	-0.244	-1.696	1.254	0.783	0.183	3.503	
Appear: Think	-0.379	-1.788	1.045	0.685	0.167	2.842	
Appear: Attitude	-0.127	-1.495	1.352	0.881	0.224	3.866	
Appear: Change	0.666	-1.006	2.152	1.947	0.366	8.601	
Appear: Time	-0.805	-1.432	-0.166	0.447	0.239	0.847	Yes
Time: Live	-0.120	-0.366	0.126	0.887	0.694	1.134	
Time: Relation	-0.257	-0.556	0.032	0.773	0.574	1.033	
Time: ETE	0.098	-0.115	0.304	1.103	0.892	1.355	
Time: Where	-0.013	-0.181	0.170	0.987	0.834	1.185	
Time: Life	0.029	-0.245	0.349	1.029	0.783	1.417	
Time: Drugs	-0.116	-0.302	0.080	0.890	0.739	1.083	
Time: Physical	0.196	-0.066	0.448	1.217	0.936	1.564	
Time: Emotion	0.053	-0.171	0.273	1.054	0.843	1.314	
Time: Self	-0.058	-0.318	0.216	0.944	0.727	1.241	
Time: Think	0.012	-0.283	0.309	1.013	0.753	1.362	
Time: Attitude	-0.111	-0.440	0.212	0.895	0.644	1.236	
Time: Change	0.071	-0.244	0.378	1.073	0.784	1.460	

/continued

	Dymanic Model 5: Court Appearances						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Appear: Time: Live	0.188	-0.077	0.470	1.207	0.926	1.600	
Appear: Time: Relation	0.226	-0.083	0.563	1.254	0.920	1.757	
Appear: Time: ETE	-0.043	-0.275	0.202	0.958	0.760	1.223	
Appear: Time: Where	0.004	-0.200	0.187	1.004	0.819	1.205	
Appear: Time: Life	-0.046	-0.380	0.287	0.955	0.684	1.332	
Appear: Time: Drugs	0.107	-0.093	0.340	1.113	0.912	1.405	
Appear: Time: Physical	-0.095	-0.389	0.198	0.910	0.678	1.219	
Appear: Time: Emotion	-0.035	-0.280	0.212	0.966	0.756	1.236	
Appear: Time: Self	0.010	-0.278	0.314	1.010	0.757	1.369	
Appear: Time: Think	-0.007	-0.336	0.329	0.993	0.715	1.389	
Appear: Time: Attitude	0.143	-0.203	0.505	1.154	0.816	1.658	
Appear: Time: Change	-0.094	-0.422	0.257	0.910	0.656	1.293	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.16	3.30E-08	0.59	1.178	1.000	1.800	Yes
Time	1.219	0.221	2.817	3.384	1.247	16.727	Yes

DIC	445.91

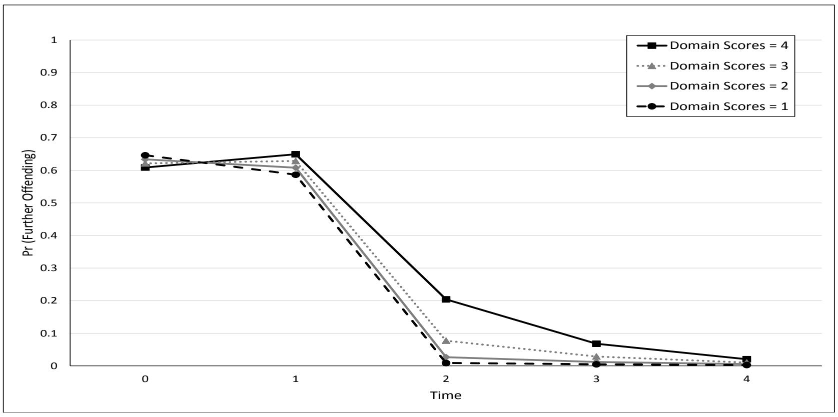
Source: Model BDm5_A, Technical Annex: p381-393.

The trajectory of the fall in the probability of further offending for those with lower average domain scores in Figures 7.5(c) and (d) is perhaps not what would be expected since the probability appears to be close to 0 from time 1 onwards. For those with ratings of 3 across each of the Domains being around 19% at Time 1, around 6% at Time 2, and 2% at Time 3. As with the model involving breaches, the small number of cases at the later time points make predictors of the probability of further offending less reliable as time progresses.

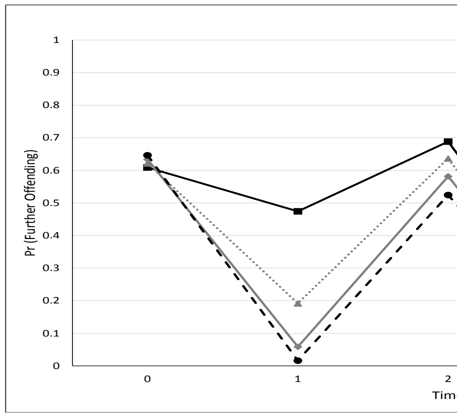
In the case of court appearances, it is likely that domain scores will be revised depending upon the outcome of the court appearance with some young people being subject to bail or remand restrictions, or depending upon their sentence, having further restrictions imposed upon them as part of their order. This could include receiving a custodial sentence. Later court appearances may be as a result of breaches or having committed further offences including where an offence committed earlier than that which led to the referral has taken longer to get to court. Notably of the 57 young people who appeared in court after time 0, 17 also had periods in custody / on remand although not necessarily in the same period.

Figure 7.5: Changes in the Probability of Further Offending in Response to a Court Appearance at Time 0 and Different Time Points

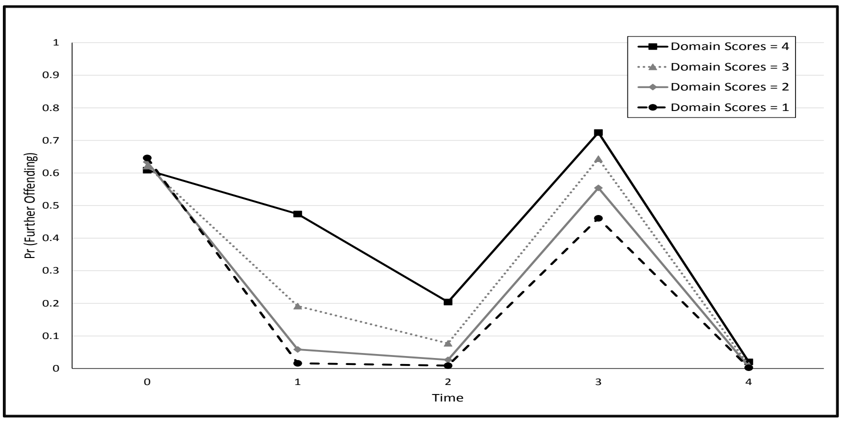
(a) Time = 1



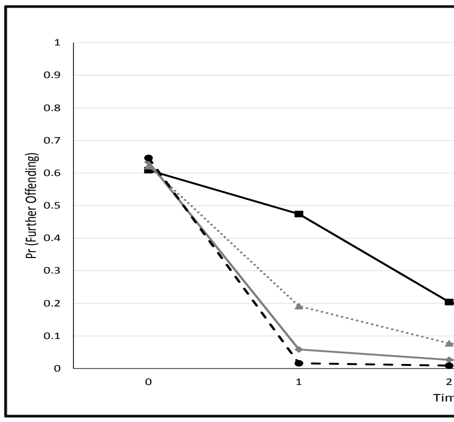
(b) Time = 2



(c) Time = 3



(d) Time = 4



Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of fu derived from Model BDm5_A.

The respective rates have been calculated based on whether or not a young person during their time under the supervision of the YOT the 'event' has occurred one or more times. As a result, were for example a young person has returned to court multiple times, this is only counted once. As can be seen from Table 7.8, the likelihood of a young person returning to court after their initial appearance at Time 0 does not appear to differ for different sub-groups, with no evidence to suggest differences between the rates for each sub-group.

Table 7.8: Court appearance rates, by sub-groups

	Comparator Groups		No.	Returned to Court	% Returned to Court	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Gender	1	Male	79	53	67.1%	0.408	0.169
	2	Female	9	4	44.4%		
Ethnicity	1	White	82	55	67.1%	0.517	0.169
	2	Non-White	6	2	33.3%		
Care Status	1	No Experience	63	38	60.3%	0.617	1.255
	2	Experience	25	19	76.0%		
Age at First Offence	1	10 to 12	22	14	63.6%	0.239	0.330
	2	13 to 17	66	43	65.2%		
Age at First Conviction	1	10 to 13	11	7	63.6%	0.184	0.412
	2	14 to 17	77	50	64.9%		
FTE *	1	FTE	33	18	54.5%	1.069	0.091
	2	Previous Offending	54	39	72.2%		
Total			**88**	**57**	**64.8%**		

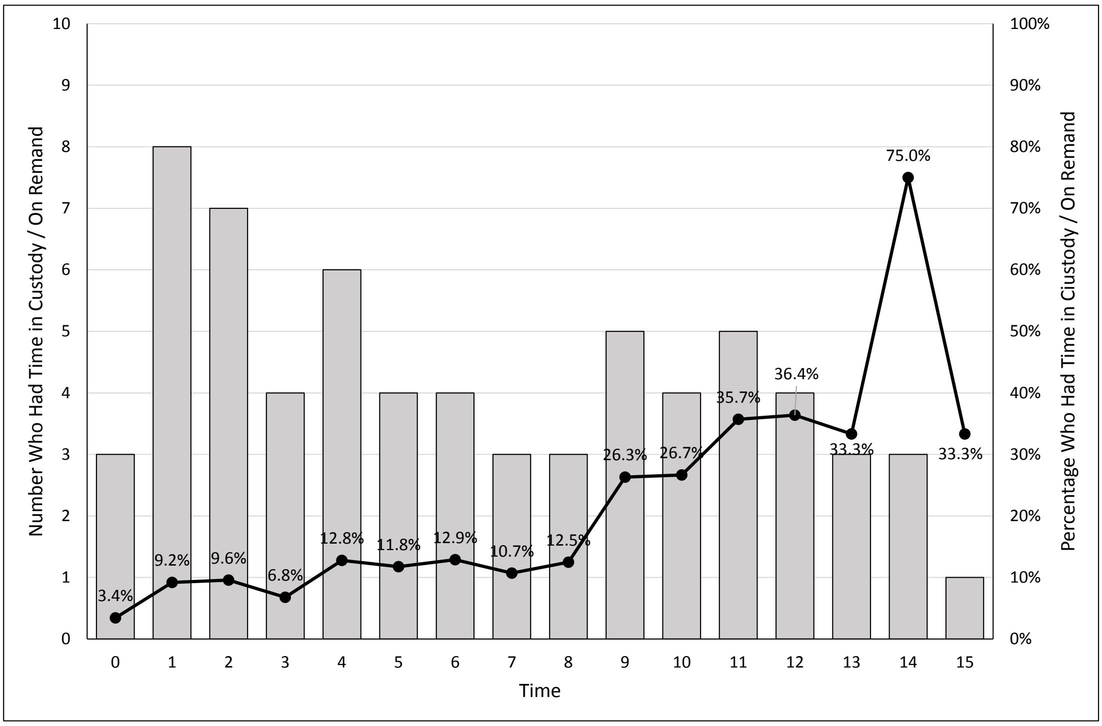
Notes: The individual whose FTE status is not known has been excluded from this summary. Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1 and are interpreted using the categories suggested by Jeffreys (1961).

Within the reoffending cohort, nearly all of those who breached at some point returned to court (94.6%, 35 out 37). As would be expected, there is also a strong relationship between returning to court and spending time either on remand or in custody. However, there are also a small number who received a custodial sentence following their primary offence.

c) *Periods in Custody*

Almost a quarter of those in the cohort (23%) have spent time in custody or on remand. This includes 3 young people who were in custody at the time of their initial assessment after joining the cohort. On average, those young people were in custody during the period of interest were in custody prior to 3.35 measurement occasions. Of the 20 young people who had time in custody, 6 had multiple periods in custody. Figure 7.6 summarises the size of the cohort subject to ASSET assessments at each measurement occasion with a trend line reflecting the proportion of the cohort that this represents.

Figure 7.6: Number and Percentage of the Cohort Who had Periods in Custody / On Remand, by Time



This model (Table 7.9) suffers less from issues around convergence (see Technical Annex, p394-406) than that for breaches, despite the lower number of cases involved. As would be expected the fixed effect between custody and time is significant – as with court appearances, suggesting that at later measurement occasions, spending time in custody/ on remand has less of an impact on the probability of further offending. This may be because the period of custody has followed a breach rather than a further offence, or because the detention and training order was for a longer period.

Table 7.9: The Dynamic Model Involving Periods in Custody or On Remand (BDm5_C)

	Dymanic Model 5: Custody						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-1.380	-3.256	0.545	0.252	0.039	1.725	
Custody (None = Ref)	8.295	-10.670	26.221	4005.485	0.000	2.44E+11	
Time	-0.142	-0.451	0.149	0.868	0.637	1.160	
Living Arrangements (Live)	-0.059	-0.548	0.414	0.942	0.578	1.513	
Family and Personal Relationships (Relation)	0.393	-0.123	0.940	1.482	0.884	2.560	
Education, Training and Employment (ETE)	-0.304	-0.689	0.100	0.738	0.502	1.105	
Neighbourhood (Where)	0.190	-0.232	0.576	1.209	0.793	1.778	
Lifestyle (Life)	0.251	-0.389	0.922	1.286	0.678	2.513	
Substance Use (Drugs)	0.367	-0.047	0.803	1.443	0.955	2.233	
Physical Health (Physical)	-0.588	-1.136	-0.081	0.555	0.321	0.922	Yes
Emotional and Mental Health (Emotion)	-0.157	-0.573	0.269	0.854	0.564	1.309	
Perceptions of Self and Others (Self)	0.186	-0.418	0.800	1.204	0.658	2.225	
Thinking and Behaviour (Think)	-0.139	-0.743	0.457	0.871	0.476	1.579	
Attitude to Offending (Attitude)	-0.081	-0.703	0.502	0.922	0.495	1.652	
Motivation to Change (Change)	0.436	-0.174	1.000	1.547	0.840	2.717	
Custody: Time	-4.947	-8.971	-1.293	0.007	0.000	0.274	Yes
Custody: Live	1.741	-2.684	6.318	5.705	0.068	554.284	
Custody: Relation	0.300	-10.651	11.071	1.349	0.000	6.43E+04	
Custody: ETE	-0.710	-7.560	5.366	0.492	0.001	214.025	
Custody: Where	-0.907	-6.603	4.644	0.404	0.001	104.010	
Custody: Life	-7.234	-13.231	-0.957	0.001	0.000	0.384	Yes
Custody: Drugs	-1.734	-7.219	3.397	0.177	0.001	29.884	
Custody: Physical	-1.560	-6.104	2.726	0.210	0.002	15.275	
Custody: Emotion	2.792	-8.357	14.399	16.313	0.000	1.79E+06	
Custody: Self	0.659	-8.023	9.339	1.933	0.000	1.14E+04	
Custody: Think	1.833	-9.165	13.883	6.253	0.000	1.07E+06	
Custody: Attitude	7.786	-4.113	20.235	2405.834	0.016	6.14E+08	
Custody: Change	-8.794	-24.027	6.465	0.000	0.000	642.177	
Time: Live	0.026	-0.079	0.135	1.027	0.924	1.145	
Time: Relation	-0.043	-0.164	0.089	0.957	0.849	1.094	
Time: ETE	0.102	0.012	0.202	1.108	1.012	1.223	Yes
Time: Where	-0.029	-0.114	0.055	0.971	0.892	1.057	
Time: Life	-0.031	-0.174	0.104	0.969	0.840	1.110	
Time: Drugs	-0.055	-0.146	0.035	0.947	0.864	1.036	
Time: Physical	0.124	-0.014	0.257	1.132	0.986	1.293	
Time: Emotion	0.057	-0.038	0.149	1.058	0.962	1.160	
Time: Self	-0.083	-0.207	0.040	0.920	0.813	1.040	
Time: Think	0.001	-0.139	0.131	1.001	0.870	1.140	
Time: Attitude	0.019	-0.113	0.152	1.019	0.893	1.164	
Time: Change	-0.052	-0.190	0.077	0.949	0.827	1.080	

/continued

	Dymanic Model 5: Custody						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Custody: Time: Live	-0.782	-1.750	0.132	0.458	0.174	1.141	
Custody: Time: Relation	-0.360	-1.713	1.061	0.698	0.180	2.889	
Custody: Time: ETE	0.940	-0.578	2.381	2.561	0.561	10.811	
Custody: Time: Where	0.903	0.094	1.710	2.466	1.099	5.529	Yes
Custody: Time: Life	0.907	-0.441	2.230	2.478	0.644	9.300	
Custody: Time: Drugs	0.989	-0.023	1.912	2.688	0.978	6.769	
Custody: Time: Physical	0.812	-0.051	1.712	2.253	0.950	5.543	
Custody: Time: Emotion	-0.286	-1.736	1.166	0.751	0.176	3.210	
Custody: Time: Self	0.050	-1.715	1.804	1.052	0.180	6.076	
Custody: Time: Think	-0.332	-2.214	1.371	0.718	0.109	3.938	
Custody: Time: Attitude	-1.339	-3.097	0.214	0.262	0.045	1.239	
Custody: Time: Change	0.868	-1.458	3.101	2.382	0.233	22.225	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	0.215	9.57E-08	0.669	1.239	1.000	1.953	Yes
Time	2.654	0.502	6.329	14.211	1.652	560.596	Yes

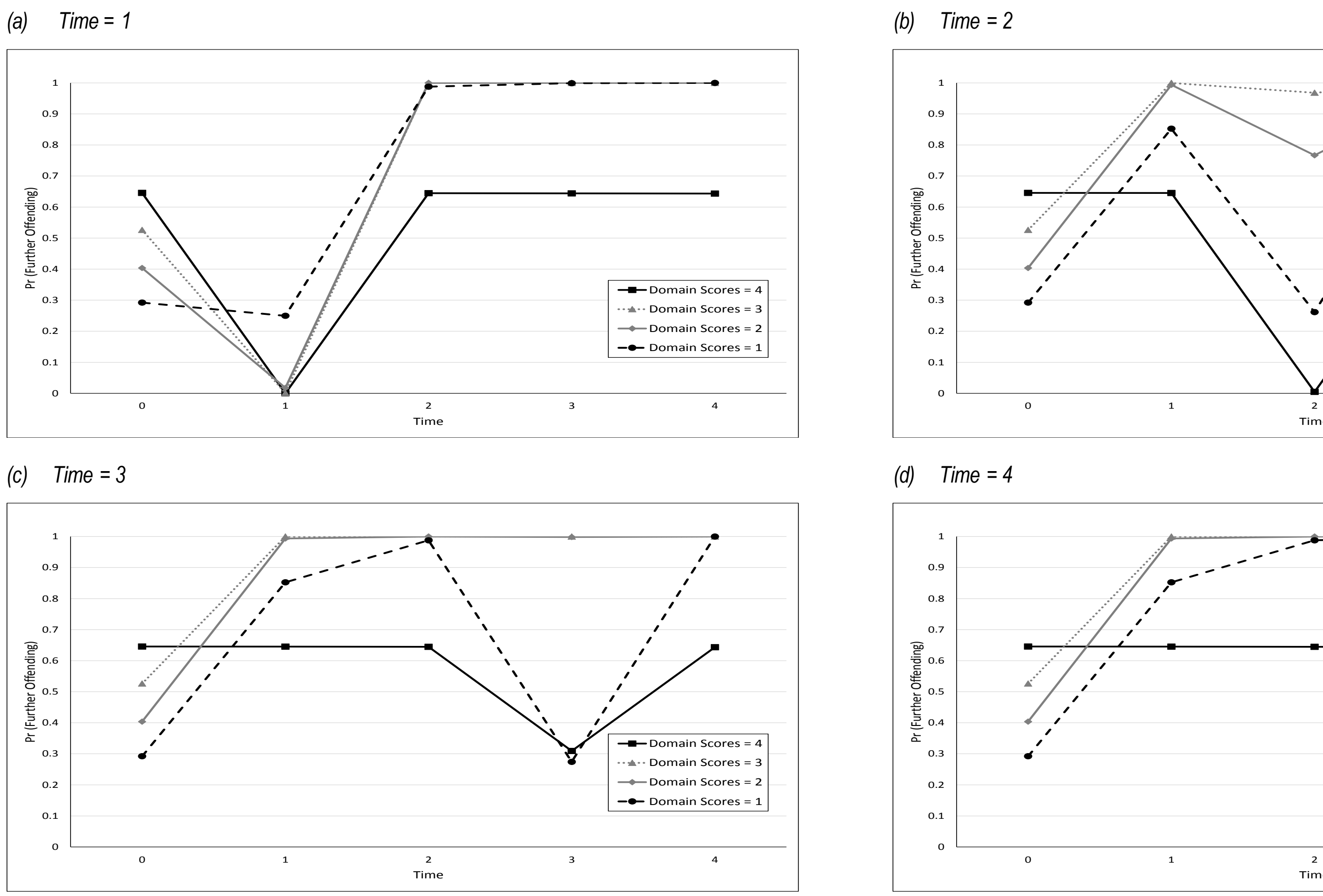
DIC	477.99

Source: Model BDm5_C, Technical Annex: p394-406.

The main effect reflecting the physical health domain as a main effect is significant as are those for the interaction effects between *Custody: Life*; *Time: ETE*; and *Custody: Time: Neighbourhood*. A fuller discussion is provided in Section 7.5. However, it is plausible that the structure and routine of the custody environment means that young people have access to appropriate health care services including GPs and dentists, and to treatment which enables them to address risky behaviours such as substance misuse. Their loss of liberty will also see them moved away from associating with friends who influence their behaviour, and from problematic neighbourhoods albeit temporarily. Whilst in the custodial environment there will be a requirement for young people to engage in education and training, and to gain skills to enable them to access employment upon release.

Estimates of the probability of further offending in response to a period in custody are given in Figure 7.7. Whilst the probability of further offending following a breach or court appearance increases, following a period in custody the probability decreases (Figures 7.7(a) and (b)). Since the way that the dummy variable has been set up can reflect that the young person is in custody at the time of the assessment, this reflects the lack of opportunity that the young person has to commit further offences at that time. However, there are indications of the poor fit of this model at later time points, especially where the ratings are fixed at 2 and 3 at Time 3 (Figure 7.7(c)). At this time point, the estimates are based on just 4 cases. The number of cases increases at Time 4 which may explain the trajectories evident in Figure 7.7(d). Following time in custody, the probability of further offending remains high especially for those with lower ratings.

Figure 7.7: Changes in the Probability of Further Offending in Response to a Period in Custody at Different Times



Notes: The domain scores have respectively been shown as being fixed at 1, 2, 3 and 4 respectively to demonstrate the estimated change in the probability of fu
derived from Model BDm5_C.

With only 20 young people having spent time in custody / on remand, when divided by sub-group, the numbers are quite low with all being male. Since the nature of the resulting order can be influenced by the young person's previous offending behaviours, there is moderate evidence in the appropriate one-sided test that their custody rate is higher than that for FTE (BF_{10} = 8.626).

Table 7.10: Custody rate, by sub-group

	Comparator Groups		No.	Remand / Custody	% Remand / Custody	Bayes Factor (BF_{10}) (H1: Group 1 ≠ Group 2)	Bayes Factor (BF_{10}) (H1: Group 1 > Group 2)
Gender	1	Male	79	20	25.3%	0.712	0.154
	2	Female	9	0	0.0%		
Ethnicity	1	White	82	18	22.0%	0.215	0.859
	2	Non-White	6	2	33.3%		
Care Status	1	No Experience	63	8	12.7%	93.8	163.2
	2	Experience	25	12	48.0%		
Age at First Offence	1	10 to 12	22	7	31.8%	0.541	0.117
	2	13 to 17	66	13	19.7%		
Age at First Conviction	1	10 to 13	11	2	18.2%	0.210	0.368
	2	14 to 17	77	18	23.4%		
FTE *	1	FTE	33	3	9.1%	5.690	0.064
	2	Previous Offending	54	17	31.5%		
Total			**88**	**20**	**22.7%**		

Notes: The individual whose FTE status is not known has been excluded from this summary. Bayes Factors have been calculated using the test for Bayesian Contingency Tables within JASP version 0.8.1.1 and are interpreted using the categories suggested by Jeffreys (1961).

The custody rate for those with experience of care is also notably higher than that for their peers who have never been looked after (BF_{10} = 163.2).

7.3 The Combined Dynamic Model for System Contact

The individual dynamic models for coming into contacts with facets of the youth justice system highlight a number of issues with convergence which limit the potential to explore the three predictors in combination i.e. incorporating interactions between *Breach: Appear, Appear: Custody, Breach: Custody* and *Breach: Appear: Custody*. From BDm5_B (summarised in Table 7.5), it was also recognised that there was a lot of uncertainty surrounding estimates of the coefficients relating to interactions involving Breach and the individual domains. There were similar issues in relation to interactions between Custody and the 12 domains (BDm5_C, Table 7.9). As a result, the combined model has been based on expanding upon BDm5_A.

From Table 7.6 it is apparent that there is a strong evidence that the breach rate for those who have experience of care is higher than that for those who have never been looked after whilst Table 7.10 highlights that there is a very strong evidence that the custody rate is also higher for this group. Although there is insufficient data to investigate interactions between these 'events', experience of care and the individual domains, the interactions between *CareExp: Breach: Time* and *CareExp: Appear: Time* have been included in the combined dynamic model for system contact. The resulting model is summarised in Table 7.11.

Table 7.11: The Dynamic Model for System Contact

	Dymanic Model including Experience of Care and Appearing in Court, with 3-way Interactions Involving Breach and Custody (BDm6)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
(Intercept)	-7.070	-11.138	-2.705	8.50E-04	1.45E-05	0.067	Yes
Experience of Care (None = Ref)	3.260	-1.268	7.553	26.055	0.281	1.91E+03	
Court Appearance (Appear) (None = Ref)	7.794	3.531	12.264	2.43E+03	34.143	2.12E+05	Yes
Breach (None = Ref)	-0.844	-2.463	0.825	0.430	0.085	2.283	
Custody (None = Ref)	-2.095	-5.608	1.259	0.123	0.004	3.523	
Time	0.332	-0.508	1.136	1.394	0.602	3.115	
Living Arrangements (Live)	-0.288	-1.899	1.365	0.750	0.150	3.917	
Family and Personal Relationships (Relation)	1.767	-0.150	3.563	5.854	0.861	35.285	
Education, Training and Employment (ETE)	-0.776	-2.187	0.504	0.460	0.112	1.655	
Neighbourhood (Where)	0.868	-0.526	2.178	2.381	0.591	8.825	
Lifestyle (Life)	0.373	-1.585	2.356	1.452	0.205	10.550	
Substance Use (Drugs)	1.181	-0.292	2.625	3.259	0.747	13.807	
Physical Health (Physical)	-0.891	-2.530	0.890	0.410	0.080	2.434	
Emotional and Mental Health (Emotion)	-0.322	-1.717	0.990	0.725	0.180	2.691	
Perceptions of Self and Others (Self)	-0.019	-1.885	1.904	0.981	0.152	6.711	
Thinking and Behaviour (Think)	0.123	-1.597	1.876	1.130	0.202	6.525	
Attitude to Offending (Attitude)	1.127	-0.759	3.071	3.087	0.468	21.564	
Motivation to Change (Change)	-1.060	-3.278	1.201	0.347	0.038	3.322	
Care: Appear	-0.746	-3.411	1.979	0.474	0.033	7.236	
Care: Breach	2.540	-0.441	5.566	12.685	0.643	261.296	
Care: Custody	1.192	-2.725	5.286	3.294	0.066	197.611	
Care: Time	-0.256	-1.153	0.611	0.774	0.316	1.843	
Care: Live	0.591	-0.839	2.049	1.806	0.432	7.759	
Care: Relation	-0.175	-1.882	1.453	0.840	0.152	4.274	
Care: ETE	0.303	-1.098	1.635	1.354	0.333	5.130	
Care: Where	-0.420	-1.709	1.026	0.657	0.181	2.790	
Care: Life	-0.888	-2.924	1.115	0.411	0.054	3.050	
Care: Drugs	-0.072	-1.344	1.155	0.930	0.261	3.174	
Care: Physical	-1.271	-3.167	0.530	0.280	0.042	1.699	
Care: Emotion	0.901	-0.489	2.245	2.462	0.613	9.437	
Care: Self	1.197	-0.765	3.070	3.311	0.465	21.541	
Care: Think	-1.347	-3.491	0.726	0.260	0.030	2.067	
Care: Attitude	-0.924	-2.768	1.040	0.397	0.063	2.831	
Care: Change	1.169	-0.860	3.318	3.218	0.423	27.609	
Time: Appear	-1.272	-2.174	-0.375	0.280	0.114	0.687	Yes
Time: Breach	0.117	-0.205	0.437	1.124	0.815	1.547	
Time: Custody	-0.011	-0.520	0.493	0.989	0.594	1.637	
Time: Live	-0.282	-0.651	0.121	0.754	0.522	1.129	
Time: Relation	-0.264	-0.689	0.149	0.768	0.502	1.161	
Time: ETE	0.144	-0.171	0.466	1.154	0.843	1.593	
Time: Where	0.019	-0.263	0.280	1.019	0.769	1.324	
Time: Life	-0.043	-0.484	0.421	0.958	0.616	1.524	
Time: Drugs	-0.011	-0.315	0.274	0.990	0.730	1.315	
Time: Physical	-0.003	-0.436	0.460	0.997	0.647	1.584	
Time: Emotion	0.161	-0.172	0.522	1.175	0.842	1.685	
Time: Self	0.135	-0.269	0.500	1.144	0.764	1.648	
Time: Think	0.001	-0.395	0.395	1.001	0.674	1.484	
Time: Attitude	-0.512	-1.041	-0.021	0.599	0.353	0.979	Yes
Time: Change	0.395	-0.102	0.924	1.485	0.903	2.519	

/ continued

	Dymanic Model including Experience of Care and Appearing in Court, with 3-way Interactions Involving Breach and Custody (BDm6)						
	Unstandardised			Standardised			Significant?
Fixed Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	
Appear: Live	0.153	-1.509	1.842	1.165	0.221	6.310	
Appear: Relation	-1.536	-3.394	0.398	0.215	0.034	1.489	
Appear: ETE	0.355	-1.100	1.733	1.426	0.333	5.659	
Appear: Where	-1.000	-2.417	0.413	0.368	0.089	1.511	
Appear: Life	0.232	-1.702	2.492	1.261	0.182	12.090	
Appear: Drugs	-1.025	-2.551	0.379	0.359	0.078	1.461	
Appear: Physical	1.166	-0.532	2.960	3.210	0.588	19.305	
Appear: Emotion	-0.207	-1.582	1.265	0.813	0.206	3.543	
Appear: Self	-0.562	-2.678	1.491	0.570	0.069	4.443	
Appear: Think	0.136	-1.875	2.072	1.146	0.153	7.944	
Appear: Attitude	-1.144	-3.125	0.900	0.319	0.044	2.460	
Appear: Change	1.419	-0.890	3.806	4.134	0.411	44.950	
Care: Time: Appear	0.435	-0.173	1.075	1.545	0.841	2.929	
Care: Time: Breach	-0.669	-1.226	-0.056	0.512	0.293	0.946	
Care: Time: Custody	0.093	-0.556	0.701	1.098	0.574	2.015	
Care: Time: Live	0.080	-0.212	0.391	1.083	0.809	1.478	
Care: Time: Relation	-0.137	-0.533	0.251	0.872	0.587	1.286	
Care: Time: ETE	0.013	-0.288	0.318	1.013	0.750	1.375	
Care: Time: Where	0.237	-0.023	0.514	1.268	0.978	1.671	
Care: Time: Life	-0.040	-0.459	0.351	0.961	0.632	1.421	
Care: Time: Drugs	-0.106	-0.402	0.197	0.899	0.669	1.218	
Care: Time: Physical	0.404	-0.005	0.826	1.498	0.995	2.283	
Care: Time: Emotion	-0.116	-0.459	0.200	0.890	0.632	1.221	
Care: Time: Self	-0.631	-1.069	-0.196	0.532	0.343	0.822	Yes
Care: Time: Think	0.437	0.031	0.898	1.547	1.032	2.456	Yes
Care: Time: Attitude	0.380	-0.065	0.817	1.462	0.937	2.264	
Care: Time: Change	-0.409	-0.841	0.017	0.664	0.431	1.017	
Appear: Time: Live	0.272	-0.113	0.654	1.313	0.893	1.923	
Appear: Time: Relation	0.324	-0.104	0.765	1.383	0.901	2.149	
Appear: Time: ETE	-0.123	-0.455	0.216	0.884	0.634	1.241	
Appear: Time: Where	-0.116	-0.399	0.173	0.891	0.671	1.188	
Appear: Time: Life	0.066	-0.405	0.555	1.069	0.667	1.742	
Appear: Time: Drugs	0.108	-0.191	0.421	1.114	0.826	1.523	
Appear: Time: Physical	-0.176	-0.615	0.252	0.839	0.541	1.286	
Appear: Time: Emotion	-0.048	-0.411	0.315	0.953	0.663	1.371	
Appear: Time: Self	0.091	-0.354	0.496	1.096	0.702	1.643	
Appear: Time: Think	-0.173	-0.607	0.275	0.841	0.545	1.317	
Appear: Time: Attitude	0.425	-0.068	0.908	1.529	0.934	2.479	
Appear: Time: Change	-0.230	-0.742	0.240	0.795	0.476	1.271	
Random Effect:	Post.Mean	Lower CI	Upper CI	Post.Mean	Lower CI	Upper CI	Significant?
Individual (Intercept)	1.795	1.56E-07	4.759	6.019	1.000	116.629	Yes
Time	1.982	0.235	4.818	7.257	1.265	123.717	Yes

DIC	433.64

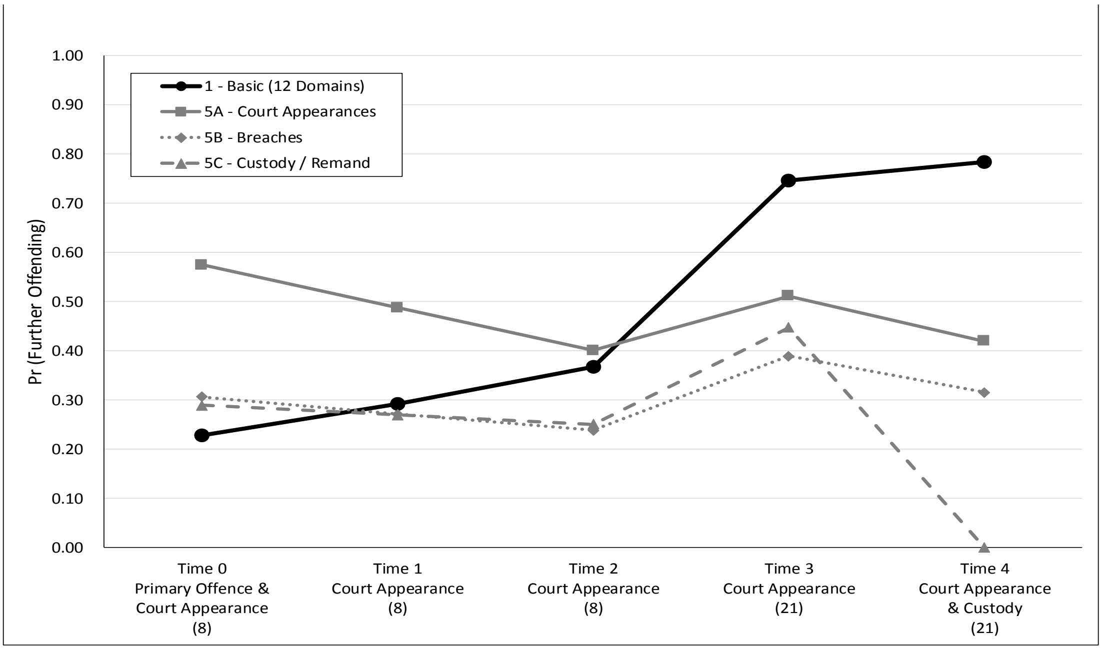
Source: Model BDm6_ch_A_BC, renamed as BDm6, Technical Annex: p407-425.

The 'events' are all time variant whereas the predictor representing experience of care, for the purposes of this analysis, is being treated as being time-invariant. To demonstrate how well this model represents the realities of the young person's change in circumstances during their time under the supervision of the YOT (RQ8), estimated probabilities of further offending have been calculated for each of the three case histories.

Case Study "Fred"

"Fred" entered the cohort having committed an offence with a gravity score of 2. As an FTE, he was initially judged to be a low risk of reoffending with a total ASSET score of just 8. As a member of the formal youth justice system, Time 0 relates to the initial ASSET Core Profile having committed an offence and attending court. In Fred's case, as he was already on a referral order having committed a theft offence (his primary offence), he was placed on ISSP Bail and Tag whilst he awaited sentencing for a burglary dwelling. This occurred between Time 3 and Time 4, with intervening court appearances relating to bail hearings. His final assessment occurs after he has been sentenced to a DTO for 10 months.

Figure 7.8: Comparisons of the Estimated Probability of Further Offending Over Time – Individual Dynamic 'Event' Models: "Fred"

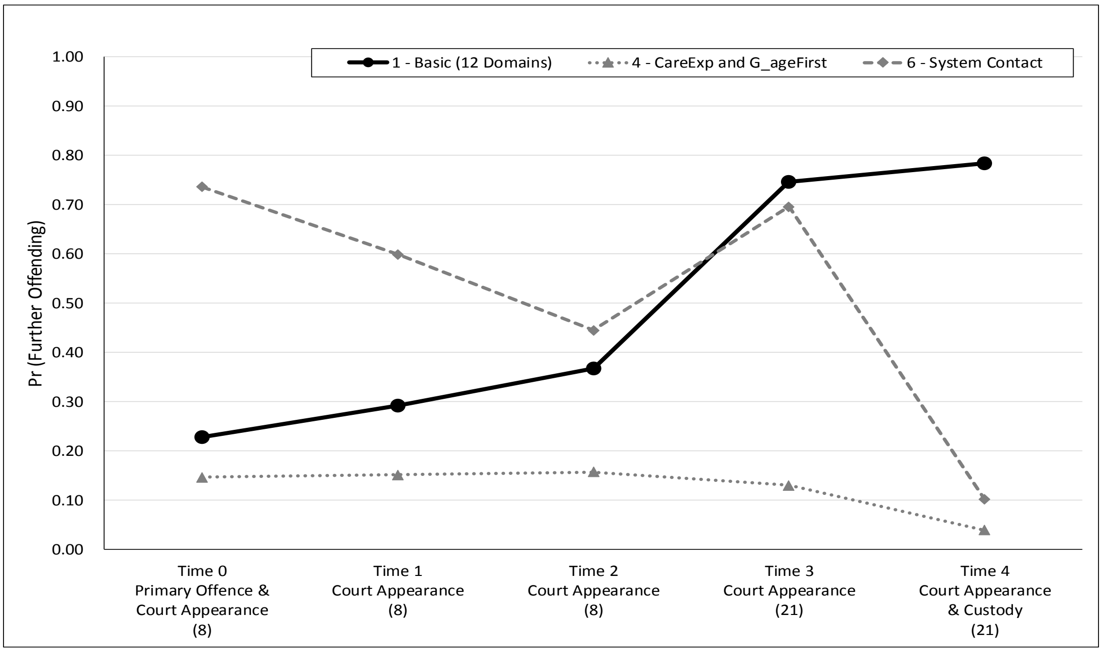


Source: BDm5_B (Breaches), BDm5_A (Court Appearances) and BDm5_C (Custody/Remand) along with BDm1.

If the initial estimated probabilities of further offending are compared in Figure 7.8, it is notable that the estimate derived from BDm5_A is 0.57 whereas that based the Basic Dynamic Model (BDm1) is 0.23. Those based on BDm5_B and BDm5_C are around 0.30. At subsequent measurement points, the estimated probabilities based the three 'event' dynamic models initially decline, reflecting the positive impact of working with the YOT to reduce the likelihood of further offending behaviours. This is in contrast to the trajectory of the probabilities of further offending between Time 0 and Time 2 based on BDm1 which is upward despite Fred's ASSET score remaining at 8 during this period.

At Time 3, when Fred was due back in court for sentencing, his ASSET score increased to 21. His final assessment was undertaken 10 days later, three days after sentencing. As would be expected, given that he is then in the secure estate, his probability of further offending has fallen despite no change in his ASSET score. All three of the event models suggest that there is a decrease in his estimated probability of further offending between Time 3 and Time 4. Although, BDm5_C suggests the most dramatic fall. This is potentially more realistic that the trend suggested by BDm1.

Figure 7.9: Comparisons of the Estimated Probability of Further Offending Over Time – System Contact Dynamic Models: "Fred"



Source: BDm4 (CareExp and G_ageFirst), BDm6 (System Contact) along with BDm1.

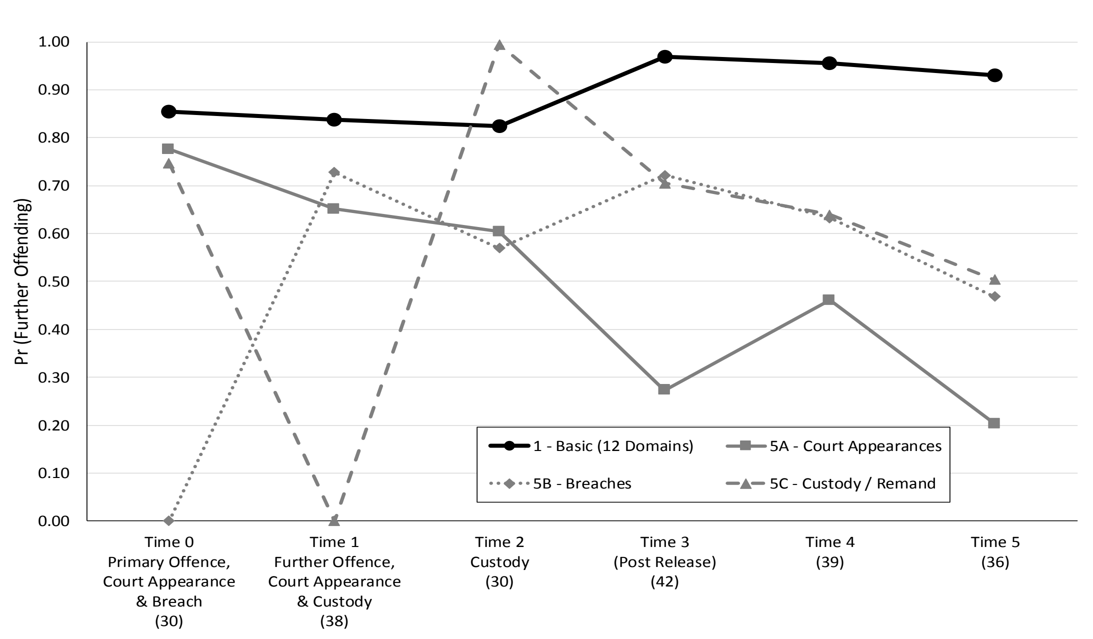
BDm6 also takes into account Fred's court appearances and being sentenced to custody – had he breached, this would also have been reflected. However, it the model was specified to reflect the impact of court appearances on the individual domains and how these changed over time, along with the experience of care. Whilst it shares features with BDm5_A, the initial probability of further offending is higher (estimated to be 0.74) as is the estimate for Time 3 (0.70 compared to 0.51). However, the response to entering the secure estate between Time 3 and 4 is greater with the probability of Fred committing any further offences estimated to be around 0.10.

Having never been looked after and being aged 14 at the time of his first offence, Fred falls into the non-reference groups for both elements of BDm4, with the estimated probabilities of further offending based on this model being notably lower at each measurement point than those based on BDm1. Although his ASSET score increased at Time 3, Fred's estimated probability of further offending fell at that time whereas this was reflected in estimated based on BDm1 and BDm6.

Case Study "Connor"

The high initial estimated probabilities of further offending based on BDm1 along with the 'event' models for court appearances and custody / remand reflect "Connor's" prior offending history including having previously been sentenced to an 8-month DTO, and the seriousness of his primary offence (an attempted burglary dwelling). However, it is notable that despite his non-compliance at Time 0, this is not reflected in BDm5_B. As a result, this model suggests that Connor's initial probability of further offending is negligible which is somewhat unrealistic.

Figure 7.10: Comparisons of the Estimated Probability of Further Offending Over Time – Individual Dynamic 'Event' Models: "Connor"



Source: BDm5_B (Breaches), BDm5_A (Court Appearances) and BDm5_C (Custody/Remand) along with BDm1.
Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with Connor having a total of 30 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that his primary offence (for the purposes of this exercise where the information has been taken from the reoffending spreadsheet) was a non-domestic burglary and as a result of his prior convictions.

Connor was returned to court between Time 0 and Time 1 having committed further offences (the offending occurred the day after his initial assessment). The offences were committed whilst he was on conditional bail. As a result, he was remanded to custody prior to being sentenced. The assessment at Time 2 took place 4 days after Time 1 by which time Connor was almost 2 weeks into his second 8-month DTO.

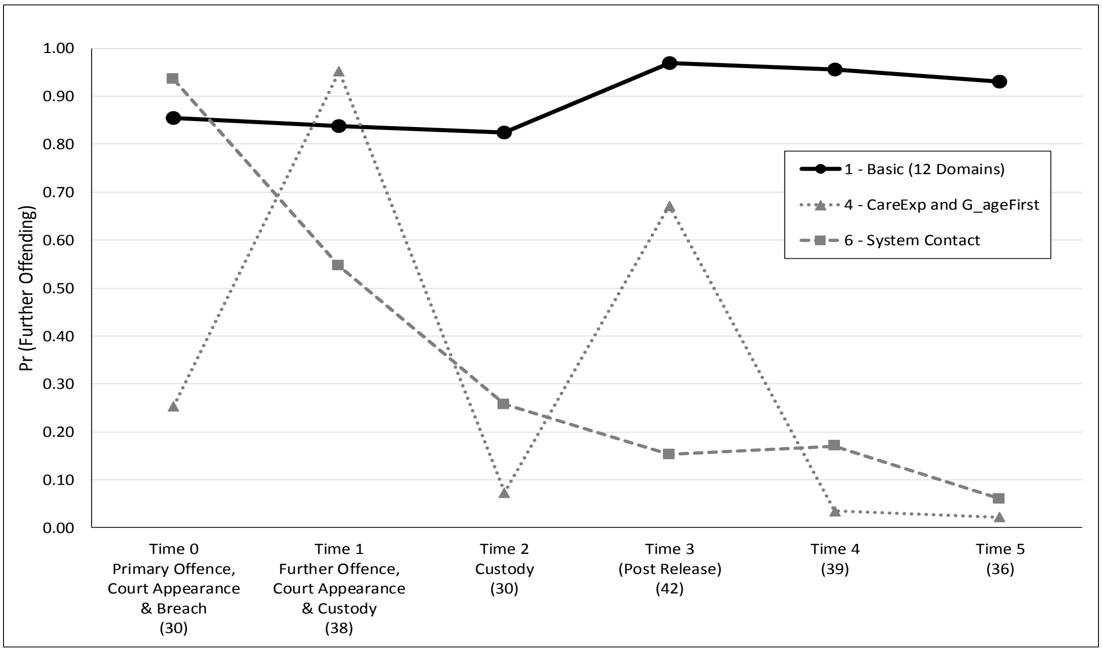
As such the opportunity to engage in any further offending behaviours is limited which is reflected in the estimated probability of further offending based on BDm5_C at Time 1. However, the same model suggests that despite a decrease in his ASSET score between Time 1 and Time 2, Connor's likelihood of further offending increased significantly to around 1.0. The estimates based on the other models summarised in Figure 7.10 reflect the anticipated decrease associated with being in the secure estate.

The assessment at Time 3 would have been approximately one month after Connor was released so that he could serve the second half of his DTO under the supervision of the YOT. By this time, he had had his 18th birthday. Time 4 reflects a review assessment whilst Time 5 reflects the end of his DTO.

Between Time 3 and Time 5, Connor's ASSET scores decreased. This is reflected in BDm1 and the 'event' models for breaches and custody / on remand, but not that for court appearances. BDm5_A suggest that the probability of further offending increased before falling again at Time 4 despite there being no 'events' and Connor's ASSET score falling from 42 to 38.

Figure 7.11 summarises the change in the estimated probabilities of further offending based on the system contact dynamic models for Connor. As discussed in Chapter Four, Connor has experience of care and was aged 14 at the time of his first offence. He was 17 at the time of his primary offence and therefore have been in the formal youth justice for around 3 years when he entered the 2012/3 reoffending cohort.

Figure 7.11: Comparisons of the Estimated Probability of Further Offending Over Time – System Contact Dynamic Models: "Connor"



Source: BDm4 (CareExp and G_ageFirst), BDm6 (System Contact) along with BDm1.
Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with Connor having a total of 30 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that his primary offence (for the purposes of this exercise where the information has been taken from the reoffending spreadsheet) was a non-domestic burglary and as a result of his prior convictions.

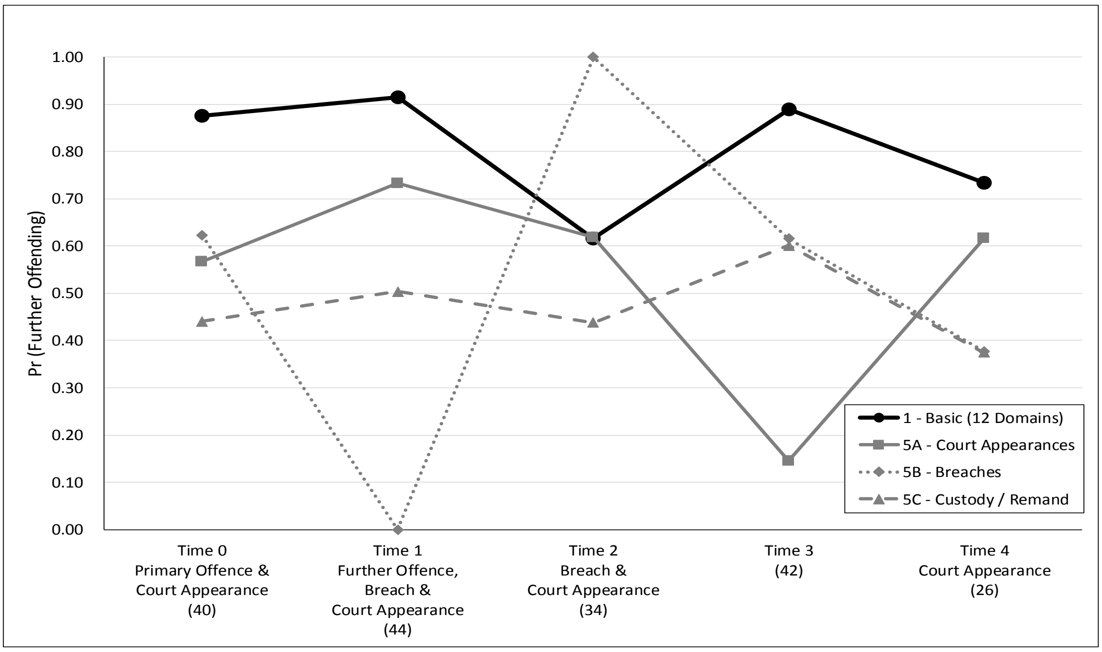
Given Connor's history of offending and non-compliance, the high initial probability of further of offending suggested by BDm4 seems unrealistic whereas that based on BDm6 is. This latter model also reflects the increased ASSET score between Time 0 and Time 1 when Connor committed further offences following the decrease when he was in custody (Time 2) and the increase that corresponds to his assessment post-release. In contrast BDm6 does not reflect these changes.

Case Study "David"

"David", like Connor has a history of prior offending and non-compliance. He committed his first offence aged 10 and therefore had been in the youth justice system for almost 7 years when he committed his primary offence. At the time of his initial assessment, David was on unconditional bail having committed a criminal damage offence and stolen a vehicle during the previous month. As a result, he was sentenced just before Time 1 to a 12-month YRO with an intensive supervision and surveillance (ISS) requirement.

The high intensity supervision phase for David's ISS would have entailed a minimum of 25 hours per week of purposeful, timetabled activity with 2 contacts per week. He would also have a curfew monitored by an electronic tag. Given his chaotic background and communication issues, it is not surprising that he struggled to comply with the requirements.

Figure 7.12: Comparisons of the Estimated Probability of Further Offending Over Time – Individual Dynamic 'Event' Models: "David"



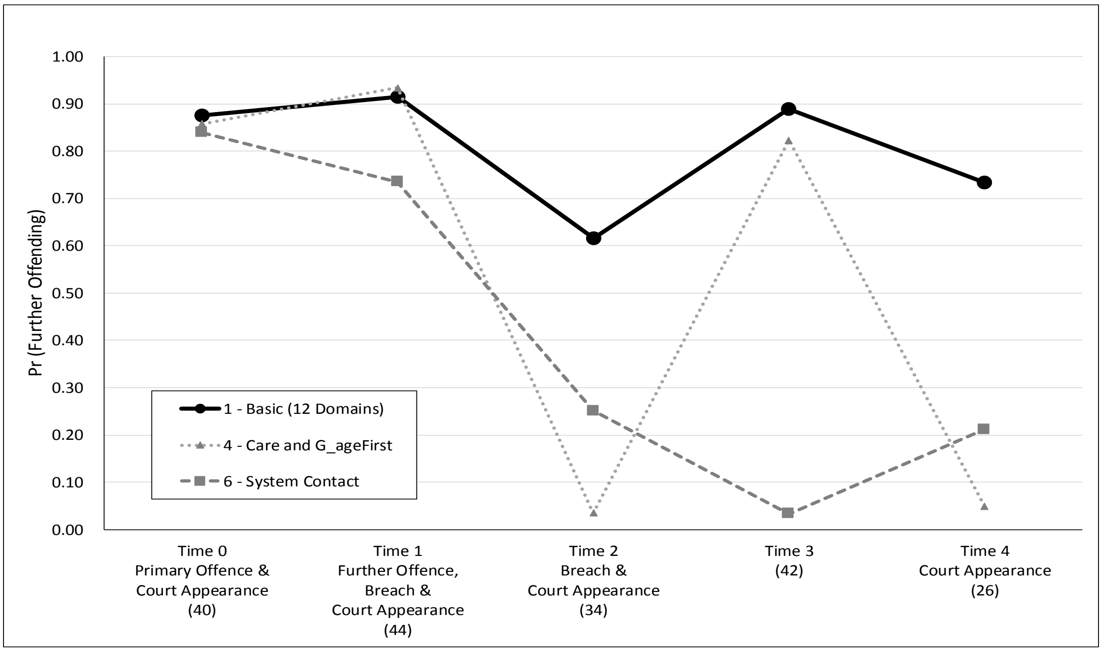
Source: BDm5_B (Breaches), BDm5_A (Court Appearances) and BDm5_C (Custody/Remand) along with BDm1.
Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with David having a total of 40 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that he was aged 10 at the time of his first Reprimand and as a result of his prior convictions.

The initial estimated probabilities based on the 'events' models are lower than that based on BDm1, with that estimated using BDm5_B being the highest of the three. This model, however, is potentially the least realistic: at Time 1 when David was considered to have a high risk of reoffending with an ASSET score of 42, had breached and returned to court after committing a further offence, his estimated probability of further offending was negligible. When his ASSET score declined between Time 1 and Time 2, under BDm5_B, his probability of further offending increased to 1.0. Just over a week later (Time 3), he was sentenced for the breaches of his YRO.

Since David did not spend any time in custody / on remand, he was in the reference category for BDm5_C. The resulting shape of the trajectory of the estimates for the probability of further offending over time, whilst lower, is not that dissimilar to that for BDm1.

As with Connor, the estimates for David based on BDm5_A, 'dip' at a time when the young person's ASSET scores increased – for David, this occurred at Time 3. This was the only measurement point where there was not an 'event'.

Figure 7.13: Comparisons of the Estimated Probability of Further Offending Over Time – System Contact Dynamic Models: "David"



Source: BDm4 (CareExp and G_ageFirst), BDm6 (System Contact) along with BDm1.
Notes: Although the ASSET scores reflected along the x-axis are out of a maximum of 48 with David having a total of 40 at Time 0, under the Scaled Approach he would have attracted additional scores due to the fact that he was aged 10 at the time of his first Reprimand and as a result of his prior convictions.

The initial estimated probabilities of further offending are similar for BDm4 and BDm6. However, whilst BDm6 suggests that over time, David's probability of further offending decreases until Time 4, the trend based on BDm4 is somewhat more erratic. Despite this, it does broadly reflect the changes in David's ASSET scores.

In utilising the ASSET scores of these three young people, some of the limitations of the models presented in this chapter are exposed. Had there been access to a larger dataset, then it is anticipated that there would be more examples of where young people had experienced multiple events. This would have enabled interactions between *Breach: Appear: Time*, *Appear: Custody: Time* and *Breach: Custody: Time*, to have been included within the dynamic models. This would have enabled a more responsive model for system contact to have been developed.

7.4 How do these findings extend the evidence base?

Breaches

YOTs are expected to bring breach proceedings after three instances of non-compliance within a youth justice order. However, they are also required to 'ensure that every effort is made to support the child or young person or parent/carer(s) in successfully completing all orders including those made in the civil courts and effectively manage compliance and enforcement issues in accordance with relevant legislation' (Youth Justice Board, 2013: 30). In ensuring compliance, they are obliged to take account of 'the young person's or parent/carer's individual needs in relation to mental health problems, learning disabilities/difficulties, and speech, language and communication difficulties' (Youth Justice Board, 2013: 30).

If a child or young person is found guilty of breaching an order or commits a further offence during the period of an order, the court has various options available depending upon the nature of the order. These include revoking the order and resentencing, imposing a custodial sentence for the breach, or if the young person is on license, they can be recalled to custody.

For the purposes of this research no distinction is made between the types of statutory order that the young person had breached. Although the dataset included examples of where the young person had been returned to court following breach and where the breach lead to a custodial sentence / return to custody, the number of cases were small hence it there remained considerable uncertainty within the models involving interactions between *Breach: Appear* and *Breach: Custody*.

Since information pertaining to this predictor has been taken from the young person's offending record held within Childview, it has not been feasible to investigate the circumstances which led to the individual being breached. However, Grandi and Adler (2016) in their research into the circumstances and characteristics of young people from a single urban YOT who breached between June and December 2012 found that the most common reason was missed appointments – a finding which concurs with (Hart, 2011a; 2011b), and failure to adhere to their electronically monitored curfew. Other reasons reported included unacceptable behaviour and entering an exclusion zone. Whilst both pieces of research involved small sample sizes and include caveats around the generalisability of findings, it is anticipated that many of the young people whose risk assessments were utilised for this research will have had similar experiences to those involved in qualitative work in this area.

Although the recommendation is that the court should take care to ensure that the requirements imposed 'are not too onerous so as to make breach of the order almost inevitable' (Sentencing Guidelines Council, 2009: s10.27), both Hart (2011a) and Grandi and Adler (2016) suggest that those who found it hardest to comply are those facing the greatest disadvantage, including family factors, cognitive or communication difficulties or social pressures.

The dynamic model involving breaches (BDm5_B) suggests that the likelihood of further offending increases if the young person has breached although the very wide credible interval highlights the amount of uncertainty around this main effect and in relation to the significant interactions between Breach and the individual domains (Table 7.7). Time helps to explain some of the uncertainty – as evidenced by the various significant 3-way interactions between Breach, Time and the individual domains. However, it would appear that there must be other factors (not included in the model) which help to explain the uncertainty.

Of the 12 domains, it is Physical Health that is a significant main effect within the dynamic model. It is also significant in interaction terms with Breach and/or Time. As can be seen from the domain description in the Technical Annex, this domain includes problematic issues around the physical immaturity / delayed development of the young person and where they are considered to be putting their own health at risk through their own behaviour along with having a health condition which affects everyday life functioning, not being registered with a GP or other health care services. In particular the domain's links with physical immaturity / delayed development tie in with Hart's finding that some children's ability and level of maturity were factors related to compliance with some being impulsive and having problem-solving skills meaning that they were easily discouraged (Hart, 2011a).

Hart also found that perhaps the most important factors in enabling compliance was having a reason not to breach: causing distress to family or ruining the 'normal life' that they aspired to. Family relationships were also important in both a positive and negative sense. The chaos described in the households of some of the children interviewed by Hart led directly to non-compliance and a number had been kicked out by their parents or passed between warring ex-partners causing distress and conflict. When parents were supportive, this was on a practical level – with parents writing appointments on the calendar, getting them up and making sure that they had the means to get there. Practitioners similarly cited family support – or lack of it – as being a vital factor related to compliance along with good accommodation and thinking / communication skills. In particular they highlighted problems experienced by looked after children, especially those in residential care where staff did not always remind them of their appointments or generally support their compliance. The large significant positive coefficient for the *Breach: Family and Personal Relationships* interaction with its wide credible interval is potentially a reflection of this.

Court Appearances

Cleghorn et al. (2011) found that although those who had attended court were fairly ambivalent, with Court being a necessary stage to 'get through' if they were being convicted of an offence, there were some, particularly those who were younger that reported feeling anxious and nervous both prior to and whilst in court. Notably they reported feeling unsupported, with court proceedings 'going over their head'. Deuchar and Sapouna (2016) similarly identified the need for young people to be supported, reassured and aware of their rights so that they could adequately understand court proceedings. In providing adequate support during this stage in the criminal justice system, they argue that it ensures that young peoples' prospects for desistence are not inadvertently damaged. However, it also needs to be acknowledged that for those who had had a long wait before their case came to trial, the time spent waiting was considered to be 'wasted' time during which their ability and motivation to engage in education and start planning for their future was severely restricted (Cleghorn et al., 2011). During this time, they may be open to temptation and can become resigned to further offending as a consequence of the constrained opportunities arising from having had contact with the youth justice system. Thus, as Corr (2014) observes criminal justice responses can serve to further marginalize young people's positions as they begin to appreciate potential barriers to 'moving on' with their lives, particularly through access to education and employment.

Whilst going to court was considered a daunting experience by the young people spoken to by both Corr and Cleghorn et al, they felt that 'it would not necessarily function as a deterrent to all young people who had offended. Rather, it was felt that it would act as a deterrent to some, whilst for others perhaps those committing more serious offences, going to court would have a very limited preventative effect' (2011: 29). Indeed, there may be some for whom going to Court enhanced their criminal status. The extent to which members of the reoffending cohort felt this cannot be ascertained from the data available. However, the rate of further offending suggests that attending court did not serve as a deterrent – whilst some were required to return to court following a breach and at least two for offences committed before their primary offence went to court, there were also individuals who committed further offences.

For those with 'previous form', the consequences of having an offender identity, can be deleterious in court particularly if they have become distrustful of authority. Hart (2011b) for example found that some of the factors which influenced sentencing decisions in relation to breaches included:

- 'The young person is sorry and pleads guilty
- If they are totally disengaged with the process, with a real attitude, that's going to be the same outside court
- If the parent comes to court for the breach, I'd feel more confident that the parent was engaged with the order
- The young person's attitude, motivation and family support
- Are they remorseful?
- A good home background, a sense of self-worth and basic education'

(Hart, 2011b: 22)

Those young people whose demeanour in court was interpreted as cheeky were identified as being more likely to receive a punitive response as were those lacking social or communication skills. However, it is also perceivable that these factors also apply when determining sentences for other offences, with magistrates not knowing what to do with particularly chaotic young people who have 'form' for not complying with the requirements of their order or who are perceived to be lacking the support of family members. Inadvertently, since those who have appeared in court previously may have a better understanding of what to expect, those FTEs who are lacking a comprehension of court processes may be disadvantaged if they not appear to be engaging.

The dynamic model involving court appearance (BDm5_A) suggests that as with breaches, the likelihood of further offending increases if the young person attends court (Table 7.7). This coefficient is similarly moderated by the *Appear: Time* interaction – the significant negative coefficient suggesting that the effect of having to return to court after the initial appearance decreases with time. None of the other main effects or interactions are significant within the model whilst the DIC of 445.9 suggests that even taking into account the additional complexity of the model, there is a significant amount of uncertainty unaccounted for relative to the equivalent model involving just the 12 domains (BDm1). Had there been sufficient data to enable the Level 2 'individual' characteristics to be incorporated into the dynamic model, based on the findings, it is anticipated that FTE status, experience of care, age at first offence and other vulnerabilities would have helped to explain some of this uncertainty. Dynamic Model 6, which included experience of care alongside court appearances and interactions relating to breaching and spending time in custody/ on remand illustrates this, with the DIC falling to 433.6 despite the additional complexity of the model.

Custody

Custody as a main effect was not found to be significant in this dynamic model (BDm5_C). However, the interaction between Custody and Time was significant, with the negative coefficient suggesting that if the time in custody / on remand occurs later in the young person's time under the supervision of the YOT, then it has less impact on the likelihood of further offending. As with BDm5_B, the Physical Health domain was a significant as a main effect. However, none of the interactions involving Physical Health were found to be significant.

YOT staff believe that young people with learning disabilities, communication difficulties, mental health problems, ADHD, and low levels of literacy are more likely than children without such impairments to receive a custodial sentence (Talbot, 2010). This, it suggested, is the coming together of a number of factors including:

- the lack of routine screening and assessment to identify the particular support needs of children who offend – an issue which ASSET Plus has sought to address
- a poor understanding across youth justice services of how impairments and difficulties can affect behaviours, which can be particularly significant during court proceedings
- limited availability of appropriate youth justice programmes, activities and support, linked to which, the increased likelihood that children with impairments and difficulties will fail to comply.

Subsequent research and pressure from organisations such as the Royal College of Speech and Language Therapist, the Prison Reform Trust and Howard League for Penal Reform have contributed to an increased awareness of these issues with the youth justice system within the YJB and individual YOTs playing an integral role in the development of good practice. However, as independent reviews such as those by Lord Lamming and David Lammy PM highlight, some of the most vulnerable groups of children continue to be over-represented, particularly in the formal youth justice system and the secure estate.

For those who have spent time in custody, the neighbourhood to which they return along with their living arrangements has been shown to have a significant bearing upon the likelihood of reoffending. Hence in recent years there has been a policy emphasis upon resettlement as part of the Transforming Youth Justice agenda. Research by Beyond Youth Custody (Bateman and Hazel, 2015) suggests that young people experience a period of reorientation and transition immediately following release during which they can become overwhelmed, lost and confused. Even though they may be returning to familiar surroundings, inevitably there will be elements of their environment which have changed whilst in custody. Interactions with people, even family and friends, can be problematic causing stress, confusion and anxiety. Whilst Bateman and Hazel suggest that there is a dearth of literature on how young people experience resettlement after prison, they emphasise that this area needs to be explored given findings from research amongst adult ex-prisoners suggesting that they are extremely vulnerable to suicide and that the first two weeks following release are associated with higher rates of drug-related mortality.

The transition from custody to community can be disorientating and destabilising, with young people not only having to renegotiate relationships and adjust to the new lifestyle, but also because the structural support such as stable accommodation, education, training, employment and financial stability on which to build their reorientation may well not be available at the time of release. This can be particularly challenging since a number of vulnerable groups are over-represented in the custody population e.g. those with poor mental health (Berelowitz and Hibbert, 2011); neurodisabilities including traumatic brain injuries and attention-deficit/hyperactivity disorder (Young and Goodwin, 2010; Hughes et al., 2012; Hughes et al., 2015); looked after children (Prison Reform Trust, 2016) and having experienced different types of trauma (Liddle et al., 2016). For these young people, their needs and vulnerabilities mean that they may not have developed strategies to cope with transitions and are more likely to have to orientate themselves around a chaotic home environment.

The low number of individuals in the reoffending cohort with experience of custody or being on remand means that it is difficult to draw firm conclusions about the impact of release from custody on the likelihood of further offending. However, the second case study presented in Section 7.4 'Connor' focuses on the changes in dynamic risk associated with a young male with ADHD upon his release from custody.

7.5 Summary

The analysis presented in this chapter sought to address three research questions:

6. How is the likelihood of further offending affected by having experience of care and a previous offending history?
7. What is the impact of coming into contact with facets of the youth justice system on the likelihood of further offending?
8. How well do ASSET scores reflect the realities of the young person's change in circumstances during their time under the supervision of the YOT?

In doing this, Chapter Seven built upon findings from previous chapters. Whilst the size of the dataset limited the extent to which different forms of system contact could be explored, it was possible to construct a model which considered both experience of care and grouped age at first offence (BDm4). As highlighted in section 7.4, when applied using the ASSET scores for the three case studies rather than artificially fixing the domain scores, some of the limitations of the model were exposed. Notably, although the various diagnostic tests were satisfied and there were no convergence issues, the comparatively small sample size meant that amongst those who had first offended aged 10-12 years, there were few cases to inform the model, particularly at later measurements. As a result, the trajectory of the estimates of further offending were more heavily influenced by the ASSET scores of those considered by practitioners to have a high risk of reoffending, resulting in an upward trend over time.

This chapter also considered system contact by considering how 'events' such as breaching, returning to court and spending time in custody/ on remand affected the likelihood of further offending (BDm5_B, BDm5_A and BDm5_C respectively). This is not something which has previously been explored in evaluations of ASSET, largely since these have confined to looking at a single assessment per individual. Whilst the 12 domains are time varying, reflecting the scores at each assessment, by extending the Basic Dynamic Model to include both a Level 2 characteristic and an 'event' brings the model closer to representing the realities of a young person's experience under the supervision of the YOT.

Had the dataset been larger, it would be desirable to look at combinations of the Level 2 predictors and the different permutations of encounters with different facets of the youth justice system for to get a greater understanding of how these typically impact upon the likelihood of further offending. From a policy and practice perspective, it would be particularly useful to increase our understandings for the following sub-groups:

- a looked after child with a prior offending history relative to their peers who have either no history of offending or have never been looked after. Ideally this should take into account the legal status of the child; whether they were looked after at the time of their initial offence; if they continued to be looked after and how they are being accommodated.

- for those who enter the youth justice system at a young age and have an established offending career relative to the young FTE and the older FTE. Potentially this require an additional predictor which takes into account their age at the time of the primary offence as well as their age at the time of their first offence and conviction.
- females with different characteristics / experiences relative to their male peers.
- BAME children with different characteristics / experiences relative to their peers, ideally with the potential to enable individual ethnic groups to be considered.

Across Chapters Five to Seven, different types of predictors have been used to extend the Basic Dynamic Model constructed in Chapter Four. This has included dichotomous, categorical and continuous measures which represent data collected by the YOT to assess the risk of individual further offending behaviour and to determine the most appropriate interventions for the child. One of the key tools used in conducting this analysis was the reoffending spreadsheets compiled by the YJB which include individual level data, to measure the performance of the YOT. Court and offending records held within Childview were also utilised with records being matched using a unique identifier. These illustrate the potential for using data linkage approaches to provide additional contextual information about the child. This could include education, health and social services records as well as the outcome for referrals for substance misuse treatment, speech-language therapy, mental health support etc.

As these three chapters have demonstrated, utilising Bayesian approaches offers a flexible means to incorporate different types of data so that new hierarchical models can be developed as and when additional information becomes available. This could either be about a specific individual e.g. as a result of further assessments being made, or about a particular issue. Whilst having a small sample size did mean that compromises needed to be made, this did have advantages since it was possible to look in more detail at the underlying data in order to understand why unexpected outcomes had occurred.

In addition to using hierarchical models, analysis has also been taken using one- and two-sided 2x2 chi squared tests to considered whether or not there was a difference in the rates for different groups. A Pearson's correlation was also undertaken to look at the relationship between the age at first offence and age at first conviction (in Section 6.7). These are just some of the commonly used statistical tests which it is possible to perform in a Bayesian framework, with Bayes Factors being used to interpret findings rather than p-values. Together, these offer practical examples of *how the relationship between risk factors and (re)offending can be explored using Bayesian approaches*, thus addressing the second research objective. A number of challenges were identified which have been touched upon within this analysis. These are considered further in Chapter Eight along with implications for policy and practice of adopting Bayesian approaches more widely within criminology.

8 Discussion

8.1 Introduction

The overarching research aim of this research is to explore the utility for using Bayesian approaches within criminology. This has been done by way of a case study focusing upon risk assessment in the youth justice system in England and Wales. The case study was chosen because the evidence base has been widely criticised and hence there is the opportunity to demonstrate how, by applying novel statistical approaches to a comparatively small dataset, knowledge and understanding can be extended. Although a series of research questions were posed, these were designed as part of the analysis led approach to demonstrate specific features of the data and how these could be explored using Bayesian techniques.

The findings presented in Chapters Four to Seven illustrate some of the strengths and limitations of applying these techniques to a comparatively small number of cases drawn from administrative data relating to the youth justice system in England and Wales. Whilst the size of the dataset is somewhat smaller than in other reviews / evaluations of ASSET (Baker et al., 2003; 2005; Wilson and Hinks, 2011), it was possible to build upon these by specifically focusing on the dynamic element of risk and to look at the impact of breaching, having to attend court and spending time in custody / on remand. However, the comparatively small size meant that it was not possible to explore some of the permutations of individual characteristics e.g. ethnicity and gender. This is frustrating in the context of the recent reviews:

- *The Lammy Review* (2017) which emphasised the diversity of the BAME community, including the potential to investigate differences by age, gender and heritage, with looked after children who are Black or from other minority ethnic groups and looked after girls identified as being minority groups with particular needs, and
- *In Care, Out of Trouble* (Prison Reform Trust, 2016) which specifically identified looked after children from minority groups e.g. those from black or from other minority ethnic backgrounds, and children and young people of Muslim faith; looked after girls; children with disabilities, learning difficulties and speech, language and communication needs; foreign national children including asylum seekers and those who have been trafficked.

Utilising the comparatively small dataset has afforded this research a distinct advantage in that it has been possible to drill down to individual cases to investigate trends and provide contextual information to assist in the interpretation of the findings. Notably understanding the 'weight' of the observed data for different sub-groups at respective measurement points assists in understanding issues around why some models have struggled to converge whilst others have generated spurious trends. Significantly the unbalanced nature of the dataset means that at later measurement points, there are fewer cases and these relate to individuals who have committed further offences. As such the influence that these cases have in interactions involving time can be distorted by what has happened to a single individual. This is perhaps most apparent for the gender predictor where the average number of measurements for each female is 4.25 compared to 6.53 for males whilst the maximums are 10 (Time 9) and 19 (Time 18) respectively (Figures 5.2 and 5.3). Similarly, when predictors are combined, there are instances where only a small number of individuals shared a particular combination of the characteristics reflected in the model. This meant that compromises needed to be made, for example using grouped age at first offence rather than FTE status alongside experience of care when exploring system contact in BDm4.

A key feature of the use of Bayesian approaches is that they enable low base rates to be taken into consideration and hence offer the potential to increase the sensitivity of risk assessment tools to explore within- and between-individual differences. Whilst there were insufficient cases to establish within the reoffending cohort any issues around dimensional identity, the inclusion of predictors for Gender and Ethnicity alongside the 12 domains does not disconfirm the notion that there may be distinct trends for females and non-White groups. It was similarly not possible to differentiate between the severities of violent offending nor to explore any differences that might exist on the basis of the type of offence. However, the potential for this has been demonstrated should access to a larger number of cases be secured.

Had the dataset been larger, it would also have been desirable to investigate potential difference in terms of the type and severity of further offences committed. Not only would this have enabled 'offending' to be de-homogenised (Case and Haines, 2009) to consider different typologies of offender, it would also have enabled theories around the persistence, escalation and degree of specialisation which form important aspects of the criminal careers approach to be considered. It is anticipated that access to PNC would be required to enable young people's offending to be tracked beyond the age of 18 as the information included within the YJB's reoffending spreadsheet was somewhat limited.

What it was possible to determine from the data was the impact of system contact whether it be 'events' representing facets of the youth justice system, having first offended at an early age or being a looked after child. Notably what was apparent in many of the models was the role of individual domains, particularly those relating to Lifestyle, Thinking and Behaviours; Perception of Self and Others, and those relating to individual factors. These highlight the strong and enduring relationship between punishment and offender identify which McAra and McVie (2015) argue we have an obligation to investigate if we wish to build a youth justice system which protects the rights of children, promotes the well-being of those young people who have offended and hence come into contact with different facets of the system, reduces crime and promotes social justice.

The hierarchical models generated were intended to mimic those which features of the ASSET Core Profile, with the motivation being to identify if a more sensitive tool could be developed – hence the choice of research questions.

The posterior mean distribution for the random effects of time and individual were found to be significant in each model suggesting that the probability of further offending differs across individuals which is what would be expected given the role of agency. Whilst there remains uncertainty within the models, it is likely that some of this could potentially be explained by the role of other variables not included in the model specification. The nature of these could as yet also be unknown.

From the trace plots and histograms for each model, the convergence is satisfactory whilst the autocorrelations of the estimates were small suggesting that adequate thinning and burnin had been allowed for. Given the comparatively small size of the dataset upon which these models have been simulated, it is anticipated that the predictive accuracy could be improved upon through the inclusion of more cases. However, in adding to the complexity of the Basic Dynamic Model (BDm1), the DIC tends to increase and therefore this is not necessarily indicative of increased predictive accuracy.

The DIC is currently the predictive measure of choice in Bayesian applications, in part because of its incorporation into the popular BUGS package (Spiegelhalter et al., 2002; 2014). It also features within the MCMCglmm package (Hadfield, 2010) used for this research. Based upon the DIC's of the respective models (Table 8.1), Dynamic Model 1 appears to be the 'best' model. However, this is also the simplest model – a limitation of the way in which the DIC is constructed is that it tends to favour simpler models with those involving more parameters being penalised for their complexity (Plummer, 2008). Of the models involving additional predictors, it is Dynamic Model 3 (BDm3) which has the lowest DIC and hence provides the 'optimal' fit (Finch et al., 2014). However, when 'real' domain scores relating to "Fred", "Connor" and "David" were used to estimate their probability of further of offending over time and compared to 'events', this revealed some of the limitations of these models.

Table 8.1: Summary of Model DIC's - Combined Models

Description	Model	DIC
1 - The Basic Dynamic Model (12 Domains)	BDm1	256.8
2 - Demographics and Care	BDm2	466.4
3 - Static Factors	BDm3	387.9
4 - Age at First Offence and Care	BDm4	425.9
5A - Court Appearances	BDm5_A	445.9
5B - Breaching	BDm5_B	449.9
5C - Custody / on Remand	BDm5_C	478.0
6 - System Contact	BDm6	433.6

It is anticipated that were this work to be repeated using a larger number of cases, then it would enable the role of the 'individual' level predictors to be explored more thoroughly. Notably there would be the potential to model permutations with more certainty, for example to explore the role of age and FTE status, and also to gain a greater understanding of multiple events e.g. where a breach leads to a court appearance and where the outcome of a court appearance is a custodial sentence / remand. A key insight gained from undertaking this research is that whilst the techniques employed enable more to be done with less, there is still a need to have cases which share the various characteristics in order to inform the model.

Whilst Chapters Four to Seven demonstrate from a practical perspective *how the relationship between risk factors and (re)offending be explored using Bayesian approaches (*the second research objective) the next section addresses this from a more theoretical perspective. As such it focuses upon how the approaches described can potentially address the criticisms of ASSET and hence issues more generally with risk assessment processes used within the criminal justice system.

8.2 Addressing the Criticisms of ASSET

As previously outlined, ASSET was chosen as a case study because it has been widely criticised by both practitioners and academics. It has since been replaced by ASSET Plus – a tool designed to address many of the criticisms and to reflect emerging practice. The main criticisms of ASSET with regard to the methodology, content and its practicality have been identified by Stephenson et al. (2011) as being:

- Factorisation
- Marginalisation of young people's perspectives
- Technicised practice
- Developmentalisation and psychosocial bias
- Predictive utility
- Repressive welfarism

Given the breadth of the criticisms, not all of these could be addresses within this research. Hence the focus has been upon those relate to the application of actuarial approaches i.e. factorisation and predictive utility. However, the findings do, in some instances, have implications which have the potential to indirectly address other aspects raised by critics.

Adulterisation and Zombification: the application and use of ASSET

In response to accusations that ASSET is an adult-led assessment which neglects the views of young people (see for example Case, 2006), Stephenson et al. suggest that this is 'perhaps largely a failure to implement ASSET properly rather than a function of the tool itself' (2011: 51). Whilst this is not a view that I share, I feel that both this and issues around the articulation of children's rights within the assessment process fall outside the scope of this research. Notably this is an issue which Baker (2014a) asserts has been addressed within the ASSET Plus framework through the inclusion of self-assessments for young people and parents/carers which can be built upon as the intervention progresses and through the engagement and participation section of Foundations for Change.

Accusations of technicised practice and the 'zombification' of practitioners (Pitts, 2001) stem from ASSET being characterised as a mechanised tick-box system. This, Stephenson et al suggests is associated with the 'abundant evidence of inconsistency of practice and neglect of guidance' (2011: 52). However, it has been acknowledged in *Breaking the Cycle: Effective Punishment, Rehabilitation and Sentencing of Offenders* that there was a need 'to move towards a lighter touch performance monitoring capability which supports a more risk-based inspection programme and increases professional discretion' (Ministry of Justice, 2010: 76). Indeed, the impetus for the review of youth justice assessments was the recognition that mechanisms were needed which 'increase discretion and reduce the amount of time frontline workers spend in front of their computers, so as to free up their time to work with young offenders' (Ministry of Justice, 2010, quoted by Teli, 2011: 5). The extent to which this has been achieved through the ASSETPlus framework has yet to be explored. However, the way in which practitioners engage with the risk assessment process similarly falls outside of the scope of this research. Although, it is recognised that it continues to be desirable to have a framework for determining the likelihood of reoffending which can be readily understood and operationalised for practitioners. Indirectly this piece of work has the potential to contribute towards this.

Privileged Policies: Repressive Welfarism, Developmentalisation and Psychosocial Bias

Of the remaining main criticisms, it could be argued that developmentalisation and psychosocial bias, and repressive welfarism are a reflection of policy. In the case of the former, the bias arises from the selective use of evidence (Case, 2007; O'Mahony, 2009; Goldson, 2010), which Case (2010) argues has privileged three developmental explanations of offending behaviour: Farrington's *criminal careers model*; Sampson and Laub's *theory of age-graded informal social control* and Thornberry's *interactional theory* - these explain 'offending as the predetermined product of exposure to psychosocial risk factors at different developmental stages (particularly childhood), and therefore, privileges risk factors located within the individual' (Case, 2010: 91). The emphasis on what is considered to be 'modifiable' has meant that the wider socio-economic problems are disregarded, privileging the 'family' under the rhetoric of care and support rather than social harms such as poverty, class and societal access to opportunities. In this way a psychosocial bias has been reinforced through the artificial restriction of the range of risk factors being explored.

Repressive welfarism is, according to Phoenix (2009a), similarly a reflection of the previous Labour government and the YJB's approach to youth crime. However, this arises from the tension between welfare and justice approaches with some risk factors for reoffending equally being constructed as social welfare needs. In acknowledging that perceptions of risk and need have become very blurred, Phoenix (2009a) asserts that in their attempts to highlight service gaps which have created a raft of unmet needs for young people and operate to push young people into less than law abiding behaviour, practitioners have inadvertently created conditions whereby 'needy' young people are rendered 'punishable'. Thus, the recognition that there is a lack of appropriate state responses to social welfare issues is resulting in vulnerable, marginalised and excluded young people being subject to more punitive (and especially penal responses).

At the heart of both of these issues, is what is being assessed in terms of content and the extent to which the assessment considers the individual risk, needs and vulnerabilities of the young person. Notably, ASSET was particularly criticised for its emphasis on negative risk factors over positive protective factors; that the approach served to identify and act upon risks associated with the young person without necessarily addressing their needs, and that it stereotyped and demonised young people, thereby facilitating a culture of control (Stephenson et al., 2007). Under the Scaled Approach, there were also concerns that in the interests of eradicating potential threats, there were also issues raised about fairness and equality due to the potential for two young people who committed the same crime being treated differently as a result of their perceived level of risk.

The YJB have sought to reflect emerging evidence in developing ASSET Plus as a successor to ASSET, particularly through the incorporation of issues reflecting heightened societal and policy concerns that have emerged since 2000. Significantly the new framework is underpinned by an evidence base that extends beyond the risk and protective factor paradigm of which many commentators had been so critical, to reflect the 'growing emphasis on the development of theory and practice models based around factors which increase the likelihood of young people desisting from offending' (Youth Justice Board, 2014). Reflecting its mandate as an evidence-based organisation, the YJB has also been keen to ensure that lessons learnt from other fields e.g. social work, health care and probation with regards to assessment practice have been incorporated along with the perceptions of practitioners and young people. As such ASSET Plus includes the following new areas:

- Speech, language and communication needs screening
- Optional alcohol use screening tools
- Financial circumstances of the young person
- Risk of/identification of radicalisation
- Gang associations
- Gambling and inappropriate uses of technology
- Identification of parental responsibilities of the young person
- Identification of carer responsibilities of the young person

Whilst this research has not explicitly explored new ground since it has focused on variables which reflect the scoring system from the Scaled Approach, the adoption of Bayesian approaches provides a mechanism for continually updating the risk assessment process as more is learnt about the young person and also about the cohort within the formal youth justice system. The flexibility that the approach affords also means that the risk assessment process could continue to evolve to reflect emerging crime types and to respond to evidence around 'What Works' with young people who offend.

A frustrating feature of the administrative data used for this research is that the information relating to these 'new' concerns, if captured would have been noted within narrative fields which are more difficult to systematically interrogate - although the Core Profile includes questions about whether the young person has a formal diagnosis of mental illness or has a statement of special educational need, the details would be recorded in the evidence box within that domain. There may also be details in information provided by partner agencies to support the writing of the pre-sentence report. As such it was not possible to explore these issues within this research. Similarly, whilst it might be recorded that a young person has been referred by the YOT say to substance misuse treatment services or CAHMS, the outcome was not routinely recorded since this data would be considered 'health' data. However, this is not to say that if concerns begin to emerge about a particular issue then, assuming relevant data could be captured, this could be explored through a modification to the model if a Bayesian approach were adopted. In this way the range of factors associated with the likelihood of further offending and/or promoting desistence could be enhanced to offer a more fit for purpose holistic assessment process.

A Blunt Tool? The Application of Actuarial Approaches

Whereas the previous criticisms relate to the application and use of ASSET by practitioners and the evidence underpinning ASSET, the criticisms around factorisation and predictive utility relate to the application of actuarial approaches. Associated this are issues around how to operationalise measures and outcomes (O'Mahony, 2009). These have a particular bearing on the 'What Works' agenda since one of the key variables in determining outcomes of interventions designed to reduce the likelihood of reoffending should logically be the ASSET Score / Band.

As highlighted in Chapter Two, there have been particular concerns about the predictive accuracy of ASSET with Smith questioning the efficacy not just of having the authoritative decision making based on unreliable information and subjective judgements, but also whether 'it is acceptable to 'get it wrong' sometimes in order to manage and control risk?' (2006: 102). In particular, he points to the very high reported rates of both false positives and false negatives (summarised in Table 2.5), highlighting that cost-benefit analysis of the kind undertake by the Audit Commission (2004), often tend to gloss over the 'massive human and financial waste resulting from the failures of pre-emptive and excessive interventions'. At a time when there is little public money, there is perhaps now even less justification for there being routine error within the technologies of assessment and classification applied in youth justice especially when it has been suggested that increased diversionary activity and the declining number of FTEs, means that those in the formal youth justice system although smaller in number, now represents a 'greater concentration of young people with complex needs and risky, entrenched behaviours. As a group, they are more likely to be challenging to work with and more likely to reoffend' (Youth Justice Board, 2016a: 13).

Issues around the predictive utility, not just of ASSET but of actuarial tools generally arise from attempts to reduce complex and interrelated experiences and circumstances into a series of ratings which indicate the likelihood of reoffending. Critics in particular point to the reductionist tendencies which have led to such tools becoming an oversimplified technical fix to the complex social realities of young people's lives (Case, 2010). They have also expressed concern that ASSET is concerned not with predicting reoffending, but with reconviction. The limitations of using proven reoffending as an outcome measure where highlighted in Chapter Three with two examples of pseudo-reconvictions being found amongst the 88 young people whose data was used for this research. However, it also needs to be acknowledged that 'reconviction is not the same as reoffending and can be influenced by the local practice of the police and other CJS agencies in securing convictions' (Howard and Kershaw, 2000: 1). Similarly, convictions can represent more than one offence and levels of attrition within the justice process can mean that there can be a significant difference between the number of offences committed, recorded, detec ted and ultimately resulting in conviction. Having a risk assessment tool therefore that is based upon an inherently flawed outcome measure, the risk of which is determined on the basis of statistical correlations and associations, renders many of the so-called risk and protective factors as being artefactual. The decision to use further offending as an outcome rather than reconviction represents an attempt to minimise the impact of this. However, as will be highlighted in later sections, issues emerged as a result of the construction of the proxy indicators designed to mimic the static factors included within ASSET which may have inadvertently added to the uncertainty, particularly in relation to the model involving offending history.

Whilst it is important to reiterate that ASSET was not intended to be an exact science, rather the individuals' ASSET score was intended to provide an indication of the likelihood of reoffending and was designed to aid practitioners in consistently and transparently identifying those domains associated with offending in order to construct robust interventions. However, it was felt that the chances of disproportionate intervention were increased under the Scaled Approach, for example a low-risk young person who had committed a serious offence receiving too intensive an intervention and vice versa. Certainly, having an approach where around one-third of profile outcomes were neither valid nor reliable was both damaging and counter-productive to the young people concerned. With their dual-purpose objectives, second- / third-generation tools such as ASSET are subject to significant methodological issues associated with the actuarial fallacy. As a result, the tools lack the sensitivity to be specific to the individual and their circumstances. With so many uncontrolled and unknown (in the sense of not being measured) variables, it has been suggested that this makes analysis using traditional statistical methods meaningless. This black box approach, in a youth justice context, means that the transferability of good practice is not always possible since the reason why some interventions work can be context specific. Hence why it is so important to shed light on the mechanisms involved.

This thesis has been concerned with the utility of Bayesian approaches for criminology. In considering this, the framework of youth justice risk and protective factors and associated risk assessment tools has been used as a case study to demonstrate what can be achieved through use of Bayesian approaches using a comparatively small administrative dataset. As demonstrated in Chapters Four to Seven it has been possible to enhance knowledge and understanding about the dynamic nature of risk and how this differs depending upon the circumstances and characteristics of the young person. Although it was necessary to make compromises due to the size of the dataset, the findings presented in Chapters Four to Seven provide the building blocks for potentially advancing this work whilst also acknowledging common problems associated with working with administrative data.

Having discussed the implications for youth justice in the previous section, the emphasis in the remainder of this chapter is upon the wider benefits that could be realised if the discipline were to embrace the adoption of Bayesian approaches. In doing this is recognised that as yet the merits of Bayesian approaches have yet to be realised by many social scientists. However, in the context of the ASA's statement advocating that other approaches should be entertained as an alternative to NHST and the advent of the digital turn in criminology, it is my belief that the time is ripe for paradigm shift.

Notably the advent of digital criminology and 'Big Data' affords significant opportunities for criminology especially given the amount of routine data captured at different points in the criminal justice system. This has been acknowledged through the creation of the ADRN and initiatives such as the ESRC's Secondary Data Analysis Initiative. Yet this also comes at a time when there are concerns about the mathematics and quantitative skills of future generations (Smith, 2017). Thus, in discussing the opportunities, it is also necessary to recognise that there will be philosophical and pedagogical barriers to overcome before the discipline can truly benefit from adopting novel statistical techniques such as Bayesian. Hence the key theme within the next section is addressing the third research objective: *What methodological challenges will need to be overcome?*

8.3 Is it Time for a Change?

Out with the Old …

In outlining the rationale for using Bayesian approaches in criminology in Chapter One, a key motivation is the ongoing debate about the appropriateness of using NHST and all its vestiges, and concerns that they are often used to support lower-quality research. Such is the strength of this debate that the ASA published a statement on p-values and statistical significance in which they advocated that alternatives such as Bayesian approaches should be entertained whilst acknowledging that these come with their own conceptual problems (Wasserstein and Lazar, 2016).

The position taken by this research is that the continued use of NHST is an obstacle to creative thinking and innovation within criminology. Associated with this is the movement towards post-positivist approaches in the discipline. Whilst both classical and positivist traditions have played a role in the development of theoretical approaches and the adoption of scientific principles within the discipline, in order for it to continue to evolve, it is necessary for criminologists to rise to the 'challenge to Import, Introspect and Innovate in order to better answer the questions of interest to the field' (Bushway and Weisburd, 2006: 1). The eclectic origins of the discipline mean that criminologists have a history of drawing upon 'sophisticated and cutting-edge approaches from other fields' and have 'given significant attention to the ways such approaches must be adapted to fit criminological problems' (Bushway and Weisburd, 2006: 1). The adoption of Bayesian approaches therefore would represent a continuation of this tradition, adapting techniques which have been successfully used in other disciplines to advance knowledge and understanding around the aetiology of offending behaviour and informing what works in terms of society responses.

Along with many of the social science disciplines, as criminology has continued to mature as a discipline, it has continued to be innovative, taking advantage for example of data visualization techniques including geospatial applications to consider crime trends (Chainey and Radcliffe, 2005; Chainey and Thompson, 2008) whilst the UK's Ministry of Justice has made inroads into data linkage to explore re-offending as part of its Justice Lab initiative (Ministry of Justice, 2014a). However, the extent to which the discipline can claim to be introspective with regard to the appropriate use of different techniques could be called into question since it has yet to shake off the shackles of NHST. Criminology is not alone in this, but as other social science disciplines start to warm to the idea of using Bayesian approaches, then I believe that it cannot afford to be left behind. This is particularly true if we wish to (1) produce quantitatively informed research to inform policy and practice, and (2) make optimum use of the growing amount of administrative data that is collected at different stages of the criminal justice system. It is therefore vital that the discipline continue to be both innovative and introspective in our analytical approaches, importing new and novel ideas where applicable from others.

In with the (not so) New

The analytical techniques utilised in Chapters Four to Seven should be familiar to most quantitative researchers and include t-tests; contingency tables to compare proportions; Pearson's correlations and logistical regression. However, these have been conducted in under a Bayesian framework. As such Bayes Factors rather than p-values have been used to interpret the significance of the various tests. Bayes Factors have the advantage that they can be interpreted directly and provide a measure of the strength of the evidence of one theory verses another. In using these rather than p-values, the potential source of confusion associated with the interpretation of hypothesis testing conducted under the Frequentist framework can avoided. Whilst not used here, equivalent tests for many of the common tools in the analytical toolbox also exist with further tests also being developed. Notably development of the open source software JASP (JASP Team, 2017b) 'provides a straightforward means of performing Bayesian analysis using a graphical "point and click" environment that will be familiar to researchers conversant with other graphical statistical packages, such as SPSS' (Quintana and Williams, Preprint: 1). As such it opens up a toolbox which had previously been inaccessible for many criminologists and social researchers. Since it offers both Frequentist and Bayesian analysis methods, JASP supports the conversion process for those whose statistical schooling has been grounded in classical approaches. Not only is this useful as a teaching aid, but when both sets of results point in the same direction, this bolsters one's confidence in the conclusions.

A similar approach was adopted with respect to the packages used to perform the hierarchical modelling which made up the majority of the analysis presented in Chapters Four to Seven. The functionality to undertake this is not available in JASP – see Table 8.2 for a list of functionality. However, it was possible to identify packages which could be used in R which had a similar syntax so that both Frequentist and Bayesian versions of the models could be specified. As can be seen from the Technical Annex, this highlighted the limitations of the Frequentist versions of the models, particularly once the complexity was extended beyond the basic dynamic model. Despite the limitations arising from the size of the dataset, it was possible to achieve more with less when conducting the analysis under the Bayesian framework using the MCMCglmm package (Hadfield, 2017).

Table 8.2: JASP Functionality

Analysis	Frequentist	Bayesian
ANOVA	✓	✓
ANCOVA	✓	✓
Binomial Test	✓	✓
Contingency Tables (incl. Chi-Squared Test)	✓	✓
Correlation: Pearson, Spearman, Kendall	✓	✓
Exploratory Factor Analysis (EFA)	✓	–
Linear Regression	✓	✓
Log-Linear Regression	✓	✓
Logistic Regression	✓	–
Principal Component Analysis (PCA)	✓	–
Repeated Measures ANOVA	✓	✓
Reliability Analyses: α, γδ, and ω	✓	–
Structural Equation Modeling (SEM)	✓	–
Summary Stats	–	✓
T-Tests: Independent, Paired, One-Sample	✓	✓

Note: Correct as at January 2018 (JASP Team, 2017b)

Big Data, Big Opportunities?

Efficiency, effectiveness, accountability and fairness have been at the heart of successive government's strategies for the criminal justice system in England and Wales (HM Government, 2007; Ministry of Justice, 2014b) with evidence suggesting that the criminal justice system can prevent crime through four principal mechanisms – deterrence, legitimacy, incapacitation and rehabilitation. Under the Transforming the Criminal Justice System agenda, there has been a particular emphasis upon digitalising the criminal justice system with reforms being mooted which will facilitate the seamless transfer of information from police to prosecution through to defence and the courts. Whilst much of this relates to speeding up the court process, there are also plans to equip police officers with the tools they need to start capturing evidence digitally at the scene of a crime, taking statements and uploading digital case information. Such steps are intended to reduce costs and delays. However, they will also mean that the amount of information collected by the different facets of the criminal justice system are set to grow exponentially. Whilst not all the data collected will be appropriate for applying Bayesian approaches and there will be a greater emphasis upon reducing duplication, it could lead to greater consistency in data collection methods across different agencies. Hence, I believe that the potential that this element of the digital turn affords to researchers interested in the aetiology of crime and the formulation of appropriate responses is significant.

Much has been made of the potential of Big Data and machine learning to the extent that these are seen almost as being a panacea. However, in the context of understanding offending behaviour and identifying appropriate and effective responses to reduce re-offending, then accountability and legitimacy should be at the fore. In particular given the concerns about the over-representation of minority groups within the criminal justice system e.g. the BAME population and looked after children / care leavers, if historic information is used to formulate interventions, then there is a risk that the practices which contributed to these biases will be amplified. This has already occurred with some of the machine learning applications intended to predict parole violations and inform predictive policing in the USA - notably, as highlighted in Chapter One, PredPol has generated significant media coverage on both sides of the Atlantic. Such problems can undermine the public's confidence in the justice system. I therefore believe that until these issues can be resolved, it is actually small sample research which affords the greatest potential for reducing disparities and identifying appropriate responses to some of the most vulnerable in the criminal justice system.

Having access to administrative data, not just from the criminal justice system, but also potentially health, education, social services and in relation to employment additionally will assist in construct validity since it will negate the need to use proxy measures, particularly with respect to offending. By facilitating criminologists in their endeavours to operationalise key concepts of interest, this will not only enable more robust analysis to be undertaken, but it will also support the investigation of new lines of enquiry. Sullivan and McGloin (2014) caution that:

> 'The reliance on existing data containing only a subset of measures on key constructs generally leads to some compromises in specifying models that fully capture the theory of interest, which can in turn color the scope of work and conclusions reached in entire bodies of literature around a theory.'

(Sullivan and McGloin, 2014: 452)

Looking forward, they advocate that in developing measures, it is important to start small, pilot and generalise. It is therefore necessary to acknowledge the contribution that data linkage could make to small sample research. The data matching techniques employed particularly lend themselves to small sample research, where there is the opportunity to investigate in more depth individual cases and supplement with the use of triangulated measures. The flexibility of conducting modelling under a Bayesian framework is that as new information comes to light, it can be systematically added to the model with priors being revised accordingly. Notably Bayes Factors can be used to compare the strength of evidence for and against the use of new or alternative constructs developed to measure potential risk and protective factors, with administrative data also assisting in determining temporal precedence.

Used properly, Bayesian reasoning has 'the potential to improve dramatically the efficiency, transparency, and fairness of the criminal justice system and the accuracy of verdicts, by enabling the relevance of evidence to be meaningfully evaluated and communicated' (Fenton and Neil, 2013: 407). Notably in the legal context, Bayesian reasoning can be used help in formulating accurate and informative opinions and it is this experience which I believe will contribute to enhancing the acceptability of Bayesian approaches in the area of risk assessment and formulating appropriate interventions. Key to this will be demonstrating the value of such novel approaches to facilitate the rigorous assessment of interventions. In this respect there is a lot to be gained from the path being taken by prevention science and public administration researchers in their employment of Bayesian .approaches.

Lessons from Public Administration Research

The nature of the data utilised within criminology includes collections arising from the use of large-scale survey methods to capture snapshots of criminal activity and the victim experience of crime; the results of experiments and evaluations, and increasingly the systematic collation of data around criminal justice processes / outcomes. Criminology's growing statistical evidence base is particularly amenable to the application of Bayesian approaches since administrative datasets often suffer from issues relating to collinearity – this was an issue within the dataset used in the case study, with the two continuous variables for age being highly correlated for FTEs. A further advantage of Bayesian approaches is that they can be applied to situations where an event can not necessarily be repeated under identical conditions and where the alternatives to the event cannot be reduced to a finite list of equally likely outcomes (as in the objective approach). This is particularly useful in criminology where we typically get a dataset that represents a fixed, unique look at the phenomenon of interest since the data is situational in time and circumstance and hence why they can never be replicated – as with data collected from risk assessments used to inform decision making at different stages of the criminal justice system.

In addition to learning from medicine, criminologists can gain a lot from the experiences of public administrators particularly given the advent of Big Data and the digital turn in criminology. Whilst public administration researchers have been slow to embrace Bayesian approaches (Gill and Witko, 2013), there are common methodological challenges for those working with quantitative data. In both disciplines, Bayesian approaches offer a workable alternative to those who have reached the limits of what can be done using Frequentist techniques; whose data is not appropriate for their application or where the problems are too complex for classical methods. As evidenced by the case study, Bayesian approaches are particularly applicable where data can be modelled as a time-series and/or using multilevel models.

In 2000, Gill and Meier set out a manifesto for methodological change in public administration research which called for investment in methods having relied heavily upon related disciplines for its methodological tools: tools which when faced with the demands made by public administrators make them less promising. As I believe is the case in criminology, Gill and Meier express concern that the implications of making a mistake can be more significant because of the way in which the evidence generated by public administrators can influence policy:

> 'If a political scientist makes a major error in his or her study of the 1992 election, it matters little. Clinton still wins. If a public administration scholar commits a major error in analyzing an education program, it can have major implications simply because it could influence public policy.'
>
> (Gill and Meier, 2000: 158)

Gorard goes further in his arguments as to why social scientists need to stop clinging on to the NHST approach to analyse their carefully collected evidence, emphasising that should they continue to do so they not only risk devaluing their efforts, but also risk damaging people's lives:

> 'The confused use of significance testing has practical and damaging consequences for people's lives. Ending the use of significance testing is a pressing ethical issue for research. Anyone knowing the problems, as described in over one hundred years, who continues to teach, use of publish significance tests is acting unethically, and knowingly risking the damage that ensues'.
>
> (Gorard, 2016: 1)

Some of the methodological advances that Gill and Meier promote in their manifesto for public administrators alongside the use of Bayesian approaches, have been realised in criminology including the creation of data archives which not only ensure that key data sets are not lost, but also that researchers can gain access to core datasets for training and research purposes. The existence of data archives also facilitates time series analysis – a technique which is well suited to before and after programme evaluation designs, but in 2000 was being under-utilised by public administrators. Certainly, in the UK context the work of the UK Data Service has been instrumental in reducing the barriers to accessing key surveys such as the Crime Survey for England and Wales; the Scottish Crime and Justice

Survey; the Edinburgh Study; the Cambridge Study in Delinquent Development; and the Offending, Crime and Justice Survey (UK Data Service, 2018).

The ADRN has secured access to data to enable for example, criminal careers and the crime drop in Scotland to be investigated; an examination of the links between homelessness and recidivism; finding work after leaving prison; and assessing the feasibility of using administrative data to examine risk factors for domestic violence and child sexual exploitation (Administrative Data Research Network, 2017). Whilst these projects are all at different stages, they illustrate ways in which, particularly linked administrative data is being used to understand and tackle some of the contemporary major social challenges. The approaches adopted represent cutting edge methodological developments pertinent to both criminology and public administration researchers.

As indicated, linking the youth offending data to other sources such as health, education and social services data would enable a more detailed model of the role of risk and protective factors and their relationship with offending behaviour to be developed. Unfortunately, this was not possible within the scope of this thesis and would have added to the already protracted process of securing access to the data. However, having this data would potentially add to understandings for example around substance misuse and treatment; mental health; learning disabilities and other developmental problems; problems in the home environment etc. A key feature of Bayesian approaches is that models can be updated as and when new information becomes available. As demonstrated through the approach adopted in relation to the case study, 'Bayesian methods support sequential learning, allow for finding predictive distributions of future results and enable borrowing strength across studies' (Berry, 2005: 296). In this way, they lend themselves not only to situations such as dynamic models of risk where there is a need to update the assessment as more is learnt about the individual, but also where there is scope to continue to add new variables to reflect changes in circumstances. Berry also highlights that 'the Bayesian paradigm allows for using historical information and results of other trials, whether they involve the same drug, similar drugs or possibly the same drug but with different patient populations.' The equivalent to this in a criminological context could relate using information from the evaluation of an intervention to reduce recidivism, to explore the potential for transferability to other localities or groups of offenders.

Rigorous Designs: Small Sample Research

Whilst the ability to harness the benefits of Big Data has had a revolutionary impact on the both the types of research questions that can be addressed and the nature of analysis that can be undertaken, as Srinivasan et al. (2015) emphasises in the context of public health, small sample research is also essential if progress is to be made in addressing inequality and ensure that it is not just majority groups which benefit from interventions. Concerns around statistical power have already been alluded to with the perception being that rigorous research requires large samples. Therefore, argue Etz and Arroyo (2015) if the importance of small sample research is to be recognised, then there will need to be 'an expansion of what constitutes rigor in analysis and design strategies … Advances with also require making room for the adoption of innovative design and statistical analysis approaches' (2015: 1033). This includes taking steps to ensure that alternatives to RCTs are accepted into the repertoire of available design and assessment tools by those funding and approving research in prevention science. Although a number of potential solutions are put forward within the special section that they are commentating on Etz and Arroyo assert that:

> 'It would be a failure of science and the imagination if newly discovered or re-discovered (i.e. Bayesian) strategies are not employed to facilitate rigorous assessment of interventions in small samples. It is imperative that the tools of science do not limit our ability to address pressing public health questions. New approaches can be used to address contemporary research questions, including providing solutions to the undue burden of disease that can and often does occur in small populations. It must be the pressing nature of the questions, not the limitations of our methods, that determines what science is undertaken.'
>
> (Etz and Arroyo, 2015: 1035)

Relating the observations from prevention science, to criminology and more specifically to risk assessment and responses to offending behaviour, there is mounting evidence that certain minority and vulnerable groups are over-represented in the criminal justice system, particularly within the secure estate (see for example Hughes et al., 2012; Prison Reform Trust, 2016; Lammy, 2017; Youth Justice Board and Ministry of Justice, 2018). These represent both a challenge to practitioners in terms of the often complex lives that many of these individuals led, but also in research terms with investigators limited by the small numbers involved and the heterogeneity of the subgroups - all too often, due to the small numbers in the general population that the group represents, when these groups are considered in the context of the offender population, they are aggregated. Common examples include components of the BAME population (typically using the headline ethnic groups although this will depend upon the geographical coverage of the analysis) and the grouping together of all 'looked after children' without distinguishing between the types of setting that the child is in or the reason that they have entered care. Within these groups there are further subgroups of particular interest e.g. on the basis of their age and/or gender, their offending history or the nature of their primary offence / disposal. When the data is 'sliced and diced' to consider some these permutations the subpopulations can start to become quite small even in the national data.

From a policy perspective, if we wish to understand why it is that these groups are over-represented in the youth justice system, then undertaking analysis which identifies whether there are differences in terms of risk and protective factors within these subgroups is key. The current analytical strategies which assume homogeneity within aggregated groups tend to mask the nuances which exist and hence impact upon the generalisability of findings. To this end, within- rather than between- group designs are advocated as a potential option when undertaking small sample research. The advantage here being that within-group designs use the sample as its own control, reducing by half the sample size required for accurate sample comparisons. In the context of longitudinal designs (as employed within this research) it is recognised that within-subject designs require more data than between-subject designs. This need for more data emerged as an issue within the hierarchical modelling conducted here when considering gender, with females typically having fewer measurement points than males.

Other instances where small subpopulations represent a challenge in the context of the youth justice system can be identified on the basis of the type of offences that they have committed with the low base rates for example for serious violent or sexual offences. These high-risk groups present difficulties especially in the context of sub-national research. In terms of risk assessment tools and interventions for designed for use with these groups, the low number of cases typically means that they have been adapted from adult versions. Here a more appropriate option for the small sample research may be the use of qualitative and mixed methods. Again, there is the potential to undertake this under a Bayesian framework since expert opinion can be utilised to inform the choice of prior.

The approach used within this research explored both within- and between- individual differences using hierarchical models. These involve two sample sizes: the number of independent sampling units, *N* (i.e. groups) and the number of secondary sampling units. Since the number of level one units vary, the average number of measurement units is denoted as *ň*. As Hoyle and Gottfredson (2015) highlight in the context of longitudinal research designs where the Level 1 units represent measurement points and Level 2 units represent individuals, for a researcher who wishes to make claims about development it is essential to have enough over-time information (i.e. a relatively large *ň*). Level 1 sample size is also important for reliability estimating group level measures. For this between-group processes rely upon aggregate within-group information for proxy measures of intergroup differences.

This proved to be a limitation not just in the context of gender, but also ethnicity and when looking at the age of first conviction, particularly in combination with other Level 2 predictors. This is reflected within models including these predictors both as main and interaction terms by the amount of uncertainty that surrounds the estimated coefficients. Thus whilst acknowledging that both *N* and *ň* are important in the context of the type of question that was being tackled using the hierarchical models, the key limitation was found to be the fact that where using default priors within software packages, Bayesian approaches still require cases which reflect the diverse nature of the data being explored, and depending upon the level of hegemony, sufficient examples upon which to determine trends under different permutations of the various predictors being tested. Despite this, it was still possible to advance the work of Wilson and Hinks (2011) using a significantly smaller sample size.

8.4 Overcoming Potential Challenges

In 1975, the statistician and leading advocate of Bayesian statistics Dennis Lindley (1923-2013) predicted that the 21st century would be Bayesian. In his speech at a conference on the Directions for Mathematical Statistics, he asserted, that:

> 'Statistics had had its greatest successes in the fields of science where the long-run frequency view of probability is appropriate …. But with the widening of the notion of probability to embrace non-repeatable situations the potential scope for statistics is enormously increased. We can now enter into fields that were previously denied to us, without any loss in the traditional ones, where propensity and exchangeability replace long-run frequencies and randomisation'.
>
> (Lindley, 1975: 113)

Particularly in the context of risk assessment in the youth justice system, there is growing awareness that this point has been reached with calls being made for post-positivist statistical analyses which reflect the complexities of the real world. The nature of the data available to researchers is changing, in particular the amount of administrative data from across the criminal justice system and beyond is growing exponentially and increasingly reflects apparent populations rather than those which need to be randomly sampled. To consider how Bayesian approaches may be used to respond to this, it is important to acknowledge the factors that have contributed to the acceptance of such techniques in other disciplines.

One of the principal reasons for presenting risk assessment in the youth justice system in England and Wales as a case study to demonstrate the utility of using Bayesian approaches in criminology is the quasi-medical nature of the risk and protective model framework that underpins it the risk assessment tool, ASSET. Associated with this is the recognition not only making an assessment of the issue, but also determining an appropriate course of action. Since third-generation tools such as ASSET are characterised by their predictive role in informing intervention planning in addition to their classification role, there are inevitable links to the 'What Works' agenda and determining the effectiveness of interventions. These mirror the diagnostic and treatment elements of epidemiological approaches in medicine.

As highlighted in Chapter Two, Bayesian statistics have now permeated all the major areas of medical statistics including clinical trials; epidemiology; meta-analysis and evidence synthesis; spatial modelling; longitudinal modelling; survival modelling; modular genetics and decision making in respect to new technologies. Such is the extent of its acceptance within the medical profession that both the National Institute of Clinical Excellence (NICE) in the UK and the Food and Drug Administration (FDA) in the United States have been open to Bayesian submissions for more than a decade, particularly in the area of medical devices (O'Hagan and Luce, 2003).

Having the Right Tools for the Job

Software such as WinBUGS, STAN and JAGS has helped to make the techniques more accessible to social scientists so that they may tackle real world problems, with the JASP interface being designed to allow statistical practitioners 'to conduct statistical analyses in seconds, and without having to learn programming or risking a programming mistake' (JASP Team, 2017c). Indeed, the JASP Team are keen to stress that they are motivated to:

> '… make it easier for statistical practitioners to conduct Bayesian analyses. We firmly believe that Bayesian statistics deserves to be applied more often and more widely than it is today, and that there is more to statistical inference than the frequentist p-value.'
>
> (JASP Team, 2017c)

Alongside the development of software, those charting the adoption of Bayesian approaches have also highlighted the significant role played by the emergence of popular text books (Aldrich, 2002; Fienberg, 2006; Kruschke, 2011; McGrayne, 2011; Andrews and Baguley, 2013). Notably Harold Jeffrey's book *Theory of* Probability, published in 1939 has played an important part in the revival of the Bayesian view of probability indeed in recognition of his pioneering role, JASP stands for Jeffreys's Amazing Statistics Program (JASP Team, 2017a). Whilst the 1950s and 1960s saw the publication of a number of significant mathematical texts which had a Bayesian slant on the decision-theoretic formulation of statistical inference and/or the notion of personal probability (also known as subjective probability), more recently there have been a number of texts aimed specifically at social scientists. These include *Bayesian Analysis for the Social Sciences,* Jackman (2009); *Bayesian* Statistics, Lee (2012); *Bayesian Data Analysis,* Gelman et al. (2013); *Bayesian Methods: A Social and Behavioral Sciences Approach,* Gill (2014); *Bayesian Statistics for the Social Sciences,* Kaplan (2014); and *Doing Bayesian Data Analysis: A Tutorial with R, JAGS and STAN,* Kruschke (2015). These have predominately been written by political scientists and psychologists, and as such incorporate real-world examples which it could be argued are more accessible than those found in texts aimed at statisticians. Alongside this are more specialist texts such as those by Gelman and Hill (2007) and Banerjee et al. (2015) which focus specifically on niche areas such as regression and multilevel/hierarchical models, and spatio-temporal techniques. Many of these have accompanying websites and in keeping with the spirit of openness and transparency which prevails amongst Bayesians, these typically include sample code and data so that others can follow the worked examples in the texts.

Together these developments provide the building blocks for the curious criminologist who is looking for solutions for many of the complex real-world problems that exist within criminology which are at or are beyond the limits of Frequentist approaches. Whilst there are some with psychology who see Bayesian as a means to address the replication crisis that their discipline is experiencing (Andrews, 2016; Dienes, 2016; Morey, 2016), what the Bayesian paradigm offers to youth justice and more widely to criminology is an opportunity to improve the reliability of research by allowing scientists to crosscheck work undertaken using more traditional or classical approaches without completely dismissing existing work. Given the assertions from critics such as Haines and Case, that RFR is heavy reliant upon a single data source which has since been replicated in a multitude of studies it would be pragmatic to revisit prior assumptions about risk factors and their relationship with youth offending. These should be re-examined with the benefit of the fresh perspective afforded by Bayesian approaches.

Do Criminologists have the Skills to Rise to the Challenges that This Would Bring?

When Lindley predicted that the twenty-first century would be Bayesian, he questioned where the next generation of statisticians would come from:

> 'The future of statistics is bright. We can expand greatly: but where are the recruits to come from? We need to attract able young people into the field: people who have the mathematical experience, and exposure to scientific ideas, to make good statisticians. My hope is that by teaching Bayesian ideas we shall succeed in this. The formal system will make it easier to teach, and will appeal to the mathematical mind. The fact that it works will bring in the interested scientist.'
>
> (Lindley, 1975: 115)

Four decades later, concerns around whether future generations of crime scholars and practitioners have the necessary statistical skills continue. Additionally, the British Society of Criminology has expressed concern as to whether they will possess the thinking and research skills necessary to engage, as public-serving intellectuals, with politics and public policy. Chamberlain (2016) observes that undergraduate criminology students worldwide tend to possess high levels of statistical anxiety and a concurrent tendency to avoid numerical study tasks, including quantitative forms of data analysis. Initiatives such as the Q-Step programme are intended to promote a step-change in quantitative social science training in the UK. However, they will take some time to bear fruit. Whilst criminology is not uniquely placed in terms of this skills deficit, if the generally low levels of quantitative literacy and research skills possessed by criminology students are not addressed through high quality, relevant and engaging skills training, then there is a risk that the legacy will be graduates who are at best proficient at blindly following instructions on what to click and then which figure to report after performing their analysis in SPSS. Ideally, I would wish to see a shift away from p-values and the routine teaching of Bayesian approaches which are generally considered to be more intuitive and easier to interpret. However, to achieve this we must first generate an interest in Bayesian approaches amongst lecturing staff and ensure that they are sufficiently curious and enthusiastic to be able to pass on the necessary skills to their students. Initially it may be necessary to utilise expertise from other disciplines to do this.

8.5 The Implications for Policy and Practice

Errors, wasted opportunities, vanishing breakthroughs, and unwarranted conclusions?

One of the key methodological issues in the social sciences is that the way in which data is collected means that it does not always fit the criteria of being randomly selected cases and/or repeatable experiments. Yet these are the assumptions upon which NHST is based. In seeking to apply techniques - calculating standard errors, confidence intervals and performing significance tests (both explicitly and disguised within more complex statistical modelling) we risk 'errors, wasted opportunities, vanishing breakthroughs, and unwarranted conclusions' (Gorard, 2014b: 3). With this in mind, the widespread adoption of Bayesian approaches which are not dependent upon sample size, random sampling or repeated experiments have the potential to negate many of the abuses which have become unfortunately become so pervasive in social science research.

Sample size has become something of an obsession as researchers seek to demonstrate that their findings are empirically sound. As budgets for research have been scaled back and the challenge of obtaining ethical approval for surveys with vulnerable people has intensified, fewer large-scale surveys are being conducted. The flip side of this is that there is increasing emphasis on using administrative data which is systematically collected for monitoring purposes to explore many of key policy issues. Such datasets frequently represent a population and whilst there may be missing cases or missing values, this is a cause of bias rather than being a consequence of random sampling variation, an issue which can be addressed through judgement but not through significance testing. Given the disparities that exist and the desire to identify interventions which are effective with all the population and not just the majority group, the role of small sample research is an important one which cannot be ignored at a time when the emphasis is on Big Data.

The inappropriateness of applying NHST to population data is one which is particularly relevant to the use of administrative datasets for social science research, necessitating the adoption of new and more novel techniques including borrowing from other disciplines so that we are well positioned to inform policy makers and practitioners alike, providing a robust evidence base upon which decisions can be made. Notably there are lessons which can be learnt from public administration researchers, who have grappled with issues such as collinearity and are becoming increasingly adept at considering data which is structurally nested such as pupils within schools, patients within hospitals and different geographical units. Criminologists can also learn from the experiences of public health and prevention researchers with respect to small sample research, although it is probably medicine that has the most to offer to the discipline. However, it is necessary to caveat this.

In medicine, the RFPP model has an epidemiological nature, utilising knowledge of the 'risk factors' for physical illnesses and 'protective factors' which mediate against these illnesses to formulate preventative interventions which are targeted at those considered to be 'at risk' or 'high risk' of developing the illness.

Given that Bayesian statistics have now permeated all the major areas of medical statistics, the quasi-medical nature of this model bodes well conceptually for the application of such approaches to youth justice and criminology more generally. Particularly in the context of analysing multiple risk factors, use of Bayesian inference in medicine has been used to demonstrate the strength of links between exposure and disease – a key diagnostic feature. As the medical profession have demonstrated, having the correct diagnosis means that an appropriate treatment plan can be developed which is tailored to the individual and their circumstances. In principle, this is what happens in youth justice as well. The problem is however, that in youth justice, 'the science is … not always as scientific as we would like and in fact substantial problems can exist with the method used to identify risk facts in that quantitative variables are, in fact, constructs of social phenomenon' (France, 2008: 4). In presenting subjective processes as objective and scientific, there is an oversimplification of the potentially complex and dynamic aspects of children's lives, experiences, perceptions and thoughts into readily quantifiable and targetable risk 'factors'.

Flexibility, Efficiency and Effectiveness

A distinct advantage of employing Bayesian approaches is that it is possible to 'feed' the model and update it as new information is gathered. This fits with the idea of evolving assessments which follow the individual as reflected by the ASSET Plus framework. There is also the potential to explore emerging issues through enhancing the data collection process e.g. by adding additional fields to the minimum dataset, employing data mining or linkage techniques, or having a targeted data collection. Anecdotal feedback about ASSET Plus is critical of how long it takes to complete the new assessment process therefore it would be necessary to be mindful of striking a balance between being motivated to increase the sophistication of the assessment process and not increasing the burden upon the practitioner.

In the context of advancing the evidence base in youth justice, a further feature which offers potential for extending knowledge is a mechanism for triangulating data from a number of different sources. Whilst Bayesian inference with its use of prior probabilities that can be drawn from previous research offers a formal process for synthesizing data from multiple sources, Bayesian evidence synthesis allows for the inclusion of other pertinent information that would otherwise be excluded as well as the potential to extend models to accommodate more complex, but frequently occurring, scenarios (Sutton and Abrams, 2001). Unlike in a meta-analysis, multiple treatment comparisons can be made, something which is much more in keeping with the suite of interventions which can be incorporated into a young person's action plan.

The transition from ASSET to ASSET Plus has meant from a policy perspective, that the aetiology of youth offending, and the need to understand the relationship with risk and protective factors, including their contribution to desistence has become increasingly important. The YJB has been at pains to stress that emerging evidence was one of the key drivers for change, acknowledging that RFPP has been the subject of increasing debate in academic literature over the past decade (Teli, 2011; Cabey, 2013) and it is not enough to just note the occurrence of risk and protective factors in a young person's life (Baker, 2014b). However, much of the evidence base relies upon just this.

Given RFR's heavy reliance on the findings from a single data source which have since been replicated in a multitude of studies, it would be pragmatic to revisit prior assumptions about risk factors and their relationship with youth offending. This can similarly be achieved using Bayesian analysis with Flam (2014b) highlighting that some statisticians and scientists are optimistic that Bayesian methods can improve the reliability of research by allowing scientists to crosscheck work undertaken with the more traditional or "classical" approach. In this way it may be possible to refine thinking which has been based on proxy measures where linked administrative data can now provide a more accurate measurement. This is something that could prove to be invaluable given the increasing complexity of those in the formal youth justice system and emerging policy concerns around for example neurodisabilities and mental ill health.

Managing an Increasingly Complex Cohort

With an increasingly complex, albeit smaller cohort in the youth offending system, the question of how policy and practice should best respond in order to control those exhibiting or at risk of offending behaviours. There are a number of emerging policy concerns associated with participatory approaches and the promotion of children's rights, and increasingly practice, especially in Wales and Scotland is being informed by an appreciation of the impact of adverse childhood experiences. However, fundamentally, there remains the need for justice to be seen to be served in the most efficient and cost effective manner.

With the advent of the new peneology, the earlier discourses of clinical diagnosis and retributive judgement were replaced with 'an actuarial language of probabilistic calculations and statistical distributions applied to populations' (Feeley and Simon, 1992). The emphasis switched from reforming the individual offender to consider aggregated groups such as "high-rate offenders" and "career criminals" with these groups, along with other categories were defined by actuarial classifications. From there the criminal justice system has evolved to become one which is more concerned with managerial process with its goal no longer being to eliminate crime, but the identification and management of unruly groups through systemic coordination. To some extent this was achieved through the deployment of techniques in both the youth and adult systems such as statistical applications for assessing risk and predicting dangerousness, and the use of electronic monitoring systems. However, it could be argued that the successes achieved were limited to the simpler cases, and if we are to stand a chance at effectively tackling the offending behaviour of the more persistent and complex cases then we need a more nuanced and flexible approach.

Moving forwards therefore, there needs to be increased recognition that 'positivism has long ceased to be a viable option (though the message has still not got through to some researchers)' (Robson and McCartan, 2016: 176). This is certainly the case in youth justices where the hegemony of positivist criminology has resulted in a system dependent up on correlations and statistical associations rather than a deeper understanding of the aetiology of youth offending. As Armstrong (and others) have highlighted 'risk is hidden beneath a plethora of correlations that in themselves tell us little about the socio-historical nature, meaning and significance of crime and its discourses in these times in which we are now living' (2004: 113). If we are to address this then we need to the right tools for the job – an approach which deals with uncertainty and is flexible enough to enable models to be refined as more information becomes available. In this way knowledge can be advanced beyond the boundaries imposed by Frequentist approaches and a more responsive means prediction developed.

Within-individual analysis has been largely neglected along with investigations to establish temporal ordering, hence findings are typically based on aggregation, imputation and extrapolation. However, a distinct advantage associated with the adoption of standardised, actuarial approaches to risk assessment as has been done in youth justice is that they necessitate the routine updating of case management systems. As a result, the temporal ordering of events can often be established in administrative datasets – a key requirement if we wish to establishing causality. In this way the multiple aims of third- and fourth-generation tools such as ASSET and ASSETPlus offer a rich resource for exploring the complex relationship between a range of different factors, further offending behaviour and crucially desistence.

The application of Bayesian techniques to administrative data representing a population, albeit at a local youth offending team level, means that risk factors can be explored in terms of their absolute rather than relative risk. This helps to address some of the concerns raised by Gottfredson and Moriarty (2006) who suggest that problems with predictive accuracy may arise as a result of the original research failing to be representative of the wider youth offending cohort – this is not the same as being representative of the population as a whole. By additionally considering base rates and hence focusing on absolute risk, it becomes possible to increase the predictive accuracy for more frequent or infrequent events such as the more serious offences which are committed less frequently by young people.

Utilising Bayesian approaches supplemented by other new and emerging forms of analysis such as data linkage affords the opportunity to re-visit the assumptions of existing RFR and to unpick the complexities of the risk factor-reoffending relationship. The same techniques can also be applied to existing survey data, offering the opportunity to drill down further than has previously been permitted by Frequentist approaches. Since Bayesian approaches incorporate prior information, it is possible to use what is already known as a starting point. In this way, existing RFR can be used as the foundation for furthering knowledge about this complex and dynamic area. However, we do not need to limit ourselves to RFR, there are a plethora of scenarios where researchers have perhaps reached the limit of what can be explored using Frequentist approaches or when it is not appropriate to apply these techniques due to the nature of the data. As suggested, a key related area to looking at the evidence base that underpins risk assessment processes is to examine 'What Works' in terms of interventions to reduce further offending. Within this thesis I have highlighted many of the qualities of Bayesian analysis which make it ideal for exploring similarly complex issues without dismissing existing research and for this learning to be extended to inform both the aetiology of offending more generally and the development of appropriate societal responses.

Next Steps

Much has been made of the notion that NHST stifles creativity. However, its continued use has potential ramifications within public policy. For example, Gorard (2014b) questions what happens if mistakes are made interpreting the findings of social research? What the costs are to the public purse when policy is developed on the basis of these findings? We therefore need to consider whether we can afford to continue to have a process of risk assessment that has been based on questionable evidence? Those involved in the development of ASSET Plus have been at pains to point out that in developing the tool, they have sought to incorporate emerging evidence, but the extent to which this has been gathered through the questionable application of methodologies and partial analysis is unknown. This means that our knowledge of the mechanisms and processes which explain the risk factor-youth offending relationship remains incomplete. Without this understanding we risk the perpetuation of a flawed system of youth justice which fails to provide timely and appropriate support to those children and young people who come into conflict with the law. The costs to the individuals, their families and the communities in which they live is difficult to measure, but what is certain is that the result is a system that is not fit for the twenty-first century.

It is my belief that if criminology is going to be able to address of the more perplexing issues that affect today's society then it needs to continue to import, introspect and innovate. Through the adoption of Bayesian approaches, there is the potential for new and varied insights to be realised which can inform policy and practice. Whilst there are pedagogical challenges to overcome, significant progress has been made in aligned disciples which has meant that as software has been developed and applied Bayesian text books written, Bayesian techniques are now becoming more accessible to social scientists, providing them with the tools to tackle real world problems.

To date criminologists have been slow to embrace Bayesian approaches. However, for the curious criminologist, they offer a much-needed additional tool in the analytical toolbox, permitting robust evidence to be accumulated in a more efficient and transparent way – something which is particularly important at a time of austerity. With the advent of digital criminology, the rise in the 'Big Data' and increased use of data linkage techniques, the raw materials required for enable new measures to be operationalised and support the investigation of new lines of enquiry have become more readily available to researchers. Hence, I believe that the time is now ripe to explore the potential that Bayesian approaches offer to criminology.

9 Appendices

Appendix 1 – University Ethics Form

Appendix 2 – Data Sharing Agreement with Western Bay YOT

Appendix 1 – University Ethics Form

Application for Standard Ethical Approval

PLEASE COMPLETE THE FORM USING TYPESCRIPT

(hand-written applications will not be considered)

Principal Investigator	Helen HODGES
Date	6th October 2014
School/Department	Criminal Justice and Criminology
E-mail address	[redacted]
Title of Proposed Research	A Bayesian Approach to Risk Assessment and Youth Offending Relationships
Type of Researcher (please tick)	Postgraduate student
Name of supervisor	Professor Kevin Haines

1. Briefly describe the main aims of the research you wish to undertake, including a statement of the intended benefits of the research. Please use non-technical language wherever possible.
To determine whether a Bayesian approach can be applied to refine the risk assessment process currently being used in the context of youth offending and hence enhance our understanding of relationships which it has previously not been possible to explore using frequentist analysis.

2. Briefly describe the overall design of the project

There are two key strands to this project:

1) Theoretical Advancement – Consideration of whether a Bayesian approach* combined with regression methods would be appropriate for advancing work around risk assessment and youth offending relationship. This will include a systematic review of literature relating to where Bayes Theorem has already been used to consider issues within the criminal justice system generally and also with young people.
2) Application – Identification of known risk and protective factors within administrative data using Bayesian techniques, followed by the exploration of further potential factors. This will be an iterative process and is likely to involve data fusion and triangulation as well as the views of subject experts including practitioners.

The research will primarily utilise existing data held by the Youth Offending Service about their clients. Secondary data analysis of qualitative and quantitative material will be employed such as official statistics provided by the Home Office or Ministry of Justice concerning youth justice and youth offending, and data already collected in pertinent studies locally in Swansea.

The Bayesian Approach

Bayes' theorem is the foundation of Bayesian inference. It shows the relation between two conditional probabilities that are the reverse of each other. This theorem is named after Reverend Thomas Bayes (1702-1761), and is also referred to as Bayes' law or Bayes' rule. Bayes' theorem expresses the conditional probability, or 'posterior probability', of an event **A** after **B** is observed in terms of the 'prior probability' of **A**, prior probability of **B**, and the conditional probability of **B** given **A**, denoted **B** | **A**. Bayes' theorem is valid in all common interpretations of probability.

Bayesian inference estimates are based on developing hypothesis given the data. As a result prior knowledge or the results of a previous model can be used to inform the current model. As a result, the approach is iterative in nature.

3. Briefly describe the methods of data collection and analysis. Please describe all measures to be employed. If questionnaire or interviews are to be used, please provide the questionnaire / interview questions and schedule – if available.

The iterative nature of the approach means that it is difficult to be specific about the methodology that will be employed at this stage. However, it is recognised that having access to the case managements data held by the Youth Offending Team (YOT) about their clients in the Youth Offending Information System (YOIS) will afford the opportunity to 'test' the Bayesian approach and enable the exploration of the often complex relationships that impact on the likelihood of offending and any subsequent desistence / recidivist behaviours.

The Primary Dataset

The YOIS is a case management system used by the YOT to capture information about their clients. It includes client level information such as:

- Asset* scorings along with those from associated tools where appropriate
- Socio-demographic information
- Details of their offence plus any subsequent offending, including where they have been involved in any anti-social behaviour
- Sentences and specific orders as determined by the court
- A record of all Interventions and Action plans with progress reports
- Case work and records of meetings with the client and other agencies
- The young person's views
- Multi-agency intelligence such as information from schools and social workers
- A record of education and/or training that the client has participated in

It has since been superseded by Childview. As a result, it is an archived version of the dataset that will be utilised.

** Asset is the structured assessment tool used by YOTs in England and Wales on all young offenders who come into contact with the criminal justice system. Its aim is to look at the young person's offence or offences and identify a multitude of factors or circumstances – ranging from lack of educational attainment to mental health problems – which may have contributed to their behaviour. The information gathered from Asset is used to inform court reports so that appropriate intervention programmes can be drawn up. Additionally it highlights any particular needs or difficulties the young person has, so that these can be addressed.*

Since its inception in 2000, the intention has been that the information collected from Asset would help to increase knowledge about offending by particular groups of young people and young people in general. Overtime it was envisaged that it would provide detailed information about the needs and problems of different groups of young people, with aggregate data from Asset highlighting the most significant and/ or significant issues associated with offending. Locally the intelligence gathered is used to guide decisions about the partnerships and programmes that will be most relevant to young offenders in that particular area whilst at a national level it is used to informs strategic planning in order to improve the use and allocation of resources.

Plans are in place to replace Asset, with AssetPlus. AssetPlus has been designed to provide a holistic end-to-end *assessment and intervention plan, allowing one record to follow a young person throughout their time in youth justice system. The earliest delivery date for trance 1 is currently June 2015.*

Potential Additional Data Sources

As the research progresses, it is envisaged that additional data sources may be used to triangulate findings. These could potentially include:

- performance and socio-demographic data held by the local authority
- published statistics from the Home Office / Ministry of Justice or relevant Government departments
- archived survey data such as that held by the UK Data Service
- data collected in pertinent studies undertaken in Swansea

It is anticipated that there will be a reliance on published data which has been validated and conforms to the standards set out by the Office of National Statistics.

Analysis

Initially the intention is to use WinBUGS to conduct analysis as this is a specialist piece of software which has been developed specifically for Bayesian analysis. The statistical techniques are likely to evolve as the research progresses and will be determine by the nature of the data itself – it will be a combination of qualitative and quantitative data which by necessity will require different analytical approaches if they are to inform the model.

Given that Bayes' rule is used to combine prior experience (in the form of a prior probability) with observed data (in the form of a likelihood) in order to determine a posterior probability, initially the analysis will be descriptive in nature.

Techniques such as regression analysis may be required to expose the relationship between the response variable and predictor variables whilst appropriate techniques may need to be employed if it is identified that there are significant issues with missing data.

4. Location of the proposed research (i.e., Departmental labs, schools, etc.)

City and County of Swansea

5. Describe the participants: give the age range, gender, inclusion and exclusion criteria, and any particular characteristics pertinent to the research project.

NA – All data subjects will have come from a variety of socio-demographic backgrounds and will feature within the dataset because they have entered into / engaged with the criminal justice system. All clients would have been aged between 10 and 17 at the time of their engagement with the YOT, and living in Swansea.

No exclusion criteria will be applied.

6. How will the participants be selected and recruited?

NA – The data subjects will have been Swansea YOT clients between 2001 and 2012.

7. What procedures (e.g., interviews, computer-based learning tasks, etc.) will be carried out on the participants?
NA

8. What potential risks to the <u>participants</u> do you foresee and how do you propose to ameliorate/deal with potential risks? For instance, provide contact details of counselling services and/or relevant community support organizations etc.
NA - There will be no direct contact with YOT clients. Analysis will be retrospective and it is anticipated that were issues were identified, the YOT would have taken timely and appropriate action to safeguard their client / others, and to respond to their individual needs. However, it is recognised that other individuals (eg family members, friends, victims) may be named within the client records. In order to protect their identities, analysis will be presented in an aggregate form with reference only being made to their relationship to the client eg 'sibling', 'parent', 'friend', 'victim' – see also sections 17 and 18.

9. What potential risks to the interests of the <u>researchers</u> do you foresee and how will you ameliorate/deal with potential risks?
<u>Personal Safety and Wellbeing</u> As there is no direct contact with clients and the research is taking the form of secondary data analysis, it is anticipated that there will be negligible risks to the researcher's personal safety. However, there is the potential given that the client records will include information about their offending behaviours that there may be details which may cause distress to the researcher. Should this scenario arise, then it will be raised with supervision so that appropriate safeguards can be put in place. As the researcher has previously worked as a police analyst, she is accustomed to viewing offender / victim records and maintaining a professional distance. <u>Data Security</u> The greatest risks are around data security as the client records will include personal and sensitive personal information about children and young people who may have additional vulnerabilities by virtue of being YOT clients. As a result, all relevant guidance relating to the secure storage and use of the data supplied will be adhered to. It is envisaged that the file size will limit the potential to save the file on P:/ drive (max capacity = 2GB) therefore a working version of the database will need to be stored on an encrypted external hard drive purchased by the department specifically for this research. As outlined in section 18, there will be two versions of the database – the first being a depersonalised version which will be used by the researcher on a day to day basis, the second being retained in its original format for reference purposes only. The later will be securely held by the supervisor on University premises. Access to the data will be limited to the researcher and supervision with advice being sought as appropriate in a timely manner from the data controller and named practitioners at the YOT. To minimise the risks of any security breach, the dataset will be password protected on the encrypted external hard drive. All versions of the data will be appropriately disposed of at the end of the research.

10. How will you brief and debrief participants? *(Please attach copy of debrief information to be given to participants)*
NA

11. Will informed consent be sought from participants?	Yes *(Please attach a copy of the consent form)*	
	No	X

If no, please explain below:

Data is being made available via Section 115 of the Crime and Disorder Act 1998 which provides an enabling power for YOTs, as local authority partnerships, to share information when it is in the public interest. Further exemption for sharing the YOIS data for research purposes can be found under the Data Protection Act 1998 as agreed by the Data Controller.

12. Will participants be informed of the proposed use of the data?	Yes *(Please attach details of the information to be given to participants)*	
	No	X

If no, please explain below:

See section 11

13. If there are doubts about participants' abilities to give informed consent, what steps have you taken to ensure that they are willing to participate?

NA

14. If participants are under 18 years of age, please describe how you will seek informed consent. If the proposed research is to be conducted in a school, please describe how you will seek general consent from the relevant authorities and attach a copy of any written consent.

NA

15. How will consent be recorded?

NA

16. Will participants be informed of the right to withdraw without penalty?	Yes
	No

If no, please detail the reasons for this:

NA – see section 11

17. How do you propose to ensure participants' confidentiality and anonymity?
Please state who will have access to the data and what measures will be adopted to maintain the confidentiality of research subjects and to comply with data protection requirements.

The data is being supplied with individual identifiers and there is the potential that other individuals may be named in narrative case reports. To protect the identity of any named individuals - clients or otherwise – analytical findings will be presented in a de-personalised form. Where the named individual is not the client, references to that individual will only be made by way of relationship labels eg 'sibling', 'parent', friend'.

The intention is to make a second copy of the database which will become the working version. As the dataset will include multiple identifiers for each client, these will be utilised to create a unique client identifier which can then be used to create a depersonalised version of the file. This is the version that will be utilised on a day to day basis by the researcher.

The original version will be retained for reference purposes only and will be securely retained by the supervisor, Professor Kevin Haines in a locked cabinet on University premises.

Throughout the process the framework set out in the Data Protection Act will be adhered to along with any locally agreed information sharing protocols set out by the YOT, the University of Swansea and the ESRC.

18. Please describe which of the following will be involved in your arrangements for storing data:

- ☐ Manual files (e.g. paper documents or X-rays)
- ☐ Home or other personal computer
- ☒ University computer
- ☐ Private company or work-based computer
- ☒ Laptop computer
- ☒ Other (please define)

<u>Please explain, for each of the above, the arrangements you will make for the security of the data (please note that any data stored on computer must have password protection as a minimum requirement):</u>

The size of the YOIS dataset is such that it cannot be stored on a networked University computer or personal laptop. An encrypted external hard drive will be purchased specifically for this project by the department. Data on the hard drive will additionally be password protected (for example if the extract is made available as a .csv file then a password known only to the researcher and supervisor will be applied. Advice will be sought if the data is supplied in an alternative format).

The researcher's laptop has a biometric securing screen which will add an additional layer of securing when being used for analysis.

Where a networked University computer is being used, the external hard drive will not be left unattended, with the intention being for analysis to be undertaken either at home or in the department's Research Room. Access to this room is restricted.

19. Does your research require the written consent of a public or private body, e.g. school, local authority or company? If so, please attach letter of consent

Permission to draw data down has been granted by Eddie Isles, Data Controller for Swansea YOS as part of the on-going research partnership between the Criminology Department and the YOS.

20. If your proposed research is with 'vulnerable' groups (e.g., children, people with a disability etc.), please attach a copy of your Criminal Records Bureau check (if UK) or equivalent

non-UK clearance.
NA – There will be no direct contact with YOT clients. However, the researcher has prior experience of working with sensitive personal data having been a police analyst before embarking on this research. As a result she has been subject to management vetting. This can be confirmed by contacting West Midlands Police. A DSB check is currently being completed which is being administered by the YOS.

DECLARATION:

I am satisfied that all ethical issues have been identified and that satisfactory procedures are in place to deal with those issues in this research project. I will abide by the procedures described in this form.

Signature of Applicant: [redacted]

Date: **6/10/14**

Supervisor declaration (for student research only)

I have discussed the ethics of the proposed research with the student and am satisfied that all ethical issues have been identified and that satisfactory procedures are in place to deal with those issues in this research project.

Signature of Supervisor: [redacted]

Date: **6/10/14**

CHECKLIST OF ATTACHMENTS:
PLEASE REMEMBER TO ATTACH COPIES OF EACH OF THE FOLLOWING (WHERE RELEVANT)

INCOMPLETE APPLICATIONS WILL NOT BE CONSIDERED

- ☐ Copy of Participant Information Sheet
- ☐ Copy of Consent Form
- ☐ Copy of Participant debrief
- ☐ Copy of any questionnaires and/or interview schedules to be employed
- ☐ Copy of written consent from local authorities or other government bodies
- ☐ If your proposed research is with 'vulnerable' groups (e.g., children, people with developmental disorder), please attach a copy of your clearance letter from the Criminal Records Bureau (if UK) or equivalent non-UK clearance.

PLEASE ATTACH A COPY OF THE RESEARCH PROPOSAL TO THIS APPLICATION

****RESEARCH MAY ONLY COMMENCE ONCE ETHICAL APPROVAL HAS BEEN OBTAINED****

Appendix 2 – Data Sharing Agreement with Western Bay YOT

City and County of Swansea

Third Party Connection Agreement

City and County of Swansea

Third Party Connection agreement

1. Introduction

1.1 This document details the terms and conditions applicable to the connection of third party access to an Authority Information System.

1.2 The agreement will allow an authorised individual to access data held on Authority systems for specific purpose(s) with specific means of access.

1.3 The system which authorised employees of **Swansea University (Helen Hodges)** will be allowed to access is **Childview**.

2. The Agreement

2.1 Details of the person who will be required to access the data held on the City and County of Swansea (CCoS) systems must be supplied to the ICT Division.

2.2 The person granted a user account will agree to abide by CCOS ICT policies and by the terms and conditions of this agreement whenever they connect to CCOS systems.

2.3 When an employee, granted a user account, leaves the position or changes post which means that access to the CCOS system is no longer required the line manager must immediately inform the IT Division of the change.

2.4 The data accessed by the non-Authority employee must not be used for any purpose not specified in this agreement and must not be supplied to any person(s) or company who are not party to this agreement.

2.5 The data will remain the property of CCOS.

3. Access Requirements

3.1 Access will be enabled using authentication controlled by CCOS.

3.2 The person given a user account will not supply details of this account i.e. user id or password, etc or allow the device used to enable the authentication to be used by any non-authorised individual.

3.3 The user will be responsible for all access from the account allocated.

4. Purpose of Connection

4.1 The connection to the database will be to allow the authorised user to interrogate data relating to **Youth Offending** services.

5. Confidentiality Agreement

5.1 All data accessed will be treated as confidential and will not be supplied to unauthorised parties or made viewable to unauthorised persons without the approval of CCOS.

Signed: [redacted] Date: 5th June 2015

Name (Print): Helen Ruth Hodges

Designation: PhD Student

Authorised by: ______________________

Job Title: ______________________

4

AGREEMENT BETWEEN BRIDGEND COUNTY BOROUGH COUNCIL AND SWANSEA UNIVERSITY

This agreement forms a Memorandum of Understanding between Bridgend County Borough Council (BCBC) and Helen Hodges (Swansea University) with respect to the methods and procedures for employees of Swansea University to access services, machines and networks detailed in Schedule 1 below for BCBC Network access.

All information contained in this agreement and the appended schedules is confidential between BCBC and Swansea University. Unauthorised disclosure except as required under UK or local law will be treated as a breach of the agreement.

For the purposes of this agreement, the responsible person for the BCBC customer is Caroline Dyer, the responsible person for the BCBC Information and Communications Technology Department (ICT) is Martin Morgans.

Variations on this agreement, including the schedules are permitted only by signed agreement of the responsible persons above (fax and electronic signatures will be deemed acceptable). Following each change, Martin Morgans will deliver new electronic copies of the agreement to the other responsible persons and file the completed agreement with the ICT Service Desk.

This agreement will remain in force until:

1. The primary contract between BCBC and Swansea University expires. For the purposes of this document, the primary contract is the Student Placement.
2. Either party requests termination
3. A breach of the agreement occurs that either party regards as serious enough to warrant termination

Confidentiality and non-disclosure of data acquired during the agreement must be respected even after the agreement terminates.

No part of this agreement restricts either party from undertaking other remedies in the event of a breach of the agreement.

Access to the BCBC network will be via Network Access. No other method of access to the network may be used, and installation of alternate access software/hardware outside this agreement will be treated as a violation of the agreement.

BCBC will supply appropriate tokens for access (e.g. usernames and passwords). Connection software and hardware will be supplied by BCBC as required. Swansea University must use the software provided in a legal manner under the applicable laws and abide by any license agreements applying to it. Any software or hardware supplied remains the property of BCBC and must be returned or disposed as appropriate at the end of the agreement.

Access will only be permitted to services, machines and networks detailed in Schedule 1 below. Any attempt to access other services, machines or networks agreement will be treated as a breach of the agreement.

Access will only be granted to the named individuals detailed in Schedule 2 below. All persons on the list must be employees of Swansea University, and, where appropriate, may be required to be vetted under access procedures as required under UK law or professional practice.

All named individuals on the list will have individual passwords, which are for use by that individual only. It is the responsibility of Swansea University to ensure that the list is kept up to date, and in particular that BCBC are informed of contract terminations so that individual accounts can be removed.

Swansea University employees must have received suitable security and awareness training within their own organisation for the role they will be performing within BCBC, and to be aware of the protection requirements imposed on BCBC by legislative and compliance requirements, in particular the Government Secure Intranet, the Payment Card Industry Data Security Standard, the Computer Misuse Act, the Regulation of Investigatory Power Act and the Data Protection Act.

Swansea University employees are required to abide by the ICT code of practice for BCBC employees when using BCBC equipment and accounts. This code of practice is supplied separately by BCBC and **must** be read and accepted by every Swansea University employee in schedule 2 below.

Swansea University undertakes to discipline their employees for breach of the BCBC ICT code of practice with appropriate severity. BCBC reserves the right to withdraw access from any Swansea University employee who has committed or is under investigation for a breach of the code.

Schedule 1 – Accessible Services, Machines and Networks

[Details of each service, machine and network to be accessed. Example below]

Type of Access	Identifiers
BCBC Domain Controllers	Domain Controllers

Schedule 2 – Named Individuals Permitted to Use Services

[Name, job title and signature for each user. Passwords will be issued over the telephone and should be at least 8 characters long and not be a word in any language. It is suggested for clarity that phonetic alphabet spellings are given for each one to reduce confusion. All passwords in a schedule must be unique.

Helen Hodges

Signature ___[redacted]______________________

BCBC Line Manager____

Date ____

10 References

Abulafia J, Bukshizki M and Cohen D. (2015) *Risk Assessments of Female Sex Offenders: Actuarial Tools Versus Clinical Criteria.* The 23rd European Congress of Psychiatry Vienna, Austria, 28–31 March. ScienceDirect, doi: 10.1016/S0924-9338(15)31364-X.

Adler JR, Edwards SK, Scally M, et al. (2016) *What Works in Managing Young People Who Offend? A Summary of the International Evidence*. Available at: https://www.gov.uk/government/publications/what-works-in-managing-young-people-who-offend. (Accessed 31/1/18).

Administrative Data Research Network. (2017) *Featured Research and Case Studies*. Available at: https://adrn.ac.uk/research-impact/research/ (Accessed 31/1/18).

Administrative Data Taskforce. (2012) *The UK Administrative Research Network: Improving Access for Research and Policy*. Available at: http://www.esrc.ac.uk/research/our-research/administrative-data-research-network/administrative-data-taskforce-adt/. (Accessed 31/1/18).

Aldrich J. (2002) How Likelihood and Identification Went Bayesian. *International Statistical Review* 70(1): 79-98.

American Psychological Association. (2010) *Publication Manual of the American Psychological Association (6th Edition).* Washington: APA.

Andrews DA and Bonta J. (2007) *Risk-Need-Responsivity Model for Offender Assessment and Rehabilitation* Available at: https://www.publicsafety.gc.ca/cnt/rsrcs/pblctns/rsk-nd-rspnsvty/index-en.aspx. (Accessed 31/1/18).

Andrews DA and Bonta J. (2010) *The Psychology of Criminal Conduct.* Abingdon: Anderson Publishing.

Andrews DA, Bonta J and Hoge RD. (1990) Classification for Effective Rehabilitation:Rediscovering Psychology. *Criminal Justice and Behavior* 17(1): 19-52.

Andrews DA, Bonta J and Wormith JS. (2006) The Recent Past and near Future of Risk and/or Need Assessment. *Crime & Delinquency* 52(1): 7-27.

Andrews M. (2016) *What Role Can Bayesian Methods Play in Resolving the Replication Crisis?* ESRC Research Methods Festival, University of Bath, 7th July. Available at: http://www.ncrm.ac.uk/RMF2016/programme/session.php?id=R6. (Accessed 31/1/18).

Andrews M and Baguley T. (2013) Prior Approval: The Growth of Bayesian Methods in Psychology. *British Journal of Mathematical and Statistical Psychology* 66(1): 1-7.

Anwar S and Loughran TA. (2011) Testing a Bayesian Learning Theory of Deterrence among Serious Juvenile Offenders. *Criminology* 49(3): 667-698.

Armstrong D. (2004) A Risky Business? Research, Policy, Governmentality and Youth Offending. *Youth Justice* 4(2): 100-116.

Armstrong D. (2006) Becoming Criminal: The Cultural Politics of Risk. *International Journal of Inclusive Education* 10(2-3): 265-278.

Ashby D. (2006) Bayesian Statistics in Medicine: A 25 Year Review. *Statistics in Medicine* 25(21): 3589-3631.

Assink M, van der Put CE and Stams G. (2016) The Development and Validation of an Actuarial Risk Assessment Tool for the Prediction of First-Time Offending. *International Journal of Offender Therapy and Comparative Criminology* 60(7): 847-864.

Audit Commission. (1998) *Misspent Youth '98: The Challenge for Youth Justice*. London: Audit Commission.

Audit Commission. (2004) *Youth Justice 2004: A Review of the Reformed Youth Justice System*. London: Audit Commission.

Baglivio MT and Jackowski K. (2013) Examining the Validity of a Juvenile Offending Risk Assessment Instrument across Gender and Race/Ethnicity. *Youth Violence and Juvenile Justice* 11(1): 26-43.

Baker K. (2004) Is ASSET Really an Asset? Assessment of Youth Offenders in Practice. In: Burnett R and Roberts C (eds) *What Works in Probation and Youth Justice: Developing Evidence-Based Practice.* Cullompton, Devon: Willan Publishing, 70-87.

Baker K. (2005) Assessment in Youth Justice: Professional Discretion and the Use of ASSET. *Youth Justice* 5(2): 106-122.

Baker K. (2014) *ASSETPLUS Rationale*. London: Youth Justice Board.

Baker K, Jones S, Merrington S, et al. (2005) *Further Development of ASSET*. London: Youth Justice Board.

Baker K, Jones S, Roberts C, et al. (2003) *The Evaluation of the Validity and Reliability of the Youth Justice Board's Assessment for Young Offenders*. Oxford: Probation Studies Unit, Centre for Criminological Research, University of Oxford.

Baker M. (2016) 1,500 Scientists Lift the Lid on Reproducibility. *Nature* 533: 452-454.

Banerjee S, Carlin BP and Gelfand AE. (2015) *Hierarchical Modelling and Analysis for Spatial Data (2nd Edition).* Boca Raton, FL: Chapman and Hall/CRC.

Barnes J, TenEyck M and Pratt TC. (2017) *How Powerful Is the Evidence in Criminology? On Whether We Should Fear a Coming Crisis of Confidence*. Open Science Framework.

Bateman T. (2011) Punishing Poverty: The 'Scaled Approach' and Youth Justice Practice. *The Howard Journal of Criminal Justice* 50(2): 171-183.

Bateman T and Hazel N. (2015) *Custody to Community: How Young People Cope with Release*. London: Beyond Youth Custody.

Bateman T and Pitts J. (2005) The RHP Companion to Youth Justice. Lyme Regis: Russell House Publishing Ltd.

Bates D, Mächler M, Bolker B, et al. (2015) Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* 67(1): 48.

Berelowitz S and Hibbert P. (2011) *'I Think I Must Have Been Born Bad' Emotional Wellbeing and Mental Health of Children and Young People in the Youth Justice System*. London: Office of the Children's Commissioner.

Berk RA, Campbell A, Klap R, et al. (1992a) A Bayesian Analysis of the Colorado Springs Spouse Abuse Experiment. *Journal of Criminal Law & Criminology* 83(1): 170-200.

Berk RA, Campbell A, Klap R, et al. (1992b) The Deterrent Effect of Arrest in Incidents of Domestic Violence - a Bayesian-Analysis of 4 Field Experiments. *American Sociological Review* 57(5): 698-708.

Berk RA, Western B and Weiss RE. (1995) Statistical Inference for Apparent Populations. *Sociological Methodology* 25: 421-458.

Berry D. (2005) Introduction to Bayesian Methods III: Use and Interpretation of Bayesian Tools in Design and Analysis. *Clinical Trials* 2: 295-300.

Berry D. (2006) Bayesian Statistics. *Medical Decision Making* 26: 429-430.

Blades R, Hart D, Lea J, et al. (2011) *Care-a Stepping Stone to Custody: The Views of Children in Care on the Links between Care, Offending and Custody*. Available at: http://www.prisonreformtrust.org.uk/Portals/0/Documents/careasteppingstonetocustody.pdf. (Accessed 31/1/18).

Blair P and Rossmo K. (2010) Evidence in Context: Bayes' Theorm and Investigations. *Police Quarterly* 13(2): 123-135.

Blattenberger G, Fowles R and Krantz J. (2010) Bayesian Models to Predict the Return to Prison. *Section on Bayesian Statistical Science–JSM*: 5216-5229.

Borum R. (1996) Improving the Clinical Practice of Violence Risk Assessment: Technology, Guidelines, and Training. *American psychologist* 51(9): 945-956.

Bottoms A. (2008) The Relationship between Theory and Empirical Observations in Criminology. In: King R and Wincup E (eds) *Doing Research on Crime and Justice. (2nd Edition)*. Oxford: Oxford University Press, 75-116.

Bradford B, Murphy K and Jackson J. (2014) Officers as Mirrors: Policing, Procedural Justice and the (Re)Production of Social Identity. *The British Journal of Criminology* 54(4): 527-550.

Brown S. (2005) *Understanding Youth Crime: Listening to Youth?* Buckingham: Open Univeristy Press.

Brownlee I. (1998) New Labour – New Penology? Punitive Rhetoric and the Limits of Managerialism in Criminal Justice Policy. *Journal of Law and Society* 25(3): 313-335.

Buchanan A and Grounds A. (2011) Forensic Psychiatry and Public Protection. *The British Journal of Psychiatry* 198(6): 420-423.

Buranyi S. (2017) Rise of the Racist Robots - How AI Is Learning All Our Worst Impulses. *The Guardian,* 8th August 2017. Available at: https://www.theguardian.com/inequality/2017/aug/08/rise-of-the-racist-robots-how-ai-is-learning-all-our-worst-impulses. (Accessed 31/1/18).

Bushway S and Weisburd D. (2006) *Acknowledging the Centrality of Quantitative Criminology in Criminology and Criminal Justice*. American Society of Criminology, 1-4.

Bushway SD, Sweeten G and Wilson DB. (2006) Size Matters: Standard Errors in the Application of Null Hypothesis Significance Testing in Criminology and Criminal Justice. *Journal of Experimental Criminology* 2(1): 1-22.

Cabey C. (2013) *Assessment and Planning Interventions Framework - ASSETPLUS: Model Document (V1.0)*. London: Youth Justice Board.

Cabinet Office. (2012) *Open Data White Paper: Unleashing the Potential*. London: HM Government.

Calle-Alonso F and Pérez Sánchez CJ. (2014) A Monte Carlo–Based Bayesian Approach for Measuring Agreement in a Qualitative Scale. *Applied Psychological Measurement* 39(3): 189-207.

Carr PJ. (2010) The Problem with Experimental Criminology: A Response to Sherman's 'Evidence and Liberty'. *Criminology & Criminal Justice* 10(1): 3-10.

Carrington PJ. (2015) The Structure of Age Homophily in Co-Offending Groups. *Journal of Contemporary Criminal Justice* 31(3): 337-353.

Case S. (2006) Young People 'at Risk' of What? Challenging Risk-Focused Early Intervention as Crime Prevention. *Youth Justice* 6(3): 171-179.

Case S. (2007) Questioning the `Evidence' of Risk That Underpins Evidence-Led Youth Justice Interventions. *Youth Justice* 7(2): 91-105.

Case S. (2010) Preventing and Reducing Risk. In: Taylor W, Earle R and Hester R (eds) *Youth Justice Handbook: Theory, Policy and Practice.* Cullompton: Willian Publishing.

Case S and Haines K. (2009) *Understanding Youth Offending: Risk Factor Research, Policy and Practice.* Cullompton: Willan Publishing.

Case S and Haines K. (2010) Risky Business? The Risk in Risk Factor Research. *Criminal Justice Matters* 80(1): 20-22.

Case S and Haines K. (2014) Youth Justice: From Linear Risk Paradigm to Complexity. In: Pycroft A and Bartollas C (eds) *Applying Complexity Theory.* Bristol: Policy Press, 113-139.

Case S and Haines K. (2015) Risk Management and Early Intervention: A Critical Analysis. In: Goldson B and Muncie J (eds) *Youth Crime and Justice.* London: Sage Publications Ltd, 100-118.

Chainey S and Radcliffe J. (2005) *GIS and Crime Mapping.* Chichester: John Wiley & Sons, Inc.

Chainey S and Thompson L. (2008) Crime Mapping Case Studies: Practice and Research. Chichester: John Wiley & Sons, Inc.

Chamberlain JM. (2016) Ensuring the Criminological Skills of the Next Generation: A Case Study on the Importance of Enhanced Quantitative Method Teaching Provision. *Journal of Further and Higher Education*: 1-12.

Chan J and Bennett Moses L. (2016) Is Big Data Challenging Criminology? *Theoretical Criminology* 20(1): 21-39.

Cleghorn N, Kinsella R and McNaughton NC. (2011) *Engaging with the Views of Young People with Experience of the Youth Justice System*. London: The Police Foundation, NatCen and the Paul Hamlyn Foundation.

Cohen J. (1994) The Earth Is Round (P<.05). *American psychologist* 49: 997-1003.

Cohen J, Nagin D, Wallstrom G, et al. (1998) Hierarchical Bayesian Analysis of Arrest Rates. *Journal of American Statsitical Association* 93(444): 1260-1270.

Corr M-L. (2014) Young People's Offending Careers and Criminal Justice Contact: A Case for Social Justice. *Youth Justice* 14(3): 255-268.

Craig LA, Browne KD and Stringer I. (2003) Risk Scales and Factors Predictive of Sexual Offence Recidivism. *Trauma, Violence, & Abuse* 4(1): 45-69.

Cunradi CB, Mair C, Ponicki W, et al. (2012) Alcohol Outlet Density and Intimate Partner Violence-Related Emergency Department Visits. *Alcoholism-Clinical and Experimental Research* 36(5): 847-853.

de Vaus D. (2001) *Research Design in Social Research.* London: SAGE Publications Ltd.

de Villemereuil P. (2012) *Estimation of a Biological Trait Heritability Using the Animal Model. How to Use the MCMCglmm R Package*. Available at: https://www.researchgate.net/profile/Pierre_De_Villemereuil/publication/257729224_Tutorial_Estimation_of_a_biological_trait_heritability_using_the_animal_model_How_to_use_the_MCMCglmm_R_package/links/0c960525c32aaa92e3000000/Tutorial-Estimation-of-a-biological-trait-heritability-using-the-animal-model-How-to-use-the-MCMCglmm-R-package.pdf. (Accessed 31/1/18).
Deandrea S, Negri E and Ruggeri F. (2014) Integrating Clinicians' Opinion in the Bayesian Meta-Analysis of Observational Studies: The Case of the Risk Factors for Falls in Community-Dwelling Older People. *Epidemiology Biostatistics and Public Health* 11(1): e8909-8901 - e8909-8914.
Deuchar R and Sapouna M. (2016) 'It's Harder to Go to Court Yourself Because You Don't Really Know What to Expect': Reducing the Negative Effects of Court Exposure on Young People – Findings from an Evaluation in Scotland. *Youth Justice* 16(2): 130-146.
Dhami MK. (2005) From Discretion to Disagreement: Explaining Disparities in Judges' Pretrial Decisions. *Behavioral Sciences & the Law* 23(3): 367-386.
DiCristina B. (1997) The Quantitative Emphasis in Criminal Justice Education. *Journal of Criminal Justice Education* 8(2): 181-199.
Dienes Z. (2016) *What Role Can Bayesian Methods Play in Resolving the Replication Crisis?* ESRC Research Methods Festival, University of Bath, 7th July. Available at: http://www.ncrm.ac.uk/RMF2016/programme/session.php?id=R6. (Accessed 31/1/18).
Dienes Z and Mclatchie N. (2017) Four Reasons to Prefer Bayesian Analyses over Significance Testing. *Psychonomic Bulletin & Review*. doi: 10.3758/s13423-017-1266-z
Douglas T, Pugh J, Singh I, et al. (2016) Risk Assessment Tools in Criminal Justice and Forensic Psychiatry: The Need for Better Data. *European Psychiatry* 42(134-137.
Economic and Social Research Council. (2016) *Secondary Data Analysis Initiative*. Available at: http://www.esrc.ac.uk/research/our-research/secondary-data-analysis-initiative/. (Accessed 31/1/18).
Efron B. (1986) Why Isn't Everyone a Bayesian? *The American Statistician* 40(1): 1-5.
Emeka TQ and Sorensen JR. (2009) Female Juvenile Risk: Is There a Need for Gendered Assessment Instruments? *Youth Violence and Juvenile Justice* 7(4): 313-330.
Erickson DJ, Carlin BP, Lenk KM, et al. (2015) Do Neighborhood Attributes Moderate the Relationship between Alcohol Establishment Density and Crime? *Prevention Science* 16(2): 254-264.
Etz KE and Arroyo JA. (2015) Small Sample Research: Considerations Beyond Statistical Power. *Prevention Science* 16(7): 1033-1036.
Farrington DP. (1996) *Understanding and Preventing Youth Crime*. York: Joseph Rowntree Foundation.
Farrington DP. (2000) Explaining and Preventing Crime: The Globalization of Knowledge - the American Society of Criminology 1999 Presidential Address. *Criminology* 38(1): 1-24.
Farrington DP. (2002) Understanding and Preventing Youth Crime. In: Muncie J, Hughes G and McLaughlin E (eds) *Youth Justice: Critical Readings.* London: Sage Publications Ltd, 425-430.
Farrington DP, Gottfredson DC, Sherman LW, et al. (2002) The Maryland Scientific Methods Scale. In: Sherman LW, Farrington DP, Welsh BC, et al. (eds) *Evidence-Based Crime Prevention.* Oxon: Routledge, 13-21.
Farrington DP and Tarling R. (1985) Prediction in Criminology. Albany, USA: State Unversity of New York Press.
Fazel S, Singh JP, Doll H, et al. (2012) Use of Risk Assessment Instruments to Predict Violence and Antisocial Behaviour in 73 Samples Involving 24 827 People: Systematic Review and Meta-Analysis. *British Medical Journal* 345: 12.
Feeley MM and Simon J. (1992) The New Penology: Notes on the Emerging Strategy of Corrections and Its Implications. *Criminology* 30(4): 449-474.
Feeley MM and Simon J. (1994) Actuarial Justice: The Emerging New Criminal Law. In: Nelken D (ed) *The Futures of Criminology.* London: Sage Publications Ltd, 173-201.
Fenton N and Neil M. (2013) *Risk Assessment and Decision Analysis with Bayesian Networks.* Croydon: Taylor & Francis Group.
Fidler F. (2010) *The American Psychological Association Publication Manual Sixth Edition: Implications for Statistics Education.* Eighth International Conference on Teaching Statistics (ICOTS8),

Ljubljana, Slovenia, 11-16 July. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.205.600&rep=rep1&type=pdf. (Accessed 31/1/18).
Fienberg SE. (2006) When Did Bayesian Inference Become "Bayesian"? *Bayesian Analysis* 1(1): 1-40.
Fienberg SE. (2011) Bayesian Models and Methods in Public Policy and Government Settings. *Statistical Science* 26(2): 212-226.
Finch WH, Bolin JE and Kelley K. (2014) *Multilevel Modeling Using R.* Boca Raton, FL: CRC Press.
Fitterer JL and Nelson TA. (2015) A Review of the Statistical and Quantitative Methods Used to Study Alcohol-Attributable Crime. *PLOS One* 10(9): 24.
Flam F. (2014) The Odds, Continually Updated. *The New York Times,* 29th September. Available at: http://www.nytimes.com/2014/09/30/science/the-odds-continually-updated.html?_r=2. (Accessed 31/1/18).
Forty R and Sturrock R. (2017) *Using Family Court Data to Explore Links between Adverse Family Experiences and Proven Youth Offending*. London: Ministry of Justice.
France A. (2008) Risk Factor Analysis and the Youth Question. *Journal of Youth Studies* 11(1): 1-15.
France A and Homel R. (2006) Societal Access Routes and Developmental Pathways: Putting Social Structure and Young People's Voice into the Analysis of Pathways into and out of Crime. *Australian and New Zealand Journal of Criminology* 39(3): 295-309.
Friedrichs DO. (2016) Edwin H. Sutherland: An Improbable Criminological Key Thinker—for Critical Criminologists and for Mainstream Criminologists. *Critical Criminology*: 1-15.
Gelman A. (2010) *What Do Practitioners Need to Know About Regression?* Statistical Modeling, Causal Inference, and Social Science, 5 December. Available at: http://andrewgelman.com/2010/12/05/what_do_practit/. (Accessed 31/1/18).
Gelman A, Carlin JB, Stern HS, et al. (2013) *Bayesian Data Analysis (3rd Edition).* Boca Raton, FL: Chapman and Hall/CRC.
Gelman A and Hill J. (2007) *Data Analysis Using Regression and Multilevel/Hierarchical Models.* New York: Cambridge University Press.
Gigerenzer G. (2004) Mindless Statistics. *The Journal of Socio-Economics* 33(5): 587-606.
Gigerenzer G and Marewski JN. (2015) Surrogate Science: The Idol of a Universal Method for Scientific Inference. *Journal of Management* 41(2): 421-440.
Gill J. (2014) *Bayesian Methods: A Social and Behavioral Sciences Approach (3rd Edition).* New York: Chapman and Hall/CRC.
Gill J and Meier KJ. (2000) Public Administration Research and Practice: A Methodological Manifesto. *Journal of Public Administration Research and Theory: J-PART* 10(1): 157-199.
Gill J and Witko C. (2013) Bayesian Analytical Methods: A Methodological Prescription for Public Administration. *Journal of Public Administration Research and Theory* 23(2): 457-494.
Gill J and Womack A. (2013) *The Multilevel Model Framework*. London: SAGE Publications Ltd, 3-20.
Gliner J, Leech N and Morgan G. (2002) Problems with Null Hypothesis Significance Testing (NHST): What Do the Textbooks Say? *Journal of Experimental Education* 71(1): 83-92.
Goldson B. (2000) 'Children in Need' or 'Young Offenders'? Hardening Ideology, Organizational Change and New Challenges for Social Work with Children in Trouble. *Child & Family Social Work* 5(3): 255-265.
Goldson B. (2002) New Labour, Social Justice and Children: Political Calculation and the Deserving-Undeserving Schism. *British Journal of Social Work* 32(6): 683-695.
Goldson B. (2010) The Sleep of (Criminological) Reason: Knowledge - Policy Rupture and New Labour's Youth Justice Legacy. *Criminology & Criminal Justice* 10(2): 155-178.
Goldson B and Muncie J. (2006) Rethinking Youth Justice: Comparative Analysis, International Human Rights and Research Evidence. *Youth Justice* 6(2): 91-106.
Good IJ. (1979) Studies in the History of Probability and Statistics. XXXVII A. M. Turing's Statistical Work in World War II. *Biometrika* 66(2): 393-396.
Gorard S. (2002) *How Can We Overcome the Methodological Schism? (or Can There be a 'Compleat' Researcher)?* Annual Conference of the British Educational Research Association, University of Exeter, 12-14 September. Available at: http://www.leeds.ac.uk/educol/documents/00002205. (Accessed 31/1/18).

Gorard S. (2014a) A Proposal for Judging the Trustworthiness of Research Findings. *Radical Statistics* 110: 47-59.
Gorard S. (2014b) The Widespread Abuse of Statistics by Researchers: What Is the Problem and What Is the Ethical Way Forward? *Psychology of Education Review* 38(1): 3-10.
Gorard S. (2016) Damaging Real Lives through Obstinacy: Re-Emphasising Why Significance Testing Is Wrong. *Sociological Research Online* 21(1): 2.
Gottfredson SD and Moriarty LJ. (2006) Statistical Risk Assessment: Old Problems and New Applications. *Crime & Delinquency* 52(1): 178-200.
Grandi LD and Adler JR. (2016) A Study into Breaches of Youth Justice Orders and the Young People Who Breach Them. *Youth Justice* 16(3): 205-225.
Gray E, Jackson J and Farrall S. (2011) Feelings and Functions in the Fear of Crime: Applying a New Approach to Victimisation Insecurity. *The British Journal of Criminology* 51(1): 75-94.
Gray P. (2005) The Politics of Risk and Young Offenders' Experiences of Social Exclusion and Restorative Justice. *British Journal of Criminology* 45(6): 938-957.
Greenwood PW. (1982) *Selective Incapacitation*. Santa Monica, CA: The RAND Corporation.
Grix J. (2002) Introducing Students to the Generic Terminology of Social Research. *Politics* 22(3): 175-186.
Hadfield JD. (2010) MCMC Methods for Multi-Response Generalized Linear Mixed Models: The MCMCglmm R Package. *Journal of Statistical Software* 33(2): 22.
Hadfield JD. (2017a) *MCMCglmm (Version 2.25) [Computer Software]*. Available at: https://cran.r-project.org/web/packages/MCMCglmm/index.html. (Accessed 31/1/18).
Hadfield JD. (2017b) *MCMCglmm Course Notes* Available at: https://cran.r-project.org/web/packages/MCMCglmm/vignettes/CourseNotes.pdf. (Accessed 31/1/18).
Haines K and Case S. (2005) Promoting Prevention: Targeting Family-Based Risk and Protective Factors for Drug Use and Youth Offending in Swansea. *The British Journal of Social Work* 35(2): 169-187.
Haines K, Case S, Davies K, et al. (2013) The Swansea Bureau: A Model of Diversion from the Youth Justice System. *International Journal of Law, Crime and Justice* 41(2): 167-187.
Haines K and Drakeford M. (1998) *Young People and Youth Justice.* London: Macmillian Press Ltd.
Hale C, Hayward K, Wahidin A, et al. (2005) *Criminology.* Oxford: Oxford University Press.
Harcourt BE. (2007) *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age.* Chicago: The University of Chicago Press.
Hare RD. (2003) *The Hare Psychopathy Checklist-Revised (2nd Edition).* Toronto: Multi-Health Systems.
Harris GT and Rice ME. (2013) Bayes and Base Rates: What Is an Informative Prior for Actuarial Violence Risk Assessment? *Behavioral Sciences & the Law* 31(1): 103-124.
Hart D. (2011a) *Into the Breach: The Enforcement of Statutory Orders in the Youth Justice System*. London: Prison Reform Trust.
Hart D. (2011b) Public Protection or Public Protection? Breach Action within the Youth Justice System. *Safer Communities* 10(4): 19-27.
HM Government. (2007) *Working Together to Cut Crime and Deliver Justice*. London: HMSO.
Hoekstra R, Morey RD, Rouder JN, et al. (2014) Robust Misinterpretation of Confidence Intervals. *Psychonomic Bulletin & Review* 21(5): 1157-1164.
Howard League for Penal Reform. (2017) *Ending the Criminalisation of Children in Residential Care: Briefing One*. London: Howard League for Penal Reform.
Howard P, Francis B, Soothill K, et al. (2009) *OGRS 3: The Revised Offender Group Reconviction Scale*. London: Ministry of Justice.
Howard P and Kershaw C. (2000) *Using Criminal Career Data in Evaluation*. British Society of Criminology, Liverpool, July 1999. Available at: http://britsoccrim.org/new/volume3/005.pdf. (Accessed 28/11/17).
Hoyle RH and Gottfredson NC. (2015) Sample Size Considerations in Prevention Research Applications of Multilevel Modeling and Structural Equation Modeling. *Prevention Science* 16(7): 987-996.
Hughes N, Williams H, Chitsabesan P, et al. (2012) *Nobody Made the Connection: The Prevalence of Neurodisability in Young People Who Offend*. Available at: https://www.childrenscommissioner.gov.uk/publication/nobody-made-the-connection/. (Accessed 31/1/18).

Hughes N, Williams WH, Chitsabesan P, et al. (2015) The Prevalence of Traumatic Brain Injury among Young Offenders in Custody: A Systematic Review. *The Journal of Head Trauma Rehabilitation* 30(2): 94-105.

Issac W and Dixon A. (2017) *Why Big-Data Analysis of Policy Activity Is Inherently Biased*. The Conversation, 10 May. Available at: http://theconversation.com/why-big-data-analysis-of-police-activity-is-inherently-biased-72640. (Accessed 31/1/18).

Jackman S. (2009) *Bayesian Analysis for the Social Sciences.* Chichester: Wiley.

Jamieson J. (2005) New Labour, Youth Justice and the Question of Respect. *Youth Justice* 5(3): 180.

Jang SJ. (1999) Age-Varying Effects of Family, School, and Peers on Delinquency: A Multilevel Modeling Test of Interactional Theory Exchange. *Criminology* 37(643-686.

JASP Team. (2017a) *FAQ: What Does JASP Stand For?* Available at: https://jasp-stats.org/faq/. (Accessed 31/1/18).

JASP Team. (2017b) *JASP (Version 0.8.5)[Computer Software].* Available at: https://jasp-stats.org/. (Accessed 31/1/18).

JASP Team. (2017c) *Our Goals.* Available at: https://jasp-stats.org/about/. (Accessed 31/1/18).

Jeffreys H. (1961) *Theory of Probability (3rd Edition).* Oxford: Oxford University Press.

Johnson C. (2016) Artificial Intelligence 'Judge' Developed by Ucl Computer Scientists *The Guardian,* 24th October. Available at: https://www.theguardian.com/technology/2016/oct/24/artificial-intelligence-judge-university-college-london-computer-scientists. (Accessed 31/1/18).

Kalinowski P, Fidler F and Cumming G. (2008) Overcoming the Inverse Probability Fallacy: A Comparison of Two Teaching Interventions. *Experimental Psychology* 4(4): 152-158.

Kaplan D. (2014) *Bayesian Statistics for the Social Sciences.* New York: The Gulford Press.

Kemshall H. (1995) Risk in Probation Practice: The Hazards and Dangers of Supervision. *Probation Journal* 42(2): 67-72.

Kemshall H. (1996) Risk Assessment: Fuzzy Thinking or 'Decisions in Action'? *Probation Journal* 43(1): 2-7.

Kemshall H. (1998) *Risk in Probation Practice.* Aldershot: Ashgate Publishing Ltd.

Kemshall H. (2008a) Risks, Rights and Justice: Understanding and Responding to Youth Risk. *Youth Justice* 8(1): 21-37.

Kemshall H. (2008b) *Understanding the Community Management of High Risk Offenders.* Maidenhead: Open University Press.

Kemshall H, Parton N, Walsh M, et al. (1997) Concepts of Risk in Relation to Organizational Structure and Functioning within the Personal Social Services and Probation. *Social Policy and Administration* 31(3): 213-232.

King R, Bird SM, Hay G, et al. (2009) Estimating Current Injectors in Scotland and Their Drug-Related Death Rate by Sex, Region and Age-Group Via Bayesian Capture—Recapture Methods. *Statistical Methods in Medical Research* 18(4): 341-359.

King R, Bird SM, Overstall AM, et al. (2014a) Estimating Prevalence of Injecting Drug Users and Associated Heroin-Related Death Rates in England by Using Regional Data and Incorporating Prior Information. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 177(1): 209-236.

King TE, Fortes GG, Balaresque P, et al. (2014b) Identification of the Remains of King Richard III. *Nature Communications* 5

Kitchin R. (2014) Big Data, New Epistemologies and Paradigm Shifts. *Big Data & Society* 1(1): 1-12.

Kivivuori J. (2007) Crime by Proxy - Coercion and Altruism in Adolescent Shoplifting. *British Journal of Criminology* 47(5): 817-833.

Kruschke JK. (2010a) *Bayesian Data Analysis*. Wiley Interdisciplinary Reviews: Cognitive Science, 658-676.

Kruschke JK. (2010b) What to Believe: Bayesian Methods for Data Analysis. *Trends in Cognitive Sciences* 14(7): 293-300.

Kruschke JK. (2011) Introduction to Special Section on Bayesian Data Analysis. *Perspectives on Psychological Science* 6(3): 272-273.

Kruschke JK. (2013) Posterior Predictive Checks Can and Should Be Bayesian: Comment on Gelman and Shalizi, 'Philosophy and the Practice of Bayesian Statistics'. *British Journal of Mathematical and Statistical Psychology* 66(1): 45-56.

Kruschke JK. (2015) *Doing Bayesian Data Analysis: A Tutorial with R and Bugs (2nd Edition).* Burlington, MA: Elsevier.
Kruschke JK, Aguinis H and Joo H. (2012) The Time Has Come: Bayesian Methods for Data Analysis in the Organizational Sciences. *Organizational Research Methods* 15(4): 722-752.
Lambdin C. (2012) Significance Tests as Sorcery: Science Is Empirical—Significance Tests Are Not. *Theory & Psychology* 22(1): 67-90.
Lammy D. (2017) *The Lammy Review: Final Report*. London: Gov.UK.
Langton S and Bannister J. (2017) Space, Place and Crime in an Era of 'Big Data'. *The Geographer – Newsletter of the Royal Scottish Geographical Society* Spring 2017: 23.
Laub JH and Sampson RJ. (1991) The Sutherland-Glueck Debate: On the Sociology of Criminological Knowledge. *American Journal of Sociology* 96(6): 1402-1440.
Law J, Quick M and Chan P. (2014) Bayesian Spatio-Temporal Modeling for Analysing Local Patterns of Crime over Time at the Small-Area Level. *Journal of Quantitative Criminology* 30(1): 57-78.
Lee PM. (2012) *Bayesian Statistics: An Introduction (4th Edition).* Chichester: Wiley.
Levine N and Block R. (2011) Bayesian Journey-to-Crime Estimation: An Improvement in Geographic Profiling Methodology. *The Professional Geographer* 63(2): 213-229.
Levine N and Lee P. (2009) Bayesian Journey-to-Crime Modelling of Juvenile and Adult Offenders by Gender in Manchester. *Journal of Investigative Psychology and Offender Profiling* 6(3): 237-252.
Lewis D-M. (2014) The Risk Factor - (Re-) Visiting Adult Offender Risk Assessments within Criminal Justice Practice. *Risk Management - Journal of Risk Crisis and Disaster* 16(2): 121-136.
Li B, Lingsma HF, Steyerberg EW, et al. (2011) Logistic Random Effects Regression Models: A Comparison of Statistical Packages for Binary and Ordinal Outcomes. *BMC Medical Research Methodology* 11(1): 77.
Liddle M, Boswell G, Wright S, et al. (2016) *Trauma and Young Offenders: A Review of the Research and Practice Literature*. London: Beyond Youth Custody.
Lindley DV. (1975) The Future of Statistics: A Bayesian 21st Century. *Advances in Applied Probability* 7: 106-115.
Liu Y, Yang M, Ramsay M, et al. (2011) A Comparison of Logistic Regression, Classification and Regression Tree, and Neural Networks Models in Predicting Violent Re-Offending. *Journal of Quantitative Criminology* 27(4): 547-573.
Lösel F. (2017) Evidence Comes by Replication, but Needs Differentiation: The Reproducibility Issue in Science and Its Relevance for Criminology. *Journal of Experimental Criminology*. doi: 10.1007/s11292-017-9297-z
Loughran TA, Paternoster R and Thomas KJ. (2014) Incentivizing Responses to Self-Report Questions in Perceptual Deterrence Studies: An Investigation of the Validity of Deterrence Theory Using Bayesian Truth Serum. *Journal of Quantitative Criminology* 30(4): 677-707.
Lum K and Isaac W. (2016) To Predict and Serve? *Significance* 13(5): 14-19.
Mair C, Gruenewald PJ, Ponicki WR, et al. (2013) Varying Impacts of Alcohol Outlet Densities on Violent Assaults: Explaining Differences across Neighborhoods. *Journal of Studies on Alcohol and Drugs* 74(1): 50-58.
Maltz MD. (1994) Deviating from the Mean: The Declining Significance of Significance. *Journal of Research in Crime and Delinquency* 31(4): 434-463.
Marx GT. (1997) Of Methods and Manners for Aspiring Sociologists: 37 Moral Imperatives. *The American Sociologist* 28(1): 102-125.
Mayer-Schibverger V and Cukier K. (2013) *Should We Use Big Data to Punish Crimes before They're Committed?* Popular Science, 6 March. Available at: http://www.popsci.com/science/article/2013-03/should-we-use-big-data-to-punish-crimes-before-theyre-committed. (Accessed 31/1/18).
McAra L and McVie S. (2005) The Usual Suspects? Street-Life, Young People and the Police. *Criminal Justice* 5(1): 5-36.
McAra L and McVie S. (2007) Youth Justice? The Impact of System Contact on Patterns of Desistance from Offending. *European Journal of Criminology* 4(3): 315-345.
McAra L and McVie S. (2010) Youth Crime and Justice: Key Messages from the Edinburgh Study of Youth Transitions and Crime. *Criminology & Criminal Justice* 10(2): 179-209.

McAra L and McVie S. (2015) The Case for Diversion and Minimum Necessary Intervention. In: Goldson B and Muncie J (eds) *Youth Crime and Justice (2nd Edition).* London: Sage, 119-136.
McElreath R. (2016) *Statistical Rethinking: A Bayesian Course with Examples in R and Stan.* Boca Raton, FL: CRC Press.
McGrayne SB. (2011) *The Theory That Would Not Die : How Bayes' Rule Cracked the Enigma Code Hunted Down Russian Submarines, and Emerged Triumphant from Two Centuries of Controversy.* New Haven and London: Yale University Press.
McKee RA and Miller CC. (2015) Institutionalizing Bayesianism within the Organizational Sciences: A Practical Guide Featuring Comments from Eminent Scholars. *Journal of Management* 41(2): 471-490.
McMahon P, Zaslavsky A, Weinstein M, et al. (2006) Estimation of Mortality Rates for Disease Simulation Models Using Bayesian Evidence Synthesis. *Medical Decision Making* 26: 497-511.
McNeeley S and Warner JJ. (2015) Replication in Criminology: A Necessary Practice. *European Journal of Criminology* 12(5): 581-597.
McNeill F. (2009) *Towards Effective Practice in Offender Supervision*. Glasgow: Scottish Centre for Crime and Justice Research.
McShane BB and Gal D. (2016) Blinding Us to the Obvious? The Effect of Statistical Training on the Evaluation of Evidence. *Management Science* 62(6): 1707-1718.
McVie S. (2016) *It's a Criminal Waste: How Using Administrative Data About Crime Could Better Inform Public Policy*. ADRN Blog, 15/11/16. Available at: https://adrn.ac.uk/understand-data/blog/it-s-a-criminal-waste/. (Accessed 5/4/17).
McVie S and Norris P. (2006) *Neighbourhood Effects on Youth Delinquency and Drug Use* Edinburgh: Centre for Law and Society, The University of Edinburgh.
Meyers JR and Schmidt F. (2008) Predictive Validity of the Structured Assessment for Violence Risk in Youth (Savry) with Juvenile Offenders. *Criminal Justice and Behavior* 35(3): 344-355.
Milner J and Myers S. (2007) *Working with Violence: Policies and Practices in Risk Assessment and Management.* Basingstoke: Palgrave Macmillan.
Ministry of Justice. (2010) *Breaking the Cycle: Effective Punishment, Rehabilitation and Sentencing of Offenders*. London: The Stationary Office.
Ministry of Justice. (2014a) *Accessing the Justice Data Lab Service*. Available at: https://www.gov.uk/government/publications/justice-data-lab. (Accessed 31/1/18).
Ministry of Justice. (2014b) *Transforming the Criminal Justice System Strategy and Action Plan – Implementation Update*. London: HMSO.
Ministry of Justice. (2017a) *Guide to Proven Reoffending Statistics*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/585963/guide-to-proven-reoffending-statistics-Jan17.pdf. (Accessed 31/1/18).
Ministry of Justice. (2017b) *How the Measure of Proven Reoffending Has Changed and the Effect of These Changes*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/658380/how-the-measure-of-reoffending-has-changed-and-the-effect-of-these-changes.pdf. (Accessed 31/1/18).
Ministry of Justice. (2017c) *Proven Reoffending Statistics Quarterly Bulletin, April 2014 to March 2015*. Available at: https://www.gov.uk/government/statistics/proven-reoffending-statistics-april-2014-to-march-2015. (Accessed 31/1/18).
Mokros A, Stadtland C, Osterheider M, et al. (2010) Assessment of Risk for Violent Recidivism through Multivariate Bayesian Classification. *Psychology, Public Policy and Law* 16(4): 418-450.
Monk D. (2009) *The Scaled Approach: Improving Positive Outcomes for Young People in the Youth Justice System*. Available at: http://embed.policyreview.tv/media/documents/LI281_DAVID_MONK.pdf. (Accessed 31/1/18).
Morey RD. (2016) *What Role Can Bayesian Methods Play in Resolving the Replication Crisis?* ESRC Research Methods Festival, University of Bath, 7th July. Available at: http://www.ncrm.ac.uk/RMF2016/programme/session.php?id=R6. (Accessed 31/1/18).
Morey RD, Hoekstra R, Rouder JN, et al. (2016) The Fallacy of Placing Confidence in Confidence Intervals. *Psychonomic Bulletin & Review* 23(1): 103-123.

Muncie J. (2009) *Youth and Crime.* London: Sage Publications Ltd.
National Crime Agency. (2017) *County Lines Violence, Exploitation & Drug Supply 2017*. London: National Crime Agency.
Neller DJ and Petris G. (2013) Sexually Violent Predators: Toward Reasonable Estimates of Recidivism Base Rates. *Behavioral Sciences & the Law* 31(4): 429-443.
Newburn T. (2007) *Criminology.* Cullompton: Willian Publishing.
Nickerson RS. (2000) Null Hypothesis Significance Testing: A Review of an Old and Continuing Controversy. *Psychological Methods* 5(2): 241-301.
O'Donoghue R. (2016) Is Kent's Predictive Policing Project the Future of Crime Prevention? . *KentOnline,* 5th April. Available at: http://www.kentonline.co.uk/sheerness/news/what-if-police-could-detect-93715/. (Accessed 31/1/18).
O'Hagan A and Luce B. (2003) *A Primer on Bayesian Statistics in Health Economics and Outcomes Research*. Available at: https://www.sheffield.ac.uk/polopoly_fs/1.80635!/file/primer.pdf (Accessed 31/1/18).
O'Mahony P. (2009) The Risk Factors Prevention Paradigm and the Causes of Youth Crime: A Deceptively Useful Analysis? *Youth Justice* 9(2): 99-114.
O'Neil C. (2017) *The Era of Blind Faith in Big Data Must End*. New York: TED Conferences, LLC
Office of National Statistics. (2013) *Census 2011 Detailed Characteristics - Ethnic Group by Sex and Age (DC2101EW)*. Available at: https://www.nomisweb.co.uk/census/2011/dc2101ew. (Accessed 31/1/18).
Ofili OU. (2014) Bail Decision Support System. *The International Journal of Engineering and Science* 3(8): 45-66.
Owen N and Cooper C. (2013) *The Start of a Criminal Career: Does the Type of Debut Offence Predict Future Offending?* London: Home Office.
Pawson R and Tilly N. (2000) *Realistic Evaluation.* London: SAGE Publications.
Paylor I. (2010) The Scaled Approach to Youth Justice: A Risky Business. *Criminal Justice Matters* 81(1): 30-31.
Pemberton C. (2009) Youth Justice: Scaled Approach and YRO Launch. *Community Care,* 30th November. Available at: http://www.communitycare.co.uk/2009/11/30/youth-justice-scaled-approach-and-yro-launch/. (Accessed 31/1/18).
Petrosino A, Turpin-Petrosino C and Guckenburg S. (2010) *Formal System Processing of Juveniles: Effects on Delinquency. Campbell Systematic Reviews*. Woburn, Mass: The Campbell Collaboration.
Phenix A, Fernandez Y, Harris AJR, et al. (2016) *Static-99R Coding Rules, Revised*. Available at: http://www.static99.org/. (Accessed 31/1/18).
Phoenix J. (2009a) Beyond Risk Assessment: The Return of Repressive Welfare? In: Barry M and McNeill F (eds) *Youth Offending and Youth Justice.* London: Jessica Kingsley Publishers, 113-131.
Phoenix J. (2009b) *Doing Youth Justice: Analysing Risk and Need Assessments in Youth Justice Practice, 2004-2005. [User Guide]. SN: 5831*. Essex: UK Data Service.
Pitts J. (2001) Korrectional Karaoke: New Labour and the Zombification of Youth Justice. *Youth Justice* 1(2): 3-16.
Pitts J. (2005) The Recent History of Youth Justice in England and Wales. In: Bateman T and Pitts J (eds) *The RHP Companion to Youth Justice.* Lyme Regis: Russeel House Publishing Ltd, 2-11.
Ployhart RE and Vandenberg RJ. (2010) Longitudinal Research: The Theory, Design, and Analysis of Change. *Journal of Management* 36(1): 94-120.
Plummer M. (2008) Penalized Loss Functions for Bayesian Model Comparison. *Biostatistics* 9(3): 523-539.
Prison Reform Trust. (2016) *In Care, out of Trouble* London: Prison Reform Trust.
Puffet N. (2010a) Cautious Welcome for Scaled Approach System. *Children and Young People Now,* 2nd July. Available at: http://www.cypnow.co.uk/cyp/news/1052628/cautious-welcome-scaled-approach (Accessed 31/1/18)
Puffet N. (2010b) YJB Considers Shake-Up. *Children and Young People Now,* 1st March. Available at: http://www.cypnow.co.uk/cyp/news/1042636/yjb-considers-assessment-shake. (Accessed 31/1/18).

Punch K, F. (2006) *Developing Effective Research Proposals.* London: SAGE.
Quinsey VL, Harris GT, Rice ME, et al. (2006) *Violent Offenders: Appraising and Managing Risk (2nd Edition).* Washington DC: American Psychological Association.
Quintana DS and Williams DR. (Preprint) *Bayesian Alternatives for Common Null-Hypothesis Significance Tests in Psychiatry: A Non-Technical Guide Using JASP*. Open Science Framework.
Raynor P. (2016) Three Narrratives of Risk: Corrections, Critique and Context. In: Trotter C, McIvor G and McNeill F (eds) *Beyond the Risk Paradigm in Criminal Justice.* London: Palgrave, 24-45.
Raynor P, Kynch J, Roberts C, et al. (2000) *Risk and Need Assessment in Probation Services: An Evaluation.* Home Office London.
Rembert DA, Henderson H and Pirtle D. (2014) Differential Racial/Ethnic Predictive Validity. *Youth Violence and Juvenile Justice* 12(2): 152-166.
Rice ME and Harris GT. (1995) Violent Recidivism: Assessing Predictive Validity. *Journal of consulting and clinical psychology* 63(5): 737.
Rice ME and Harris GT. (2005) Comparing Effect Sizes in Follow-up Studies: Roc Area, Cohen's D, and R. *Law and Human Behavior* 29(5): 615-620.
Robinson D and Koepke L. (2016) *Stuck in a Pattern: Early Evidence on “Predictive Policing” and Civil Rights* Washington DC: Upturn.
Robinson G. (2002) Exploring Risk Management in Probation Practice. *Punishment & Society* 4(1): 5-25.
Robson C and McCartan K. (2016) *Real World Research.* Wiley.
Robson K and Pevalin D. (2016) *Multilevel Modeling in Plain Language.* London: Sage.
Rose D. (2016) Drugs, Mental Disorder and Risk. In: Trotter C (ed) *Beyond the Risk Paradigm in Criminal Justice.* London: Palgrave, 92-107.
Rouder JN, Speckman PL, Sun D, et al. (2009) Bayesian T Tests for Accepting and Rejecting the Null Hypothesis. *Psychonomic Bulletin & Review* 16(2): 225-237.
Rowlingson K. (2004) Secondary Data Analysis. In: Becker S and Bryman A (eds) *Understanding Research for Social Policy and Practice.* Bristol: The Policy Press, 138-142.
Salsburg D. (2001) *The Lady Tasting Tea: How Statistics Revolutionised Science in the Twentieth Century.* New York: Holt Paperbacks.
Sampson RJ. (2010) Gold Standard Myths: Observations on the Experimental Turn in Quantitative Criminology. *Journal of Quantitative Criminology* 26(4): 489-500.
Schwalbe CS. (2007) Risk Assessment for Juvenile Justice: A Meta-Analysis. *Law and Human Behavior* 31(5): 449-462.
Schwalbe CS. (2008) A Meta-Analysis of Juvenile Justice Risk Assessment Instruments: Predictive Validity by Gender. *Criminal Justice and Behavior* 35(11): 1367-1381.
Schwalbe CS, Fraser MW, Day SH, et al. (2006) Classifying Juvenile Offenders According to Risk of Recidivism Predictive Validity, Race/Ethnicity, and Gender. *Criminal Justice and Behavior* 33(3): 305-324.
Sentencing Council. (2017) *Sentencing Children and Young People: Definitive Guide*. London: Sentencing Council.
Sentencing Guidelines Council. (2009) *Overarching Principles - Sentencing Youths: Definitive Guidelines*. London: Sentencing Guidelines Council.
Shapiro A. (2017) Reform Predictive Policing. *Nature* 541: 458-460.
Sharland E. (2005) Young People, Risk Taking and Risk Making: Some Thoughts for Social Work. *British Journal of Social Work* 36(2): 247-265.
Sherman LW. (2009) Evidence and Liberty: The Promise of Experimental Criminology. *Criminology & Criminal Justice* 9(1): 5-28.
Simon J and Feeley MM. (2003) The Form and Limits of the New Penology. In: Blomberg T and Cohen S (eds) *Punishment and Social Control.* New York: Walter de Gruyter Inc, 75-116.
Simpson E. (2010) Edward Simpson: Bayes at Bletchley Park. *Significance* 7(2): 76-80.
Smith A. (2017) *Report of Professor Sir Adrian Smith's Review of Post-16 Mathematics*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/630488/AS_review_report.pdf. (Accessed 31/1/18).
Smith DJ and McAra L. (2004) *Gender and Youth Offending*. Edinburgh: University of Edinburgh.

Smith DJ and McVie S. (2003) Theory and Method in the Edinburgh Study of Youth Transitions and Crime. *The British Journal of Criminology* 43(1): 169-195.
Smith GJD, Bennett Moses L and Chan J. (2017) The Challenges of Doing Criminology in the Big Data Era: Towards a Digital and Data-Driven Approach. *The British Journal of Criminology* 57(2): 259-274.
Smith R. (2006) Actuarialism and Early Intervention in Contemporary Youth Justice. In: Goldson B and Muncie J (eds) *Youth Crime and Justice.* London: Sage Publications Ltd, 92-109.
Snijders TA and Bosker RJ. (2012) *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling (2nd Edition).* London: SAGE.
Spiegelhalter DJ, Abrams KR and Myles JP. (2004) *Bayesian Approaches to Clinical Trials and Health-Care Evaluation.* Chichester: John Wiley & Sons.
Spiegelhalter DJ, Best NG, Carlin BP, et al. (2002) Bayesian Measures of Model Complexity and Fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 64(4): 583-616.
Spiegelhalter DJ, Best NG, Carlin BP, et al. (2014) The Deviance Information Criterion: 12 Years On. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 76(3): 485-493.
Srinivasan S, Moser RP, Willis G, et al. (2015) Small Is Essential: Importance of Subpopulation Research in Cancer Control. *American Journal of Public Health* 105(Suppl 3): S371-S373.
Staines J. (2016) *Risk, Adverse Influence and Criminalisation: Understanding the over-Representation of Looked after Children in the Youth Justice System*. London: Prison Reform Trust.
Stephenson M, Henri G and Brown S. (2007) *Effective Practice in Youth Justice.* Cullompton: Willian Publishing.
Stephenson M, Henri G and Brown S. (2011) *Effective Practice in Youth Justice.* Abingdon, Oxon: Routledge.
Stone J. (2013) *Bayes' Rule: A Tutorial Introduction to Bayesian Analysis.* Milton Keynes: Sebtel Press.
Sullivan CJ and McGloin JM. (2014) Looking Back to Move Forward. *Journal of Research in Crime and Delinquency* 51(4): 445-466.
Sullivan CJ and Mieczkowski T. (2008) Bayesian Analysis and the Accumulation of Evidence in Crime and Justice Intervention Studies. *Journal of Experimental Criminology* 4(4): 381-402.
Sutherland A. (2009) The Scaled Approach in Youth Justice: Fools Rush in…. *Youth Justice* 9(1): 44-60.
Sutherland A, Disley E, Cattell J, et al. (2017) *An Analysis of Trends in First Time Entrants to the Youth Justice System*. Available at: https://www.gov.uk/government/publications/analysis-of-trends-in-first-time-entrants-to-the-youth-justice-system. (Accessed 31/1/18).
Sutton AJ and Abrams KR. (2001) Bayesian Methods in Meta-Analysis and Evidence Synthesis. *Statistical Methods in Medical Research* 10(4): 277-303.
Talbot J. (2010) *Seen and Heard: Supporting Vulnerable Children in the Youth Justice System*. London: Prison Reform Trust.
Tarran B. (2014) *How Turing - and Bayes - Cracked Enigma*. Available at: http://www.statslife.org.uk/history-of-stats-science/1909-how-turing-and-bayes-cracked-the-enigma-code. (Accessed 31/1/18).
Teli B. (2011) *Assessment and Planning Interventions: Review and Redesign Project*. London: Youth Justice Board.
The Communication Trust. (2014) *Doing Justice to Speech, Language and Communication Needs: Proceedings of a Round Table on Speech Language and Communication Needs in the Youth Justice Sector – November 2014*. London: The Communication Trust.
Thornberry TP, Lizotte AJ, Krohn MD, et al. (1994) Delinquent Peers, Beliefs, and Delinquent Behavior: A Longitudinal Test of Interactional Theory. *Criminology* 32: 47-84.
Trafimow D and Marks M. (2015) Editorial. *Basic Applied Social Psychology* 37: 1-2.
Tully RJ, Chou SN and Browne KD. (2013) A Systematic Review on the Effectiveness of Sex Offender Risk Assessment Tools in Predicting Sexual Recidivism of Adult Male Sex Offenders. *Clinical Psychology Review* 33(2): 287-316.
Turnbull G and Spence J. (2011) What's at Risk? The Proliferation of Risk across Child and Youth Policy in England. *Journal of Youth Studies* 14(8): 939-959.
UK Data Service. (2018) *Data by Theme: Crime*. Available at: https://www.ukdataservice.ac.uk/get-data/themes/crime. (Accessed 31/1/18).

van der Put CE. (2014) Youth Actuarial Risk Assessment Tool (Y-Arat): The Development of an Actuarial Risk Assessment Instrument for Predicting General Offense Recidivism on the Basis of Police Records. *Assessment* 21(3): 340-351.
van der Put CE, Deković M, Hoeve M, et al. (2014) Risk Assessment of Girls: Are There Any Sex Differences in Risk Factors for Re-Offending and in Risk Profiles? *Crime & Delinquency* 60(7): 1033-1056.
Vaswani N and Merone L. (2014) Are There Risks with Risk Assessment? A Study of the Predictive Accuracy of the Youth Level of Service–Case Management Inventory with Young Offenders in Scotland. *British Journal of Social Work* 44(8): 2163-2181.
Wagenmakers E-J, Love J, Marsman M, et al. (2017) Bayesian Inference for Psychology. Part II: Example Applications with JASP. *Psychonomic Bulletin & Review*. doi: 10.3758/s13423-017-1323-7
Wagner K and Gill J. (2005) Bayesian Inference in Public Administration Research: Substantive Differences from Somewhat Different Assumptions. *Journal of Public Administration* 28: 5-35.
Walklate S and Mythen G. (2011) Beyond Risk Theory: Experiential Knowledge and 'Knowing Otherwise'. *Criminology & Criminal Justice* 11(2): 99-113.
Wang M and Zhang L. (2012) A Bayesian Quantile Regression Analysis of Potential Risk Factors for Violent Crimes in USA. *Open Journal of Statistics* 2: 526-533.
Warr M. (2012) The Social Side of Delinquent Behavior. In: Feld BC and Bishop DM (eds) *The Oxford Handbook of Juvenile Crime and Juvenile Justice.* New York: Oxford University Press, 226-245.
Wasserstein RL and Lazar NA. (2016) The ASA's Statement on P-Values: Context, Process, and Purpose. *The American Statistician* 70(2): 129-133.
Weisburd D, Mazerolle L and Petrosino A. (2007) The Academy of Experimental Criminology: Advancing Randomized Trials in Crime and Justice. *The Criminologist* 32(3): 1-7.
Welsh Assembly Government and Youth Justice Board. (2009) *All Wales Youth Offending Strategy: Delivery Plan 2009-11*. Available at: http://dera.ioe.ac.uk/9616/13/fileDownload.asp_file%3DAll%2BWales%2BYouth%2BOffending%2BStrategy%2B-%2BDelivery%2BPlan%2B2009-11_Redacted.pdf. (Accessed 31/1/18).
Welsh Government and Youth Justice Board. (2014) *Youth Justice Strategy for Wales: Children and Young People First*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/374572/Youth_Justice_Strategy_English.PDF. (Accessed 31/1/18).
West DJ and Farrington D. (1977) *The Delinquent Way of Life.* London: Heinemann.
Western B. (1999) Bayesian Analysis for Sociologists: An Introduction. *Sociological Methods & Research* 28(1): 7-34.
White P. (2009) *Developing Research Questions: A Guide for Social Scientists.* Basingstoke: Palgrave Macmillan.
Wilson AJ, Réale D, Clements MN, et al. (2010) An Ecologist's Guide to the Animal Model. *Journal of Animal Ecology* 79(1): 13-26.
Wilson E. (2013) *Youth Justice Interventions - Findings from the Juvenile Cohort Study (JCS)*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/266405/juvenile-cohort-study.pdf. (Accessed 31/1/18).
Wilson E and Hinks S. (2011) *Assessing the Predictive Validity of the ASSET Youth Risk Assessment Tool Using the Juvenile Cohort Study (JCS)*. London: Ministry of Justice.
Woolston C. (2015) Psychology Journal Bans P-Values. *Nature. doi:* 0.1038/519009f
Young S and Goodwin E. (2010) Attention-Deficit/Hyperactivity Disorder in Persistent Criminal Offenders: The Need for Specialist Treatment Programs. *Expert Review of Neurotherapeutics* 10(10): 1497-1500.
Youth Justice Board. (2005a) *Risk and Protective Factors*. London: Youth Justice Board.
Youth Justice Board. (2005b) *Risk and Protective Factors (Summary Report)*. London: Youth Justice Board.
Youth Justice Board. (2008a) *ASSET Core Profile - Guidance*. Available at: https://www.gov.uk/government/publications/asset-documents. (Accessed 31/1/18).

Youth Justice Board. (2008b) *ASSET Core Profile - Introduction*. Available at: https://www.gov.uk/government/publications/asset-documents. (Accessed 31/1/18).
Youth Justice Board. (2008c) *Youth Justice: The Scaled Approach Consultation Summary. Summary of Issues Raised in Consultation and Next Steps*.
Youth Justice Board. (2008d) *Youth Justice: The Scaled Approach: A Framework for Assessment and Interventions: Post-Consultation.*
Youth Justice Board. (2009a) *Scaled Approach Making Strides*. Available at: http://www.cjp.org.uk/news/archive/scaled-approach-making-strides-15-10-2009/. (Accessed 31/1/18).
Youth Justice Board. (2009b) *Youth Justice: The Scaled Approach: A Framework for Assessment and Interventions: Post-Consultation (Version 2)*. Available at: http://webarchive.nationalarchives.gov.uk/+/http://www.yjb.gov.uk/publications/Resources/Downloads/Youth%20Justice%20-%20The%20Scaled%20Approach%202009.pdf. (Accessed 31/1/18).
Youth Justice Board. (2010a) *Process Evaluation of the Pilot of a Risk-Based Approach to Interventions*. London: Youth Justice Board.
Youth Justice Board. (2010b) *Youth Justice: The Scaled Approach - a Framework for Assessment and Interventions*. Available at: http://webarchive.nationalarchives.gov.uk/20110601215311/https://www.yjb.gov.uk/Publications/Resources/Downloads/Youth%20Justice%20the%20Scaled%20Approach%20-%20A%20framework%20for%20assessment%20and%20interventions.pdf. (Accessed 31/1/18).
Youth Justice Board. (2013) *National Standards for Youth Justice Services*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/296274/national-standards-youth-justice-services.pdf. (Accessed 31/1/18).
Youth Justice Board. (2014) *ASSETPLUS Framework Model*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/362278/AssetPlus_framework_diagram.pdf. (Accessed 31/1/18).
Youth Justice Board. (2016a) *Understanding and Improving Reoffending Performance: A Summary of Learning from the YJBs Reoffending Programme with Implications for Practice*. Available at: https://yjresourcehub.uk/yjb-effective-practice/youth-justice-kits/item/download/563_c323b3ab846cf1babaf74c698a02ed12.html.
Youth Justice Board. (2016b) *Understanding and Improving Reoffending Performance: Annex B - What Does ASSET Data Tell Us About Changes in the Youth Justice Cohort over Time?* Available at: https://yjresourcehub.uk/yjb-effective-practice/youth-justice-kits/item/download/567_5f1df82e058308c67a2ec3cdb35b294e.html. (Accessed 31/1/18).
Youth Justice Board. (2017a) *ASSETPLUS Deployment List 30-08-17*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/658941/AssetPlus_deployment_list_30-08-2017.xls. (Accessed 21/11/17).
Youth Justice Board. (2017b) *Youth Justice Resource Hub: How to Reduce Reoffending by Children and Young People*. Available at: https://yjresourcehub.uk/yjb-effective-practice/youth-justice-kits/item/469-how-to-reduce-reoffending-by-children-and-young-people.html. (Accessed 31/1/18).
Youth Justice Board and Ministry of Justice. (2015a) *Youth Justice Statistics 2013/14 - England and Wales (Supplementary Volumes)*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/399654/youth-justice-stats-2013-14-supp-volumes.zip. (Accessed 31/1/18).
Youth Justice Board and Ministry of Justice. (2015b) *Youth Justice Statistics 2013/14 for England and Wales*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/399379/youth-justice-annual-stats-13-14.pdf. (Accessed 31/1/18).
Youth Justice Board and Ministry of Justice. (2015c) *Youth Justice Statistics Glossary*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/399562/youth-justice-stats-glossary.pdf. (Accessed 31/1/18).

Youth Justice Board and Ministry of Justice. (2018) *Youth Justice Statistics 2016/17 for England and Wales*. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/676072/youth_justice_statistics_2016-17.pdf. (Accessed 31/1/18).

Youth Justice Board and Royal College of Speech and Language Therapists. (2015) *Practice Advice: Speech, Language and Communication Needs (SLCN) in the Youth Justice System*. Available at: https://www.gov.uk/government/publications/speech-language-and-communication-needs-in-the-youth-justice-system/practice-advice-speech-language-and-communication-needs-slcn-in-the-youth-justice-system. (Accessed 31/1/18).

Zahriyeh E. (2014) *Maths Equation Could Help Find Missing Malaysian Plan*. Available at: http://america.aljazeera.com/articles/2014/3/12/mathematical-equationcouldhelpfindmissingmalaysianplane.html#. (Accessed 31/1/18).

Zhu L, Gorman DM and Horel S. (2006) Hierarchical Bayesian Spatial Models for Alcohol Availability, Drug "Hot Spots" and Violent Crime. *International Journal of Health Geographics* 5(54): 1-12.

Zwahlen M. (2009) Commentary: Cornfield on Cigarette Smoking and Lung Cancer and How to Assess Causality. *International Journal of Epidemiology* 38(5): 1197-1198.

Towards A Bayesian Approach in Criminology: A Case Study of Risk Assessment in Youth Justice

Technical Annex

Helen Hodges

Submitted to Swansea University in fulfilment of the requirements for the Degree of Doctor of Philosophy

Swansea University

2018

Contents

List of Models

1. Domain Descriptors

The following is a summary of the descriptors of the 12 domains taken from the *ASSET Core Profile – Guidance* (Youth Justice Board, 2008a). The document was provided to practitioners to support them in their completion of the assessment. Although the roll out of ASSETPlus was completed in July 2017, it is currently possible to access a full set of the paperwork associated with the ASSET Core Profile from:

https://www.gov.uk/government/publications/asset-documents

Living Arrangements

This domain is concerned with the extent to which the young person's living arrangements are associated with the likelihood of further offending. In addition to considering who the young person has mostly been living with over the last six months (or if in custody, the six months prior to this), practitioners are asked to identify if any of the following apply:

- No fixed abode
- Unsuitable, does not meet his/her needs
- Living with known offender/s
- Disorganised / chaotic
- Other problems eg isolation, accommodation provides opportunities for offending, availability of drugs within the house / home.

Examples of high ratings (3 or 4) include:

- The young person lives with known offenders who are clearly involving or encouraging him/her in offending behaviour.
- The young person is living on the streets and is offending to survive.
- Accommodation is stable, but s/he is living with someone they have previously stolen from or assaulted.
- Living arrangements give the young person access to potential vulnerable victims (e.g. younger siblings).

Family and Personal Relationships

This section focuses on some of the key relationships in a young person's life and highlights situations where s/he may have lost contact with someone. The phrase 'in contact with' captures a variety of interactions, both positive and negative (eg personal contact, letters, phone calls and so on). Problematic issues considered as part of the assessment include:

- Evidence of family members or carers with whom the young person has been in contact over the last six months being involved in criminal activity, heavy alcohol misuse, drug or solvent misuse
- Significant adults failing to communicate with or show care/interest in the young person
- Experience of abuse
- Witnessing other violence in family context
- Significant bereavement or loss
- Difficulties with care of his/her own children

Examples of high ratings (3 or 4) include:

- There is a close family member who is criminally active and is involving him/her in offending.
- Supervision is inconsistent and parents/carers do not know where the young person goes or who s/he is with.
- The young person is offending to obtain attention from carers who show no interest in him/her.
- Combinations of problems present at the same time (e.g. one parent with a mental health problem and one who is criminally active).

Education, Training and Employment (ETE)

Assessments should draw on a range of evidence including:

- educational records such as test/exam results, educational plans (in particular Statements of Educational Need and Personal Education Plans for young people in the care of the local authority), school/college reports, records of achievement/progress files;
- interviews/discussion with young people, their parents/carers and other professionals such as teachers/tutors;
- practitioner observation of the way in which a young person speaks, listens, reads, writes and approaches concepts related to number, time, directions etc.

The assessment focuses upon:

- Engagement in education, training or employment ie whether of compulsory school age, number of hours of ETE arranged each week; number of hours of ETE currently engaged in / receiving each week and if there is evidence of non-attendance
- Educational attainment including if special education needs (SEN) has been identified
- Other factors eg being bullied or being a bully

Examples of high ratings (3 or 4) include:

- Most of his/her offending occurs when s/he is not attending school/college/training/ employment.
- The young person offends whilst on school premises and sees school as providing opportunities for offending.
- The young person thinks that getting a job is a waste of time because it won't pay as much as s/he could get from crime.
- The young person regularly uses work opportunities (e.g. access to certain people or resources) for offending.
- The young person lacks training/work, is persistently bored and offends to fill up the time.

Neighbourhood

Practitioners are required to provide a brief description of the neighbourhood in which the young person spends most of their time and to consider issues such as:

- Obvious signs of drug dealing and/or usage
- Isolated location / lack of accessible transport
- Lack of age-appropriate facilities eg youth clubs, sports facilities
- Racial or ethnic tensions

- Other problems eg lack of amenities such as shops or post office, opportunities to sell stolen goods, red-light district, tensions between police and the local community

Examples of high ratings (3 or 4) include:

- All of the young person's offending occurs within the same neighbourhood.
- Many opportunities for offending in the area which seem attractive and profitable to him/her.

Lifestyle

This domain considers if the young person:

- Has a lack of age-appropriate friendships (if friends/ associates are noticeably younger / older)
- Is associating with predominately pro-criminal peers
- Has a lack of non-criminal friends
- Is participating in reckless activities (not just offending)
- Has inadequate legitimate personal income

Examples of high ratings (3 or 4) include:

- All of the young person's offending occurs with a particular group of friends
- The young person is offending to obtain money for a gambling habit
- The young person is bored, has little to do and sees offending as a necessary way of getting some excitement in life
- The young person is involving younger friends in offending

Substance Use

This domain focuses on the young person's attitudes and choices about substance use, and in particular occasions when s/he has used substances independently or with friends / associates. It is not limited to drug use as issues about tobacco, alcohol and solves, especially at a young age are also taken into account. Ratings are based upon:

- Historic substance use including experimental and one-off use
- Recent use ie usage that is an on-going aspect of the young person's life (although this does not necessarily relate to frequent use)
- Practices which put him / her at particular risk
- Seeing substance use as a positive and/or essential to life
- Noticeably detrimental effect on education, relationships, daily functioning

Practitioners are advised that some information will not always be disclosed, particularly at first interview and hence ratings may be revised as a result of information coming to light later on as well as if there is a real difference observed in the pattern of substance use.

Examples of high ratings (3 or 4) include:

- A 'yes' response to the question about offending to obtain money for substances.
- All his/her offending occurs whilst under the influence of substances.

- The young person's attitudes and willingness to experiment with substances increases the likelihood of him/her being found in possession of illegal drugs.

Physical Health

Practitioners are advised that a comprehensive assessment of the young person requires some consideration of his/her physical health and development. Health problems may have an adverse impact on many other aspects of his/her life, including educational and school experiences, peer group interactions, self-presentation and self-esteem.

Health needs will clearly vary according to age and gender and this needs to be borne in mind throughout the section. Consideration should also be given to any cultural or religious beliefs of the young person and his/her family which may affect health care. Problematic issues include:

- Health condition which significantly affects everyday life functioning
- Physical immaturity / delayed development
- Problems caused by not being registered with GP
- Lack of access to other appropriate health care services eg dentist
- Health put at risk through his/her own behaviour

The links between physical health and offending behaviour will usually be indirect and consequently there will be a tendency towards lower ratings in this section. For example:

- a condition which leads to disruptive behaviour at school and possible exclusion
- an impairment which makes it more difficult for him/her to find suitable work or training
- the young person's frustration with a health problem contributes to aggressive behaviour
- other negative effects e.g. poor school attendance, low self-esteem

Emotional and Mental Health

In making their assessment practitioners are reminded that mental and emotional well-being will be influenced by issues such as personal relationships and social environment as well as medical factors. Different cultural groups will vary in their views about what constitutes emotional well-being and this needs to be borne in mind. The following three factors, however, may provide a useful framework for understanding the young person's mental health needs within the context of his/her particular situation.

- Events/circumstances
- Support networks
- Coping abilities

This section may raise some issues which cannot be fully assessed in the context of the Core Profile eg issues about mental illness or suicide attempts. The expectation is therefore that ASSET should act as a 'trigger' to highlight areas where further specialist assessment may be required.

The focus of the assessment is upon if:

- The young person's daily functioning is significantly affected by emotions or thoughts resulting from coming to term with significant past event/s; their current circumstances or concerns about the future
- There has been a formal diagnosis of mental illness

- Any other contact with, or referrals to, mental health services
- There are indications that any of the following apply to the young person
    - S/he is affected by other emotional or psychological difficulties
    - S/he has deliberately harmed her/himself
    - S/he has previously attempted suicide

Examples of high ratings (3 or 4) include:

- There is a direct link with symptoms of mental illness (e.g. offending due to hallucinations, delusions, hearing voices).
- The young person is struggling to cope with strong feelings of anger/hatred and is likely to take this out on other people.
- Offending happens at specific times (e.g. when s/he fails to take medication or misses appointments with psychiatrist).

Perception of Self and Others

This domain is concerned with whether s/he:

- has difficulties with self-identity
- has inappropriate self-esteem
- has a general mistrust of others
- displays discriminatory attitudes towards others
- perceives him/herself as having a criminal identity

Examples of high ratings (3 or 4) include:

- Discriminatory attitudes that provide a clear motive for his/her offending
- The young person sees crime as his/her 'career' and thinks that s/he will always be involved in offending
- The young person's self-esteem is dependent on the sense of achievement that s/he gets from offending

Thinking and Behaviour

This section draws together information about the young person from other sections of the ASSET to identify patterns of thinking and types of behaviours which cause difficulties for him/her. As such the practitioner is asked to identify if the young person's actions are characterised by any of the following:

- Lack of understanding of consequences
- Impulsiveness
- Need for excitement
- Giving in easily to pressure from others
- Inappropriate social and communication skills

And of the young person displays any of the following types of behaviour in different settings:

- Destruction of property
- Aggression towards others
- Sexually inappropriate behaviour

- Attempts to manipulate / control others

Examples of high ratings (3 or 4) include:

- Combination of impulsiveness, poor temper control and aggression means a high risk of violent behaviour
- The young person's need for excitement frequently leads him/her into offending situations

Attitudes to Offending

Ratings this domain are based upon whether the young person displays any of the following attitudes in relation to the offences which triggered the assessment. However, if there were any significant issues about attitudes to past offences then these could also be included:

- Denial of the seriousness of his/her behaviour
- Reluctance to accept responsibility for involvement in most recent offence(s)
- Lack of understanding about the impact of his/her behaviour on victims
- Lack of remorse
- Lack of understanding about impact of his/her behaviour on family / carers
- A belief that certain types of offences are acceptable
- A belief that certain people /groups are acceptable 'targets' of offending behaviour
- S/he thinks that further offending is inevitable

Examples of high ratings (3 or 4) include:

- Attitude that provides a direct motive for his/her offending.
- The young person's genuine belief that further offending is inevitable.
- Clusters of these attitudes.

Motivation to Change

This domain considers whether the young person displays any of the following attitudes:

- An appropriate understanding of the problematic aspects of his/her own behaviour
- Understanding of the consequences for him/herself of further offending
- Has identified clear reasons or incentives for him/her to avoid further offending
- Shows real evidence of wanting to stop offending

Examples of high ratings (3 or 4) include:

- The young person has no understanding of the problematic aspects of his/her behaviour.
- The young person cannot identify any incentives to stop offending.
- There is no evidence from his/her behaviour of a desire to change.

2. Youth Justice Board Gravity Scores, by Offence Category

The following has been taken from Appendix B of the ASSET Guidance (Youth Justice Board, 2008a: 3-9)

Violence against the person

Abduction/Kidnapping • Abduction of female by force • Child abduction • False imprisonment • Hijacking • Kidnapping	**7**
Assault police officer • Assault with intent to resist arrest or assaulting a person assisting a police constable	**3**
Common assault • Assault and battery • Assault by beating	**3**
Grievous Bodily Harm	**6**
Manslaughter • Child destruction, infanticide or manslaughter due to diminished responsibility	**8**
Murder • Attempted murder	**8**
Indictable firearms offences • Possessing a real or imitation firearm at the time of committing or being arrested for an offence specified in Schedule 1 of the Firearms Act 1968 • Possession of real or imitation firearms/explosives with intent to commit an indictable offence including resisting arrest • Possession of real or imitation firearms/explosives with intent to cause violence	**5**
Other wounding • Administering poison with intent to injure or annoy • Assault occasioning actual bodily harm (ABH)	**4**
Possession of an offensive weapon • Having an article with a blade or point in a public place	**3**
Threatening, abusive or insulting words or behaviour	**3**
Threat or conspiracy to murder • Soliciting to commit murder	**5**
Wounding or other act endangering life • Attempting to choke, suffocate with intent to commit an indictable offence (garrotting) • Burning or maiming by explosion • Creating danger by causing anything to be on the road, or interfering with a vehicle or traffic equipment • Causing explosions or casting corrosive fluids with intent to do grievous bodily harm • Endangering life or causing harm by administering poison • Endangering railway passengers (by placing anything on railway, taking up rails, changing points and signals or by throwing anything at railway carriages) • Causing danger to road users (throwing stones etc.) • Possession of firearms with intent to endanger life or injure property • Using chloroform to commit or assist in committing an indictable offence • Using firearms or imitation firearms with intent to resist arrest	**7**
Wounding with intent to cause grievous bodily harm (section 18)*	**7**
Other/unspecified violence against the person	**4**

Sexual Offences

Buggery	**7**
Gross indecency with a child	**5**
Incest • Incest with a female under 13 • Inciting a girl under 16 to have incestuous sexual intercourse	**7**
Indecent assault	**5**
Indecent behaviour/exposure	**4**
Rape • Assault with intent to commit rape or buggery • Attempted rape • Conspiracy to rape	**8**
Unlawful sexual intercourse with female under 13	**4**
Unlawful sexual intercourse with female under 16	**3**
Other/unspecified sexual offences	**5**

Death or Injury by Dangerous Driving

Death by dangerous driving • Causing death by aggravated vehicle taking • Causing death by dangerous driving when under the influence of drink or drugs	**8**
Injury by dangerous driving • Causing injury by aggravated vehicle taking • Causing injury by dangerous driving when under the influence of drink or drugs	**5**

Motoring Offences

Dangerous driving	**5**
Driving when under the influence of drink / drugs	**3**
Driving whilst disqualified	**5**
Interfering with a motor vehicle	**3**
Refusing to give a breath test	**4**
Road Traffic / Additional Offences • Driving without due care and attention • Driving on a footpath or/and common land • Driving defective motor vehicle • Exceeding speed limit • Failure to wear a seatbelt • Failure to comply with a road traffic sign • Failure to give particulars after an accident • Failure to produce documents • Failure to report an accident • Failure to stop when requested by a constable • Failure to stop after an accident • Forge vehicle records/licence • No insurance • No L plates • No licence • No MOT	**2**

• Not wearing protective headgear • Not well maintained indicators/stop/hazard and light reflectors • Pedal cycle offences	
Other / Unspecified motoring offences	**3**

Robbery

Robbery • Assault with intent to rob • Conspiracy to rob	**6**

Domestic Burglary

Aggravated burglary of a dwelling • Burglary with violence or threat of violence	**7**
Burglary in a dwelling • Conspiracy to commit burglary of a dwelling	**6**
Other/unspecified domestic burglary	**6**

Non-Domestic Burglary

Aggravated burglary of a non-dwelling • Burglary with violence or threat of violence	**7**
Burglary in a non-dwelling • Conspiracy to commit burglary of a non-dwelling	**4**
Found on enclosed premises	**3**
Other/unspecified non-domestic burglary	**4**

Vehicle theft / unauthorised vehicle taking

Aggravated vehicle taking • Injury to person, damage to property or car	**5**
Being carried • Being carried (aggravated)	**3**
Vehicle taking • Theft of motor vehicle • Unauthorised vehicle taking (TWOC/TADA)	**4**
Other/unspecified vehicle theft/taking	**4**

Theft and Handling Stolen Goods

Handling stolen goods • Receiving stolen goods • Undertaking or assisting in the retention, removal, disposal or realisation of stolen goods, or arranging to do so	**3**
Theft • Extracting electricity • Making off without payment • Going equipped for stealing • Intent to steal	**3**
Other/unspecified theft and handling	**3**

Fraud and forgery

Forgery • Forgery, or use of false prescription	**3**
Fraud • Acting as a peddler without certificate • Counterfeiting • Conspiracy to defraud • Fraudulent use of documents • Obtaining pecuniary advantage by deception • Obtaining property by deception	**3**
Public / private service vehicle and rail fare evasion	**1**
Other/unspecified fraud and forgery	**2**

Arson

Arson endangering life • Arson reckless as to whether life is in danger	**6**
Arson not endangering life	**5**
Other/unspecified arson	**5**

Criminal Damage

Criminal damage endangering life • Forgery, or use of false prescription	**6**
Other criminal damage over £2,000 • Equipped with intent to commit criminal damage • Threat to commit criminal damage	**3**
Other criminal damage under £2,000 • Equipped with intent to commit criminal damage • Threat to commit criminal damage	**2**
Other/unspecified criminal damage	**3**

Drugs

Permitting use of premises for use of Class B or Class C drug	**3**
Possession – Class A drug	**3**
Possession – Class B drug	**2**
Possession – Class C drug	**2**
Supply – Class A drug • Possessing a class A drug with intent to supply • Offering to supply a class A drug	**6**
Supply – Class B drug • Possessing a class B drug with intent to supply • Offering to supply a class B drug	**4**
Supply – Class C drug • Possessing a class C drug with intent to supply • Offering to supply a class C drug	**4**
Unlawful importation or exportation of a controlled drug	**5**
Other/unspecified drug offence	**2**

Public Order

Affray	**4**
Bomb hoax • Supply false information about the presence of bombs • Dispatching articles to create a bomb hoax	**5**
Breach of the peace • Behaviour likely to cause breach of the peace	**2**
Drunk and disorderly	**1**
Other Public Order Act offences • Section 4 Public Order Act 1986 (fear or provocation of violence) • Section 4a Public Order Act 1986 (intentional harassment, alarm or distress) • Section 5 Public Order Act 1986 (harassment, alarm or distress) • Placing people in fear of violence	**2**
Rioting	**6**
Violent Disorder	**5**
Other/unspecified drug offence	**2**

Other

Other specified offences • Absconding from lawful custody • Air weapons offences • Blackmail • Cruelty to animals or unlawful killing of animals • Firearms Act Offences (e.g. no firearm licence) • Interfering with witness/perverting justice • Obstruct police or fire service • Public nuisance (common law offence) • Resisting arrest • Sending indecent/offensive articles • Trespassing on a railway	 **5** **3** **5** **3** **2** **5** **3** **2** **2** **4** **2**
Other minor offences • Abusive language • Begging • Consuming alcohol under the age of 18 in a public place • Concealment of birth • Cycling in pedestrian area • Failure to make children attend school • Infuriating an animal (Section1 (1) (a) Protection of Animals Act 1911) • Inciting a child away from local authority care • Littering • Nuisance on educational premises • Urinating in a public place • Vagrancy • Making hoax/abusive or malicious telephone calls • Non-payment of financial penalty • Purchasing alcohol under the age of 18 • Wasting police time	**1**
Other / unspecified offence	**3**

Racially Aggravated

Criminal damage – racially aggravated	**3**
Other wounding – racially aggravated • Actual bodily harm • Common assault • Intentional harassment, alarm or distress • Putting people in fear of violence • Threatening, abusive or insulting words or behaviour	**3**
Wounding or other act endangering life – racially aggravated • Wounding with intent to do grievous bodily harm	**6**
Other/unspecified racially aggravated offence	**3**

Breach of conditional discharge

This only applies where the breach has resulted in an additional substantive outcome. Where a young person has been re-sentenced, please refer back to the original offence for the seriousness score.

Breach of conditions of discharge	**1**

Breach of bail

This only applies where the breach has resulted in an additional substantive outcome. Where a young person has been re-sentenced, please refer back to the original offence for the seriousness score.

Breach of conditions of bail	**2**

Breach of statutory order

This only applies where the breach has resulted in an additional substantive outcome. Where a young person has been re-sentenced, please refer back to the original offence for the seriousness score.

Breach of order or licence conditions	**4**

3. Set Up

Set Up the Workspace and Install Relevant Packages

Clear global environment from existing objects

```
rm(list = ls())
```

Set working directory

```
setwd("G:/_My Research - current/_A. Hierarchical Bayesian/Modelling")
```

Load packages
Save package names as a vector of strings

```
pkgs <- c("arm", "foreign", "scales","rjags", R2WinBUGS", "superdiag",
"lme4", "BayesFactor", "MCMCglmm", "sjmisc", "sjPlot")
```

Install uninstalled packages

```
lapply(pkgs[!(pkgs %in% installed.packages())], install.packages)
```

Load all packages to library

```
lapply(pkgs, library, character.only = TRUE)
```

Data

Load data

```
dataFULL <- read.csv("Asset_R_Version.csv", header = TRUE, skip = 0)
head(dataFULL)

dim(dataFULL)
# [1] 552  61
```
- 552 x ASSETS with 61 variables, some of which have missing data

Load data modified version of the dataset as MCMCglmm doesn't handle missing data

```
dataNM <- read.csv("Asset_R_Version - No Miss.csv", header = TRUE, skip
= 0)
head(dataNM)

data.nomiss <- na.omit(dataNM)
dim(data.nomiss)
# [1] 545  30
```
- have lost 7 ASSET records as a result of doing this, but now no missing data

```
data <- data.nomiss
```

4. Variables in the Model

Type	Coding		Notes
Outcome Variable	FO.bin <- data$Further_Offending		Time-varying, dichotomous measure reflecting where further offending has occurred prior to the ASSET. 1 = Further Offending
Time	time <- data$time		Time 0 = initial assessment. As a result, the intercept can be interpreted as the predicted outcome for the baseline. Continuous, max = 19

Research.ID
Individual
	Generate a new Individual ID with consecutive integers:
	
	for(i in 1:length(unique(data$Research.ID))){
	data$pid[data$Research.ID ==
	unique(data$Research.ID)[i]] <- I
	}
	Individual <- data$pid
			There are 87 individuals in the dataset since offending and court records for 1 individual were not available.

12 Domains	live <- data$live	Living Arrangements	*Finch et al. (2014) suggest that to apply multilevel models to longitudinal data problems time-varying predictors will appear at Level 1 because they are associated with specific measurements, whereas time-invariant predictors will appear at Level 2 or higher because they are associated with the individual (or higher level) across all measurement conditions.* Ratings from 0-4, collected at each measurement point. 0 is meaningful therefore there the predictors did not need to be centred.
	relation <- data$relation	Family and Personal Relationships	
	ete <- data$ete	Education, Training and Employment	
	where <- data$where	Neighbourhood	
	life <- data$life	Lifestyle	
	drugs <- data$drugs	Substance Use	
	physical <- data$physical	Physical Health	
	emotion <- data$emotion	Emotional and Mental Health	
	self <- data$self	Perception of Self and Others	
	think <- data$think	Thinking and Behaviours	
	attitude <- data$attitude	Attitude to Change	
	change <- data$change	Motivation to Change	

Type	Coding	Notes
Demographics	female <- data$Gender	Dummy Variable, female = 1
	Create dichotomous variables for ethnicity: ethnic.bin <-(ifelse(data$Head_Ethnic > 0, 1, 0)) bme <- ethnic.bin	Headline ethnicity originally set up as a factor, differentiating between White, Black, Asian, Mixed and Other. Aggregated into a dummy variable with non-Whites = 1
Care Experience	careExp <- data$careExp	Experience of care (subject to a care order, eligible or relevant child). Dummy variable, experience of care = 1
Offending History	fte <- data$FTE	Dummy variable, FTE at time of primary offence, FTE = 1
	ageFirst <- data$AgeFirst ageFirst10 <- (data$AgeFirst)-10	Age at first reprimand, warning, caution, youth restorative disposal or informal action. Centred to reflect the age of criminal responsibility at 10 years. Continuous, max = 7 (17 years)
	G_ageFirst <- data$G_ageFirst	Age at first offence originally set up as a continuous variable. Aggregated into a dummy variable based on the thresholds used in the Scaled Approach, those aged 13-17 = 1
	ageCon <- data$AgeCon ageCon10 <- (data$AgeCon)-10	Age at first conviction. Centred to reflect the age of criminal responsibility at 10 years. Continuous, max = 7 (17 years)
	G_ageCon <- data$G_ageCon	Age at first conviction originally set up as a continuous variable. Aggregated into a dummy variable based on the thresholds used in the Scaled Approach, those aged 14-17 = 1
Primary Offence	I_Cat <- data$I_Cat I_Cat2 <- data$I_Cat2	YJB Offence Category. Originally set up as a factor. However, it was necessary to group the offences into Other, Serious Acquisitive Crimes (SAC) and Violence Against the Person (VAP).
	I_Seriousness <- data$I_Seriousness I_Seriousness2 <- (data$I_Seriousness)-2	YJB Gravity Score. Centred to reflect the lowest gravity score within the dataset ie 2. Continuous, max = 4 (Gravity = 6)
Facets of the Youth Justice System	breach <- data$breach	Dummy variable, Breach before ASSET, breach = 1
	appear <- data$appear	Dummy variable, court appearance before ASSET, appear = 1
	custody <- data$custody	Dummy variable, time in custody before ASSET, custody = 1

5. Diagnostic Tools

Bayesian

The following descriptions are taken from https://cran.r-project.org/web/packages/coda/coda.pdf

(1) Convergence

- **The Raftery and Lewis's Diagnostic**

`raftery.diag` is a run length control diagnostic based on a criterion of accuracy of estimation of the quantile q. It is intended for use on a short pilot run of a Markov chain. The number of iterations required to estimate the quantile *q* to within an accuracy of +/- *r* with probability *p* is calculated. Separate calculations are performed for each variable within each chain.

If the number of iterations in data is too small, an error message is printed indicating the minimum length of pilot run. The minimum length is the required sample size for a chain with no correlation between consecutive samples. Positive autocorrelation will increase the required sample size above this minimum value. An estimate I (the `dependence factor') of the extent to which autocorrelation inflates the required sample size is also provided. Values of I larger than 5 indicate strong autocorrelation which may be due to a poor choice of starting value, high posterior correlations or `stickiness' of the MCMC algorithm.

The number of `burn in' iterations to be discarded at the beginning of the chain is also calculated.

- **Heidelberger and Welch's Convergence Diagnostic**

`heidel.diag` is a run length control diagnostic based on a criterion of relative accuracy for the estimate of the mean. The default setting corresponds to a relative accuracy of two significant digits. `heidel.diag` also implements a convergence diagnostic, and removes up to half the chain in order to ensure that the means are estimated from a chain that has converged.

(2) Autocorrelation of the Fixed and Random Effects

`autocorr` calculates the autocorrelation function for the Markov chain mcmc.obj at the lags given by lags. The lag values are taken to be relative to the thinning interval if relative=TRUE. High autocorrelations within chains indicate slow mixing and, usually, slow convergence. It may be useful to thin out a chain with high autocorrelations before calculating summary statistics: a thinned chain may contain most of the information, but take up less space in memory. Re-running the MCMC sampler with a different parameterization can help to reduce autocorrelation.

When using the MCMCglmm package, the autocorrelation of the random and fixed effects are determined using `autocorr(Model$VCV)` and `autocorr(Model$Sol)` respectively.

(3) Diagnosing the results using plots

Plotting the samples drawn by MCMCglmm provides an indication as to whether or not they are an accurate representation of the true posterior.

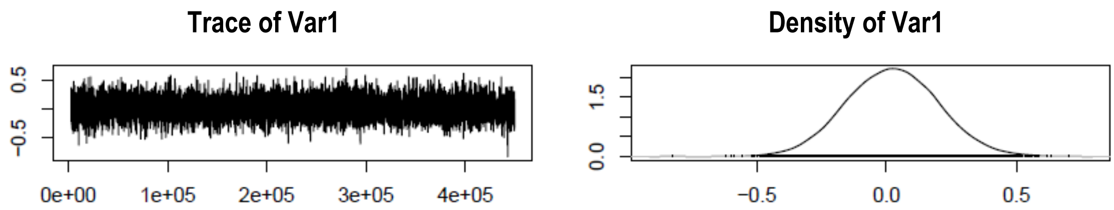
Two plots are generated:

(1) Trace Plots (on the left)

These show the values that the parameter took during the runtime of the chain. The index of the sample is on the x-axis and the value of the parameter in that sample is on the y-axis.

(2) Marginal Density Plot (on the right)

Basically, it is the (smoothened) histogram of the values in the trace-plot, i.e. the distribution of the values of the parameter in the chain, ignoring burn-in samples. Ideally, we would like to have something like the following:



In this trace plot of random data, there is no autocorrelation of consecutive samples and the distribution of samples is stationary. It is very likely that taking more samples would not shift the distribution substantially. Hence, if we see a plot like this, we would be more confident that our posterior is a good approximation of the true posterior.

The following illustrate the impact of altering number of iterations and the thining. This worked example uses generated from this dataset used within the research. However, only selected output has been included so that particular features can be highlighted:

a) Iterations = 45,000, thinning = 10, no burn in

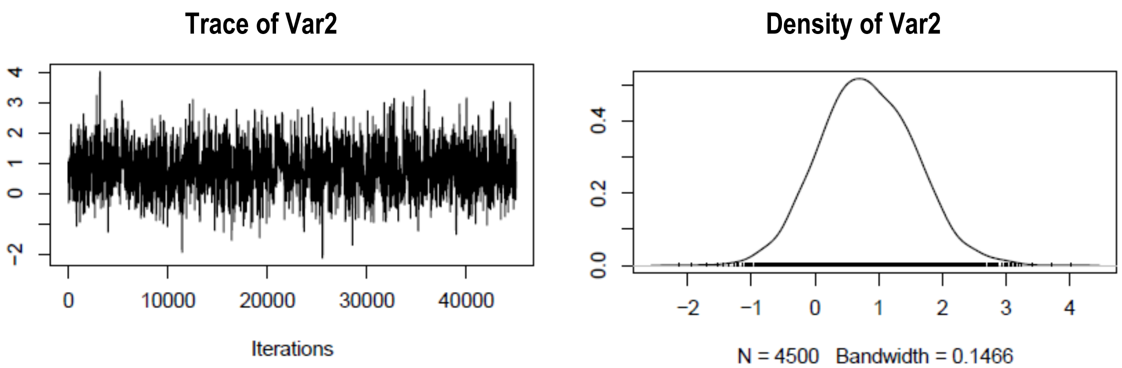
Although 45,000 iterations have been specified, at least 253,770 are required. As a result the Heidelberger and Welch's Convergence Diagnostic has also failed.

```
> raftery.diag(BDmV$VCV)

# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#             Burn-in  Total  Lower bound  Dependence
#             (M)      (N)    (Nmin)       factor (I)
# time        30       40610  3746         10.8
# Research.ID 240      253770 3746         67.7
# units       <NA>     <NA>   3746           NA

# > heidel.diag(BDmV$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# time        passed        1        0.458
# Research.ID passed        1        0.599
# units       failed       NA          NA
#
#             Halfwidth Mean  Halfwidth
#             test
# time        passed    1.192 0.0299
# Research.ID failed    0.108 0.0208
# units       <NA>         NA    NA
```

```
# > autocorr(BDmV$VCV)
# , , time
#
#                time Research.ID units
# Lag 0    1.00000000  0.09560622   NaN
# Lag 10   0.21702019  0.10497827   NaN
# Lag 50   0.07568027  0.07589393   NaN
# Lag 100  0.03701067  0.08500584   NaN
# Lag 500 -0.01679534  0.02849165   NaN

# , , Research.ID
#
#               time Research.ID units
# Lag 0   0.09560622  1.00000000   NaN
# Lag 10  0.11750572  0.85406270   NaN
# Lag 50  0.10893764  0.60844216   NaN
# Lag 100 0.09619258  0.43483078   NaN
# Lag 500 0.01924176  0.04950928   NaN

# > autocorr(BDmV$Sol)
# , , (Intercept)
#
#           (Intercept)          Var2
# Lag 0    1.000000000 -0.0975568632
# Lag 10   0.090389102 -0.0500507058
# Lag 50   0.010201388 -0.0109155178
# Lag 100  0.006959891 -0.0000599145
# Lag 500 -0.001169191  0.0179285597
#
# , , Var2
#
#          (Intercept)        Var2
# Lag 0    -0.09755686  1.00000000
# Lag 10   -0.04957144  0.58024097
# Lag 50   -0.02127955  0.10449429
# Lag 100  -0.01061948  0.02154623
# Lag 500   0.01364890 -0.04114473
```

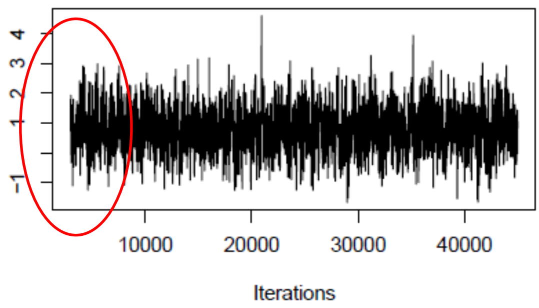
Thinning has been specified at 10. However, from the autocorrelation of the random effects, it is apparent that taking every 10th lag is not sufficient and therefore the level of thining will need to be increased.

From the autocorrelation of the fixed effects, it is apparent that it will also need to increase the level of thinning for the intercept and Var2.

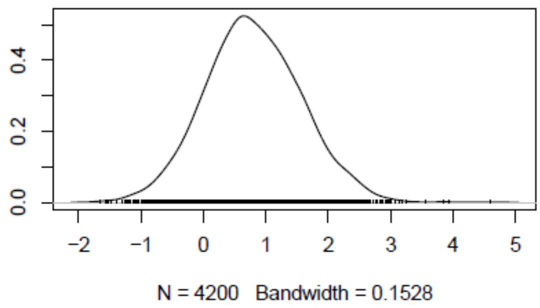


b) Adding a burn-in: Iterations = 45,000, thinning = 10, burn-in = 3000

Trace of Var2



Density of Var2



As a result of the burn-in, the initial 3,000 iterations are disgarded. The marginal density plot also ignores the burn-in samples.

c) Increasing the number of iterations: Iterations = 450,000, thinning = 10, burn-in = 3000

```
# > raftery.diag(BDmX$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         30       41800  3746         11.2
# Research.ID  250      257400 3746         68.7
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDmX$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed       8941      0.625
# Research.ID  passed          1      0.718
# units        failed         NA         NA
#
# Halfwidth Mean  Halfwidth
# test
# time         passed    1.189 0.01149
# Research.ID  passed    0.103 0.00575
# units        <NA>         NA      NA
```

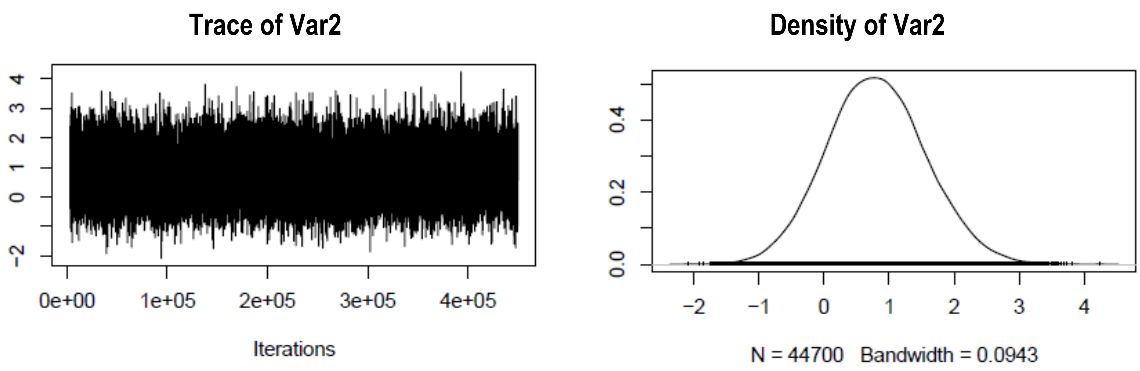
Increasing the number of iterations means that the Heidelberger and Welch's Convergence Diagnostic has now passed.

```
# > autocorr(BDmX$VCV)
# , , time
#
#                 time   Research.ID units
# Lag 0    1.000000000  0.093104274   NaN
# Lag 10   0.240452118  0.093178406   NaN
# Lag 50   0.073303630  0.072341194   NaN
# Lag 100  0.029057995  0.057966907   NaN
# Lag 500  0.004070538 -0.002289258   NaN
#
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0     0.093104274  1.00000000   NaN
# Lag 10    0.092006577  0.83073369   NaN
# Lag 50    0.075602205  0.54080369   NaN
# Lag 100   0.060887395  0.35935538   NaN
# Lag 500  -0.002803081  0.04396342   NaN
```

Increasing the number of iterations does not address the autocorrelation issues. From the correlation for the Research.ID estimate and the the 100 and 500 lags prior, it is anticipated that the thinning would need to be set at around 400.

```
# > autocorr(BDmX$Sol)
# , , (Intercept)
#
#            (Intercept)         Var2
# Lag 0    1.0000000000 -0.073046075
# Lag 10   0.0930400542 -0.035182562
# Lag 50   0.0147681874  0.004807200
# Lag 100  0.0004768857  0.005582624
# Lag 500 -0.0012901273 -0.003398919
#
# , , Var2
#
#           (Intercept)        Var2
# Lag 0   -0.073046075 1.000000000
# Lag 10  -0.033584955 0.501666266
# Lag 50   0.002370054 0.063430438
# Lag 100  0.003715037 0.018460995
# Lag 500 -0.005370409 0.002488963
```

From the autocorrelation of the fixed effects, it is apparent that increasing the thinning to 400 would also address the autocorrelation for Var2.



d) Increasing the thinning: Iterations = 450,000, thinning = 400, burn-in = 3000

```
# > autocorr(BDmY$VCV)
# , , time
#
#                  time  Research.ID units
# Lag 0        1.00000000  0.146865220   NaN
# Lag 400     -0.01395309 -0.009564833   NaN
# Lag 2000     0.05340397  0.037991869   NaN
# Lag 4000    -0.02413828 -0.043849576   NaN
# Lag 20000    0.06278588  0.070181759   NaN
# , , Research.ID
#
#                   time Research.ID units
# Lag 0       0.146865220  1.00000000   NaN
# Lag 400    -0.006984661  0.06498608   NaN
# Lag 2000   -0.011059708 -0.04775259   NaN
# Lag 4000   -0.001414651 -0.01193795   NaN
# Lag 20000  -0.012707379  0.07274378   NaN

# > autocorr(BDmY$Sol)
# , , (Intercept)
#
#             (Intercept)         Var2
# Lag 0       1.000000000 -0.062247979
# Lag 400    -0.008271763  0.061059975
# Lag 2000   -0.029974919 -0.001250977
# Lag 4000   -0.011891520 -0.043217453
# Lag 20000  -0.023855922  0.011969542
```

From the autocorrelation of the random and fixed effects (continued on next page), the effect of increasing the thinning is that the autocorrelation at a lag of 400 is sufficiently small for us to have confidence in our thinning the results at 400.

```
# , , Var2
#
#            (Intercept)         Var2
# Lag 0      -0.06224798   1.000000000
# Lag 400    -0.05929586   0.001477662
# Lag 2000   -0.03636059  -0.019774663
# Lag 4000    0.02452572   0.011603689
# Lag 20000   0.04105996  -0.004374761
```

Increasing the thinning unfortunately means that the sample size is now too small. The number of iterations needs to be increased:

3,746 x 400 = 1,498,400 where 400 is the level of thinning. 1,498,400 + 3,000 = 1,501,400 where 3,000 is the burn-in.

The suggested number of iterations is therefore at least 1,501,400.

```
# > raftery.diag(BDmY$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
# You need a sample size of at least 3746 with these values of q, r and s

# > heidel.diag(BDmY$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.653
# Research.ID passed         1         0.887
# units        failed       NA            NA
#
#              Halfwidth Mean   Halfwidth
#              test
# time         passed    1.1990 0.04129
# Research.ID passed     0.0976 0.00906
# units        <NA>          NA      NA
```

e) Increasing the number of iterations to reflect the level of thinning required: Iterations = 1,600,000, thinning = 400, burn-in = 3000

```
# > raftery.diag(BDmV$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total   Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# time         800      1517600 3746         405
# Research.ID 800       1486800 3746         397
# units        <NA>     <NA>    3746          NA
```

The number of iterations is sufficient to pass the Raftery and Lewis's Diagnostic.

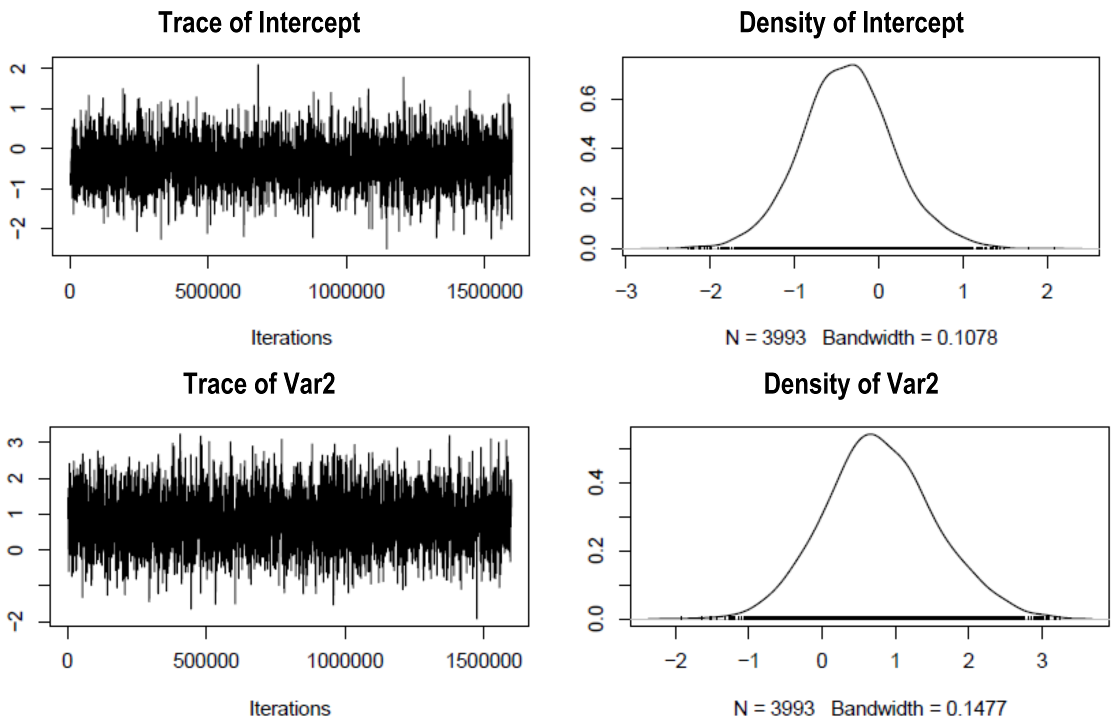
```
# > heidel.diag(BDmV$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.773
# Research.ID passed         1         0.970
# units        failed       NA            NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    1.19 0.02028
# Research.ID passed     0.10 0.00413
# units        <NA>        NA      NA
```

Heidelberger and Welch's Convergence Diagnostic has also passed.

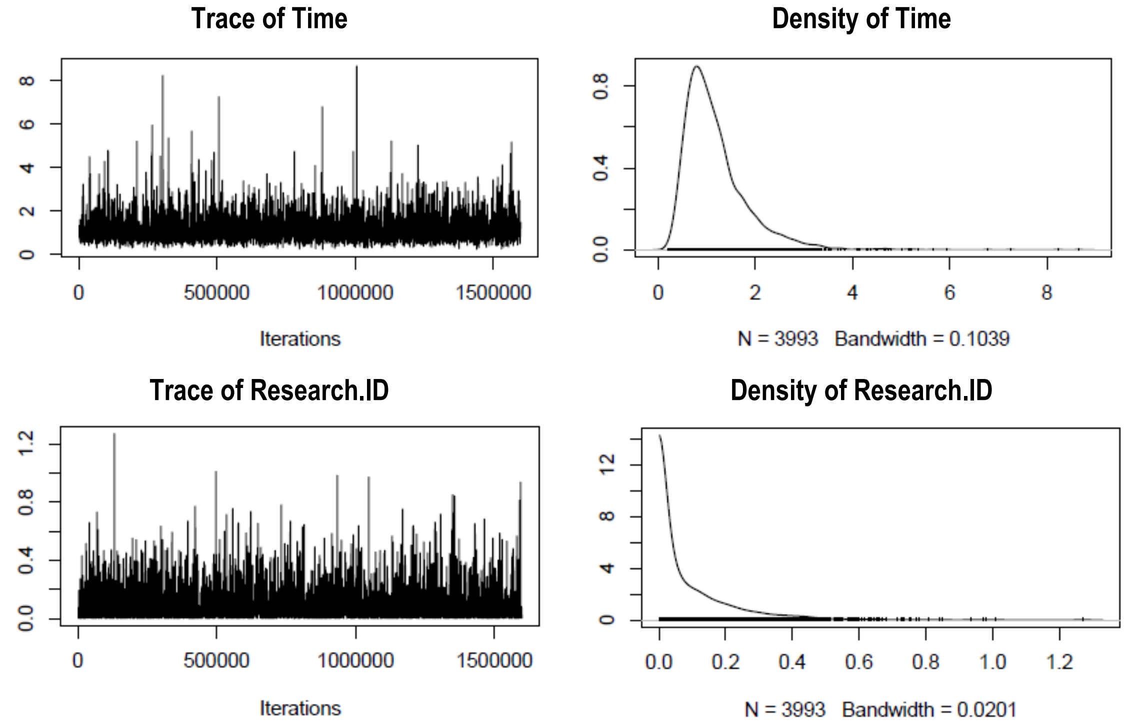
```
# > autocorr(BDmV$VCV)
# , , time
#
#                    time   Research.ID units
# Lag 0        1.0000000000  0.1136034628   NaN
# Lag 400      0.0008692463  0.0245738240   NaN
# Lag 2000    -0.0041377257 -0.0003811657   NaN
# Lag 4000    -0.0056005973  0.0209390534   NaN
# Lag 20000   -0.0190469813  0.0112988965   NaN
#
# , , Research.ID
#
#                    time  Research.ID units
# Lag 0        0.1136034628  1.000000000   NaN
# Lag 400     -0.0168533996  0.032801356   NaN
# Lag 2000     0.0086282809 -0.013635002   NaN
# Lag 4000    -0.0200363783 -0.004135535   NaN
# Lag 20000   -0.0003727364  0.034539765   NaN

# > autocorr(BDmV$Sol)
# , , (Intercept)
#
#               (Intercept)          Var2
# Lag 0        1.0000000000 -0.071137486
# Lag 400     -0.0100298651  0.010267656
# Lag 2000    -0.0062669628 -0.015188591
# Lag 4000    -0.0026029877 -0.008659013
# Lag 20000    0.0009154883 -0.016637784
#
# , , Var2
#
#             (Intercept)         Var2
# Lag 0      -0.071137486  1.000000000
# Lag 400     0.005935828 -0.025136013
# Lag 2000    0.011889933  0.011888022
# Lag 4000   -0.023326682  0.005705630
# Lag 20000  -0.012038490  0.001086895
```

All concerns around autocorrelation have been addressed for both the random and fixed effects in the model.

Fixed Effects

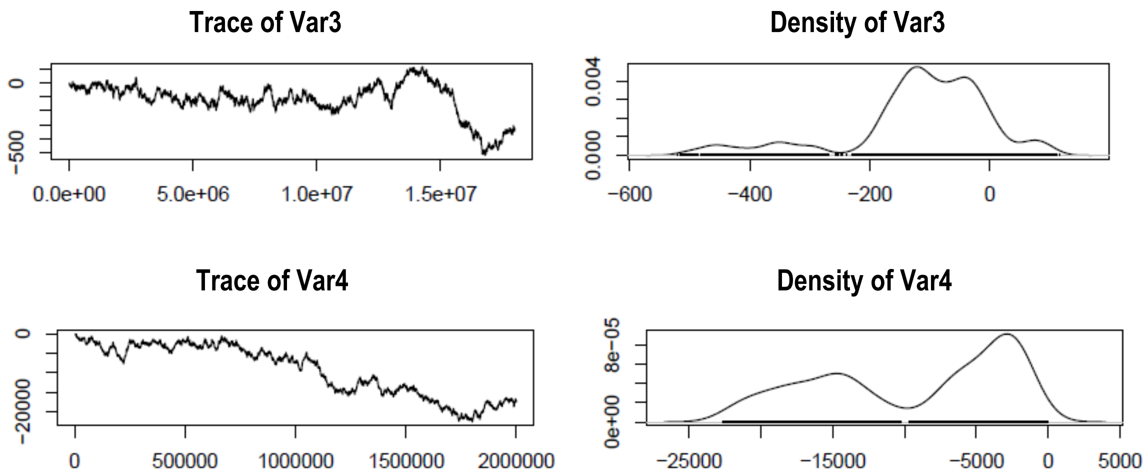


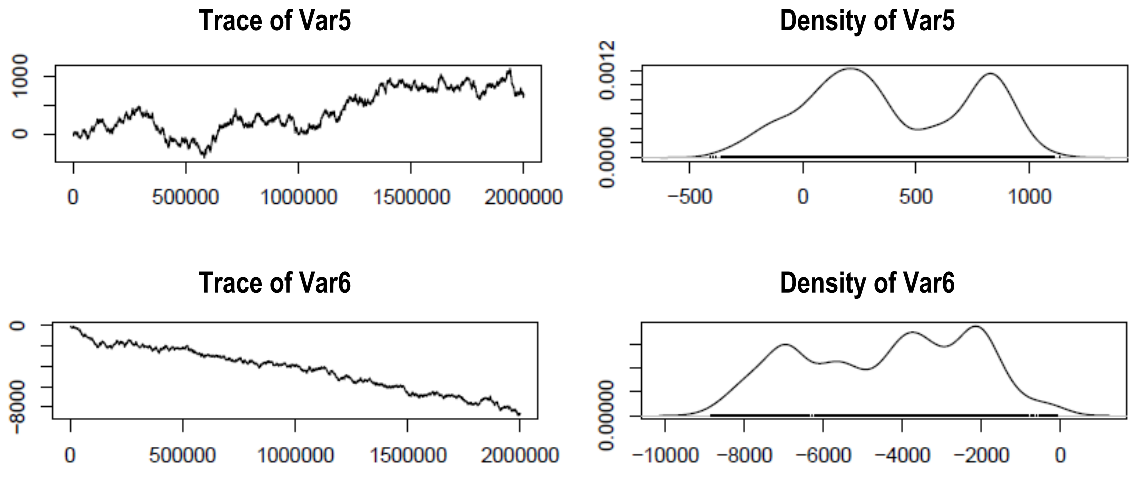
Random Effects



Whilst the worked example, illustrates where it is possible to improve the level of convergence by taking into account any autocorrelation, this is not always feasible to address. The following trace plots and marginal density plots reflect where there continue to be issues with convergence. Typically these reflect where the distrubtion of the samples is not stationary ie the sampling process dwells in one part of the parameter sample and then visits other parts of the parameter space. In the case of Var3, around $1.5e^7$ iterations, the trace suddenly moves to more negative values not visited before.

The unstable posterior reflected in the marginal density plots is also reflected in the summary output for the model, with the credible interval being particularly wide.





Frequentist

The Interclass Correlation (ICC) – used to inspect the variance components at different levels of the model

```
vcomps.icc <- function(model) {
  vc <- summary(model)$varcor
  vcomps <- c(unlist(lapply(vc, diag)), attr(vc, "sc")^2)
  icc <- vcomps[1] / (vcomps[1] + vcomps[2])
  icc.vcomps <- c(vcomps, icc)
  icc.vcomps <- (as.numeric(round(icc.vcomps, 3)))
  names(icc.vcomps) <- c("Var (Level 2)", "Var (Level 1)", "ICC")
  return(icc.vcomps)
}
```

In cases where the measurements are clustered or nested within a higher level unit (eg individuals), it is possible to estimate the correlation among measurements within the nested structure using the ICC. It ranges from 0 (no variation amongst clusters) to 1 (variance among clusters but no within-cluster variance).

The ICC is an important tool in multilevel modelling, because it indicates the degree to which a multilevel structure may impact the outcome variable of interest. Larger ICC values are indicative of a greater amount of clustering (Finch, 2014). The ICC is obtained using **`vcomps.icc()`**.

ANOVA (Goodness of Fit) - when the fits of nested models are compared, the difference in the chi-square values for each model deviance can be used to compare the model fit. After each of the models in question has been run, the difference in chi-squares values can be obtained using the `anova()` function call (Finch, 2014). For example to compare Model 1 and Model 2, this would be specified as **`anova(m1,m2)`**.

6. Model Specifications, Outputs and Plots

Chapter Four – Preparatory models to explore the risk assessment domains

The Empty or Null Model (Table 4.7)

Bayesian Model (Bm0)

Set Prior. This is equivalent to an inverse-gamma prior with shape and scale equal to 0.001

```
prior1 = list(R = list(V = 1, fix=1),
              G = list(G1 = list(V = 1, nu = 0.002)))
```

Define the model

```
Bm0 <- MCMCglmm(FO.bin~1, random=~Research.ID, family="ordinal",
data=data, prior=prior1,nitt=500000, thin=100, burnin=3000, DIC=TRUE)
```

Checks for suitable convergence

```
raftery.diag(Bm0$VCV)
heidel.diag(Bm0$VCV)

# > raftery.diag(Bm0$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#             Burn-in  Total  Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# Research.ID 200      388700 3746          104
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm0$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# Research.ID passed         1        0.818
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# Research.ID passed    0.013 0.00056
# units        <NA>         NA       NA

autocorr(Bm0$VCV)   # Fixed Effects
autocorr(Bm0$Sol)   # Random Effects
summary(Bm0)

# > autocorr(Bm0$VCV)
# , , Research.ID
#
#             Research.ID units
# Lag 0      1.0000000000   NaN
# Lag 100    0.1200025141   NaN
# Lag 500   -0.0008324842   NaN
```

```
# Lag 1000 -0.0087259947   NaN
# Lag 5000  0.0064546242   NaN
# , , units
#          Research.ID units
# Lag 0            NaN   NaN
# Lag 100          NaN   NaN
# Lag 500          NaN   NaN
# Lag 1000         NaN   NaN
# Lag 5000         NaN   NaN

# > autocorr(Bm0$Sol)
# , , (Intercept)
#
#           (Intercept)
# Lag 0     1.000000000
# Lag 100  -0.025353441
# Lag 500  -0.007952866
# Lag 1000 -0.013580734
# Lag 5000 -0.007591946

# > summary(Bm0)

# Iterations = 3001:499901
# Thinning interval  = 100
# Sample size  = 4970
#
# DIC: 661.9164
#
# G-structure:  ~Research.ID            # The G-structure relates to the random effects
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID   0.01304 0.0001645  0.04934     3805
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ 1
#
#             post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)   -0.6235  -0.7893  -0.4743     5228 <2e-04 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m0)

```
m0 <- glmer(FO.bin ~ 1 + (1|Individual), data=data, family=binomial)
summary(m0)
vcomps.icc(m0)

#  Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ 1 + (1 | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 695.5    704.1   -345.7    691.5      543
#
# Scaled residuals:
#   Min      1Q  Median      3Q     Max
# -0.7023 -0.7023 -0.7023  1.4240  1.4240
#
# Random effects:
# Groups     Name        Variance  Std.Dev.
# Individual (Intercept)  4.046e-14 2.011e-07
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#             Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.70694    0.09108  -7.762 8.37e-15 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# vcomps.icc(m0)
# Var (Level 2) Var (Level 1)           ICC
#             0             1             0
```

Random Intercept Model with Single Predictor (Table 4.8)

Bayesian (BmT0)

Define the model

```
BmT0 <- MCMCglmm(FO.bin~time, random=~Research.ID, family="ordinal",
data=data.nomiss, prior=prior1,
nitt=400000, thin=100, burnin=3000,DIC=TRUE)
```

Checks for suitable convergence

```
raftery.diag(BmT0$VCV)
heidel.diag(BmT0$VCV)

# > raftery.diag(BmT0$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
# You need a sample size of at least 3746 with these values of q, r and
s

# > heidel.diag(BmT0$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# Research.ID passed        1        0.288
# units       failed       NA           NA
#
#             Halfwidth Mean   Halfwidth
#             test
# Research.ID passed    0.0393 0.00231
# units       <NA>          NA       NA

autocorr(BmT0$VCV)
autocorr(BmT0$Sol)
summary(BmT0)

# > autocorr(BmT0$VCV)
# , , Research.ID
#
#           Research.ID units
# Lag 0      1.00000000   NaN
# Lag 100    0.26774836   NaN
# Lag 500   -0.01226357   NaN
# Lag 1000  -0.01703518   NaN
# Lag 5000   0.01897040   NaN
#
# , , units
#           Research.ID units
# Lag 0             NaN   NaN
# Lag 100           NaN   NaN
# Lag 500           NaN   NaN
# Lag 1000          NaN   NaN
# Lag 5000          NaN   NaN
```

```
# > autocorr(BmT0$Sol)
# , , (Intercept)
#
#           (Intercept)         time
# Lag 0      1.00000000 -0.690072079
# Lag 100   -0.00753330  0.004994688
# Lag 500    0.01872514 -0.007190335
# Lag 1000   0.00616116  0.010418220
# Lag 5000  -0.00786192 -0.011225626
#
# , , time
#
#           (Intercept)          time
# Lag 0     -0.69007208  1.0000000000
# Lag 100   -0.00819074  0.0281879104
# Lag 500   -0.03153885  0.0064899493
# Lag 1000  -0.00671117  0.0005722035
# Lag 5000   0.02124475 -0.0103156742


# > summary(BmT0)
#
# Iterations = 3001:399901
# Thinning interval  = 100
# Sample size  = 3970
#
# DIC: 617.9063
#
# G-structure:  ~Research.ID
#
#              post.mean  l-95% CI u-95% CI eff.samp
# Research.ID   0.03929 0.0002057   0.1473     2032
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ time     # The Fixed effects are summarised in the table
#
#              post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)  -0.04434 -0.27916  0.19142     3970  0.719
# time         -0.15859 -0.20837 -0.10792     3751 <3e-04 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (mT0)

To compare two mixed effects models (eg containing one or two random factors), use the 'anova()' function.

```
mT0 <- glmer(FO.bin ~ time + (1|Individual), data=data, family=binomial)
summary(mT0)
vcomps.icc(mT0)
anova(m0,mT0)

#  Generalized  linear  mixed  model  fit  by  maximum  likelihood  (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ time + (1 | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 650.2    663.1   -322.1    644.2      542
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -0.9867 -0.7453 -0.4990  1.0085  4.2468
#
# Random effects:
# Groups     Name          Variance Std.Dev.
# Individual (Intercept)    0.01499  0.1224
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.01273    0.13745  -0.093    0.926
# time        -0.19532    0.03571  -5.469 4.52e-08 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Correlation of Fixed Effects:
#      (Intr)
# time -0.674

# vcomps.icc(mT0)
# Var (Level 2) Var (Level 1)           ICC
#         0.015         1.000         0.015

# anova(m0,mT0)
# Data: data
# Models:
#   m0: FO.bin ~ 1 + (1 | Individual)
# mT0: FO.bin ~ time + (1 | Individual)
#     Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
# m0   2 695.47 704.07 -345.73   691.47
# mT0  3 650.25 663.15 -322.12   644.25 47.22      1  6.345e-12 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Random Intercept Model with ASSET Domain Predictors (Table 4.9)

Bayesian Model (BmT1)

Define the model

```
BmT1 <- MCMCglmm(FO.bin~live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time,
random=~Research.ID, data=data, family="ordinal",prior=prior1,
nitt=450000, thin=100, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(BmT1$VCV)
heidel.diag(BmT1$VCV)

# > raftery.diag(BmT1$VCV)
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# Research.ID 300      436700 3746         117
# units        <NA>     <NA>   3746          NA

# > heidel.diag(BmT1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# Research.ID passed        1         0.615
# units        failed       NA           NA
#
#              Halfwidth Mean   Halfwidth
#              test
# Research.ID passed    0.0398 0.00226
# units        <NA>         NA       NA

autocorr(BmT1$VCV)
autocorr(BmT1$Sol)
summary(BmT1)

# > autocorr(BmT1$VCV)
# , , Research.ID
#
#            Research.ID units
# Lag 0      1.000000000   NaN
# Lag 100    0.275442195   NaN
# Lag 500    0.007239953   NaN
# Lag 1000  -0.004602040   NaN
# Lag 5000  -0.018960512   NaN
# , , units
#
#           Research.ID units
# Lag 0             NaN   NaN
# Lag 100           NaN   NaN
# Lag 500           NaN   NaN
# Lag 1000          NaN   NaN
# Lag 5000          NaN   NaN
```

```
# > autocorr(BmT1$Sol)
# , , (Intercept)
#
#            (Intercept)         live    relation          ete        where
# Lag 0      1.000000000  0.138105623 -0.27470106 -0.105749427 -0.155871007
# Lag 100    0.007863293  0.016837122 -0.02927257 -0.009209767 -0.016519472
# Lag 500   -0.024569853  0.001266714 -0.02876811  0.008866710  0.007199433
# Lag 1000   0.014236859  0.005321858 -0.01279099 -0.012769111 -0.004053826
# Lag 5000  -0.004510504 -0.028422527  0.02210170 -0.034197392  0.015310806
#                  life       drugs    physical       emotion        self
# Lag 0    -0.1237376554 -0.067756072 -0.072630744  0.0935901783 -0.02189999
# Lag 100   0.0300320330  0.018761463 -0.022201789 -0.0082015744  0.01191903
# Lag 500   0.0163712664 -0.005243658 -0.009234019  0.0009888832  0.01337088
# Lag 1000-0.0053397639 -0.005338754 -0.001041516  0.0092124675  0.01017249
# Lag 5000 0.0003161113 -0.032062873  0.010372113  0.0216230554 -0.01188551
#                 think      attitude       change         time
# Lag 0     -0.219199695 -0.0508180945  0.147446792 -0.168592943
# Lag 100    0.005511250  0.0038778346 -0.022561246 -0.007800222
# Lag 500    0.017643891 -0.0005804438 -0.008132722  0.009090352
# Lag 1000  -0.002458205 -0.0074515684  0.020255829  0.005673557
# Lag 5000   0.009418056  0.0090976883  0.012420050 -0.008485558
#
# , , live
#
#            (Intercept)        live     relation          ete        where
# Lag 0      0.138105623  1.00000000 -0.445722473 -0.056696164 -0.242879373
# Lag 100    0.006291193  0.00957419  0.024741679  0.004512347  0.006809061
# Lag 500   -0.020410848 -0.02938598 -0.003781546  0.015967253 -0.012710666
# Lag 1000  -0.005533788  0.00871252 -0.025898498  0.031042056 -0.036029812
# Lag 5000  -0.032738740 -0.01307108  0.012394007 -0.004096550  0.021889769
#                  life        drugs     physical      emotion         self
# Lag 0     -0.037509332 -0.112359099  0.098562052 -0.058457573 -0.093584572
# Lag 100   -0.033121224  0.020549898 -0.019515574 -0.006466047 -0.014345296
# Lag 500    0.012621718  0.015810305 -0.014063417 -0.016721578  0.045298429
# Lag 1000  -0.019104003  0.002800952  0.001180771  0.011586698 -0.001287353
# Lag 5000   0.008653998  0.002799877 -0.005849772  0.004342091 -0.022126015
#                 think      attitude       change        time
# Lag 0     -0.006114182 -0.0184723567 -0.027367977 0.033790060
# Lag 100    0.003812418 -0.0014402237 -0.001720479 0.013739641
# Lag 500    0.012683901  0.0104836201 -0.039759149 0.014184735
# Lag 1000   0.005595850 -0.0008709535  0.023294526 0.009592674
# Lag 5000   0.013976630 -0.0039204703  0.005478852 0.011021547
#
# , , relation
#
#            (Intercept)         live     relation          ete        where
# Lag 0     -0.274701060 -0.445722473  1.000000000 -0.036142294  0.073059952
# Lag 100    0.000836537 -0.012615402  0.002683440 -0.006479633 -0.002493101
# Lag 500   -0.004965937  0.016028266 -0.001131968 -0.010120483 -0.020537121
# Lag 1000   0.013367149 -0.016615384  0.028559258 -0.008925903  0.040946523
# Lag 5000   0.003138686  0.005841548  0.002980745  0.012910679  0.011886865
#                   life        drugs      physical      emotion
# Lag 0     -0.1406468351  0.074217315  0.0098466744 -0.148097317
# Lag 100   -0.0001036040 -0.008006841  0.0177173467  0.005244173
# Lag 500   -0.0256991898  0.005404712  0.0223973265 -0.017211558
# Lag 1000  -0.0009989126 -0.005490307 -0.0006669385 -0.003223926
# Lag 5000  -0.0041032333 -0.018112194  0.0205775769  0.008871682
#                  self         think     attitude       change         time
# Lag 0    -0.1160987243 -0.1163405488 -0.056326062  0.052009800  0.039618618
# Lag 100   0.0001262834 -0.0006205736  0.001080656  0.003428920  0.000511065
# Lag 500   0.0086052744  0.0110687391  0.015963202 -0.006031163  0.007179481
# Lag 1000 -0.0100163584 -0.0133700099 -0.020262059  0.008033462  0.022435192
# Lag 5000 -0.0025069494 -0.0122798758  0.009019438 -0.013260262 -0.013754303
```

```
# , , ete
#
#           (Intercept)         live     relation          ete        where
# Lag 0    -0.105749427 -0.056696164 -0.036142294  1.000000000  0.028817983
# Lag 100   0.005490964 -0.018349391  0.021524796  0.004189422  0.001179484
# Lag 500  -0.002712283  0.016069378 -0.010986226  0.003197274 -0.008713517
# Lag 1000 -0.005407203  0.004385392  0.009333889 -0.008905876  0.002139151
# Lag 5000  0.019246209  0.021076178 -0.024533151 -0.021835755 -0.029731110
#                  life        drugs     physical      emotion         self
# Lag 0    -0.252863414 -0.034125337 -0.004972655  0.133751177 -0.054646983
# Lag 100   0.001162236 -0.017047188  0.008751258 -0.005561564 -0.010136744
# Lag 500   0.011364317 -0.012505576 -0.005797026  0.012858616 -0.009023064
# Lag 1000  0.015545099 -0.010916958  0.013097714 -0.031856788  0.010959384
# Lag 5000  0.014358725 -0.001701914  0.007565102 -0.005912576  0.002481918
#                  think     attitude       change          time
# Lag 0    -0.1891437390  0.042990223 -0.173178568 -0.0147856203
# Lag 100   0.0008127225  0.009032788 -0.007966839 -0.0005821301
# Lag 500   0.0138092375 -0.002190327 -0.012341399 -0.0162766608
# Lag 1000  0.0192390419 -0.016032645 -0.023191845  0.0242162366
# Lag 5000 -0.0101626099 -0.002390908  0.019135316  0.0068627378
#
# , , where
#
#           (Intercept)          live     relation         ete        where
# Lag 0    -0.155871007 -2.428794e-01  0.073059952 0.028817983  1.000000000
# Lag 100  -0.017602676 -7.172619e-03  0.010800940 0.004743026  0.012856346
# Lag 500   0.002443797 -1.114601e-02  0.003174008 0.019351423  0.028702704
# Lag 1000  0.006327795  1.018817e-02 -0.004622109 0.001831222  0.004412651
# Lag 5000  0.010192958  3.438532e-05  0.004461607 0.020581365 -0.015874385
#                  life        drugs     physical      emotion        self
# Lag 0    -0.119124122 -0.147143794 -0.040254021  0.119249878 -0.21333411
# Lag 100  -0.004512959 -0.016450580  0.026138900  0.026294906 -0.01325020
# Lag 500  -0.015142636 -0.029789875  0.045742628 -0.022721318 -0.03281284
# Lag 1000 -0.006317684  0.009428902  0.014405990  0.002015866  0.00651467
# Lag 5000 -0.008157773  0.020547894 -0.005666149 -0.003438319  0.02161977
#                 think     attitude       change         time
# Lag 0     0.072111453  0.058967884 -0.069975838  0.044139885
# Lag 100  -0.009842345 -0.002919175  0.014397251 -0.001432793
# Lag 500   0.026019419 -0.003962727  0.004765189 -0.005659999
# Lag 1000 -0.009923357 -0.006372526 -0.016416674  0.002221189
# Lag 5000 -0.005953476 -0.020867682 -0.006314939 -0.012625325
#
# , , life
#
#          (Intercept)          live     relation          ete        where
# Lag 0    -0.12373766 -0.0375093315 -0.140646835 -0.252863414 -0.119124122
# Lag 100   0.01629430  0.0006764497 -0.001899090 -0.015380985 -0.015656199
# Lag 500  -0.00792608 -0.0090048289  0.016277001  0.010434049  0.015635770
# Lag 1000 -0.01094020 -0.0049430092 -0.002077380  0.008461706 -0.008269025
# Lag 5000 -0.01135050 -0.0171192934 -0.007036729  0.002788170  0.007116658
#                   life        drugs     physical      emotion         self
# Lag 0     1.0000000000 -0.268319245 -0.119320424 -0.044786641  0.021607955
# Lag 100   0.0084772791 -0.017573605 -0.025055889 -0.024608287  0.023969243
# Lag 500   0.0094162457 -0.009887186  0.002505599  0.020407422 -0.014374086
# Lag 1000 -0.0002666081  0.003864836 -0.009632434  0.011392318  0.005424431
# Lag 5000  0.0175343600  0.011227940 -0.029029946  0.005482723  0.027971819
#                 think     attitude        change         time
# Lag 0    -0.119384947 -0.028559246 -0.2397402260 -0.023497688
# Lag 100   0.012572771 -0.008082531  0.0183008344 -0.013753256
# Lag 500  -0.021592329  0.004975796 -0.0066227951  0.009490776
# Lag 1000  0.000425438  0.016535872 -0.0064686913 -0.024249169
# Lag 5000 -0.005416513 -0.012806412 -0.0005590547  0.025479733
```

```
# , , drugs
#
#            (Intercept)         live     relation         ete         where
# Lag 0    -0.067756072 -0.112359099  0.074217315 -0.03412534 -0.1471437944
# Lag 100   0.016879293 -0.004851408 -0.004214082 -0.01172230 -0.0035628504
# Lag 500   0.007874338 -0.008695900  0.022969672 -0.03395216  0.0007198891
# Lag 1000  0.023556170 -0.004976084  0.011273070 -0.01545739 -0.0011773252
# Lag 5000  0.008633030  0.031786735 -0.013551989 -0.01391970 -0.0016997452
#                  life        drugs      physical       emotion
# Lag 0    -0.268319245  1.000000000 -0.2445370296 -0.0743947160
# Lag 100  -0.006023183  0.032179570 -0.0094263087  0.0199804642
# Lag 500   0.008346838  0.040999021 -0.0260922929  0.0005414461
# Lag 1000  0.024545451  0.008917227  0.0009279025 -0.0017562784
# Lag 5000 -0.009790384 -0.025419289  0.0217770742 -0.0131052522
#                   self        think     attitude       change         time
# Lag 0     1.404803e-01  0.039995270 -0.178377605  0.023003406 -0.197638512
# Lag 100  -1.064849e-02 -0.003593708 -0.003141479 -0.001074605 -0.023040557
# Lag 500   1.896564e-05 -0.042434938  0.012780976  0.016252478 -0.020596347
# Lag 1000  4.846684e-03 -0.024289769 -0.023909628  0.006911310 -0.025924610
# Lag 5000 -7.030460e-04 -0.000304144  0.022604459 -0.001046631  0.001038766
#
# , , physical
#
#            (Intercept)         live    relation          ete        where
# Lag 0    -0.072630744  0.098562052 0.009846674 -0.004972655 -0.040254021
# Lag 100  -0.028398080 -0.027508078 0.023855813  0.022399391  0.016092455
# Lag 500  -0.009930701 -0.014461389 0.006412308  0.019439838 -0.016493687
# Lag 1000 -0.020209353 -0.019750807 0.024500117  0.021240311 -0.016915643
# Lag 5000  0.009963561  0.004723713 0.002758368  0.001322679  0.007691818
#                  life        drugs    physical      emotion          self
# Lag 0    -0.119320424 -0.244537030 1.000000000 -0.056721220 -0.1504465203
# Lag 100  -0.016952894 -0.014713497 0.017578503  0.013117661  0.0147338969
# Lag 500  -0.011847721  0.008352896 0.009991897  0.007491271  0.0116100947
# Lag 1000 -0.001173295 -0.007069218 0.007601973  0.008023989 -0.0008950325
# Lag 5000 -0.025301161  0.020778483 0.013762928  0.005349245  0.0027666705
#                 think      attitude       change          time
# Lag 0    0.0193711042 -0.0016352929 -0.048023124  1.751355e-01
# Lag 100  0.0003269336 -0.0008438154 -0.017388215  3.246553e-02
# Lag 500  0.0138073512 -0.0214846774 -0.001306269  7.043082e-03
# Lag 1000 0.0006756416 -0.0028450402  0.007261829 -9.536211e-04
# Lag 5000 0.0056037692 -0.0126276992 -0.010453512 -4.700056e-05
#
# , , emotion
#
#            (Intercept)          live      relation          ete        where
# Lag 0     0.093590178 -0.0584575731 -1.480973e-01  0.133751177  0.119249878
# Lag 100  -0.022150464 -0.0174058848  1.524913e-02 -0.014637893 -0.005180496
# Lag 500   0.004394519  0.0208201837 -1.381593e-02 -0.001504463  0.003748726
# Lag 1000  0.012570234  0.0007488643 -7.407586e-05 -0.024076964  0.014419465
# Lag 5000  0.015080141 -0.0069757401 -8.229555e-03 -0.024761111 -0.021984719
#                  life        drugs     physical     emotion          self
# Lag 0    -0.044786641 -0.074394716 -0.056721220 1.000000000 -0.2952872584
# Lag 100   0.016780846 -0.012232529  0.004954021 0.022878047  0.0020936492
# Lag 500  -0.003965532 -0.007488998  0.041525341 0.002823440 -0.0602534838
# Lag 1000 -0.010964102  0.012061771 -0.031830742 0.004903546 -0.0283505722
# Lag 5000  0.015388165  0.005773828  0.004341517 0.003380630 -0.0006855952
#                 think      attitude       change         time
# Lag 0    -0.271028635 -0.0609953095  0.193432396 -0.193515853
# Lag 100  -0.003745777  0.0264882572 -0.018082136 -0.017359466
# Lag 500   0.037138180  0.0022651697 -0.011864921  0.008764329
# Lag 1000  0.000985325  0.0366632478  0.008991351 -0.020491649
# Lag 5000 -0.012740536 -0.0003695486  0.014603623  0.018851386
```

```
# , , self
#
#           (Intercept)          live      relation          ete        where
# Lag 0    -0.021899992 -0.0935845721 -0.1160987243 -0.054646983 -0.213334107
# Lag 100   0.004694350  0.0064651181 -0.0074326016  0.008194081  0.007218730
# Lag 500   0.035456597  0.0013030569 -0.0096995239 -0.030153288 -0.001391407
# Lag 1000 -0.002198942  0.0207272434  0.0007651656 -0.006636560  0.002275150
# Lag 5000  0.002975827 -0.0007022726  0.0030765382  0.005115291 -0.017601465
#                 life        drugs     physical     emotion         self
# Lag 0      0.02160795  0.140480264 -0.150446520 -0.29528726  1.000000000
# Lag 100    0.01401670 -0.002414697 -0.025539712 -0.02549879  0.017900871
# Lag 500    0.03231027 -0.019089838 -0.032784105  0.01307621 -0.003615705
# Lag 1000   0.01094902 -0.014657482  0.028354294 -0.01728504 -0.007377589
# Lag 5000  -0.01448224  0.007539066 -0.009184255  0.01199149  0.002741438
#                think     attitude       change        time
# Lag 0     -0.14236148 -0.081322258 -0.157078302 -0.01283048
# Lag 100   -0.01445404  0.001232059  0.003032603  0.00537420
# Lag 500   -0.01215964 -0.037676267  0.042132336  0.02086534
# Lag 1000   0.01819311  0.003500111 -0.026085832 -0.01225481
# Lag 5000   0.01109574 -0.003481848 -0.007361364  0.02673689
#
# , , think
#
#           (Intercept)         live     relation          ete        where
# Lag 0    -0.219199695 -0.006114182 -0.116340549 -0.189143739  0.072111453
# Lag 100  -0.021769473  0.023383087 -0.012288300  0.014009920  0.008168164
# Lag 500  -0.002891099 -0.021559141  0.027804734 -0.003971135  0.007549533
# Lag 1000  0.002032673 -0.010475877 -0.015984863  0.016716280 -0.010607292
# Lag 5000 -0.008655999  0.015421068  0.004171083  0.006635467 -0.005943082
#                  life         drugs     physical      emotion         self
# Lag 0    -0.1193849473  0.0399952702  0.019371104 -0.271028635 -0.142361480
# Lag 100  -0.0389503754  0.0342026130  0.037831380  0.014596581 -0.017915743
# Lag 500   0.0003701084 -0.0224389278  0.001427134  0.015229429  0.017531222
# Lag 1000  0.0014511177 -0.0006703074 -0.021277582 -0.003569331  0.006435089
# Lag 5000  0.0103821272  0.0156421226  0.004444693 -0.017234635 -0.012110705
#                 think     attitude       change          time
# Lag 0     1.000000000 -0.276394641 -0.092280076  0.0483639560
# Lag 100   0.012183885 -0.020794979  0.011346286  0.0098665230
# Lag 500  -0.032049545 -0.005876325  0.030429353 -0.0150727622
# Lag 1000  0.011740681 -0.008254883  0.008563996  0.0003833775
# Lag 5000  0.003812763 -0.005513180 -0.007979497 -0.0110805460
#
# , , attitude
#
#           (Intercept)         live     relation         ete         where
# Lag 0    -0.050818094 -0.018472357 -0.056326062  0.04299022  0.0589678838
# Lag 100   0.008306048  0.015040144 -0.011771942  0.01823193  0.0125966124
# Lag 500   0.003286589  0.015196757 -0.021706802  0.02575367 -0.0014406523
# Lag 1000  0.006859883  0.011267134 -0.009736417 -0.01967175 -0.0148398127
# Lag 5000 -0.011136134 -0.006374838  0.008702020  0.03273192 -0.0006193147
#                  life        drugs     physical      emotion         self
# Lag 0    -0.028559246 -0.1783776053 -0.001635293 -0.060995310 -0.081322258
# Lag 100   0.026349964 -0.0288949142 -0.000871868 -0.017628715  0.001683372
# Lag 500  -0.007187253  0.0244049850 -0.010020953 -0.005053965  0.016389131
# Lag 1000  0.007481606  0.0048839891  0.025120915  0.005273549 -0.010606652
# Lag 5000 -0.001805850  0.0004414057 -0.021523800  0.016287507  0.007830559
#                 think     attitude        change        time
# Lag 0    -0.276394641  1.000000000 -0.4461459896 -0.01323617
# Lag 100  -0.029604351  0.016315034 -0.0059234949 -0.02061202
# Lag 500   0.002461319 -0.015348838 -0.0083866788 -0.01524927
# Lag 1000 -0.016111286  0.007809587 -0.0039383832  0.03011363
# Lag 5000 -0.011492423 -0.008114627 -0.0007076998 -0.02420581
```

```
# , , change
#
#           (Intercept)         live     relation          ete        where
# Lag 0     0.147446792 -0.027367977  0.052009800 -0.173178568 -0.069975838
# Lag 100   0.001856443 -0.010161436 -0.003837123 -0.018859748 -0.009244444
# Lag 500   0.006103523  0.014367875 -0.002123628 -0.015280144  0.001553429
# Lag 1000 -0.018553724 -0.007831916  0.004006253  0.003242855  0.026808660
# Lag 5000  0.016764131  0.002012612 -0.005852405 -0.012556114  0.009118517
#                  life       drugs     physical      emotion         self
# Lag 0    -0.239740226  0.023003406 -0.048023124  0.193432396 -0.157078302
# Lag 100  -0.002283749  0.012210911 -0.007962654  0.009608748 -0.004258208
# Lag 500  -0.029972014  0.014557943 -0.002453572 -0.028652475 -0.005233773
# Lag 1000 -0.006295340  0.005676729 -0.015905515  0.007910407  0.013704591
# Lag 5000 -0.005804796 -0.015483260  0.008514317 -0.029666158 -0.012670136
#                 think     attitude        change         time
# Lag 0    -0.092280076 -0.446145990  1.0000000000 -0.086925877
# Lag 100   0.016427906  0.001020846  0.0004632003  0.023928930
# Lag 500   0.017773268  0.029353352 -0.0091544084  0.005866766
# Lag 1000 -0.009273122  0.020768639 -0.0078100486 -0.016294826
# Lag 5000  0.005646959  0.027037423  0.0017171021 -0.007028875
#
# , , time
#
#           (Intercept)          live      relation          ete        where
# Lag 0    -0.168592943  0.0337900603  0.0396186182 -0.014785620  0.044139885
# Lag 100   0.001836040 -0.0020516068  0.0009650311  0.020884954 -0.003350313
# Lag 500   0.008349279 -0.0008131586  0.0276059672  0.007329273 -0.007032670
# Lag 1000 -0.011083737  0.0168953076 -0.0041272340  0.021068117 -0.006198540
# Lag 5000 -0.010487649 -0.0125175643  0.0208364774  0.021977402  0.024960663
#                  life        drugs     physical      emotion         self
# Lag 0    -0.023497688 -0.197638512  0.175135541 -0.193515853 -0.012830483
# Lag 100   0.006569744 -0.027624544  0.027941557  0.002959881 -0.012870800
# Lag 500   0.002048655  0.000168952  0.001937751 -0.004501781 -0.019341277
# Lag 1000 -0.024675636 -0.015636374  0.014454882 -0.010196731 -0.001500948
# Lag 5000 -0.010793346  0.024544669 -0.019862982 -0.009617345 -0.009962652
#                 think      attitude       change         time
# Lag 0     0.048363956 -0.0132361699 -0.086925877  1.000000000
# Lag 100   0.014462671 -0.0106738121 -0.018964675  0.029698335
# Lag 500  -0.012283828 -0.0001553871  0.004747318 -0.013978310
# Lag 1000  0.035021393 -0.0025759763 -0.007256890 -0.003763277
# Lag 5000  0.006412168 -0.0049360270 -0.009889771  0.008045195

# > summary(BmT1)
#
# Iterations = 3001:449901
# Thinning interval  = 100
# Sample size  = 4470
#
# DIC: 608.5101
#
# G-structure:  ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID   0.03981 0.0001804    0.158     2331
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time
```

```
#              post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -0.894163 -1.378001 -0.424683     4470 <2e-04 ***
# live         0.008920 -0.203724  0.232958     4470  0.932
# relation     0.176279 -0.061815  0.422334     4470  0.154
# ete          0.056468 -0.150502  0.261424     4470  0.591
# where        0.055921 -0.127418  0.237966     4470  0.554
# life         0.075037 -0.203504  0.368719     4470  0.613
# drugs        0.119362 -0.072913  0.323908     4118  0.235
# physical    -0.127727 -0.360492  0.103784     4470  0.290
# emotion     -0.043632 -0.251832  0.164170     4269  0.688
# self        -0.026218 -0.301421  0.231035     4470  0.840
# think       -0.005587 -0.273853  0.277080     4163  0.969
# attitude    -0.049629 -0.344929  0.260087     4470  0.741
# change       0.163208 -0.111506  0.454477     4470  0.255
# time        -0.188383 -0.243954 -0.133420     4211 <2e-04 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (riT12)

```
riT12 <- glmer(FO.bin ~ live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time +
(1|Individual), data=data, family=binomial)
summary(riT12)
vcomps.icc(riT12)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time + (1 |
Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 649.3    713.9   -309.7    619.3      530
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.5080 -0.6982 -0.4617  0.8971  5.6151
#
# Random effects:
# Groups     Name        Variance  Std.Dev.
# Individual (Intercept)  1.738e-19 4.169e-10
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.966400   0.280998  -3.439 0.000584 ***
# live        -0.001446   0.126874  -0.011 0.990909
# relation     0.206349   0.142525   1.448 0.147669
# ete          0.060296   0.119784   0.503 0.614706
# where        0.060431   0.109997   0.549 0.582742
# life         0.077839   0.172008   0.453 0.650888
# drugs        0.139375   0.116218   1.199 0.230431
# physical    -0.147090   0.133580  -1.101 0.270836
# emotion     -0.052016   0.120454  -0.432 0.665864
# self        -0.035476   0.157037  -0.226 0.821275
# think       -0.007154   0.166976  -0.043 0.965823
# attitude    -0.043224   0.175457  -0.246 0.805410
# change       0.196357   0.166078   1.182 0.237080
# time        -0.231412   0.035454  -6.527  6.7e-11 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


# vcomps.icc(riT12)
# Var (Level 2) Var (Level 1)           ICC
#             0             1             0
```

Random Intercept and Varying Slope Model, with Single Predictor (Table 4.10)

Bayesian Model (BmTV0)

Define the Prior - Adding an additional random effect means that it is necessary to revise the prior. The specified prior is equivalent to an inverse-gamma prior with shape and scale equal to 0.001

```
prior2 = list(G = list(G1 = list(V = 1, nu = 0.002),
              G2 = list(V = 1, nu = 0.002)),
              R = list(V = 1, fix=1))
```

Define the Model

```
BmTV0 <- MCMCglmm(FO.bin~time, random=~time+Research.ID,
                  data=data, family="ordinal", prior=prior2,
                  nitt=400000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(BmTV0$VCV)
heidel.diag(BmTV0$VCV)

# > raftery.diag(BmTV0$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         20       39580  3746          10.6
# Research.ID  360      470970 3746         126.0
# units        <NA>     <NA>   3746            NA

# > heidel.diag(BmTV0$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed       3971      0.0991
# Research.ID  passed          1      0.1421
# units        failed         NA          NA
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.094 0.01011
# Research.ID  passed    0.112 0.00588
# units        <NA>         NA      NA

autocorr(BmTV0$VCV)
autocorr(BmTV0$Sol)
summary(BmTV0)

# > autocorr(BmTV0$VCV)
# , , time
#
#                 time Research.ID units
# Lag 0    1.000000000 0.090958876   NaN
# Lag 10   0.220187465 0.087437721   NaN
# Lag 50   0.059864015 0.066924896   NaN
# Lag 100  0.021494226 0.049771038   NaN
# Lag 500 -0.005119204 0.005532562   NaN
```

```
# , , Research.ID
#
#                  time Research.ID units
# Lag 0    0.090958876  1.00000000   NaN
# Lag 10   0.094136527  0.83231572   NaN
# Lag 50   0.070967064  0.53210930   NaN
# Lag 100  0.039002612  0.34550053   NaN
# Lag 500 -0.001371053  0.02365533   NaN

# > autocorr(BmTV0$Sol)
# , , (Intercept)
#
#          (Intercept)         time
# Lag 0    1.000000000 -0.812343407
# Lag 10   0.075272013 -0.109478950
# Lag 50   0.003451320 -0.011884345
# Lag 100  0.005037339 -0.004734358
# Lag 500 -0.003686134 -0.001248339
#
# , , time
#
#          (Intercept)          time
# Lag 0   -0.812343407  1.0000000000
# Lag 10  -0.115843181  0.2335925050
# Lag 50  -0.011527092  0.0509443219
# Lag 100 -0.003765124  0.0199909220
# Lag 500  0.006337957 -0.0002469737

# > summary(BmTV0)
#
# Iterations = 3001:399991
# Thinning interval  = 10
# Sample size  = 39700
#
# DIC: 488.281
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.092   0.2965    2.235    15011
#

# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID     0.112 0.0001432   0.3775     1919
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ time
#
#             post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)  -0.12906 -1.15428  0.90858    30170 0.7829
# time         -0.13577 -0.26456 -0.01306    17074 0.0279 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (mTV0)

```
mTV0  <-  glmer(FO.bin  ~  time  +  (1+  time|Individual),  data=data,
family=binomial)
summary(mTV0)
anova(m0,mT0,mTV0)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ time + (1 + time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 642.0    663.5   -316.0    632.0      540
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.1791 -0.7100 -0.3958  0.8557  3.4696
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.002844 0.05333
#            time        0.053025 0.23027  -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept)   0.3060     0.1921   1.593 0.111080
# time         -0.4348     0.1259  -3.454 0.000552 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Correlation of Fixed Effects:
#      (Intr)
# time -0.781

# vcomps.icc(mTV0)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.003         0.053         1.000         0.051

# anova(m0,mT0,mTV0)
# Data: data
# Models:
#   m0: FO.bin ~ 1 + (1 | Individual)
# mT0: FO.bin ~ time + (1 | Individual)
# mTV0: FO.bin ~ time + (1 + time | Individual)
#      Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m0    2 695.47 704.07 -345.73   691.47
# mT0   3 650.25 663.15 -322.12   644.25 47.220      1  6.345e-12 ***
# mTV0  5 642.01 663.52 -316.01   632.01 12.233      2   0.002206 **
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The Basic Model: Random Intercept and Varying Slope Model, with ASSET Domain Predictors (Table 4.11)

Bayesian Model (BmTV1)

Define the model

```
BmTV1 <- MCMCglmm(FO.bin~live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=450000, thin=50, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(BmTV1$VCV)
heidel.diag(BmTV1$VCV)

# > raftery.diag(BmTV1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      191950 3746         51.2
# Research.ID  250      281050 3746         75.0
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BmTV1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.190
# Research.ID  passed        1        0.269
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.267 0.01587
# Research.ID  passed    0.101 0.00538
# units        <NA>         NA      NA


autocorr(BmTV1$VCV)
autocorr(BmTV1$Sol)  # Output not included here
summary(BmTV1)

# > autocorr(BmTV1$VCV)
# , , time
#
#                   time Research.ID units
# Lag 0     1.000000000  0.08807041   NaN
# Lag 50    0.080969092  0.06047113   NaN
# Lag 250   0.012768860  0.03055977   NaN
# Lag 500   0.006517602  0.01335818   NaN
# Lag 2500 -0.005364365  0.01774194   NaN
```

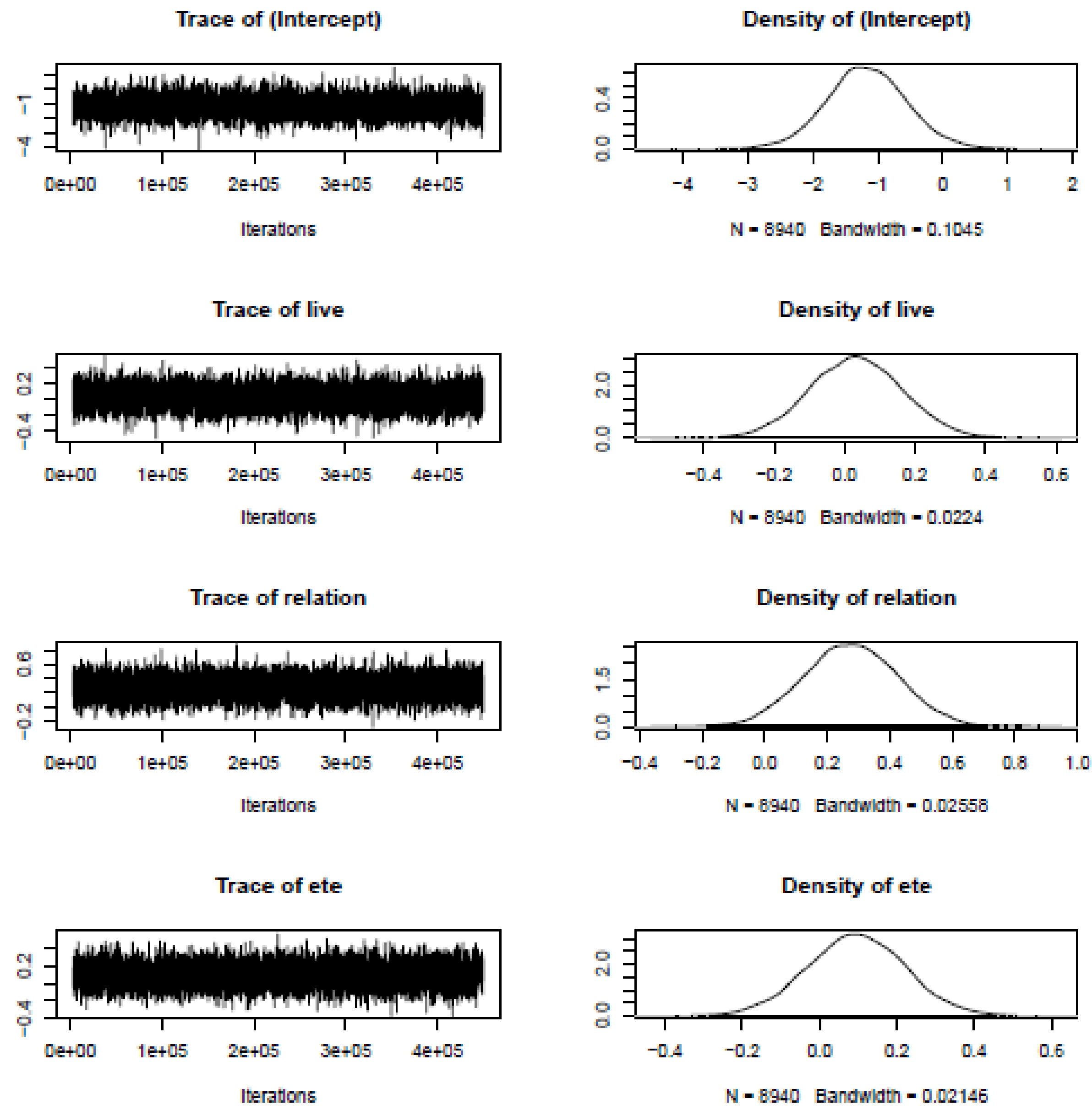
```
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0     0.088070409  1.000000000   NaN
# Lag 50    0.054449767  0.529526809   NaN
# Lag 250   0.009476399  0.116072227   NaN
# Lag 500  -0.004061057  0.046259125   NaN
# Lag 2500  0.012095471 -0.009394492   NaN

# > summary(BmTV1)
#
# Iterations = 3001:449951
# Thinning interval  = 50
# Sample size  = 8940
#
# DIC: 476.2024
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.267   0.3383    2.605     7097
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1012 0.0001991   0.3662     2128
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time
#
#             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -1.167664 -2.379203  0.129185     8215 0.0707 .
# live         0.032575 -0.215542  0.292597     8632 0.8002
# relation     0.274841 -0.026145  0.556036     8554 0.0655 .
# ete          0.094214 -0.152122  0.342431     8673 0.4539
# where        0.043844 -0.166174  0.262407     8486 0.6940
# life         0.023587 -0.315998  0.371261     8595 0.8944
# drugs        0.158307 -0.086784  0.387551     7924 0.1837
# physical    -0.113791 -0.394300  0.165188     7831 0.4430
# emotion     -0.003105 -0.248524  0.241652     8391 0.9864
# self        -0.137766 -0.443388  0.182123    10034 0.3884
# think       -0.159533 -0.507704  0.157158     8558 0.3456
# attitude     0.043206 -0.298160  0.388774     8218 0.8083
# change       0.231104 -0.095384  0.581951     8216 0.1758
# time        -0.152938 -0.283388 -0.017813     7624 0.0199 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

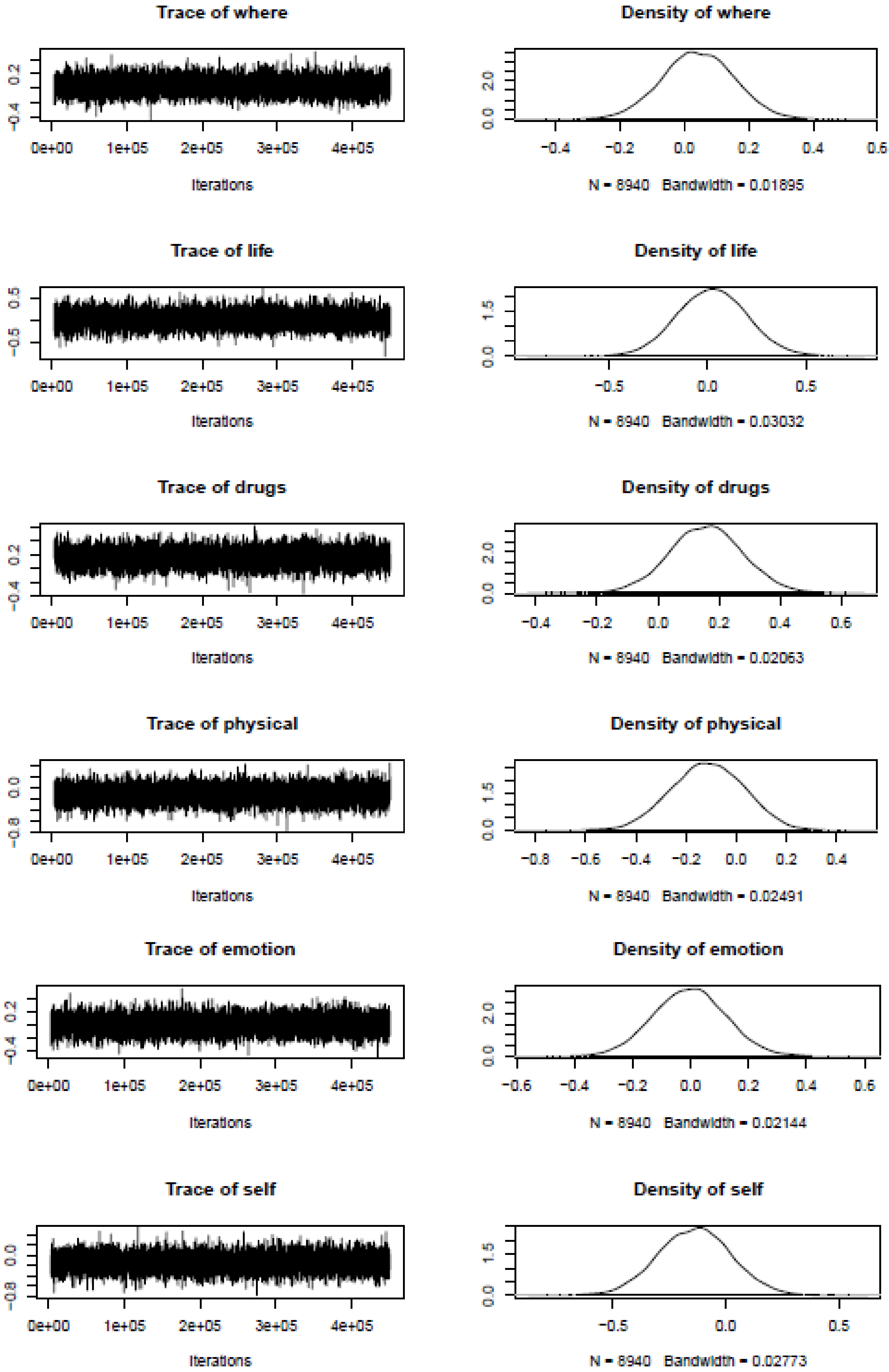
Trace Plots and Posterior Density Plots

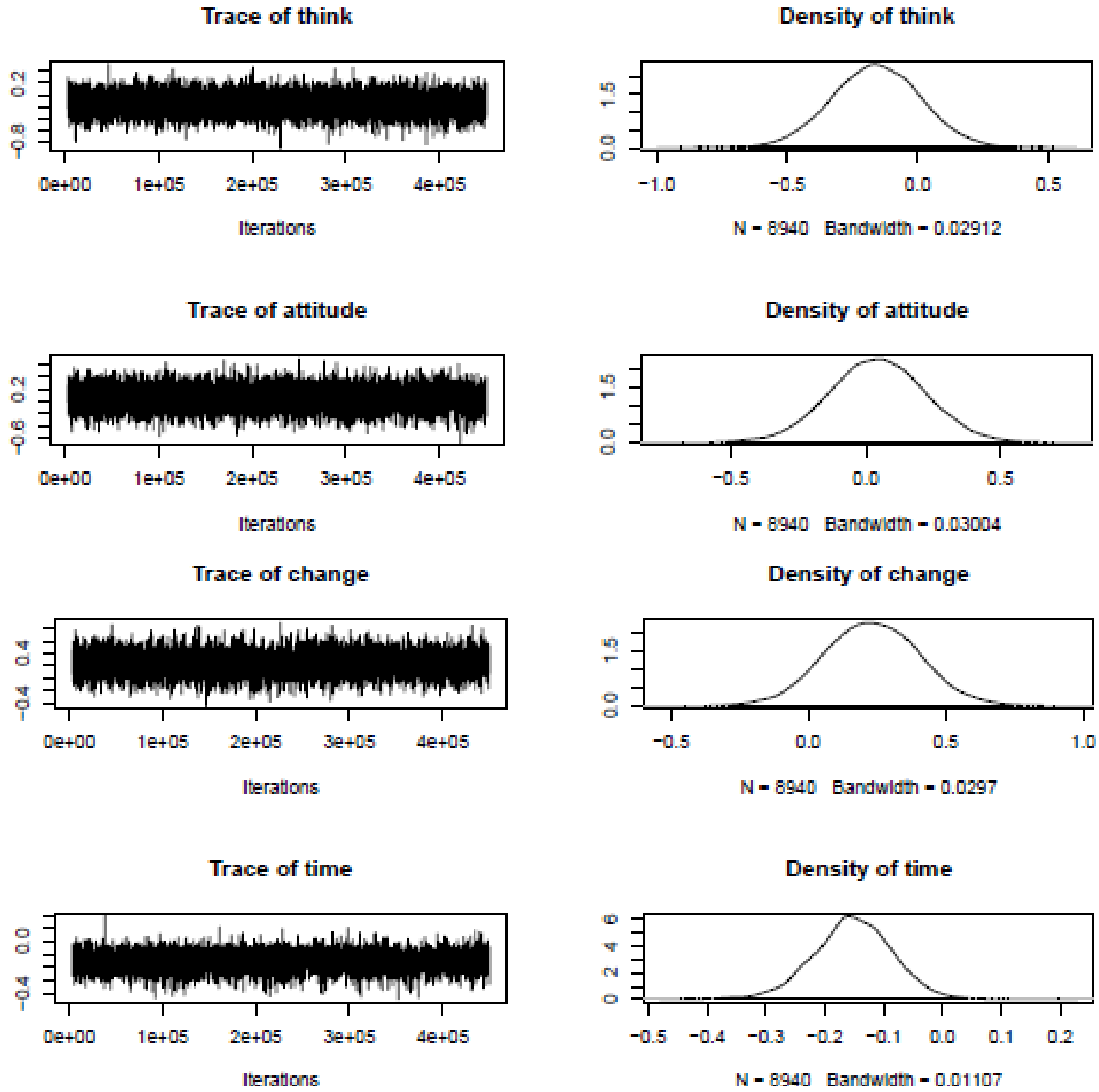
To simplify naming conventions, BmTV1 is renamed as Bm1 whilst the Frequentist equivalent riTV12 is renamed m1. This represents the Basic model.

```
m1 <- riTV12
Bm1 <- BmTV1
```

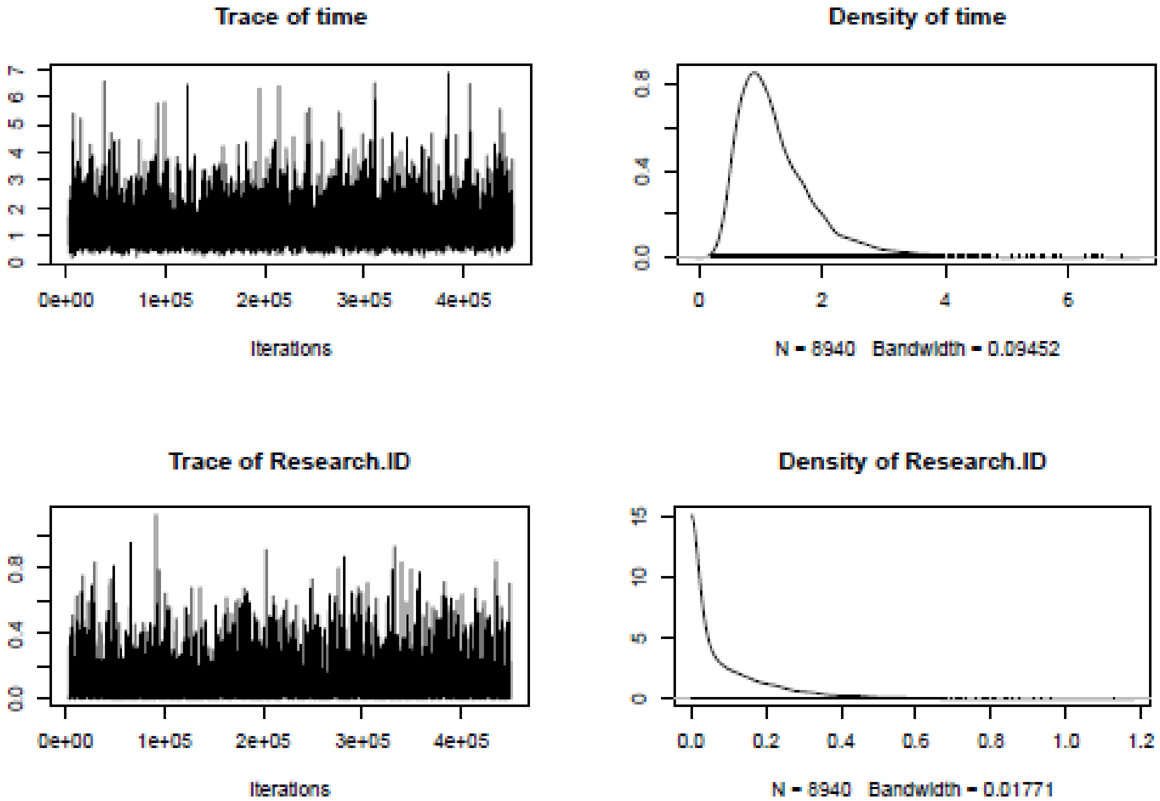
<u>Fixed Effects</u>




Trace of where
Iterations
Density of where
N = 8940 Bandwidth = 0.01895
Trace of life
Iterations
Density of life
N = 8940 Bandwidth = 0.03032
Trace of drugs
Iterations
Density of drugs
N = 8940 Bandwidth = 0.02063
Trace of physical
Iterations
Density of physical
N = 8940 Bandwidth = 0.02491
Trace of emotion
Iterations
Density of emotion
N = 8940 Bandwidth = 0.02144
Trace of self
Iterations
Density of self
N = 8940 Bandwidth = 0.02773


Trace of think
Iterations
Density of think
N = 8940 Bandwidth = 0.02912
Trace of attitude
Iterations
Density of attitude
N = 8940 Bandwidth = 0.03004
Trace of change
Iterations
Density of change
N = 8940 Bandwidth = 0.0297
Trace of time
Iterations
Density of time
N = 8940 Bandwidth = 0.01107

Random Effects



Frequentist Model (riTV12)

```
riTV12 <- glmer(FO.bin ~ live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time +
(1+time|Individual), data=data, family=binomial)
summary(riTV12)
vcomps.icc(riTV12)
anova(riT12,riTV12)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time + (1 + time
| individual)
# Data: data

#   AIC      BIC   logLik deviance df.resid
# 640.6    713.7   -303.3    606.6      528
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6408 -0.6710 -0.3654  0.8157  3.6026
#
# Random effects:
#   Groups     Name       Variance Std.Dev. Corr
# Individual (Intercept) 0.04494  0.2120
#            time        0.05497  0.2345   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.804813   0.321559  -2.503   0.0123 *
# live        -0.060778   0.141765  -0.429   0.6681
# relation     0.191887   0.157645   1.217   0.2235
# ete          0.002169   0.129967   0.017   0.9867
# where        0.149188   0.127610   1.169   0.2424
# life         0.017652   0.190802   0.093   0.9263
# drugs        0.264045   0.133073   1.984   0.0472 *
# physical    -0.227978   0.149079  -1.529   0.1262
# emotion     -0.034077   0.133536  -0.255   0.7986
# self        -0.063418   0.175315  -0.362   0.7175
# think        0.123343   0.186594   0.661   0.5086
# attitude    -0.064021   0.189739  -0.337   0.7358
# change       0.214656   0.180874   1.187   0.2353
# time        -0.444691   0.108372  -4.103 4.07e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.0337704 (tol = 0.001,
component 1)

# vcomps.icc(riTV12)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#          0.045         0.055         1.000         0.450
```

```
# anova(riT12,riTV12)
# Data: data
# Models:
# riT12: FO.bin ~ live + relation + ete + where + life + drugs +
physical +
#   riT12:     emotion + self + think + attitude + change + time + (1 |
#   riT12:     Individual)
# riTV12: FO.bin ~ live + relation + ete + where + life + drugs +
physical   #   riTV12:     + emotion + self + think + attitude + change
+ time + (1 +
#   riTV12:     time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# riT12  15 649.34 713.86 -309.67   619.34 55.114      1  1.138e-13 ***
# riTV12 17 640.59 713.70 -303.29   606.59 12.755      2     0.0017 **
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Dynamic Model 1 (Table 4.12)

Bayesian (BDm1)

Revise the prior

```
priorD <- list(R=list(V=1, fixed=1),
                     G=list(G1=list(V=1, nu=1, alpha.mu=0, alpha.V=1000),
                            G2=list(V=1, nu=1, alpha.mu=0,
                            alpha.V=1000)))
```

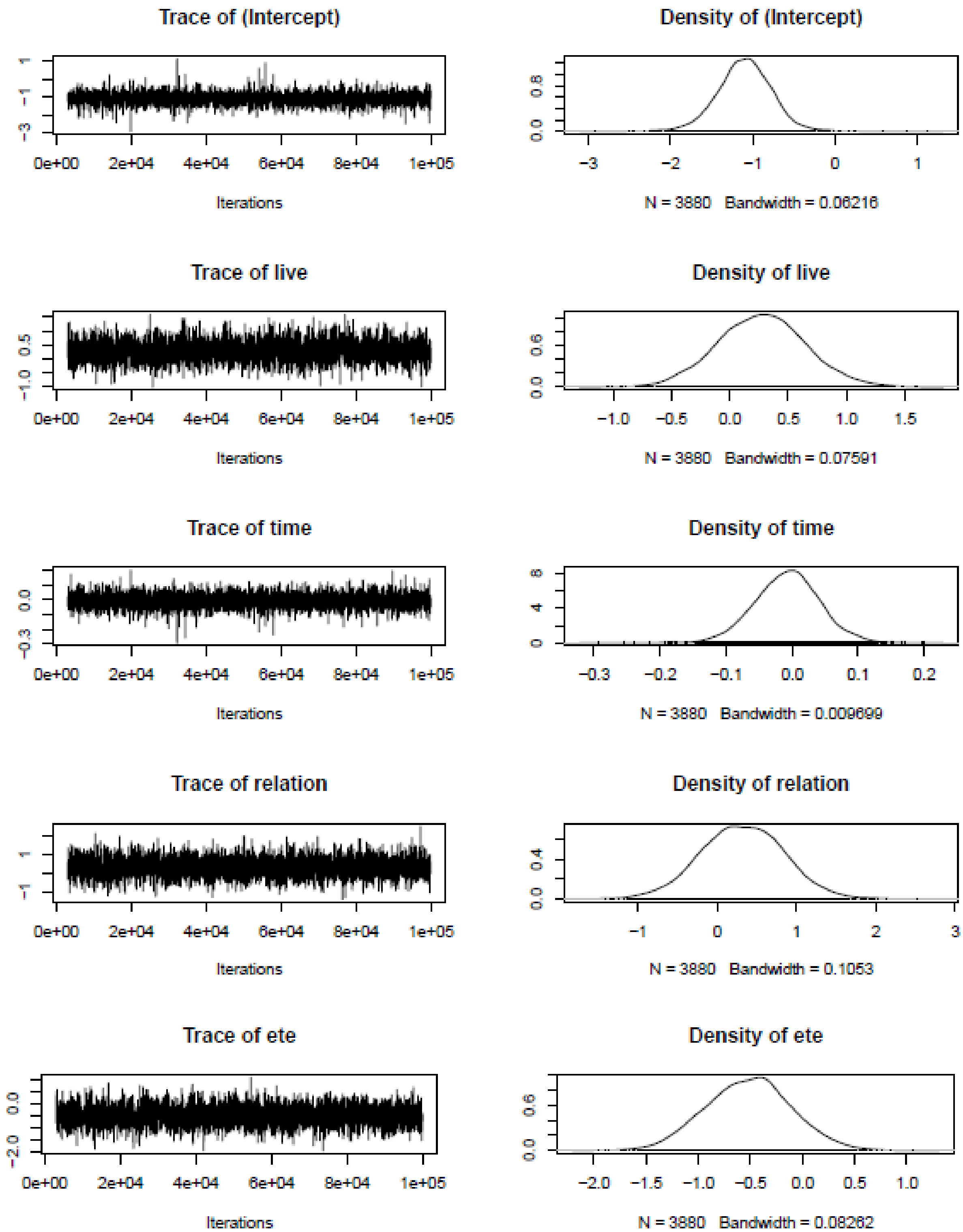
Define the model

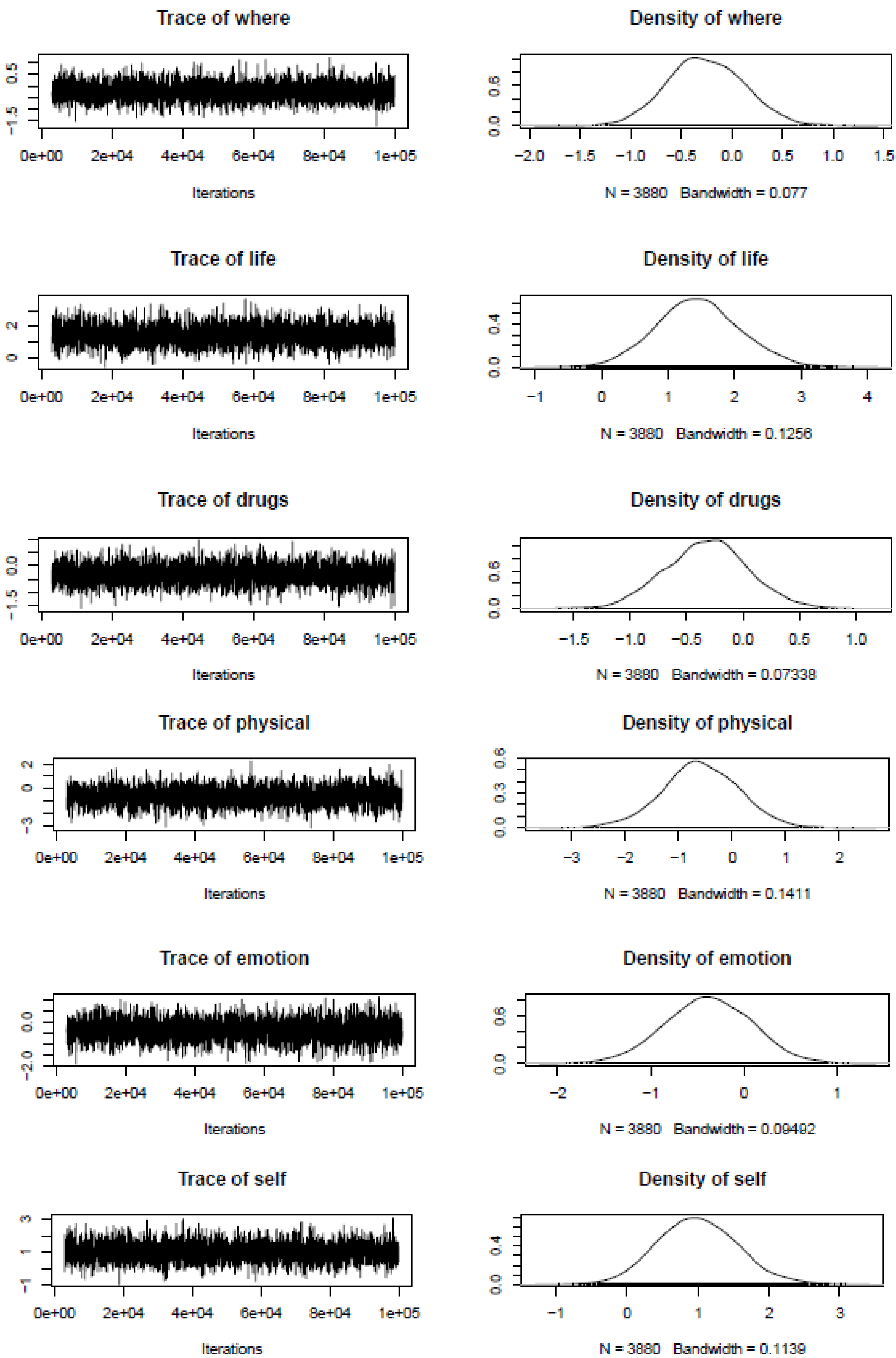
```
BDm1 <- MCMCglmm(FO.bin~live*time + relation*time + ete*time + where*time +
life*time + drugs*time + physical*time + emotion*time + self*time +
think*time + attitude*time + change*time, prior=priorD, slice=TRUE,
random=~time+Research.ID, data=dataD, family="ordinal", nitt=100000,
thin=25, burnin = 3000)

raftery.diag(BDm1$VCV)
heidel.diag(BDm1$VCV)

# > raftery.diag(BDm1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#             Burn-in  Total Lower bound  Dependence
#             (M)      (N)   (Nmin)       factor (I)
# time        50       96900 3746         25.9
# Research.ID 50       94875 3746         25.3
# units       <NA>     <NA>  3746           NA

# > heidel.diag(BDm1$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# time        passed        1        0.267
# Research.ID passed        1        0.890
# units       failed       NA           NA
#
#             Halfwidth Mean  Halfwidth
#             test
# time        passed    0.126 0.00799
# Research.ID passed    0.179 0.01131
# units       <NA>         NA      NA

autocorr(BDm1$VCV)
autocorr(BDm1$Sol)  # Output not included here
summary(BmD1)

# > autocorr(BDm1$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0     1.000000000  0.04708121   NaN
# Lag 25    0.110677138  0.03540381   NaN
# Lag 125   0.003534931 -0.01634387   NaN
# Lag 250   0.016628289  0.02512167   NaN
# Lag 1250 -0.007247478  0.02136882   NaN

# , , Research.ID
#
```

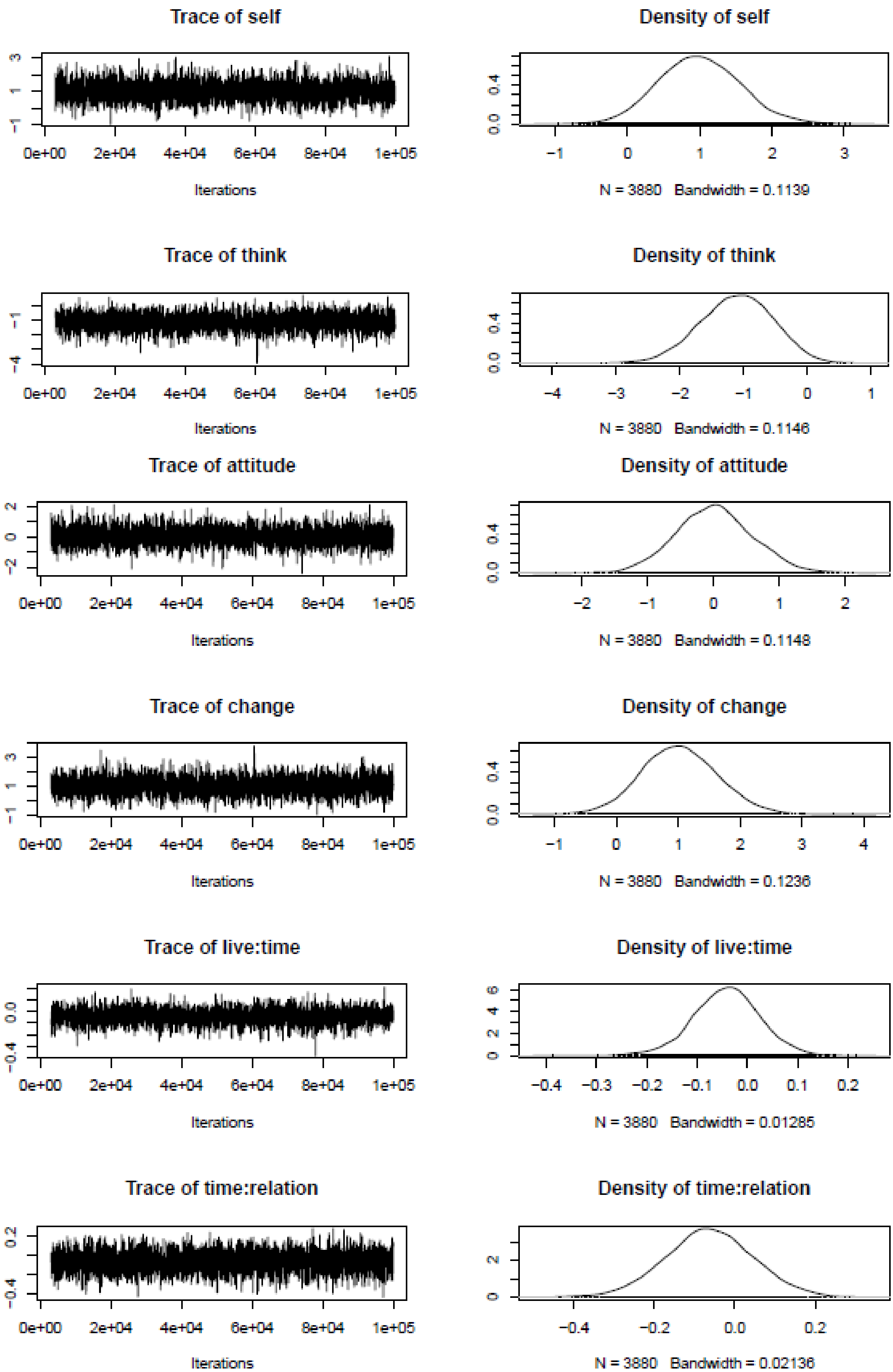
```
#                   time  Research.ID units
# Lag 0      0.047081205  1.000000000   NaN
# Lag 25     0.024996348  0.267709123   NaN
# Lag 125  -0.018980326  0.008959189   NaN
# Lag 250  -0.003648318  0.024686331   NaN
# Lag 1250  0.010969437 -0.011849702   NaN

# > summary(BDm1)
#
# Iterations = 3001:99976
# Thinning interval  = 25
# Sample size  = 3880
#
# DIC: 256.7685
#
# G-structure:  ~time
#
#      post.mean  l-95% CI u-95% CI eff.samp
# time    0.1256 5.323e-10    0.514     3106
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1795 9.492e-10   0.6967     2241
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ live * time + relation * time + ete * time +
where * time + life * time + drugs * time + physical * time + emotion * time
+ self * time + think * time + attitude * time + change * time
#
#               post.mean  l-95% CI  u-95% CI eff.samp   pMCMC
# (Intercept)   -1.099293 -1.768100 -0.483032     3880 0.00464 **
# live           0.274354 -0.473108  1.000087     3880 0.46443
# time          -0.007806 -0.108684  0.088136     3880 0.88660
# relation       0.318821 -0.697119  1.330631     3880 0.53918
# ete           -0.517253 -1.305867  0.273578     3603 0.20412
# where         -0.254326 -0.985130  0.470509     3880 0.49691
# life           1.453845  0.236683  2.692430     3465 0.01701 *
# drugs         -0.320386 -1.041075  0.363981     3795 0.36804
# physical      -0.585962 -1.956317  0.864474     3880 0.41495
# emotion       -0.381394 -1.312536  0.516139     3236 0.42526
# self           0.999534 -0.123335  2.080452     3880 0.06392 .
# think         -1.108685 -2.252432 -0.096264     3201 0.03608 *
# attitude       0.014151 -1.141829  1.116151     3880 0.98608
# change         1.024381 -0.156305  2.237721     3880 0.08557 .
# live:time     -0.041411 -0.164750  0.097044     4360 0.51289
# time:relation -0.063148 -0.270436  0.151189     3880 0.54742
# time:ete       0.079856 -0.076648  0.219397     3649 0.28299
# time:where     0.070927 -0.050467  0.193485     3660 0.26753
# time:life     -0.203933 -0.417106  0.007728     3457 0.05258 .
# time:drugs     0.088687 -0.054268  0.236397     3476 0.22165
# time:physical  0.032870 -0.174077  0.234888     3537 0.76082
# time:emotion   0.104259 -0.082341  0.301297     2906 0.28763
# time:self     -0.264901 -0.488104 -0.040072     3637 0.01856 *
# time:think     0.288283  0.051094  0.533046     3265 0.01031 *
# time:attitude  0.068214 -0.177873  0.308844     3880 0.58454
# time:change   -0.161395 -0.412144  0.080089     3880 0.20567
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

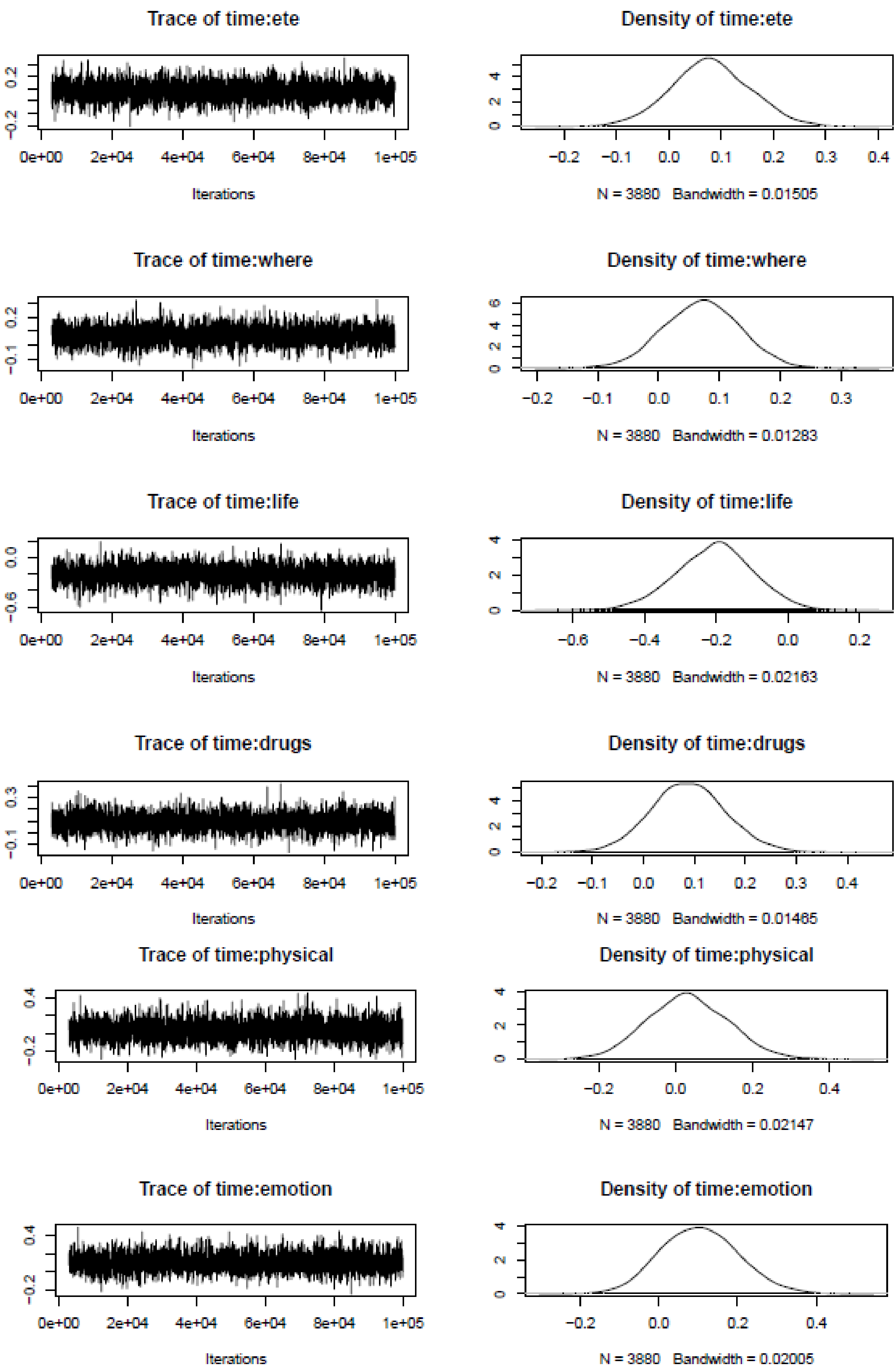
Trace Plots and Posterior Density Plots

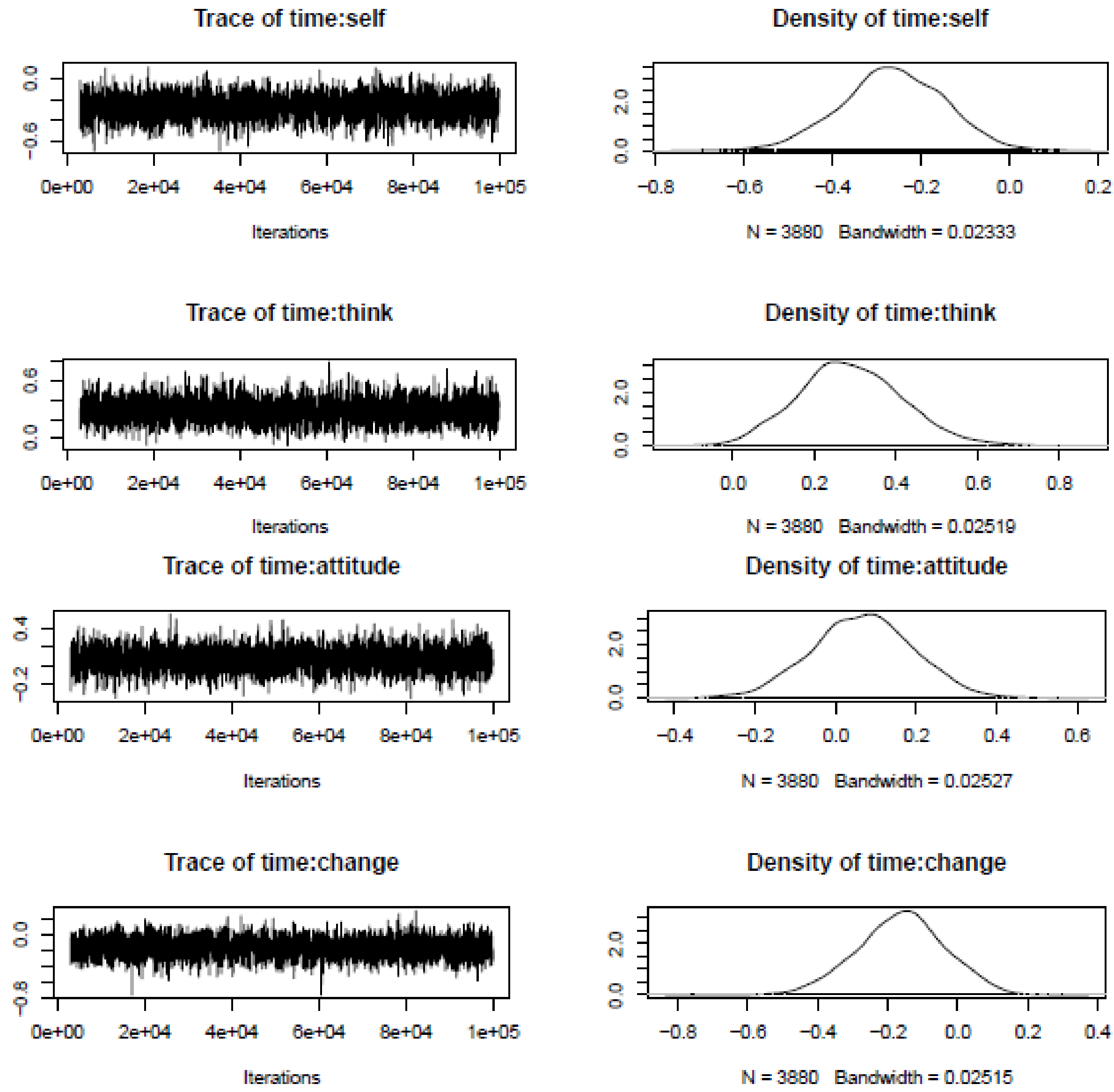
<u>Fixed Effects</u>



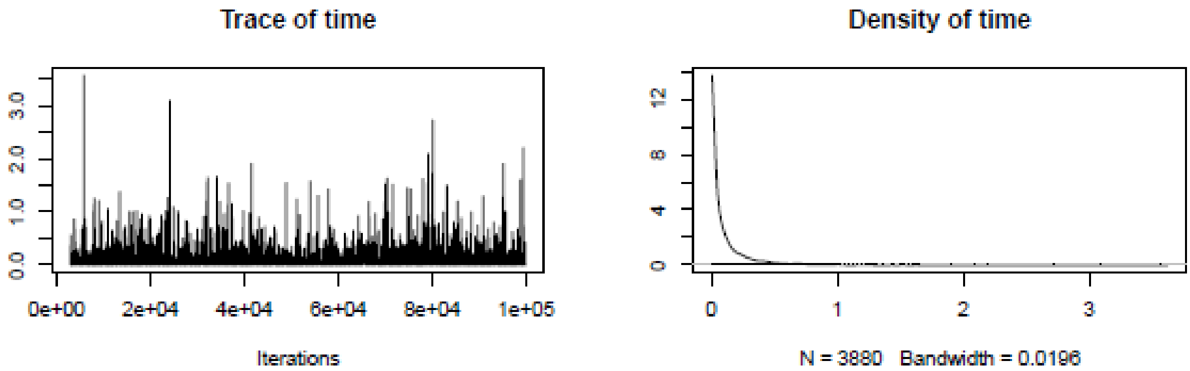

Trace of where
Iterations
Density of where
N = 3880 Bandwidth = 0.077
Trace of life
Iterations
Density of life
N = 3880 Bandwidth = 0.1256
Trace of drugs
Iterations
Density of drugs
N = 3880 Bandwidth = 0.07338
Trace of physical
Iterations
Density of physical
N = 3880 Bandwidth = 0.1411
Trace of emotion
Iterations
Density of emotion
N = 3880 Bandwidth = 0.09492
Trace of self
Iterations
Density of self
N = 3880 Bandwidth = 0.1139

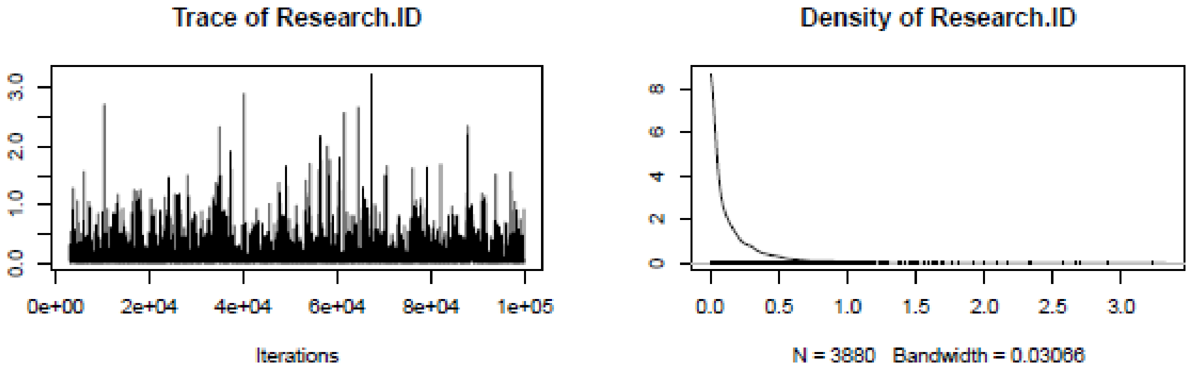

Trace of self
Iterations
Density of self
N = 3880 Bandwidth = 0.1139
Trace of think
Iterations
Density of think
N = 3880 Bandwidth = 0.1146
Trace of attitude
Iterations
Density of attitude
N = 3880 Bandwidth = 0.1148
Trace of change
Iterations
Density of change
N = 3880 Bandwidth = 0.1236
Trace of live:time
Iterations
Density of live:time
N = 3880 Bandwidth = 0.01285
Trace of time:relation
Iterations
Density of time:relation
N = 3880 Bandwidth = 0.02136


Trace of time:ete
Iterations
Density of time:ete
N = 3880 Bandwidth = 0.01505
Trace of time:where
Iterations
Density of time:where
N = 3880 Bandwidth = 0.01283
Trace of time:life
Iterations
Density of time:life
N = 3880 Bandwidth = 0.02163
Trace of time:drugs
Iterations
Density of time:drugs
N = 3880 Bandwidth = 0.01465
Trace of time:physical
Iterations
Density of time:physical
N = 3880 Bandwidth = 0.02147
Trace of time:emotion
Iterations
Density of time:emotion
N = 3880 Bandwidth = 0.02005



Random Effects




Trace of Research.ID
Iterations
0e+00
2e+04
4e+04
6e+04
8e+04
1e+05
0.0
1.0
2.0
3.0
Density of Research.ID
N = 3880 Bandwidth = 0.03066
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0
2
4
6
8

Chapter Five – Dimensional Identity

Model 1.1 – Basic Model + Gender (Table 5.3)

Bayesian Model (Bm1_d1)

Define the Model

```
Bm1_d1 <- MCMCglmm(FO.bin ~ Gender + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=200000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_d1$VCV)
heidel.diag(Bm1_d1$VCV)

# > raftery.diag(Bm1_d1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         30       40900  3746         10.9
# Research.ID  180      192390 3746         51.4
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_d1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.373
# Research.ID  passed        1        0.120
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.287 0.01625
# Research.ID  passed    0.117 0.00976
# units        <NA>         NA      NA

autocorr(Bm1_d1$VCV)
autocorr(Bm1_d1$Sol)  # Output not included here
summary(Bm1_d1)

# > autocorr(Bm1_d1$VCV)
# , , time
#
#                 time Research.ID units
# Lag 0   1.000000000  0.09087863   NaN
# Lag 10  0.237849550  0.08965712   NaN
# Lag 50  0.056871410  0.06523485   NaN
# Lag 100 0.016558650  0.04408850   NaN
# Lag 500 0.005634137  0.01533107   NaN
```

```
# , , Research.ID
#
#                time Research.ID units
# Lag 0   0.090878629  1.00000000   NaN
# Lag 10  0.091271314  0.83083775   NaN
# Lag 50  0.061804731  0.53913872   NaN
# Lag 100 0.048403914  0.36202784   NaN
# Lag 500 0.006324401  0.02848811   NaN

# > summary(Bm1_d1)
#
# Iterations = 3001:199991
# Thinning interval  = 10
# Sample size  = 19700
#
# DIC: 476.5217
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.287   0.3385    2.641     7406
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1167 0.0001455   0.4066      818
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ Gender + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time
#
#              post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept) -1.1647853 -2.3850494  0.0885680    11959 0.0678 .
# Gender       0.1580480 -0.7976444  1.1070293     7304 0.7464
# live         0.0327661 -0.2282674  0.2929174     8043 0.8143
# relation     0.2713415 -0.0172386  0.5658504     7956 0.0670 .
# ete          0.0869890 -0.1673220  0.3286078     7284 0.4898
# where        0.0462148 -0.1775761  0.2627354     8045 0.6828
# life         0.0210105 -0.3302826  0.3628579     7998 0.9053
# drugs        0.1631163 -0.0848979  0.4044527     6615 0.1909
# physical    -0.1165311 -0.3959244  0.1724497     6926 0.4284
# emotion     -0.0005269 -0.2483140  0.2412072     8134 0.9930
# self        -0.1440720 -0.4745562  0.1664353     7790 0.3779
# think       -0.1640159 -0.4936070  0.1765183     8259 0.3342
# attitude     0.0549124 -0.2892740  0.4117808     7889 0.7553
# change       0.2413716 -0.1093709  0.5816189     7799 0.1699
# time        -0.1560156 -0.2904756 -0.0193178     7907 0.0192 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_d1)

```
m1_d1 <- glmer(FO.bin ~ female + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_d1)
vcomps.icc(m1_d1)
anova(m1,m1_d1)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ female + live + relation + ete + where + life +
drugs +
# physical + emotion + self + think + attitude + change + time + time |
# Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 642.3    719.7   -303.2    606.3      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6466 -0.6592 -0.3607  0.8073  3.5315
#
# Random effects:
# Groups     Name        Variance Std.Dev.  Corr
# Individual (Intercept) 0.04379  0.2093
#            time        0.05671  0.2381   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.816964   0.323416  -2.526   0.0115 *
# female       0.256270   0.484524   0.529   0.5969
# live        -0.069666   0.143170  -0.487   0.6265
# relation     0.186065   0.158260   1.176   0.2397
# ete         -0.010873   0.132635  -0.082   0.9347
# where        0.157046   0.128563   1.222   0.2219
# life        -0.001129   0.194759  -0.006   0.9954
# drugs        0.285365   0.140153   2.036   0.0417 *
# physical    -0.234340   0.149915  -1.563   0.1180
# emotion     -0.030698   0.134064  -0.229   0.8189
# self        -0.069852   0.176310  -0.396   0.6920
# think        0.126025   0.187054   0.674   0.5005
# attitude    -0.051817   0.191182  -0.271   0.7864
# change       0.231999   0.184799   1.255   0.2093
# time        -0.450298   0.110239  -4.085 4.41e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.0285184 (tol = 0.001,
component 1)

# vcomps.icc(m1_d1)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.044         0.057         1.000         0.436
```

```
# anova(m1,m1_d1)
# Data: data
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1_d1: FO.bin ~ female + live + relation + ete + where + life + drugs
+
#   m1_d1:     physical + emotion + self + think + attitude + change +
time
#   m1_d1:     (time | Individual)
#       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1    17 640.59 713.70 -303.29   606.59
# m1_d1 18 642.31 719.73 -303.16   606.31 0.2759      1     0.5994
```

Model 1.2 – Basic Model + Ethnicity (Table 5.3)

Bayesian Model (Bm1_d2)

Define the model

```
Bm1_d2 <- MCMCglmm(FO.bin ~ bme + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID,  data=data,  family="ordinal",  prior=prior2,
nitt=350000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_d2$VCV)
heidel.diag(Bm1_d2$VCV)

# > raftery.diag(Bm1_d2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         60       79840  3746         21.3
# Research.ID 250       305800 3746         81.6
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_d2$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.172
# Research.ID passed         1         0.162
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.285 0.01167
# Research.ID passed     0.107 0.00647
# units        <NA>        NA       NA

autocorr(Bm1_d2$VCV)
autocorr(Bm1_d2$Sol)  # Output not included here
summary(Bm1_d2)

# > autocorr(Bm1_d2$VCV)
# , , time
#
# time Research.ID units
# Lag 0   1.000000000  0.10334474   NaN
# Lag 10  0.208838902  0.09832453   NaN
# Lag 50  0.055704278  0.07438763   NaN
# Lag 100 0.019072673  0.04650159   NaN
# Lag 500 0.007534222  0.01002055   NaN
```

```
# , , Research.ID
#
# time Research.ID units
# Lag 0   0.103344738  1.00000000   NaN
# Lag 10  0.104413281  0.83040832   NaN
# Lag 50  0.085765868  0.53950367   NaN
# Lag 100 0.058448597  0.34912110   NaN
# Lag 500 0.001731731  0.03797534   NaN

# > summary(Bm1_d2)
#
# Iterations = 3001:349991
# Thinning interval  = 10
# Sample size  = 34700
#
# DIC: 475.1873
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.285   0.3464    2.614    13878
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1067 0.0001506   0.3773     1626
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ bme + live + relation + ete + where + life
+ drugs + physical + emotion + self + think + attitude + change + time
#
#             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -1.071268 -2.294722  0.209363    22677 0.0926 .
# bme         -0.734875 -1.745215  0.273161    10475 0.1450
# live         0.029232 -0.231328  0.285087    14208 0.8273
# relation     0.251609 -0.038589  0.543862    14325 0.0938 .
# ete          0.081078 -0.164414  0.329474    12979 0.5169
# where        0.059101 -0.162490  0.277894    13976 0.5943
# life        -0.022480 -0.371586  0.322205    14684 0.8954
# drugs        0.175110 -0.058481  0.416670    12792 0.1437
# physical    -0.145566 -0.434849  0.139254    12054 0.3187
# emotion     -0.003584 -0.247074  0.238657    13909 0.9707
# self        -0.113530 -0.439152  0.199268    13063 0.4871
# think       -0.129309 -0.470417  0.201008    15289 0.4450
# attitude     0.056360 -0.296622  0.399672    14041 0.7482
# change       0.226895 -0.107961  0.568496    14251 0.1887
# time        -0.156272 -0.290243 -0.024568    16028 0.0187 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_d2)

```
m1_d2 <- glmer(FO.bin ~ bme + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_d2)
vcomps.icc(m1_d2)
anova(m1,m1_d2)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ bme + live + relation + ete + where + life + drugs +
# physical + emotion + self + think + attitude + change + time + (time |
# Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 640.9    718.3   -302.4    604.9      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6281 -0.6679 -0.3598  0.8133  3.5657
#
# Random effects:
# Groups     Name        Variance Std.Dev.  Corr
# Individual (Intercept) 0.04566  0.2137
#            time        0.05726  0.2393   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#             Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.70242    0.33188  -2.117   0.0343 *
# bme         -0.67306    0.53273  -1.263   0.2064
# live        -0.06946    0.14227  -0.488   0.6254
# relation     0.16630    0.15898   1.046   0.2955
# ete         -0.01515    0.13152  -0.115   0.9083
# where        0.15525    0.12807   1.212   0.2254
# life        -0.02243    0.19364  -0.116   0.9078
# drugs        0.28803    0.13456   2.140   0.0323 *
# physical    -0.25490    0.15142  -1.683   0.0923 .
# emotion     -0.03136    0.13432  -0.233   0.8154
# self        -0.03008    0.17802  -0.169   0.8658
# think        0.14860    0.18898   0.786   0.4317
# attitude    -0.05739    0.19022  -0.302   0.7629
# change       0.20968    0.18170   1.154   0.2485
# time        -0.45309    0.10954  -4.136 3.53e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.0377799 (tol = 0.001,
component 1)

# vcomps.icc(m1_d2)
# Var (Level 2) Var (Level 1)          ICC          <NA>
#         0.046         0.057        1.000         0.444
```

```
# anova(m1,m1_d2)
# Data: data
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1_d2: FO.bin ~ bme + live + relation + ete + where + life + drugs +
#    m1_d2:      physical + emotion + self + think + attitude + change +
time
#   m1_d2:      (time | Individual)
#       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1    17 640.59 713.70 -303.29   606.59
# m1_d2 18 640.87 718.28 -302.44   604.87 1.7189      1     0.1898
```

Model 1.3 – Basic Model + Demographics (Table 5.3)

Bayesian Model (Bm_d12)

Define the model

```
Bm1_d12 <- MCMCglmm(FO.bin ~ Gender + bme + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=400000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_d12$VCV)
heidel.diag(Bm1_d12$VCV)

# > raftery.diag(Bm1_d12$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#             Burn-in  Total  Lower bound  Dependence
#             (M)      (N)    (Nmin)       factor (I)
# time        30       41180  3746         11.0
# Research.ID 280      353500 3746         94.4
# units       <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_d12$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# time        passed         1       0.223
# Research.ID passed         1       0.246
# units       failed        NA          NA
#
#             Halfwidth Mean  Halfwidth
#             test
# time        passed    1.315 0.01231
# Research.ID passed    0.132 0.00761
# units       <NA>         NA      NA

autocorr(Bm1_d12$VCV)
autocorr(Bm1_d12$Sol)  # Output not included here
summary(Bm1_d12)

# > autocorr(Bm1_d12$VCV)
# , , time
#
#                 time Research.ID units
# Lag 0    1.000000000 0.105494303   NaN
# Lag 10   0.220382531 0.112436258   NaN
# Lag 50   0.067279674 0.080136094   NaN
# Lag 100  0.023622258 0.056133559   NaN
# Lag 500 -0.007097033 0.001498984   NaN
```

```
# , , Research.ID
#
#                time Research.ID units
# Lag 0   0.105494303  1.00000000   NaN
# Lag 10  0.104781134  0.83041967   NaN
# Lag 50  0.082903746  0.55643290   NaN
# Lag 100 0.066739672  0.38893823   NaN
# Lag 500 0.009216065  0.03243227   NaN

# Iterations = 3001:399991
# Thinning interval  = 10
# Sample size  = 39700
#
# DIC: 475.2987
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.315    0.347    2.657    13143
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID     0.132 0.0001368   0.4477     1612
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ Gender + bme + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time
#
#              post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept) -1.0914900 -2.3854024  0.1552390    23527 0.0841 .
# Gender       0.1436045 -0.8491936  1.0854630    14573 0.7657
# bme         -0.7386974 -1.7734664  0.2815369    12336 0.1472
# live         0.0284664 -0.2340738  0.2871356    16684 0.8301
# relation     0.2514009 -0.0530534  0.5443329    16169 0.0968 .
# ete          0.0742845 -0.1760727  0.3300405    14706 0.5591
# where        0.0611691 -0.1665028  0.2800282    14913 0.5870
# life        -0.0224438 -0.3726158  0.3338553    16277 0.8965
# drugs        0.1898542 -0.0579971  0.4336380    12535 0.1273
# physical    -0.1542425 -0.4499178  0.1346726    14502 0.2984
# emotion      0.0006891 -0.2519455  0.2417349    16211 0.9981
# self        -0.1244381 -0.4590369  0.1924738    15494 0.4546
# think       -0.1340234 -0.4673611  0.2059961    16963 0.4342
# attitude     0.0625229 -0.2881987  0.4208373    16192 0.7250
# change       0.2367497 -0.1025553  0.5933242    15815 0.1860
# time        -0.1583036 -0.2969935 -0.0268651    15685 0.0181 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_d12)

```
m1_d12 <- glmer(FO.bin ~ female + bme + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time + (time|Individual), data=data, family=binomial)
summary(m1_d12)
vcomps.icc(m1_d12)
anova(m1_d1,m1_d12)
anova(m1_d2,m1_d12)
anova(m1,m1_d12)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ female + bme + live + relation + ete + where + life
+
#    drugs + physical + emotion + self + think + attitude + change +
time + (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 642.6    724.3   -302.3    604.6      526
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6310 -0.6627 -0.3596  0.7882  3.5527
#
# Random effects:
# Groups     Name        Variance Std.Dev.  Corr
# Individual (Intercept) 0.04645  0.2155
#            time        0.05888  0.2427   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#             Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.72060    0.33333  -2.162   0.0306 *
# female       0.26051    0.48395   0.538   0.5904
# bme         -0.67064    0.53409  -1.256   0.2092
# live        -0.08095    0.14365  -0.564   0.5731
# relation     0.16332    0.15955   1.024   0.3060
# ete         -0.02867    0.13414  -0.214   0.8308
# where        0.16147    0.12892   1.252   0.2104
# life        -0.03821    0.19747  -0.193   0.8466
# drugs        0.30988    0.14160   2.188   0.0286 *
# physical    -0.26288    0.15218  -1.727   0.0841 .
# emotion     -0.03003    0.13479  -0.223   0.8237
# self        -0.03534    0.17893  -0.198   0.8434
# think        0.15203    0.18939   0.803   0.4221
# attitude    -0.04990    0.19166  -0.260   0.7946
# change       0.23100    0.18553   1.245   0.2131
# time        -0.45661    0.11059  -4.129 3.64e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.129599 (tol = 0.001,
component 1)failure to converge in 10000 evaluations

# vcomps.icc(m1_d12)
# Var (Level 2) Var (Level 1)          ICC          <NA>
#         0.046         0.059        1.000         0.441
```

```
# anova(m1_d1,m1_d12)
# Data: data
# Models:
#    m1_d1: FO.bin ~ female + live + relation + ete + where + life +
drugs +
#   m1_d1:      physical + emotion + self + think + attitude + change +
time
#   m1_d1:     (time | Individual)
# m1_d12: FO.bin ~ female + bme + live + relation + ete + where + life +
#   m1_d12:      drugs + physical + emotion + self + think + attitude +
change
#   m1_d12:     time + (time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1_d1  18 642.31 719.73 -303.16   606.31
# m1_d12 19 642.61 724.32 -302.30   604.61 1.7072      1     0.1914

# anova(m1_d2,m1_d12)
# Data: data
# Models:
#   m1_d2: FO.bin ~ bme + live + relation + ete + where + life + drugs +
#   m1_d2:      physical + emotion + self + think + attitude + change +
time
#   m1_d2:     (time | Individual)
# m1_d12: FO.bin ~ female + bme + live + relation + ete + where + life +
#   m1_d12:      drugs + physical + emotion + self + think + attitude +
change
#   m1_d12:     time + (time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1_d2  18 640.87 718.28 -302.44   604.87
# m1_d12 19 642.61 724.32 -302.30   604.61 0.2642      1     0.6073

# anova(m1,m1_d12)
# Data: data
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1_d12: FO.bin ~ female + bme + live + relation + ete + where + life +
#   m1_d12:      drugs + physical + emotion + self + think + attitude +
change
#   m1_d12:     time + (time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1     17 640.59 713.70 -303.29   606.59
# m1_d12 19 642.61 724.32 -302.30   604.61 1.9831      2      0.371
```

Dynamic Model involving Gender (Table 5.4)

Bayesian Model (BDm2_d1)

Define the model

```
BDm2_d1 <- MCMCglmm(FO.bin ~ Gender*time*live + Gender*time*relation +
Gender*time*ete + Gender*time*where + Gender*time*life +
Gender*time*drugs + Gender*time*physical + Gender*time*emotion +
Gender*time*self + Gender*time*think + Gender*time*attitude +
Gender*time*change,random=~time+Research.ID, data=data,
family="ordinal",prior=priorD, slice=TRUE,nitt=2000000, thin=500,
burnin=3000)
```

Checks for suitable convergence

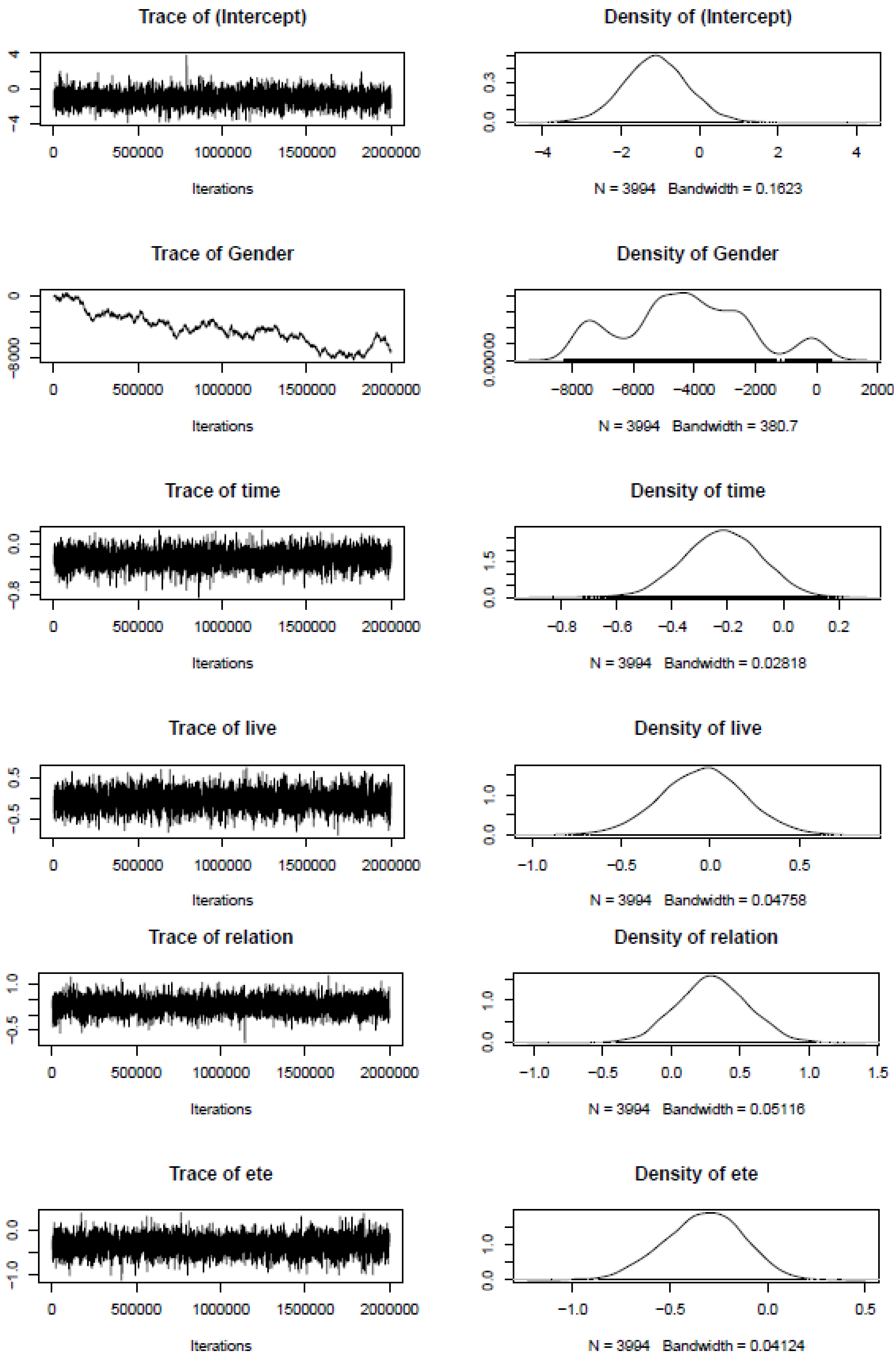
```
raftery.diag(BDm2_d1$VCV)
heidel.diag(BDm2_d1$VCV)

# > raftery.diag(BDm2_d1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total   Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# time         1000     1935500 3746         517
# Research.ID  1000     1820000 3746         486
# units        <NA>     <NA>    3746          NA

# > heidel.diag(BDm2_d1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.847
# Research.ID  passed        1        0.287
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.962 0.03649
# Research.ID  passed    0.216 0.00623
# units        <NA>         NA      NA

autocorr(BDm2_d1$VCV)
autocorr(BDm2_d1$Sol)   # Output not included here
summary(BDm2_d1)

# > autocorr(BDm2_d1$VCV)
# , , time
#
#                     time Research.ID units
# Lag 0      1.000000000  0.10130974   NaN
# Lag 500    0.022216300 -0.00288786   NaN
# Lag 2500  -0.002768079 -0.01168471   NaN
# Lag 5000  -0.016717989  0.02190236   NaN
# Lag 25000  0.032606363 -0.01352863   NaN
# , , Research.ID
#
```

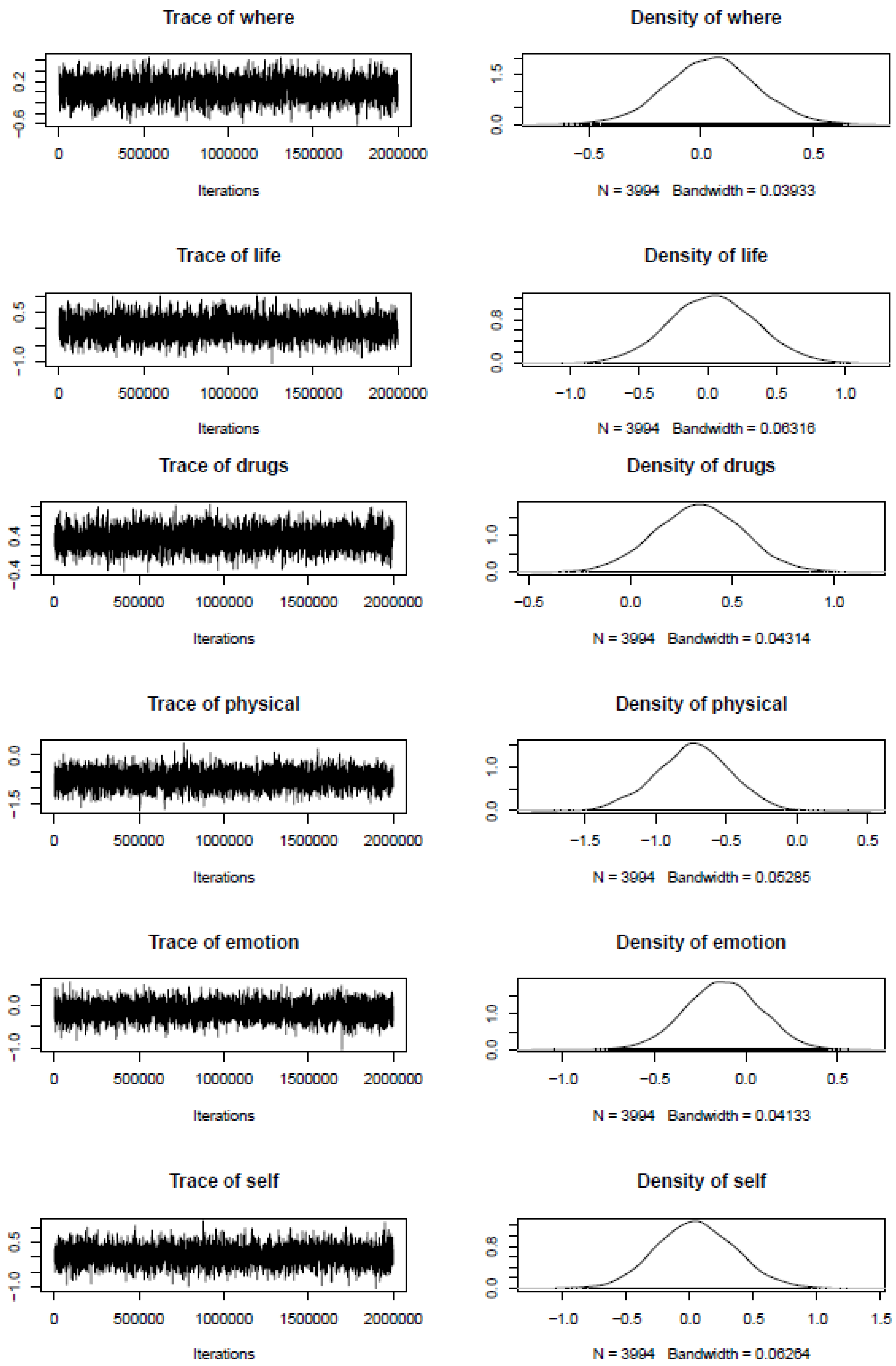
```
#                    time  Research.ID units
# Lag 0      0.101309743  1.000000000   NaN
# Lag 500    0.001103226 -0.007825477   NaN
# Lag 2500  -0.020051011 -0.006015421   NaN
# Lag 5000  -0.001875668 -0.002853057   NaN
# Lag 25000 -0.011140664 -0.034607606   NaN

# > summary(BDm2_d1)
#
# Iterations = 3001:1999501
# Thinning interval  = 500
# Sample size  = 3994
#
# DIC: 451.5695
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.962   0.4669    4.205     3994
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID    0.2159 1.41e-07   0.6111     3994
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ Gender * time * live + Gender * time * relation + Gender * time * ete + Gender * time * where + Gender * time * life + Gender * time * drugs + Gender * time * physical + Gender * time * emotion + Gender * time * self + Gender * time * think + Gender * time * attitude + Gender * time * change
#
#                      post.mean   l-95% CI   u-95% CI eff.samp   pMCMC
# (Intercept)         -1.117e+00 -2.745e+00  5.383e-01 3994.000 0.17927
# Gender              -4.286e+03 -7.928e+03 -1.530e+02    3.189 0.05008 .
# time                -2.200e-01 -4.905e-01  4.792e-02 3994.000 0.10416
# live                -4.133e-02 -5.145e-01  4.181e-01 3994.000 0.86730
# relation             2.998e-01 -1.590e-01  8.223e-01 5094.923 0.25038
# ete                 -3.273e-01 -7.397e-01  4.421e-02 3994.000 0.09314 .
# where                4.778e-02 -3.492e-01  4.337e-01 3994.000 0.80871
# life                 3.861e-02 -5.695e-01  6.513e-01 3859.766 0.90536
# drugs                3.376e-01 -7.446e-02  7.618e-01 3994.000 0.11768
# physical            -7.326e-01 -1.273e+00 -2.357e-01 3994.000 0.00551 **
# emotion             -1.257e-01 -5.142e-01  2.841e-01 3994.000 0.53330
# self                 4.772e-02 -5.556e-01  6.550e-01 3994.000 0.88933
# think               -7.992e-02 -6.510e-01  4.673e-01 3994.000 0.77967
# attitude             3.801e-02 -5.332e-01  6.185e-01 4029.835 0.91387
# change               7.180e-01  9.972e-02  1.371e+00 3994.000 0.02604 *
# Gender:time          1.987e+03 -1.020e+02  3.763e+03    5.386 0.08363 .
# Gender:live         -4.281e+02 -2.063e+03  5.420e+02    9.141 0.56585
# time:live            2.092e-02 -7.687e-02  1.116e-01 4546.477 0.66049
# Gender:relation      5.743e+02 -1.086e+03  2.229e+03    4.084 0.65048
# time:relation       -1.430e-02 -1.265e-01  9.898e-02 3994.000 0.81122
# Gender:ete           8.286e+02 -1.319e+03  3.225e+03    2.321 0.70956
# time:ete             1.044e-01  1.919e-02  1.976e-01 3994.000 0.01552 *
# Gender:where         1.921e+03 -6.953e+01  3.169e+03    3.816 0.06610 .
# time:where           8.942e-03 -6.999e-02  8.106e-02 4448.395 0.82123
# Gender:life         -3.269e+03 -7.131e+03  2.766e+02    4.017 0.10566
# time:life            1.687e-03 -1.219e-01  1.198e-01 3715.491 0.98648
# Gender:drugs         7.369e+02 -1.511e+03  2.668e+03    4.898 0.39960
```

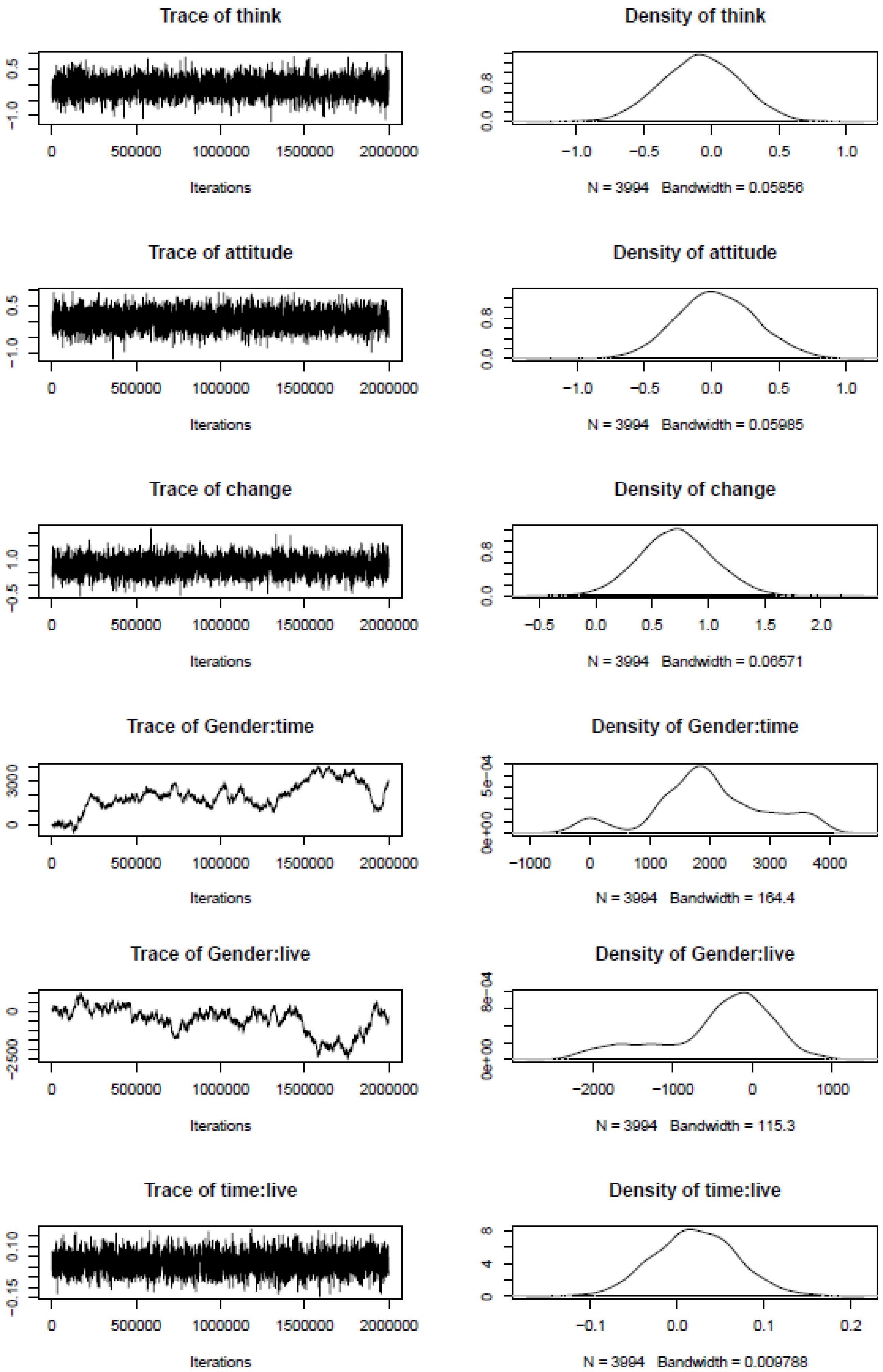
```
# time:drugs           -4.043e-02 -1.296e-01  3.850e-02 3994.000 0.34352
# Gender:physical       1.387e+03 -1.280e+02  3.209e+03    8.101 0.01753 *
# time:physical         1.511e-01  2.579e-02  2.643e-01 3994.000 0.01452 *
# Gender:emotion        1.584e+03 -4.972e+02  3.372e+03    4.550 0.27942
# time:emotion          3.766e-02 -4.556e-02  1.184e-01 3994.000 0.38508
# Gender:self          -2.575e+03 -4.725e+03  1.814e+02    3.270 0.14422
# time:self            -8.228e-02 -1.977e-01  4.638e-02 4012.090 0.17426
# Gender:think          1.307e+03 -7.479e+02  3.240e+03    4.347 0.31397
# time:think           -1.076e-02 -1.262e-01  1.151e-01 3994.000 0.86530
# Gender:attitude       1.605e+03 -4.773e+01  3.607e+03    3.055 0.01703 *
# time:attitude         7.461e-03 -1.149e-01  1.255e-01 4066.529 0.90636
# Gender:change         2.017e+03 -3.554e+02  4.101e+03    5.061 0.19479
# time:change          -9.188e-02 -2.136e-01  3.857e-02 3994.000 0.15173
# Gender:time:live     -1.831e+02 -1.051e+03  2.068e+02    8.403 0.43766
# Gender:time:relation -4.104e+02 -1.144e+03  3.200e+02    7.176 0.34402
# Gender:time:ete       4.202e+01 -9.539e+02  1.082e+03    2.804 0.97847
# Gender:time:where    -5.802e+02 -1.372e+03  1.504e+02    6.364 0.21532
# Gender:time:life      9.794e+02 -4.245e+02  2.278e+03    3.357 0.19980
# Gender:time:drugs     4.980e+01 -3.737e+02  4.109e+02    5.642 0.76014
# Gender:time:physical -1.193e+03 -2.069e+03 -4.253e+01    7.112 0.01302 *
# Gender:time:emotion  -7.681e+02 -1.842e+03  6.582e+02    2.356 0.50526
# Gender:time:self      1.528e+03 -2.440e+02  3.165e+03    2.438 0.18678
# Gender:time:think    -1.615e+02 -4.698e+02  1.884e+02    4.057 0.47772
# Gender:time:attitude -1.308e+03 -1.979e+03 -3.331e+02   10.187 < 3e-04 ***
# Gender:time:change   -1.139e+03 -2.395e+03  6.089e+02    3.372 0.19529
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

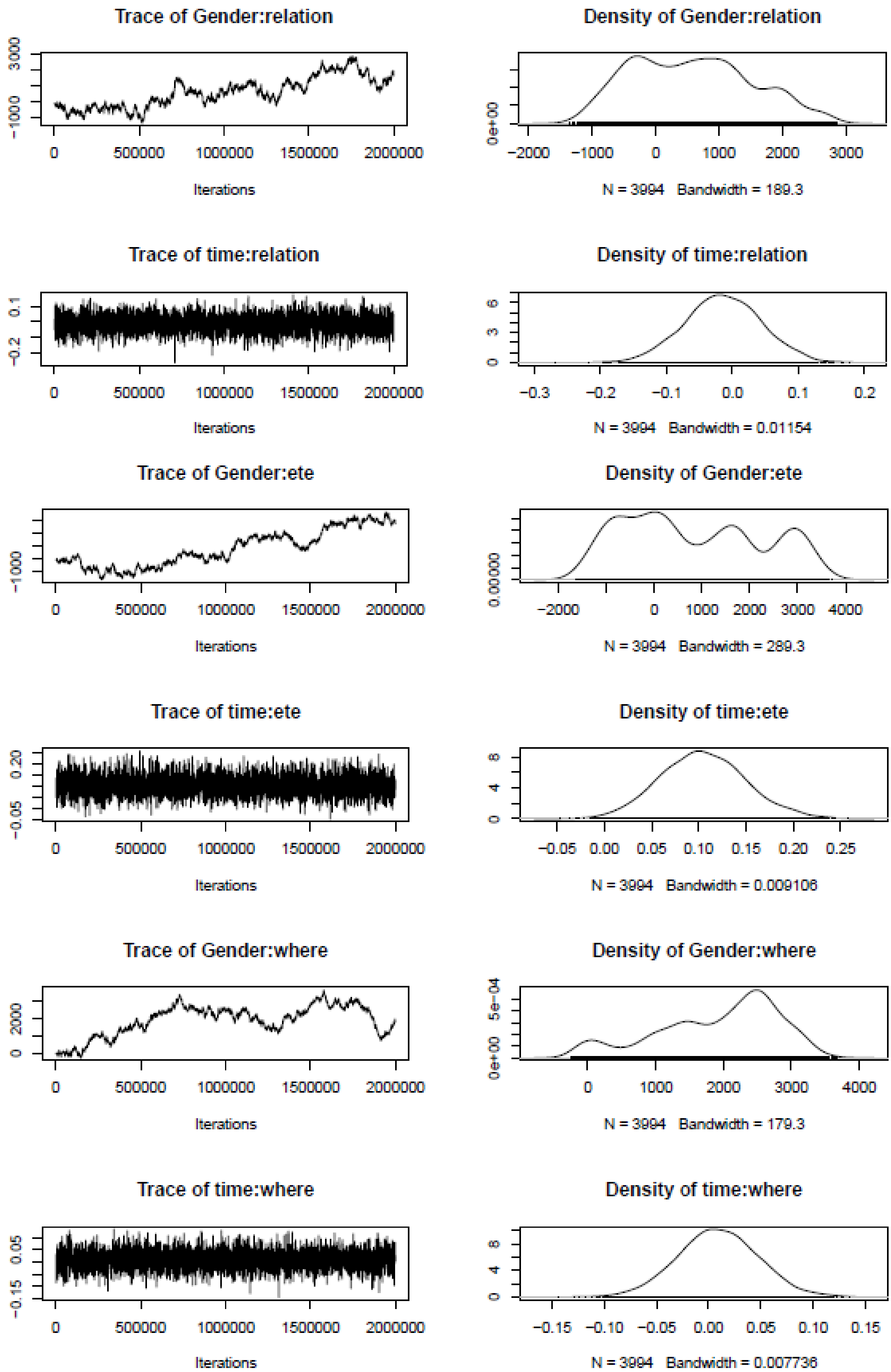
Trace of the Sampled Output and Density Estimates

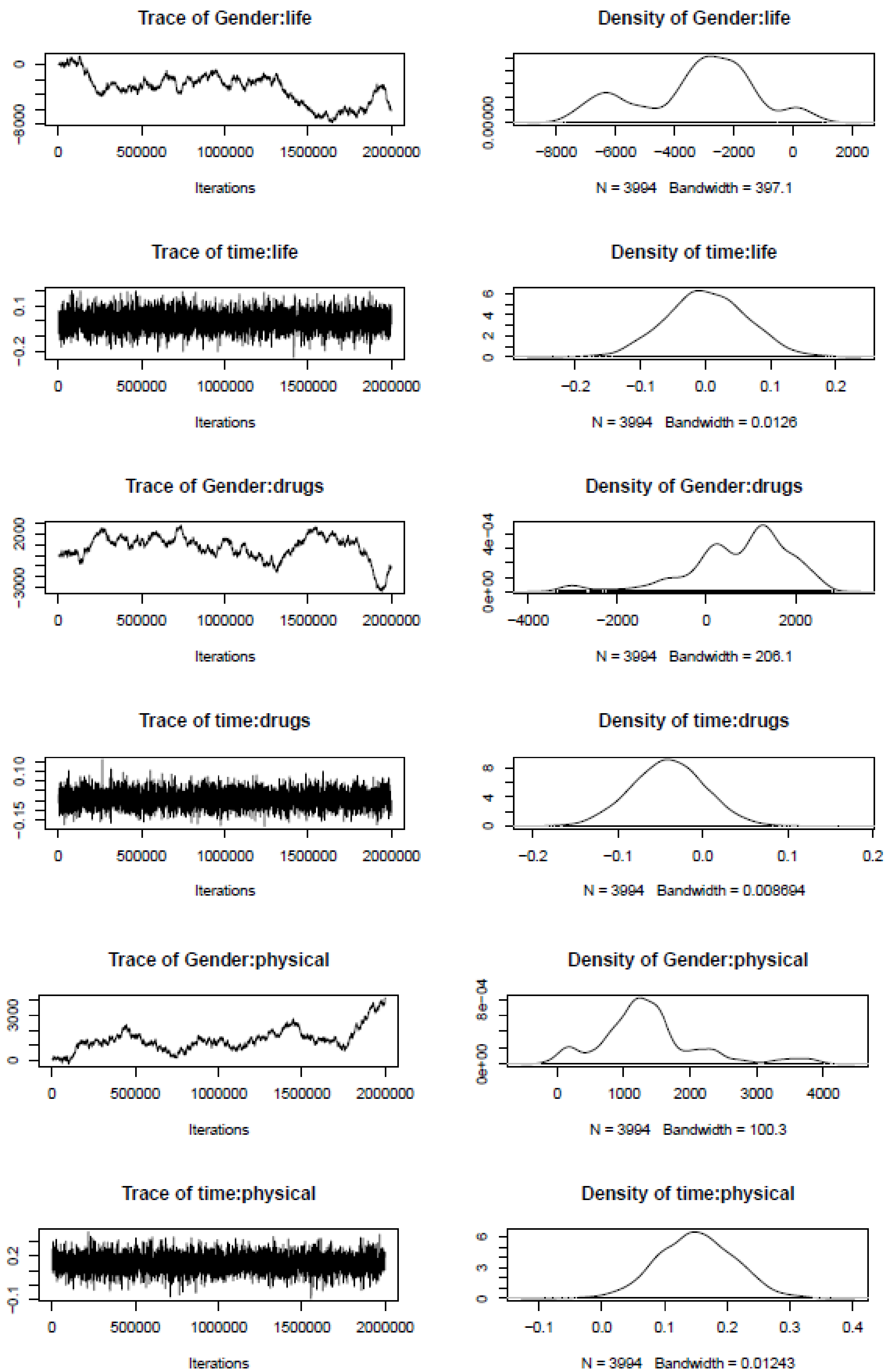
Fixed Effects

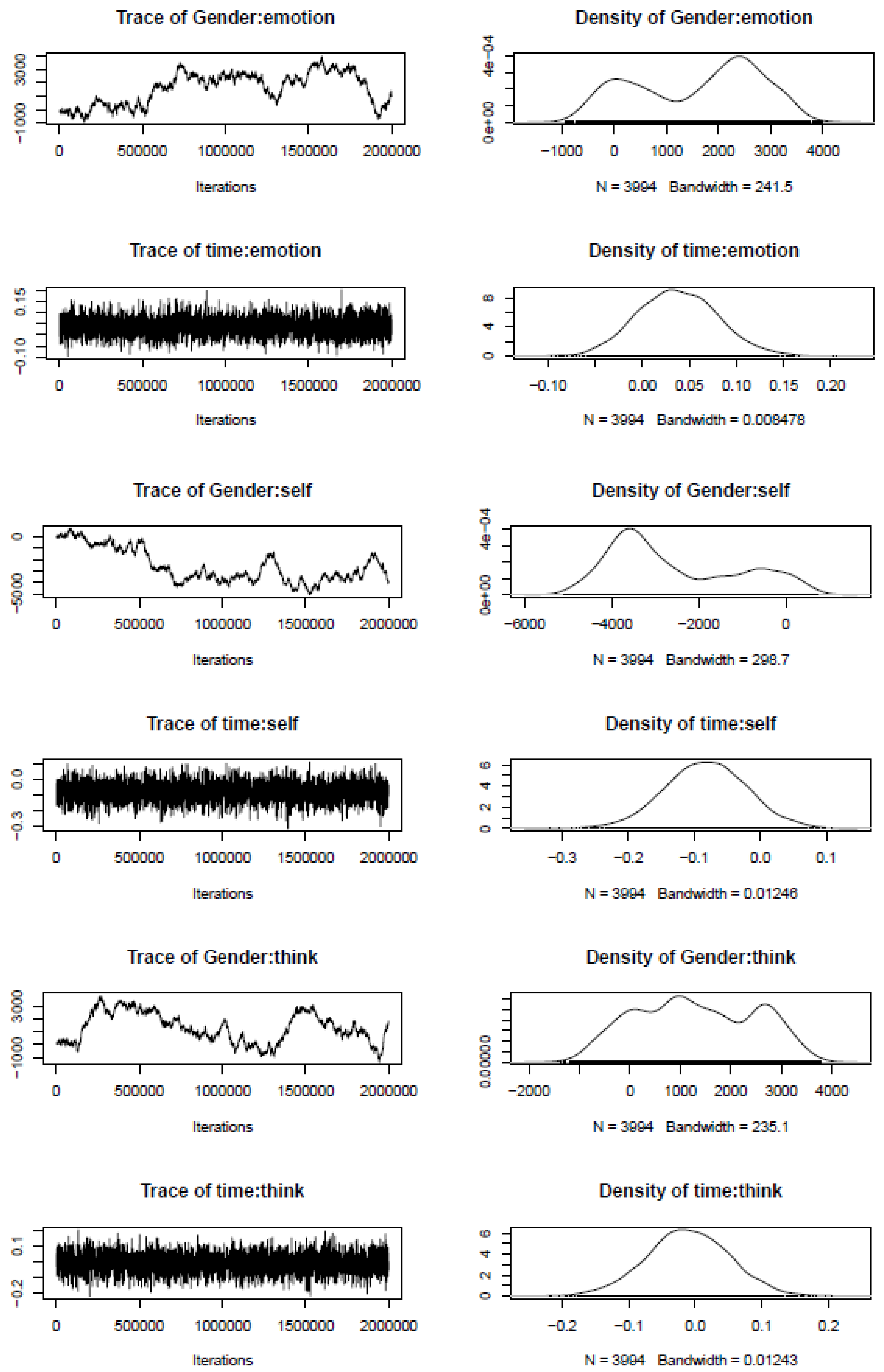


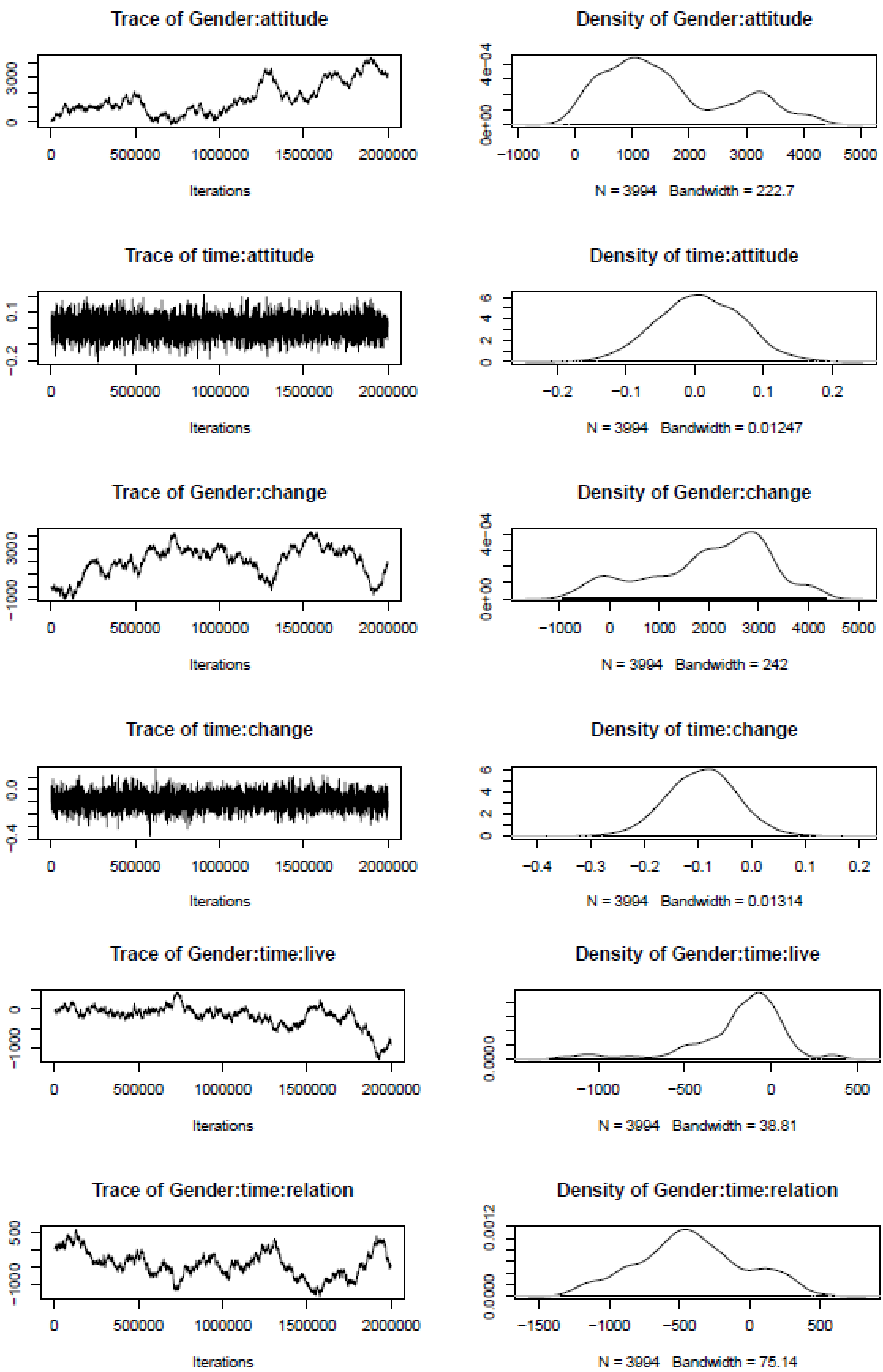

Trace of where
Iterations
Density of where
N = 3994 Bandwidth = 0.03933
Trace of life
Iterations
Density of life
N = 3994 Bandwidth = 0.06316
Trace of drugs
Iterations
Density of drugs
N = 3994 Bandwidth = 0.04314
Trace of physical
Iterations
Density of physical
N = 3994 Bandwidth = 0.05285
Trace of emotion
Iterations
Density of emotion
N = 3994 Bandwidth = 0.04133
Trace of self
Iterations
Density of self
N = 3994 Bandwidth = 0.06264

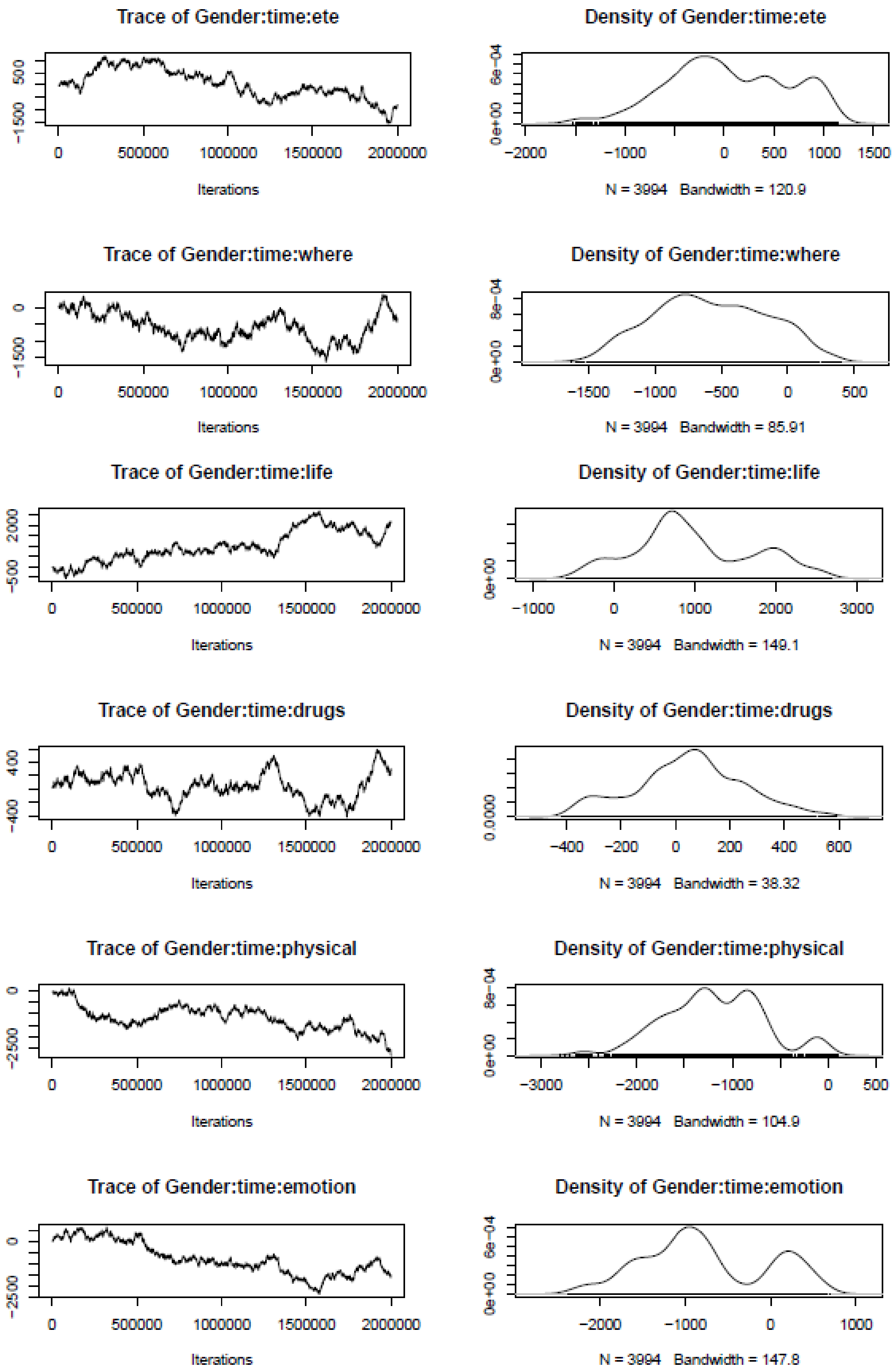

Trace of think
Iterations
Density of think
N = 3994 Bandwidth = 0.05856
Trace of attitude
Iterations
Density of attitude
N = 3994 Bandwidth = 0.05985
Trace of change
Iterations
Density of change
N = 3994 Bandwidth = 0.06571
Trace of Gender:time
Iterations
Density of Gender:time
N = 3994 Bandwidth = 164.4
Trace of Gender:live
Iterations
Density of Gender:live
N = 3994 Bandwidth = 115.3
Trace of time:live
Iterations
Density of time:live
N = 3994 Bandwidth = 0.009788

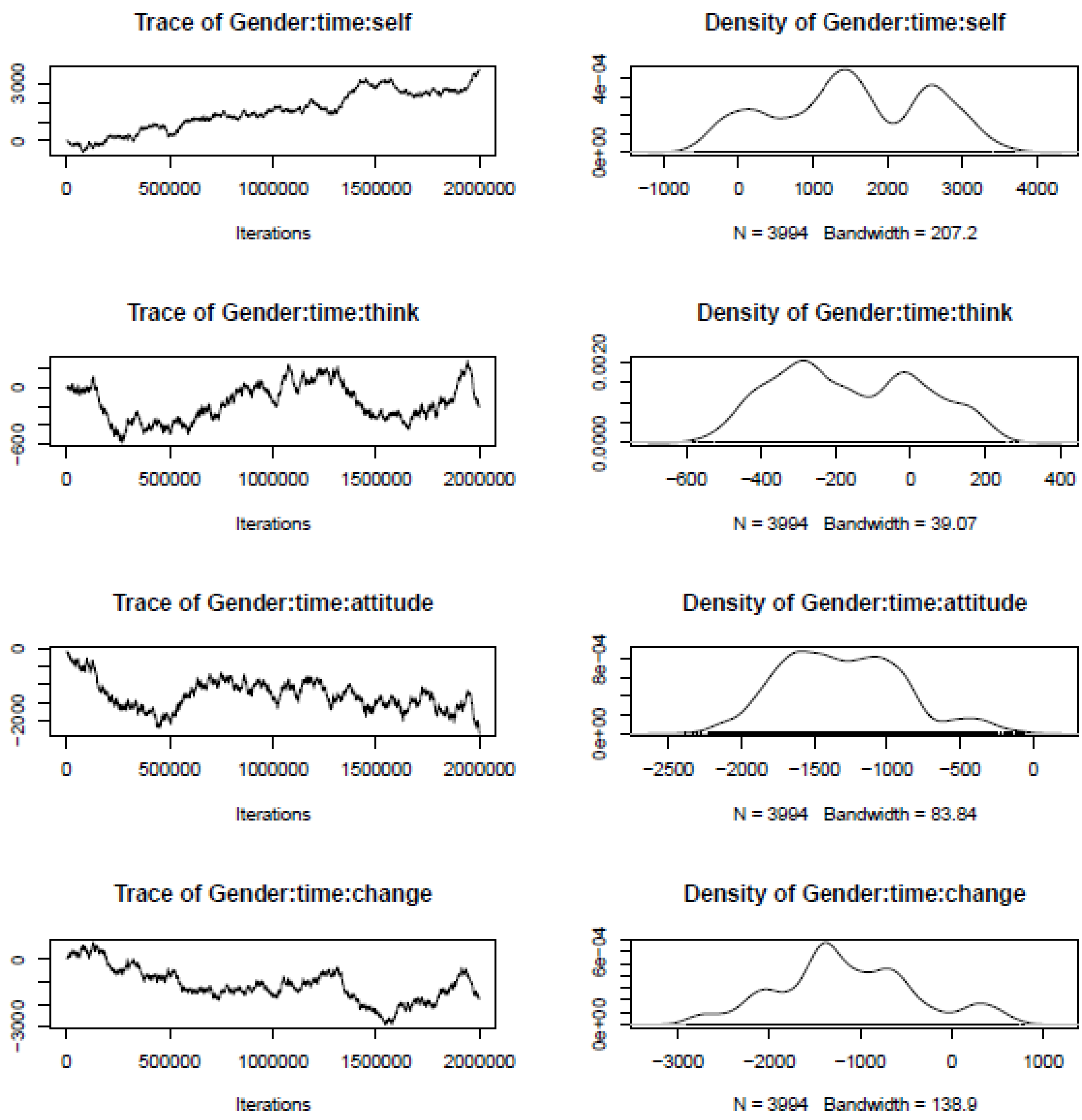

Trace of Gender:relation
Iterations
Density of Gender:relation
N = 3994 Bandwidth = 189.3
Trace of time:relation
Iterations
Density of time:relation
N = 3994 Bandwidth = 0.01154
Trace of Gender:ete
Iterations
Density of Gender:ete
N = 3994 Bandwidth = 289.3
Trace of time:ete
Iterations
Density of time:ete
N = 3994 Bandwidth = 0.009106
Trace of Gender:where
Iterations
Density of Gender:where
N = 3994 Bandwidth = 179.3
Trace of time:where
Iterations
Density of time:where
N = 3994 Bandwidth = 0.007736


Trace of Gender:life
0
-8000
0 500000 1000000 1500000 2000000
Iterations
Density of Gender:life
0.00000
-8000 -6000 -4000 -2000 0 2000
N = 3994 Bandwidth = 397.1
Trace of time:life
0.1
-0.2
0 500000 1000000 1500000 2000000
Iterations
Density of time:life
0 2 4 6
-0.2 -0.1 0.0 0.1 0.2
N = 3994 Bandwidth = 0.0126
Trace of Gender:drugs
2000
-3000
0 500000 1000000 1500000 2000000
Iterations
Density of Gender:drugs
0e+00 4e-04
-4000 -2000 0 2000
N = 3994 Bandwidth = 206.1
Trace of time:drugs
0.10
-0.15
0 500000 1000000 1500000 2000000
Iterations
Density of time:drugs
0 4 8
-0.2 -0.1 0.0 0.1 0.2
N = 3994 Bandwidth = 0.008694
Trace of Gender:physical
0 3000
0 500000 1000000 1500000 2000000
Iterations
Density of Gender:physical
0e+00 8e-04
0 1000 2000 3000 4000
N = 3994 Bandwidth = 100.3
Trace of time:physical
0.2
-0.1
0 500000 1000000 1500000 2000000
Iterations
Density of time:physical
0 3 6
-0.1 0.0 0.1 0.2 0.3 0.4
N = 3994 Bandwidth = 0.01243

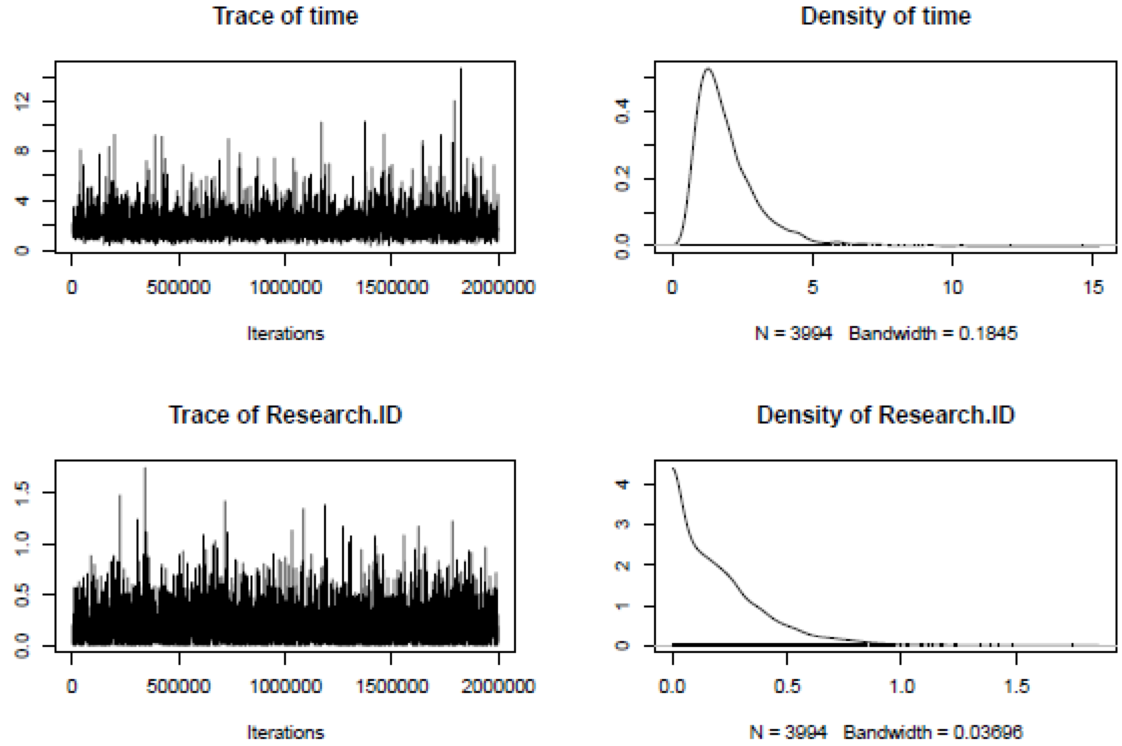

Trace of Gender:emotion
Iterations
Density of Gender:emotion
N = 3994 Bandwidth = 241.5
Trace of time:emotion
Iterations
Density of time:emotion
N = 3994 Bandwidth = 0.008478
Trace of Gender:self
Iterations
Density of Gender:self
N = 3994 Bandwidth = 298.7
Trace of time:self
Iterations
Density of time:self
N = 3994 Bandwidth = 0.01246
Trace of Gender:think
Iterations
Density of Gender:think
N = 3994 Bandwidth = 235.1
Trace of time:think
Iterations
Density of time:think
N = 3994 Bandwidth = 0.01243


Trace of Gender:attitude
Iterations
Density of Gender:attitude
N = 3994 Bandwidth = 222.7
Trace of time:attitude
Iterations
Density of time:attitude
N = 3994 Bandwidth = 0.01247
Trace of Gender:change
Iterations
Density of Gender:change
N = 3994 Bandwidth = 242
Trace of time:change
Iterations
Density of time:change
N = 3994 Bandwidth = 0.01314
Trace of Gender:time:live
Iterations
Density of Gender:time:live
N = 3994 Bandwidth = 38.81
Trace of Gender:time:relation
Iterations
Density of Gender:time:relation
N = 3994 Bandwidth = 75.14


Trace of Gender:time:ete
Iterations
Density of Gender:time:ete
N = 3994 Bandwidth = 120.9
Trace of Gender:time:where
Iterations
Density of Gender:time:where
N = 3994 Bandwidth = 85.91
Trace of Gender:time:life
Iterations
Density of Gender:time:life
N = 3994 Bandwidth = 149.1
Trace of Gender:time:drugs
Iterations
Density of Gender:time:drugs
N = 3994 Bandwidth = 38.32
Trace of Gender:time:physical
Iterations
Density of Gender:time:physical
N = 3994 Bandwidth = 104.9
Trace of Gender:time:emotion
Iterations
Density of Gender:time:emotion
N = 3994 Bandwidth = 147.8


Trace of Gender:time:self
Iterations
Density of Gender:time:self
N = 3994 Bandwidth = 207.2
Trace of Gender:time:think
Iterations
Density of Gender:time:think
N = 3994 Bandwidth = 39.07
Trace of Gender:time:attitude
Iterations
Density of Gender:time:attitude
N = 3994 Bandwidth = 83.84
Trace of Gender:time:change
Iterations
Density of Gender:time:change
N = 3994 Bandwidth = 138.9

Random Effects



Dynamic Model involving Ethnicity (Table 5.5)

Bayesian Model (BDm2_d2)

Define the model

```
BDm2_d2 <- MCMCglmm(FO.bin ~ bme*time*live + bme*time*relation +
bme*time*ete + bme*time*where + bme*time*life + bme*time*drugs +
bme*time*physical + bme*time*emotion + bme*time*self + bme*time*think +
bme*time*attitude + bme*time*change,
random=~time+Research.ID, data=data, family="ordinal",prior=priorD,
slice=TRUE, nitt=950000, thin=250, burnin=3000)
```

Checks for suitable convergence

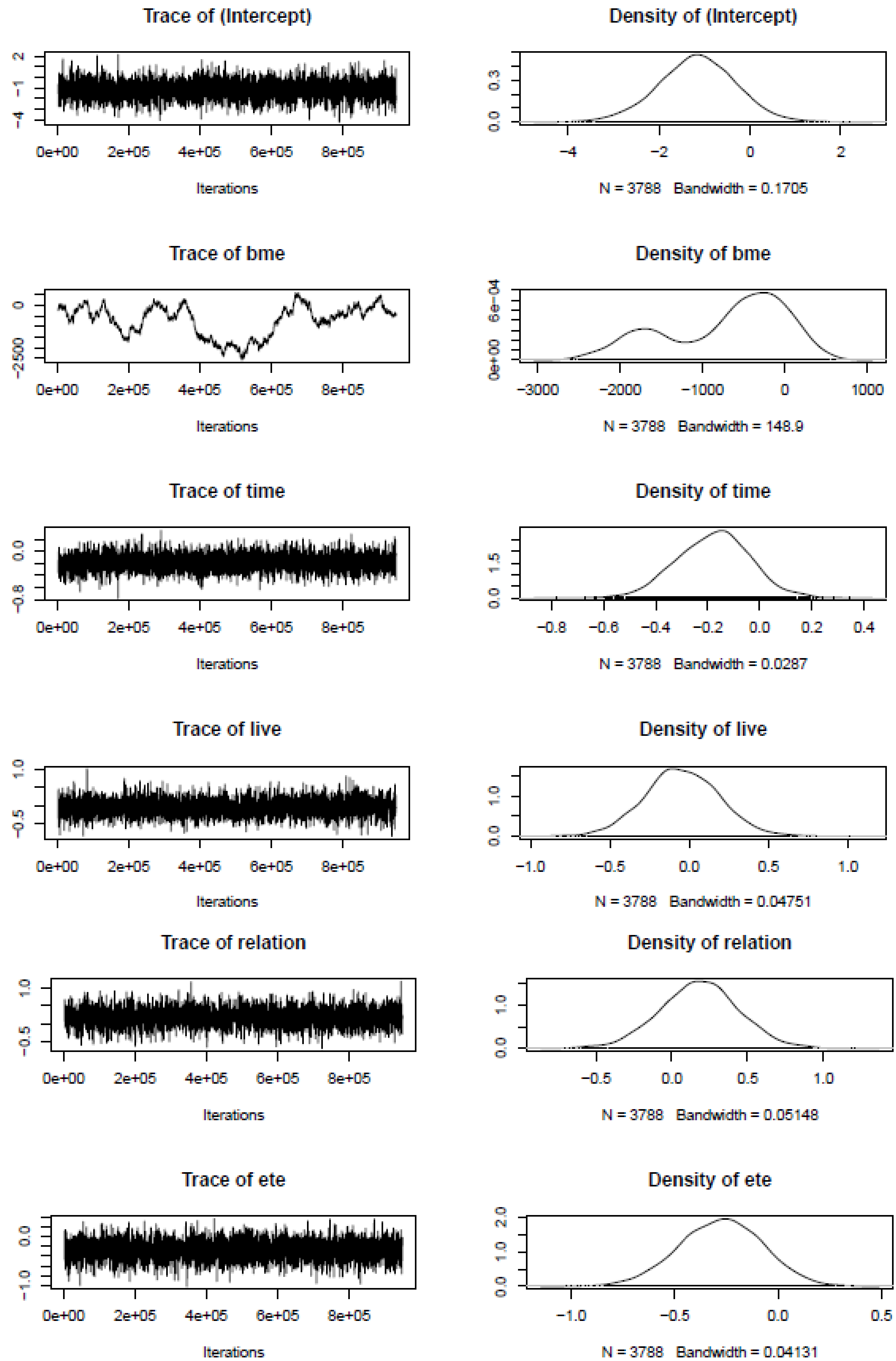
```
raftery.diag(BDm2_d2$VCV)
heidel.diag(BDm2_d2$VCV)

# > raftery.diag(BDm2_d2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#             Burn-in  Total  Lower bound  Dependence
#             (M)      (N)    (Nmin)       factor (I)
# time        500      973500 3746         260
# Research.ID 500      932250 3746         249
# units       <NA>     <NA>   3746          NA

# > heidel.diag(BDm2_d2$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# time        passed         1         0.280
# Research.ID passed         1         0.955
# units       failed        NA            NA
#
#             Halfwidth Mean  Halfwidth
#             test
# time        passed    2.158 0.04671
# Research.ID passed    0.211 0.00651
# units       <NA>         NA      NA

autocorr(BDm2_d2$VCV)
autocorr(BDm2_d2$Sol)   # Output not included here
summary(BDm2_d2)

# > autocorr(BDm2_d2$VCV)
# , , time
#
#                  time   Research.ID units
# Lag 0      1.000000000  0.120545820   NaN
# Lag 250    0.054109420 -0.002755681   NaN
# Lag 1250   0.015767568 -0.016032984   NaN
# Lag 2500  -0.007349312 -0.025947465   NaN
# Lag 12500 -0.012511331  0.006229553   NaN
```

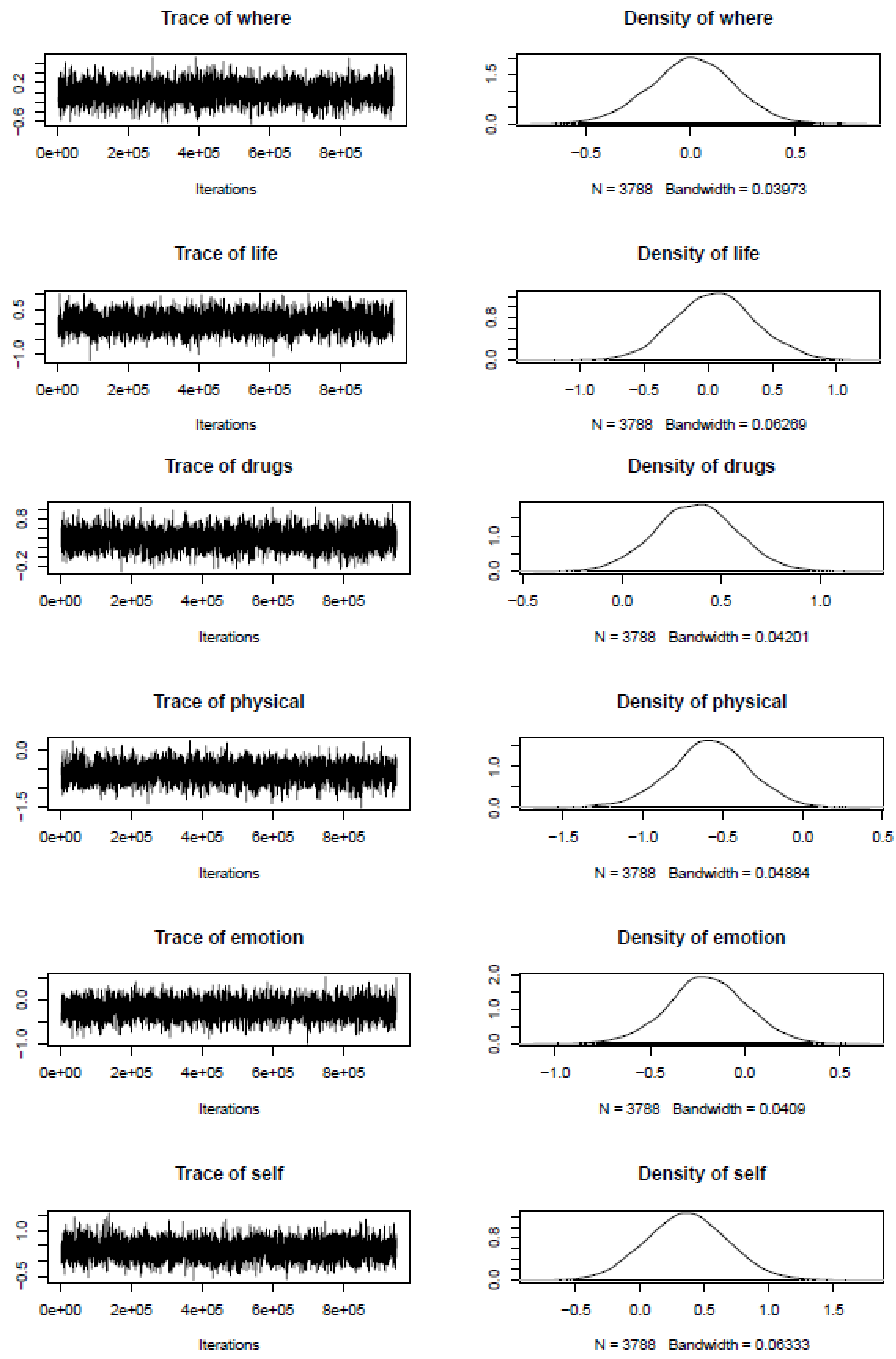
```
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0      0.12054582  1.000000000   NaN
# Lag 250    0.01537522 -0.005472931   NaN
# Lag 1250   0.01890197  0.002750872   NaN
# Lag 2500   0.01914272  0.020831004   NaN
# Lag 12500 0.01823663 -0.013391927   NaN

# > summary(BDm2_d2)
#
# Iterations = 3001:949751
# Thinning interval  = 250
# Sample size  = 3788
#
# DIC: 453.1886
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.158   0.4943    4.716     2945
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2114 1.043e-08   0.5931     3620
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ bme * time * live + bme * time * relation +
bme * time * ete + bme * time * where + bme * time * life + bme * time *
drugs + bme * time * physical + bme * time * emotion + bme * time * self
+ bme * time * think + bme * time * attitude + bme * time * change
#
#                    post.mean   l-95% CI   u-95% CI eff.samp   pMCMC
# (Intercept)       -1.161e+00 -2.883e+00  4.803e-01 4021.206 0.16262
# bme               -7.094e+02 -2.192e+03  3.194e+02    4.192 0.30359
# time              -1.778e-01 -4.831e-01  6.970e-02 4208.504 0.19060
# live              -4.515e-02 -4.876e-01  4.177e-01 3788.000 0.84055
# relation           1.830e-01 -3.101e-01  7.027e-01 3788.000 0.46990
# ete               -2.768e-01 -6.562e-01  1.293e-01 3788.000 0.16631
# where              5.862e-03 -3.999e-01  3.813e-01 3788.000 0.96515
# life               5.916e-02 -5.461e-01  6.621e-01 3626.543 0.85692
# drugs              3.732e-01 -4.184e-02  7.686e-01 3788.000 0.07286 .
# physical          -5.830e-01 -1.066e+00 -9.352e-02 3788.000 0.01637 *
# emotion           -1.969e-01 -5.928e-01  2.221e-01 3788.000 0.34108
# self               3.657e-01 -2.260e-01  9.803e-01 3626.078 0.24762
# think              1.291e-01 -4.249e-01  7.506e-01 4030.452 0.67265
# attitude           4.791e-02 -5.148e-01  6.127e-01 3788.000 0.86642
# change             2.638e-01 -3.221e-01  8.180e-01 3788.000 0.36589
# bme:time           9.258e+01 -2.451e+02  4.942e+02    5.031 0.75502
# bme:live          -2.992e+03 -6.403e+03  1.768e+02    2.077 0.12091
# time:live          1.617e-02 -8.317e-02  1.095e-01 3190.312 0.73495
# bme:relation       3.027e+02 -1.924e+03  2.533e+03    5.787 0.75290
# time:relation      4.322e-03 -1.083e-01  1.202e-01 3788.000 0.94034
# bme:ete            1.134e+03  3.059e+02  1.902e+03    2.560 < 3e-04 ***
# time:ete           1.059e-01  1.862e-02  1.981e-01 3788.000 0.01637 *
# bme:where          3.182e+03  1.073e+03  5.074e+03    5.815 < 3e-04 ***
# time:where         1.263e-02 -6.319e-02  8.586e-02 3587.579 0.75977
```

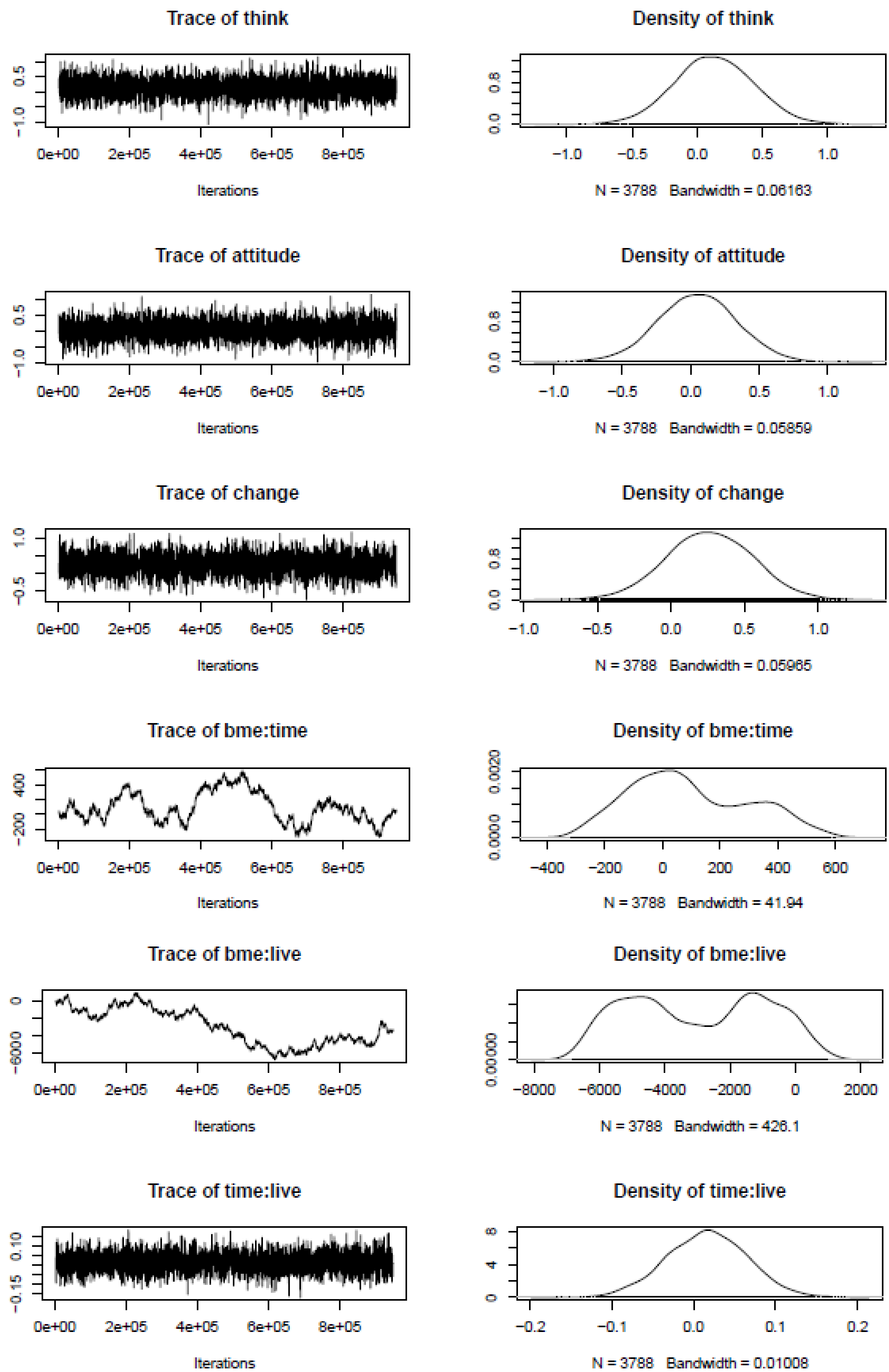
```
# bme:life           1.826e+03 -3.642e+03  7.020e+03    3.417 0.68532
# time:life         -1.983e-02 -1.535e-01  9.794e-02 3411.550 0.76346
# bme:drugs         -4.159e+03 -7.652e+03 -5.366e+02    4.040 0.01584 *
# time:drugs        -5.296e-02 -1.480e-01  2.746e-02 3788.000 0.21595
# bme:physical       2.834e+03 -5.230e+02  6.935e+03    4.854 0.17107
# time:physical      1.437e-01  2.539e-02  2.628e-01 3788.000 0.01690 *
# bme:emotion        2.114e+02 -3.392e+02  6.880e+02    5.331 0.56019
# time:emotion       5.068e-02 -3.738e-02  1.338e-01 3426.153 0.24393
# bme:self           2.670e+03  7.365e+02  4.807e+03    2.603 < 3e-04 ***
# time:self         -1.164e-01 -2.346e-01  5.888e-03 3788.000 0.05755 .
# bme:think         -5.015e+03 -8.640e+03 -1.847e+03    4.417 < 3e-04 ***
# time:think        -4.337e-02 -1.732e-01  8.765e-02 4052.388 0.49578
# bme:attitude       5.100e+03  1.193e+03  8.550e+03    5.882 < 3e-04 ***
# time:attitude     -1.411e-02 -1.410e-01  1.091e-01 3788.000 0.80781
# bme:change        -4.327e+02 -2.133e+03  1.198e+03    4.390 0.75766
# time:change       -1.619e-02 -1.450e-01  1.036e-01 4035.009 0.78933
# bme:time:live      2.532e+02 -2.550e+02  8.112e+02    3.544 0.36642
# bme:time:relation -7.506e+02 -2.087e+03  4.111e+02    5.198 0.43770
# bme:time:ete       1.053e+02 -2.126e+02  4.236e+02    9.685 0.59662
# bme:time:where     2.860e+02 -1.205e+02  9.193e+02    3.853 0.38332
# bme:time:life      3.332e+02 -1.106e+03  1.927e+03    4.104 0.83105
# bme:time:drugs    -2.891e+02 -9.244e+02  4.320e+02    3.754 0.61140
# bme:time:physical -6.738e+02 -1.751e+03  2.545e+02    4.368 0.27138
# bme:time:emotion   6.762e+02  1.719e+02  1.145e+03    4.573 0.01214 *
# bme:time:self     -9.421e+02 -1.468e+03 -2.519e+02    3.592 < 3e-04 ***
# bme:time:think     3.535e+02 -1.506e+01  8.676e+02    6.752 0.07973 .
# bme:time:attitude  6.794e+02 -1.384e+02  1.745e+03    5.509 0.22281
# bme:time:change   -8.833e+02 -1.613e+03 -2.127e+02    4.370 0.00264 **
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

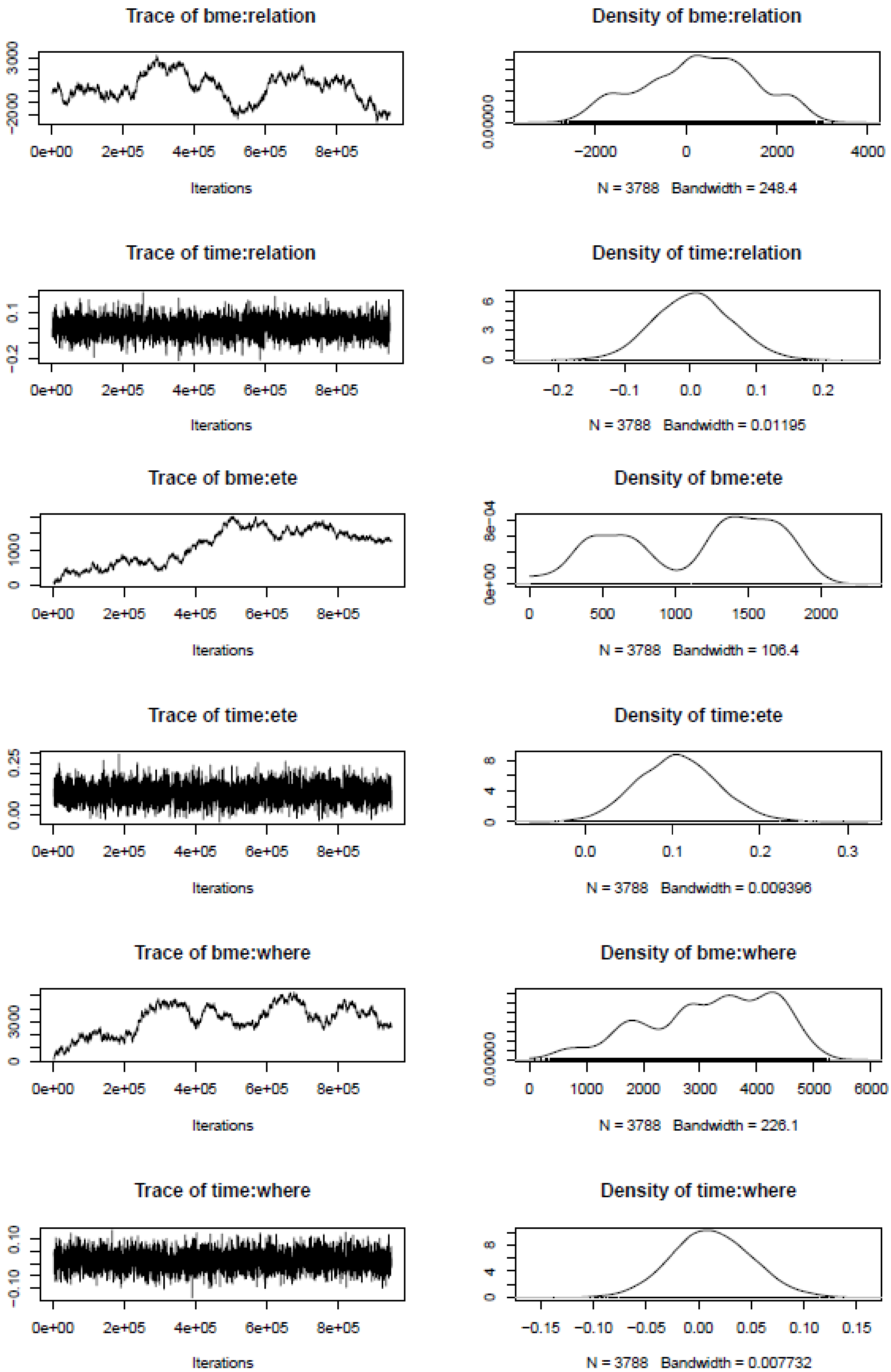
Trace of the Sampled Output and Density Estimates

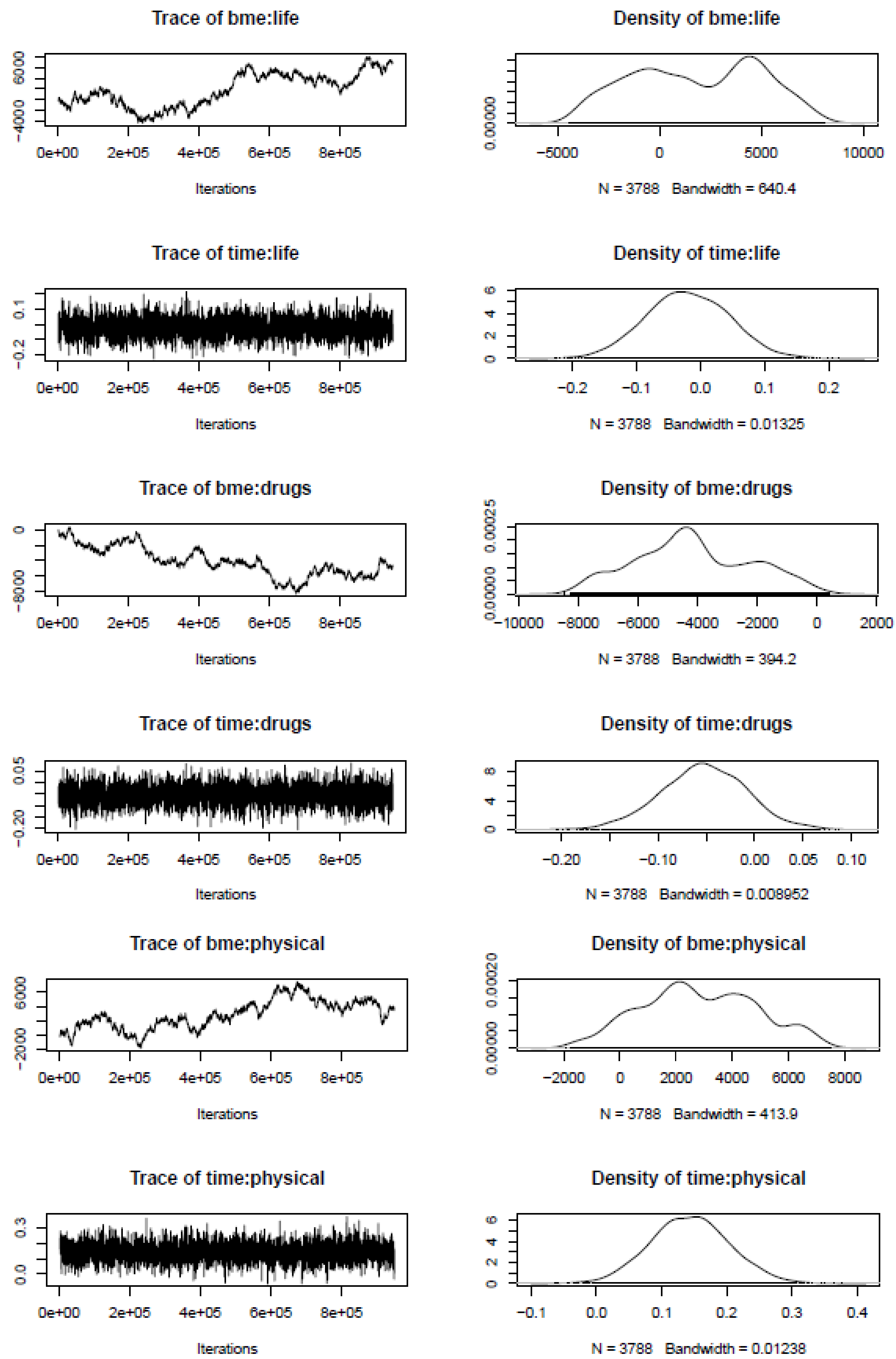
<u>Fixed Effects</u>

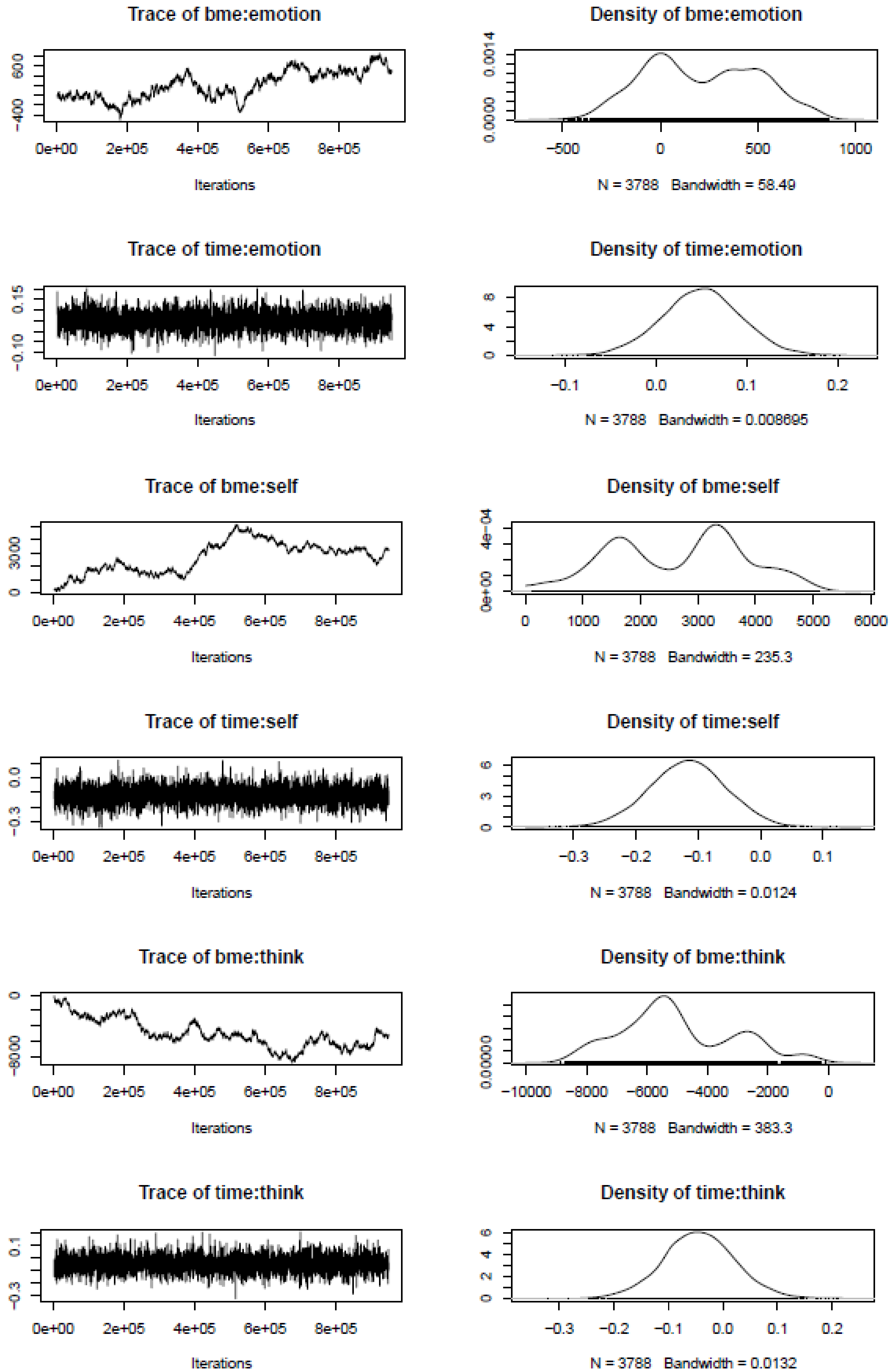


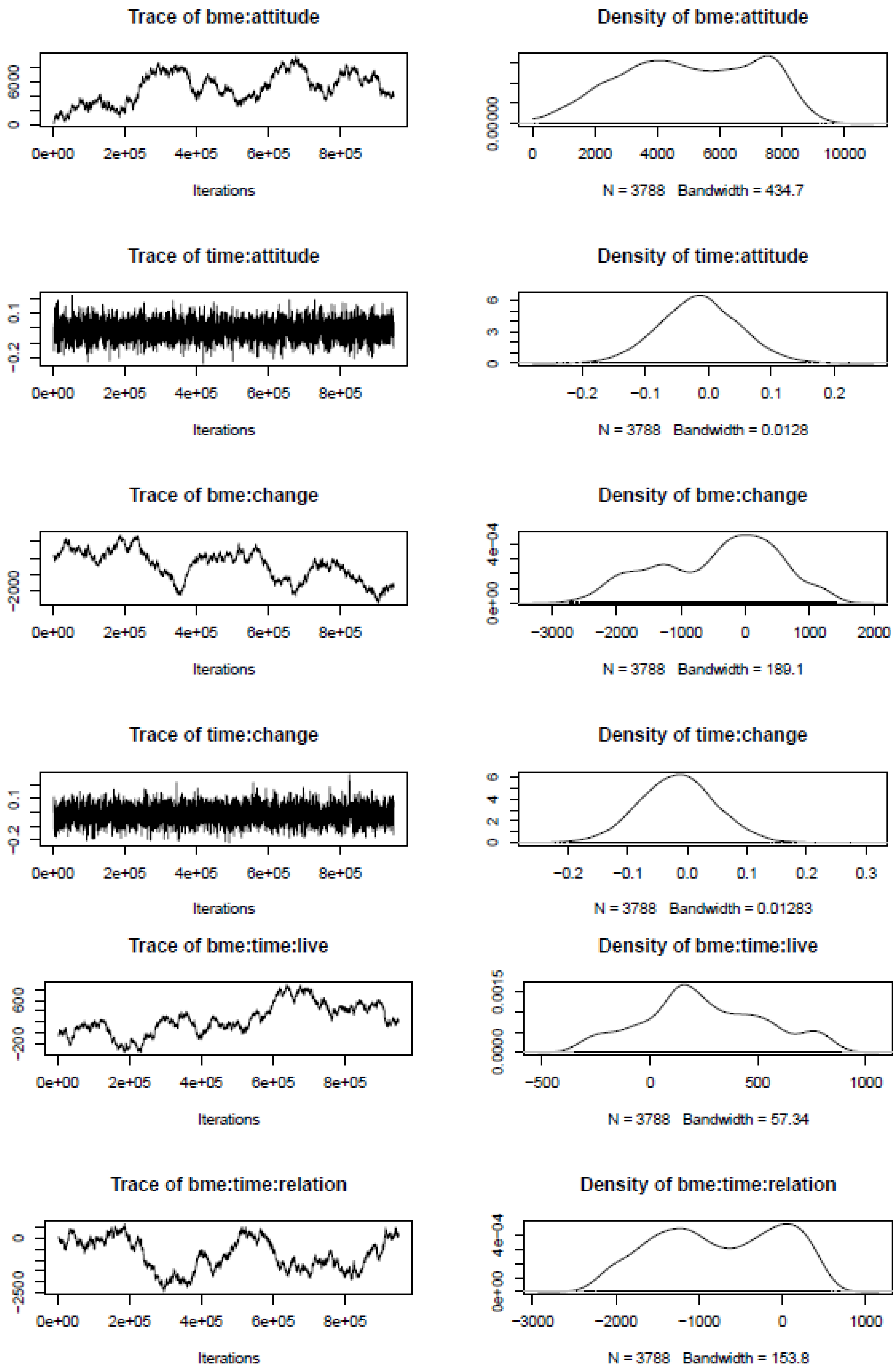

Trace of where
Iterations
Density of where
N = 3788 Bandwidth = 0.03973
Trace of life
Iterations
Density of life
N = 3788 Bandwidth = 0.06269
Trace of drugs
Iterations
Density of drugs
N = 3788 Bandwidth = 0.04201
Trace of physical
Iterations
Density of physical
N = 3788 Bandwidth = 0.04884
Trace of emotion
Iterations
Density of emotion
N = 3788 Bandwidth = 0.0409
Trace of self
Iterations
Density of self
N = 3788 Bandwidth = 0.06333

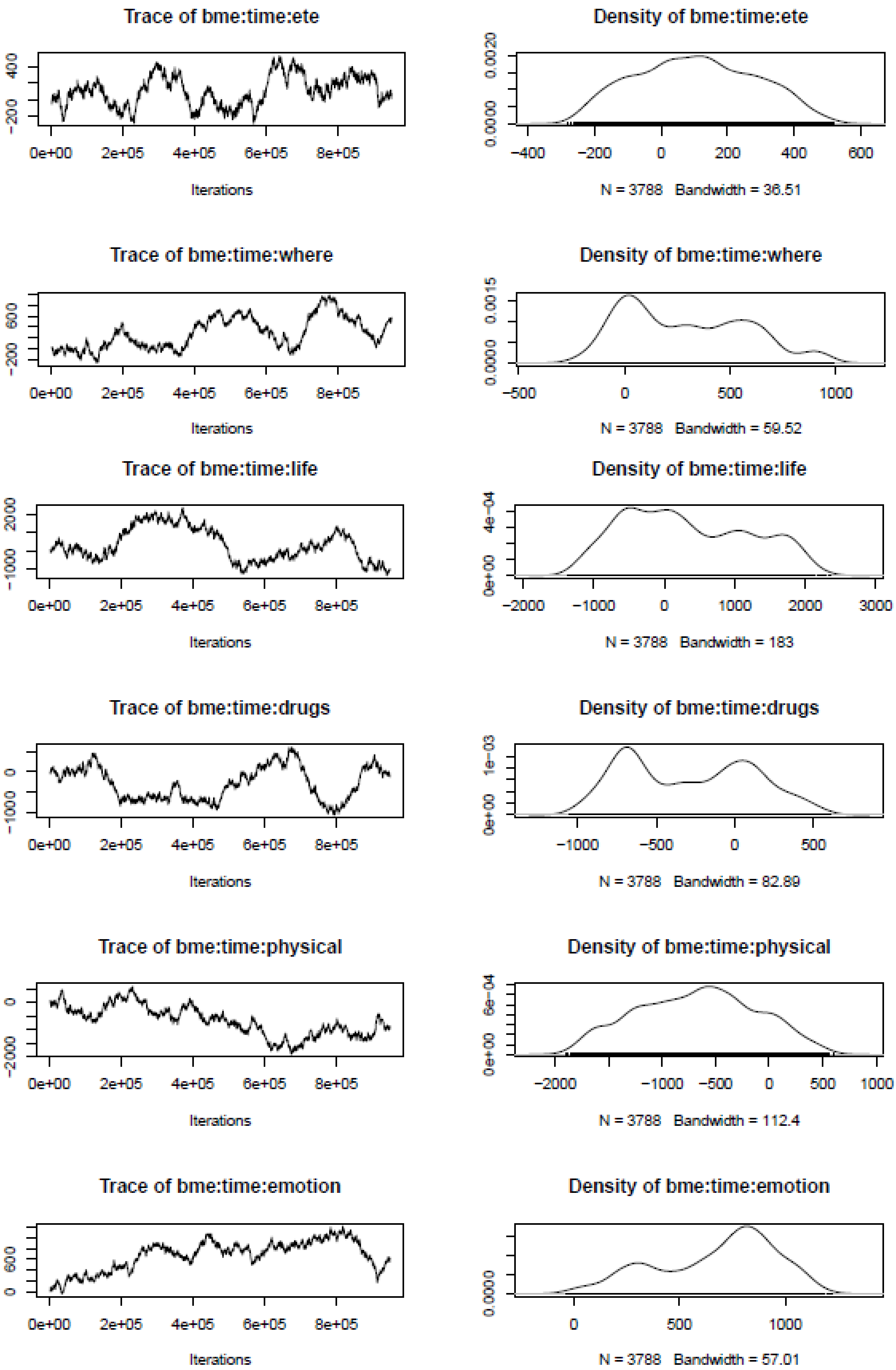

Trace of think
Iterations
Density of think
N = 3788 Bandwidth = 0.06163
Trace of attitude
Iterations
Density of attitude
N = 3788 Bandwidth = 0.05859
Trace of change
Iterations
Density of change
N = 3788 Bandwidth = 0.05965
Trace of bme:time
Iterations
Density of bme:time
N = 3788 Bandwidth = 41.94
Trace of bme:live
Iterations
Density of bme:live
N = 3788 Bandwidth = 426.1
Trace of time:live
Iterations
Density of time:live
N = 3788 Bandwidth = 0.01008

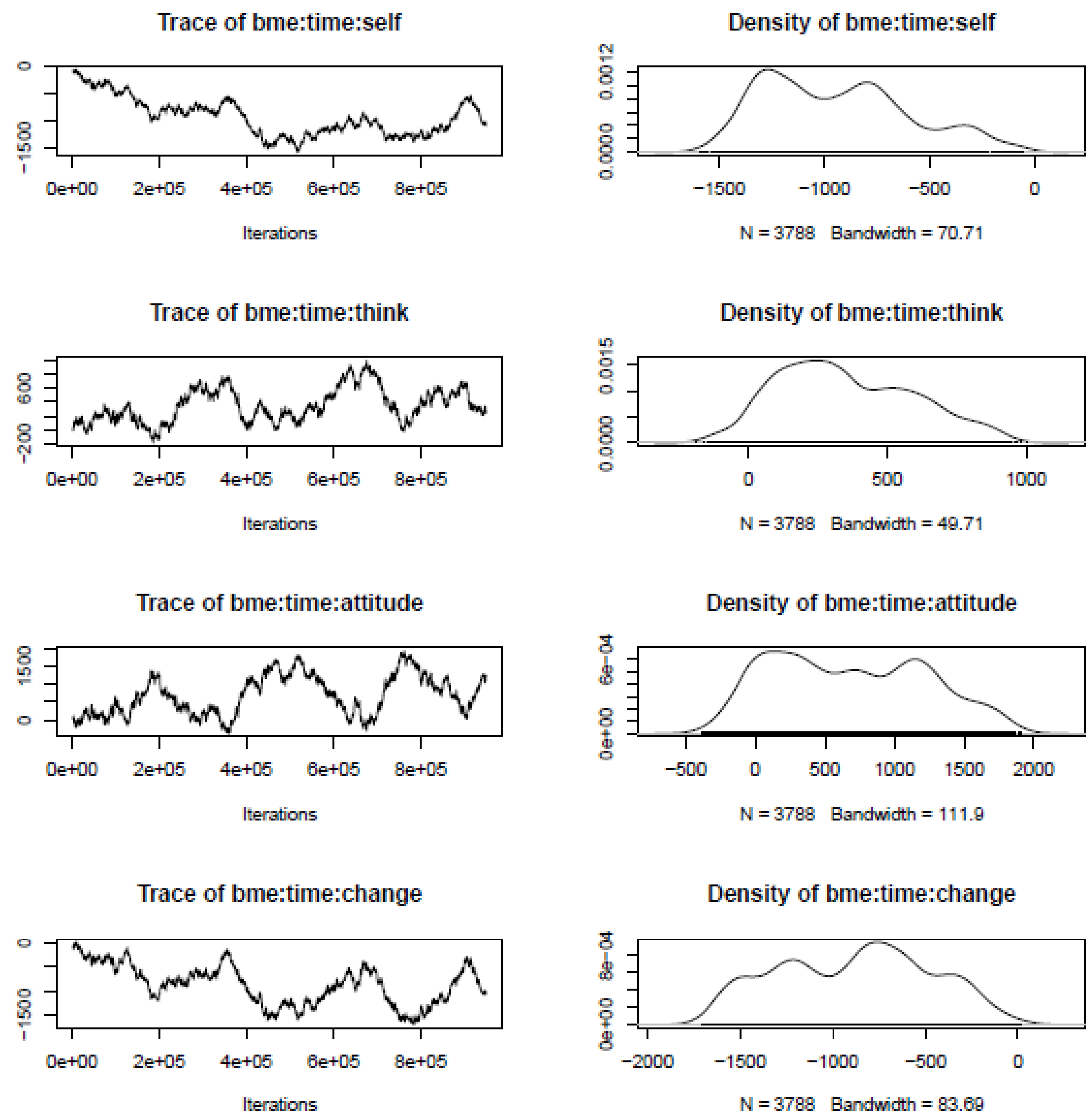

Trace of bme:relation
Iterations
Density of bme:relation
N = 3788 Bandwidth = 248.4
Trace of time:relation
Iterations
Density of time:relation
N = 3788 Bandwidth = 0.01195
Trace of bme:ete
Iterations
Density of bme:ete
N = 3788 Bandwidth = 106.4
Trace of time:ete
Iterations
Density of time:ete
N = 3788 Bandwidth = 0.009396
Trace of bme:where
Iterations
Density of bme:where
N = 3788 Bandwidth = 226.1
Trace of time:where
Iterations
Density of time:where
N = 3788 Bandwidth = 0.007732


Trace of bme:life
Iterations
Density of bme:life
N = 3788 Bandwidth = 640.4
Trace of time:life
Iterations
Density of time:life
N = 3788 Bandwidth = 0.01325
Trace of bme:drugs
Iterations
Density of bme:drugs
N = 3788 Bandwidth = 394.2
Trace of time:drugs
Iterations
Density of time:drugs
N = 3788 Bandwidth = 0.008952
Trace of bme:physical
Iterations
Density of bme:physical
N = 3788 Bandwidth = 413.9
Trace of time:physical
Iterations
Density of time:physical
N = 3788 Bandwidth = 0.01238

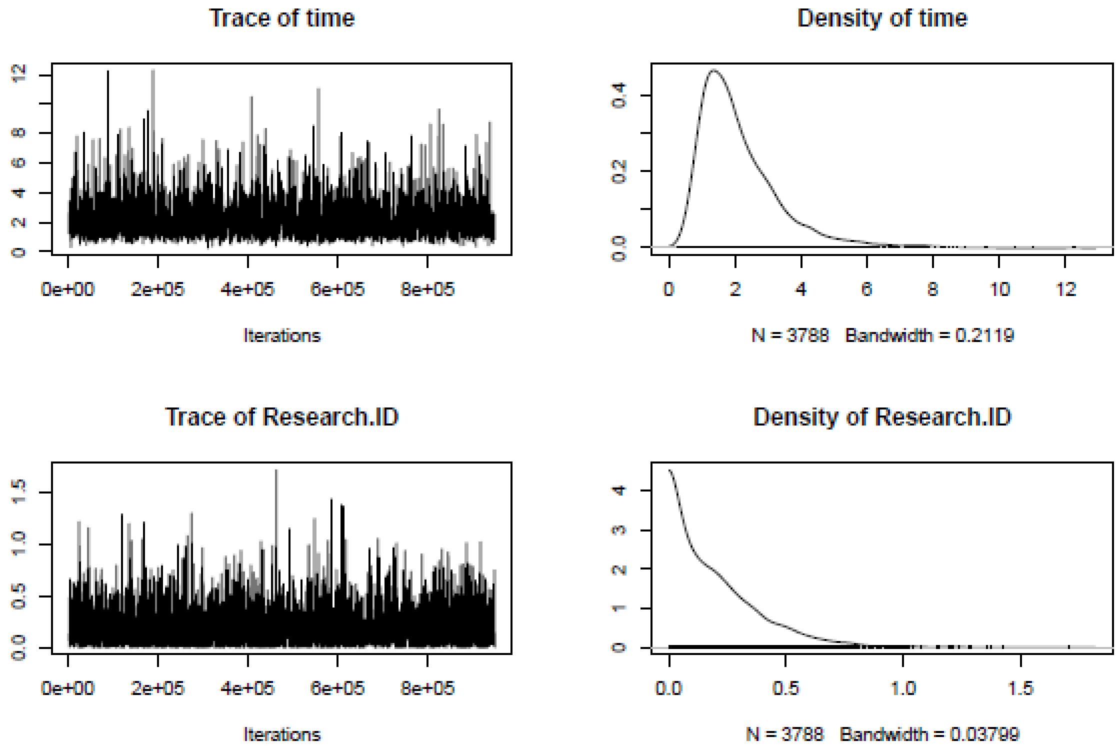

Trace of bme:emotion
-400
600
0e+00
2e+05
4e+05
6e+05
8e+05
Iterations
Density of bme:emotion
0.0000
0.0014
-500
0
500
1000
N = 3788 Bandwidth = 58.49
Trace of time:emotion
-0.10
0.15
0e+00
2e+05
4e+05
6e+05
8e+05
Iterations
Density of time:emotion
0
4
8
-0.1
0.0
0.1
0.2
N = 3788 Bandwidth = 0.008695
Trace of bme:self
0
3000
0e+00
2e+05
4e+05
6e+05
8e+05
Iterations
Density of bme:self
0e+00
4e-04
0
1000
2000
3000
4000
5000
6000
N = 3788 Bandwidth = 235.3
Trace of time:self
-0.3
0.0
0e+00
2e+05
4e+05
6e+05
8e+05
Iterations
Density of time:self
0
3
6
-0.3
-0.2
-0.1
0.0
0.1
N = 3788 Bandwidth = 0.0124
Trace of bme:think
-8000
0
0e+00
2e+05
4e+05
6e+05
8e+05
Iterations
Density of bme:think
0.00000
-10000
-8000
-6000
-4000
-2000
0
N = 3788 Bandwidth = 383.3
Trace of time:think
-0.3
0.1
0e+00
2e+05
4e+05
6e+05
8e+05
Iterations
Density of time:think
0
2
4
6
-0.3
-0.2
-0.1
0.0
0.1
0.2
N = 3788 Bandwidth = 0.0132


Trace of bme:attitude
Iterations
Density of bme:attitude
N = 3788 Bandwidth = 434.7
Trace of time:attitude
Iterations
Density of time:attitude
N = 3788 Bandwidth = 0.0128
Trace of bme:change
Iterations
Density of bme:change
N = 3788 Bandwidth = 189.1
Trace of time:change
Iterations
Density of time:change
N = 3788 Bandwidth = 0.01283
Trace of bme:time:live
Iterations
Density of bme:time:live
N = 3788 Bandwidth = 57.34
Trace of bme:time:relation
Iterations
Density of bme:time:relation
N = 3788 Bandwidth = 153.8


Trace of bme:time:ete
Iterations
Density of bme:time:ete
N = 3788 Bandwidth = 36.51
Trace of bme:time:where
Iterations
Density of bme:time:where
N = 3788 Bandwidth = 59.52
Trace of bme:time:life
Iterations
Density of bme:time:life
N = 3788 Bandwidth = 183
Trace of bme:time:drugs
Iterations
Density of bme:time:drugs
N = 3788 Bandwidth = 82.89
Trace of bme:time:physical
Iterations
Density of bme:time:physical
N = 3788 Bandwidth = 112.4
Trace of bme:time:emotion
Iterations
Density of bme:time:emotion
N = 3788 Bandwidth = 57.01


Trace of bme:time:self
Density of bme:time:self
Iterations
N = 3788 Bandwidth = 70.71
Trace of bme:time:think
Density of bme:time:think
Iterations
N = 3788 Bandwidth = 49.71
Trace of bme:time:attitude
Density of bme:time:attitude
Iterations
N = 3788 Bandwidth = 111.9
Trace of bme:time:change
Density of bme:time:change
Iterations
N = 3788 Bandwidth = 83.69

Random Effects



Model 1.4 – Basic Model + Care (Table 5.11)

Bayesian Model (Bm1_ch)

Define the model

```
Bm1_ch <- MCMCglmm(FO.bin~careExp + live + relation + ete + where + life
+ drugs + physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=45000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_ch$VCV)
heidel.diag(Bm1_ch$VCV)

# > raftery.diag(Bm1_ch$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         40       47810  3746         12.8
# Research.ID 140       161340 3746         43.1
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_ch$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed         1         0.325
# Research.ID passed          1         0.381
# units        failed        NA            NA
#
#              Halfwidth Mean   Halfwidth
#              test
# time         passed    1.2909 0.0279
# Research.ID failed     0.0919 0.0179
# units        <NA>          NA     NA


autocorr(Bm1_ch$VCV)
autocorr(Bm1_ch$Sol)  #Output not included here
summary(Bm1_ch)


# > autocorr(Bm1_ch$VCV)
# , , time
#
#                   time Research.ID units
# Lag 0     1.00000000 0.103044572   NaN
# Lag 10    0.17842345 0.089227846   NaN
# Lag 50    0.01527860 0.063190835   NaN
# Lag 100   0.01412455 0.018619479   NaN
# Lag 500 -0.01119659 0.001229506   NaN
```

```
# , , Research.ID
#
#                time Research.ID units
# Lag 0   0.10304457  1.00000000   NaN
# Lag 10  0.08794714  0.85296995   NaN
# Lag 50  0.07012424  0.56303723   NaN
# Lag 100 0.03567890  0.39473928   NaN
# Lag 500 0.01213976 -0.02964642   NaN

# > summary(Bm1_ch)
#
# Iterations = 3001:44991
# Thinning interval  = 10
# Sample size  = 4200
#
# DIC: 473.4785
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.291   0.3486    2.634     2251
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID   0.09192 0.0001851   0.3479    181.4
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ careExp + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time
#
#             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -1.231971 -2.471842  0.005721     2306 0.0533 .
# careExp      0.500442  0.015506  0.966553     1823 0.0367 *
# live         0.018145 -0.222019  0.282261     1579 0.8838
# relation     0.216831 -0.071174  0.515904     1836 0.1367
# ete          0.139449 -0.106452  0.391722     1600 0.2700
# where        0.010304 -0.227048  0.207897     1691 0.9290
# life         0.099242 -0.247519  0.460059     1757 0.5833
# drugs        0.147229 -0.091833  0.384890     1459 0.2190
# physical    -0.088006 -0.376450  0.178860     1731 0.5333
# emotion     -0.042499 -0.292168  0.194430     1608 0.7376
# self        -0.142212 -0.448259  0.164266     1775 0.3690
# think       -0.168944 -0.528077  0.146318     1659 0.3295
# attitude    -0.011636 -0.360112  0.327539     1936 0.9629
# change       0.247410 -0.101729  0.582791     1717 0.1519
# time        -0.160202 -0.303996 -0.035370     1817 0.0181 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_ch)

```
m1_ch <- glmer(FO.bin ~ careExp + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_ch)
vcomps.icc(m1_ch)
anova(m1,m1_ch)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ careExp + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 638.2    715.6   -301.1    602.2      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.8429 -0.6641 -0.3578  0.7878  3.9355
#
# Random effects:
# Groups     Name          Variance Std.Dev.  Corr
# Individual (Intercept)    0.05704  0.2388
#            time           0.05252  0.2292   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.88631    0.32204  -2.752  0.00592 **
# careExp      0.57019    0.27349   2.085  0.03708 *
# live        -0.07663    0.14187  -0.540  0.58909
# relation     0.12688    0.16017   0.792  0.42828
# ete          0.05676    0.13232   0.429  0.66794
# where        0.13726    0.12793   1.073  0.28330
# life         0.09480    0.19472   0.487  0.62634
# drugs        0.24731    0.13302   1.859  0.06300 .
# physical    -0.19492    0.14969  -1.302  0.19288
# emotion     -0.07064    0.13464  -0.525  0.59979
# self        -0.08128    0.17519  -0.464  0.64267
# think        0.12101    0.18743   0.646  0.51851
# attitude    -0.10310    0.19247  -0.536  0.59219
# change       0.19631    0.18254   1.075  0.28219
# time        -0.44605    0.10475  -4.258 2.06e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.0590983 (tol = 0.001,
component 1)

# vcomps.icc(m1_ch)
# Var (Level 2) Var (Level 1)          ICC          <NA>
#        0.057         0.053        1.000         0.521
```

```
# anova(m1,m1_ch)
# Data: data
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1_ch: FO.bin ~ careExp + live + relation + ete + where + life + drugs
+
#   m1_ch:     physical + emotion + self + think + attitude + change +
time
#   m1_ch:     (time | Individual)
#       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1    17 640.59 713.70 -303.29   606.59
# m1_ch 18 638.16 715.58 -301.08   602.16 4.4241      1    0.03543 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Dynamic Model involving Care (Table 5.12)

Bayesian Model (BDm2_ch)

Define the model

```
BDm2_ch <- MCMCglmm(FO.bin ~ careExp*time*live + careExp*time*relation +
careExp*time*ete + careExp*time*where + careExp*time*life +
careExp*time*drugs + careExp*time*physical + careExp*time*emotion +
careExp*time*self + careExp*time*think + careExp*time*attitude +
careExp*time*change, random=~time+Research.ID, data=data,
family="ordinal",prior=priorD, slice=TRUE, nitt=610000, thin=50,
burnin=3000)
```

Checks for suitable convergence

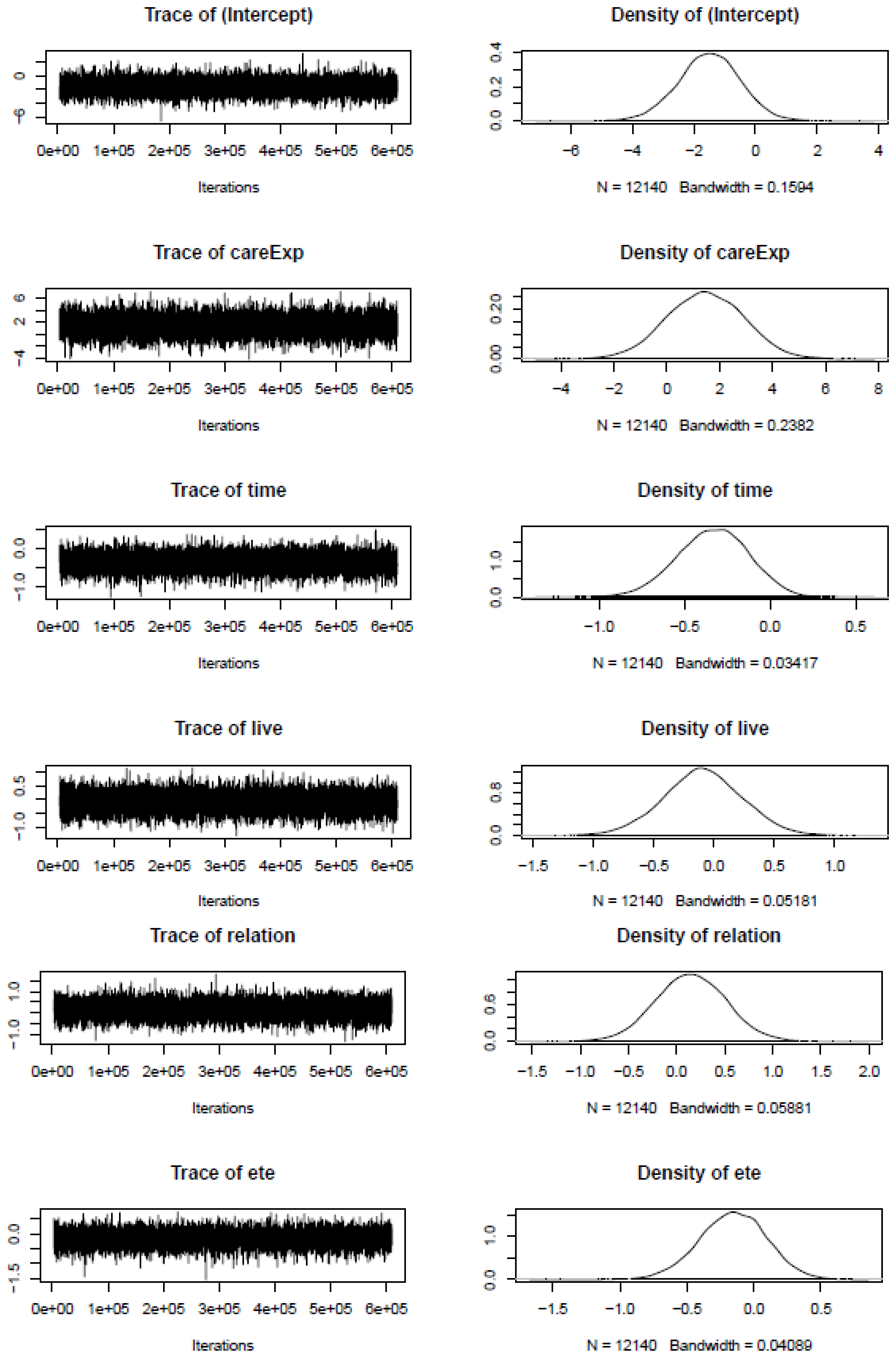
```
raftery.diag(BDm2_ch$VCV)
heidel.diag(BDm2_ch$VCV)

# > raftery.diag(BDm2_ch$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      190750 3746         50.9
# Research.ID 150       212600 3746         56.8
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm2_ch$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.709
# Research.ID passed         1         0.893
# units        failed       NA           NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    2.19 0.0436
# Research.ID passed     0.52 0.0119
# units        <NA>        NA     NA

autocorr(BDm2_ch$VCV)
autocorr(BDm2_ch$Sol)   # Output not included here
summary(BDm2_ch)

# > autocorr(BDm2_ch$VCV)
# , , time
#
#                  time  Research.ID units
# Lag 0      1.00000000 0.1763369024   NaN
# Lag 50     0.21161657 0.1089536873   NaN
# Lag 250    0.07316243 0.0128896879   NaN
# Lag 500    0.03507482 0.0033102515   NaN
# Lag 2500 -0.01381879 0.0006672579   NaN
```

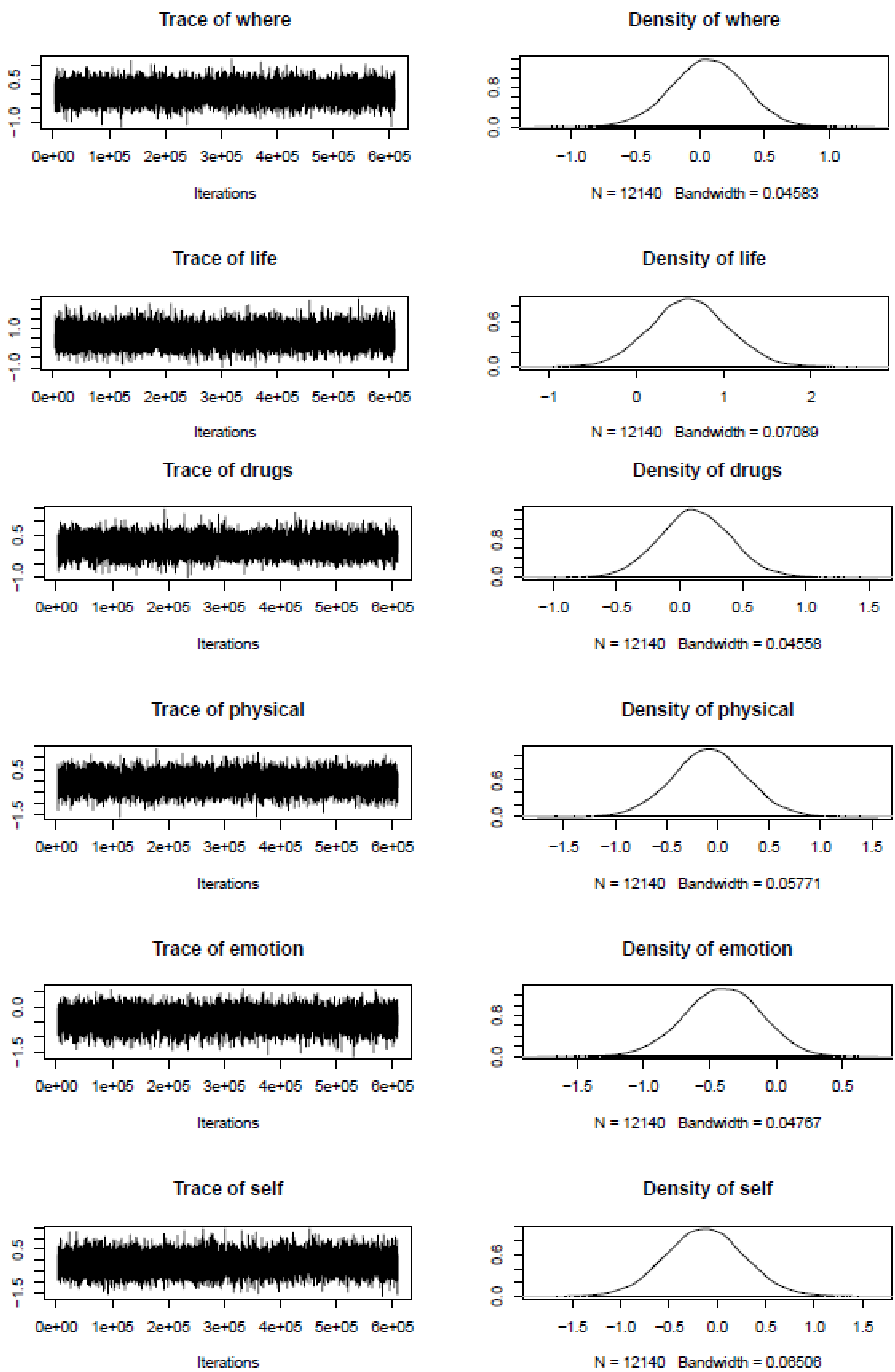
```
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0    0.176336902  1.000000000   NaN
# Lag 50   0.092697981  0.327867146   NaN
# Lag 250  0.012944845  0.036265473   NaN
# Lag 500  0.010912702  0.006884412   NaN
# Lag 2500 0.000570001 -0.014192001   NaN

# > summary(BDm2_ch)
#
# Iterations = 3001:609951
# Thinning interval  = 50
# Sample size  = 12140
#
# DIC: 471.3558
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.188   0.4347    4.774     3797
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.5204 9.933e-08    1.322     4846
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ careExp * time * live + careExp * time * relation + careExp * time * ete + careExp * time * where + careExp * time * life + careExp * time * drugs + careExp * time * physical + careExp * time * emotion + careExp * time * self + careExp * time * think + careExp * time * attitude + careExp * time * change
#
#                       post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept)          -1.5006060 -3.5068863  0.4385874    12140 0.1308
# careExp               1.4616134 -1.4186288  4.3093564    12140 0.3208
# time                 -0.3348908 -0.7527175  0.0661430    10864 0.1023
# live                 -0.0912494 -0.7292091  0.5524237    12140 0.7682
# relation              0.1489800 -0.5466273  0.8834765    12140 0.6845
# ete                  -0.1569215 -0.6684595  0.3238617    10600 0.5433
# where                 0.0604514 -0.5006738  0.6084334    12140 0.8216
# life                  0.6111956 -0.2386689  1.4842207    11153 0.1667
# drugs                 0.1252316 -0.4354656  0.6724279    12490 0.6544
# physical             -0.0816915 -0.8040407  0.6326083    11542 0.8173
# emotion              -0.4047903 -0.9994379  0.1522395    10786 0.1651
# self                 -0.1291181 -0.9200429  0.6800993    12140 0.7470
# think                 0.0953434 -0.6760123  0.8577796    11742 0.8040
# attitude              0.0700295 -0.7504779  0.8708394    12140 0.8605
# change                0.2076011 -0.5193295  0.9598645    11782 0.5807
# careExp:time         -0.0747139 -0.7077206  0.5644968    11579 0.8117
# careExp:live          0.4526319 -0.5642784  1.5248171    12140 0.4026
# time:live            -0.0353201 -0.2017512  0.1209635    12416 0.6764
# careExp:relation     -0.0460228 -1.2487679  1.2217250    12140 0.9506
# time:relation         0.0054537 -0.1745003  0.1827576    12140 0.9389
# careExp:ete           0.2594888 -0.7528231  1.2737662    12140 0.6188
# time:ete              0.0572724 -0.0664879  0.1830022    12140 0.3735
# careExp:where        -0.3113261 -1.3084709  0.6729885    11338 0.5407
```

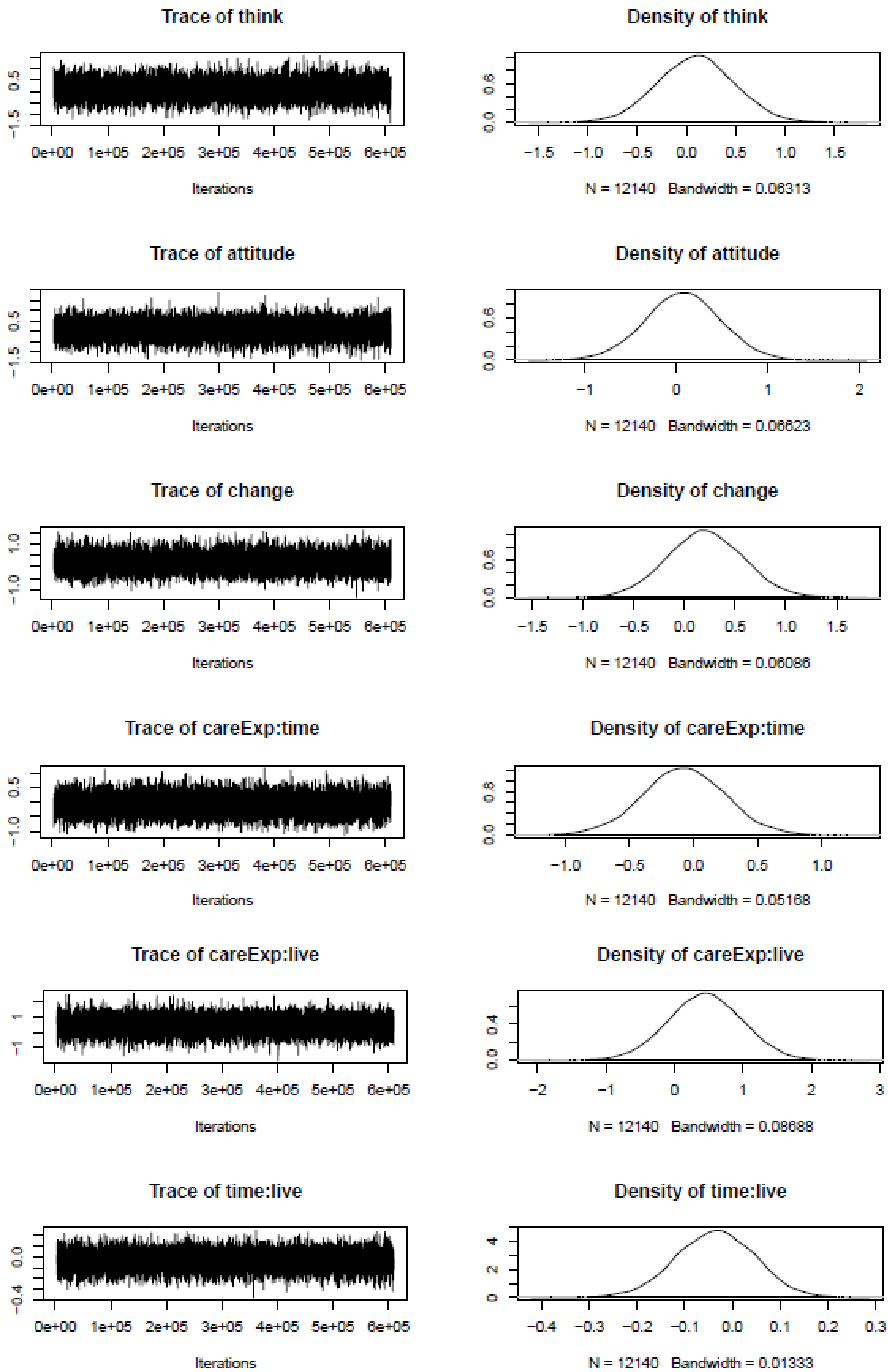
```
# time:where           -0.0538686 -0.1914446  0.0765889    11230 0.4288
# careExp:life         -0.6325248 -2.1092239  0.8256715    12406 0.3923
# time:life            -0.0051764 -0.1871814  0.1923293    11861 0.9540
# careExp:drugs         0.3260131 -0.6140927  1.2670934    12534 0.4932
# time:drugs            0.0363598 -0.1003575  0.1718449    11731 0.6097
# careExp:physical     -0.8900624 -2.1145396  0.3651294    10770 0.1590
# time:physical        -0.0423870 -0.2686424  0.1790588    11347 0.7147
# careExp:emotion       0.3923488 -0.6489381  1.4002455    11614 0.4549
# time:emotion          0.0528995 -0.0889530  0.1980607    11667 0.4723
# careExp:self          0.8715772 -0.5587058  2.3038163    11113 0.2329
# time:self             0.0719019 -0.1046936  0.2634116    12140 0.4445
# careExp:think        -0.8408783 -2.3139680  0.6180410    11816 0.2603
# time:think           -0.0121284 -0.2074019  0.1795310    11074 0.9056
# careExp:attitude     -0.1176196 -1.4198052  1.2722378    11550 0.8639
# time:attitude        -0.0945612 -0.2964184  0.1043443    12140 0.3677
# careExp:change        0.1257902 -1.3930247  1.5208195    11563 0.8524
# time:change           0.0266534 -0.1733894  0.2363857    12140 0.8064
# careExp:time:live     0.0210127 -0.1987465  0.2485695    11663 0.8619
# careExp:time:relation -0.0002072 -0.2833647  0.2782756    11624 0.9911
# careExp:time:ete      0.0044299 -0.1989134  0.2156877    11565 0.9634
# careExp:time:where    0.1777905 -0.0152111  0.3747486    12140 0.0697 .
# careExp:time:life    -0.0828341 -0.3738983  0.2001525    11541 0.5750
# careExp:time:drugs   -0.0723851 -0.2913360  0.1429795    11502 0.5115
# careExp:time:physical  0.2420940 -0.0631206  0.5322557    11487 0.1119
# careExp:time:emotion  0.0402425 -0.1949566  0.2788018    12140 0.7331
# careExp:time:self    -0.3409189 -0.6439077 -0.0449812    10560 0.0213 *
# careExp:time:think    0.0847188 -0.2086670  0.3877198    10400 0.5815
# careExp:time:attitude  0.1298185 -0.1740126  0.4431976    11599 0.4183
# careExp:time:change  -0.0580154 -0.3539014  0.2478403    11777 0.7025
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

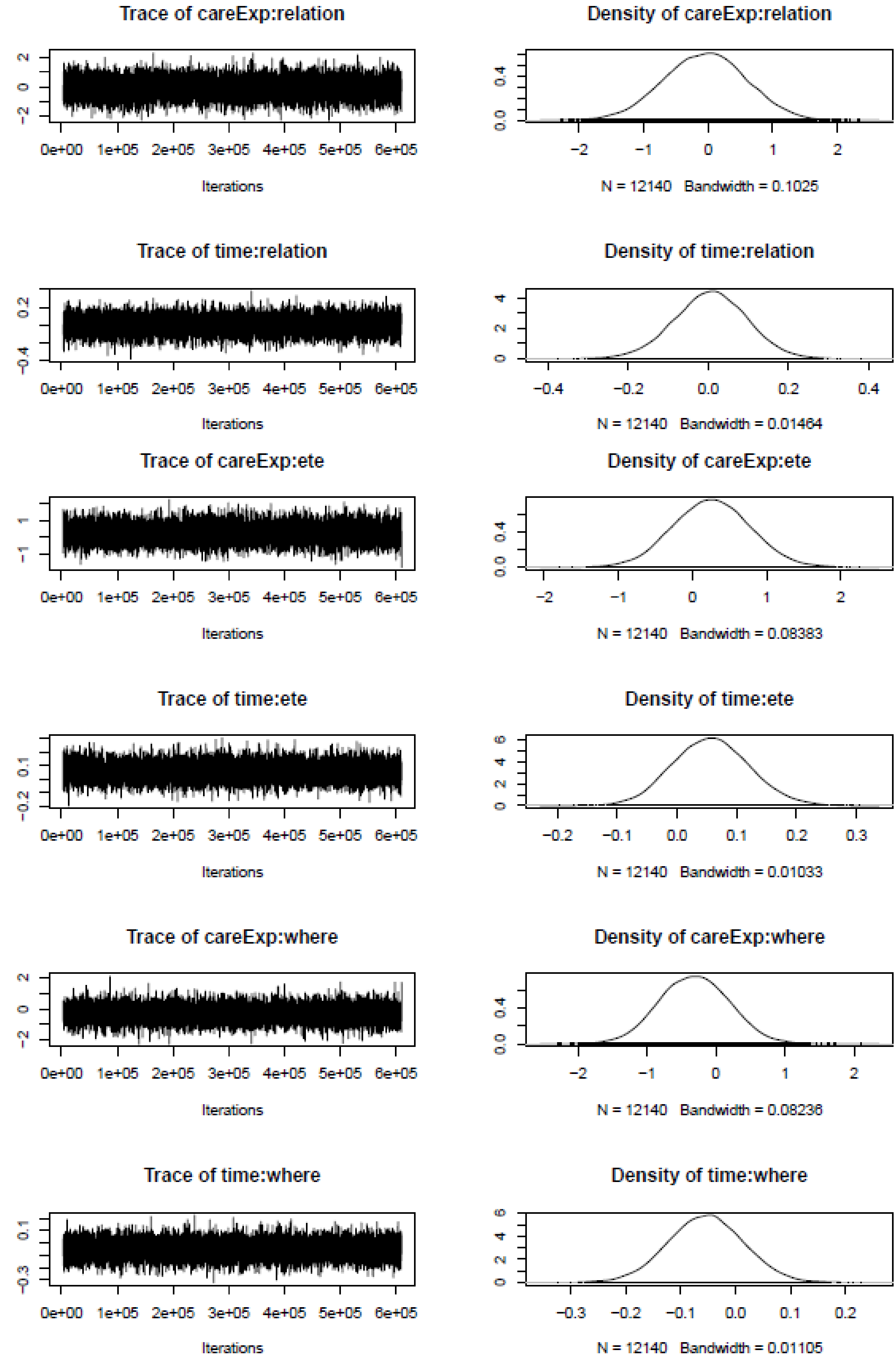
Trace of the Sampled Output and Density Estimates

Fixed Effects

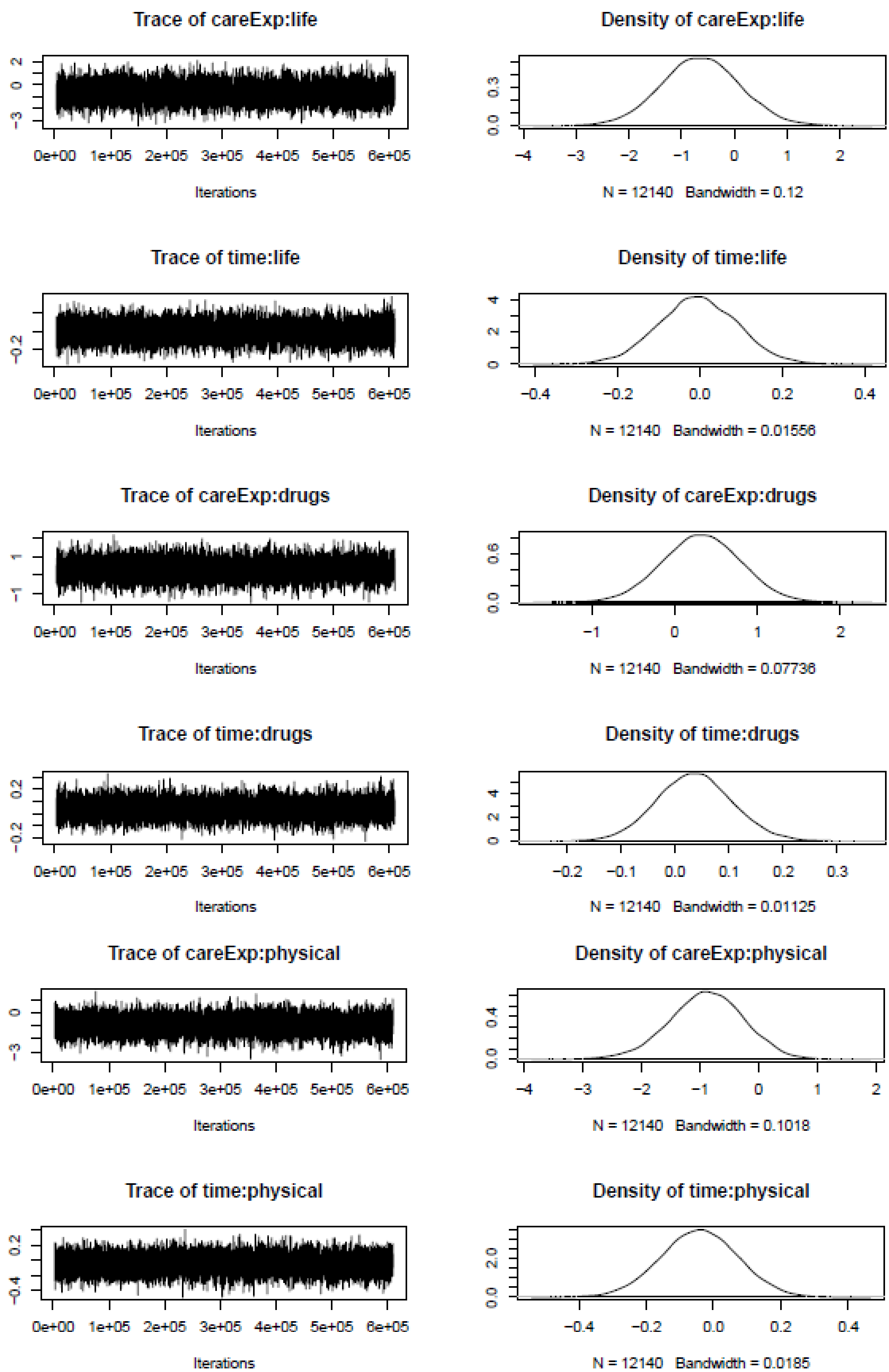


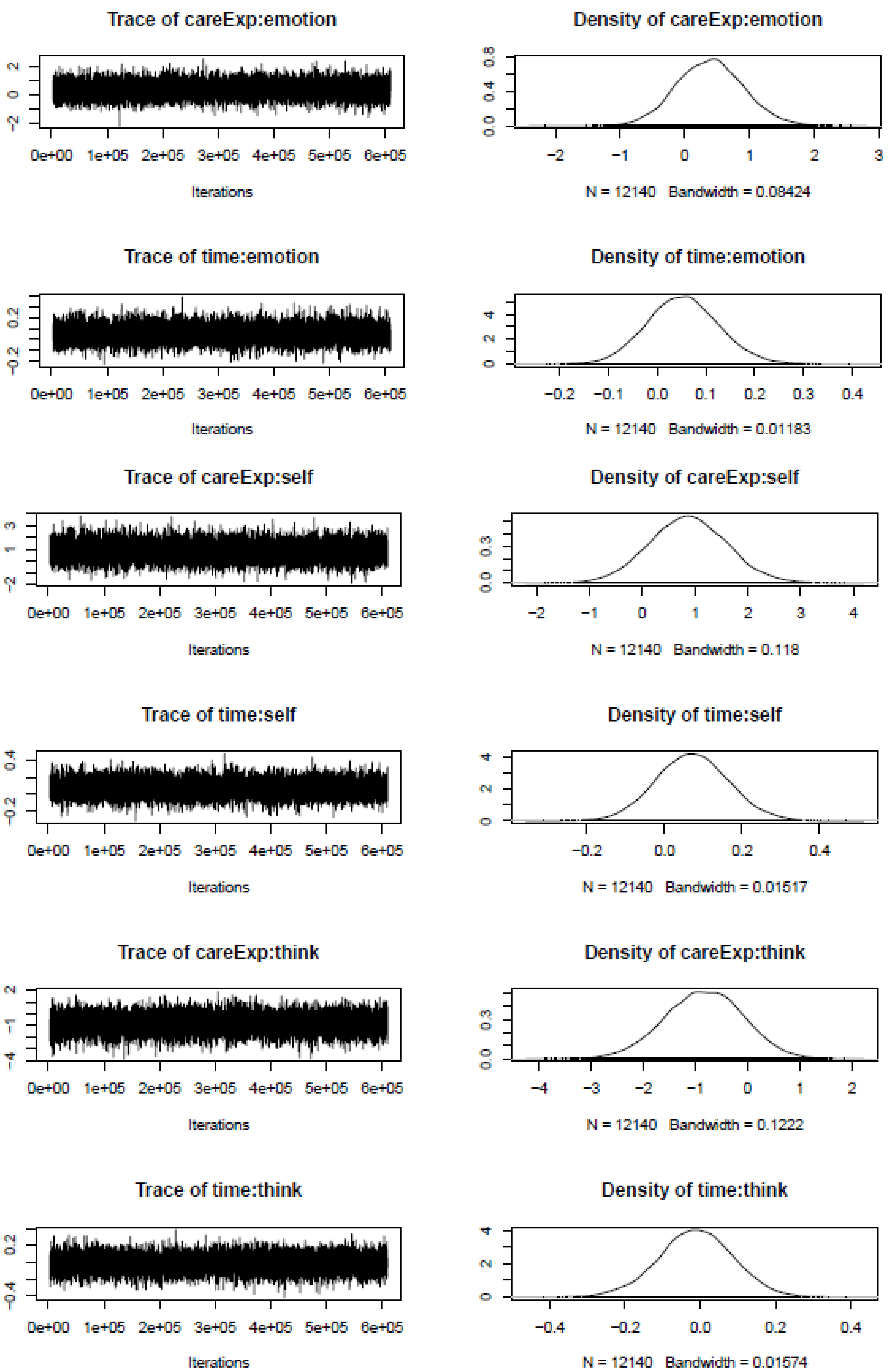

Trace of where
Iterations
Density of where
N = 12140 Bandwidth = 0.04583
Trace of life
Iterations
Density of life
N = 12140 Bandwidth = 0.07089
Trace of drugs
Iterations
Density of drugs
N = 12140 Bandwidth = 0.04558
Trace of physical
Iterations
Density of physical
N = 12140 Bandwidth = 0.05771
Trace of emotion
Iterations
Density of emotion
N = 12140 Bandwidth = 0.04767
Trace of self
Iterations
Density of self
N = 12140 Bandwidth = 0.06506

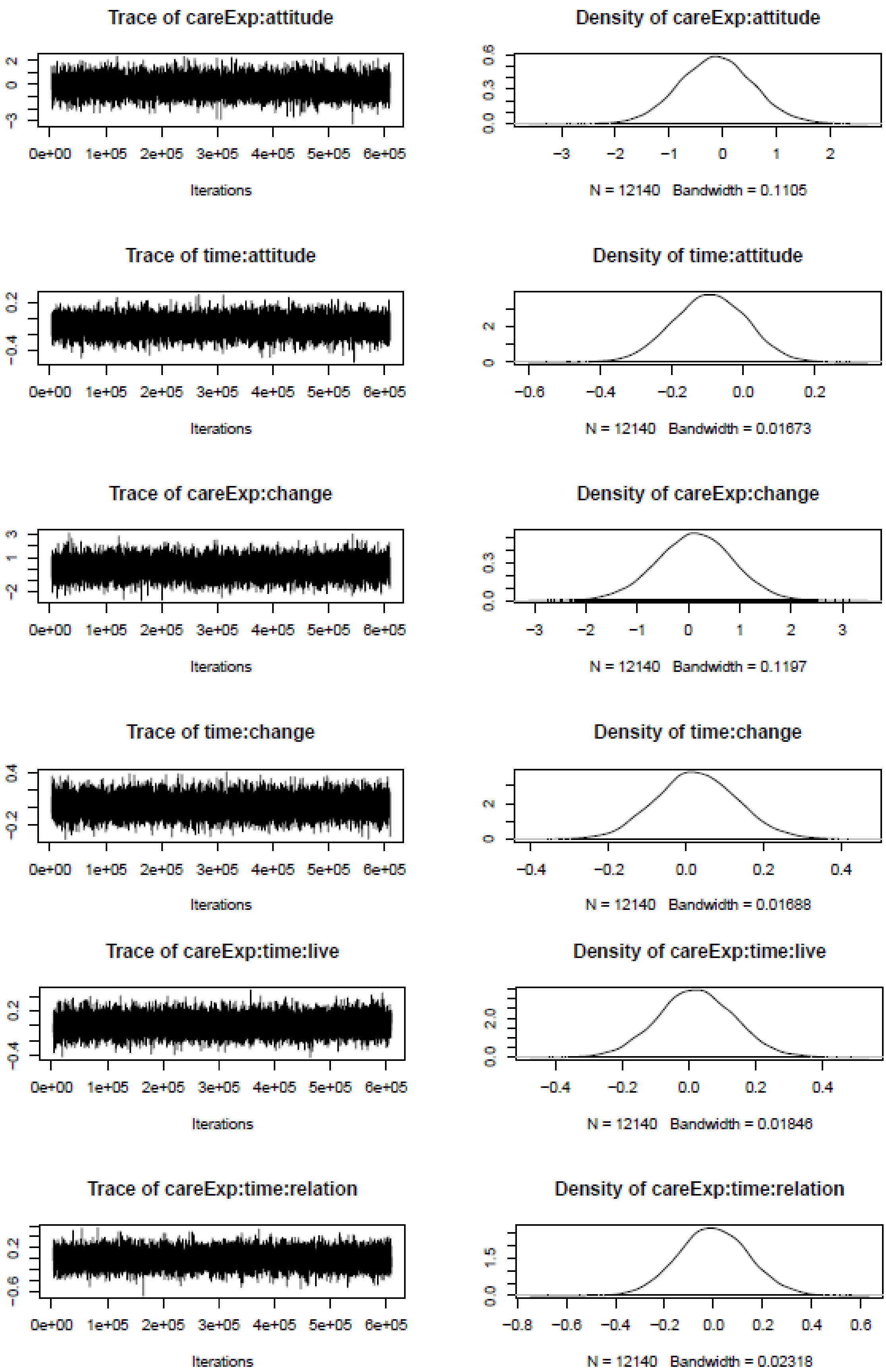

Trace of think
Iterations
Density of think
N = 12140 Bandwidth = 0.06313
Trace of attitude
Iterations
Density of attitude
N = 12140 Bandwidth = 0.06623
Trace of change
Iterations
Density of change
N = 12140 Bandwidth = 0.06086
Trace of careExp:time
Iterations
Density of careExp:time
N = 12140 Bandwidth = 0.05168
Trace of careExp:live
Iterations
Density of careExp:live
N = 12140 Bandwidth = 0.08688
Trace of time:live
Iterations
Density of time:live
N = 12140 Bandwidth = 0.01333

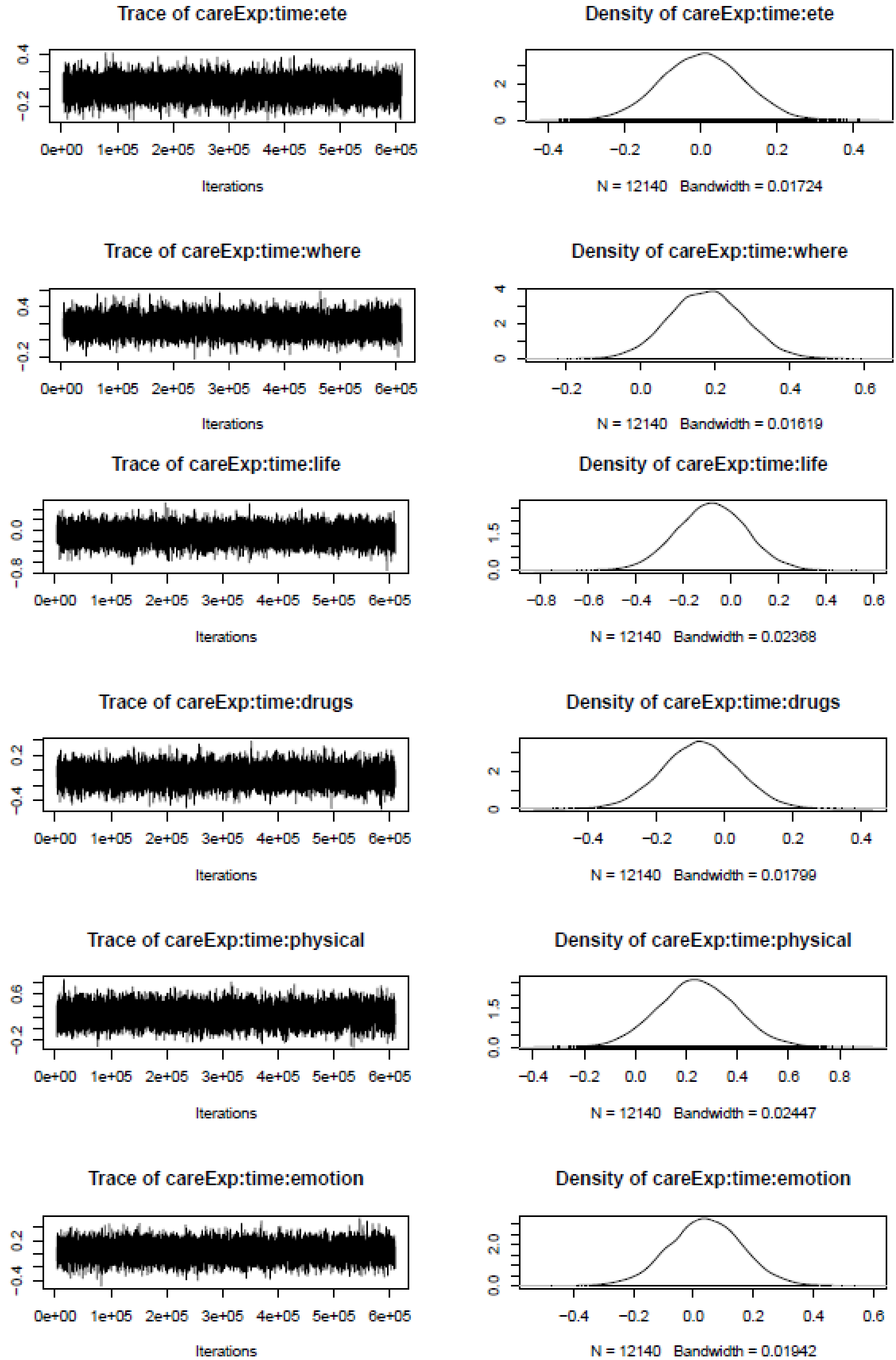


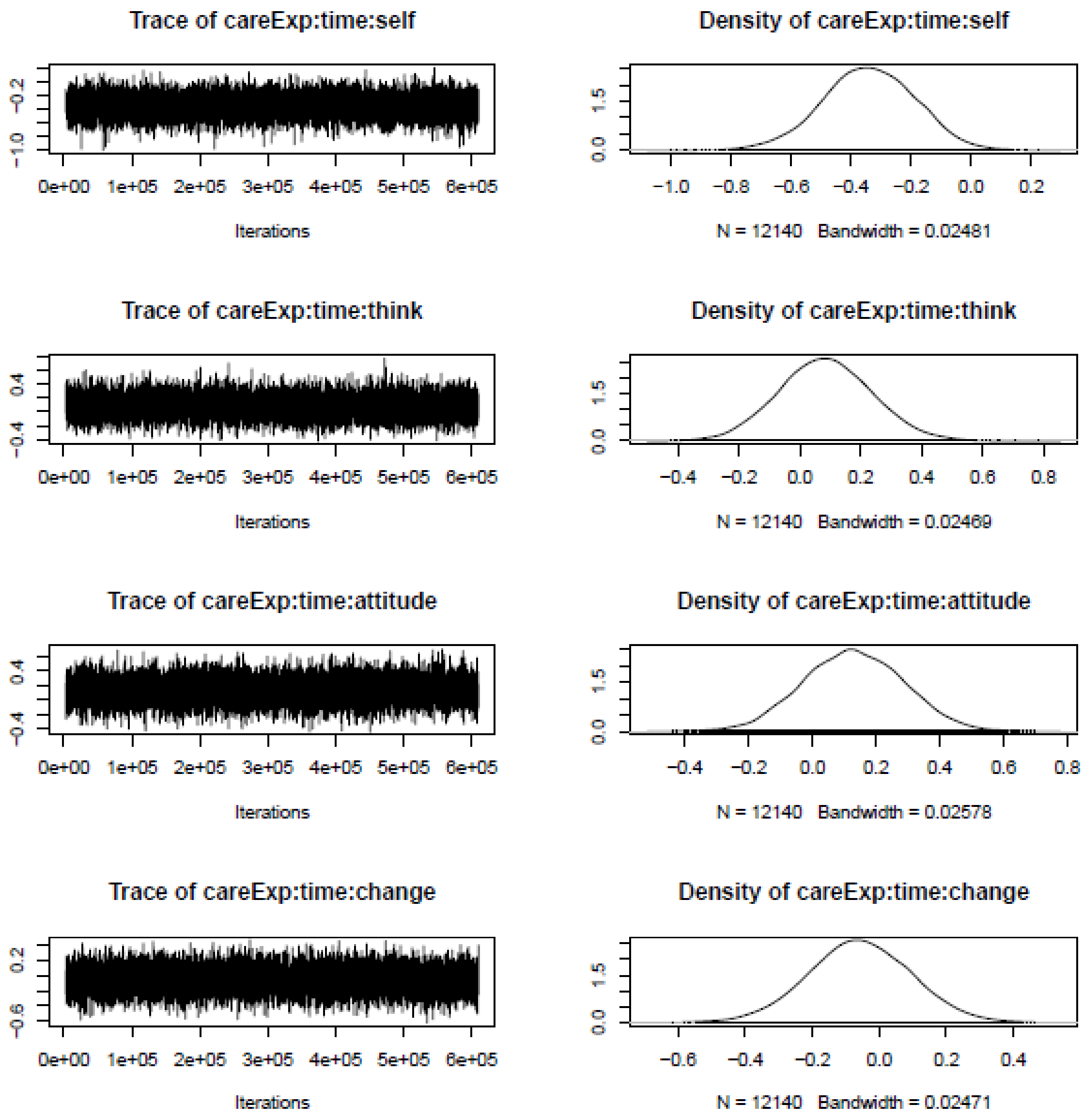
Trace of careExp:relation
Iterations
Density of careExp:relation
N = 12140 Bandwidth = 0.1025
Trace of time:relation
Iterations
Density of time:relation
N = 12140 Bandwidth = 0.01464
Trace of careExp:ete
Iterations
Density of careExp:ete
N = 12140 Bandwidth = 0.08383
Trace of time:ete
Iterations
Density of time:ete
N = 12140 Bandwidth = 0.01033
Trace of careExp:where
Iterations
Density of careExp:where
N = 12140 Bandwidth = 0.08236
Trace of time:where
Iterations
Density of time:where
N = 12140 Bandwidth = 0.01105


Trace of careExp:life
Density of careExp:life
Iterations
N = 12140 Bandwidth = 0.12
Trace of time:life
Density of time:life
Iterations
N = 12140 Bandwidth = 0.01556
Trace of careExp:drugs
Density of careExp:drugs
Iterations
N = 12140 Bandwidth = 0.07736
Trace of time:drugs
Density of time:drugs
Iterations
N = 12140 Bandwidth = 0.01125
Trace of careExp:physical
Density of careExp:physical
Iterations
N = 12140 Bandwidth = 0.1018
Trace of time:physical
Density of time:physical
Iterations
N = 12140 Bandwidth = 0.0185

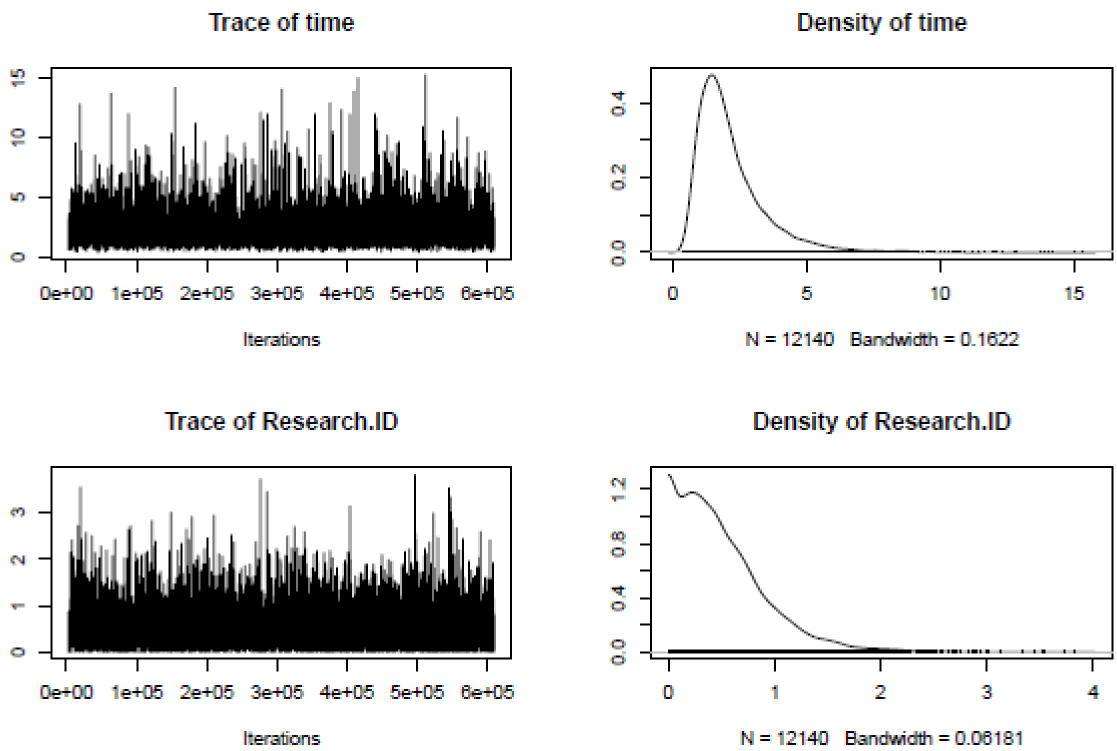

Trace of careExp:emotion
Iterations
Density of careExp:emotion
N = 12140 Bandwidth = 0.08424
Trace of time:emotion
Iterations
Density of time:emotion
N = 12140 Bandwidth = 0.01183
Trace of careExp:self
Iterations
Density of careExp:self
N = 12140 Bandwidth = 0.118
Trace of time:self
Iterations
Density of time:self
N = 12140 Bandwidth = 0.01517
Trace of careExp:think
Iterations
Density of careExp:think
N = 12140 Bandwidth = 0.1222
Trace of time:think
Iterations
Density of time:think
N = 12140 Bandwidth = 0.01574


Trace of careExp:attitude
Iterations
Density of careExp:attitude
N = 12140 Bandwidth = 0.1105
Trace of time:attitude
Iterations
Density of time:attitude
N = 12140 Bandwidth = 0.01673
Trace of careExp:change
Iterations
Density of careExp:change
N = 12140 Bandwidth = 0.1197
Trace of time:change
Iterations
Density of time:change
N = 12140 Bandwidth = 0.01688
Trace of careExp:time:live
Iterations
Density of careExp:time:live
N = 12140 Bandwidth = 0.01846
Trace of careExp:time:relation
Iterations
Density of careExp:time:relation
N = 12140 Bandwidth = 0.02318


Trace of careExp:time:ete
Iterations
Density of careExp:time:ete
N = 12140 Bandwidth = 0.01724
Trace of careExp:time:where
Iterations
Density of careExp:time:where
N = 12140 Bandwidth = 0.01619
Trace of careExp:time:life
Iterations
Density of careExp:time:life
N = 12140 Bandwidth = 0.02368
Trace of careExp:time:drugs
Iterations
Density of careExp:time:drugs
N = 12140 Bandwidth = 0.01799
Trace of careExp:time:physical
Iterations
Density of careExp:time:physical
N = 12140 Bandwidth = 0.02447
Trace of careExp:time:emotion
Iterations
Density of careExp:time:emotion
N = 12140 Bandwidth = 0.01942


Trace of careExp:time:self
Iterations
Density of careExp:time:self
N = 12140 Bandwidth = 0.02481
Trace of careExp:time:think
Iterations
Density of careExp:time:think
N = 12140 Bandwidth = 0.02469
Trace of careExp:time:attitude
Iterations
Density of careExp:time:attitude
N = 12140 Bandwidth = 0.02578
Trace of careExp:time:change
Iterations
Density of careExp:time:change
N = 12140 Bandwidth = 0.02471

Random Effects



Model 2 (Table 5.13)

Bayesian Model (Bm2)

Define the model

```
Bm1_d1.ch_d2.ch <- MCMCglmm(FO.bin ~ Gender*careExp + careExp* bme +
live + relation + ete + where + life + drugs + physical +
emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data, family="ordinal",prior=prior2,
nitt=300000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_d1.ch_d2.ch$VCV)
heidel.diag(Bm1_d1.ch_d2.ch$VCV)

# > raftery.diag(Bm1_d1.ch_d2.ch$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         60       84280  3746         22.5
# Research.ID 240       262200 3746         70.0
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_d1.ch_d2.ch$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.732
# Research.ID passed        1        0.157
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.462 0.01675
# Research.ID passed    0.122 0.00856
# units        <NA>        NA       NA

autocorr(Bm1_d1.ch_d2.ch$VCV)
autocorr(Bm1_d1.ch_d2.ch$Sol) # Output not included here
summary(Bm1_d1.ch_d2.ch)

# > autocorr(Bm1_d1.ch_d2.ch$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0   1.000000000 0.099145333   NaN
# Lag 10  0.246424077 0.093653972   NaN
# Lag 50  0.077801500 0.081693680   NaN
# Lag 100 0.028270559 0.054352519   NaN
# Lag 500 0.002707661 0.008955053   NaN
```

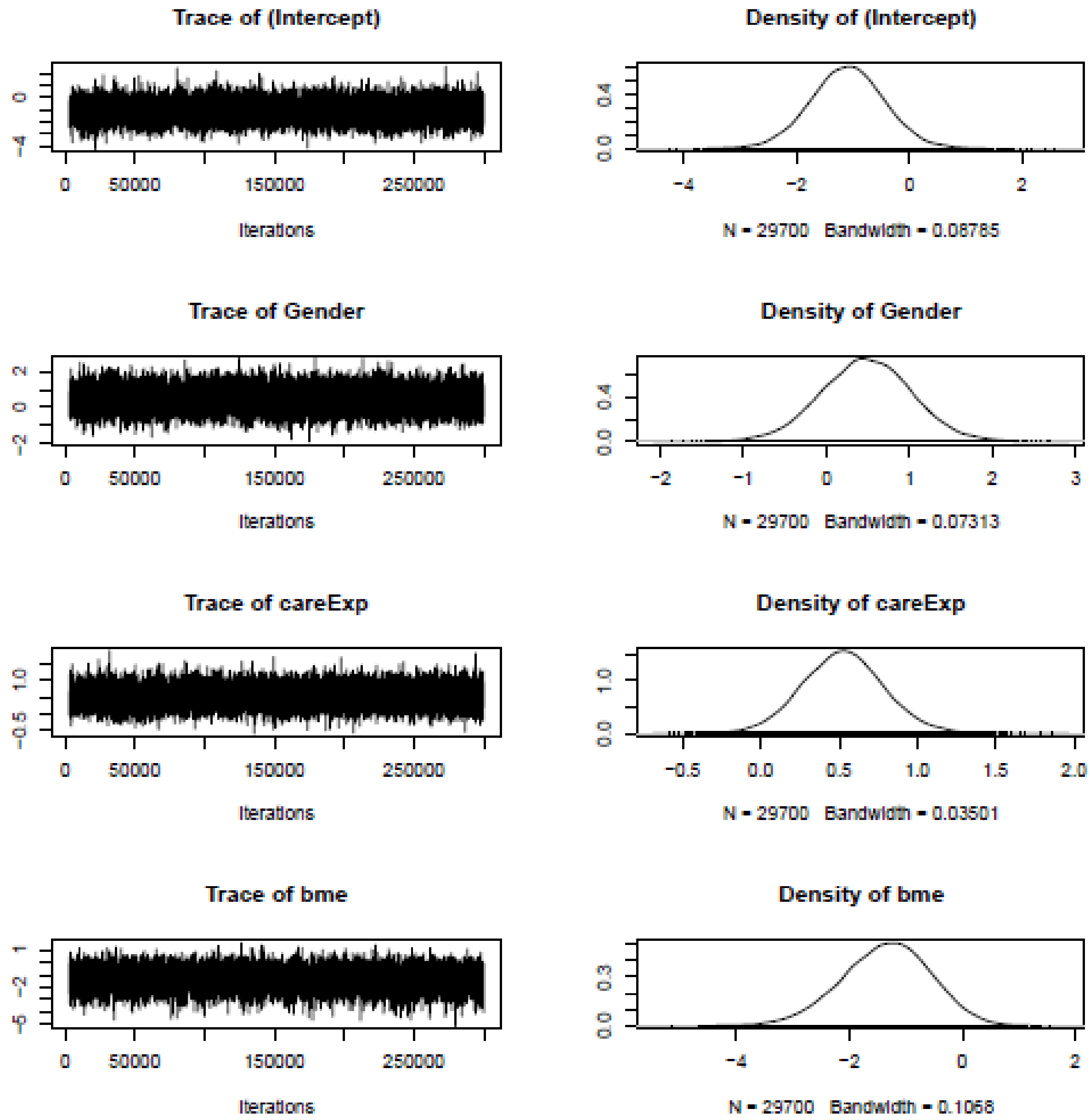
```
# , , Research.ID
#
#                   time Research.ID units
# Lag 0    9.914533e-02   1.0000000   NaN
# Lag 10   9.839811e-02   0.8399556   NaN
# Lag 50   7.938951e-02   0.5536247   NaN
# Lag 100  6.182236e-02   0.3713785   NaN
# Lag 500 -8.357084e-05   0.0510840   NaN

# summary(Bm1_d1.ch_d2.ch)
# Iterations = 3001:299991
# Thinning interval  = 10
# Sample size  = 29700
#
# DIC: 471.5332
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.462   0.4014    3.037     8834
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1223 0.0001872   0.4318     1225
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ Gender * careExp + careExp * bme + live +
relation + ete + where + life + drugs + physical + emotion + self +
think + attitude + change + time
#
#                post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)    -1.095644 -2.413168  0.230494    16537 0.1007
# Gender          0.482130 -0.577083  1.557372    11344 0.3738
# careExp         0.525940  0.008654  1.043865    11257 0.0435 *
# bme            -1.348708 -2.882832  0.205759     5327 0.0732 .
# live           -0.005256 -0.268183  0.263138    11617 0.9623
# relation        0.213696 -0.091283  0.513920    11871 0.1642
# ete             0.103139 -0.153487  0.368602     9691 0.4331
# where           0.035536 -0.185793  0.268224    12159 0.7638
# life            0.033118 -0.333120  0.393961    12352 0.8681
# drugs           0.189403 -0.050614  0.444932     8770 0.1241
# physical       -0.123222 -0.411478  0.182121    10830 0.4059
# emotion        -0.058842 -0.302857  0.193286    11679 0.6415
# self           -0.158397 -0.479698  0.173754    11422 0.3457
# think          -0.146528 -0.491669  0.187608    12751 0.3992
# attitude        0.030165 -0.340953  0.390326    11744 0.8640
# change          0.264750 -0.085623  0.614431    11595 0.1358
# time           -0.168255 -0.313994 -0.028628    10338 0.0186 *
# Gender:careExp -1.715413 -4.507975  1.065176     6579 0.2261
# careExp:bme     1.196213 -0.889555  3.307559     7436 0.2517
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

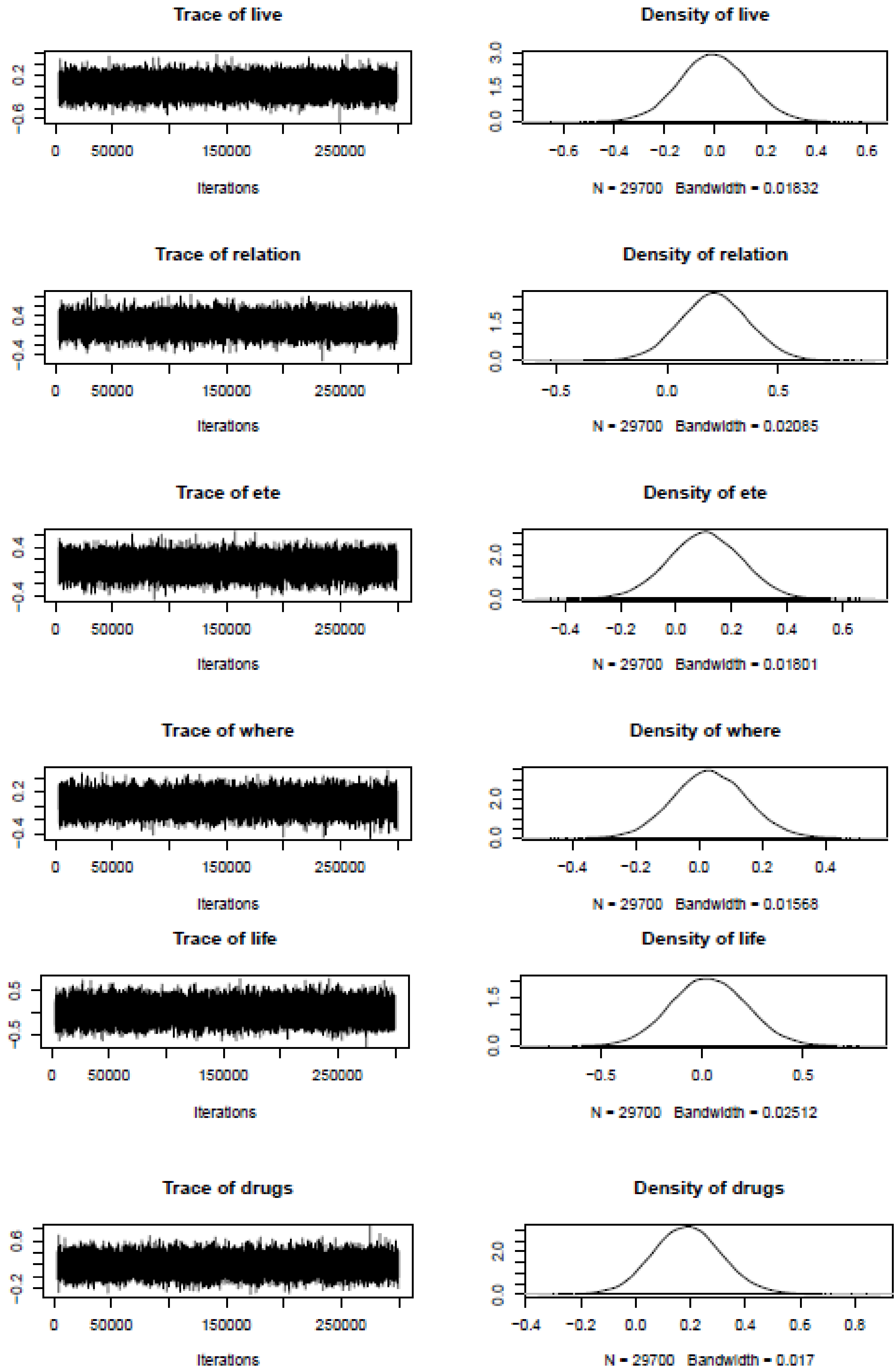
Trace Plots and Posterior Density Plots

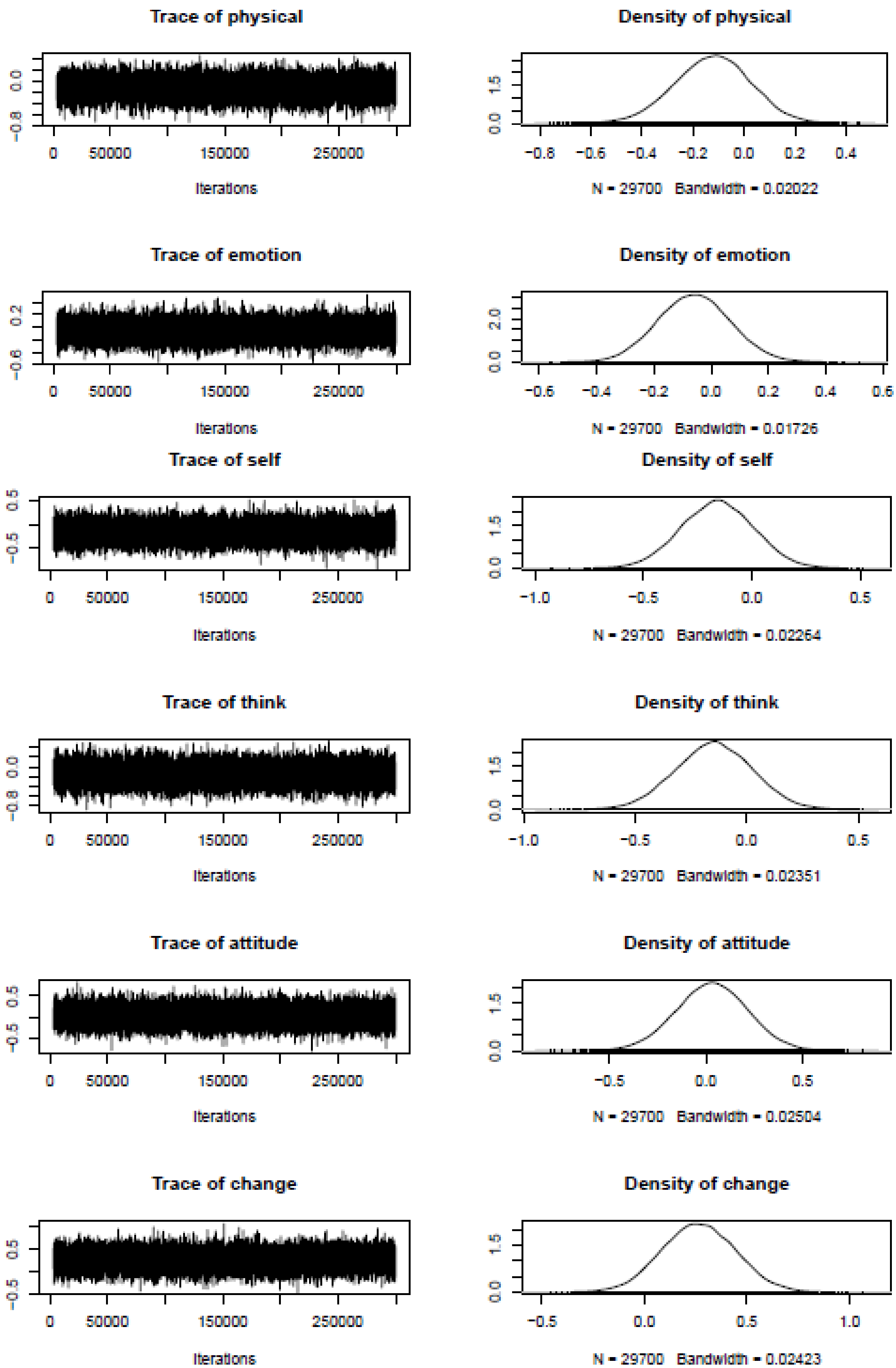
To simplify naming conventions, Bm1_d1.ch_d2.ch is renamed as Bm2 whilst the Frequentist equivalent m1_d1.ch_d2_ch is renamed as m2.

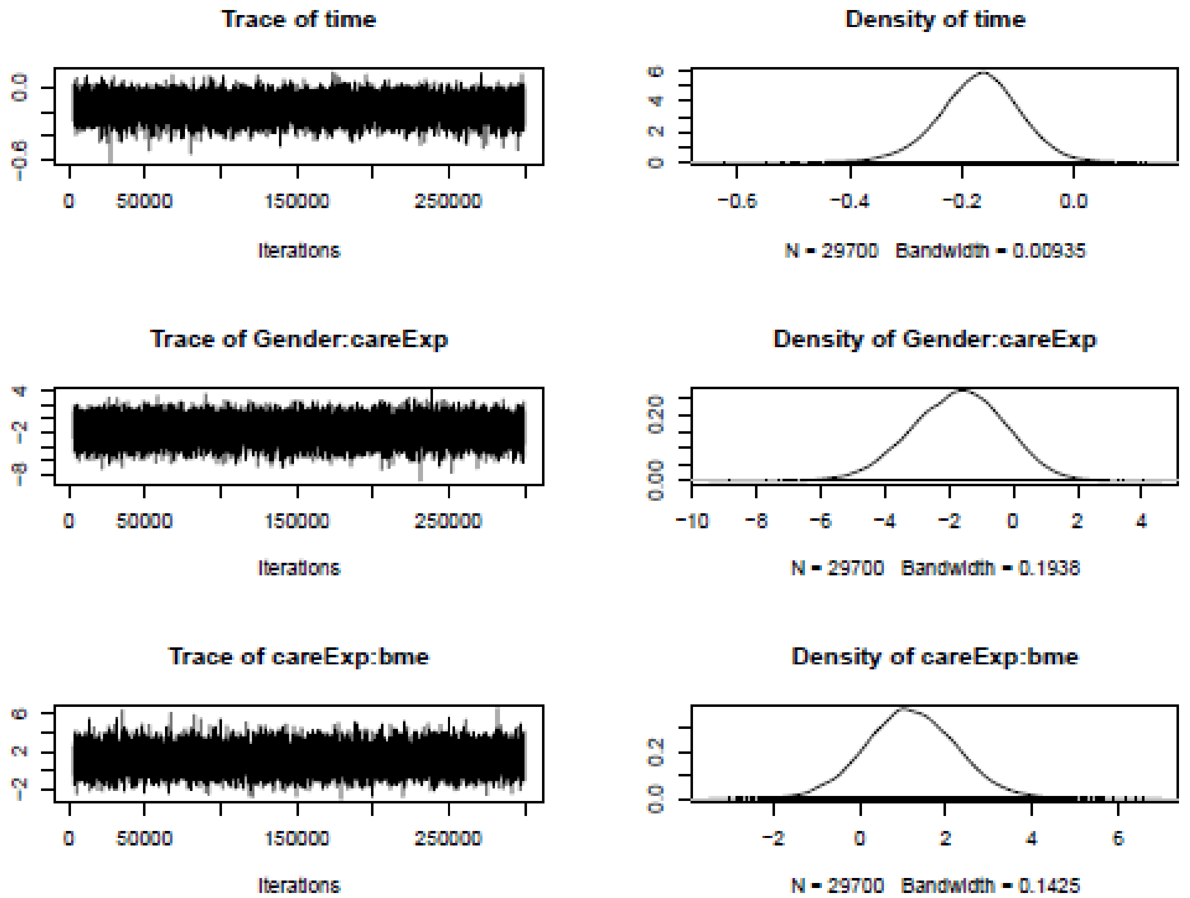
```
Bm2 <- Bm1_d1.ch_d2.ch
m2 <- m1_d1.ch_d2.ch
```

<u>Fixed Effects</u>

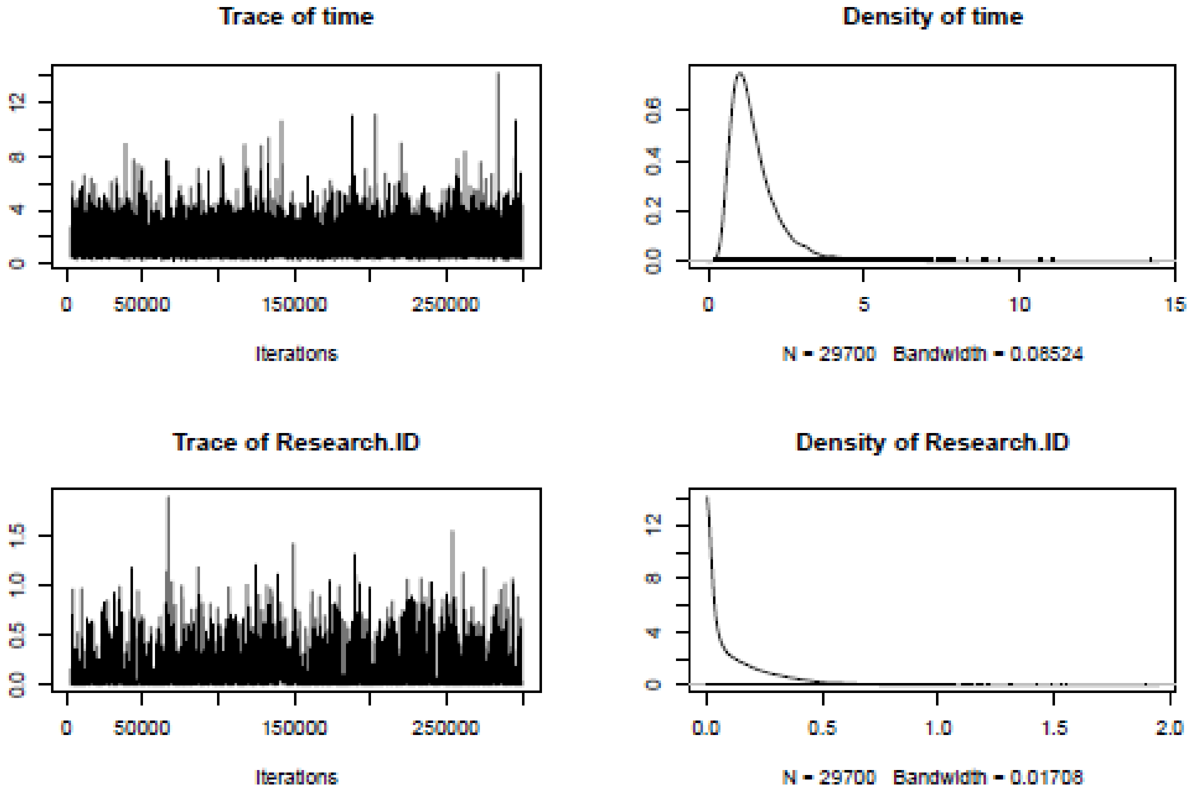



Trace of live
Iterations
Density of live
N = 29700 Bandwidth = 0.01832
Trace of relation
Iterations
Density of relation
N = 29700 Bandwidth = 0.02085
Trace of ete
Iterations
Density of ete
N = 29700 Bandwidth = 0.01801
Trace of where
Iterations
Density of where
N = 29700 Bandwidth = 0.01568
Trace of life
Iterations
Density of life
N = 29700 Bandwidth = 0.02512
Trace of drugs
Iterations
Density of drugs
N = 29700 Bandwidth = 0.017


Trace of physical
Iterations
Density of physical
N = 29700 Bandwidth = 0.02022
Trace of emotion
Iterations
Density of emotion
N = 29700 Bandwidth = 0.01726
Trace of self
Iterations
Density of self
N = 29700 Bandwidth = 0.02264
Trace of think
Iterations
Density of think
N = 29700 Bandwidth = 0.02351
Trace of attitude
Iterations
Density of attitude
N = 29700 Bandwidth = 0.02504
Trace of change
Iterations
Density of change
N = 29700 Bandwidth = 0.02423



Random Effects



Frequentist Model (m1_d1.ch_d2.ch)

```
m1_d1.ch_d2.ch <- glmer(FO.bin ~ female*careExp + careExp*bme + live +
relation + ete + where + life + drugs + physical + emotion + self +
think + attitude + change + time + (time|Individual), data=data,
family=binomial)
summary(m1_d1.ch_d2.ch)
vcomps.icc(m1_d1.ch_d2.ch)
anova(m1_d12_ch,m1_d1.ch_d2.ch)
anova(m1,m1_d1.ch_d2.ch)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ female * careExp + careExp * bme + live + relation +
#   ete + where + life + drugs + physical + emotion + self +
#   think + attitude + change + time + (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 643.6    738.3   -299.8    599.6      523
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.8541 -0.6682 -0.3541  0.7763  3.6209
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.07066  0.2658
#            time        0.05808  0.2410   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                   Estimate Std. Error z value Pr(>|z|)
# (Intercept)     -0.764603   0.339776  -2.250   0.0244 *
# female           0.524890   0.566987   0.926   0.3546
# careExp          0.598552   0.290209   2.062   0.0392 *
# bme             -0.773253   0.656496  -1.178   0.2389
# live            -0.114424   0.145383  -0.787   0.4313
# relation         0.111470   0.162349   0.687   0.4923
# ete              0.015565   0.137881   0.113   0.9101
# where            0.163501   0.130230   1.255   0.2093
# life             0.009882   0.203963   0.048   0.9614
# drugs            0.303134   0.142475   2.128   0.0334 *
# physical        -0.212755   0.153957  -1.382   0.1670
# emotion         -0.079389   0.137445  -0.578   0.5635
# self            -0.091114   0.182496  -0.499   0.6176
# think            0.145743   0.191514   0.761   0.4467
# attitude        -0.058874   0.197060  -0.299   0.7651
# change           0.224052   0.187956   1.192   0.2332
# time            -0.461982   0.108437  -4.260 2.04e-05 ***
# female:careExp -0.894353   1.159862  -0.771   0.4407
# careExp:bme     0.560683   1.119857   0.501   0.6166
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
#  Model failed to converge with max|grad| = 0.260456 (tol = 0.001,
component 1)
```

```
# vcomps.icc(m1_d1.ch_d2.ch)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.071         0.058         1.000         0.549

# anova(m1_d12_ch,m1_d1.ch_d2.ch)
# Data: data
# Models:
# m1_d12_ch: FO.bin ~ female + bme + careExp + live + relation + ete +
#   m1_d12_ch:     life + drugs + physical + emotion + self + think +
#   m1_d12_ch:    attitude + where + change + time + (time | Individual)
# m1_d1.ch_d2.ch: FO.bin ~ female * careExp + careExp * bme + live +
#   m1_d1.ch_d2.ch:  relation + ete + where + life + drugs + physical +
#  m1_d1.ch_d2.ch:  emotion + self +think + attitude + change + time +
#  m1_d1.ch_d2.ch:  (time | Individual)
#                    Df     AIC     BIC   logLik deviance   Chisq Chi Df
Pr(>Chisq)
# m1_d12_ch      20 640.49 726.50 -300.24   600.49
#  m1_d1.ch_d2.ch  22  643.64  738.26  -299.82    599.64  0.8425         2
0.6562

# anova(m1,m1_d1.ch_d2.ch)
# Data: data
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1_d1.ch_d2.ch: FO.bin ~ female * careExp + careExp * bme + live +
#   m1_d1.ch_d2.ch:    relation + ete + where + life + drugs + physical
+
#   m1_d1.ch_d2.ch:    emotion + self +think + attitude + change + time
+
#   m1_d1.ch_d2.ch:  (time | Individual)
#                    Df     AIC     BIC   logLik deviance   Chisq Chi Df
Pr(>Chisq)
# m1             17 640.59 713.70 -303.29   606.59
#  m1_d1.ch_d2.ch  22  643.64  738.26  -299.82    599.64  6.9449         5
0.2248
```

Dynamic Model 2 (Table 5.14)

Bayesian Model (BDm2)

Define the Model

```
BDm2 <- MCMCglmm(FO.bin ~ careExp*time*live + careExp*time*relation +
careExp*time*ete + careExp*time*where + careExp*time*life +
careExp*time*drugs + careExp*time*physical + careExp*time*emotion +
careExp*time*self + careExp*time*think + careExp*time*attitude +
careExp*time*change  +  Gender*time  +  bme*time  +  Gender*careExp  +
bme*careExp,random=~time+Research.ID,data=data,family="ordinal",
prior=priorD, slice=TRUE, nitt=610000, thin=100, burnin=3000)
```

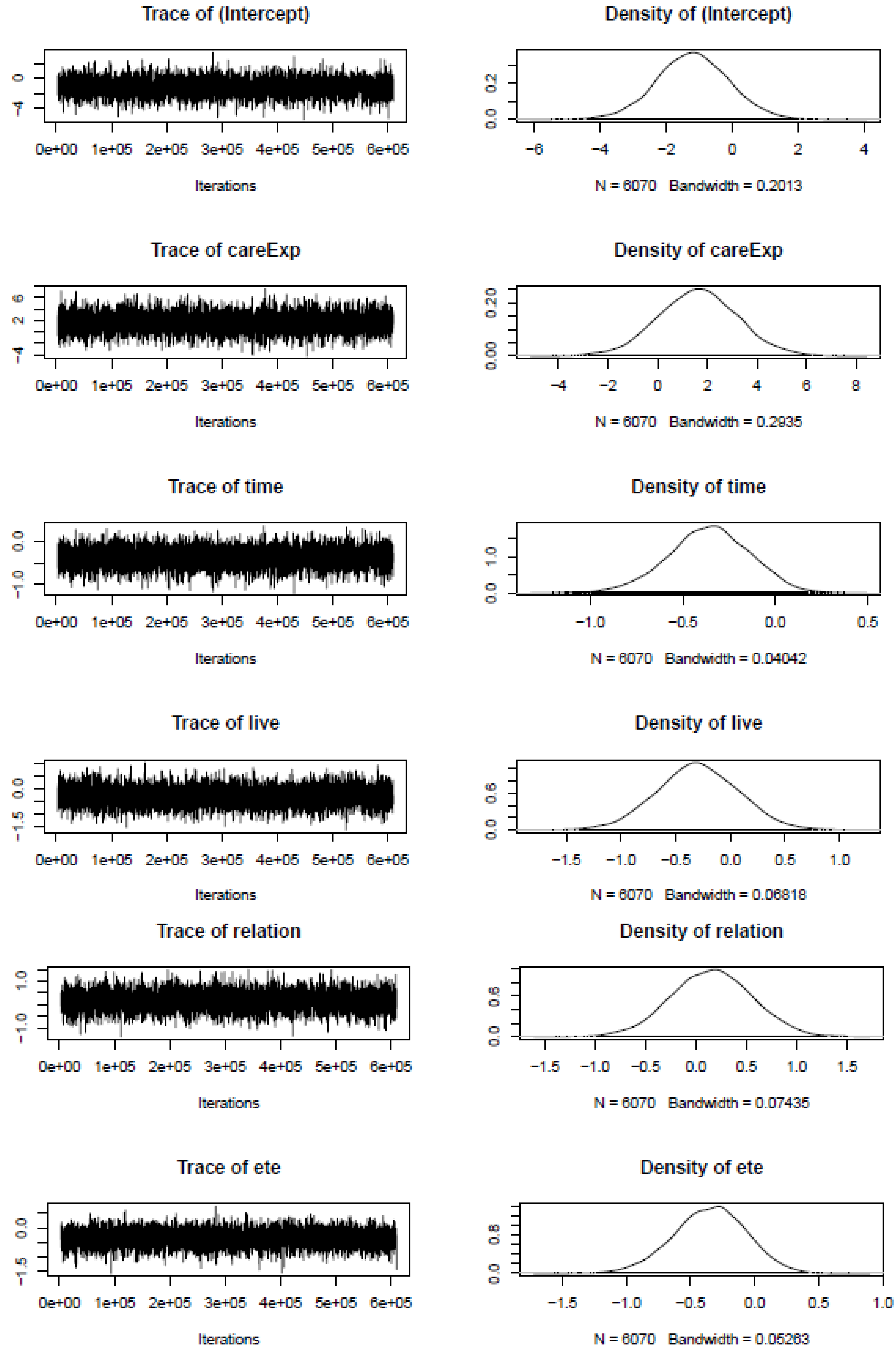
Checks for suitable convergence

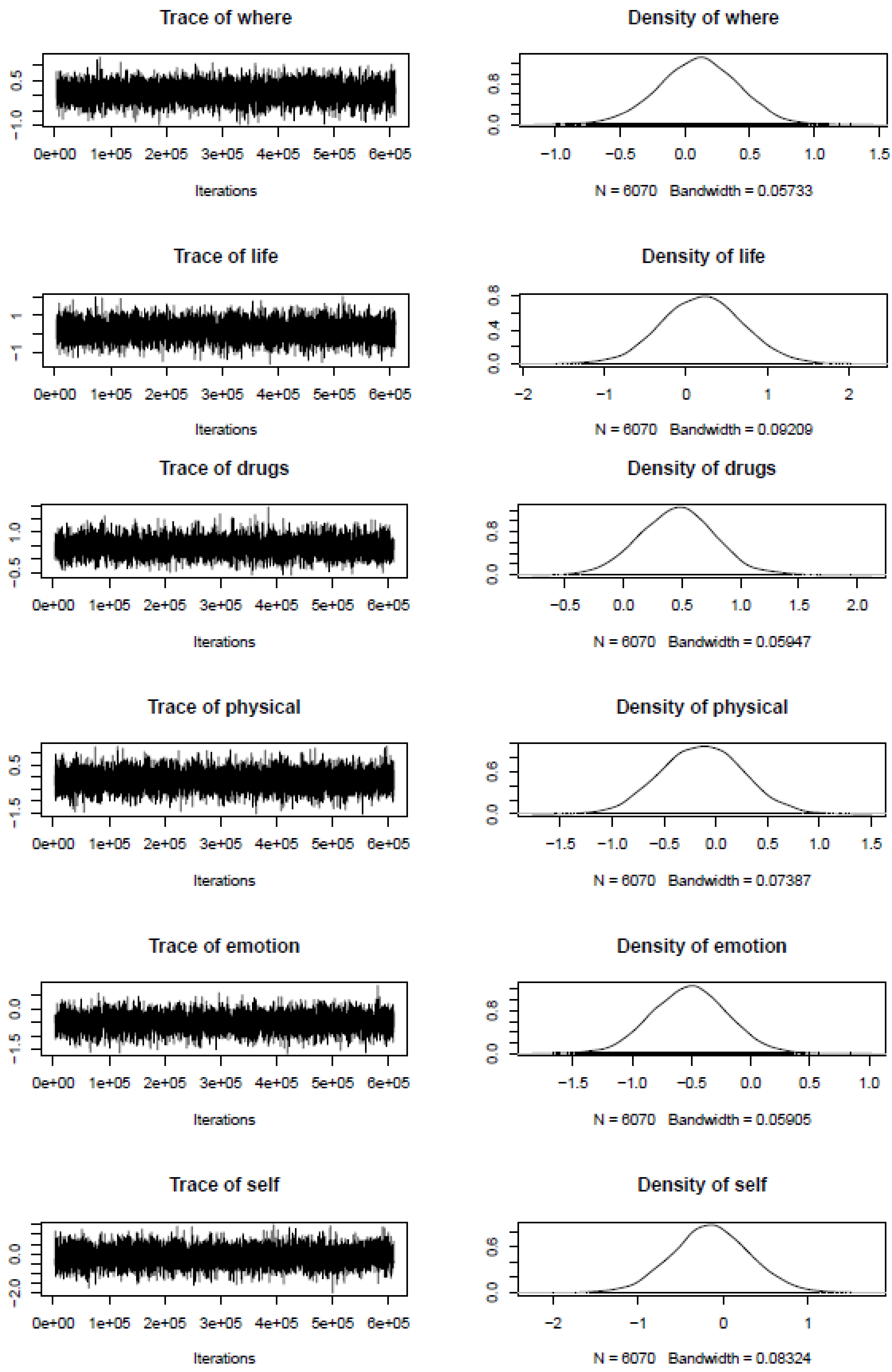
```
raftery.diag(BDm2$VCV)
heidel.diag(BDm2$VCV)

# > raftery.diag(BDm2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         200      381500 3746         102
# Research.ID  200      381500 3746         102
# units        <NA>     <NA>   3746          NA

# > heidel.diag(BDm2$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.986
# Research.ID  passed        1        0.529
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    2.733 0.0717
# Research.ID  passed    0.717 0.0178
# units        <NA>         NA     NA

autocorr(BDm2$VCV)
autocorr(BDm2$Sol)
summary(BDm2)

# > autocorr(BDm2$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0    1.000000000 0.212306037   NaN
# Lag 100  0.190383537 0.104649157   NaN
# Lag 500  0.075846506 0.033637194   NaN
# Lag 1000 0.016749652 0.006117096   NaN
# Lag 5000 0.008501232 0.019328903   NaN
```

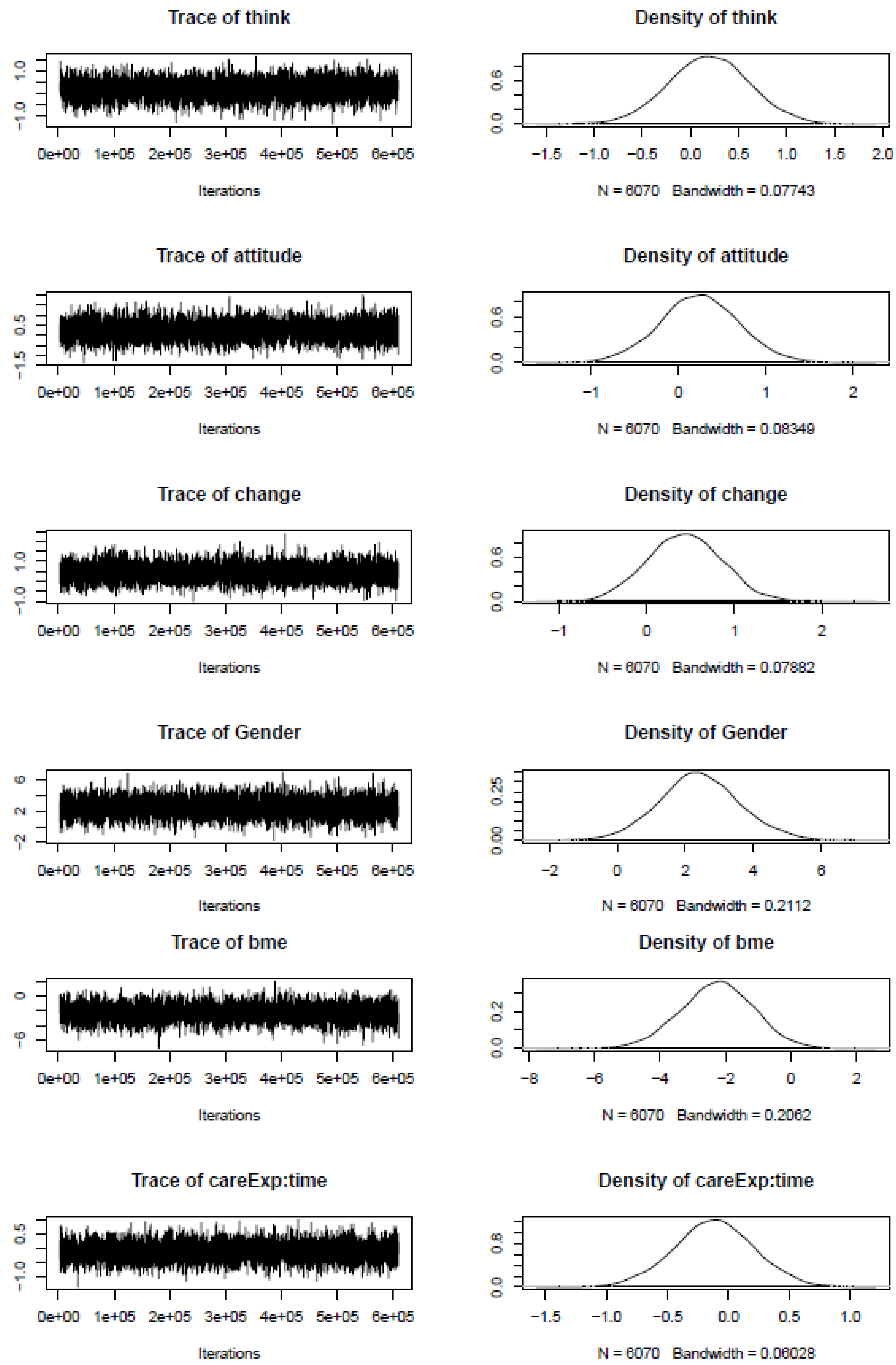
```
# , , Research.ID
#
#                    time  Research.ID units
# Lag 0     0.2123060367  1.000000000   NaN
# Lag 100   0.0787991168  0.199184649   NaN
# Lag 500   0.0143398445  0.034649830   NaN
# Lag 1000 -0.0002890653 -0.004066214   NaN
# Lag 5000  0.0181625190  0.019330229   NaN

# > summary(BDm2)
#
# Iterations = 3001:609901
# Thinning interval  = 100
# Sample size  = 6070
#
# DIC: 466.3842
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.733   0.6108    6.169     2286
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.7174 1.025e-05    1.671     3283
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ careExp * time * live + careExp * time *
relation + careExp * time * ete + careExp * time * where + careExp *
time * life + careExp * time * drugs + careExp * time * physical +
careExp * time * emotion + careExp * time * self + careExp * time *
think + careExp * time * attitude + careExp * time * change + Gender *
time + bme * time + Gender * careExp + bme * careExp
#
#                       post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept)          -1.187e+00 -3.288e+00  1.019e+00     4988 0.2682
# careExp               1.631e+00 -1.623e+00  4.751e+00     6070 0.3081
# time                 -3.589e-01 -8.006e-01  6.710e-02     6299 0.0962 .
# live                 -2.980e-01 -1.011e+00  4.167e-01     6070 0.4221
# relation              1.585e-01 -6.030e-01  9.645e-01     5713 0.6969
# ete                  -3.485e-01 -9.121e-01  1.991e-01     5466 0.2109
# where                 1.048e-01 -5.176e-01  6.867e-01     6070 0.7166
# life                  2.001e-01 -7.307e-01  1.209e+00     6070 0.6932
# drugs                 4.616e-01 -1.953e-01  1.070e+00     5638 0.1512
# physical             -1.328e-01 -8.795e-01  6.634e-01     6070 0.7483
# emotion              -5.136e-01 -1.133e+00  1.086e-01     5829 0.1044
# self                 -1.403e-01 -9.874e-01  7.877e-01     8390 0.7440
# think                 1.956e-01 -5.914e-01  1.043e+00     7272 0.6349
# attitude              2.399e-01 -6.575e-01  1.119e+00     6070 0.5852
# change                4.361e-01 -3.978e-01  1.244e+00     6070 0.3094
# Gender                2.425e+00  1.527e-01  4.799e+00     5558 0.0379 *
# bme                  -2.263e+00 -4.420e+00 -4.272e-02     6070 0.0405 *
# careExp:time         -1.146e-01 -7.600e-01  5.367e-01     6295 0.7193
# careExp:live          6.741e-01 -5.441e-01  1.783e+00     6070 0.2586
# time:live             3.975e-03 -1.683e-01  1.806e-01     6070 0.9634
# careExp:relation     -1.332e-01 -1.495e+00  1.192e+00     6070 0.8610
# time:relation        -1.051e-02 -2.074e-01  1.792e-01     6070 0.9315
```

```
# careExp:ete            3.877e-01 -6.496e-01  1.531e+00     6070 0.4909
# time:ete               7.096e-02 -5.909e-02  2.048e-01     6070 0.2903
# careExp:where         -3.539e-01 -1.392e+00  7.186e-01     6070 0.5041
# time:where            -6.834e-02 -2.171e-01  7.370e-02     6070 0.3631
# careExp:life          -1.832e-01 -1.699e+00  1.520e+00     6543 0.8191
# time:life              4.953e-02 -1.457e-01  2.588e-01     6070 0.6333
# careExp:drugs         -3.639e-02 -1.096e+00  9.659e-01     5757 0.9562
# time:drugs             3.633e-05 -1.437e-01  1.402e-01     5744 0.9875
# careExp:physical      -1.068e+00 -2.521e+00  1.933e-01     5711 0.1031
# time:physical         -3.015e-02 -2.675e-01  2.032e-01     5828 0.8102
# careExp:emotion        5.222e-01 -6.132e-01  1.546e+00     5830 0.3417
# time:emotion           8.171e-02 -6.889e-02  2.408e-01     6070 0.2988
# careExp:self           9.415e-01 -5.440e-01  2.572e+00     5767 0.2244
# time:self              9.441e-02 -1.029e-01  3.149e-01     7403 0.3667
# careExp:think         -1.011e+00 -2.562e+00  5.609e-01     6070 0.1931
# time:think            -3.026e-02 -2.352e-01  1.753e-01     6070 0.7746
# careExp:attitude      -1.966e-01 -1.613e+00  1.262e+00     5794 0.7951
# time:attitude         -1.142e-01 -3.252e-01  9.315e-02     6070 0.2876
# careExp:change        -5.140e-02 -1.584e+00  1.581e+00     6070 0.9562
# time:change           -2.803e-02 -2.524e-01  1.847e-01     6070 0.8020
# time:Gender           -5.284e-01 -1.149e+00  9.237e-02     6070 0.0867 .
# time:bme               2.098e-01 -2.793e-01  6.640e-01     5609 0.3855
# careExp:Gender        -3.429e+00 -7.727e+00  5.753e-01     5706 0.0913 .
# careExp:bme            2.162e-01 -3.551e+00  3.906e+00     6070 0.9002
# careExp:time:live     -2.034e-02 -2.656e-01  2.079e-01     6344 0.8662
# careExp:time:relation  2.541e-02 -2.671e-01  3.308e-01     6070 0.8738
# careExp:time:ete       2.410e-03 -2.235e-01  2.260e-01     6070 0.9769
# careExp:time:where     2.015e-01 -6.136e-04  4.166e-01     5503 0.0583 .
# careExp:time:life     -1.447e-01 -4.702e-01  1.487e-01     5262 0.3674
# careExp:time:drugs    -3.269e-02 -2.616e-01  2.086e-01     5782 0.7740
# careExp:time:physical  2.517e-01 -4.746e-02  5.744e-01     6070 0.1077
# careExp:time:emotion   1.780e-02 -2.191e-01  2.731e-01     6070 0.8896
# careExp:time:self     -3.814e-01 -7.122e-01 -5.440e-02     6070 0.0194 *
# careExp:time:think     1.209e-01 -2.028e-01  4.299e-01     6070 0.4547
# careExp:time:attitude  1.237e-01 -2.212e-01  4.450e-01     6718 0.4643
# careExp:time:change   -8.874e-03 -3.321e-01  3.035e-01     6070 0.9651
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

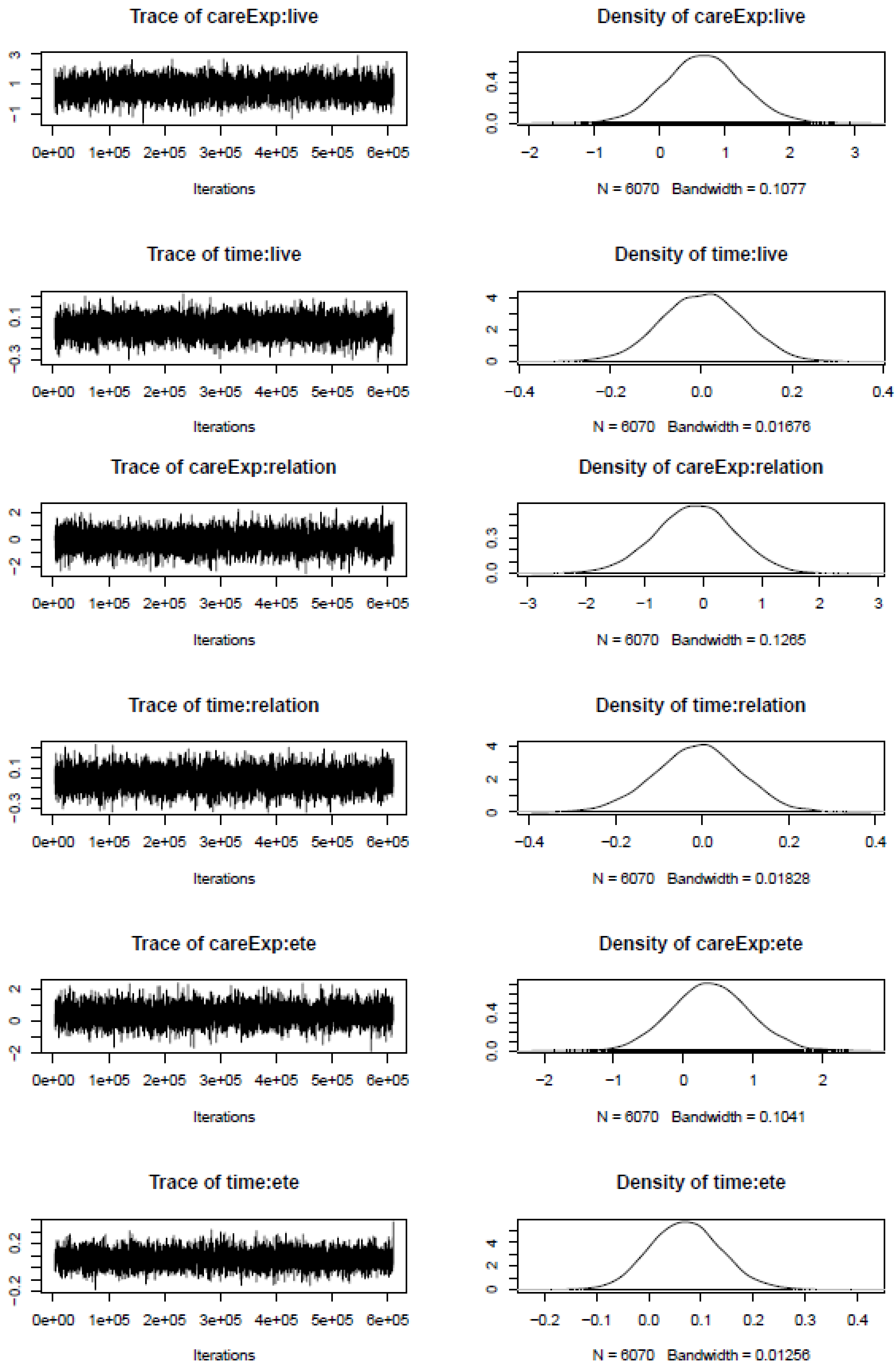
Trace Plots and Posterior Density Plots

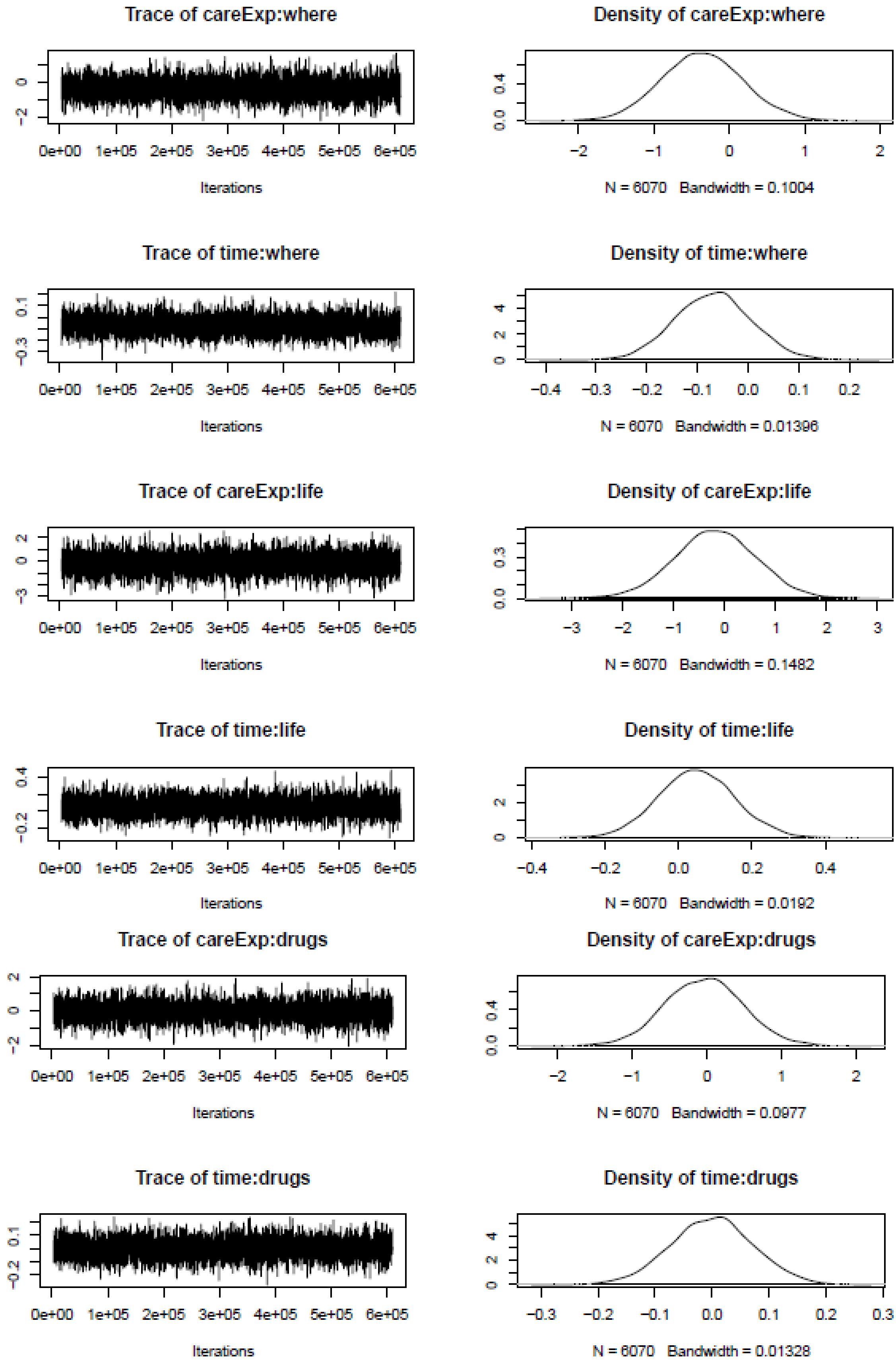


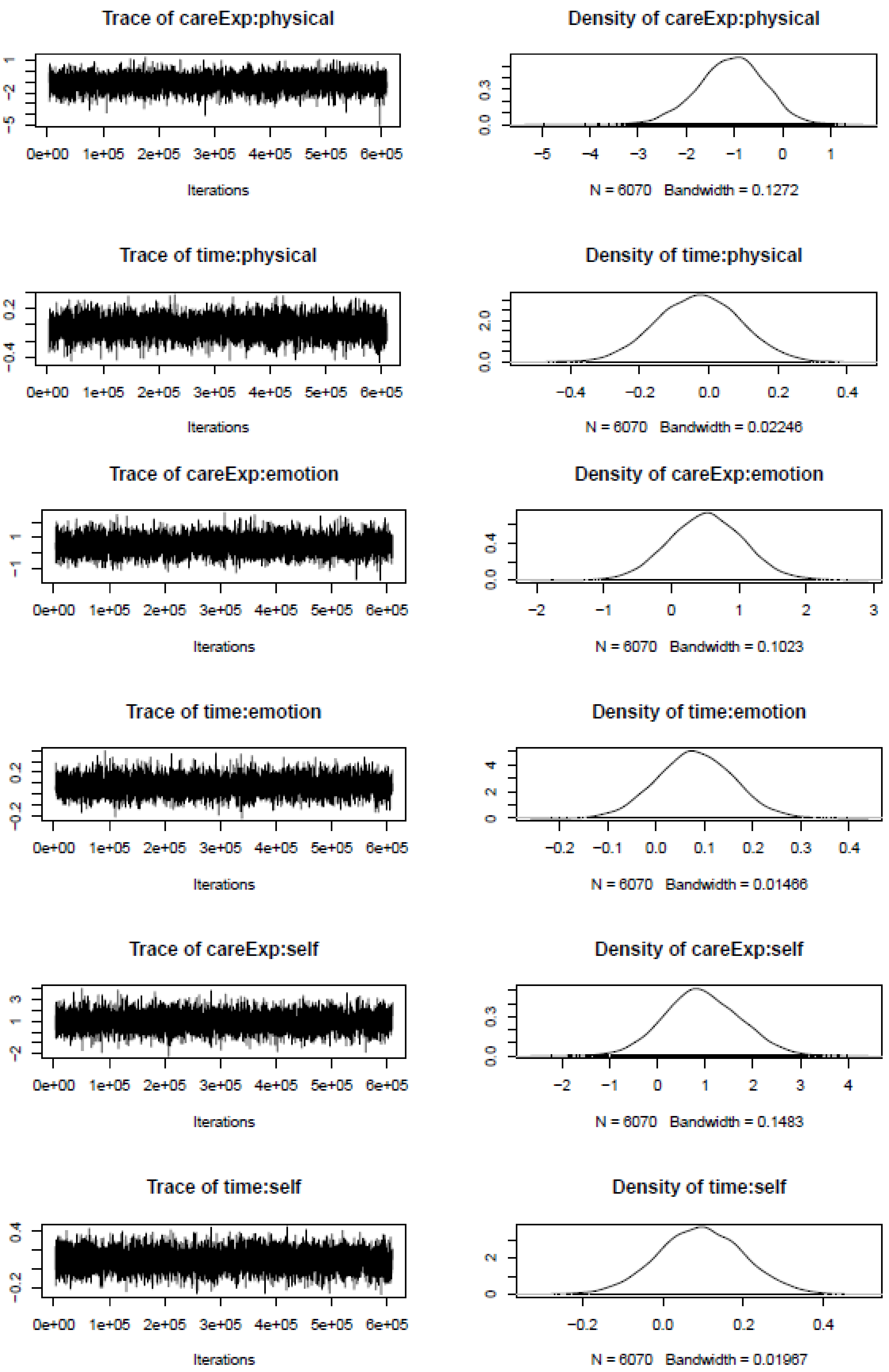

Trace of where
Iterations
Density of where
N = 6070 Bandwidth = 0.05733
Trace of life
Iterations
Density of life
N = 6070 Bandwidth = 0.09209
Trace of drugs
Iterations
Density of drugs
N = 6070 Bandwidth = 0.05947
Trace of physical
Iterations
Density of physical
N = 6070 Bandwidth = 0.07387
Trace of emotion
Iterations
Density of emotion
N = 6070 Bandwidth = 0.05905
Trace of self
Iterations
Density of self
N = 6070 Bandwidth = 0.08324

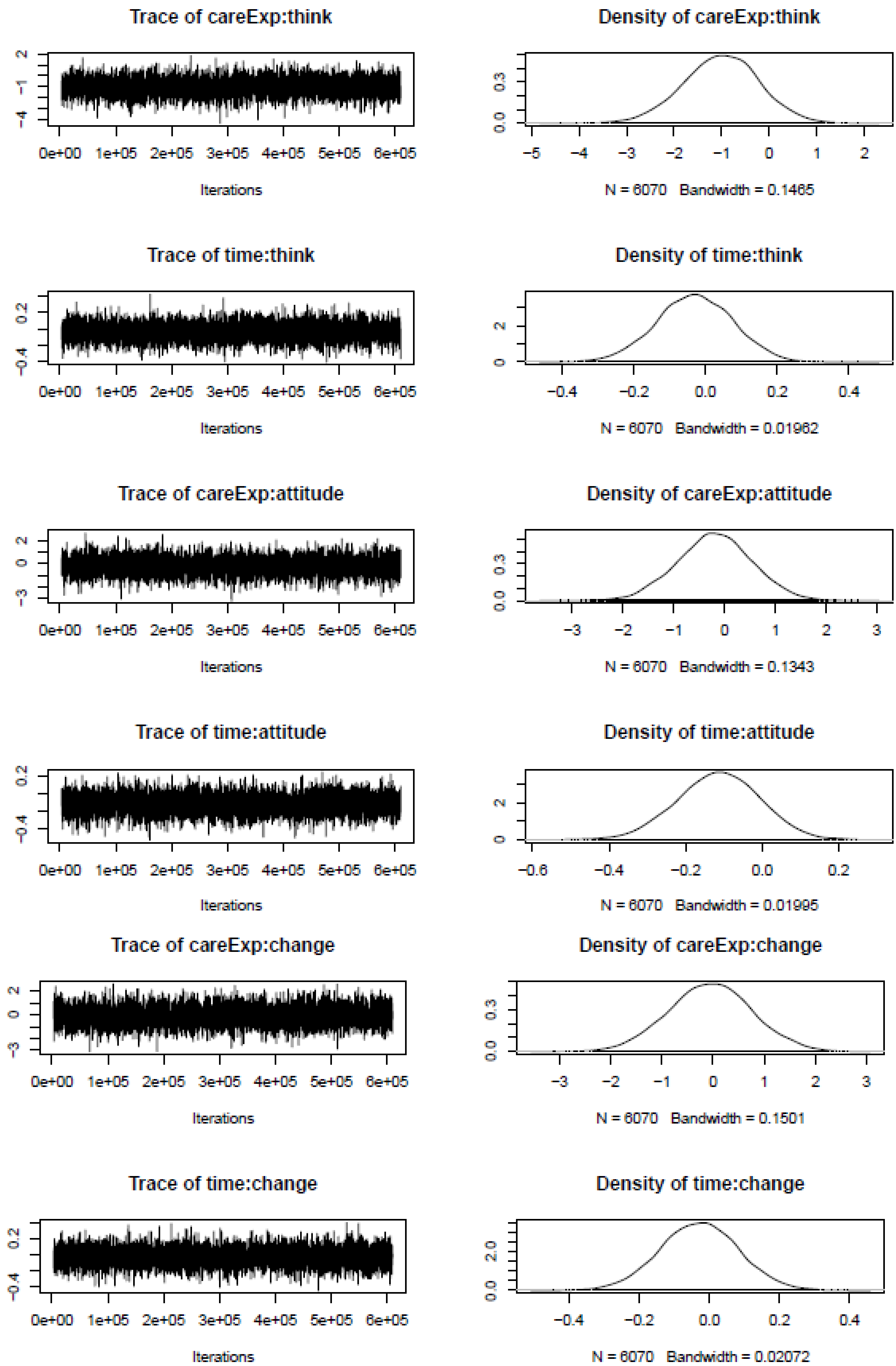


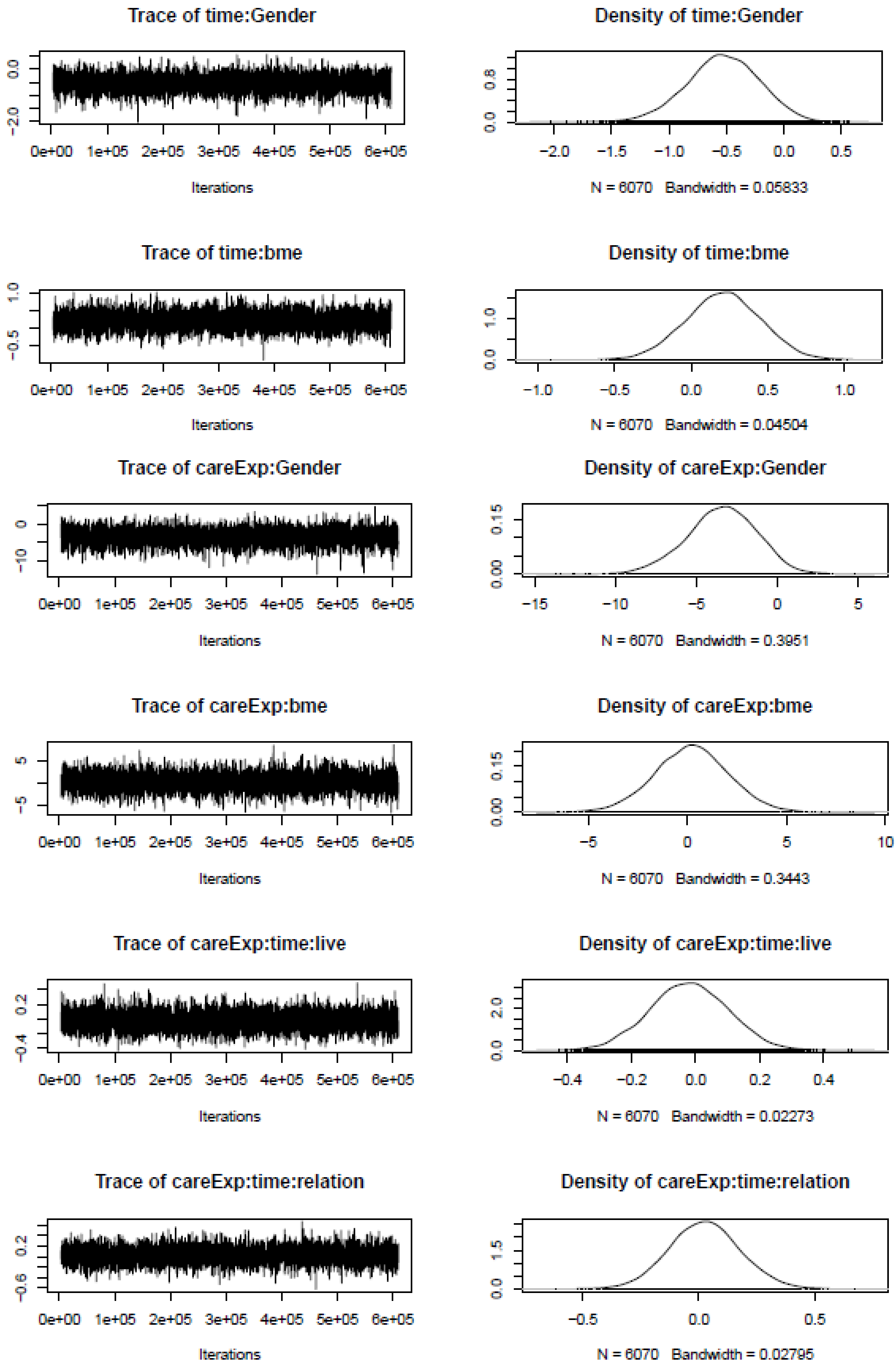
Trace of think
Iterations
Density of think
N = 6070 Bandwidth = 0.07743
Trace of attitude
Iterations
Density of attitude
N = 6070 Bandwidth = 0.08349
Trace of change
Iterations
Density of change
N = 6070 Bandwidth = 0.07882
Trace of Gender
Iterations
Density of Gender
N = 6070 Bandwidth = 0.2112
Trace of bme
Iterations
Density of bme
N = 6070 Bandwidth = 0.2062
Trace of careExp:time
Iterations
Density of careExp:time
N = 6070 Bandwidth = 0.06028

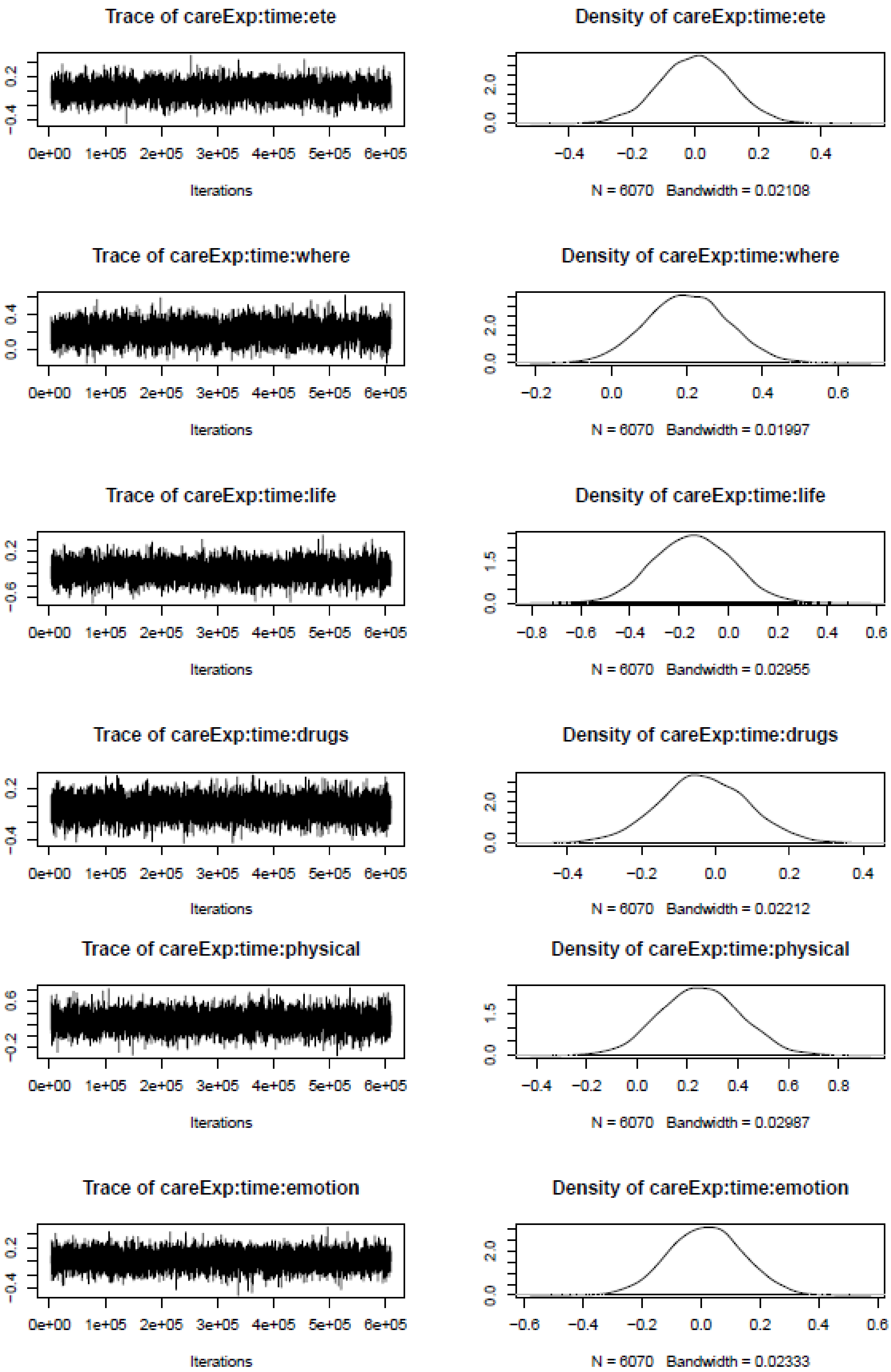

Trace of careExp:live
Iterations
Density of careExp:live
N = 6070 Bandwidth = 0.1077
Trace of time:live
Iterations
Density of time:live
N = 6070 Bandwidth = 0.01676
Trace of careExp:relation
Iterations
Density of careExp:relation
N = 6070 Bandwidth = 0.1265
Trace of time:relation
Iterations
Density of time:relation
N = 6070 Bandwidth = 0.01828
Trace of careExp:ete
Iterations
Density of careExp:ete
N = 6070 Bandwidth = 0.1041
Trace of time:ete
Iterations
Density of time:ete
N = 6070 Bandwidth = 0.01256

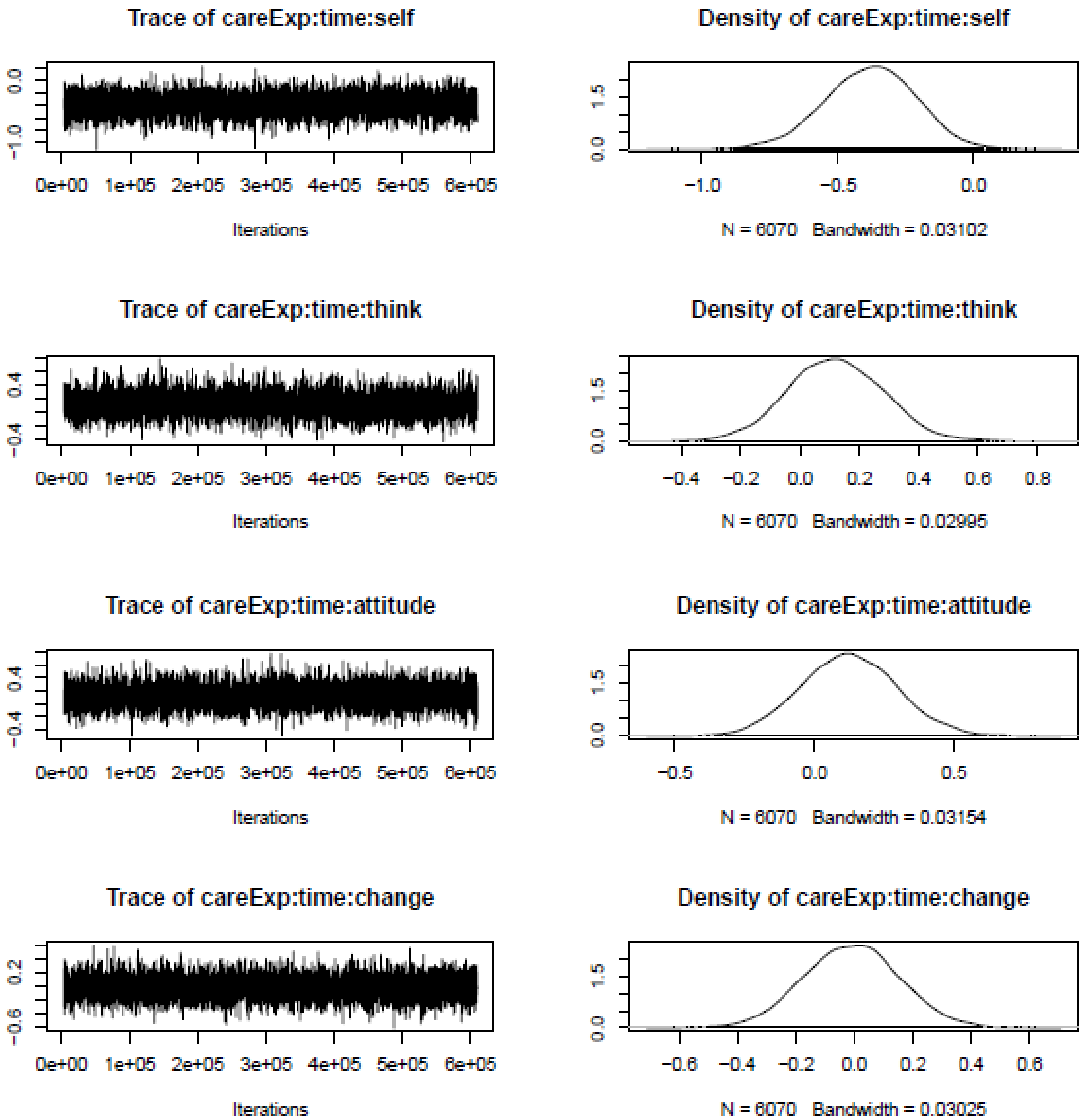

Trace of careExp:where
Iterations
Density of careExp:where
N = 6070 Bandwidth = 0.1004
Trace of time:where
Iterations
Density of time:where
N = 6070 Bandwidth = 0.01396
Trace of careExp:life
Iterations
Density of careExp:life
N = 6070 Bandwidth = 0.1482
Trace of time:life
Iterations
Density of time:life
N = 6070 Bandwidth = 0.0192
Trace of careExp:drugs
Iterations
Density of careExp:drugs
N = 6070 Bandwidth = 0.0977
Trace of time:drugs
Iterations
Density of time:drugs
N = 6070 Bandwidth = 0.01328


Trace of careExp:physical
Iterations
Density of careExp:physical
N = 6070 Bandwidth = 0.1272
Trace of time:physical
Iterations
Density of time:physical
N = 6070 Bandwidth = 0.02246
Trace of careExp:emotion
Iterations
Density of careExp:emotion
N = 6070 Bandwidth = 0.1023
Trace of time:emotion
Iterations
Density of time:emotion
N = 6070 Bandwidth = 0.01466
Trace of careExp:self
Iterations
Density of careExp:self
N = 6070 Bandwidth = 0.1483
Trace of time:self
Iterations
Density of time:self
N = 6070 Bandwidth = 0.01967

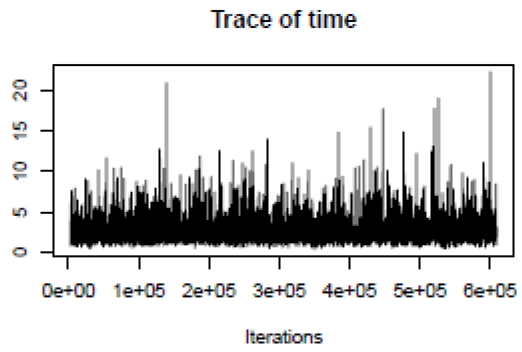

Trace of careExp:think
Iterations
Density of careExp:think
N = 6070 Bandwidth = 0.1465
Trace of time:think
Iterations
Density of time:think
N = 6070 Bandwidth = 0.01962
Trace of careExp:attitude
Iterations
Density of careExp:attitude
N = 6070 Bandwidth = 0.1343
Trace of time:attitude
Iterations
Density of time:attitude
N = 6070 Bandwidth = 0.01995
Trace of careExp:change
Iterations
Density of careExp:change
N = 6070 Bandwidth = 0.1501
Trace of time:change
Iterations
Density of time:change
N = 6070 Bandwidth = 0.02072

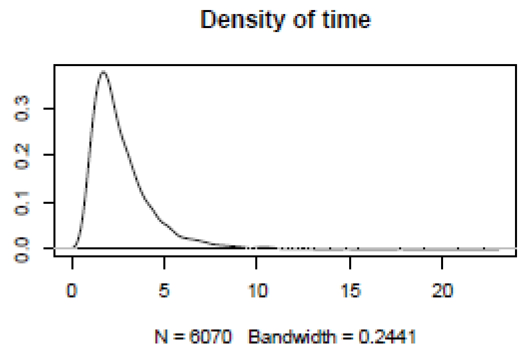

Trace of time:Gender
Iterations
Density of time:Gender
N = 6070   Bandwidth = 0.05833
Trace of time:bme
Iterations
Density of time:bme
N = 6070   Bandwidth = 0.04504
Trace of careExp:Gender
Iterations
Density of careExp:Gender
N = 6070   Bandwidth = 0.3951
Trace of careExp:bme
Iterations
Density of careExp:bme
N = 6070   Bandwidth = 0.3443
Trace of careExp:time:live
Iterations
Density of careExp:time:live
N = 6070   Bandwidth = 0.02273
Trace of careExp:time:relation
Iterations
Density of careExp:time:relation
N = 6070   Bandwidth = 0.02795

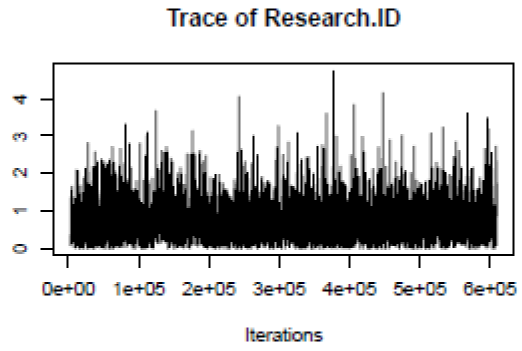

Trace of careExp:time:ete
Iterations
Density of careExp:time:ete
N = 6070 Bandwidth = 0.02108
Trace of careExp:time:where
Iterations
Density of careExp:time:where
N = 6070 Bandwidth = 0.01997
Trace of careExp:time:life
Iterations
Density of careExp:time:life
N = 6070 Bandwidth = 0.02955
Trace of careExp:time:drugs
Iterations
Density of careExp:time:drugs
N = 6070 Bandwidth = 0.02212
Trace of careExp:time:physical
Iterations
Density of careExp:time:physical
N = 6070 Bandwidth = 0.02987
Trace of careExp:time:emotion
Iterations
Density of careExp:time:emotion
N = 6070 Bandwidth = 0.02333

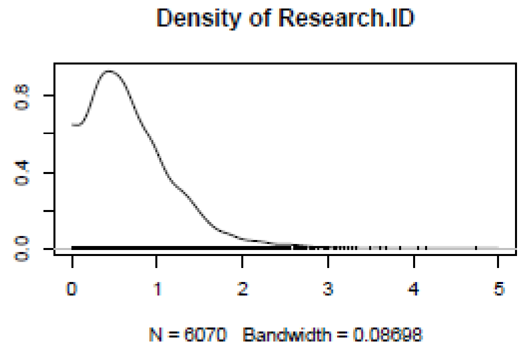

Trace of careExp:time:self
Iterations
Density of careExp:time:self
N = 6070 Bandwidth = 0.03102
Trace of careExp:time:think
Iterations
Density of careExp:time:think
N = 6070 Bandwidth = 0.02995
Trace of careExp:time:attitude
Iterations
Density of careExp:time:attitude
N = 6070 Bandwidth = 0.03154
Trace of careExp:time:change
Iterations
Density of careExp:time:change
N = 6070 Bandwidth = 0.03025

Random Effects









Chapter Six – Static Factors

Model 1.5 – Basic Model + Grouped Age at First Offence (Table 6.4)

Bayesian Model (Bm1G_cc2)

Define the model

```
Bm1G_cc2 <- MCMCglmm(FO.bin~G_ageFirst + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time, random=~time+Research.ID, data=data3,family="ordinal",
prior=priorD,slice=TRUE,nitt=200000,thin=50, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_cc2$VCV)
heidel.diag(Bm1G_cc2$VCV)

# > raftery.diag(Bm1G_cc2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#             Burn-in  Total  Lower bound  Dependence
#             (M)      (N)    (Nmin)       factor (I)
# time        100      186450 3746         49.8
# Research.ID 100      190400 3746         50.8
# units       <NA>     <NA>   3746           NA

# > heidel.diag(Bm1G_cc2$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# time        passed        1        0.445
# Research.ID passed        1        0.388
# units       failed       NA           NA
#
#             Halfwidth Mean  Halfwidth
#             test
# time        passed    1.512 0.04027
# Research.ID passed    0.214 0.00688
# units       <NA>         NA      NA

autocorr(Bm1G_cc2$VCV)
autocorr(Bm1G_cc2$Sol)
summary(Bm1G_cc2)

# > autocorr(Bm1G_cc2$VCV)
# , , time
#
#                 time  Research.ID units
# Lag 0    1.00000000 0.1149023324   NaN
# Lag 50   0.17080881 0.0398726557   NaN
# Lag 250  0.07689705 0.0101720897   NaN
# Lag 500  0.04092844 0.0001018026   NaN
# Lag 2500 0.01264580 0.0142367500   NaN
```

```
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0      0.114902332  1.000000000   NaN
# Lag 50     0.039724703  0.148984629   NaN
# Lag 250    0.021887065  0.002086222   NaN
# Lag 500   -0.005897988  0.008875116   NaN
# Lag 2500   0.007294192 -0.026803881   NaN

# > summary(Bm1G_cc2)
#
# Iterations = 3001:199951
# Thinning interval  = 50
# Sample size  = 3940
#
# DIC: 473.4398
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.512   0.3602    3.126     1722
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2142 4.151e-09   0.5938     2917
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageFirst + live + relation + ete + where
+ life + drugs + physical + emotion + self + think + attitude + change +
time
#
#                          post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)               -1.07200 -2.41713  0.34775     3940 0.1203
# G_ageFirst13 to 17 years  -0.14675 -0.67469  0.33679     3940 0.5655
# live                       0.02921 -0.25012  0.29558     3940 0.8624
# relation                   0.27155 -0.01043  0.59021     3527 0.0726 .
# ete                        0.07681 -0.18224  0.33170     3630 0.5533
# where                      0.05107 -0.18901  0.27680     4244 0.6721
# life                       0.03808 -0.30797  0.38171     3715 0.8325
# drugs                      0.17654 -0.06343  0.43986     3940 0.1518
# physical                  -0.12083 -0.41654  0.18566     3940 0.4117
# emotion                    0.01462 -0.21362  0.27842     3940 0.9203
# self                      -0.13506 -0.46833  0.17491     3940 0.4041
# think                     -0.16869 -0.49823  0.17024     3940 0.3274
# attitude                   0.02796 -0.32020  0.39328     3940 0.8822
# change                     0.23895 -0.11558  0.57699     3940 0.1863
# time                      -0.16326 -0.31086 -0.01844     3940 0.0284 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_cc2)

```
m1G_cc2 <- glmer(FO.bin ~ G_ageFirst + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time + (time|Individual), data=data, family=binomial)
summary(m1G_cc2)
vcomps.icc(m1G_cc2)
anova(m1,m1G_cc2)
```

Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model failed to converge with max|grad| = 0.0360707 (tol = 0.001, component 1)

```
# > summary(m1G_cc2)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ G_ageFirst + live + relation + ete + where + life +
#   drugs + physical + emotion + self + think + attitude + change +
time + (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 642.5    719.9   -303.3    606.5      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6688 -0.6683 -0.3657  0.8210  3.6161
#
# Random effects:
# Groups     Name        Variance Std.Dev.  Corr
# Individual (Intercept) 0.04508  0.2123
#            time        0.05330  0.2309   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                            Estimate Std. Error z value Pr(>|z|)
# Intercept)                -0.758031   0.376421  -2.014   0.0440 *
# G_ageFirst13 to 17 years -0.065516   0.273335  -0.240   0.8106
# live                      -0.068365   0.143999  -0.475   0.6350
# relation                   0.192954   0.157399   1.226   0.2202
# ete                        0.002639   0.129792   0.020   0.9838
# where                      0.150261   0.127519   1.178   0.2387
# life                       0.020749   0.190939   0.109   0.9135
# drugs                      0.264647   0.132960   1.990   0.0465 *
# physical                  -0.223508   0.149796  -1.492   0.1357
# emotion                   -0.033675   0.133387  -0.252   0.8007
# self                      -0.060519   0.175111  -0.346   0.7296
# think                      0.121178   0.186468   0.650   0.5158
# attitude                  -0.068246   0.190813  -0.358   0.7206
# change                     0.215122   0.180713   1.190   0.2339
# time                      -0.441566   0.107563  -4.105 4.04e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


# convergence code: 0
# Model failed to converge with max|grad| = 0.0360707 (tol = 0.001,
component 1)
```

```
# > vcomps.icc(m1G_cc2)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.045         0.053         1.000         0.458

# > anova(m1,m1G_cc2)
# Data: data
# Models:
#  m1: FO.bin ~ live + relation + ete + where + life + drugs + physical+
#  m1: emotion + self + think + attitude + change + time +
   m1: (time | individual)
#  m1G_cc2: FO.bin ~ G_ageFirst + live + relation + ete + where + life +
#  m1G_cc2: drugs + physical + emotion + self + think + attitude +
#  m1G_cc2: change + time + (time | Individual)
#         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1      17 640.59 713.70 -303.29   606.59
# m1G_cc2 18 642.53 719.95 -303.27   606.53 0.0538      1     0.8166
```

Model 1.6 – Basic Model + Grouped Age at First Conviction (Table 6.4)

Bayesian Model (Bm1G_cc3)

Define the model

```
Bm1G_cc3 <- MCMCglmm(FO.bin~G_ageCon + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time,random=~time+Research.ID, data=data3,family="ordinal",prior=priorD,
slice=TRUE,nitt=200000, thin=50, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_cc3$VCV)
heidel.diag(Bm1G_cc3$VCV)

# > raftery.diag(Bm1G_cc3$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      194550 3746         51.9
# Research.ID 150       202950 3746         54.2
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1G_cc3$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.198
# Research.ID passed         1        0.563
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.525 0.04199
# Research.ID passed     0.187 0.00649
# units        <NA>         NA      NA

autocorr(Bm1G_cc3$VCV)
autocorr(Bm1G_cc3$Sol)
summary(Bm1G_cc3)

# > autocorr(Bm1G_cc3$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0    1.000000000  0.13081047   NaN
# Lag 50   0.149052437  0.03745390   NaN
# Lag 250  0.070202109  0.03472865   NaN
# Lag 500  0.005285157  0.02037196   NaN
# Lag 2500 0.015767015  0.02139104   NaN
```

```
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0     0.13081047  1.000000000   NaN
# Lag 50    0.03139942  0.141831229   NaN
# Lag 250   0.02623208  0.015465146   NaN
# Lag 500  -0.01884868 -0.007141770   NaN
# Lag 2500 -0.00829845  0.006617908   NaN

# > summary(Bm1G_cc3)
#
# Iterations = 3001:199951
# Thinning interval  = 50
# Sample size  = 3940
#
# DIC: 473.0988
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.525   0.3797    3.175     1757
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1869 1.714e-09   0.5438     2960
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageCon + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time
#
#                        post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)            -0.886417 -2.320268  0.560274     3940 0.2152
# G_ageCon14 to 17 years -0.332701 -0.956824  0.335320     4150 0.3071
# live                    0.033061 -0.231689  0.302904     3940 0.8299
# relation                0.281920 -0.019498  0.594894     3600 0.0751 .
# ete                     0.091457 -0.162625  0.350561     3940 0.4787
# where                   0.030717 -0.186685  0.262579     3519 0.7904
# life                    0.035387 -0.316716  0.389783     3940 0.8325
# drugs                   0.177183 -0.079247  0.423160     3940 0.1508
# physical               -0.108519 -0.423421  0.166291     3940 0.4797
# emotion                -0.005253 -0.244155  0.245863     3940 0.9635
# self                   -0.156001 -0.483367  0.175095     3694 0.3467
# think                  -0.176913 -0.506710  0.151957     3940 0.3000
# attitude                0.046032 -0.311901  0.387009     4130 0.7964
# change                  0.236306 -0.092322  0.603445     3775 0.1838
# time                   -0.158850 -0.308647 -0.018145     4700 0.0340 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_cc3)

```
m1G_cc3 <- glmer(FO.bin ~ G_ageCon + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time + (time|Individual), data=data, family=binomial)
summary(m1G_cc3)
vcomps.icc(m1G_cc3)
anova(m1,m1G_cc3)
```

Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model failed to converge with max|grad| = 0.118701 (tol = 0.001, component 1)

```
# > summary(m1G_cc3)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ G_ageCon + live + relation + ete + where + life +
drugs +  physical + emotion + self + think + attitude + change + time +
(time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 642.6    720.0   -303.3    606.6      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6913 -0.6700 -0.3649  0.8181  3.6209
#
# Random effects:
# Groups     Name        Variance Std.Dev.  Corr
# Individual (Intercept) 0.04412  0.2101
#            time        0.05214  0.2283   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                          Estimate Std. Error z value Pr(>|z|)
# (Intercept)             -0.732614   0.461693  -1.587   0.1126
# G_ageCon14 to 17 years -0.078581   0.366735  -0.214   0.8303
# live                    -0.062225   0.141472  -0.440   0.6601
# relation                 0.192131   0.157284   1.222   0.2219
# ete                      0.003273   0.130095   0.025   0.9799
# where                    0.146402   0.128305   1.141   0.2539
# life                     0.018552   0.190497   0.097   0.9224
# drugs                    0.262823   0.132802   1.979   0.0478 *
# physical                -0.222190   0.149825  -1.483   0.1381
# emotion                 -0.029698   0.133220  -0.223   0.8236
# self                    -0.069276   0.176786  -0.392   0.6952
# think                    0.115759   0.187469   0.617   0.5369
# attitude                -0.060917   0.189322  -0.322   0.7476
# change                   0.216249   0.180654   1.197   0.2313
# time                    -0.438439   0.108879  -4.027 5.65e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


#   convergence code: 0
#   Model failed to converge with max|grad| = 0.118701 (tol = 0.001,
component 1)
```

```
# > vcomps.icc(m1G_cc3)
#   Var (Level 2) Var (Level 1)           ICC          <NA>
#           0.044         0.052         1.000         0.458

# > anova(m1,m1G_cc3)
# Data: data
# Models:
#   m1: FO.bin ~ live + relation + ete + where + life + drugs + physical
#   m1: + emotion + self + think + attitude + change + time + (time |
#   m1: Individual)
#   m1G_cc3: FO.bin ~ G_ageCon + live + relation + ete + where + life +
#   m1G_cc3: drugs + physical + emotion + self + think + attitude +
#   m1G_cc3: change + time + (time | Individual)
#         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1      17 640.59 713.70 -303.29   606.59
# m1G_cc3 18 642.55 719.97 -303.28   606.55 0.0364      1     0.8486
```

Model 1.7 – Basic Model + FTE (Table 6.5)

Bayesian Model (Bm1_cc1)

Define the model

```
Bm1_cc1 <- MCMCglmm(FO.bin~FTE + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=400000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_cc1$VCV)
heidel.diag(Bm1_cc1$VCV)

# > raftery.diag(Bm1_cc1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         30       41690  3746         11.1
# Research.ID 250       268650 3746         71.7
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_cc1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.709
# Research.ID passed         1        0.558
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.289 0.01274
# Research.ID passed     0.113 0.00664
# units        <NA>         NA      NA

autocorr(Bm1_cc1$VCV)
autocorr(Bm1_cc1$Sol)    # Output not included here
summary(Bm1_cc1)

# > autocorr(Bm1_cc1$VCV)
# , , time
#
#                 time  Research.ID units
# Lag 0   1.000000000  0.093231187   NaN
# Lag 10  0.223650496  0.090827425   NaN
# Lag 50  0.077561135  0.071376824   NaN
# Lag 100 0.032019145  0.051475480   NaN
# Lag 500 0.007348098 -0.005736716   NaN
```

```
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0    0.093231187  1.000000000   NaN
# Lag 10   0.092300428  0.833072503   NaN
# Lag 50   0.075804854  0.553472403   NaN
# Lag 100  0.045673932  0.363528077   NaN
# Lag 500 -0.005817017 -0.006492372   NaN

# > summary(Bm1_cc1)
#
# Iterations = 3001:399991
# Thinning interval  = 10
# Sample size  = 39700
#
# DIC: 476.7039
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.289   0.3567    2.672    12444
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1131 0.0001664   0.4026     1770
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ FTE + live + relation + ete + where + life
+ drugs + physical + emotion + self + think + attitude + change + time
#
#             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -1.212461 -2.493554  0.057642    24716 0.0609 .
# FTE          0.083277 -0.377381  0.541366    17027 0.7121
# live         0.035606 -0.221392  0.296553    15974 0.7905
# relation     0.278421 -0.016225  0.570105    15836 0.0603 .
# ete          0.088605 -0.159408  0.332646    15774 0.4741
# where        0.038362 -0.184443  0.252103    16974 0.7261
# life         0.030893 -0.307605  0.379795    16907 0.8579
# drugs        0.158679 -0.081241  0.400695    12976 0.1941
# physical    -0.107319 -0.395482  0.177187    13912 0.4654
# emotion     -0.003835 -0.249326  0.237891    16109 0.9698
# self        -0.132154 -0.447166  0.177059    15965 0.4067
# think       -0.155249 -0.485381  0.173934    17408 0.3508
# attitude     0.037632 -0.316093  0.379314    16404 0.8247
# change       0.231627 -0.101783  0.577007    16228 0.1775
# time        -0.154720 -0.294414 -0.021795    16185 0.0237 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_cc1)

```
m1_cc1 <- glmer(FO.bin ~ fte + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_cc1)
vcomps.icc(m1_cc1)
anova(m1, m1_cc1)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ fte + live + relation + ete + where + life + drugs +
#   physical + emotion + self + think + attitude + change + time +
#   (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 642.6    720.0   -303.3    606.6      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6322 -0.6770 -0.3657  0.8169  3.6043

# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.04332  0.2081
#            time        0.05421  0.2328   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.8302833  0.3585833  -2.315   0.0206 *
# fte          0.0415228  0.2524687   0.164   0.8694
# live        -0.0578698  0.1430367  -0.405   0.6858
# relation     0.1922638  0.1576628   1.219   0.2227
# ete          0.0004378  0.1304144   0.003   0.9973
# where        0.1489590  0.1277292   1.166   0.2435
# life         0.0177395  0.1907501   0.093   0.9259
# drugs        0.2636056  0.1331381   1.980   0.0477 *
# physical    -0.2248271  0.1496182  -1.503   0.1329
# emotion     -0.0325638  0.1335213  -0.244   0.8073
# self        -0.0610678  0.1758137  -0.347   0.7283
# think        0.1222262  0.1865238   0.655   0.5123
# attitude    -0.0622195  0.1898107  -0.328   0.7431
# change       0.2125984  0.1808557   1.176   0.2398
# time        -0.4432764  0.1083026  -4.093 4.26e-05 ***
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.0330474 (tol = 0.001,
component 1)


# vcomps.icc(m1_cc1)
# Var (Level 2) Var (Level 1)          ICC          <NA>
#         0.043         0.054        1.000         0.444
```

```
# anova(m1, m1_cc1)
# Data: data
# Models:
# m1: FO.bin ~ time + live + relation + ete + where + life + drugs +
#   m1:     physical + emotion + self + think + attitude + change + (time |
#   m1:     Individual)
# m1_cc1: FO.bin ~ fte + live + relation + ete + where + life + drugs +
#   m1_cc1:     physical + emotion + self + think + attitude + change + time
#   m1_cc1:     +(time | Individual)
#        Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
# m1     17 640.59 713.70 -303.29   606.59
# m1_cc1 18 642.56 719.98 -303.28   606.56 0.027      1     0.8695
```

Model 1.8 – Basic Model + Offence Category (Table 6.7)

Bayesian Model (Bm1_o1)

Define the model

```
Bm1_o1 <- MCMCglmm(FO.bin ~ as.factor(I_Cat) + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time,
random=~time+Research.ID, data=data3, family="ordinal",prior=priorD,
slice=TRUE,nitt=600000, thin=150, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_o1$VCV)
heidel.diag(Bm1_o1$VCV)

# > raftery.diag(Bm1_o1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         300      570750 3746         152
# Research.ID 300       582600 3746         156
# units        <NA>     <NA>   3746          NA
#
# > heidel.diag(Bm1_o1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.659
# Research.ID passed         1        0.468
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.660 0.04163
# Research.ID passed     0.276 0.00787
# units        <NA>         NA      NA

autocorr(Bm1_o1$VCV)
autocorr(Bm1_o1$Sol)  # Output not included here
summary(Bm1_o1)

# > autocorr(Bm1_o1$VCV)
# , , time
#
#                   time Research.ID units
# Lag 0    1.0000000000  0.14026704   NaN
# Lag 150  0.1652044569  0.04845871   NaN
# Lag 750  0.0003311391  0.02789120   NaN
# Lag 1500 0.0239732450  0.02010955   NaN
# Lag 7500 0.0007777259 -0.01814886   NaN
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0     0.140267038  1.000000000   NaN
```

```
# Lag 150   0.006986667  0.027493834   NaN
# Lag 750  -0.023268556  0.012748812   NaN
# Lag 1500 -0.005292637 -0.004091367   NaN
# Lag 7500 -0.017437349 -0.020941913   NaN

# > summary(Bm1_o1)
#
# Iterations = 3001:599851
# Thinning interval  = 150
# Sample size  = 3980
#
# DIC: 474.536
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time      1.66   0.4389    3.541     2306
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2764 2.936e-07    0.761     3766
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ as.factor(I_Cat) + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time
#
#                                                      post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)                                          -0.782872 -2.312961  0.704472     3980 0.3035
# as.factor(I_Cat)Domestic Burglary                    -0.094862 -1.182858  1.087508     3768 0.8583
# as.factor(I_Cat)Drugs                                -0.982489 -2.062979  0.122987     3923 0.0769 .
# as.factor(I_Cat)Motoring Offences                    -0.307171 -1.689818  0.990634     3980 0.6317
# as.factor(I_Cat)Non Domestic Burglary                 0.043594 -1.638337  1.747351     3980 0.9437
# as.factor(I_Cat)Other                                -0.744404 -4.289181  2.689208     4243 0.6925
# as.factor(I_Cat)Public Order                         -0.869911 -1.908572  0.271954     3980 0.1221
# as.factor(I_Cat)Racially Aggravated                  -1.456734 -5.018024  2.069311     3980 0.4528
# as.factor(I_Cat)Robbery                              -0.959941 -2.157523  0.238449     3980 0.1121
# as.factor(I_Cat)Sexual Offences                      -1.981059 -4.987371  0.946802     4645 0.1804
# as.factor(I_Cat)Theft And Handling Stolen Goods      -0.407037 -1.466040  0.623414     3980 0.4457
# as.factor(I_Cat)Vehicle Theft / Unauthorised Taking -0.216092 -1.143821  0.742028     4179 0.6583
# as.factor(I_Cat)Violence Against The Person          -0.220664 -1.111260  0.567894     3980 0.6131
# live                                                  0.097227 -0.175749  0.402288     3980 0.5116
# relation                                              0.298045 -0.019922  0.619944     4203 0.0693 .
# ete                                                   0.045941 -0.217120  0.316105     3980 0.7302
# where                                                 0.050383 -0.200537  0.295319     3980 0.6774
# life                                                 -0.007257 -0.385664  0.376289     3289 0.9759
# drugs                                                 0.309860  0.039504  0.594035     3980 0.0271 *
# physical                                             -0.181456 -0.500287  0.151750     3980 0.2678
# emotion                                              -0.019930 -0.269472  0.267340     3980 0.8884
# self                                                 -0.113845 -0.458792  0.226425     3980 0.5015
# think                                                -0.215182 -0.570623  0.176636     3980 0.2528
# attitude                                              0.037911 -0.352306  0.413338     3980 0.8402
# change                                                0.219671 -0.157627  0.570315     3980 0.2457
# time                                                 -0.182750 -0.343162 -0.042300     4222 0.0166 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_o1)

```
m1_o1 <- glmer(FO.bin ~ as.factor(I_Cat) + live + relation + ete + where
+ life + drugs + physical + emotion + self + think + attitude + change +
time + time|Individual), data=data3, family=binomial)
summary(m1_o1)
vcomps.icc(m1_o1)
anova(m1_o1,m1_o1a)
```

Warning message:

In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model failed to converge with max|grad| = 0.109368 (tol = 0.001, component 1)

```
# > summary(m1_o1)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial ( logit )
# Formula: FO.bin ~ as.factor(I_Cat) + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time + (time | Individual)
# Data: data3
#
#   AIC      BIC   logLik deviance df.resid
# 657.1    781.8   -299.6    599.1      516
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -2.0267 -0.6646 -0.3588  0.8112  3.7450
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.07214  0.2686
#            time        0.04347  0.2085   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                                                          Estimate Std. Error z value Pr(>|z|)
# (Intercept)                                             -0.414796   0.456019  -0.910   0.3630
# as.factor(I_Cat)Domestic Burglary                       -0.225663   0.542671  -0.416   0.6775
# as.factor(I_Cat)Drugs                                   -0.836899   0.538080  -1.555   0.1199
# as.factor(I_Cat)Motoring Offences                       -0.189013   0.687615  -0.275   0.7834
# as.factor(I_Cat)Non Domestic Burglary                    0.456535   0.931904   0.490   0.6242
# as.factor(I_Cat)Other                                   -0.286017   1.339457  -0.214   0.8309
# as.factor(I_Cat)Public Order                            -0.783258   0.491401  -1.594   0.1110
# as.factor(I_Cat)Racially Aggravated                     -0.396151   1.308967  -0.303   0.7622
# as.factor(I_Cat)Robbery                                 -0.925634   0.566008  -1.635   0.1020
# as.factor(I_Cat)Sexual Offences                         -0.827565   1.253581  -0.660   0.5092
# as.factor(I_Cat)Theft And Handling Stolen Goods         -0.397216   0.496988  -0.799   0.4241
# as.factor(I_Cat)Vehicle Theft / Unauthorised Taking     -0.101326   0.501862  -0.202   0.8400
# as.factor(I_Cat)Violence Against The Person             -0.255274   0.425643  -0.600   0.5487
# live                                                     0.024074   0.149557   0.161   0.8721
# relation                                                 0.163467   0.161519   1.012   0.3115
# ete                                                     -0.008100   0.133417  -0.061   0.9516
# where                                                    0.130701   0.132094   0.989   0.3224
# life                                                     0.002379   0.196768   0.012   0.9904
# drugs                                                    0.328044   0.141160   2.324   0.0201 *
# physical                                                -0.240586   0.163264  -1.474   0.1406
# emotion                                                 -0.060676   0.136754  -0.444   0.6573
# self                                                    -0.071118   0.181263  -0.392   0.6948
# think                                                    0.067143   0.202506   0.332   0.7402
# attitude                                                -0.039646   0.203323  -0.195   0.8454
# change                                                   0.201639   0.185684   1.086   0.2775
# time                                                    -0.416487   0.098703  -4.220 2.45e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# convergence code: 0
# Model failed to converge with max|grad| = 0.109368 (tol = 0.001,
component 1)

# > vcomps.icc(m1_o1)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.072         0.043         1.000         0.624

# > anova(m1_o1,m1_o1a)
# Data: data3
# Models:
#   m1_o1a: FO.bin ~ as.factor(I_Cat2) + live + relation + ete + where +
#   m1_o1a:   life + drugs + physical + emotion + self + think + attitude +
#   m1_o1a:   change + time + (time | Individual)
# m1_o1: FO.bin ~ as.factor(I_Cat) + live + relation + ete + where + life +
#   m1_o1:  drugs + physical + emotion + self + think + attitude + change +
#   m1_o1:  time + (time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1_o1a 19 644.39 726.11 -303.20   606.39
# m1_o1  29 657.11 781.83 -299.56   599.11 7.2829     10     0.6985
```

Model 1.9 – Basic Model + Grouped YJB Offence Category (Table 6.7)

Create a new predictor which groups the YJB Offence Categories

- VAP = Violence against the person
- SAC = burglary (domestic and non-domestic), robbery and vehicle theft / TWOC
- Other = Everything else

Since factors default to being in alphabetical order, 'Other' will be the reference category

Bayesian Model (Bm1G_o1)

Define the model

```
Bm1G_o1 <- MCMCglmm(FO.bin ~ as.factor(I_Cat2) + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
slice=TRUE, nitt=600000, thin=150, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_o1$VCV)
heidel.diag(Bm1G_o1$VCV)

# > raftery.diag(Bm1G_o1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         300      559200 3746         149
# Research.ID  300      594600 3746         159
# units        <NA>     <NA>   3746          NA
#
# > heidel.diag(Bm1G_o1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.0543
# Research.ID  passed        1        0.3306
# units        failed       NA            NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    1.54 0.03273
# Research.ID  passed    0.22 0.00617
# units        <NA>        NA      NA

autocorr(Bm1G_o1$VCV)
autocorr(Bm1G_o1$Sol) # Output not included here
summary(Bm1G_o1)
```

```
# > autocorr(Bm1G_o1$VCV)
# , , time
#
#                  time  Research.ID units
# Lag 0     1.000000000  0.141669215   NaN
# Lag 150   0.117048026  0.007268354   NaN
# Lag 750   0.023893442 -0.005368376   NaN
# Lag 1500 -0.011537089 -0.004579650   NaN
# Lag 7500 -0.008860934  0.029158813   NaN
#
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0    0.141669215  1.000000000   NaN
# Lag 150  0.041990099  0.036827366   NaN
# Lag 750  0.005681475 -0.011765765   NaN
# Lag 1500 0.024775869  0.004587169   NaN
# Lag 7500 0.020486473  0.014626207   NaN

# > summary(Bm1G_o1)
#
# Iterations = 3001:599851
# Thinning interval  = 150
# Sample size  = 3980
#
# DIC: 473.7723
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time      1.54    0.378    3.236     2892
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2197 4.209e-07    0.588     3696
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ as.factor(I_Cat2) + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time
#
#                      post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)           -1.29655 -2.62834  0.12535     3980 0.0623 .
# as.factor(I_Cat2)SAC   0.16237 -0.36085  0.77296     4208 0.5558
# as.factor(I_Cat2)VAP   0.23382 -0.35229  0.80994     3980 0.4256
# live                   0.05245 -0.21143  0.32365     3980 0.7045
# relation               0.27026 -0.01654  0.59166     3980 0.0799 .
# ete                    0.08097 -0.18404  0.31697     4479 0.5387
# where                  0.04954 -0.19422  0.26914     4162 0.6749
# life                   0.03622 -0.32851  0.39200     3980 0.8352
# drugs                  0.18297 -0.05460  0.43770     4391 0.1412
# physical              -0.11571 -0.41754  0.17107     3980 0.4603
# emotion                0.01507 -0.23195  0.26983     3980 0.9095
# self                  -0.15805 -0.48322  0.16698     4218 0.3553
# think                 -0.16829 -0.51744  0.16763     4749 0.3337
# attitude               0.03878 -0.33607  0.38174     3980 0.8402
# change                 0.23445 -0.11599  0.58682     3980 0.1864
# time                  -0.16548 -0.32216 -0.02939     3980 0.0251 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_o1)

```
m1G_o1 <- glmer(FO.bin ~ as.factor(I_Cat2) + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time +  time|Individual), data=data3, family=binomial)
summary(m1G_o1)
vcomps.icc(m1G_o1)
anova(m1,m1G_o1)

# > summary(m1G_o1)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ as.factor(I_Cat2) + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude +
change + time + (time | Individual)
# Data: data3
#
#   AIC      BIC   logLik deviance df.resid
# 644.4    726.1   -303.2    606.4      526
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6217 -0.6773 -0.3642  0.8099  3.5589
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.04473  0.2115
#            time        0.05420  0.2328   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                        Estimate Std. Error z value Pr(>|z|)
# (Intercept)           -0.846339   0.336507  -2.515   0.0119 *
# as.factor(I_Cat2)SAC  0.093918   0.300962   0.312   0.7550
# as.factor(I_Cat2)VAP  0.120896   0.306852   0.394   0.6936
# live                  -0.050070   0.144713  -0.346   0.7293
# relation               0.184386   0.158702   1.162   0.2453
# ete                    0.005343   0.130020   0.041   0.9672
# where                  0.146720   0.128425   1.142   0.2533
# life                   0.015251   0.191101   0.080   0.9364
# drugs                  0.268087   0.134764   1.989   0.0467 *
# physical              -0.214207   0.152696  -1.403   0.1607
# emotion               -0.030376   0.133955  -0.227   0.8206
# self                  -0.072524   0.176473  -0.411   0.6811
# think                  0.108903   0.189296   0.575   0.5651
# attitude              -0.051835   0.191847  -0.270   0.7870
# change                 0.208678   0.181197   1.152   0.2495
# time                  -0.444244   0.108857  -4.081 4.48e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.0153217 (tol = 0.001,
component 1)

# > vcomps.icc(m1G_o1)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.045         0.054         1.000         0.452
```

```
# > anova(m1,m1G_o1)
# Data: data3
# Models:
#   m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1G_o1: FO.bin ~ as.factor(I_Cat2) + live + relation + ete + where +
#   m1G_o1:   life + drugs + physical + emotion + self + think + attitude +
#   m1G_o1:   change + time + (time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1     17 640.59 713.70 -303.29   606.59
# m1G_o1 19 644.39 726.11 -303.20   606.39 0.1953      2      0.907
```

Model 3 – Basic Model + Static Factors (Table 6.8)

Bayesian Model (Bm1G_cc123o1)

Define the model

```
Bm1G_cc123o1 <- MCMCglmm(FO.bin~FTE + G_ageFirst + G_ageCon +
as.factor(I_Cat2) + live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
nitt=1500000, thin=100, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_cc123o1$VCV)
heidel.diag(Bm1G_cc123o1$VCV)

# > raftery.diag(Bm1G_cc123o1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
# Burn-in  Total  Lower bound  Dependence
# (M)      (N)    (Nmin)       factor (I)
# time        200      372700 3746          99.5
# Research.ID 200      385100 3746         103.0
# units       <NA>     <NA>   3746            NA
#
# > heidel.diag(Bm1G_cc123o1$VCV)
#
#             Stationarity start     p-value
#             test         iteration
# time        passed        1        0.383
# Research.ID passed        1        0.197
# units       failed       NA           NA
#
#             Halfwidth Mean  Halfwidth
#             test
# time        passed    1.554 0.01796
# Research.ID passed    0.234 0.00422
# units       <NA>         NA      NA

autocorr(Bm1G_cc123o1$VCV)
autocorr(Bm1G_cc123o1$Sol)   # not included here
summary(Bm1G_cc123o1)

# > autocorr(Bm1G_cc123o1$VCV)
# , , time
#
#                 time Research.ID units
# Lag 0    1.000000000 0.120995135   NaN
# Lag 100  0.126393627 0.038845282   NaN
# Lag 500  0.025283173 0.006934089   NaN
# Lag 1000 0.008862484 0.020349735   NaN
# Lag 5000 0.011279276 0.004829848   NaN
```

```
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0     0.120995135  1.000000000   NaN
# Lag 100   0.027333459  0.167508941   NaN
# Lag 500   0.015084321  0.015962329   NaN
# Lag 1000  0.027187822  0.003195177   NaN
# Lag 5000 -0.001865371 -0.016088398   NaN

# > summary(Bm1G_cc123o1)
#
# Iterations = 3001:1499901
# Thinning interval  = 100
# Sample size  = 14970
#
# DIC: 474.8028
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.554   0.4044    3.255     9561
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2336 4.384e-13    0.648     9953
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
#  Location  effects:  FO.bin  ~  FTE  +  G_ageFirst  +  G_ageCon  +
as.factor(I_Cat2) + live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time
#
#                           post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)                -0.94621 -2.50572  0.60540    14266 0.2162
# FTE                         0.12227 -0.44052  0.68452    14303 0.6530
# G_ageFirst13 to 17 years   -0.19653 -0.78993  0.40267    13606 0.5051
# G_ageCon14 to 17 years     -0.29551 -1.03047  0.43564    14589 0.4191
# as.factor(I_Cat2)SAC        0.23283 -0.34184  0.79777    14970 0.4090
# as.factor(I_Cat2)VAP        0.21450 -0.41486  0.85504    14970 0.5014
# live                        0.03934 -0.23535  0.31119    14970 0.7747
# relation                    0.28521 -0.02761  0.59160    14970 0.0704 .
# ete                         0.07741 -0.16746  0.34364    14970 0.5476
# where                       0.03365 -0.19443  0.27370    14567 0.7846
# life                        0.04845 -0.30632  0.40664    14623 0.7969
# drugs                       0.20084 -0.05091  0.45915    14970 0.1137
# physical                   -0.07605 -0.39547  0.24161    14621 0.6457
# emotion                     0.01531 -0.24242  0.26741    13354 0.9122
# self                       -0.16783 -0.50459  0.16147    14970 0.3246
# think                      -0.19374 -0.54927  0.14365    15583 0.2792
# attitude                    0.02101 -0.35253  0.38391    15292 0.9085
# change                      0.24359 -0.09981  0.61183    14970 0.1758
# time                       -0.16958 -0.32382 -0.02967    13294 0.0192 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_cc123o1)

```
m1G_cc123_o1 <- glmer(FO.bin ~ FTE + G_ageFirst + G_ageCon +
as.factor(I_Cat2) + live + relation + ete + where + life + drugs +
physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1G_cc123_o1)
vcomps.icc(m1G_cc123_o1)
anova(m1,m1G_cc123_o1)
anova(m1G_cc2,m1G_cc123_o1)
anova(m1G_cc3,m1G_cc123_o1)
anova(m1_cc1,m1G_cc123_o1)
anova(m1G_o1,m1G_cc123_o1)
```

Warning message:

```
  In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv,
  : Model failed to converge with max|grad| = 0.120329 (tol = 0.001,
  component 1)
```

```
# > summary(m1G_cc123_o1)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ FTE + G_ageFirst + G_ageCon + as.factor(I_Cat2) +
live + relation + ete + where + life + drugs + physical + emotion +
self + think + attitude + change + time + (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 650.2    744.8   -303.1    606.2      523
#
# Scaled residuals:
#    Min      1Q  Median      3Q     Max
# -1.6814 -0.6779 -0.3627  0.8023  3.6248
#
# Random effects:
# Groups     Name        Variance Std.Dev.   Corr
# Individual (Intercept) 0.04788  0.2188
#            time        0.05007  0.2238    -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                         Estimate Std. Error z value Pr(>|z|)
# (Intercept)            -0.777103   0.505143  -1.538   0.1240
# FTE                     0.075141   0.274954   0.273   0.7846
# G_ageFirst13 to 17 years -0.108871   0.311316  -0.350   0.7266
# G_ageCon14 to 17 years  -0.047178   0.391837  -0.120   0.9042
# as.factor(I_Cat2)SAC    0.109939   0.303292   0.362   0.7170
# as.factor(I_Cat2)VAP    0.133847   0.312434   0.428   0.6684
# live                   -0.055030   0.146285  -0.376   0.7068
# relation                0.189210   0.158349   1.195   0.2321
# ete                     0.004379   0.130512   0.034   0.9732
# where                   0.142074   0.129640   1.096   0.2731
# life                    0.021111   0.190724   0.111   0.9119
# drugs                   0.270813   0.135024   2.006   0.0449 *
# physical               -0.199397   0.156077  -1.278   0.2014
# emotion                -0.027674   0.133562  -0.207   0.8359
# self                   -0.070244   0.179325  -0.392   0.6953
# think                   0.099418   0.190051   0.523   0.6009
# attitude               -0.059488   0.192979  -0.308   0.7579
# change                  0.213222   0.180682   1.180   0.2380
# time                   -0.434316   0.109200  -3.977 6.97e-05 ***
#    ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# convergence code: 0
# Model failed to converge with max|grad| = 0.120329 (tol = 0.001,
component 1)
#
# > vcomps.icc(m1G_cc123_o1)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.048         0.050         1.000         0.489
#
# > anova(m1,m1G_cc123_o1)
# Data: data
# Models:
#   m1: FO.bin ~ live + relation + ete + where + life + drugs + physical
#   m1: + emotion + self + think + attitude + change + time + (time |
#   m1: Individual)
#   m1G_cc123_o1: FO.bin ~ FTE + G_ageFirst + G_ageCon +
#   m1G_cc123_o1: as.factor(I_Cat2) + live + relation + ete + where +
#   m1G_cc123_o1: life + drugs + physical + emotion + self + think +
#   m1G_cc123_o1: attitude + change + time + (time | Individual)
#              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1           17 640.59 713.70 -303.29   606.59
# m1G_cc123_o1 22 650.21 744.82 -303.10   606.21 0.3827      5     0.9958

# > anova(m1G_cc2,m1G_cc123_o1)
# Data: data
# Models:
#   m1G_cc2: FO.bin ~ G_ageFirst + live + relation + ete + where + life +
#   m1G_cc2: drugs + physical + emotion + self + think + attitude + change +
#   m1G_cc2: time + (time | Individual)
#   m1G_cc123_o1: FO.bin ~ FTE + G_ageFirst + G_ageCon + as.factor(I_Cat2) +
#   m1G_cc123_o1: live + relation + ete + where + life + drugs + physical +
#   m1G_cc123_o1: emotion + self + think + attitude + change + time +
#   m1G_cc123_o1: (time | Individual)
#              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1G_cc2      18 642.53 719.95 -303.27   606.53
# m1G_cc123_o1 22 650.21 744.82 -303.10   606.21 0.3289      4     0.9879

# > anova(m1G_cc3,m1G_cc123_o1)
# Data: data
# Models:
#   m1G_cc3: FO.bin ~ G_ageCon + live + relation + ete + where + life + drugs +
#   m1G_cc3: physical + emotion + self + think + attitude + change + time +
#   m1G_cc3: (time | Individual)
#   m1G_cc123_o1: FO.bin ~ FTE + G_ageFirst + G_ageCon + as.factor(I_Cat2) +
#   m1G_cc123_o1: live + relation + ete + where + life + drugs + physical +
#   m1G_cc123_o1: emotion +self + think + attitude + change + time +
#   m1G_cc123_o1: (time | Individual)
#              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1G_cc3      18 642.55 719.97 -303.28   606.55
# m1G_cc123_o1 22 650.21 744.82 -303.10   606.21 0.3463      4     0.9866

# > anova(m1_cc1,m1G_cc123_o1)
# Data: data
# Models:
#   m1_cc1: FO.bin ~ fte + live + relation + ete + where + life + drugs +
#   m1_cc1: physical + emotion + self + think + attitude + change + time +
#   m1_cc1: (time | Individual)
#   m1G_cc123_o1: FO.bin ~ FTE + G_ageFirst + G_ageCon + as.factor(I_Cat2) +
#   m1G_cc123_o1: live + relation + ete + where + life + drugs + physical +
#   m1G_cc123_o1: emotion +self + think + attitude + change + time +
#   m1G_cc123_o1: (time | Individual)
#              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1_cc1       18 642.56 719.98 -303.28   606.56
# m1G_cc123_o1 22 650.21 744.82 -303.10   606.21 0.3557      4     0.9859
```

```
# > anova(m1G_o1,m1G_cc123_o1)
# Data: data
# Models:
#   m1G_o1: FO.bin ~ as.factor(I_Cat2) + live + relation + ete + where +
#   m1G_o1: life + drugs + physical + emotion + self + think + attitude +
#   m1G_o1: change + time + (time | Individual)
#   m1G_cc123_o1: FO.bin ~ FTE + G_ageFirst + G_ageCon + as.factor(I_Cat2) +
#   m1G_cc123_o1: live + relation + ete + where + life + drugs + physical +
#   m1G_cc123_o1: emotion +self + think + attitude + change + time +
#   m1G_cc123_o1: (time | Individual)
#              Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1G_o1       19 644.39 726.11 -303.2   606.39
# m1G_cc123_o1 22 650.21 744.82 -303.1   606.21 0.1874      3     0.9796
```

Model 3a – Basic Model + FTE Status, Grouped Age at First Offence and Grouped YJB Offence Category (Table 6.11)

Bayesian Model (Bm1G_cc12_o1)

Define the model

```
BDm1G_cc12_o1  <-  MCMCglmm(FO.bin  ~  FTE*G_ageFirst*as.factor(I_Cat2)  +
live + relation + ete + where + life + drugs + physical + emotion +
self + think + attitude + change + time,
random=~time+Research.ID,  data=data3,  family="ordinal",  prior=priorD,
slice=TRUE,nitt=450000, thin=100, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_cc12o1$VCV)
heidel.diag(Bm1G_cc12o1$VCV)

# > raftery.diag(BDm1G_cc12_o1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         200      384000 3746         103.0
# Research.ID 200      370200 3746          98.8
# units        <NA>     <NA>   3746            NA
#
# > heidel.diag(BDm1G_cc12_o1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.136
# Research.ID passed        1         0.895
# units        failed       NA            NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.652 0.03480
# Research.ID passed    0.266 0.00853
# units        <NA>         NA      NA

autocorr(BDm1G_cc12_o1$VCV)
autocorr(BDm1G_cc12_o1$Sol)     # not included here
summary(BDm1G_cc12_o1)

# > autocorr(BDm1G_cc12_o1$VCV)
# , , time
#
#                  time  Research.ID units
# Lag 0     1.000000000 0.1417745486   NaN
# Lag 100   0.127834810 0.0804718700   NaN
# Lag 500   0.001649094 0.0028076019   NaN
# Lag 1000 -0.009378689 0.0313687812   NaN
# Lag 5000  0.013752415 0.0008637349   NaN
```

```
# , , Research.ID
#
#                   time Research.ID units
# Lag 0     0.141774549 1.000000000   NaN
# Lag 100   0.043586664 0.166112055   NaN
# Lag 500  -0.002643632 0.025044603   NaN
# Lag 1000 -0.010033952 0.002412812   NaN
# Lag 5000  0.004565026 0.015434418   NaN

# > summary(BDm1G_cc12_o1)
#
# Iterations = 3001:449901
# Thinning interval  = 100
# Sample size  = 4470
#
# DIC: 472.8584
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.652   0.4538    3.467     2767
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2662 4.899e-08   0.7114     2987
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ FTE * G_ageFirst * as.factor(I_Cat2) + live
+ relation + ete + where + life + drugs + physical + emotion + self +
think + attitude + change + time
#
#                                             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)                                 -1.221472 -2.795094  0.177518     4470 0.1002
# FTE                                         -0.160114 -3.810807  3.637091     4470 0.9530
# G_ageFirst13 to 17 years                     0.156251 -0.631053  0.978762     5053 0.6922
# as.factor(I_Cat2)SAC                         0.965021 -0.067527  2.011483     4278 0.0541 .
# as.factor(I_Cat2)VAP                         0.372537 -0.968804  1.792520     4470 0.5991
# live                                         0.047930 -0.236001  0.323732     4252 0.7432
# relation                                     0.298158 -0.020692  0.623885     4381 0.0644 .
# ete                                          0.035970 -0.229406  0.304404     4274 0.7857
# where                                        0.044472 -0.186304  0.285187     4252 0.7128
# life                                        -0.007186 -0.391334  0.356035     4470 0.9808
# drugs                                        0.224787 -0.048427  0.491334     4080 0.0984 .
# physical                                    -0.103379 -0.425692  0.209846     4489 0.5329
# emotion                                      0.075981 -0.198544  0.324439     4470 0.5817
# self                                        -0.198048 -0.549869  0.136098     4470 0.2600
# think                                       -0.153693 -0.517817  0.186829     4261 0.3812
# attitude                                    -0.002526 -0.366654  0.374989     5060 0.9960
# change                                       0.256893 -0.113785  0.613091     4699 0.1611
# time                                        -0.188336 -0.340348 -0.046058     4053 0.0125 *
# FTE:G_ageFirst13 to 17 years                -0.100178 -3.940264  3.737549     4470 0.9508
# FTE:as.factor(I_Cat2)SAC                     1.187145 -0.126777  2.674126     4454 0.0881 .
# FTE:as.factor(I_Cat2)VAP                    -1.037201 -5.595150  3.492769     4470 0.6716
# G_ageFirst13 to 17 years:as.factor(I_Cat2)SAC     -1.642960 -3.028161 -0.165301     4536 0.0233 *
# G_ageFirst13 to 17 years:as.factor(I_Cat2)VAP     -0.356763 -2.053456  1.285833     4470 0.6698
# FTE:G_ageFirst13 to 17 years:as.factor(I_Cat2)VAP  1.540343 -3.256317  6.169858     4470 0.5441
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_cc12_o1)

```
m1G_cc12_o1 <- glmer(FO.bin ~ FTE + G_ageFirst + as.factor(I_Cat2) +
live + relation + ete + where + life + drugs + physical + emotion + self
+ think + attitude + change + time + (time|Individual), data=data,
family=binomial)
summary(m1G_cc12_o1)
vcomps.icc(m1G_cc12_o1)
anova(m1,m1G_cc12_o1)
```

Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model failed to converge with max|grad| = 0.0334511 (tol = 0.001, component 1)

```
# > summary(m1G_cc12_o1)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ FTE + G_ageFirst + as.factor(I_Cat2) + live +
relation + ete + where + life + drugs + physical + emotion + self +
think + attitude + change + time + (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 648.2    738.5   -303.1    606.2      524
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6513 -0.6708 -0.3622  0.8144  3.5947
#
# Random effects:
# Groups     Name        Variance Std.Dev.  Corr
# Individual (Intercept) 0.04790  0.2189
#            time        0.05108  0.2260   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                            Estimate Std. Error z value Pr(>|z|)
# (Intercept)               -0.809440   0.390383  -2.073   0.0381 *
# FTE                        0.080666   0.274660   0.294   0.7690
# G_ageFirst13 to 17 years -0.122175   0.301837  -0.405   0.6856
# as.factor(I_Cat2)SAC       0.103659   0.300178   0.345   0.7298
# as.factor(I_Cat2)VAP       0.127454   0.308422   0.413   0.6794
# live                      -0.055406   0.146240  -0.379   0.7048
# relation                   0.186529   0.158221   1.179   0.2384
# ete                        0.005522   0.130146   0.042   0.9662
# where                      0.142902   0.128136   1.115   0.2647
# life                       0.021325   0.190869   0.112   0.9110
# drugs                      0.269132   0.134645   1.999   0.0456 *
# physical                  -0.198356   0.155171  -1.278   0.2011
# emotion                   -0.026260   0.133616  -0.197   0.8442
# self                      -0.065545   0.176788  -0.371   0.7108
# think                      0.101140   0.189248   0.534   0.5930
# attitude                  -0.062416   0.192992  -0.323   0.7464
# change                     0.213181   0.180734   1.180   0.2382
# time                      -0.436650   0.107919  -4.046 5.21e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# convergence code: 0
# Model failed to converge with max|grad| = 0.0334511 (tol = 0.001,
component 1)

# > vcomps.icc(m1G_cc12_o1)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.048         0.051         1.000         0.484

# > anova(m1,m1G_cc12_o1)
# Data: data
# Models:
#   m1: FO.bin ~ live + relation + ete + where + life + drugs + physical
#   m1: + emotion + self + think + attitude + change + time + (time |
#   m1: Individual)
#   m1G_cc12_o1: FO.bin ~ FTE + G_ageFirst + as.factor(I_Cat2) + live +
#   m1G_cc12_o1: relation + ete + where + life + drugs + physical +
#   m1G_cc12_o1: emotion + self + think + attitude + change + time +
#   m1G_cc12_o1: (time | Individual)
#            Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1         17 640.59 713.70 -303.29   606.59
# m1G_cc12_o1 21 648.22 738.54 -303.11   606.22 0.3683      4      0.985
```

Model 1.10 – Basic Model + YJB Gravity Score (Table 6.12)

Bayesian Model (Bm1_o2a)

Define the model

```
Bm1_o2a <- MCMCglmm(FO.bin ~ I_Seriousness2 + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time, random=~time+Research.ID, data=data3, family="ordinal",
prior=priorD, slice=TRUE, nitt=600000, thin=150, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_o2a$VCV)
heidel.diag(Bm1_o2a$VCV)

# > raftery.diag(Bm1_o2a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         300      570750 3746         152
# Research.ID  300      547800 3746         146
# units        <NA>     <NA>   3746          NA
#
# > heidel.diag(Bm1_o2a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.197
# Research.ID  passed        1        0.569
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.503 0.03177
# Research.ID  passed    0.211 0.00581
# units        <NA>         NA      NA

autocorr(Bm1_o2a$VCV)
autocorr(Bm1_o2a$Sol)  # Output not included here
summary(Bm1_o2a)

# > autocorr(Bm1_o2a$VCV)
# , , time
#
#                     time  Research.ID units
# Lag 0      1.0000000000  0.137773410   NaN
# Lag 150    0.0773521774  0.027785917   NaN
# Lag 750    0.0104185140  0.027379150   NaN
# Lag 1500  -0.0006742669 -0.021816145   NaN
# Lag 7500  -0.0010158853  0.008001073   NaN
```

```
# , , Research.ID
#
#                   time Research.ID units
# Lag 0     0.137773410 1.000000000   NaN
# Lag 150   0.013458602 0.000307127   NaN
# Lag 750  -0.001195099 0.007752196   NaN
# Lag 1500  0.030230243 0.004600528   NaN
# Lag 7500 -0.022971336 0.017912415   NaN

# > summary(Bm1_o2a)
#
# Iterations = 3001:599851
# Thinning interval  = 150
# Sample size  = 3980
#
# DIC: 473.6892
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.503   0.4184    3.106     2709
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2107 2.839e-11   0.5725     3980
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ I_Seriousness2 + live + relation + ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time
#
#                post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)    -1.195182 -2.565127  0.302977     3980 0.1040
# I_Seriousness2 0.001380 -0.160553  0.162860     3980 0.9759
# live            0.041726 -0.212621  0.318790     3980 0.7774
# relation        0.276946 -0.007281  0.596184     4228 0.0714 .
# ete             0.074335 -0.174531  0.331579     3980 0.5613
# where           0.047107 -0.196143  0.257219     3980 0.6965
# life            0.040414 -0.316824  0.404039     3980 0.8090
# drugs           0.172303 -0.081022  0.408336     3980 0.1623
# physical       -0.132136 -0.432314  0.163439     3595 0.3925
# emotion         0.003535 -0.248338  0.250646     3980 0.9693
# self           -0.136753 -0.446290  0.195323     3980 0.4131
# think          -0.157411 -0.508338  0.158245     3980 0.3698
# attitude        0.034359 -0.327638  0.386171     3980 0.8593
# change          0.231173 -0.112874  0.585629     4399 0.1819
# time           -0.161095 -0.306581 -0.023258     3980 0.0216 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_o2)

```
m1_o2 <- glmer(FO.bin ~ I_Seriousness +
                  live + relation + ete + where + life + drugs +
physical +
                  emotion + self + think + attitude + change + time +
                  (time|Individual), data=data3, family=binomial)
summary(m1_o2)
vcomps.icc(m1_o2)
anova(m1,m1_o2)

# > summary(m1_o2)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ I_Seriousness + live + relation + ete + where + life
+
#    drugs + physical + emotion + self + think + attitude + change +
time + (time | Individual)
# Data: data3
#
#   AIC      BIC   logLik deviance df.resid
# 642.1    719.5   -303.0    606.1      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.6947 -0.6685 -0.3581  0.8074  3.6310
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept)  0.04452  0.2110
#            time         0.05482  0.2341   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#               Estimate Std. Error z value Pr(>|z|)
# (Intercept)   -0.601925   0.426631  -1.411   0.1583
# I_Seriousness -0.060591   0.085219  -0.711   0.4771
# live          -0.078744   0.145040  -0.543   0.5872
# relation       0.188512   0.157751   1.195   0.2321
# ete           -0.008879   0.131076  -0.068   0.9460
# where          0.162874   0.129087   1.262   0.2070
# life           0.023217   0.190693   0.122   0.9031
# drugs          0.264263   0.132879   1.989   0.0467 *
# physical      -0.240813   0.150518  -1.600   0.1096
# emotion       -0.032168   0.133515  -0.241   0.8096
# self          -0.052977   0.175934  -0.301   0.7633
# think          0.130266   0.186904   0.697   0.4858
# attitude      -0.057933   0.189803  -0.305   0.7602
# change         0.212254   0.180809   1.174   0.2404
# time          -0.445184   0.105972  -4.201 2.66e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
#  Model failed to converge with max|grad| = 0.0842756 (tol = 0.001,
component 1)

# > vcomps.icc(m1_o2)
# Var (Level 2) Var (Level 1)          ICC          <NA>
#         0.045         0.055        1.000         0.448
```

```
# > anova(m1,m1_o2)
# Data: data3
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1_o2: FO.bin ~ I_Seriousness + live + relation + ete + where + life +
#   m1_o2:  drugs + physical + emotion + self + think + attitude + change +
#   m1_o2:  time + (time | Individual)
#       Df    AIC   BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
# m1    17 640.59 713.7 -303.29   606.59
# m1_o2 18 642.08 719.5 -303.04   606.08 0.505      1     0.4773
```

Model 3b – Basic Model + FTE Status, Grouped Age at First Offence and YJB Gravity Score (Table 6.15)

Bayesian Model (Bm1G_cc12o2a)

Define the model

```
BDm1G_cc12_o2a <- MCMCglmm(FO.bin ~ FTE*G_ageFirst*I_Seriousness2 + live
+ relation + ete + where + life + drugs + physical + emotion +
self + think + attitude + change + time,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
slice=TRUE, nitt=450000, thin=100, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_cc12o2a$VCV)
heidel.diag(Bm1G_cc12o2a$VCV)

# > raftery.diag(BDm1G_cc12_o2a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         200      363500 3746          97
# Research.ID 200       384000 3746         103
# units        <NA>     <NA>   3746          NA
#
# > heidel.diag(BDm1G_cc12_o2a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed       448       0.181
# Research.ID passed          1       0.741
# units        failed        NA          NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.546 0.0325
# Research.ID passed     0.188 0.0064
# units        <NA>         NA     NA

autocorr(BDm1G_cc12_o2a$VCV)
autocorr(BDm1G_cc12_o2a$Sol)   # not included here
summary(BDm1G_cc12_o2a)

# > autocorr(BDm1G_cc12_o2a$VCV)
# , , time
#
#                  time  Research.ID units
# Lag 0      1.000000000  0.105383993   NaN
# Lag 100    0.087918598  0.036043386   NaN
# Lag 500   -0.001962589 -0.005114291   NaN
# Lag 1000   0.014627160 -0.038804289   NaN
# Lag 5000  -0.008579891 -0.025825999   NaN
```

```
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0     0.105383993  1.000000000   NaN
# Lag 100   0.044692939  0.148738091   NaN
# Lag 500   0.017140789  0.015101120   NaN
# Lag 1000  0.006522036 -0.005058144   NaN
# Lag 5000 -0.005915407  0.035708376   NaN

# > summary(BDm1G_cc12_o2a)
#
# Iterations = 3001:449901
# Thinning interval  = 100
# Sample size  = 4470
#
# DIC: 471.5861
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.561   0.3957    3.257     3003
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1876 4.433e-09   0.5576     3312
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ FTE * G_ageFirst * I_Seriousness2 + live + relation + ete + where + life + drugs + physical + emotion + self + think + attitude + change + time
#
#                                        post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)                            -1.376761 -2.866087  0.051983     4258 0.0626 .
# FTE                                    -0.975282 -3.207266  1.003389     4248 0.3597
# G_ageFirst13 to 17 years                0.321873 -0.413488  1.082531     4470 0.4036
# I_Seriousness2                          0.335475  0.021163  0.664861     4470 0.0376 *
# live                                    0.036028 -0.233984  0.319061     4745 0.8040
# relation                                0.279297 -0.023517  0.581920     4470 0.0747 .
# ete                                     0.074171 -0.178806  0.323021     4851 0.5588
# where                                   0.078317 -0.139276  0.317684     4470 0.4949
# life                                    0.021974 -0.323675  0.372514     5005 0.8998
# drugs                                   0.159855 -0.088366  0.427290     4470 0.2251
# physical                               -0.123274 -0.433965  0.182179     4470 0.4291
# emotion                                 0.034133 -0.217314  0.291318     4470 0.8063
# self                                   -0.122157 -0.460571  0.193227     4470 0.4805
# think                                  -0.139222 -0.464491  0.217475     4470 0.4273
# attitude                               -0.009082 -0.376918  0.349739     4470 0.9754
# change                                  0.238641 -0.102423  0.607201     4256 0.1803
# time                                   -0.176166 -0.329672 -0.038366     4256 0.0157 *
# FTE:G_ageFirst13 to 17 years            1.023147 -1.085733  3.198545     4470 0.3539
# FTE:I_Seriousness2                      0.146509 -0.278461  0.556266     4898 0.4783
# G_ageFirst13 to 17 years:I_Seriousness2 -0.528627 -0.953742 -0.116212     4470 0.0107 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_cc12_o2a)

```
m1G_cc12_o2a <- glmer(FO.bin ~ FTE + G_ageFirst + serious2 + live +
relation + ete + where + life + drugs + physical + emotion + self +
think + attitude + change + time + (time|Individual), data=data,
family=binomial)
summary(m1G_cc12_o2a)
vcomps.icc(m1G_cc12_o2a)
anova(m1,m1G_cc12_o2a)
anova(m1G_cc12_o1,m1G_cc12_o2a)
```

Warning message:

```
  In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv,
  : Model failed to converge with max|grad| = 0.0181997 (tol = 0.001,
  component 1)
```

```
# > summary(m1G_cc12_o2a)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ FTE + G_ageFirst + serious2 + live + relation + ete
+ where + life + drugs + physical + emotion + self + think + attitude +
change + time + (time | Individual)
# Data: data
#
# AIC      BIC    logLik deviance df.resid
# 646      732     -303      606      525
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.7037 -0.6691 -0.3597  0.8139  3.6475
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.04675  0.2162
#            time        0.05356  0.2314   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                           Estimate Std. Error z value Pr(>|z|)
# (Intercept)               -0.72687    0.39459  -1.842   0.0655 .
# FTE                        0.07502    0.27592   0.272   0.7857
# G_ageFirst13 to 17 years -0.06934    0.30247  -0.229   0.8187
# serious2                  -0.05730    0.08597  -0.667   0.5051
# live                      -0.08188    0.14682  -0.558   0.5770
# relation                   0.19420    0.15766   1.232   0.2180
# ete                       -0.01006    0.13149  -0.077   0.9390
# where                      0.16186    0.12908   1.254   0.2099
# life                       0.02379    0.19092   0.125   0.9008
# drugs                      0.26754    0.13307   2.011   0.0444 *
# physical                  -0.23019    0.15337  -1.501   0.1334
# emotion                   -0.03068    0.13343  -0.230   0.8181
# self                      -0.04917    0.17667  -0.278   0.7808
# think                      0.12952    0.18700   0.693   0.4886
# attitude                  -0.06626    0.19180  -0.345   0.7297
# change                     0.21585    0.18088   1.193   0.2327
# time                      -0.44247    0.10666  -4.148 3.35e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# convergence code: 0
# Model failed to converge with max|grad| = 0.0181997 (tol = 0.001,
component 1)

# > vcomps.icc(m1G_cc12_o2a)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.047         0.054         1.000         0.466

# > anova(m1,m1G_cc12_o2a)
# Data: data
# Models:
#   m1: FO.bin ~ live + relation + ete + where + life + drugs + physical
#   m1: + emotion + self + think + attitude + change + time + (time |
#   m1: Individual)
#   m1G_cc12_o2a: FO.bin ~ FTE + G_ageFirst + serious2 + live + relation
#   m1G_cc12_o2a: + ete + where + life + drugs + physical + emotion +
#   m1G_cc12_o2a: self + think + attitude + change + time + (time |
#   m1G_cc12_o2a: Individual)
#              Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1           17 640.59 713.70 -303.29   606.59
# m1G_cc12_o2a 20 645.99 732.01 -303.00   605.99 0.5971      3     0.8971

# > anova(m1G_cc12_o1,m1G_cc12_o2a)
# Data: data
# Models:
#   m1G_cc12_o2a: FO.bin ~ FTE + G_ageFirst + serious2 + live + relation
#   m1G_cc12_o2a: + ete + where + life + drugs + physical + emotion +
#   m1G_cc12_o2a: self + think + attitude + change + time + (time |
#   m1G_cc12_o2a: Individual)
#   m1G_cc12_o1: FO.bin ~ FTE + G_ageFirst + as.factor(I_Cat2) + live +
#   m1G_cc12_o1: relation + ete + where + life + drugs + physical +
#   m1G_cc12_o1: emotion + self + think + attitude + change + time +
#   m1G_cc12_o1: (time | Individual)
#              Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
# m1G_cc12_o2a 20 645.99 732.01 -303.00   605.99
# m1G_cc12_o1  21 648.22 738.54 -303.11   606.22     0      1          1
```

Dynamic Model involving FTE Status (Table 6.16)

Bayesian Model (BDm3_cc1)

Define the model

```
BDm3_cc1 <- MCMCglmm(FO.bin ~ FTE*time*live + FTE*time*relation +
FTE*time*ete + FTE*time*where + FTE*time*life + FTE*time*drugs +
FTE*time*physical + FTE*time*emotion + FTE*time*self + FTE*time*think +
FTE*time*attitude + FTE*time*change,
random=~time+Research.ID, data=data, family="ordinal", prior=priorD,
slice=TRUE, nitt=250000, thin=50, burnin=3000)
```

Checks for suitable convergence

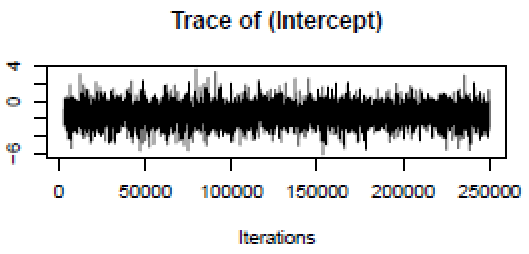
```
raftery.diag(BDm3_cc1$VCV)
heidel.diag(BDm3_cc1$VCV)

# > raftery.diag(BDm3_cc1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      197350 3746         52.7
# Research.ID 150       229250 3746         61.2
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm3_cc1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.674
# Research.ID passed         1        0.978
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    3.136 0.1107
# Research.ID passed     0.713 0.0235
# units        <NA>         NA     NA

autocorr(BDm3_cc1$VCV)
autocorr(BDm3_cc1$Sol)    # Output not included here
summary(BDm3_cc1)

# > autocorr(BDm3_cc1$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0    1.000000000 0.214009688   NaN
# Lag 50   0.281376999 0.151575646   NaN
# Lag 250  0.082176634 0.032776477   NaN
# Lag 500  0.033886911 0.009994427   NaN
# Lag 2500 0.009178118 0.012569447   NaN
```

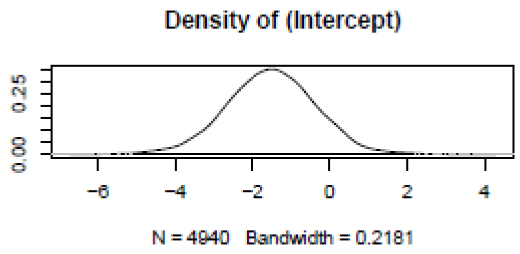
```
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0     0.214009688  1.000000000   NaN
# Lag 50    0.148050531  0.361249403   NaN
# Lag 250   0.019233034  0.048626928   NaN
# Lag 500  -0.003267157  0.002574476   NaN
# Lag 2500  0.009523299 -0.017283899   NaN

# > summary(BDm3_cc1)
#
# Iterations = 3001:249951
# Thinning interval  = 50
# Sample size  = 4940
#
# DIC: 458.2845
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     3.136   0.5226    6.932     1334
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.7125 3.544e-10    1.741     1955
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ FTE * time * live + FTE * time * relation +
FTE * time * ete + FTE * time * where + FTE * time * life + FTE * time *
drugs + FTE * time * physical + FTE * time * emotion + FTE * time * self
+ FTE * time * think + FTE * time * attitude + FTE * time * change
#
#                   post.mean   l-95% CI   u-95% CI eff.samp   pMCMC
# (Intercept)       -1.5419100 -3.8526595  0.7324976     4940 0.17126
# FTE                0.9951851 -1.6676585  3.6604664     4579 0.46559
# time              -0.1637634 -0.5232623  0.2044623     4743 0.38138
# live              -0.0469520 -0.6118585  0.5736681     4940 0.88057
# relation           0.6396332 -0.0177094  1.3436175     4940 0.06518 .
# ete               -0.3010141 -0.8277057  0.1649559     4193 0.21943
# where              0.1976180 -0.3177581  0.7374720     4709 0.44777
# life               0.3623372 -0.5113980  1.3326759     4597 0.44332
# drugs              0.2072300 -0.2769498  0.7674670     4757 0.43077
# physical          -0.4110273 -1.0627900  0.2394447     4503 0.21134
# emotion            0.0063996 -0.4797172  0.5505957     4509 0.97976
# self              -0.5215866 -1.3641125  0.3163048     4940 0.22065
# think             -0.0029852 -0.7737536  0.8144392     4940 0.99919
# attitude           0.4486572 -0.3353608  1.3237557     4940 0.29838
# change            -0.0869050 -0.9074972  0.7135178     4940 0.83077
# FTE:time          -0.7664684 -1.5317667 -0.0455493     3202 0.03765 *
# FTE:live           1.0990438 -0.3213707  2.5475102     4121 0.13198
# time:live          0.0193099 -0.1046443  0.1507931     4940 0.77368
# FTE:relation      -1.5719277 -3.0796567 -0.2079262     4218 0.02996 *
# time:relation     -0.0713774 -0.2205946  0.0807968     4520 0.36356
# FTE:ete            0.2662041 -0.9475354  1.5852466     4691 0.67409
# time:ete           0.0532188 -0.0576688  0.1584740     4666 0.31538
# FTE:where         -1.4788806 -2.6777294 -0.2941987     3682 0.01498 *
# time:where        -0.0046218 -0.1115762  0.0973955     4575 0.92753
```

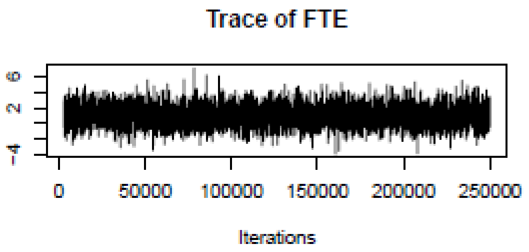
```
# FTE:life           0.9916816 -0.6515429  2.7006459     4237 0.24615    
# time:life         -0.0068196 -0.1795075  0.1819226     4659 0.95061    
# FTE:drugs         -0.6965924 -1.9733197  0.5383916     4430 0.28623    
# time:drugs        -0.0266508 -0.1375709  0.0896788     4940 0.62753    
# FTE:physical      -0.4060459 -1.7663980  1.0158650     4112 0.58097    
# time:physical      0.1148929 -0.0526034  0.2748870     4624 0.16194    
# FTE:emotion       -0.5261318 -1.6914322  0.5482584     4355 0.35992    
# time:emotion       0.0083038 -0.1055163  0.1125855     4517 0.88502    
# FTE:self           2.3921137  0.9035888  3.9304515     3943 0.00162 ** 
# time:self          0.0843226 -0.0823312  0.2394500     4640 0.30486    
# FTE:think         -0.4835213 -1.9276197  0.9895073     4738 0.50729    
# time:think        -0.0623785 -0.2446857  0.1129572     4672 0.48907    
# FTE:attitude      -1.2487718 -2.6864267  0.2305503     3974 0.09352 .  
# time:attitude     -0.1005846 -0.2852418  0.0654212     4940 0.26680    
# FTE:change         1.1932741 -0.3988753  2.7338544     4201 0.13441    
# time:change        0.0469474 -0.1133549  0.2148000     4664 0.58381    
# FTE:time:live     -0.2429895 -0.5944883  0.1048186     2604 0.17854    
# FTE:time:relation  0.3806582  0.0238632  0.7509608     3355 0.04372 *  
# FTE:time:ete       0.2541658 -0.1228007  0.6112065     3052 0.16559    
# FTE:time:where     0.2509095  0.0286526  0.4960120     3268 0.03482 *  
# FTE:time:life     -0.4413192 -0.8623134  0.0001852     4042 0.03603 *  
# FTE:time:drugs     0.2602919 -0.0610515  0.6078128     3737 0.11822    
# FTE:time:physical -0.0480137 -0.4309057  0.3473896     3481 0.81215    
# FTE:time:emotion   0.1573710 -0.0932918  0.4260784     3784 0.24413    
# FTE:time:self     -0.6139503 -0.9711916 -0.2666042     3384 < 2e-04 ***
# FTE:time:think     0.1844859 -0.1434362  0.5318857     4232 0.27611    
# FTE:time:attitude  0.2963801 -0.0768483  0.7144638     3638 0.14089    
# FTE:time:change   -0.2266278 -0.6057061  0.1558307     4541 0.25668    
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

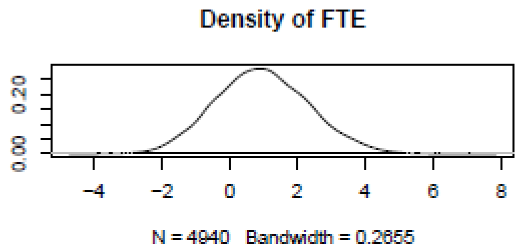
Trace Plots and Posterior Density Plots

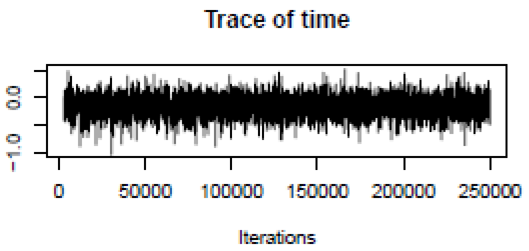
Fixed Effects

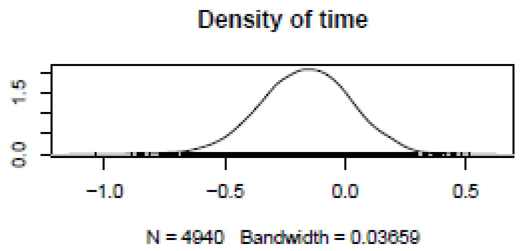


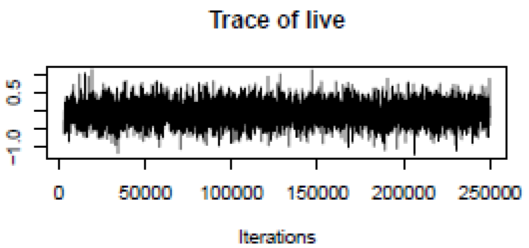


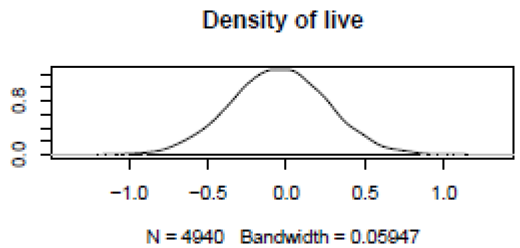


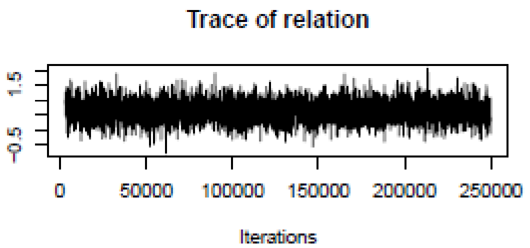


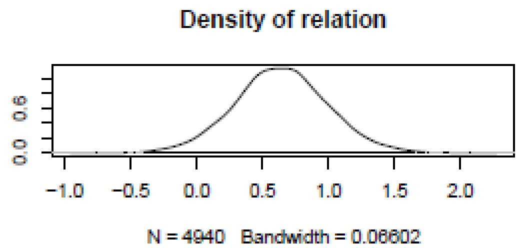


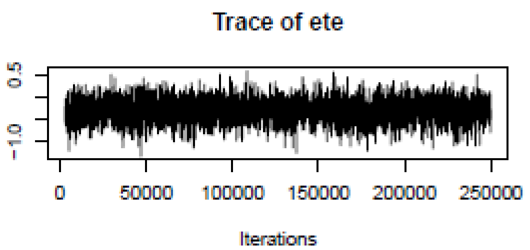


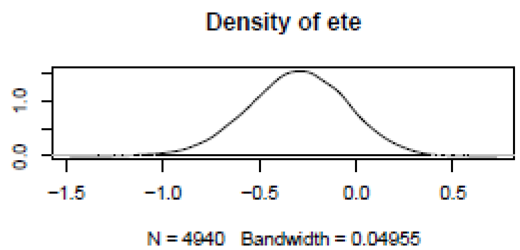


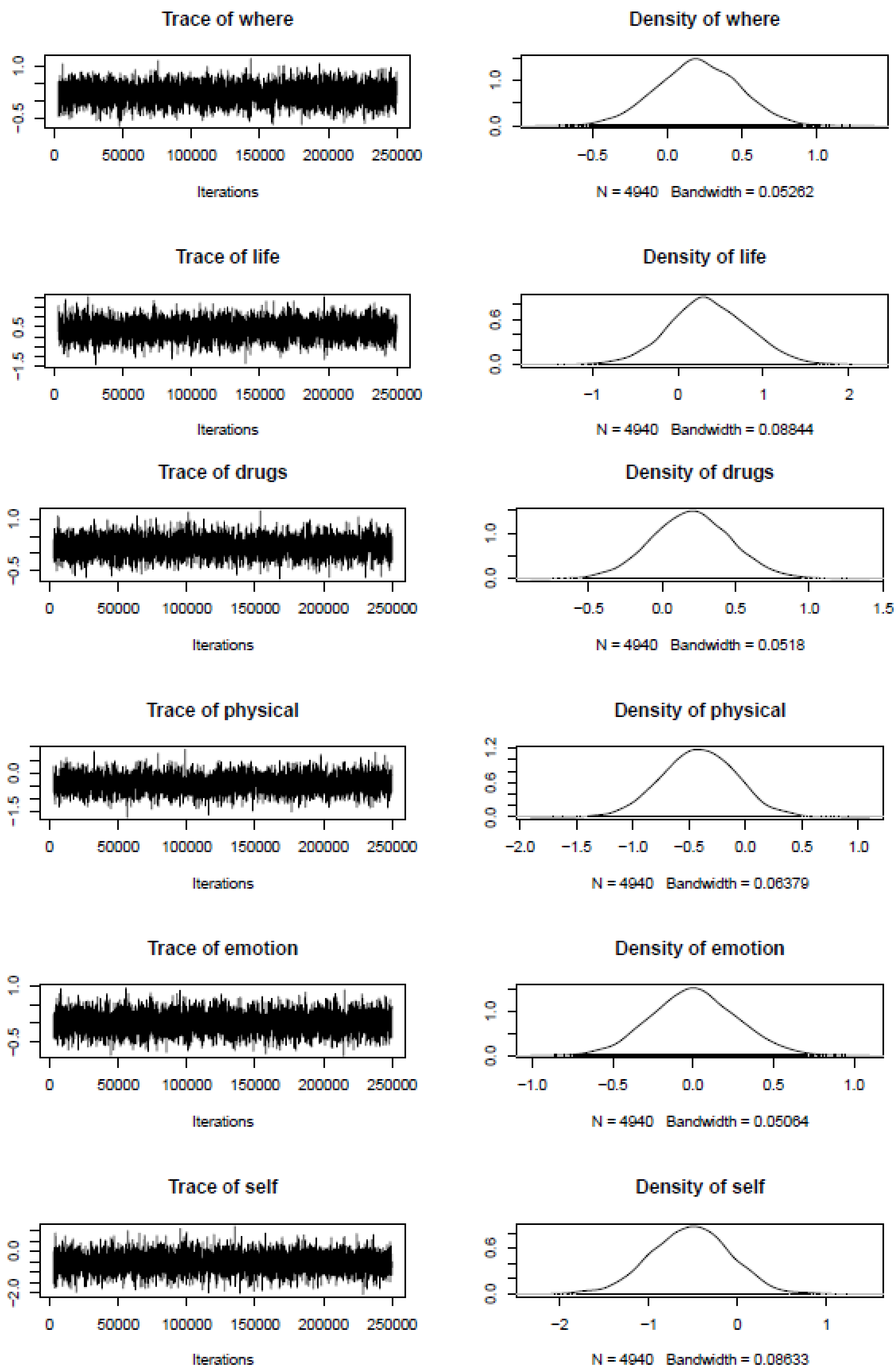


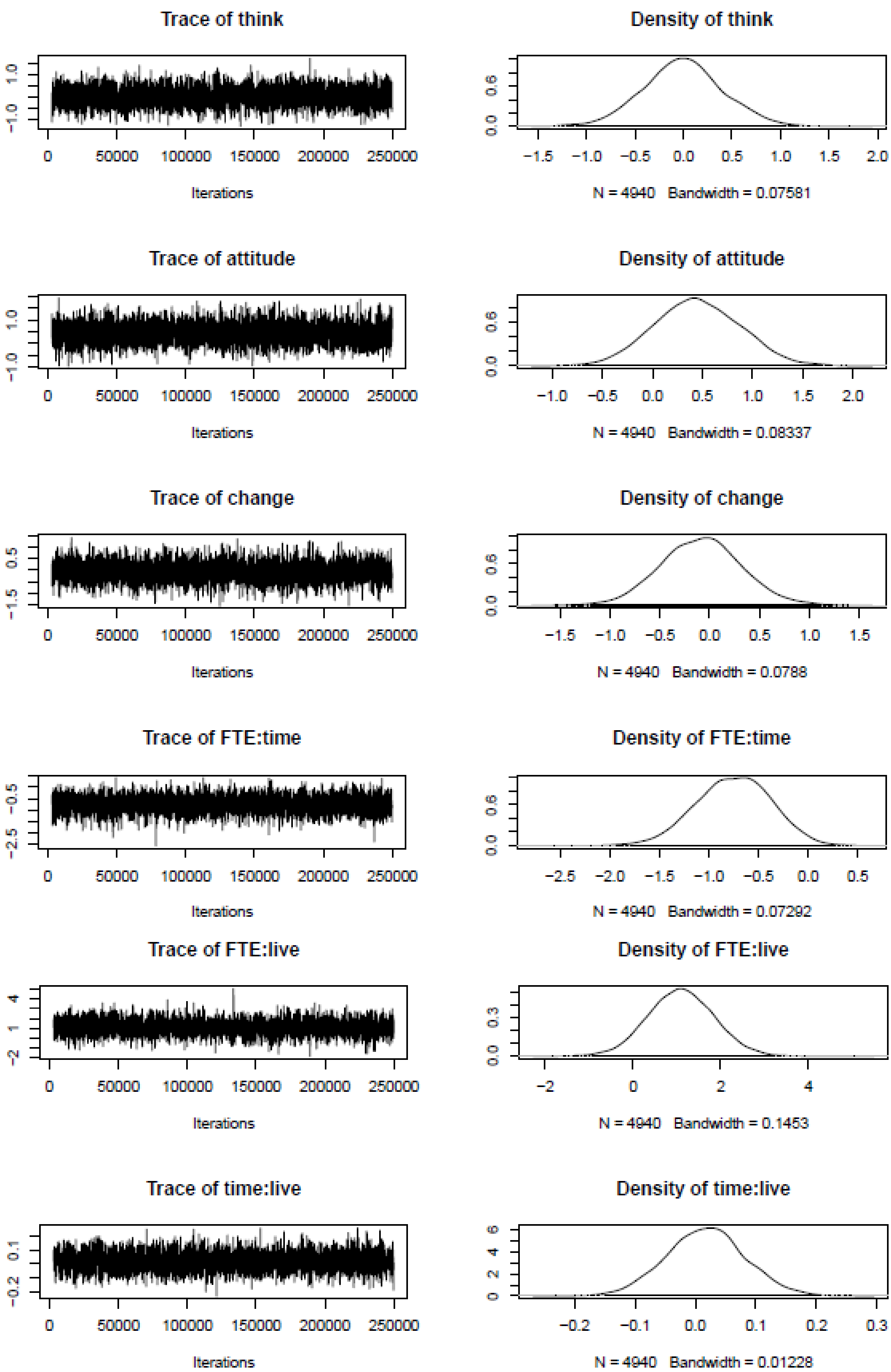


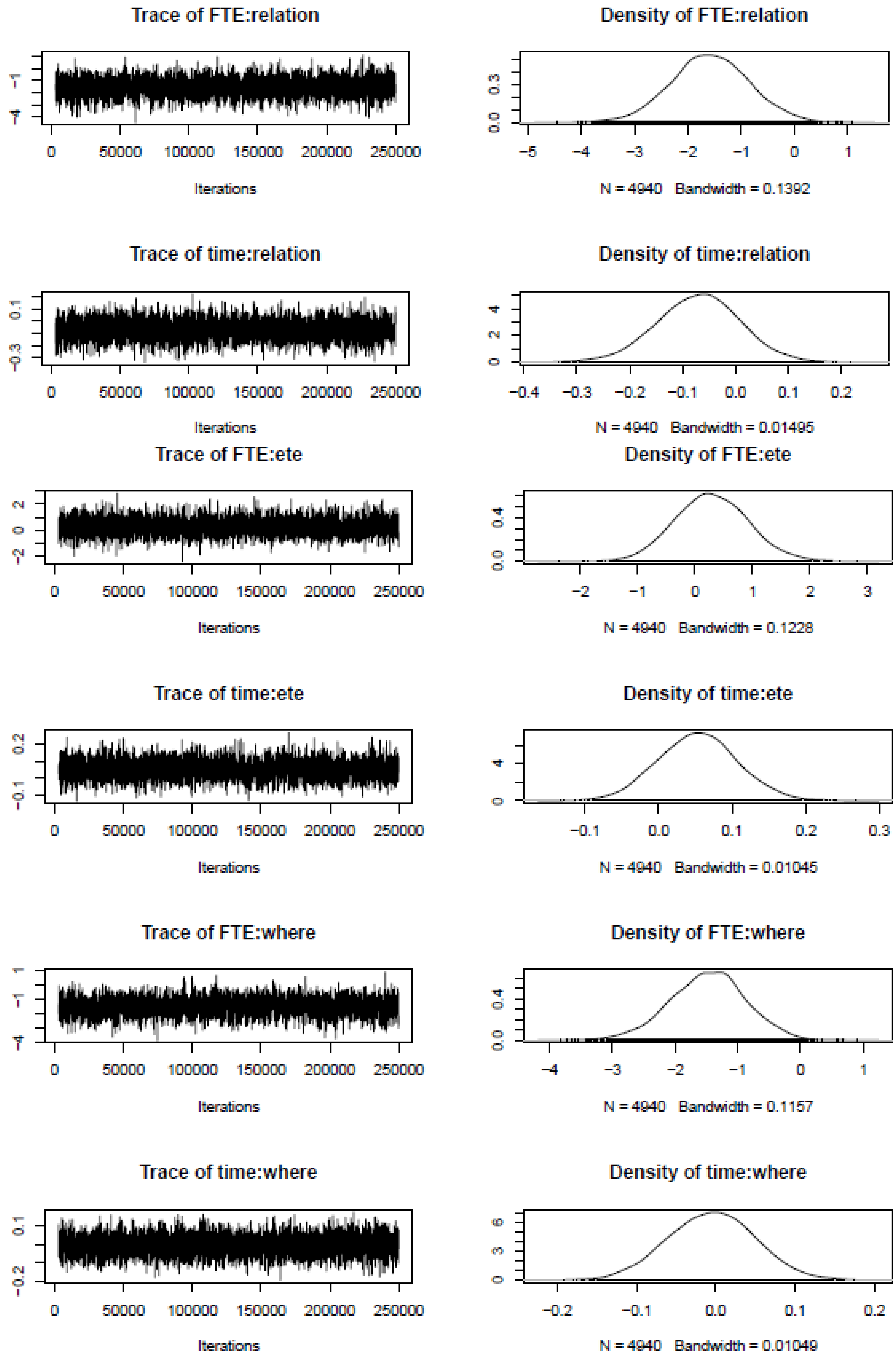


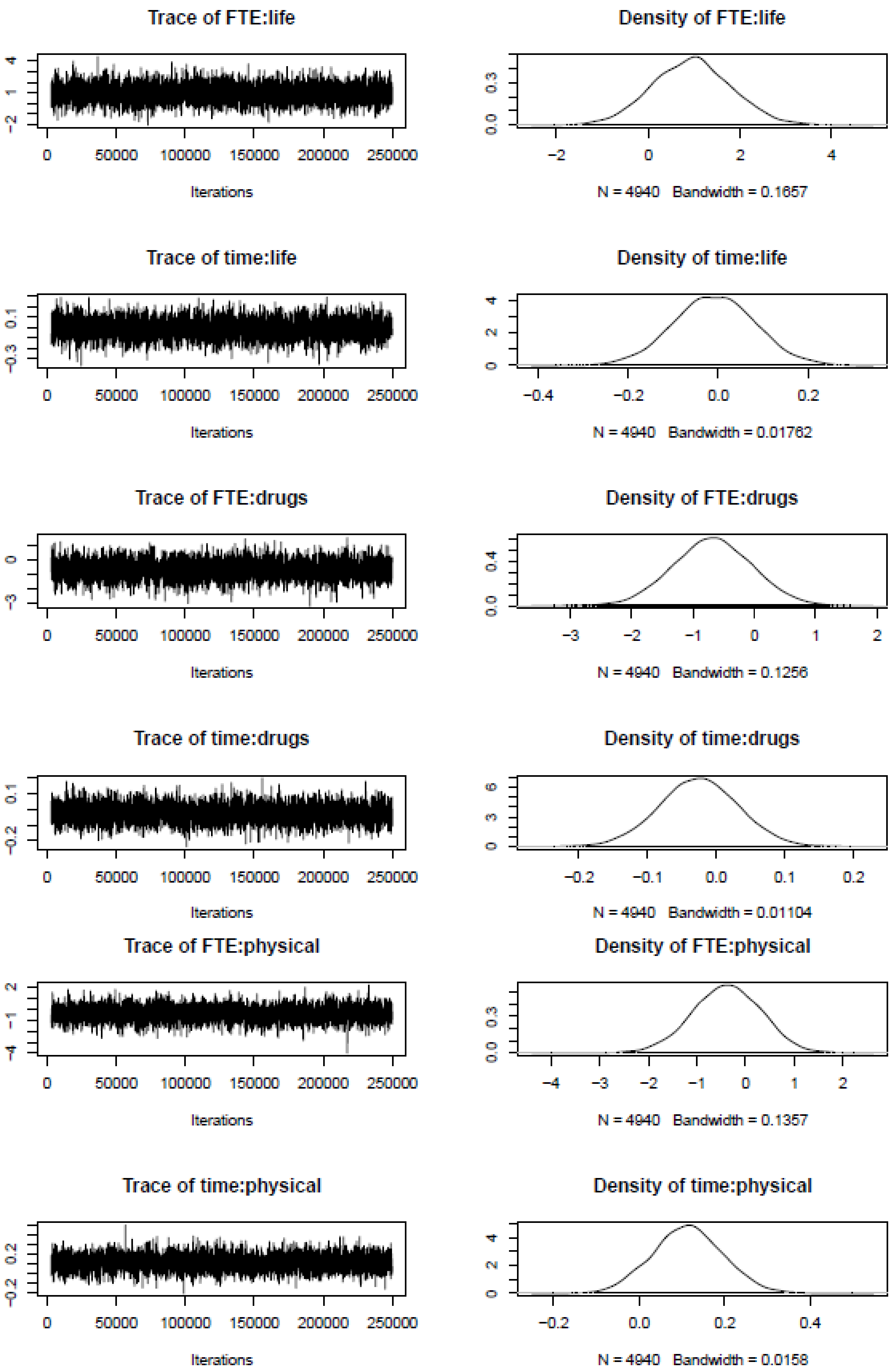


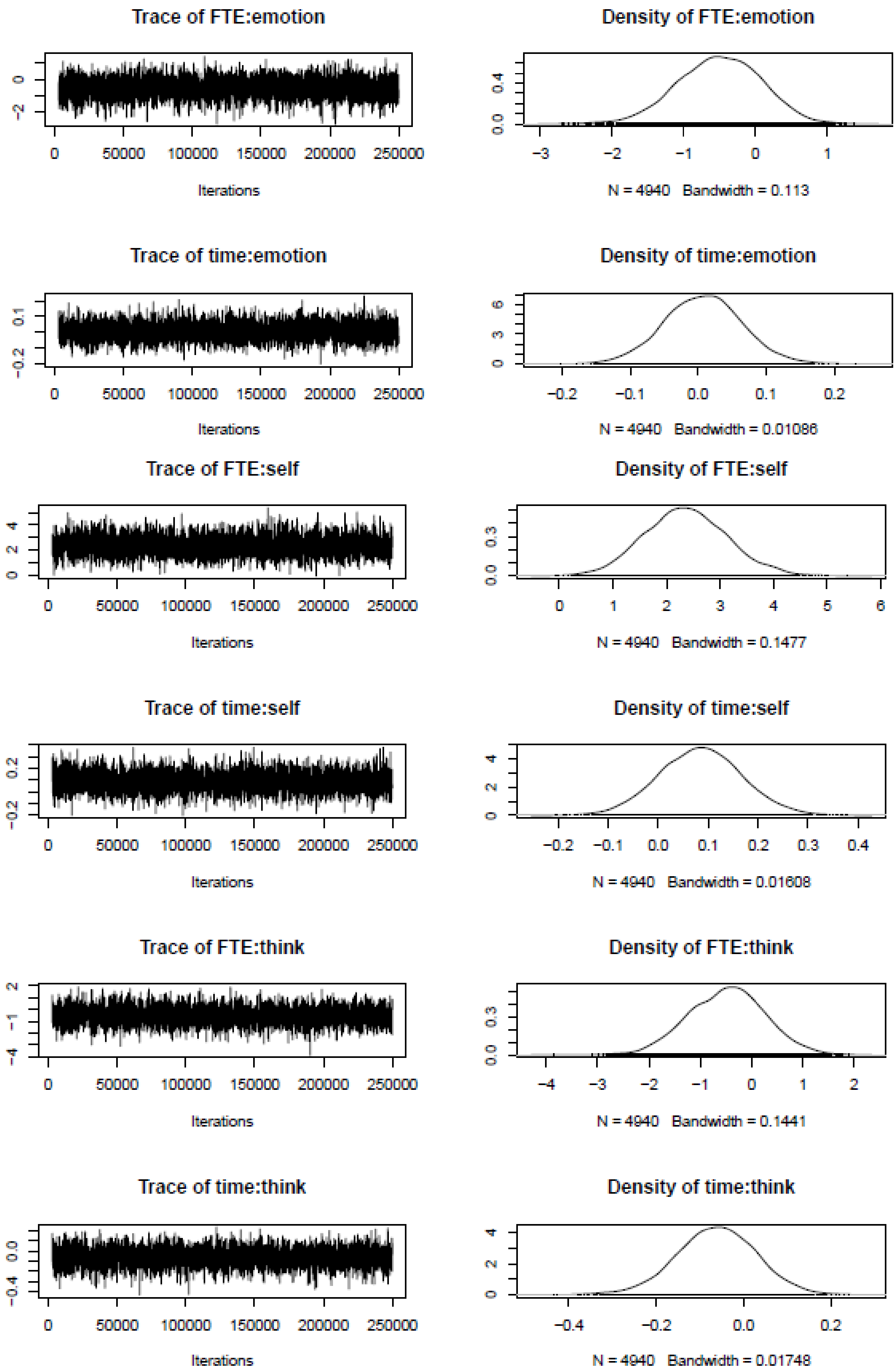


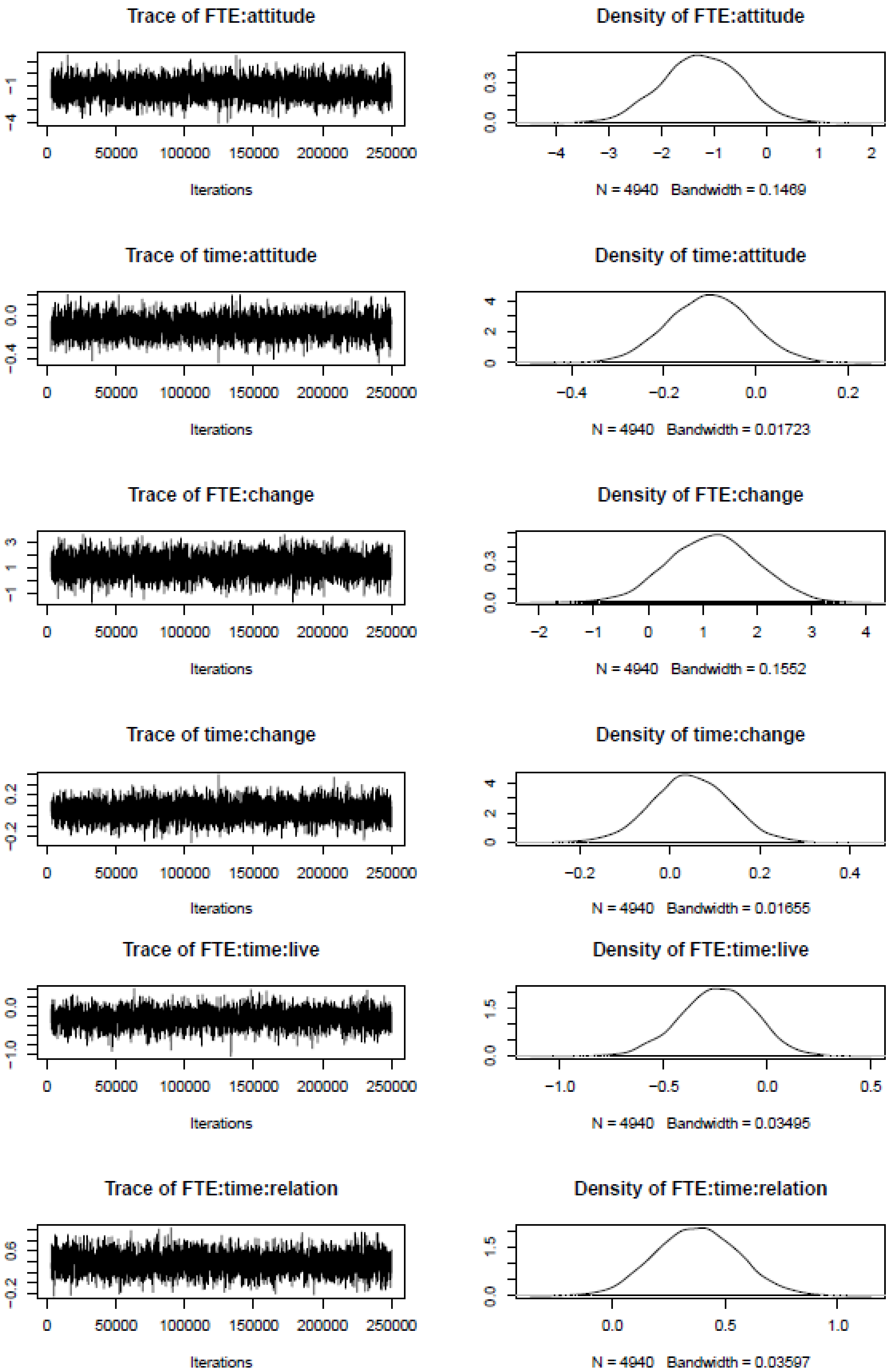

Trace of where
Iterations
Density of where
N = 4940 Bandwidth = 0.05262
Trace of life
Iterations
Density of life
N = 4940 Bandwidth = 0.08844
Trace of drugs
Iterations
Density of drugs
N = 4940 Bandwidth = 0.0518
Trace of physical
Iterations
Density of physical
N = 4940 Bandwidth = 0.06379
Trace of emotion
Iterations
Density of emotion
N = 4940 Bandwidth = 0.05064
Trace of self
Iterations
Density of self
N = 4940 Bandwidth = 0.08633

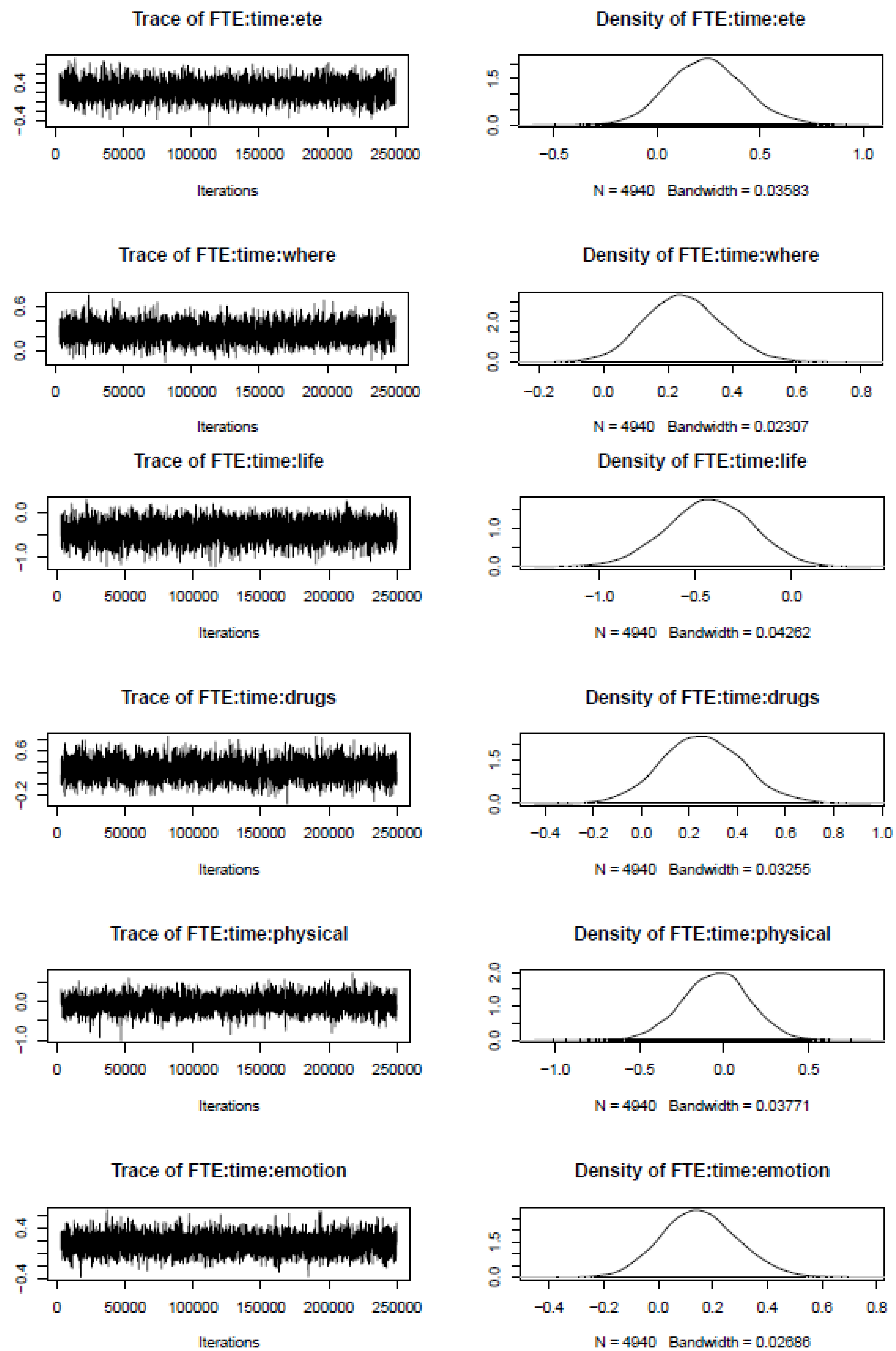

Trace of think
Density of think
Iterations
N = 4940 Bandwidth = 0.07581
Trace of attitude
Density of attitude
Iterations
N = 4940 Bandwidth = 0.08337
Trace of change
Density of change
Iterations
N = 4940 Bandwidth = 0.0788
Trace of FTE:time
Density of FTE:time
Iterations
N = 4940 Bandwidth = 0.07292
Trace of FTE:live
Density of FTE:live
Iterations
N = 4940 Bandwidth = 0.1453
Trace of time:live
Density of time:live
Iterations
N = 4940 Bandwidth = 0.01228

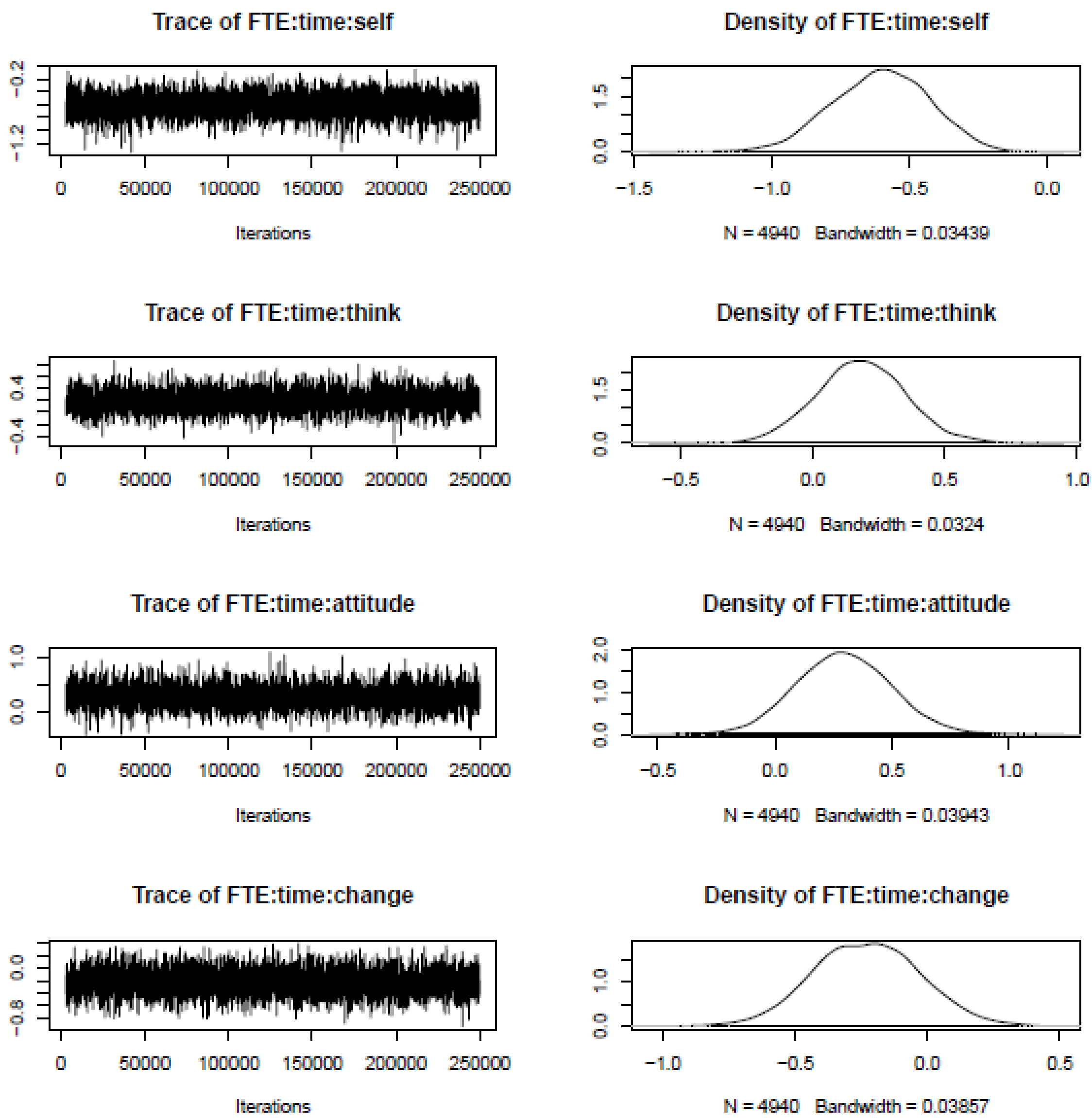

Trace of FTE:relation
Iterations
Density of FTE:relation
N = 4940 Bandwidth = 0.1392
Trace of time:relation
Iterations
Density of time:relation
N = 4940 Bandwidth = 0.01495
Trace of FTE:ete
Iterations
Density of FTE:ete
N = 4940 Bandwidth = 0.1228
Trace of time:ete
Iterations
Density of time:ete
N = 4940 Bandwidth = 0.01045
Trace of FTE:where
Iterations
Density of FTE:where
N = 4940 Bandwidth = 0.1157
Trace of time:where
Iterations
Density of time:where
N = 4940 Bandwidth = 0.01049


Trace of FTE:life
Iterations
Density of FTE:life
N = 4940 Bandwidth = 0.1657
Trace of time:life
Iterations
Density of time:life
N = 4940 Bandwidth = 0.01762
Trace of FTE:drugs
Iterations
Density of FTE:drugs
N = 4940 Bandwidth = 0.1256
Trace of time:drugs
Iterations
Density of time:drugs
N = 4940 Bandwidth = 0.01104
Trace of FTE:physical
Iterations
Density of FTE:physical
N = 4940 Bandwidth = 0.1357
Trace of time:physical
Iterations
Density of time:physical
N = 4940 Bandwidth = 0.0158

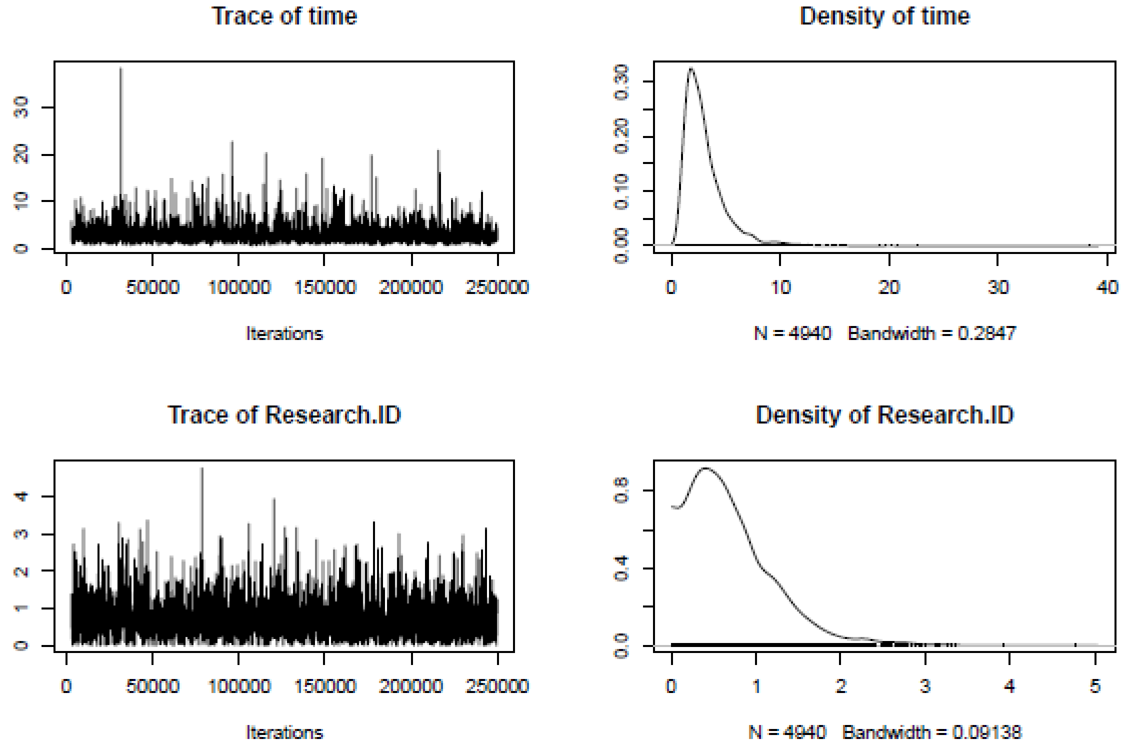

Trace of FTE:emotion
Iterations
Density of FTE:emotion
N = 4940   Bandwidth = 0.113
Trace of time:emotion
Iterations
Density of time:emotion
N = 4940   Bandwidth = 0.01086
Trace of FTE:self
Iterations
Density of FTE:self
N = 4940   Bandwidth = 0.1477
Trace of time:self
Iterations
Density of time:self
N = 4940   Bandwidth = 0.01608
Trace of FTE:think
Iterations
Density of FTE:think
N = 4940   Bandwidth = 0.1441
Trace of time:think
Iterations
Density of time:think
N = 4940   Bandwidth = 0.01748


Trace of FTE:attitude
Iterations
Density of FTE:attitude
N = 4940   Bandwidth = 0.1469
Trace of time:attitude
Iterations
Density of time:attitude
N = 4940   Bandwidth = 0.01723
Trace of FTE:change
Iterations
Density of FTE:change
N = 4940   Bandwidth = 0.1552
Trace of time:change
Iterations
Density of time:change
N = 4940   Bandwidth = 0.01655
Trace of FTE:time:live
Iterations
Density of FTE:time:live
N = 4940   Bandwidth = 0.03495
Trace of FTE:time:relation
Iterations
Density of FTE:time:relation
N = 4940   Bandwidth = 0.03597


Trace of FTE:time:ete
Iterations
Density of FTE:time:ete
N = 4940 Bandwidth = 0.03583
Trace of FTE:time:where
Iterations
Density of FTE:time:where
N = 4940 Bandwidth = 0.02307
Trace of FTE:time:life
Iterations
Density of FTE:time:life
N = 4940 Bandwidth = 0.04262
Trace of FTE:time:drugs
Iterations
Density of FTE:time:drugs
N = 4940 Bandwidth = 0.03255
Trace of FTE:time:physical
Iterations
Density of FTE:time:physical
N = 4940 Bandwidth = 0.03771
Trace of FTE:time:emotion
Iterations
Density of FTE:time:emotion
N = 4940 Bandwidth = 0.02686


Trace of FTE:time:self
Iterations
Density of FTE:time:self
N = 4940 Bandwidth = 0.03439
Trace of FTE:time:think
Iterations
Density of FTE:time:think
N = 4940 Bandwidth = 0.0324
Trace of FTE:time:attitude
Iterations
Density of FTE:time:attitude
N = 4940 Bandwidth = 0.03943
Trace of FTE:time:change
Iterations
Density of FTE:time:change
N = 4940 Bandwidth = 0.03857

Random Effects



Dynamic Model involving Grouped Age at First Offence (Table 6.17)

Bayesian Model (BDm3G_cc2)

Define the model

```
BDm1G_cc2 <- MCMCglmm(FO.bin ~ G_ageFirst*time*live +
G_ageFirst*time*relation + G_ageFirst*time*ete + G_ageFirst*time*where +
G_ageFirst*time*life + G_ageFirst*time*drugs + G_ageFirst*time*physical
+ G_ageFirst*time*emotion + G_ageFirst*time*self + G_ageFirst*time*think
+
G_ageFirst*time*attitude + G_ageFirst*time*change,
random=~time+Research.ID, data=data3, family="ordinal",prior=priorD,
slice=TRUE, nitt=300000, thin=75, burnin=3000)
```

Checks for suitable convergence

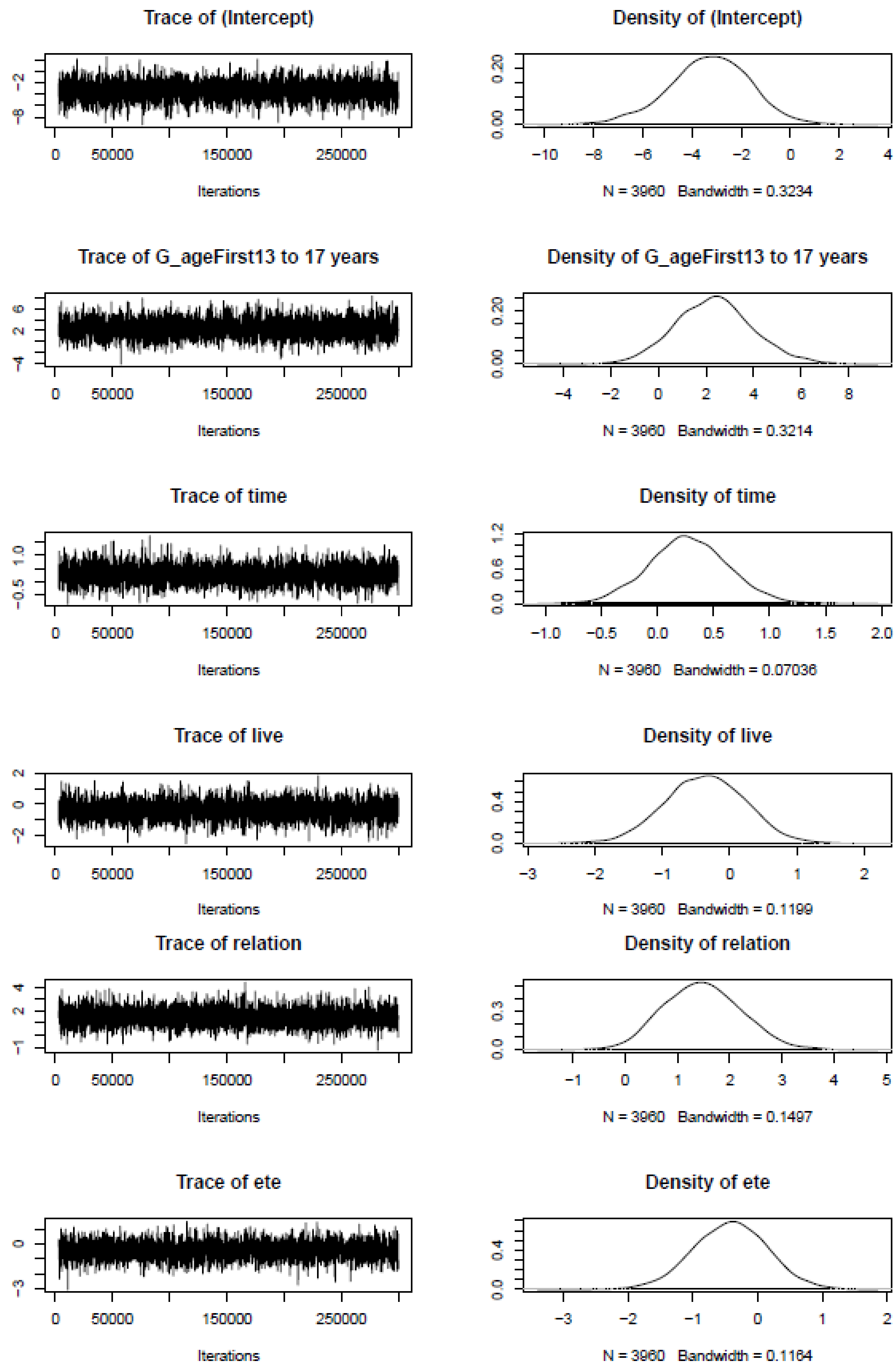
```
raftery.diag(BDm1G_cc2$VCV)
heidel.diag(BDm1G_cc2$VCV)

# > raftery.diag(BDm1G_cc2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         150      296250 3746         79.1
# Research.ID  150      293400 3746         78.3
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm1G_cc2$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.645
# Research.ID  passed        1         0.597
# units        failed       NA            NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    2.814 0.1177
# Research.ID  passed    0.714 0.0225
# units        <NA>         NA     NA

autocorr(BDm1G_cc2$VCV)
autocorr(BDm1G_cc2$SOL)    # Output not included here
summary(BDm1G_cc2)

# > autocorr(BDm1G_cc2$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0      1.00000000  0.25291164   NaN
# Lag 75     0.24432466  0.15185189   NaN
# Lag 375    0.10990396  0.05776905   NaN
# Lag 750    0.01855186  0.04781434   NaN
# Lag 3750  -0.01632509  0.01789682   NaN
```

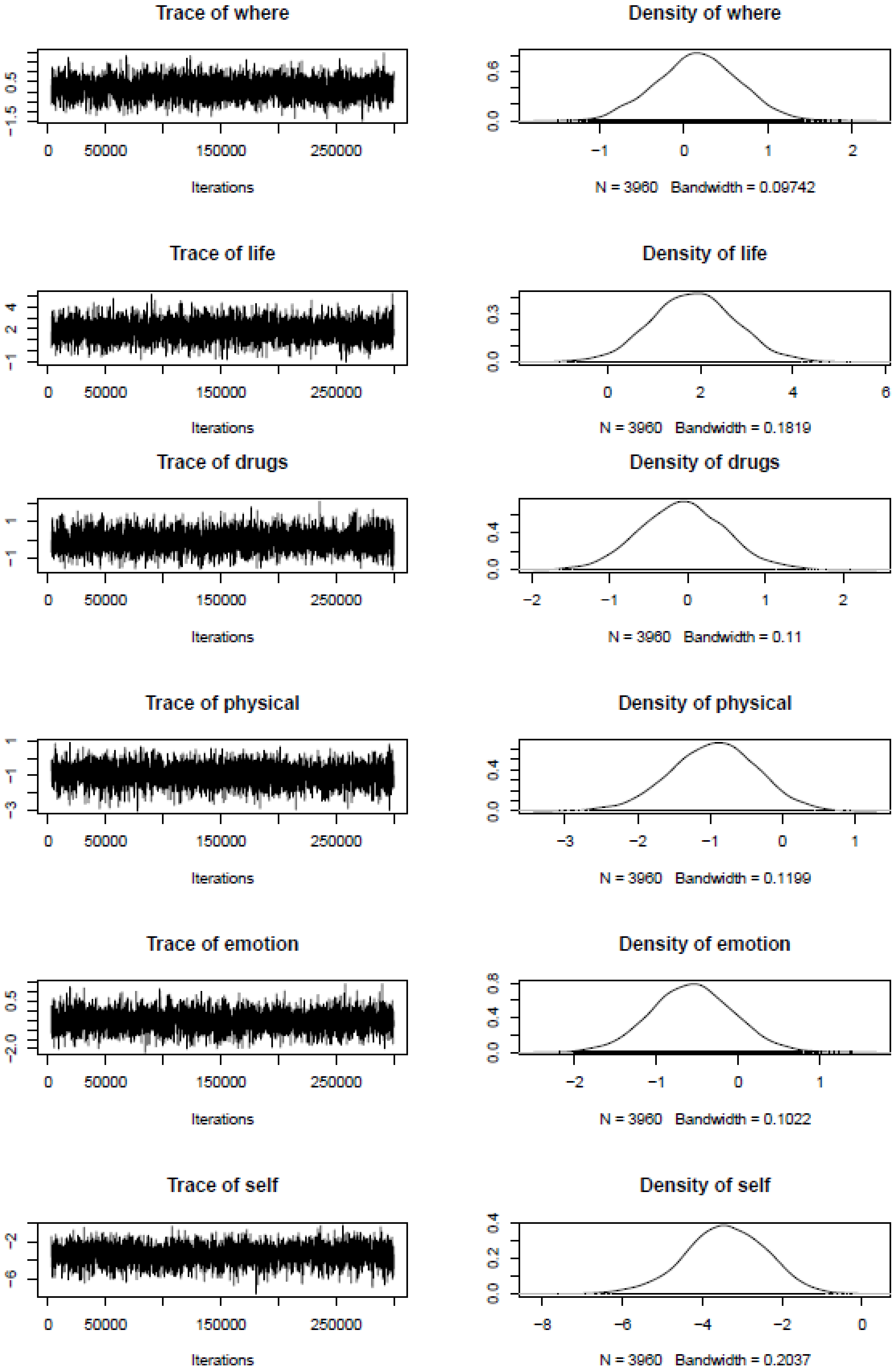
```
# , , Research.ID
#
#                   time   Research.ID units
# Lag 0      0.252911641  1.0000000000   NaN
# Lag 75     0.135278733  0.2675357467   NaN
# Lag 375    0.008563601 -0.0005601686   NaN
# Lag 750   -0.021136408  0.0191800615   NaN
# Lag 3750 -0.001763547  0.0230252246   NaN

# > summary(BDm1G_cc2)
#
# Iterations = 3001:299926
# Thinning interval  = 75
# Sample size  = 3960
#
# DIC: 448.731
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.814   0.6303    6.402     1086
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.7135 6.792e-06    1.704     2045
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageFirst * time * live + G_ageFirst *
time * relation + G_ageFirst * time * ete + G_ageFirst * time * where +
G_ageFirst * time * life + G_ageFirst * time * drugs + G_ageFirst * time
* physical + G_ageFirst * time * emotion + G_ageFirst * time * self +
G_ageFirst * time * think + G_ageFirst * time * attitude + G_ageFirst *
time * change
#
#                                      post.mean   l-95% CI   u-95% CI eff.samp   pMCMC
# (Intercept)                         -3.2847659 -6.9524202 -0.4065147     3960 0.04040 *
# G_ageFirst13 to 17 years             2.3402100 -0.9276130  5.4881873     4185 0.14545
# time                                 0.2773252 -0.4209483  0.9630134     3960 0.42172
# live                                -0.3672508 -1.5297222  0.7622080     3747 0.54293
# relation                             1.4787343  0.0710142  2.9053088     3585 0.03283 *
# ete                                 -0.4192868 -1.4838287  0.7939630     3755 0.46364
# where                                0.1649984 -0.8036577  1.0905241     3686 0.72424
# life                                 1.8556394  0.1053869  3.6427701     3340 0.03990 *
# drugs                               -0.0547609 -1.1474769  0.9926245     3960 0.91515
# physical                            -0.9474147 -2.0659547  0.2825911     3782 0.10253
# emotion                             -0.5590327 -1.5471306  0.4463329     3960 0.26869
# self                                -3.4170557 -5.4112381 -1.4800003     3176 < 3e-04 ***
# think                                0.6215859 -1.1685762  2.2468235     3608 0.46515
# attitude                             1.7056578 -0.1632752  3.7830839     3960 0.08333 .
# change                               0.2856350 -1.3586660  1.9171532     3960 0.72980
# G_ageFirst13 to 17 years:time       -0.5593925 -1.2953368  0.2077654     4231 0.13485
# G_ageFirst13 to 17 years:live        0.4839768 -0.7927949  1.8847179     3960 0.48131
# time:live                           -0.1458708 -0.4102137  0.1445866     3596 0.29899
# G_ageFirst13 to 17 years:relation   -1.5837160 -3.2375158 -0.0477182     3600 0.04596 *
# time:relation                       -0.3507082 -0.7175506 -0.0006591     3438 0.04495 *
# G_ageFirst13 to 17 years:ete         0.1345336 -1.0953193  1.3074669     3960 0.82879
# time:ete                             0.1577297 -0.0857178  0.4116789     3960 0.21818
# G_ageFirst13 to 17 years:where      -0.0578319 -1.1582725  1.0729601     4206 0.91465
# time:where                          -0.1184164 -0.3150333  0.0957921     3248 0.26465
# G_ageFirst13 to 17 years:life       -1.6241170 -3.6123758  0.2387693     3434 0.10101
# time:life                           -0.4192854 -0.8167063 -0.0158616     3558 0.04394 *
# G_ageFirst13 to 17 years:drugs       0.3416374 -0.8101754  1.5389287     3960 0.56010
# time:drugs                           0.2288912 -0.0109135  0.4593892     3580 0.05960 .
```

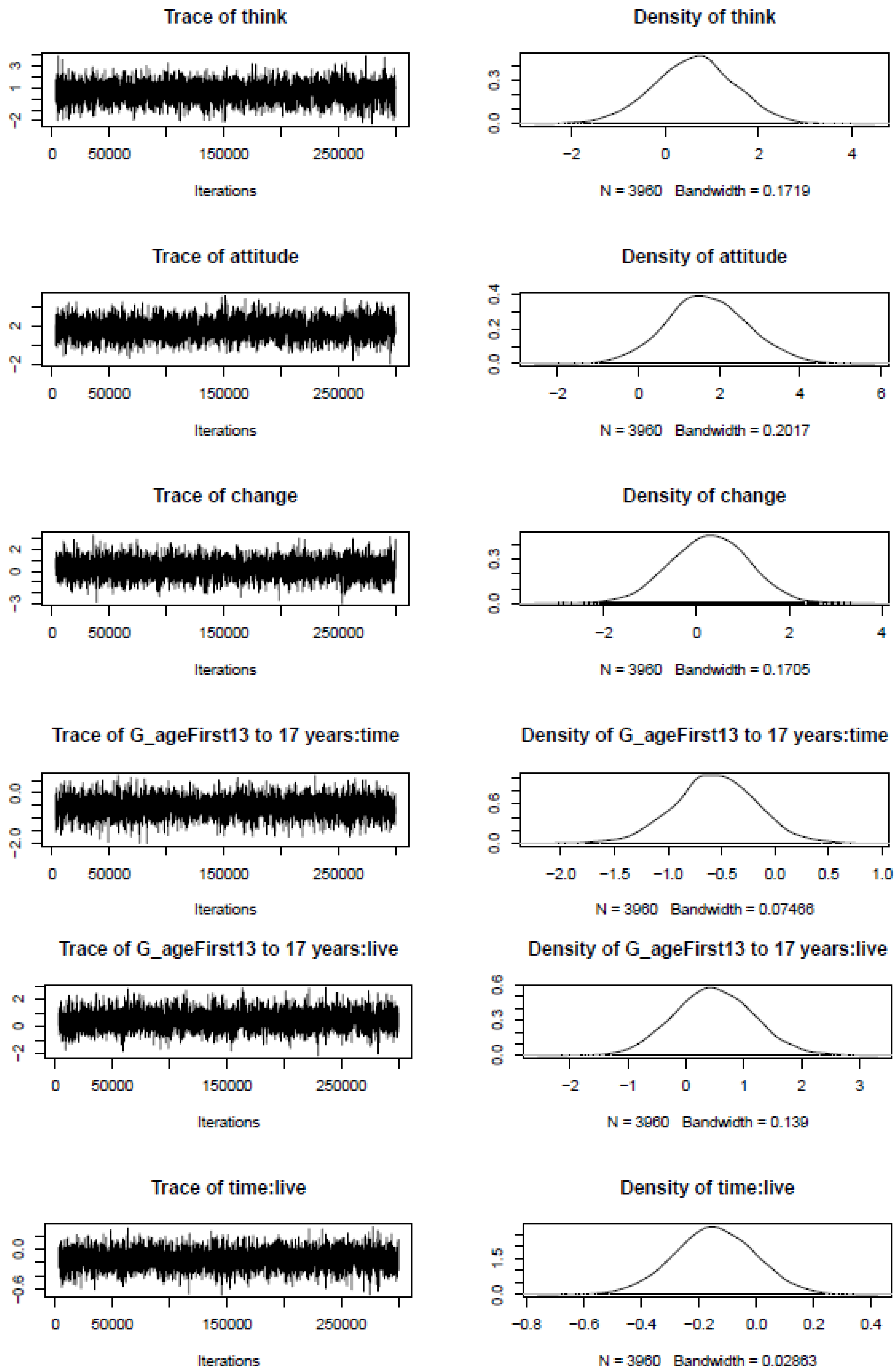
```
# G_ageFirst13 to 17 years:physical       0.3435236 -0.9764159  1.6941419     3753 0.62828
# time:physical                           0.2308078 -0.0683627  0.5411290     3545 0.13333
# G_ageFirst13 to 17 years:emotion        0.0307492 -1.0568400  1.2438148     3960 0.94091
# time:emotion                            0.3046012  0.0595439  0.5276048     3531 0.00606 **
# G_ageFirst13 to 17 years:self           4.4803614  2.2374407  6.6353715     3028 < 3e-04 ***
# time:self                               0.8036061  0.3829278  1.2477935     3147 < 3e-04 ***
# G_ageFirst13 to 17 years:think         -0.5943523 -2.5323291  1.2160011     3675 0.52323
# time:think                             -0.1862604 -0.5055324  0.1582307     3652 0.26313
# G_ageFirst13 to 17 years:attitude      -1.3566192 -3.4785136  0.7029933     3960 0.21061
# time:attitude                          -0.5482123 -0.9108689 -0.1409793     3595 0.00253 **
# G_ageFirst13 to 17 years:change        -0.4479941 -2.2598633  1.3140810     3960 0.63535
# time:change                             0.1505321 -0.1660888  0.5260582     3960 0.39697
# G_ageFirst13 to 17 years:time:live      0.1912950 -0.1408373  0.4712829     3694 0.21717
# G_ageFirst13 to 17 years:time:relation  0.4132628  0.0184364  0.7937224     3624 0.02576 *
# G_ageFirst13 to 17 years:time:ete      -0.0491961 -0.3231560  0.2329085     3960 0.73333
# G_ageFirst13 to 17 years:time:where     0.1418814 -0.1114780  0.3588265     3960 0.22879
# G_ageFirst13 to 17 years:time:life      0.3306582 -0.1480004  0.7400301     3512 0.14747
# G_ageFirst13 to 17 years:time:drugs    -0.2593390 -0.5249014  0.0153898     3589 0.06212 .
# G_ageFirst13 to 17 years:time:physical -0.1282970 -0.4640656  0.2295947     3818 0.45960
# G_ageFirst13 to 17 years:time:emotion  -0.1714936 -0.4672399  0.1178732     3410 0.23384
# G_ageFirst13 to 17 years:time:self     -1.0639765 -1.5556306 -0.5935499     3077 < 3e-04 ***
# G_ageFirst13 to 17 years:time:think     0.1894370 -0.2089464  0.5328839     3488 0.32273
# G_ageFirst13 to 17 years:time:attitude  0.4248375  0.0095216  0.8697492     3717 0.04848 *
# G_ageFirst13 to 17 years:time:change   -0.0937168 -0.4902018  0.2769845     3960 0.63232
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

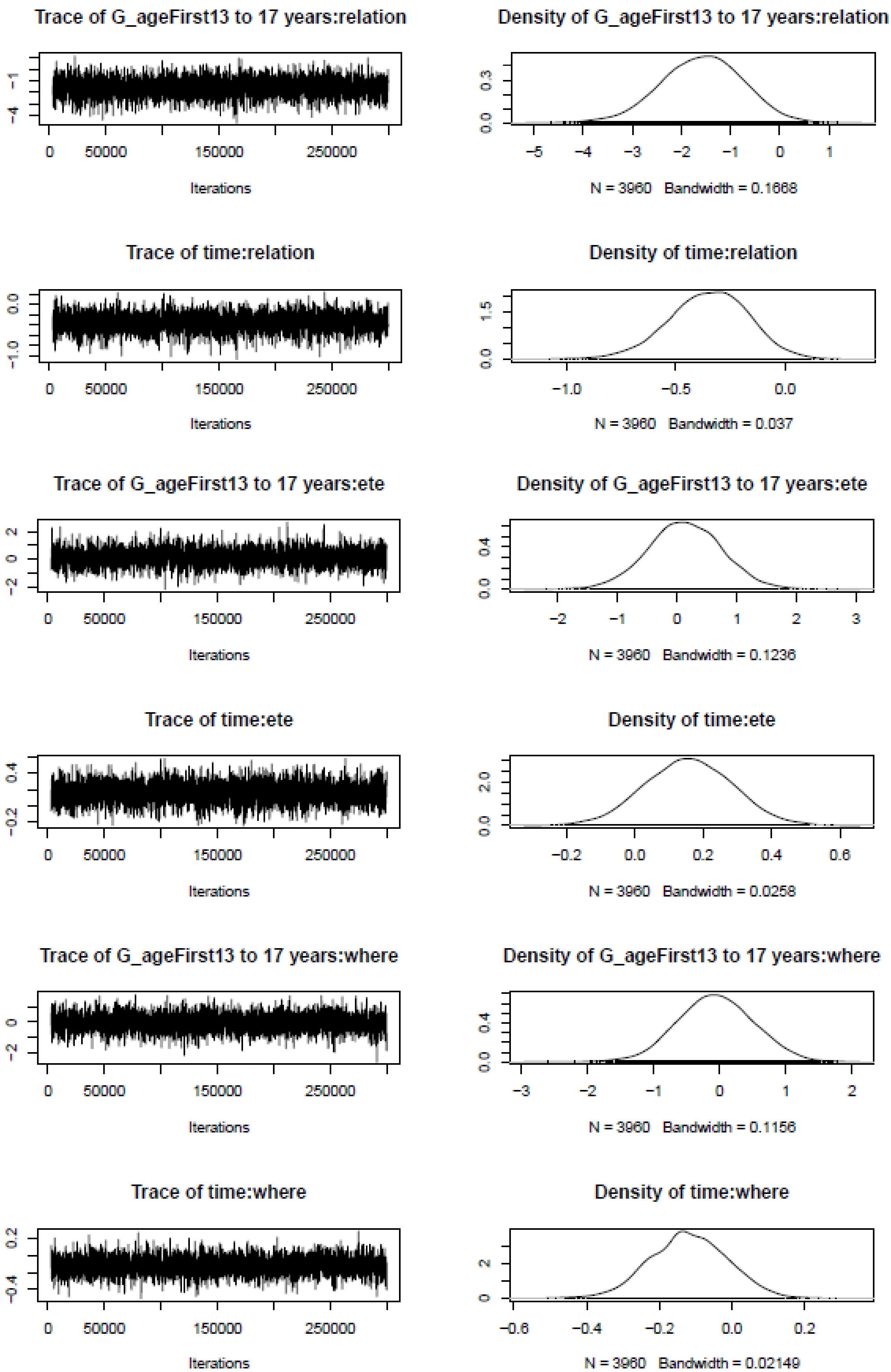
Trace Plots and Posterior Density Plots

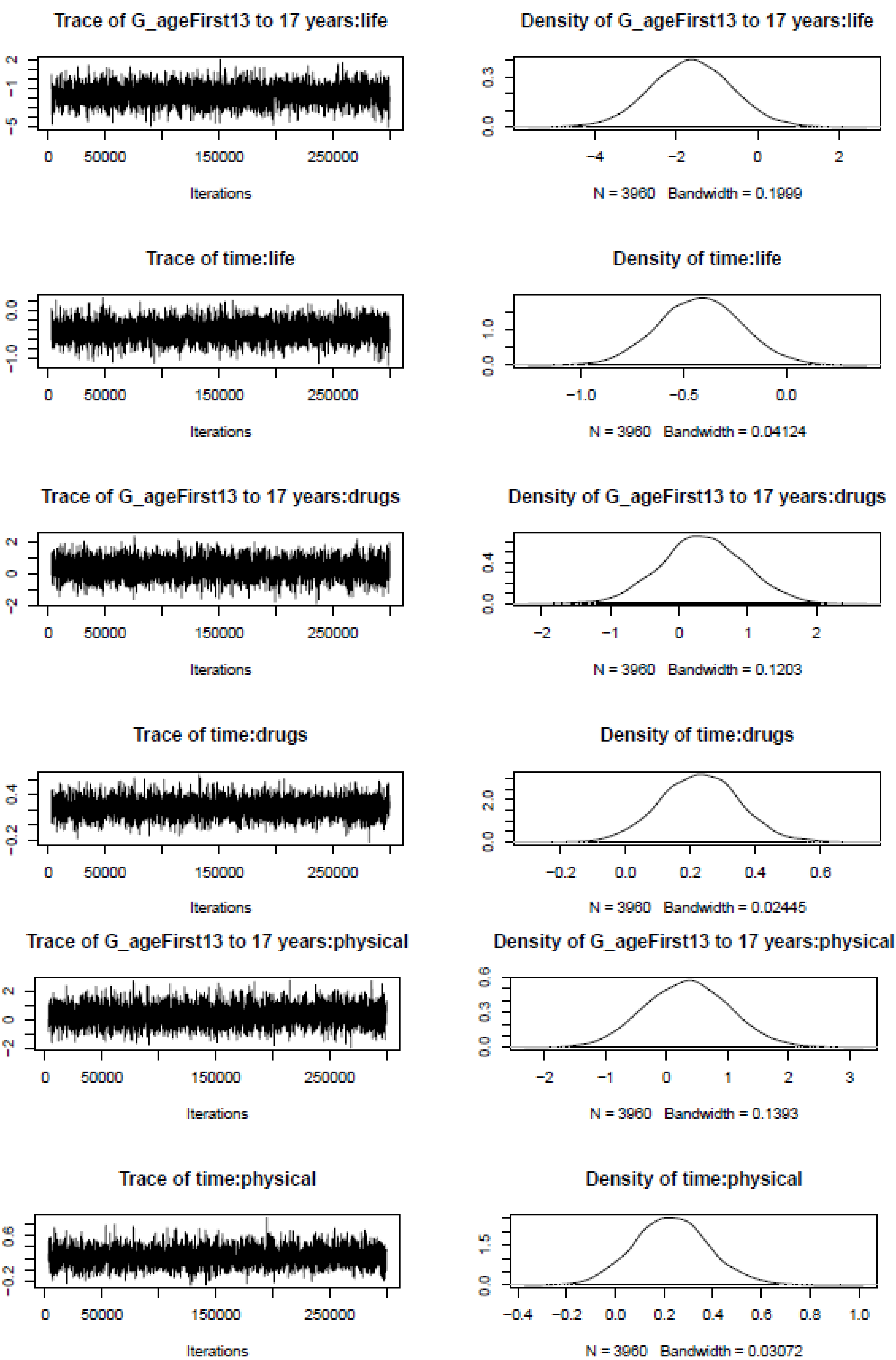
Fixed Effects

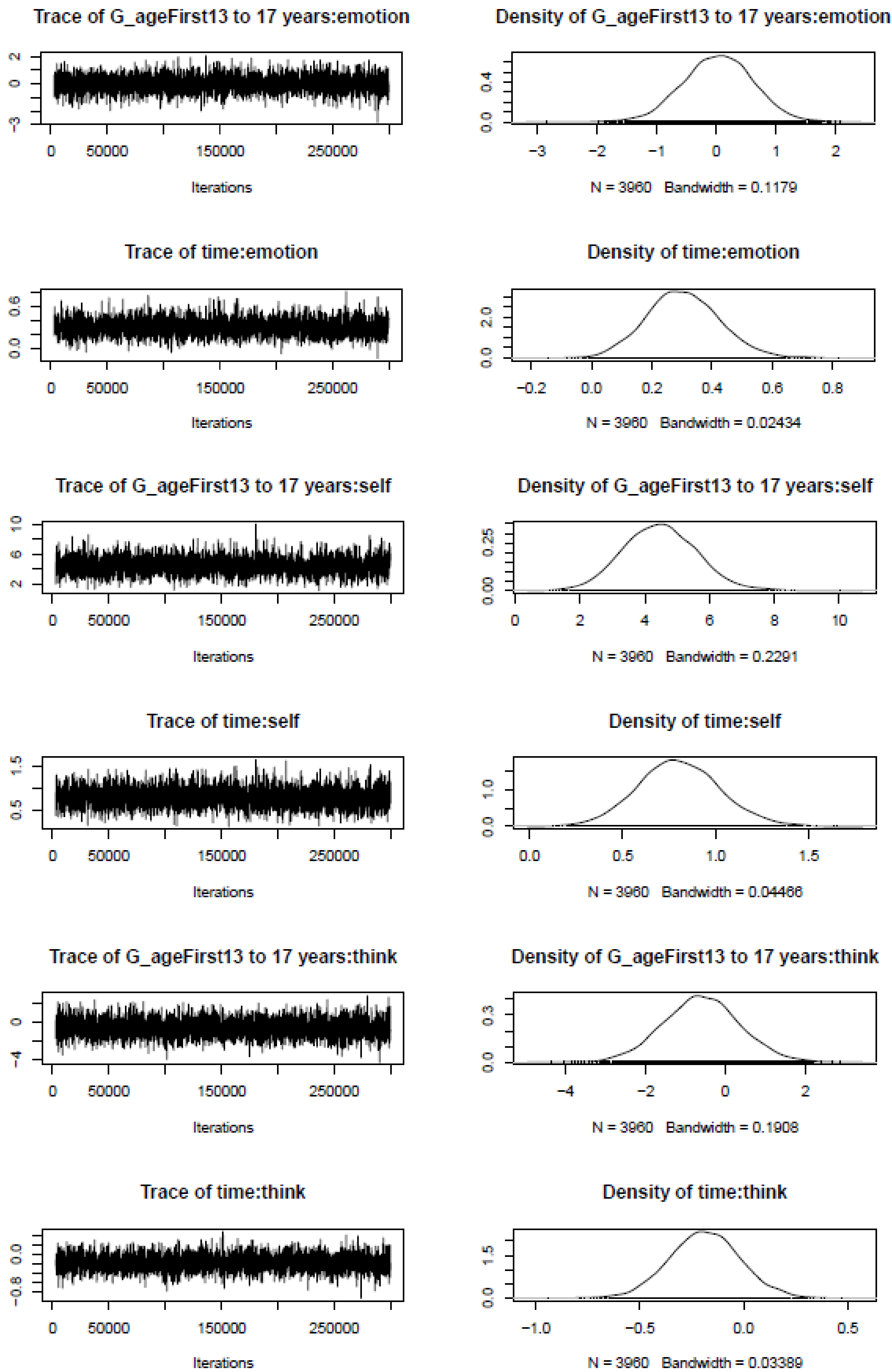


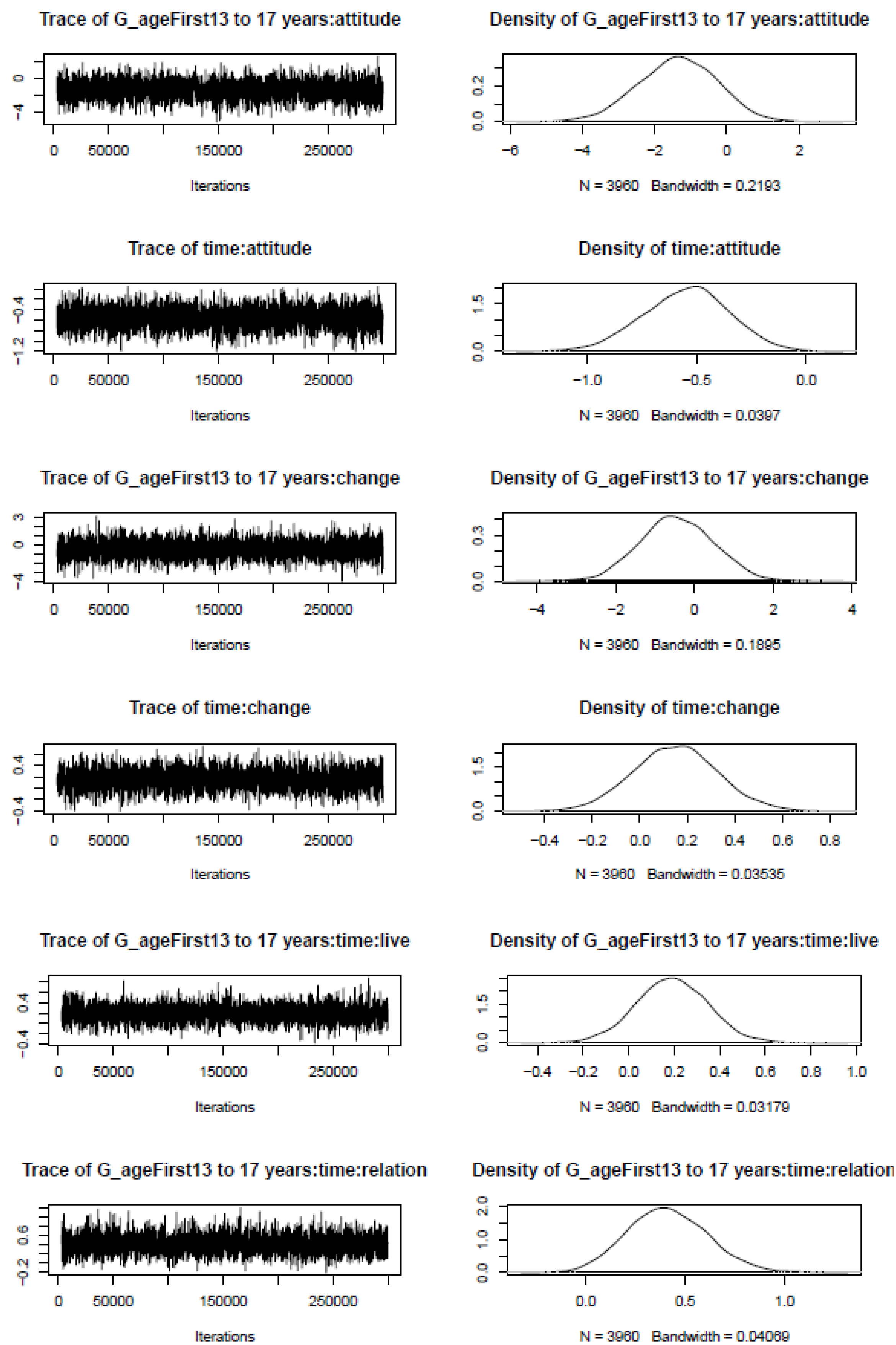

Trace of where
Density of where
Iterations
N = 3960 Bandwidth = 0.09742
Trace of life
Density of life
Iterations
N = 3960 Bandwidth = 0.1819
Trace of drugs
Density of drugs
Iterations
N = 3960 Bandwidth = 0.11
Trace of physical
Density of physical
Iterations
N = 3960 Bandwidth = 0.1199
Trace of emotion
Density of emotion
Iterations
N = 3960 Bandwidth = 0.1022
Trace of self
Density of self
Iterations
N = 3960 Bandwidth = 0.2037

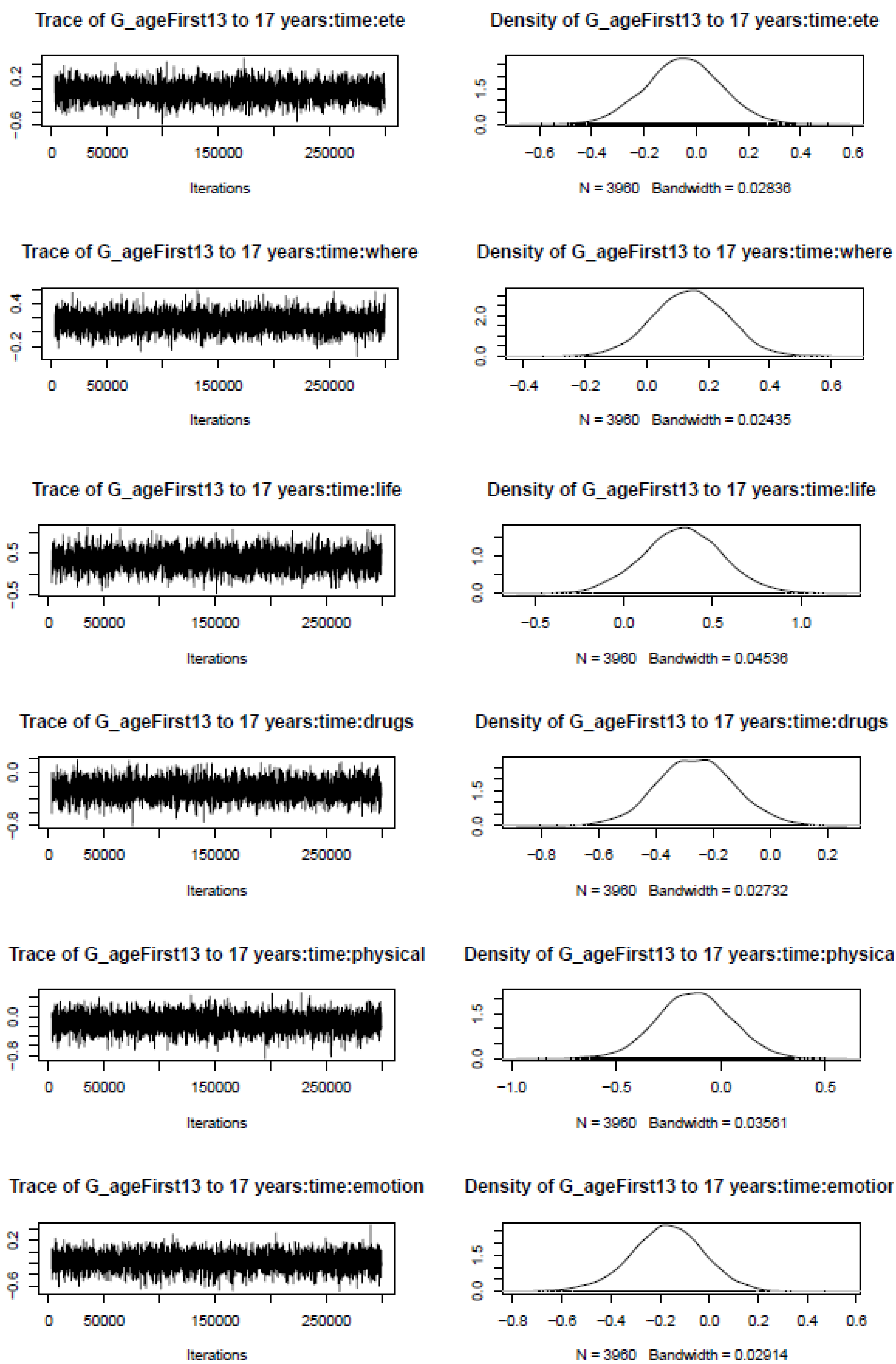

Trace of think
Density of think
Iterations
N = 3960 Bandwidth = 0.1719
Trace of attitude
Density of attitude
Iterations
N = 3960 Bandwidth = 0.2017
Trace of change
Density of change
Iterations
N = 3960 Bandwidth = 0.1705
Trace of G_ageFirst13 to 17 years:time
Density of G_ageFirst13 to 17 years:time
Iterations
N = 3960 Bandwidth = 0.07466
Trace of G_ageFirst13 to 17 years:live
Density of G_ageFirst13 to 17 years:live
Iterations
N = 3960 Bandwidth = 0.139
Trace of time:live
Density of time:live
Iterations
N = 3960 Bandwidth = 0.02863

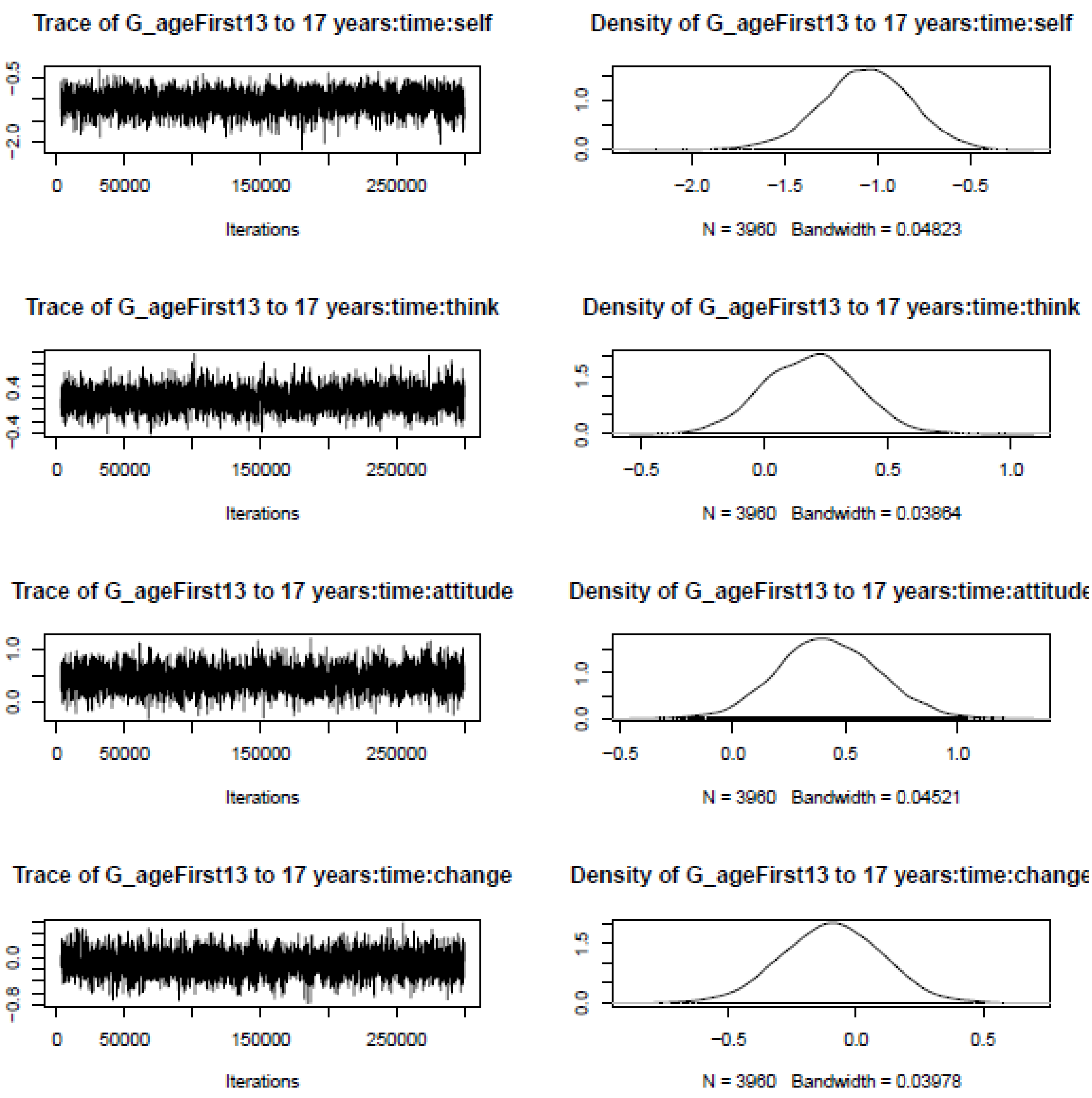

Trace of G_ageFirst13 to 17 years:relation
Iterations
Density of G_ageFirst13 to 17 years:relation
N = 3960 Bandwidth = 0.1668
Trace of time:relation
Iterations
Density of time:relation
N = 3960 Bandwidth = 0.037
Trace of G_ageFirst13 to 17 years:ete
Iterations
Density of G_ageFirst13 to 17 years:ete
N = 3960 Bandwidth = 0.1236
Trace of time:ete
Iterations
Density of time:ete
N = 3960 Bandwidth = 0.0258
Trace of G_ageFirst13 to 17 years:where
Iterations
Density of G_ageFirst13 to 17 years:where
N = 3960 Bandwidth = 0.1156
Trace of time:where
Iterations
Density of time:where
N = 3960 Bandwidth = 0.02149


Trace of G_ageFirst13 to 17 years:life
Iterations
Density of G_ageFirst13 to 17 years:life
N = 3960 Bandwidth = 0.1999
Trace of time:life
Iterations
Density of time:life
N = 3960 Bandwidth = 0.04124
Trace of G_ageFirst13 to 17 years:drugs
Iterations
Density of G_ageFirst13 to 17 years:drugs
N = 3960 Bandwidth = 0.1203
Trace of time:drugs
Iterations
Density of time:drugs
N = 3960 Bandwidth = 0.02445
Trace of G_ageFirst13 to 17 years:physical
Iterations
Density of G_ageFirst13 to 17 years:physical
N = 3960 Bandwidth = 0.1393
Trace of time:physical
Iterations
Density of time:physical
N = 3960 Bandwidth = 0.03072

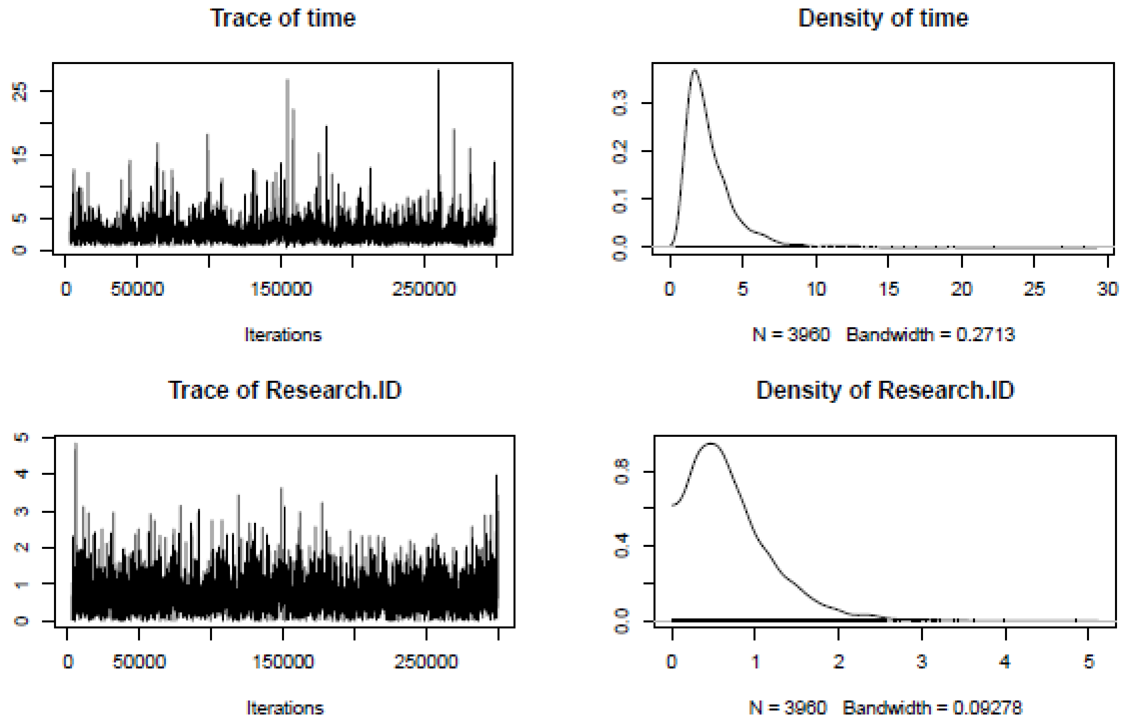

Trace of G_ageFirst13 to 17 years:emotion
Iterations
Density of G_ageFirst13 to 17 years:emotion
N = 3960 Bandwidth = 0.1179
Trace of time:emotion
Iterations
Density of time:emotion
N = 3960 Bandwidth = 0.02434
Trace of G_ageFirst13 to 17 years:self
Iterations
Density of G_ageFirst13 to 17 years:self
N = 3960 Bandwidth = 0.2291
Trace of time:self
Iterations
Density of time:self
N = 3960 Bandwidth = 0.04466
Trace of G_ageFirst13 to 17 years:think
Iterations
Density of G_ageFirst13 to 17 years:think
N = 3960 Bandwidth = 0.1908
Trace of time:think
Iterations
Density of time:think
N = 3960 Bandwidth = 0.03389


Trace of G_ageFirst13 to 17 years:attitude
Iterations
0 50000 150000 250000
Density of G_ageFirst13 to 17 years:attitude
N = 3960 Bandwidth = 0.2193
Trace of time:attitude
Iterations
Density of time:attitude
N = 3960 Bandwidth = 0.0397
Trace of G_ageFirst13 to 17 years:change
Iterations
Density of G_ageFirst13 to 17 years:change
N = 3960 Bandwidth = 0.1895
Trace of time:change
Iterations
Density of time:change
N = 3960 Bandwidth = 0.03535
Trace of G_ageFirst13 to 17 years:time:live
Iterations
Density of G_ageFirst13 to 17 years:time:live
N = 3960 Bandwidth = 0.03179
Trace of G_ageFirst13 to 17 years:time:relation
Iterations
Density of G_ageFirst13 to 17 years:time:relation
N = 3960 Bandwidth = 0.04069


Trace of G_ageFirst13 to 17 years:time:ete
Iterations
Density of G_ageFirst13 to 17 years:time:ete
N = 3960 Bandwidth = 0.02836
Trace of G_ageFirst13 to 17 years:time:where
Iterations
Density of G_ageFirst13 to 17 years:time:where
N = 3960 Bandwidth = 0.02435
Trace of G_ageFirst13 to 17 years:time:life
Iterations
Density of G_ageFirst13 to 17 years:time:life
N = 3960 Bandwidth = 0.04536
Trace of G_ageFirst13 to 17 years:time:drugs
Iterations
Density of G_ageFirst13 to 17 years:time:drugs
N = 3960 Bandwidth = 0.02732
Trace of G_ageFirst13 to 17 years:time:physical
Iterations
Density of G_ageFirst13 to 17 years:time:physica
N = 3960 Bandwidth = 0.03561
Trace of G_ageFirst13 to 17 years:time:emotion
Iterations
Density of G_ageFirst13 to 17 years:time:emotior
N = 3960 Bandwidth = 0.02914


Trace of G_ageFirst13 to 17 years:time:self
Iterations
Density of G_ageFirst13 to 17 years:time:self
N = 3960 Bandwidth = 0.04823
Trace of G_ageFirst13 to 17 years:time:think
Iterations
Density of G_ageFirst13 to 17 years:time:think
N = 3960 Bandwidth = 0.03864
Trace of G_ageFirst13 to 17 years:time:attitude
Iterations
Density of G_ageFirst13 to 17 years:time:attitude
N = 3960 Bandwidth = 0.04521
Trace of G_ageFirst13 to 17 years:time:change
Iterations
Density of G_ageFirst13 to 17 years:time:change
N = 3960 Bandwidth = 0.03978

Random Effects



Dynamic Model involving Grouped YJB Offence Category (Table 6.18)

Bayesian Model (BDm3G_o1)

Define the model

```
BDm3G_o1 <- MCMCglmm(FO.bin ~ as.factor(I_Cat2)*time*live +
as.factor(I_Cat2)*time*relation + as.factor(I_Cat2)*time*ete +
as.factor(I_Cat2)*time*where + as.factor(I_Cat2)*time*life +
as.factor(I_Cat2)*time*drugs + as.factor(I_Cat2)*time*physical +
as.factor(I_Cat2)*time*emotion + as.factor(I_Cat2)*time*self +
as.factor(I_Cat2)*time*think + as.factor(I_Cat2)*time*attitude +
as.factor(I_Cat2)*time*change,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
slice=TRUE, nitt=800000, thin=150, burnin=3000)
```

Checks for suitable convergence

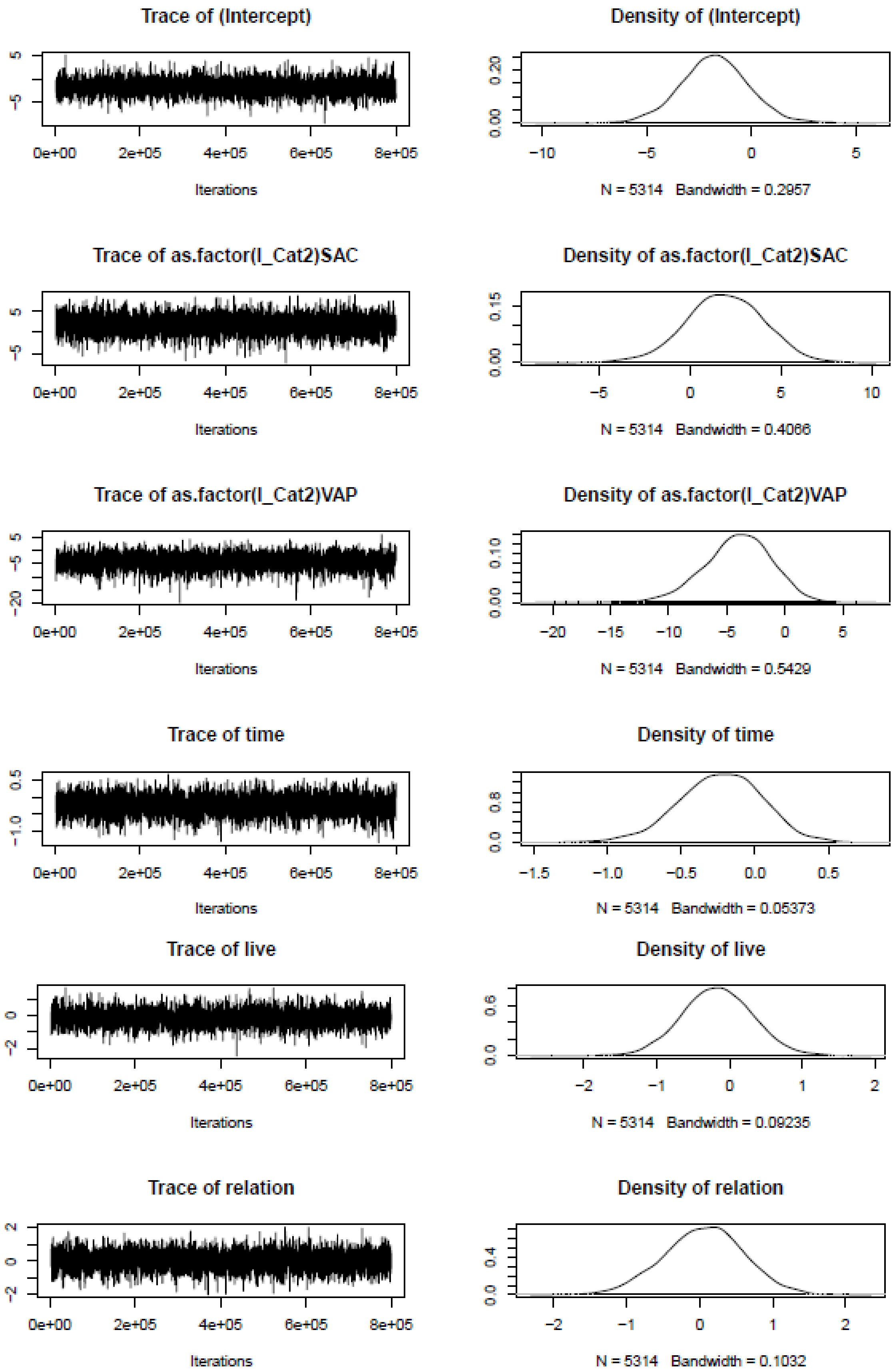
```
raftery.diag(BDm3G_o1$VCV)
heidel.diag(BDm3G_o1$VCV)

# > raftery.diag(BDm3G_o1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         450      633750 3746         169
# Research.ID 450       663900 3746         177
# units        <NA>     <NA>   3746          NA

# > heidel.diag(BDm3G_o1$VCV)
#
#              Stationarity start     p-value
# test         iteration
# time         passed       533       0.0616
# Research.ID passed          1       0.1875
# units        failed        NA           NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    6.22 0.1892
# Research.ID passed     2.75 0.0831
# units        <NA>        NA     NA

autocorr(BDm3G_o1$VCV)
autocorr(BDm3G_o1$Sol)
summary(BDm3G_o1)

# > autocorr(BDm3G_o1$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0      1.00000000  0.32665057   NaN
# Lag 150    0.23172876  0.19456716   NaN
# Lag 750    0.06188851  0.05196407   NaN
# Lag 1500   0.01675111  0.02264537   NaN
# Lag 7500  -0.03520887 -0.03831574   NaN
```

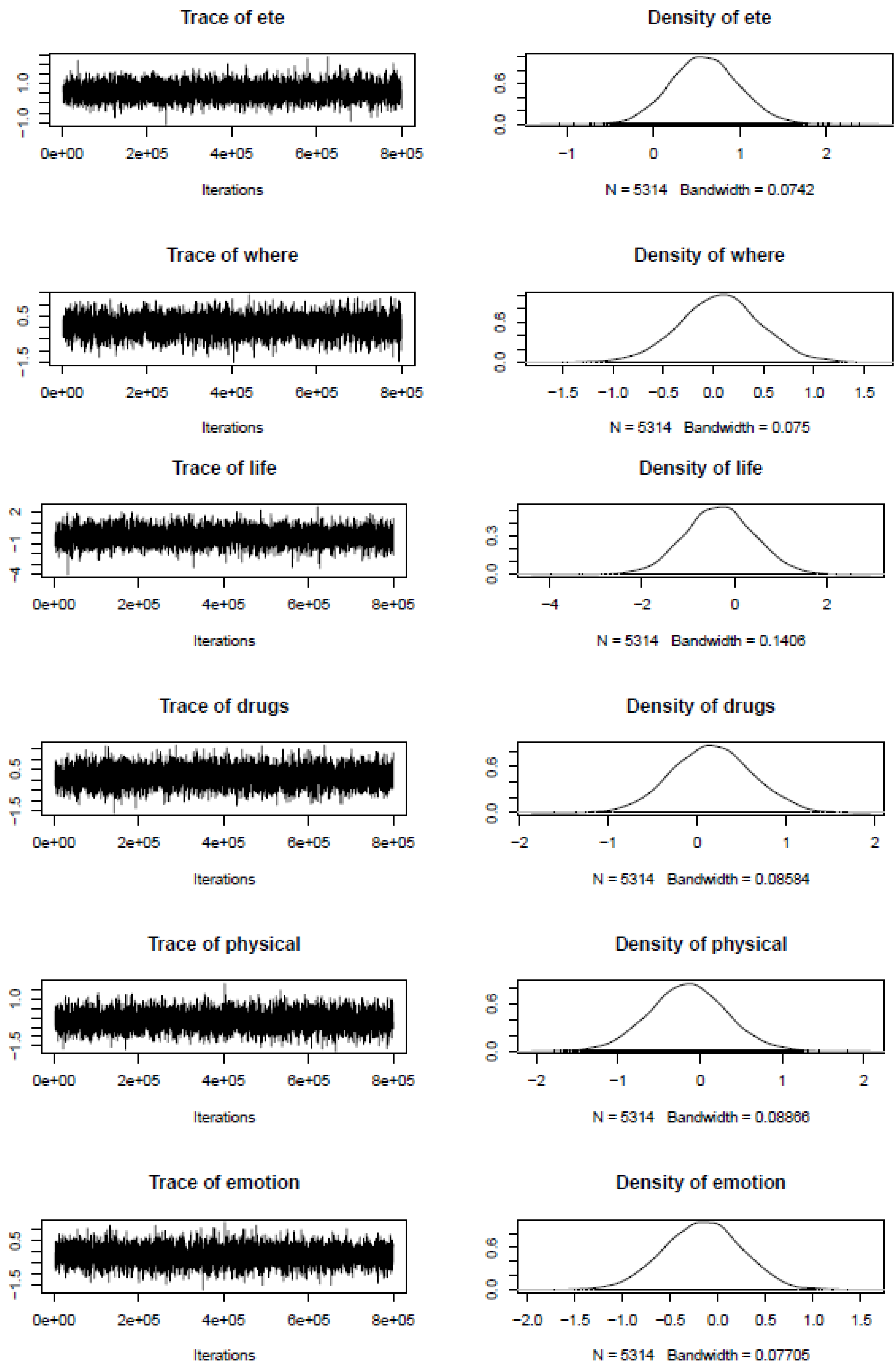
```
# , , Research.ID
#
#                  time Research.ID units
# Lag 0     0.326650566  1.00000000   NaN
# Lag 150   0.190069580  0.39265659   NaN
# Lag 750  -0.001913535  0.07721970   NaN
# Lag 1500  0.022406209  0.01832236   NaN
# Lag 7500 -0.024629865 -0.03381193   NaN

# > summary(BDm3G_o1)
#
# Iterations = 3001:799951
# Thinning interval  = 150
# Sample size  = 5314
#
# DIC: 442.9881
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     6.166    1.181    13.85     2049
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID      2.75 1.211e-05    6.118     1734
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ as.factor(I_Cat2) * time * live + as.factor(I_Cat2) * time * relation + as.factor(I_Cat2) * time * ete + as.factor(I_Cat2) * time * where + as.factor(I_Cat2) * time * life + as.factor(I_Cat2) * time * drugs + as.factor(I_Cat2) * time * physical + as.factor(I_Cat2) * time * emotion + as.factor(I_Cat2) * time * self + as.factor(I_Cat2) * time * think + as.factor(I_Cat2) * time * attitude + as.factor(I_Cat2) * time * change
#
#                                 post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept)                     -1.743030  -5.109128   1.286888     5314 0.2668
# as.factor(I_Cat2)SAC             1.923846  -2.330737   6.124417     5371 0.3564
# as.factor(I_Cat2)VAP            -4.070462 -10.078364   1.331009     4011 0.1487
# time                            -0.233496  -0.829545   0.284217     4760 0.4106
# live                            -0.165068  -1.120142   0.776695     4801 0.7237
# relation                         0.057571  -1.039752   1.106227     4821 0.8984
# ete                              0.595150  -0.181684   1.354952     5314 0.1272
# where                            0.069036  -0.742589   0.837369     5314 0.8528
# life                            -0.324920  -1.832372   1.123411     4640 0.6526
# drugs                            0.169672  -0.690701   1.064228     5314 0.7079
# physical                        -0.148377  -1.086310   0.759873     5314 0.7426
# emotion                         -0.158188  -0.907967   0.651592     5314 0.7030
# self                             0.380673  -0.912085   1.582271     5314 0.5487
# think                           -0.046085  -1.145426   0.969706     4870 0.9285
# attitude                        -0.149377  -1.454059   1.052661     4565 0.8329
# change                           0.719236  -0.531317   1.898862     4369 0.2360
# as.factor(I_Cat2)SAC:time       -0.745699  -1.622663   0.181712     4681 0.1050
# as.factor(I_Cat2)VAP:time        0.829010  -0.266606   2.085354     3738 0.1581
# as.factor(I_Cat2)SAC:live        0.522071  -1.104146   2.222313     5031 0.5382
# as.factor(I_Cat2)VAP:live        1.306643  -1.290030   3.651997     4835 0.3003
# time:live                        0.041381  -0.159009   0.243105     5314 0.6876
# as.factor(I_Cat2)SAC:relation    0.777475  -1.043755   2.586648     4980 0.3982
# as.factor(I_Cat2)VAP:relation   -0.995666  -3.458619   1.719297     5229 0.4291
# time:relation                    0.154804  -0.141690   0.470028     4809 0.3252
# as.factor(I_Cat2)SAC:ete        -0.517502  -2.148162   1.167896     5314 0.5371
# as.factor(I_Cat2)VAP:ete        -3.461143  -5.758350  -1.406969     3415 <2e-04 ***
```

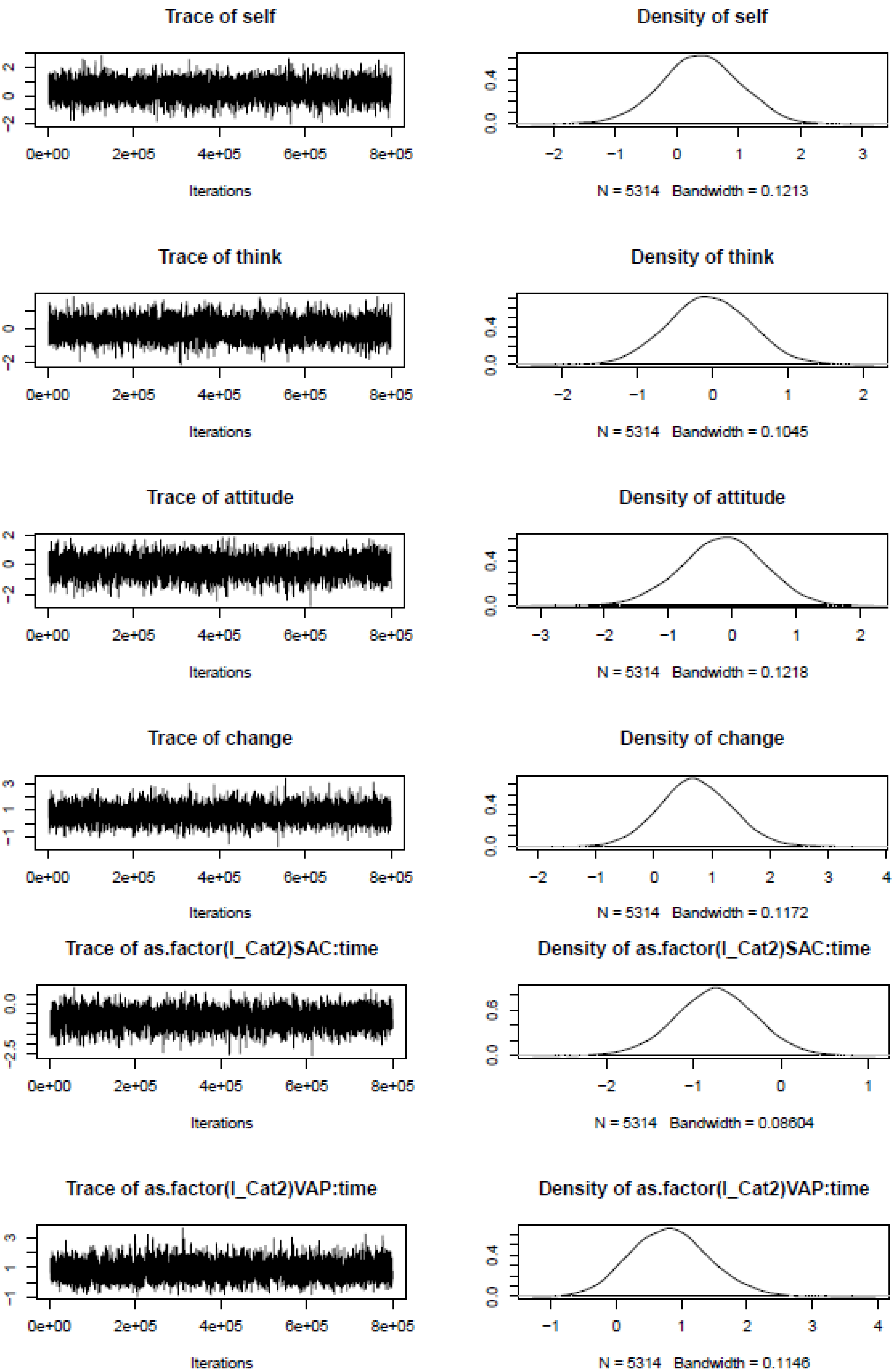
```
# time:ete                             -0.154801  -0.350280   0.036448     5038 0.1099
# as.factor(I_Cat2)SAC:where            0.897084  -0.563835   2.340939     4858 0.2160
# as.factor(I_Cat2)VAP:where           -1.226223  -3.083528   0.683675     5314 0.1938
# time:where                            0.030290  -0.126869   0.192574     5314 0.7136
# as.factor(I_Cat2)SAC:life             0.620042  -1.803513   2.927807     5057 0.6123
# as.factor(I_Cat2)VAP:life             3.031500   0.436828   5.904368     3828 0.0154 *
# time:life                             0.078644  -0.257402   0.427629     4736 0.6541
# as.factor(I_Cat2)SAC:drugs            0.380963  -1.101983   1.852875     4895 0.6105
# as.factor(I_Cat2)VAP:drugs            0.397904  -1.539619   2.111969     5314 0.6752
# time:drugs                            0.058170  -0.128232   0.265204     5314 0.5736
# as.factor(I_Cat2)SAC:physical        -1.795189  -3.841906   0.215249     5085 0.0813 .
# as.factor(I_Cat2)VAP:physical        -0.864645  -3.450338   1.666862     4968 0.5070
# time:physical                         0.032043  -0.215322   0.300231     5314 0.7986
# as.factor(I_Cat2)SAC:emotion          0.044915  -1.556007   1.693744     5314 0.9590
# as.factor(I_Cat2)VAP:emotion         -0.457527  -2.159855   1.204326     4309 0.6112
# time:emotion                         -0.094117  -0.335147   0.128959     5314 0.4324
# as.factor(I_Cat2)SAC:self            -1.012361  -3.082461   1.149123     4808 0.3624
# as.factor(I_Cat2)VAP:self             0.187958  -2.047094   2.612903     4430 0.8728
# time:self                            -0.159196  -0.418112   0.101368     5314 0.2209
# as.factor(I_Cat2)SAC:think           -0.253472  -2.462002   1.974100     4839 0.8479
# as.factor(I_Cat2)VAP:think            2.360754  -0.711508   5.592396     4932 0.1393
# time:think                            0.065423  -0.211664   0.327670     5314 0.6255
# as.factor(I_Cat2)SAC:attitude         0.256100  -1.893079   2.417996     5314 0.8190
# as.factor(I_Cat2)VAP:attitude         0.384825  -2.933205   3.469433     5314 0.8344
# time:attitude                        -0.075963  -0.376581   0.229499     5314 0.6116
# as.factor(I_Cat2)SAC:change          -1.331381  -4.311756   1.749860     4344 0.3820
# as.factor(I_Cat2)VAP:change           0.768872  -1.766975   3.111716     5274 0.5167
# time:change                          -0.061904  -0.339219   0.216316     4524 0.6522
# as.factor(I_Cat2)SAC:time:live        0.048123  -0.299609   0.404217     4948 0.7881
# as.factor(I_Cat2)VAP:time:live       -0.221061  -0.781783   0.292283     5314 0.4230
# as.factor(I_Cat2)SAC:time:relation   -0.354845  -0.793085   0.062665     4517 0.0997 .
# as.factor(I_Cat2)VAP:time:relation    0.409128  -0.222372   1.120088     5314 0.2247
# as.factor(I_Cat2)SAC:time:ete         0.260361  -0.076479   0.613711     5314 0.1385
# as.factor(I_Cat2)VAP:time:ete         0.994206   0.409849   1.611091     3148 <2e-04 ***
# as.factor(I_Cat2)SAC:time:where      -0.283551  -0.564248   0.021767     5314 0.0531 .
# as.factor(I_Cat2)VAP:time:where       0.445649   0.010154   0.930464     4135 0.0489 *
# as.factor(I_Cat2)SAC:time:life       -0.114294  -0.600907   0.382499     4394 0.6571
# as.factor(I_Cat2)VAP:time:life       -0.597604  -1.196980  -0.016437     3787 0.0373 *
# as.factor(I_Cat2)SAC:time:drugs      -0.007908  -0.358715   0.300204     5051 0.9710
# as.factor(I_Cat2)VAP:time:drugs      -0.240944  -0.640630   0.165758     5078 0.2386
# as.factor(I_Cat2)SAC:time:physical    0.134442  -0.319428   0.588156     4816 0.5706
# as.factor(I_Cat2)VAP:time:physical    0.006648  -0.700826   0.761486     5314 0.9947
# as.factor(I_Cat2)SAC:time:emotion     0.314734  -0.025479   0.650132     5105 0.0640 .
# as.factor(I_Cat2)VAP:time:emotion     0.455581  -0.017742   0.978476     4500 0.0636 .
# as.factor(I_Cat2)SAC:time:self        0.356921  -0.081653   0.845260     5031 0.1234
# as.factor(I_Cat2)VAP:time:self        0.011821  -0.494148   0.496503     4948 0.9552
# as.factor(I_Cat2)SAC:time:think      -0.232814  -0.749425   0.267215     5314 0.3764
# as.factor(I_Cat2)VAP:time:think      -0.751560  -1.455873  -0.122303     4777 0.0199 *
# as.factor(I_Cat2)SAC:time:attitude    0.126537  -0.371688   0.635780     5055 0.6172
# as.factor(I_Cat2)VAP:time:attitude   -0.518966  -1.395638   0.233665     4222 0.2047
# as.factor(I_Cat2)SAC:time:change      0.167923  -0.378097   0.764096     4901 0.5600
# as.factor(I_Cat2)VAP:time:change     -0.306902  -0.811149   0.170330     5314 0.2115
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

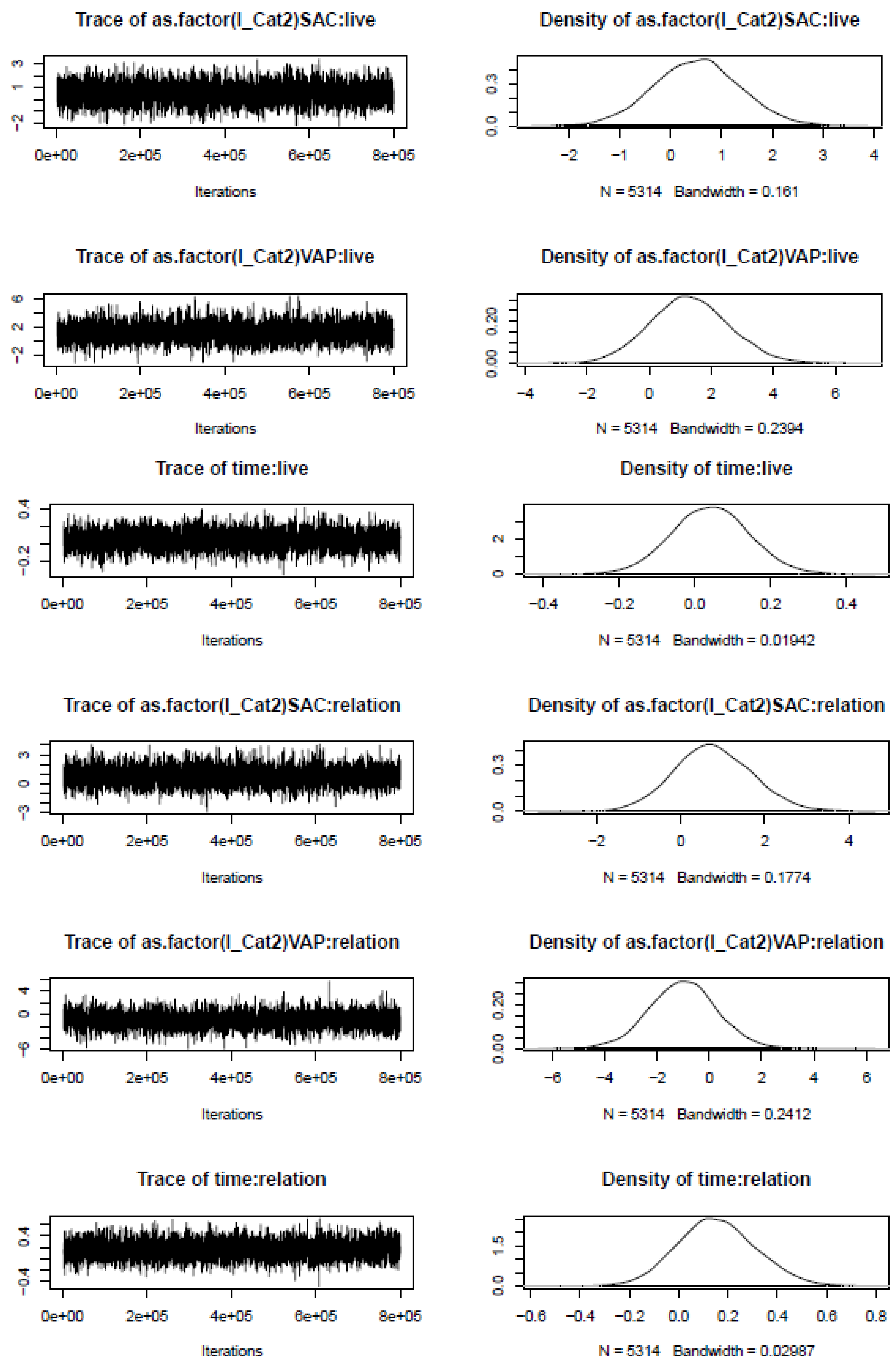
Trace Plots and Posterior Density Plots

<u>Fixed Effects</u>

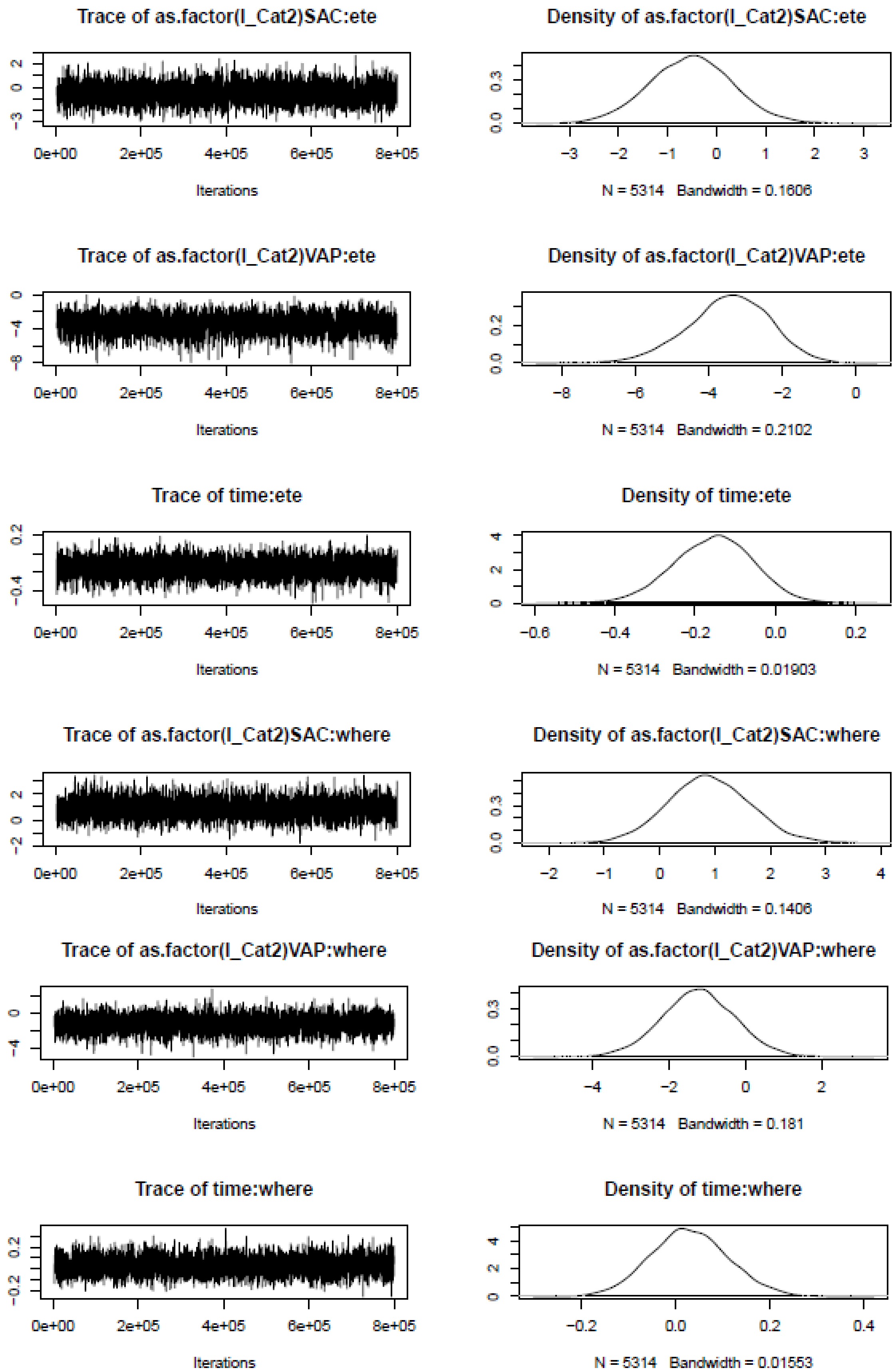


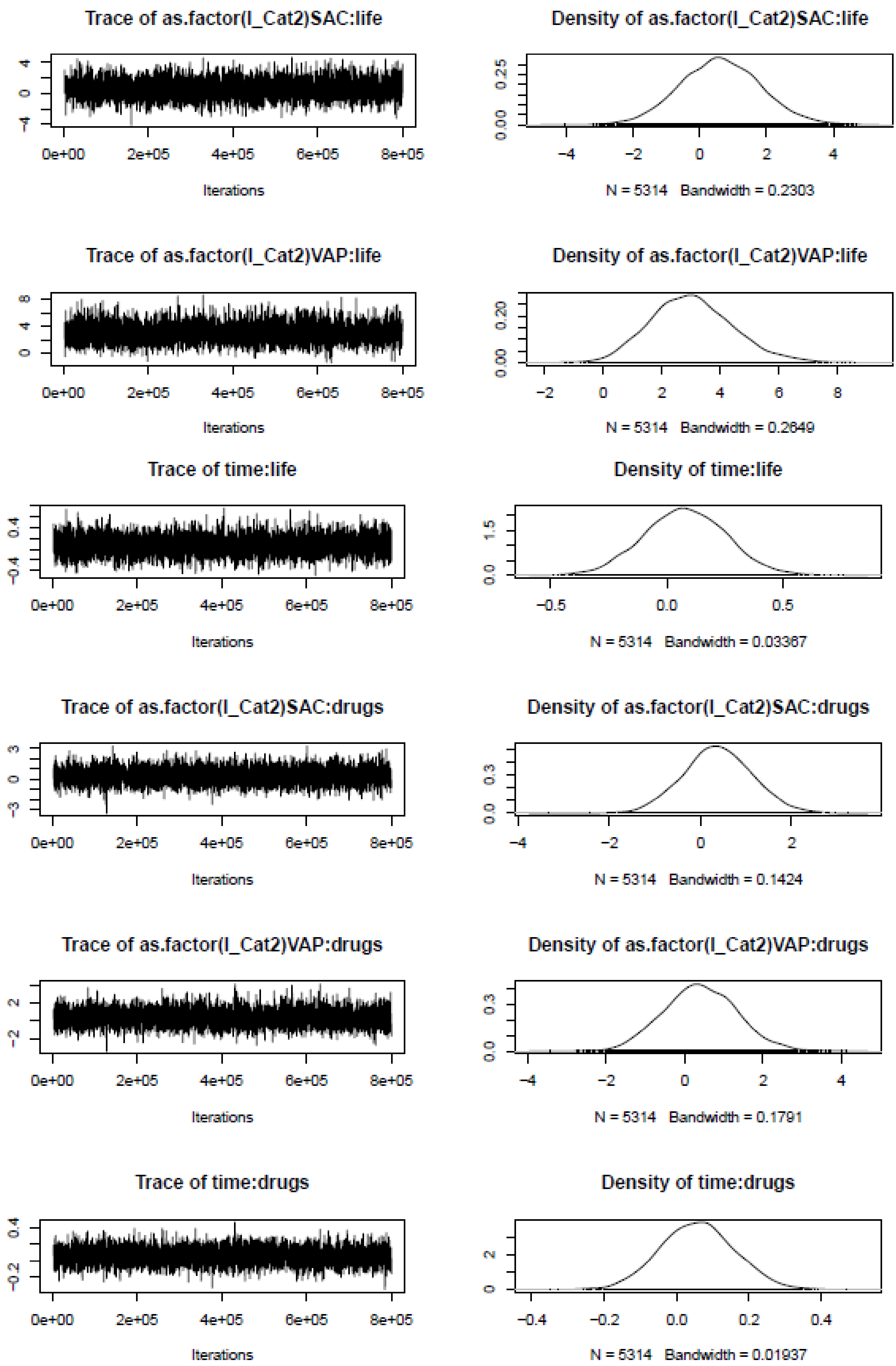

Trace of ete
Iterations
Density of ete
N = 5314 Bandwidth = 0.0742
Trace of where
Iterations
Density of where
N = 5314 Bandwidth = 0.075
Trace of life
Iterations
Density of life
N = 5314 Bandwidth = 0.1406
Trace of drugs
Iterations
Density of drugs
N = 5314 Bandwidth = 0.08584
Trace of physical
Iterations
Density of physical
N = 5314 Bandwidth = 0.08866
Trace of emotion
Iterations
Density of emotion
N = 5314 Bandwidth = 0.07705

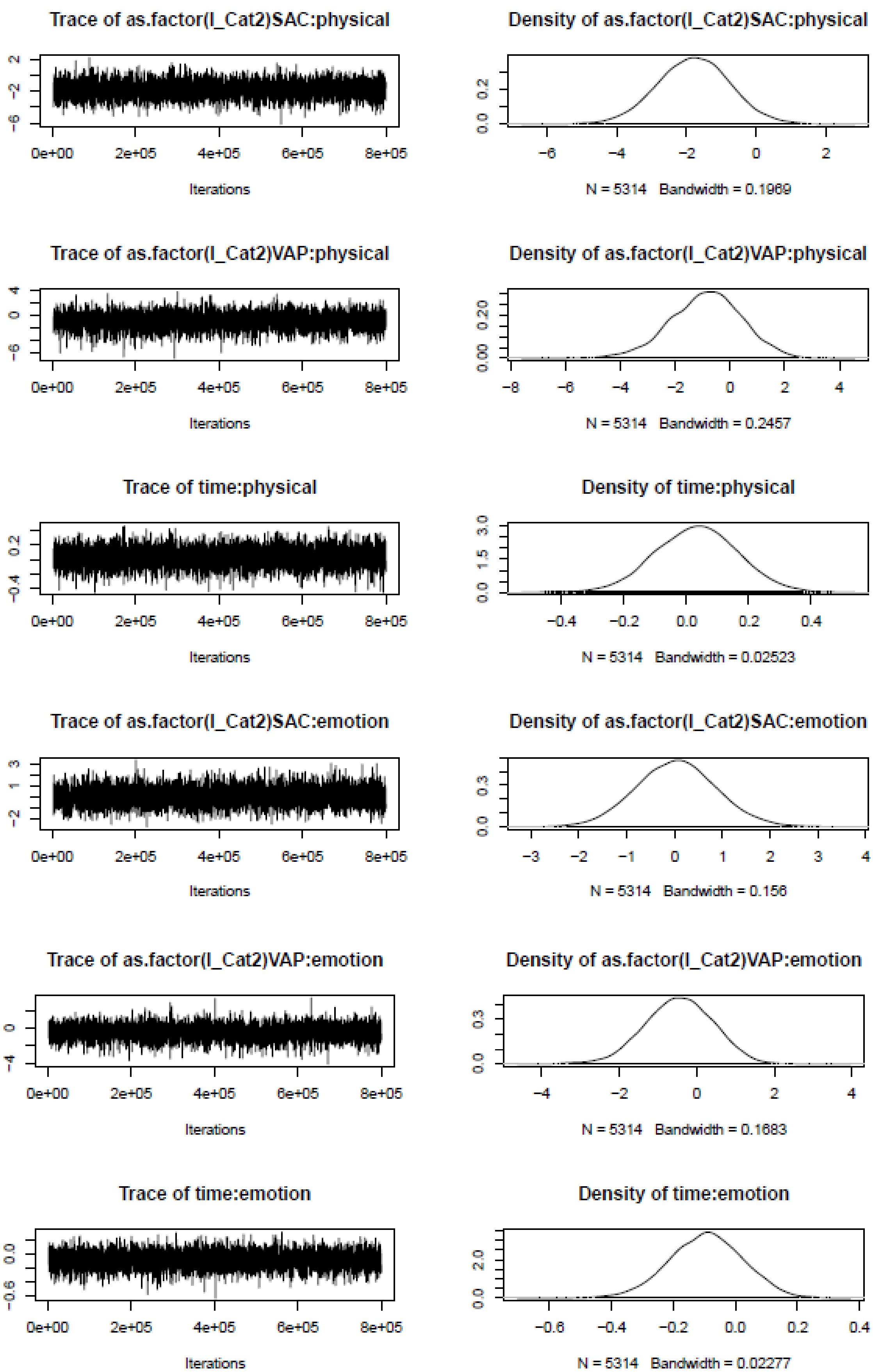

Trace of self
Iterations
Density of self
N = 5314 Bandwidth = 0.1213
Trace of think
Iterations
Density of think
N = 5314 Bandwidth = 0.1045
Trace of attitude
Iterations
Density of attitude
N = 5314 Bandwidth = 0.1218
Trace of change
Iterations
Density of change
N = 5314 Bandwidth = 0.1172
Trace of as.factor(I_Cat2)SAC:time
Iterations
Density of as.factor(I_Cat2)SAC:time
N = 5314 Bandwidth = 0.08604
Trace of as.factor(I_Cat2)VAP:time
Iterations
Density of as.factor(I_Cat2)VAP:time
N = 5314 Bandwidth = 0.1146

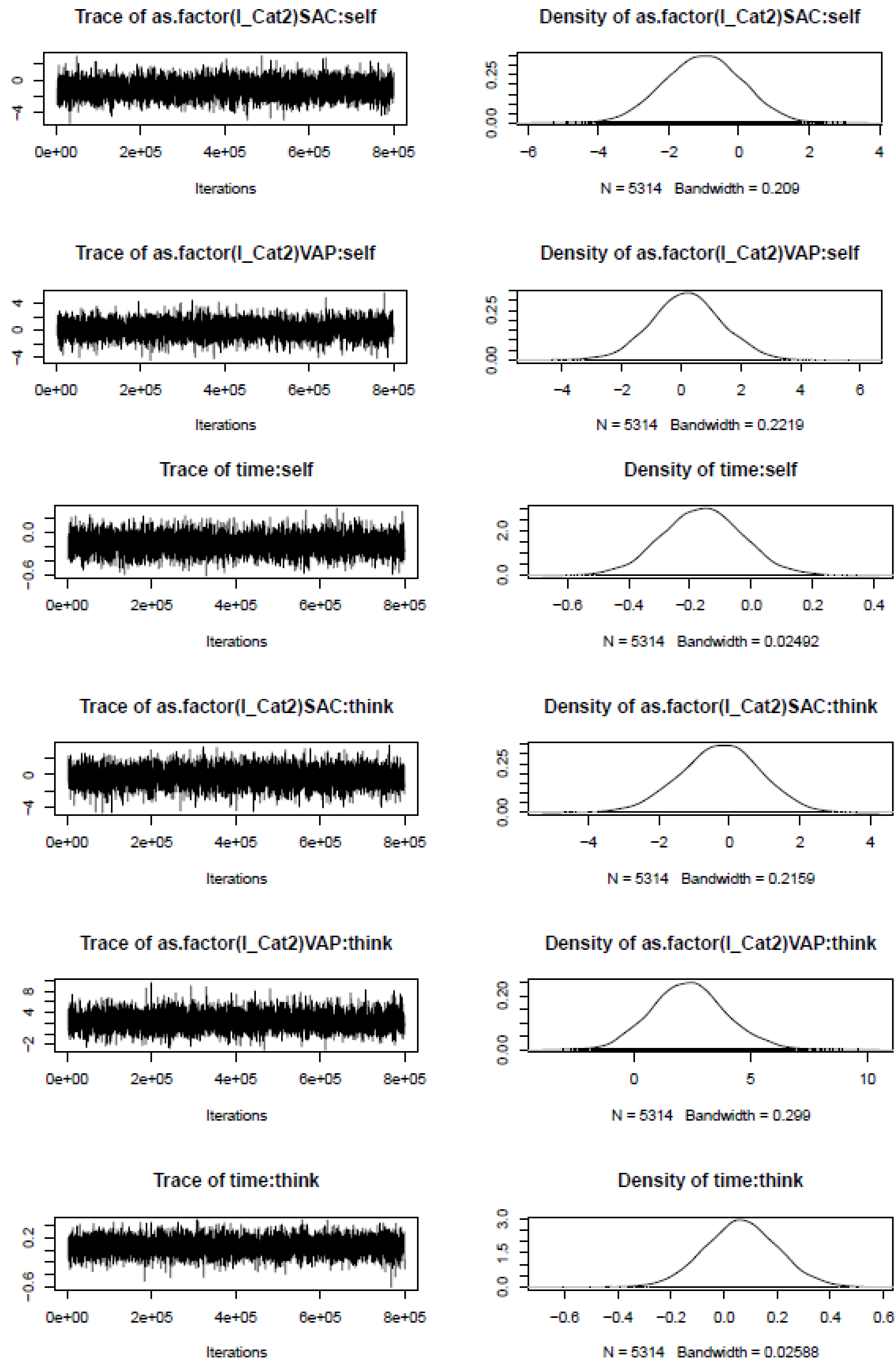


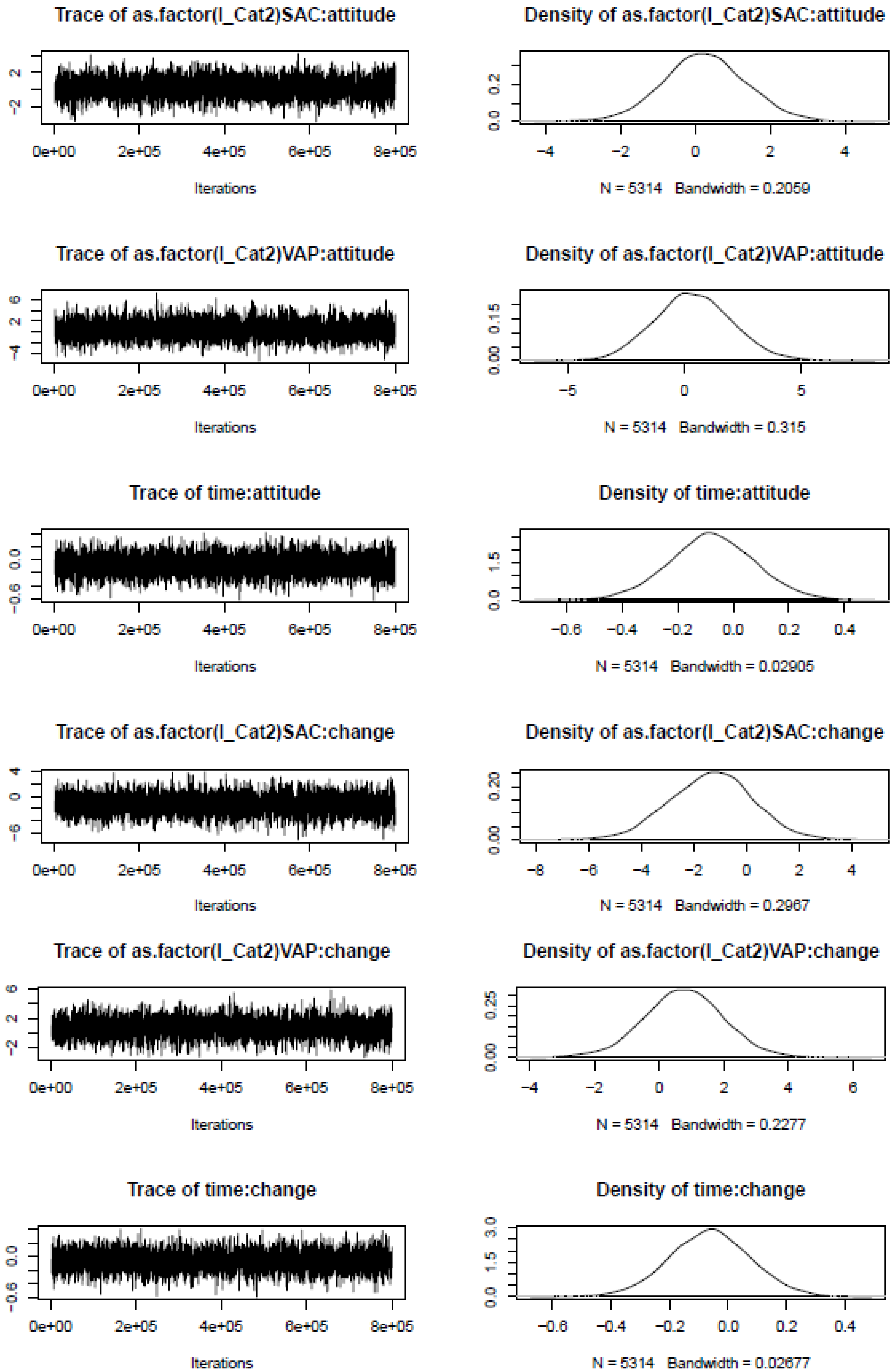
Trace of as.factor(I_Cat2)SAC:live
Iterations
Density of as.factor(I_Cat2)SAC:live
N = 5314 Bandwidth = 0.161
Trace of as.factor(I_Cat2)VAP:live
Iterations
Density of as.factor(I_Cat2)VAP:live
N = 5314 Bandwidth = 0.2394
Trace of time:live
Iterations
Density of time:live
N = 5314 Bandwidth = 0.01942
Trace of as.factor(I_Cat2)SAC:relation
Iterations
Density of as.factor(I_Cat2)SAC:relation
N = 5314 Bandwidth = 0.1774
Trace of as.factor(I_Cat2)VAP:relation
Iterations
Density of as.factor(I_Cat2)VAP:relation
N = 5314 Bandwidth = 0.2412
Trace of time:relation
Iterations
Density of time:relation
N = 5314 Bandwidth = 0.02987

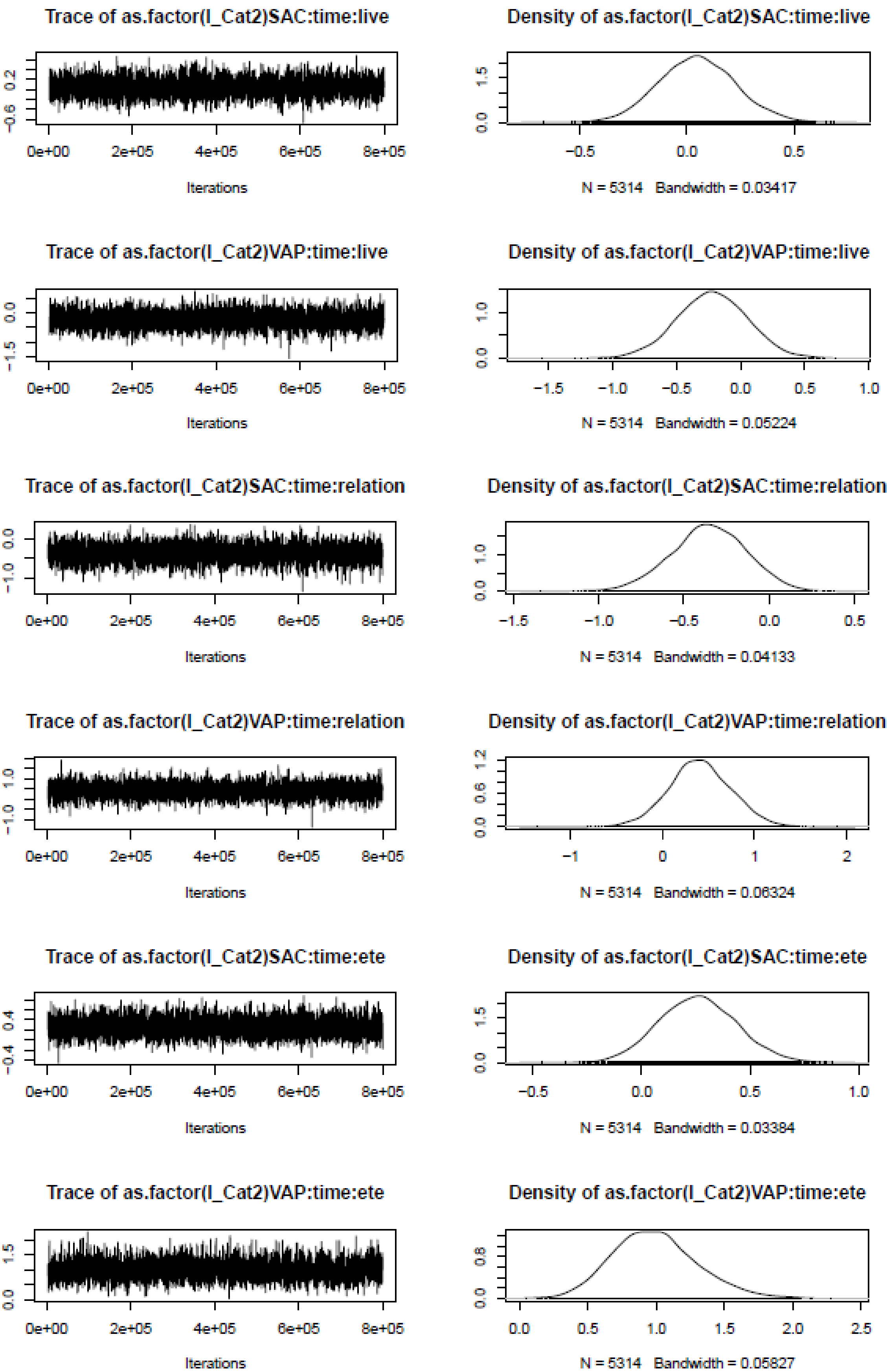

Trace of as.factor(I_Cat2)SAC:ete
Iterations
Density of as.factor(I_Cat2)SAC:ete
N = 5314 Bandwidth = 0.1606
Trace of as.factor(I_Cat2)VAP:ete
Iterations
Density of as.factor(I_Cat2)VAP:ete
N = 5314 Bandwidth = 0.2102
Trace of time:ete
Iterations
Density of time:ete
N = 5314 Bandwidth = 0.01903
Trace of as.factor(I_Cat2)SAC:where
Iterations
Density of as.factor(I_Cat2)SAC:where
N = 5314 Bandwidth = 0.1406
Trace of as.factor(I_Cat2)VAP:where
Iterations
Density of as.factor(I_Cat2)VAP:where
N = 5314 Bandwidth = 0.181
Trace of time:where
Iterations
Density of time:where
N = 5314 Bandwidth = 0.01553

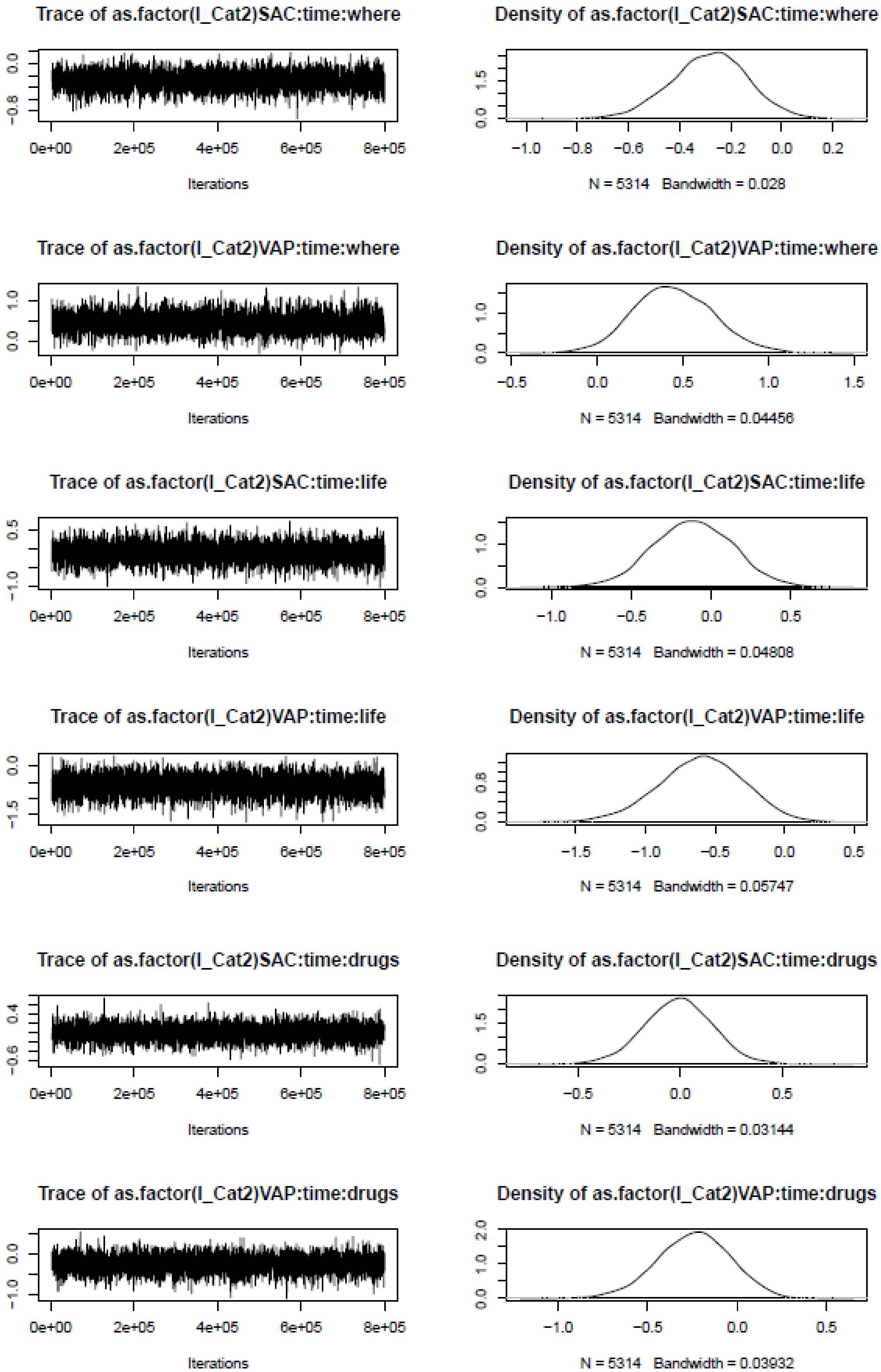

Trace of as.factor(I_Cat2)SAC:life
Iterations
Density of as.factor(I_Cat2)SAC:life
N = 5314 Bandwidth = 0.2303
Trace of as.factor(I_Cat2)VAP:life
Iterations
Density of as.factor(I_Cat2)VAP:life
N = 5314 Bandwidth = 0.2649
Trace of time:life
Iterations
Density of time:life
N = 5314 Bandwidth = 0.03367
Trace of as.factor(I_Cat2)SAC:drugs
Iterations
Density of as.factor(I_Cat2)SAC:drugs
N = 5314 Bandwidth = 0.1424
Trace of as.factor(I_Cat2)VAP:drugs
Iterations
Density of as.factor(I_Cat2)VAP:drugs
N = 5314 Bandwidth = 0.1791
Trace of time:drugs
Iterations
Density of time:drugs
N = 5314 Bandwidth = 0.01937

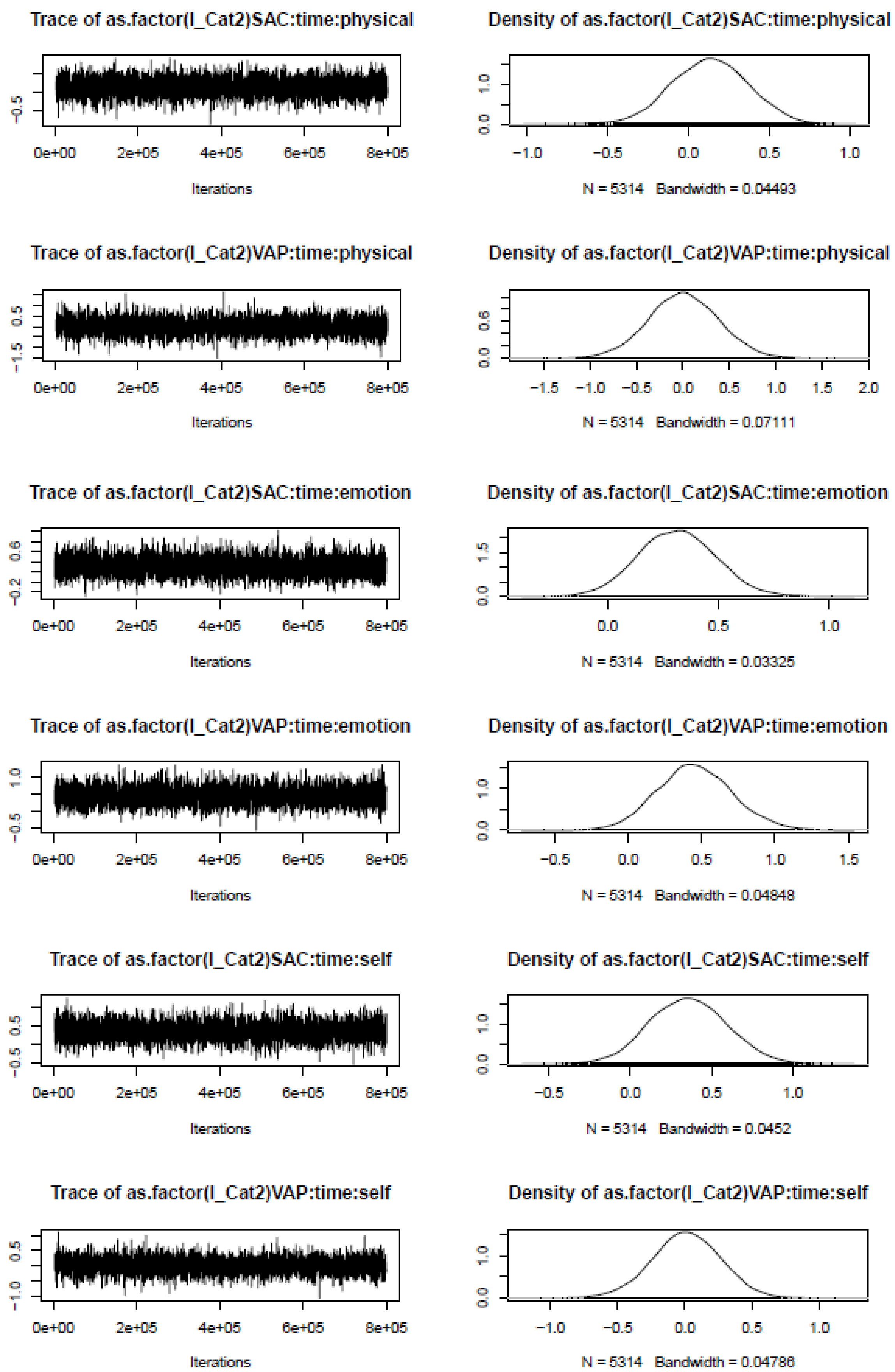

Trace of as.factor(I_Cat2)SAC:physical
Iterations
Density of as.factor(I_Cat2)SAC:physical
N = 5314 Bandwidth = 0.1969
Trace of as.factor(I_Cat2)VAP:physical
Iterations
Density of as.factor(I_Cat2)VAP:physical
N = 5314 Bandwidth = 0.2457
Trace of time:physical
Iterations
Density of time:physical
N = 5314 Bandwidth = 0.02523
Trace of as.factor(I_Cat2)SAC:emotion
Iterations
Density of as.factor(I_Cat2)SAC:emotion
N = 5314 Bandwidth = 0.156
Trace of as.factor(I_Cat2)VAP:emotion
Iterations
Density of as.factor(I_Cat2)VAP:emotion
N = 5314 Bandwidth = 0.1683
Trace of time:emotion
Iterations
Density of time:emotion
N = 5314 Bandwidth = 0.02277

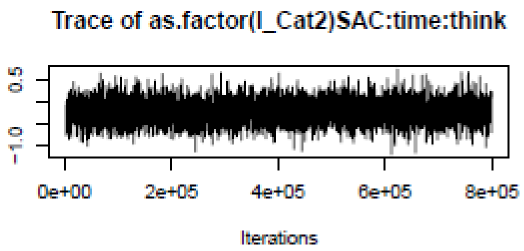

Trace of as.factor(l_Cat2)SAC:self
Iterations
Density of as.factor(l_Cat2)SAC:self
N = 5314 Bandwidth = 0.209
Trace of as.factor(l_Cat2)VAP:self
Iterations
Density of as.factor(l_Cat2)VAP:self
N = 5314 Bandwidth = 0.2219
Trace of time:self
Iterations
Density of time:self
N = 5314 Bandwidth = 0.02492
Trace of as.factor(l_Cat2)SAC:think
Iterations
Density of as.factor(l_Cat2)SAC:think
N = 5314 Bandwidth = 0.2159
Trace of as.factor(l_Cat2)VAP:think
Iterations
Density of as.factor(l_Cat2)VAP:think
N = 5314 Bandwidth = 0.299
Trace of time:think
Iterations
Density of time:think
N = 5314 Bandwidth = 0.02588

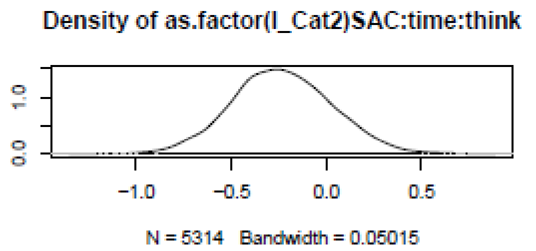

Trace of as.factor(I_Cat2)SAC:attitude
Iterations
Density of as.factor(I_Cat2)SAC:attitude
N = 5314 Bandwidth = 0.2059
Trace of as.factor(I_Cat2)VAP:attitude
Iterations
Density of as.factor(I_Cat2)VAP:attitude
N = 5314 Bandwidth = 0.315
Trace of time:attitude
Iterations
Density of time:attitude
N = 5314 Bandwidth = 0.02905
Trace of as.factor(I_Cat2)SAC:change
Iterations
Density of as.factor(I_Cat2)SAC:change
N = 5314 Bandwidth = 0.2967
Trace of as.factor(I_Cat2)VAP:change
Iterations
Density of as.factor(I_Cat2)VAP:change
N = 5314 Bandwidth = 0.2277
Trace of time:change
Iterations
Density of time:change
N = 5314 Bandwidth = 0.02677

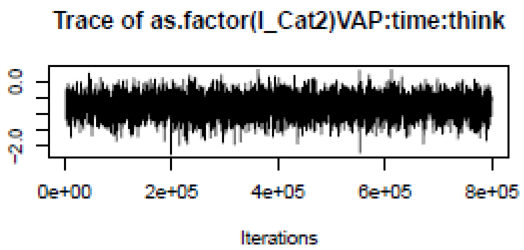

Trace of as.factor(I_Cat2)SAC:time:live
Iterations
Density of as.factor(I_Cat2)SAC:time:live
N = 5314 Bandwidth = 0.03417
Trace of as.factor(I_Cat2)VAP:time:live
Iterations
Density of as.factor(I_Cat2)VAP:time:live
N = 5314 Bandwidth = 0.05224
Trace of as.factor(I_Cat2)SAC:time:relation
Iterations
Density of as.factor(I_Cat2)SAC:time:relation
N = 5314 Bandwidth = 0.04133
Trace of as.factor(I_Cat2)VAP:time:relation
Iterations
Density of as.factor(I_Cat2)VAP:time:relation
N = 5314 Bandwidth = 0.06324
Trace of as.factor(I_Cat2)SAC:time:ete
Iterations
Density of as.factor(I_Cat2)SAC:time:ete
N = 5314 Bandwidth = 0.03384
Trace of as.factor(I_Cat2)VAP:time:ete
Iterations
Density of as.factor(I_Cat2)VAP:time:ete
N = 5314 Bandwidth = 0.05827

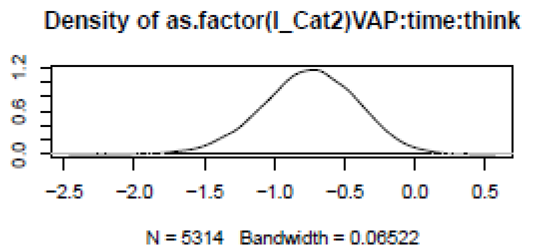

Trace of as.factor(I_Cat2)SAC:time:where
Iterations
Density of as.factor(I_Cat2)SAC:time:where
N = 5314 Bandwidth = 0.028
Trace of as.factor(I_Cat2)VAP:time:where
Iterations
Density of as.factor(I_Cat2)VAP:time:where
N = 5314 Bandwidth = 0.04456
Trace of as.factor(I_Cat2)SAC:time:life
Iterations
Density of as.factor(I_Cat2)SAC:time:life
N = 5314 Bandwidth = 0.04808
Trace of as.factor(I_Cat2)VAP:time:life
Iterations
Density of as.factor(I_Cat2)VAP:time:life
N = 5314 Bandwidth = 0.05747
Trace of as.factor(I_Cat2)SAC:time:drugs
Iterations
Density of as.factor(I_Cat2)SAC:time:drugs
N = 5314 Bandwidth = 0.03144
Trace of as.factor(I_Cat2)VAP:time:drugs
Iterations
Density of as.factor(I_Cat2)VAP:time:drugs
N = 5314 Bandwidth = 0.03932

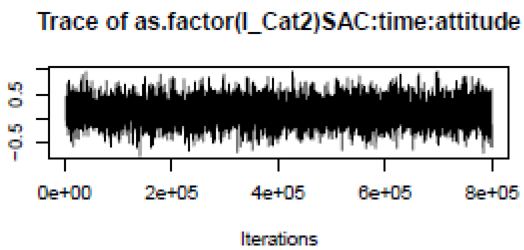

Trace of as.factor(I_Cat2)SAC:time:physical
Iterations
Density of as.factor(I_Cat2)SAC:time:physical
N = 5314 Bandwidth = 0.04493
Trace of as.factor(I_Cat2)VAP:time:physical
Iterations
Density of as.factor(I_Cat2)VAP:time:physical
N = 5314 Bandwidth = 0.07111
Trace of as.factor(I_Cat2)SAC:time:emotion
Iterations
Density of as.factor(I_Cat2)SAC:time:emotion
N = 5314 Bandwidth = 0.03325
Trace of as.factor(I_Cat2)VAP:time:emotion
Iterations
Density of as.factor(I_Cat2)VAP:time:emotion
N = 5314 Bandwidth = 0.04848
Trace of as.factor(I_Cat2)SAC:time:self
Iterations
Density of as.factor(I_Cat2)SAC:time:self
N = 5314 Bandwidth = 0.0452
Trace of as.factor(I_Cat2)VAP:time:self
Iterations
Density of as.factor(I_Cat2)VAP:time:self
N = 5314 Bandwidth = 0.04786

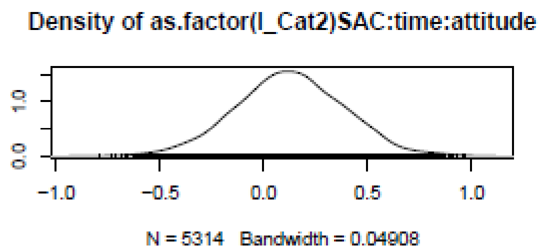

Trace of as.factor(I_Cat2)SAC:time:think
Iterations

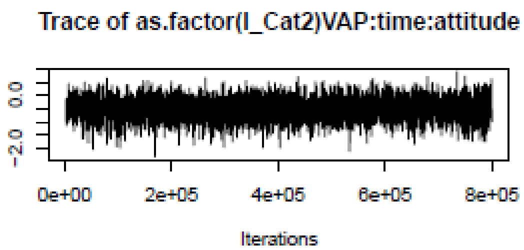

Density of as.factor(I_Cat2)SAC:time:think
N = 5314 Bandwidth = 0.05015

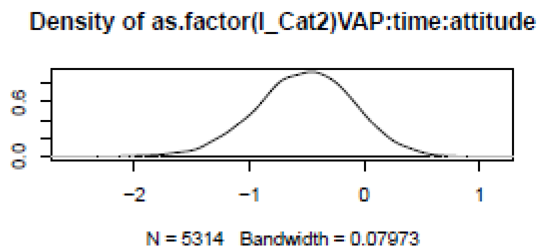

Trace of as.factor(I_Cat2)VAP:time:think
Iterations

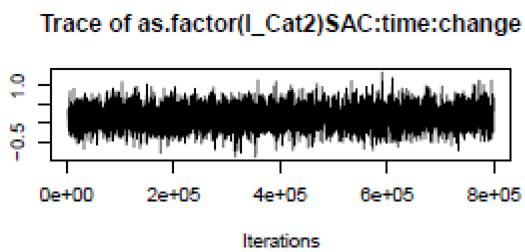

Density of as.factor(I_Cat2)VAP:time:think
N = 5314 Bandwidth = 0.06522

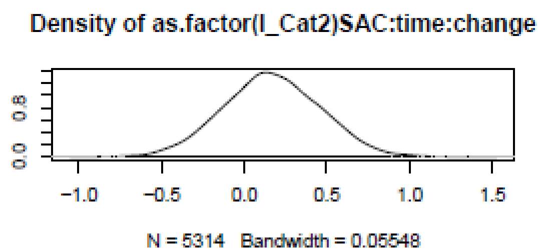

Trace of as.factor(I_Cat2)SAC:time:attitude
Iterations

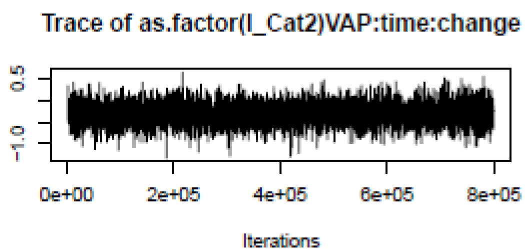

Density of as.factor(I_Cat2)SAC:time:attitude
N = 5314 Bandwidth = 0.04908

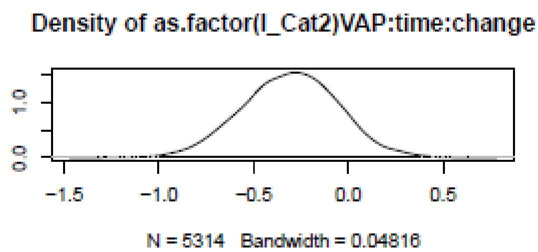

Trace of as.factor(I_Cat2)VAP:time:attitude
Iterations


Density of as.factor(I_Cat2)VAP:time:attitude
N = 5314 Bandwidth = 0.07973

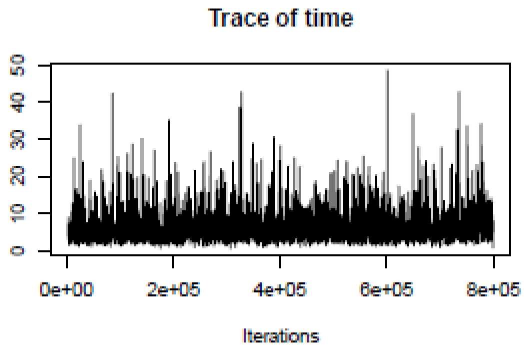

Trace of as.factor(I_Cat2)SAC:time:change
Iterations

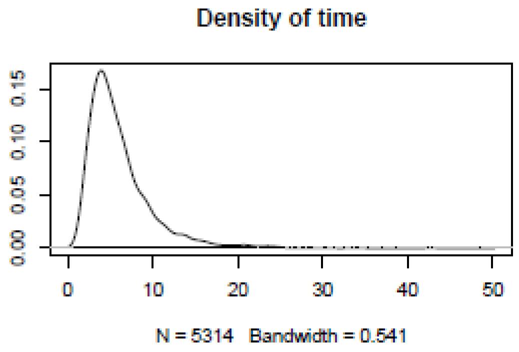

Density of as.factor(I_Cat2)SAC:time:change
N = 5314 Bandwidth = 0.05548

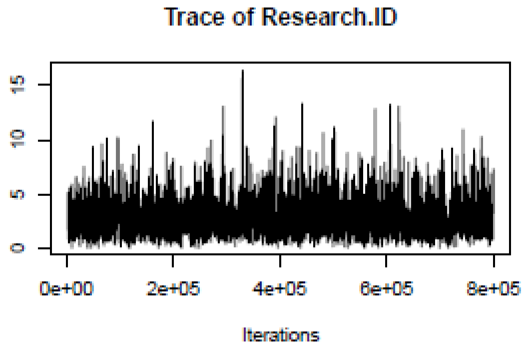

Trace of as.factor(I_Cat2)VAP:time:change
Iterations

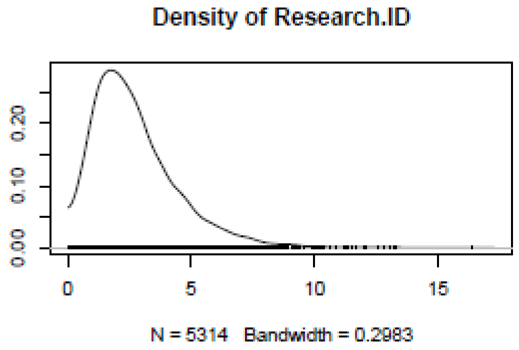

Density of as.factor(I_Cat2)VAP:time:change
N = 5314 Bandwidth = 0.04816

Random Effects









Dynamic Model involving YJB Gravity Score (Table 6.19)

Bayesian Model (BDm3_o2a)

Define the model

```
BDm3_o2a <- MCMCglmm(FO.bin ~ I_Seriousness2*time*live +
I_Seriousness2*time*relation + I_Seriousness2*time*ete +
I_Seriousness2*time*where + I_Seriousness2*time*life +
I_Seriousness2*time*drugs + I_Seriousness2*time*physical +
I_Seriousness2*time*emotion + I_Seriousness2*time*self +
I_Seriousness2*time*think + I_Seriousness2*time*attitude +
I_Seriousness2*time*change,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
slice=TRUE, nitt=300000, thin=50, burnin=3000)
```

Checks for suitable convergence

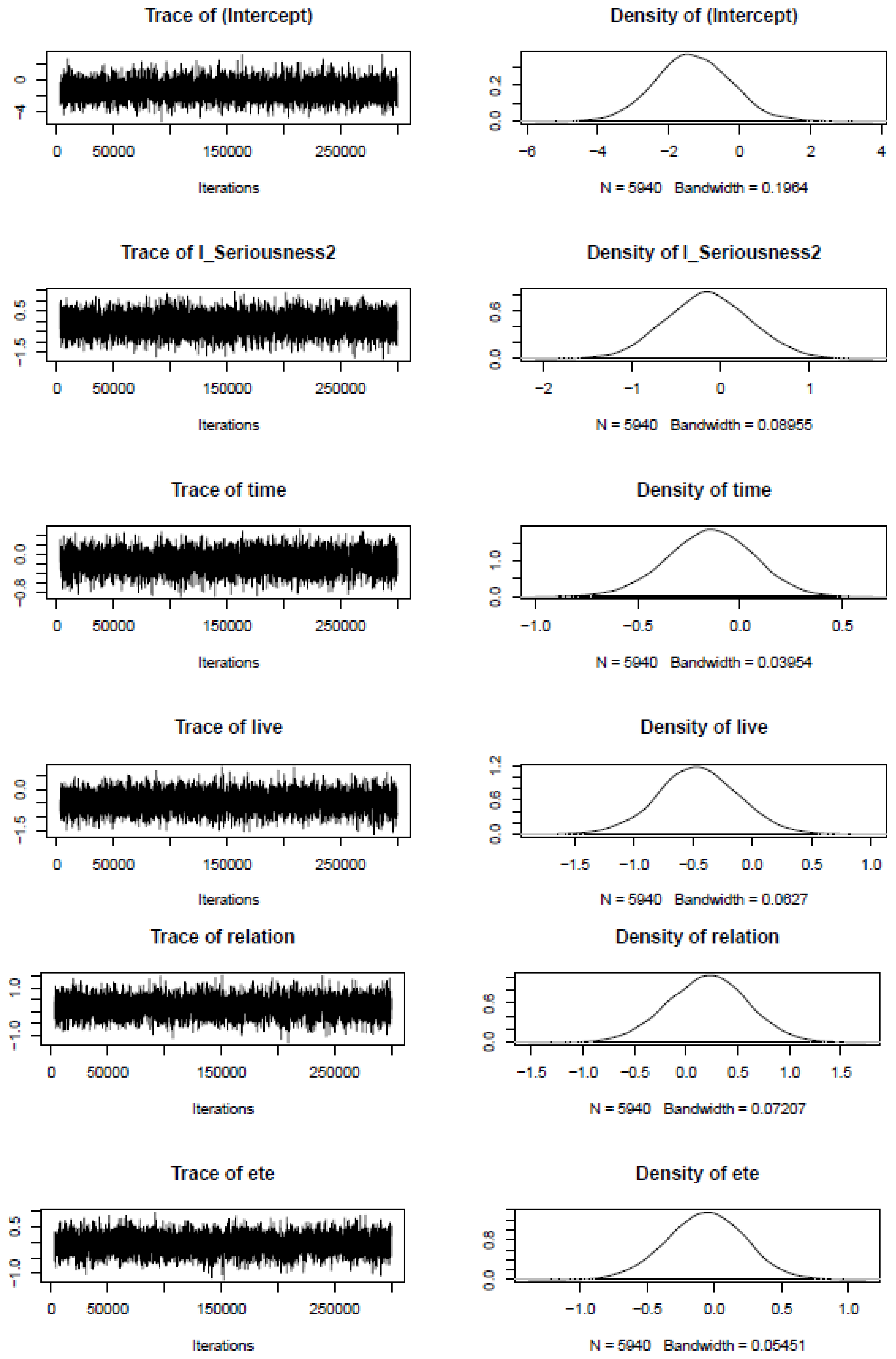
```
raftery.diag(BDm3_o2a$VCV)
heidel.diag(BDm3_o2a$VCV)

# > raftery.diag(BDm3_o2a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         150      207850 3746         55.5
# Research.ID  100      191350 3746         51.1
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm3_o2a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.408
# Research.ID  passed        1        0.282
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    2.614 0.0814
# Research.ID  passed    0.335 0.0113
# units        <NA>         NA     NA

autocorr(BDm3_o2a$VCV)
autocorr(BDm3_o2a$Sol)    # Output not included here
summary(BDm3_o2a)

# > autocorr(BDm3_o2a$VCV)
# , , time
#
#                  time   Research.ID units
# Lag 0      1.00000000  0.188798875   NaN
# Lag 50     0.25334352  0.092709218   NaN
# Lag 250    0.06566426 -0.002437446   NaN
# Lag 500    0.06085530 -0.005251981   NaN
# Lag 2500 -0.01207543  0.004623263   NaN
```

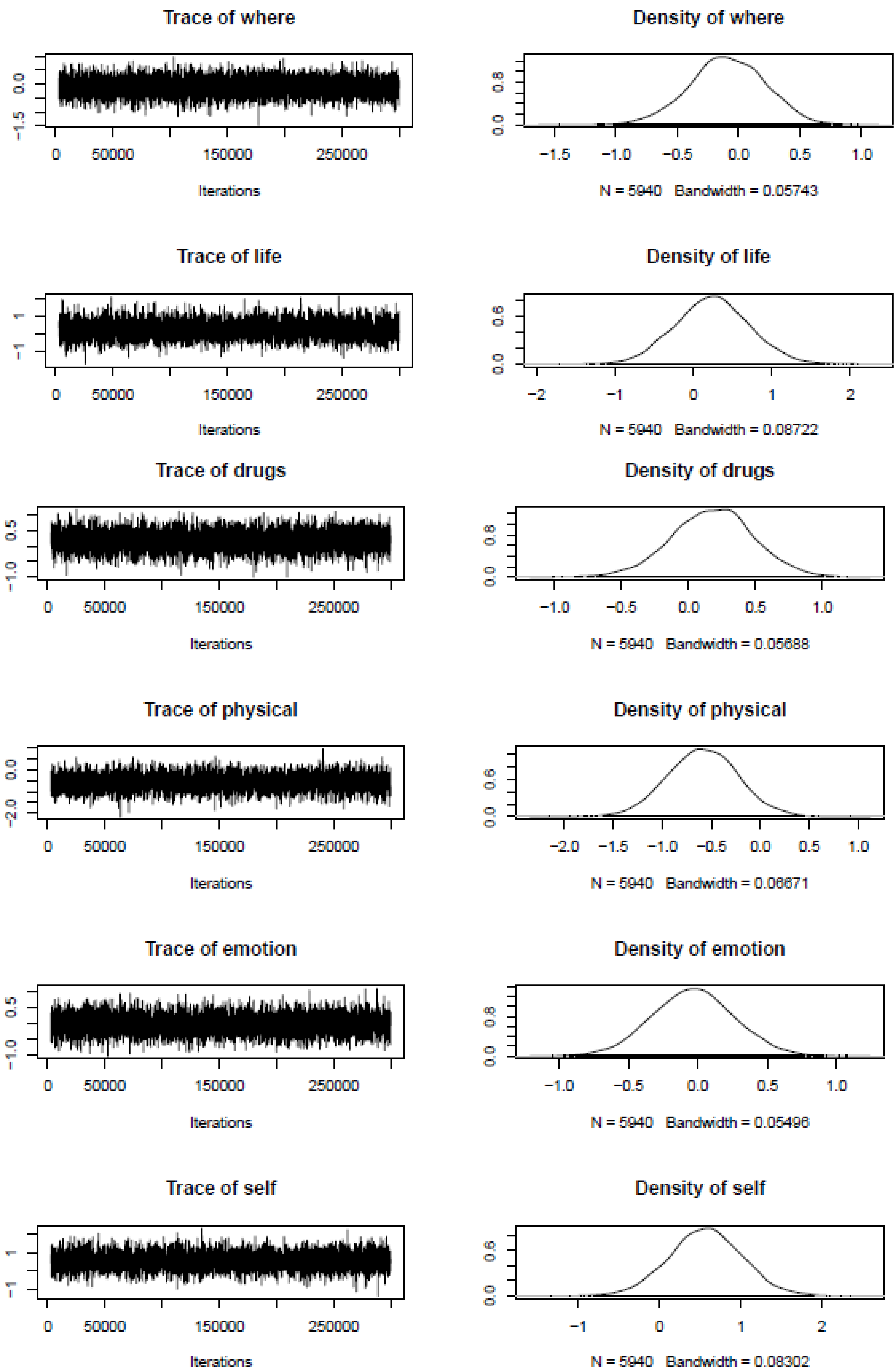
```
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0      0.18879887  1.000000000   NaN
# Lag 50     0.09573174  0.300913551   NaN
# Lag 250    0.01540702 -0.008722053   NaN
# Lag 500    0.02353935  0.008647625   NaN
# Lag 2500 -0.01579473 -0.001792250   NaN

# > summary(BDm3_o2a)
#
# Iterations = 3001:299951
# Thinning interval  = 50
# Sample size  = 5940
#
# DIC: 472.6568
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.614   0.5683    5.735     1603
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.3352 6.612e-07    0.981     3192
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ I_Seriousness2 * time * live + I_Seriousness2 * time * relation + I_Seriousness2 * time * ete + I_Seriousness2 * time * where + I_Seriousness2 * time * life + I_Seriousness2 * time * drugs + I_Seriousness2 * time * physical + I_Seriousness2 * time * emotion + I_Seriousness2 * time * self + I_Seriousness2 * time * think + I_Seriousness2 * time * attitude + I_Seriousness2 * time * change
#
#                            post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)                -1.305924 -3.401056  0.771829     5940 0.2165
# I_Seriousness2             -0.142531 -1.058536  0.809526     5940 0.7586
# time                       -0.145489 -0.571825  0.256788     5879 0.4987
# live                       -0.458659 -1.156282  0.190430     5940 0.1788
# relation                    0.206956 -0.552453  0.960456     5940 0.5845
# ete                        -0.064044 -0.663588  0.487447     5713 0.8276
# where                      -0.090915 -0.669091  0.533306     5940 0.7727
# life                        0.243964 -0.633041  1.211178     5940 0.6020
# drugs                       0.180107 -0.423368  0.786922     5951 0.5498
# physical                   -0.587529 -1.281764  0.120313     5523 0.1003
# emotion                    -0.031714 -0.630174  0.526432     5940 0.9104
# self                        0.567467 -0.288063  1.476084     5940 0.2057
# think                      -0.248456 -0.984418  0.555612     5700 0.5128
# attitude                   -0.024787 -0.894667  0.835222     5940 0.9539
# change                      0.849719 -0.077195  1.783158     5544 0.0697 .
# I_Seriousness2:time        -0.008014 -0.245021  0.232383     5650 0.9589
# I_Seriousness2:live         0.284555 -0.094311  0.690382     5940 0.1606
# time:live                   0.079343 -0.065763  0.238573     5940 0.3064
# I_Seriousness2:relation     0.014695 -0.402926  0.474916     5708 0.9643
# time:relation               0.122312 -0.093174  0.332038     5607 0.2562
# I_Seriousness2:ete         -0.109748 -0.494809  0.245838     5940 0.5657
# time:ete                    0.022004 -0.132828  0.182313     5940 0.7808
# I_Seriousness2:where        0.145337 -0.192853  0.504260     5940 0.4135
```

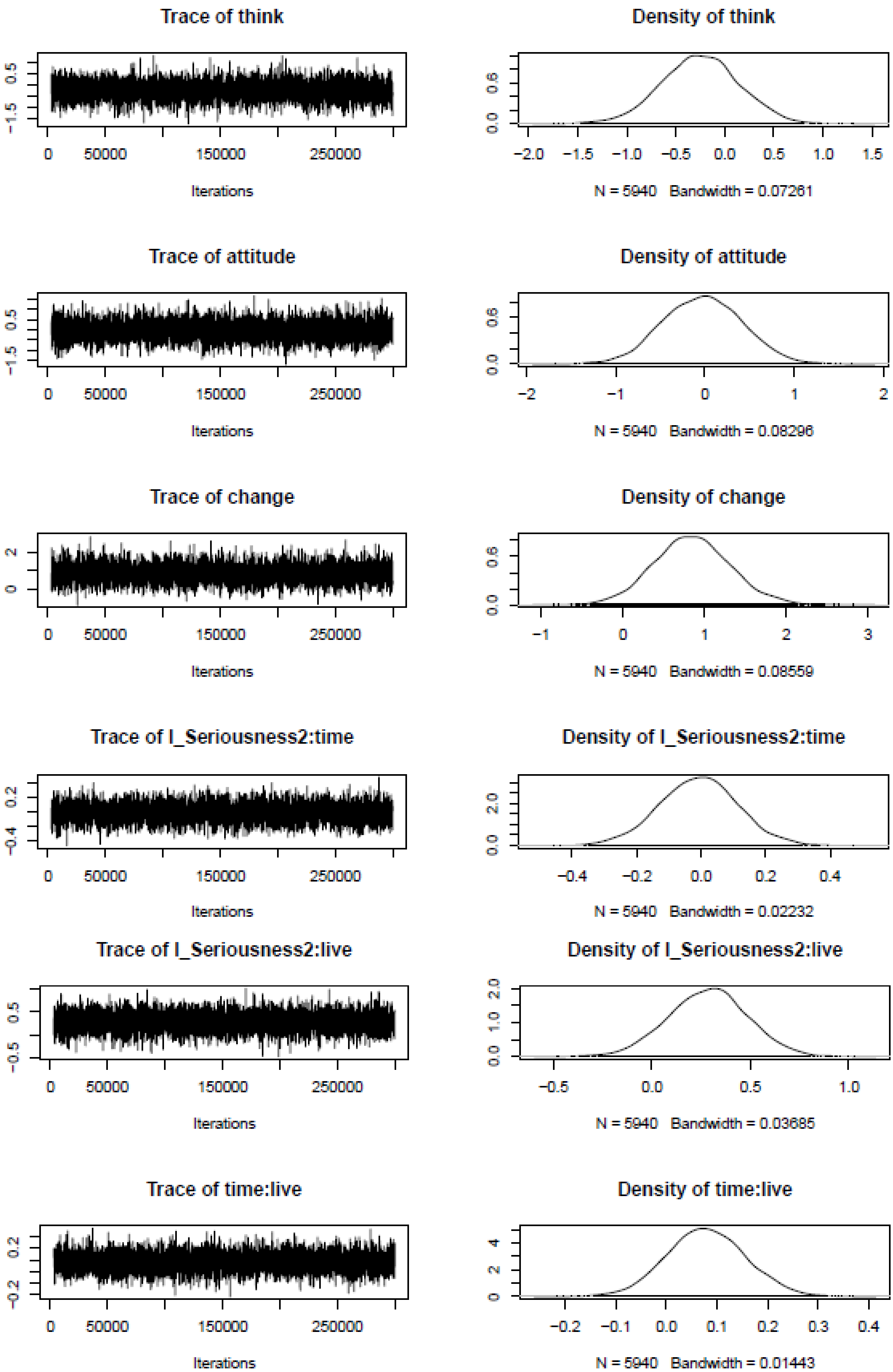
```
# time:where                    0.094178 -0.027000  0.221081     5644 0.1360
# I_Seriousness2:life           0.139833 -0.405590  0.728629     5940 0.6185
# time:life                    -0.092217 -0.312441  0.123750     5940 0.4003
# I_Seriousness2:drugs          0.063997 -0.264648  0.409112     5585 0.7259
# time:drugs                   -0.025601 -0.167658  0.111594     5633 0.7185
# I_Seriousness2:physical      -0.060273 -0.521057  0.392685     5940 0.7842
# time:physical                 0.199929 -0.002092  0.399439     5940 0.0498 *
# I_Seriousness2:emotion       -0.072991 -0.434191  0.327760     5940 0.7098
# time:emotion                 -0.110317 -0.275915  0.048075     5722 0.1771
# I_Seriousness2:self          -0.140216 -0.589479  0.339813     5940 0.5347
# time:self                    -0.174124 -0.360654  0.013717     5940 0.0677 .
# I_Seriousness2:think          0.111828 -0.490262  0.672283     5320 0.6993
# time:think                    0.146009 -0.036335  0.328914     6052 0.1108
# I_Seriousness2:attitude      -0.018562 -0.553642  0.489033     5940 0.9515
# time:attitude                -0.030912 -0.232776  0.171855     5690 0.7818
# I_Seriousness2:change        -0.338732 -1.016097  0.332771     5203 0.3229
# time:change                  -0.199377 -0.408117  0.003843     5444 0.0542 .
# I_Seriousness2:time:live     -0.014201 -0.107432  0.081197     5717 0.7596
# I_Seriousness2:time:relation -0.103629 -0.232662  0.018253     5258 0.1013
# I_Seriousness2:time:ete       0.060503 -0.044713  0.162669     5940 0.2455
# I_Seriousness2:time:where    -0.086823 -0.167473 -0.006410     5421 0.0333 *
# I_Seriousness2:time:life      0.028103 -0.109776  0.160810     5940 0.6788
# I_Seriousness2:time:drugs    -0.008477 -0.091934  0.066844     6019 0.8397
# I_Seriousness2:time:physical -0.060205 -0.181013  0.055330     5655 0.3101
# I_Seriousness2:time:emotion   0.127336  0.033734  0.222735     5545 0.0064 **
# I_Seriousness2:time:self      0.058461 -0.053778  0.162463     5940 0.2768
# I_Seriousness2:time:think    -0.131243 -0.270675  0.006453     5940 0.0673 .
# I_Seriousness2:time:attitude  0.026384 -0.110086  0.153196     5684 0.6933
# I_Seriousness2:time:change    0.095821 -0.043597  0.237323     5112 0.1781
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

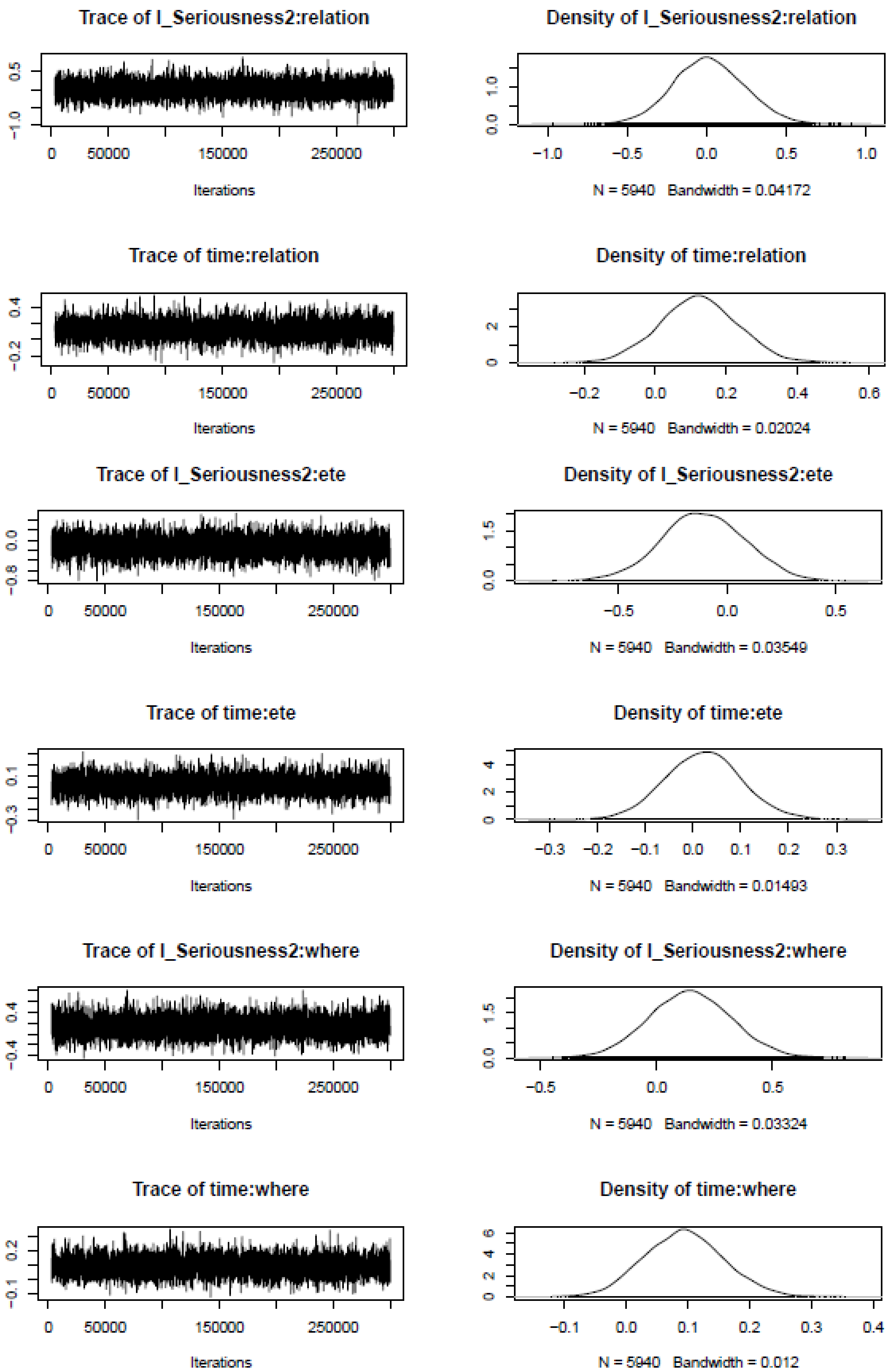
Trace Plots and Posterior Density Plots

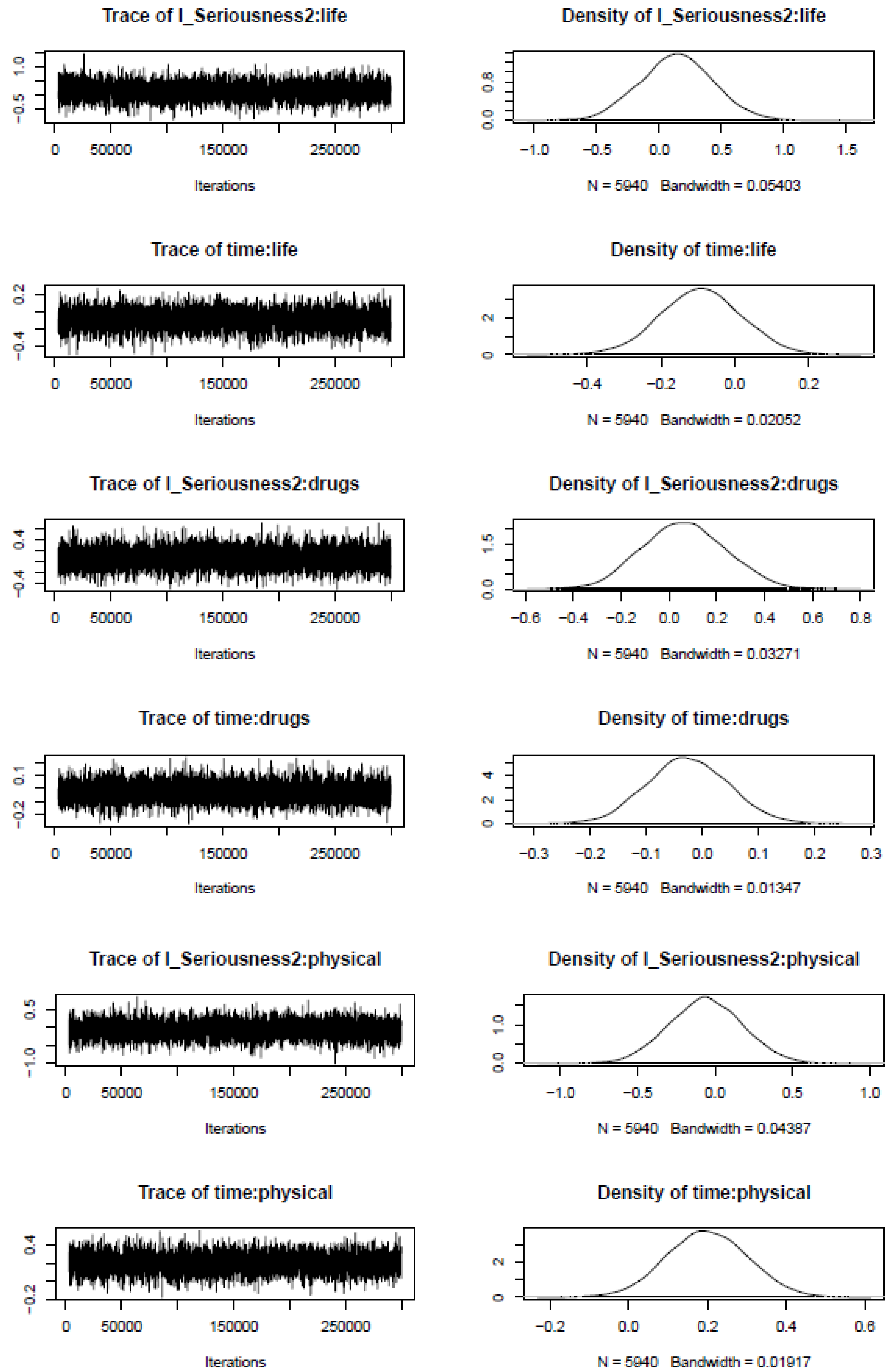
Fixed Effects

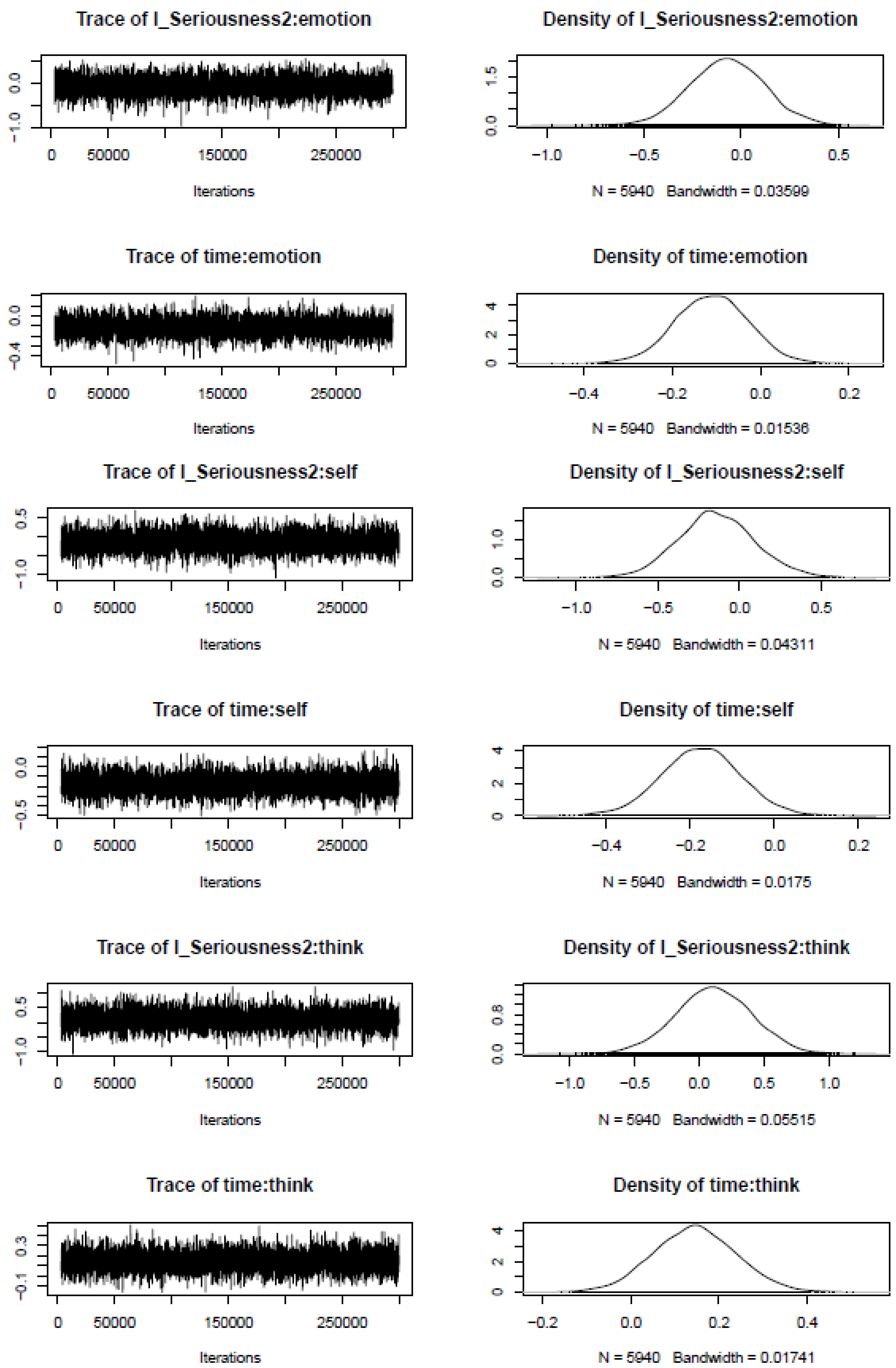


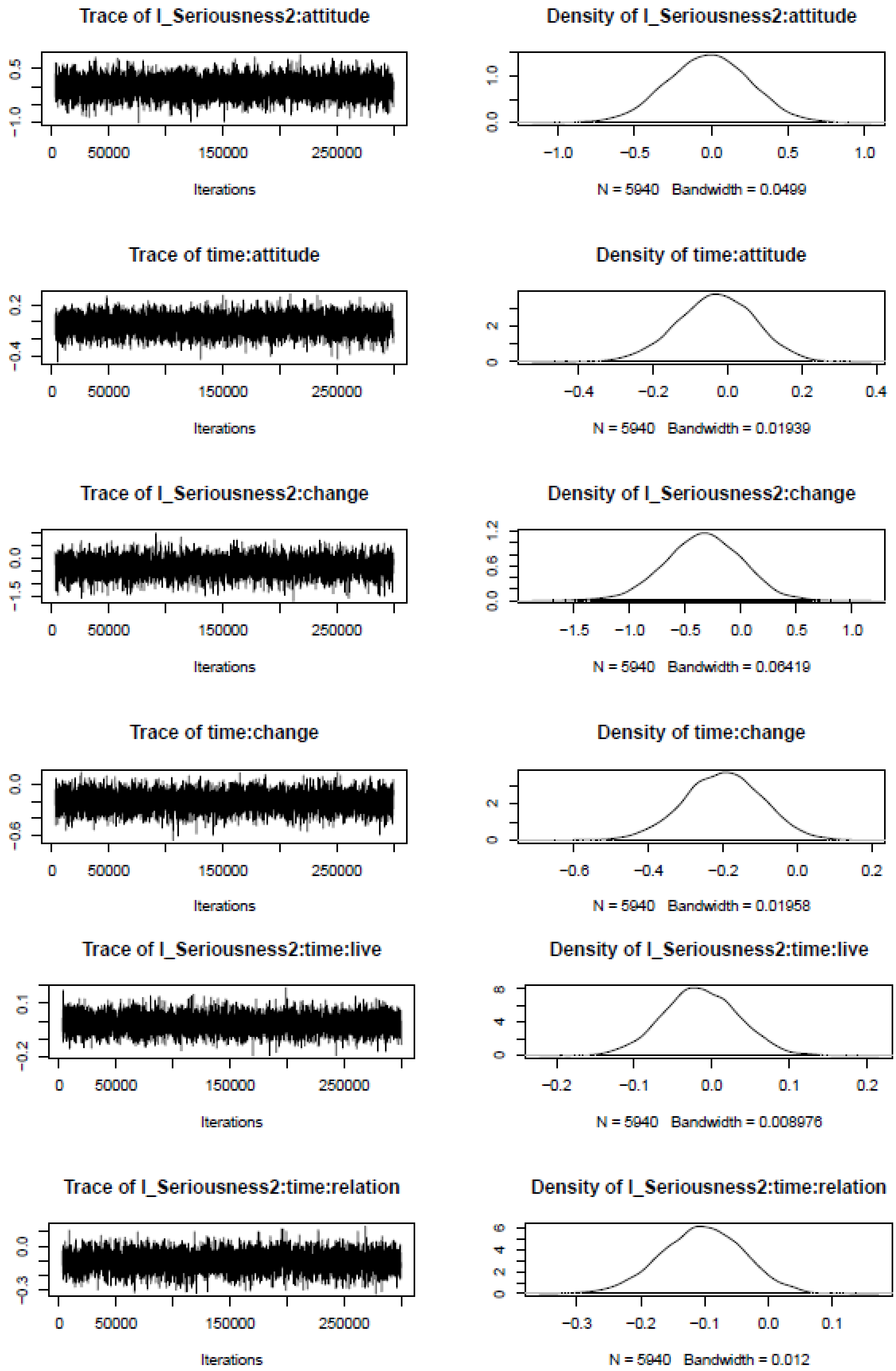

Trace of where
Iterations
Density of where
N = 5940 Bandwidth = 0.05743
Trace of life
Iterations
Density of life
N = 5940 Bandwidth = 0.08722
Trace of drugs
Iterations
Density of drugs
N = 5940 Bandwidth = 0.05688
Trace of physical
Iterations
Density of physical
N = 5940 Bandwidth = 0.06671
Trace of emotion
Iterations
Density of emotion
N = 5940 Bandwidth = 0.05496
Trace of self
Iterations
Density of self
N = 5940 Bandwidth = 0.08302

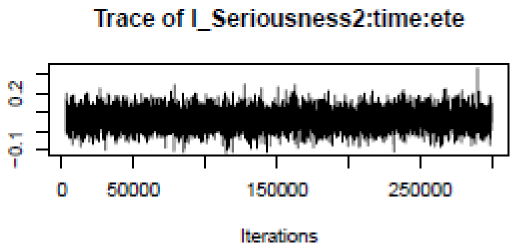
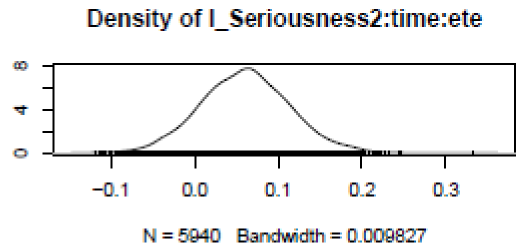
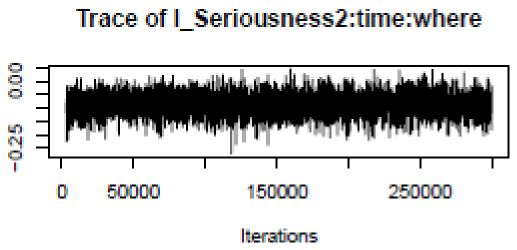
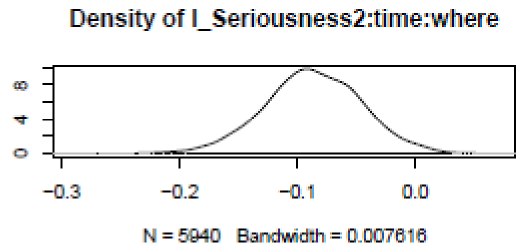
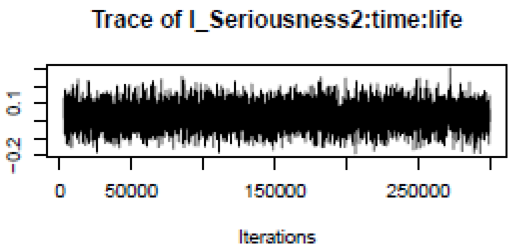
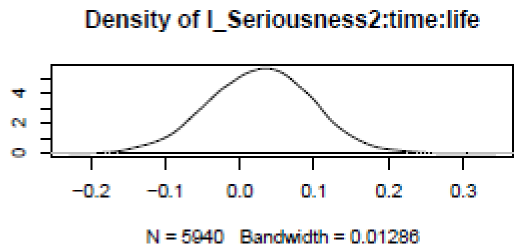
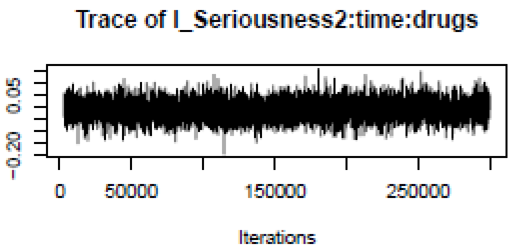
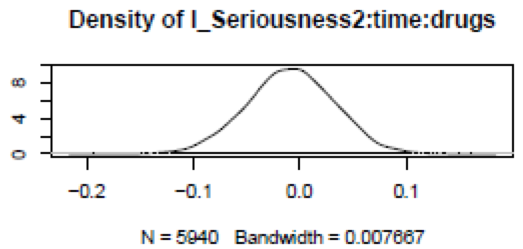

Trace of think
Iterations
Density of think
N = 5940 Bandwidth = 0.07261
Trace of attitude
Iterations
Density of attitude
N = 5940 Bandwidth = 0.08296
Trace of change
Iterations
Density of change
N = 5940 Bandwidth = 0.08559
Trace of I_Seriousness2:time
Iterations
Density of I_Seriousness2:time
N = 5940 Bandwidth = 0.02232
Trace of I_Seriousness2:live
Iterations
Density of I_Seriousness2:live
N = 5940 Bandwidth = 0.03685
Trace of time:live
Iterations
Density of time:live
N = 5940 Bandwidth = 0.01443

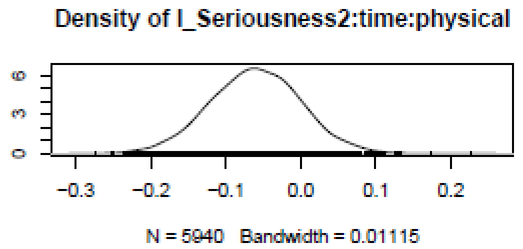

Trace of l_Seriousness2:relation
Iterations
Density of l_Seriousness2:relation
N = 5940 Bandwidth = 0.04172
Trace of time:relation
Iterations
Density of time:relation
N = 5940 Bandwidth = 0.02024
Trace of l_Seriousness2:ete
Iterations
Density of l_Seriousness2:ete
N = 5940 Bandwidth = 0.03549
Trace of time:ete
Iterations
Density of time:ete
N = 5940 Bandwidth = 0.01493
Trace of l_Seriousness2:where
Iterations
Density of l_Seriousness2:where
N = 5940 Bandwidth = 0.03324
Trace of time:where
Iterations
Density of time:where
N = 5940 Bandwidth = 0.012

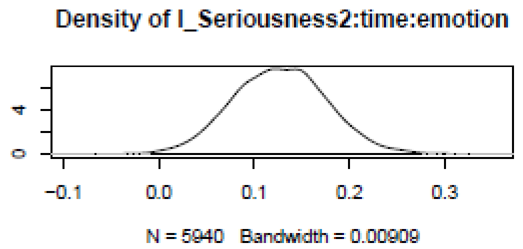

Trace of I_Seriousness2:life
Iterations
Density of I_Seriousness2:life
N = 5940 Bandwidth = 0.05403
Trace of time:life
Iterations
Density of time:life
N = 5940 Bandwidth = 0.02052
Trace of I_Seriousness2:drugs
Iterations
Density of I_Seriousness2:drugs
N = 5940 Bandwidth = 0.03271
Trace of time:drugs
Iterations
Density of time:drugs
N = 5940 Bandwidth = 0.01347
Trace of I_Seriousness2:physical
Iterations
Density of I_Seriousness2:physical
N = 5940 Bandwidth = 0.04387
Trace of time:physical
Iterations
Density of time:physical
N = 5940 Bandwidth = 0.01917

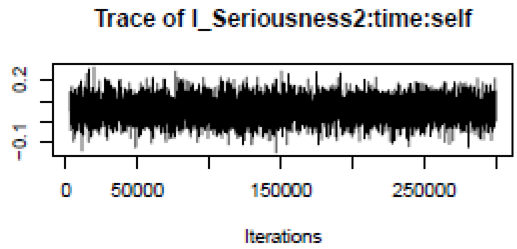

Trace of I_Seriousness2:emotion
Iterations
Density of I_Seriousness2:emotion
N = 5940 Bandwidth = 0.03599
Trace of time:emotion
Iterations
Density of time:emotion
N = 5940 Bandwidth = 0.01536
Trace of I_Seriousness2:self
Iterations
Density of I_Seriousness2:self
N = 5940 Bandwidth = 0.04311
Trace of time:self
Iterations
Density of time:self
N = 5940 Bandwidth = 0.0175
Trace of I_Seriousness2:think
Iterations
Density of I_Seriousness2:think
N = 5940 Bandwidth = 0.05515
Trace of time:think
Iterations
Density of time:think
N = 5940 Bandwidth = 0.01741

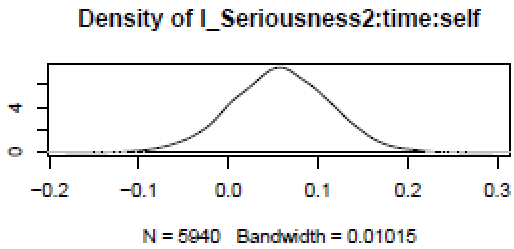

Trace of I_Seriousness2:attitude
Iterations
Density of I_Seriousness2:attitude
N = 5940 Bandwidth = 0.0499
Trace of time:attitude
Iterations
Density of time:attitude
N = 5940 Bandwidth = 0.01939
Trace of I_Seriousness2:change
Iterations
Density of I_Seriousness2:change
N = 5940 Bandwidth = 0.06419
Trace of time:change
Iterations
Density of time:change
N = 5940 Bandwidth = 0.01958
Trace of I_Seriousness2:time:live
Iterations
Density of I_Seriousness2:time:live
N = 5940 Bandwidth = 0.008976
Trace of I_Seriousness2:time:relation
Iterations
Density of I_Seriousness2:time:relation
N = 5940 Bandwidth = 0.012

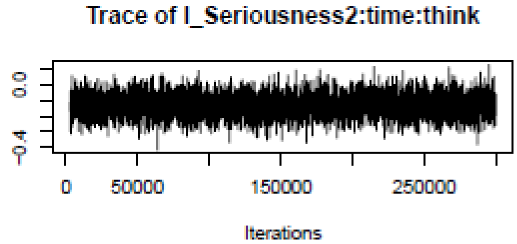

Trace of l_Seriousness2:time:ete
0.2
−0.1
0
50000
150000
250000
Iterations

Density of l_Seriousness2:time:ete
0
4
8
−0.1
0.0
0.1
0.2
0.3
N = 5940   Bandwidth = 0.009827

Trace of l_Seriousness2:time:where
0.00
−0.25
0
50000
150000
250000
Iterations

Density of l_Seriousness2:time:where
0
4
8
−0.3
−0.2
−0.1
0.0
N = 5940   Bandwidth = 0.007616

Trace of l_Seriousness2:time:life
0.1
−0.2
0
50000
150000
250000
Iterations

Density of l_Seriousness2:time:life
0
2
4
−0.2
−0.1
0.0
0.1
0.2
0.3
N = 5940   Bandwidth = 0.01286

Trace of l_Seriousness2:time:drugs
0.05
−0.20
0
50000
150000
250000
Iterations

Density of l_Seriousness2:time:drugs
0
4
8
−0.2
−0.1
0.0
0.1
N = 5940   Bandwidth = 0.007667

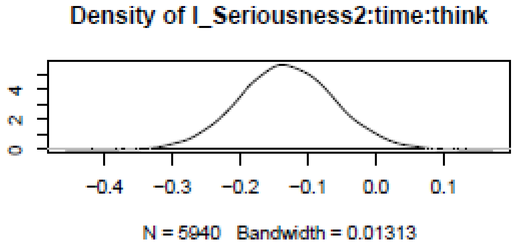
Trace of l_Seriousness2:time:physical
0.1
−0.2
0
50000
150000
250000
Iterations

Density of l_Seriousness2:time:physical
0
3
6
−0.3
−0.2
−0.1
0.0
0.1
0.2
N = 5940   Bandwidth = 0.01115

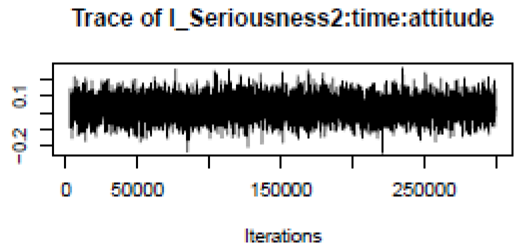
Trace of l_Seriousness2:time:emotion
0.2
0.0
0
50000
150000
250000
Iterations

Density of l_Seriousness2:time:emotion
0
4
−0.1
0.0
0.1
0.2
0.3
N = 5940   Bandwidth = 0.00909

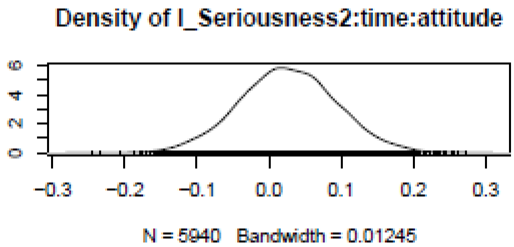


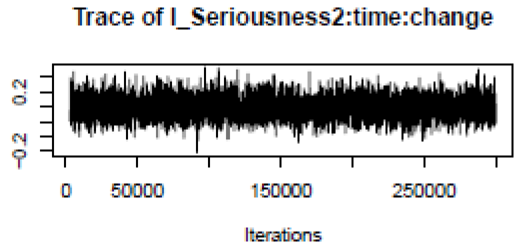


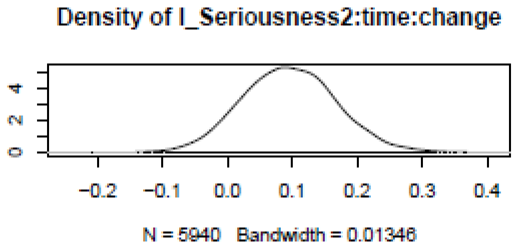




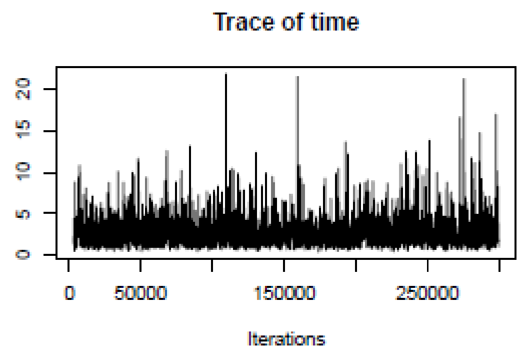


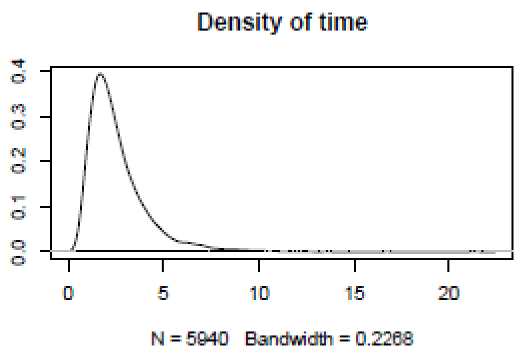


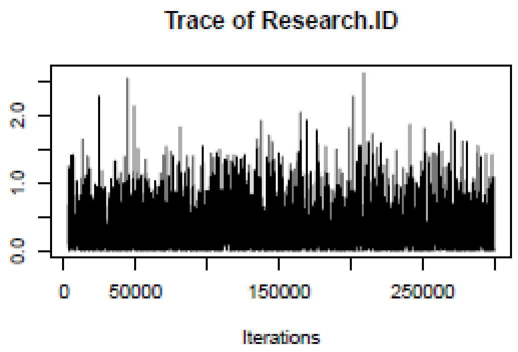


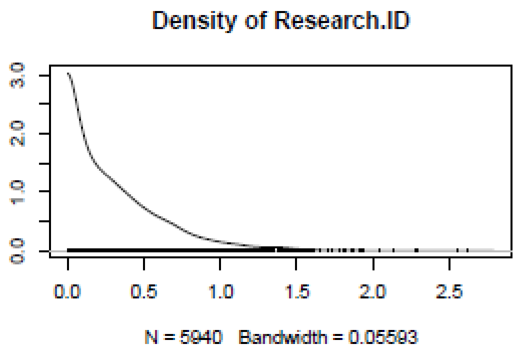


Random Effects






Trace of Research.ID
0.0
1.0
2.0
0
50000
150000
250000
Iterations


Density of Research.ID
0.0
1.0
2.0
3.0
0.0
0.5
1.0
1.5
2.0
2.5
N = 5940 Bandwidth = 0.05593

The Combined Model involving Offending History: Version 1

Bayesian Model (BDm3G_cc12o2a)

Define the Model

```
BDm3G_cc12o2a  <-  MCMCglmm(FO.bin~FTE*time*live  +  FTE*time*relation  +
FTE*time*ete + FTE*time*where + FTE*time*life + FTE*time*drugs +
FTE*time*physical + FTE*time*emotion + FTE*time*self +
FTE*time*think + FTE*time*attitude + FTE*time*change +
G_ageFirst*time*live + G_ageFirst*time*relation +
G_ageFirst*time*ete + G_ageFirst*time*where + G_ageFirst*time*life +
G_ageFirst*time*drugs + G_ageFirst*time*physical +
G_ageFirst*time*emotion + G_ageFirst*time*self +
G_ageFirst*time*think + G_ageFirst*time*attitude +
G_ageFirst*time*change +
I_Seriousness2*time*live + I_Seriousness2*time*relation +
I_Seriousness2*time*ete + I_Seriousness2*time*where +
I_Seriousness2*time*life + I_Seriousness2*time*drugs +
I_Seriousness2*time*physical + I_Seriousness2*time*emotion +
I_Seriousness2*time*self + I_Seriousness2*time*think +
I_Seriousness2*time*attitude + I_Seriousness2*time*change +
FTE*G_ageFirst + FTE*I_Seriousness2 + G_ageFirst*I_Seriousness2,
random=~time+Research.ID,data=data3, family="ordinal", prior=priorD,
nitt=40000000, thin=10000, burnin=30000)
```

Checks for suitable convergence

```
raftery.diag(BDm3G_cc12o2a$VCV)
heidel.diag(BDm3G_cc12o2a$VCV)

# > raftery.diag(BDm3G_cc12o2a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total    Lower bound  Dependence
#              (M)      (N)      (Nmin)       factor (I)
# time         30000    43770000 3746         11700
# Research.ID 80000    98040000 3746         26200
# units        <NA>     <NA>     3746            NA

# > heidel.diag(BDm3G_cc12o2a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.688
# Research.ID passed        1         0.822
# units        failed       NA            NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    253  11.3
# Research.ID passed    397  21.8
# units        <NA>       NA    NA
```

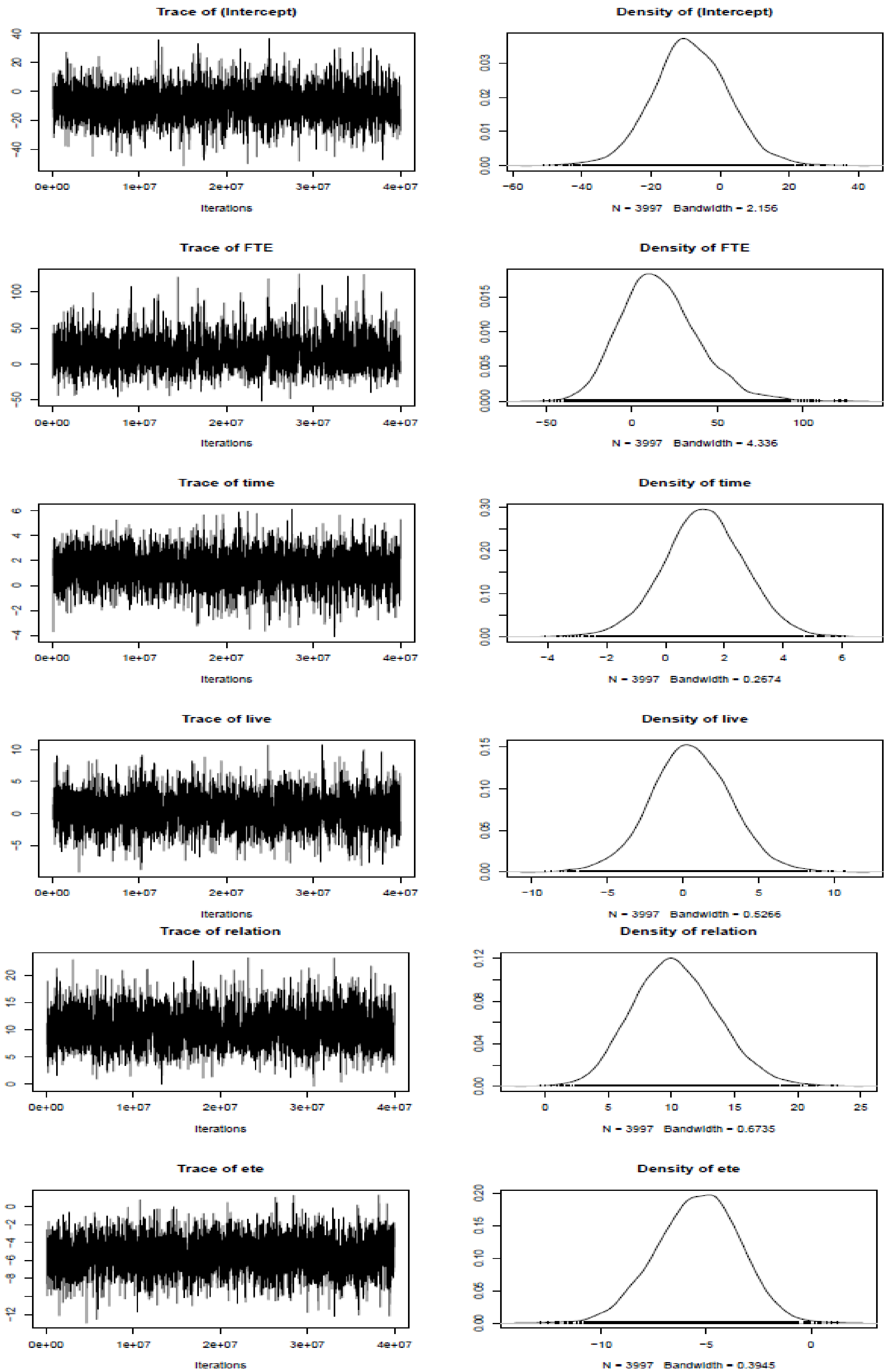
```
autocorr(BDm3G_cc12o2a$VCV)
autocorr(BDm3G_cc12o2a$Sol)  # not included here
summary(BDm3G_cc12o2a)

# > autocorr(BDm3G_cc12o2a$VCV)
# , , time
#
#                    time Research.ID units
# Lag 0      1.000000000  0.44086665   NaN
# Lag 10000  0.307690198  0.39294697   NaN
# Lag 50000  0.146400555  0.21663189   NaN
# Lag 1e+05  0.055869316  0.08286068   NaN
# Lag 5e+05 -0.006920889  0.01347865   NaN
#
# , , Research.ID
#
#                  time Research.ID units
# Lag 0     0.44086665  1.00000000   NaN
# Lag 10000 0.41379438  0.70295239   NaN
# Lag 50000 0.24649516  0.37439811   NaN
# Lag 1e+05 0.09991674  0.16991526   NaN
# Lag 5e+05 0.02266190  0.04686541   NaN

# > summary(BDm3G_cc12o2a)
#
# Iterations = 30001:39990001
# Thinning interval  = 10000
# Sample size  = 3997
#
# DIC: 295.0014
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     252.5    43.53    566.1    874.2
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID     396.8    77.77    834.5    383.3
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ FTE * time * live + FTE * time * relation +
FTE * time * ete + FTE * time * where + FTE * time * life + FTE * time *
drugs + FTE * time * physical + FTE * time * emotion + FTE * time * self
+ FTE * time * think + FTE * time * attitude + FTE * time * change +
G_ageFirst * time * live + G_ageFirst * time * relation + G_ageFirst *
time * ete + G_ageFirst * time * where + G_ageFirst * time * life +
G_ageFirst * time * drugs + G_ageFirst * time * physical + G_ageFirst *
time * emotion + G_ageFirst * time * self + G_ageFirst * time * think +
G_ageFirst * time * attitude + G_ageFirst * time * change +
I_Seriousness2 * time * live + I_Seriousness2 * time * relation +
I_Seriousness2 * time * ete + I_Seriousness2 * time * where +
I_Seriousness2 * time * life + I_Seriousness2 * time * drugs +
I_Seriousness2 * time * physical + I_Seriousness2 * time * emotion +
I_Seriousness2 * time * self + I_Seriousness2 * time * think +
```

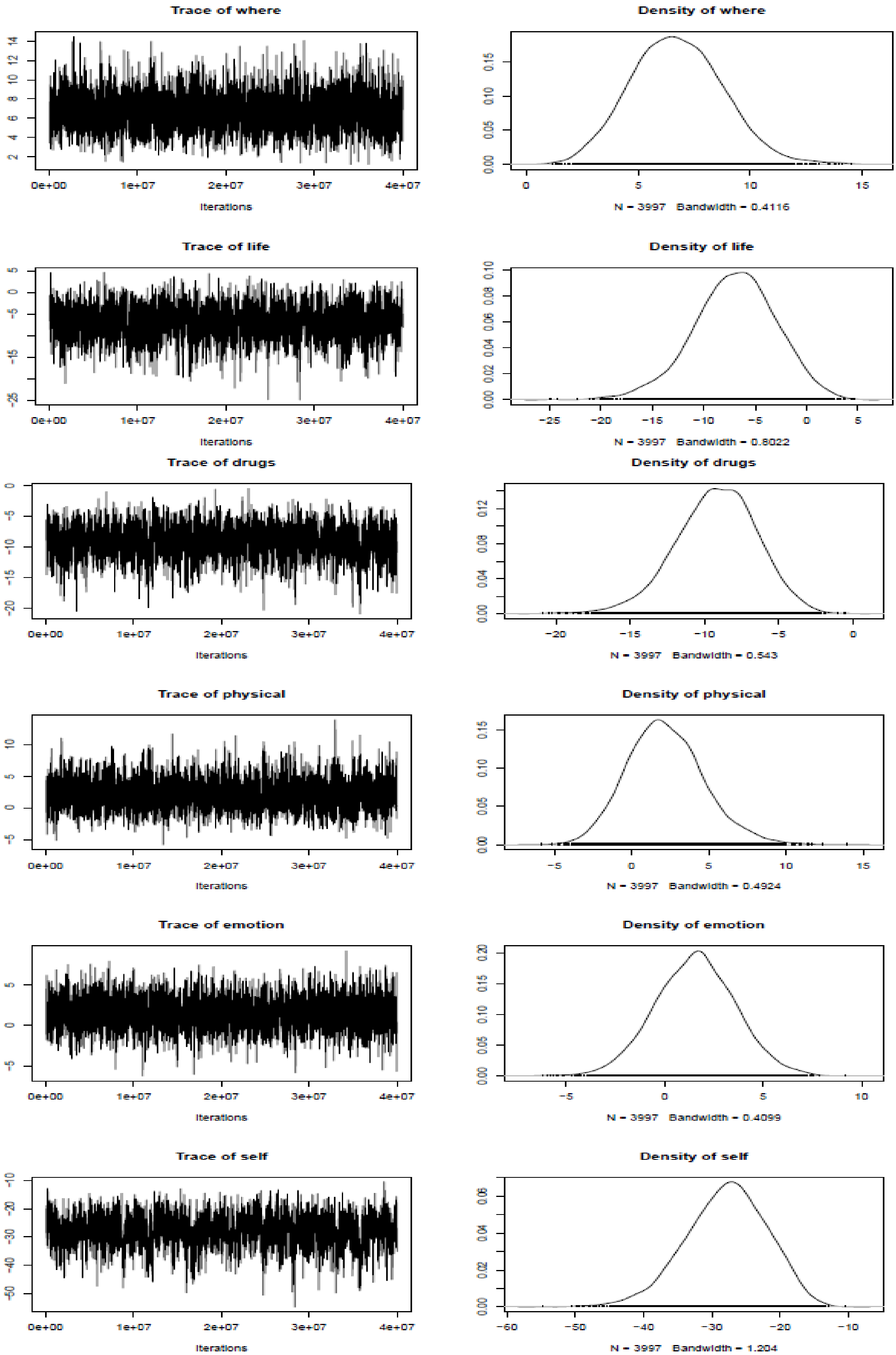
```
I_Seriousness2 * time * attitude + I_Seriousness2 * time * change + FTE
* G_ageFirst + FTE * I_Seriousness2 + G_ageFirst * I_Seriousness2
#
#                                          post.mean  l-95% CI  u-95% CI eff.samp   pMCMC
# (Intercept)                               -8.44750 -30.73758  13.02716   3997.0 0.43132
# FTE                                       16.17202 -25.81242  61.55305   1247.0 0.48186
# time                                       1.30756  -1.33139   4.07595   3678.9 0.32324
# live                                       0.50805  -5.02432   5.52199   2979.1 0.85814
# relation                                  10.33569   4.10967  16.95180   2947.1 0.00100 **
# ete                                       -5.40679  -9.29989  -1.79054   3085.3 0.00450 **
# where                                      6.73509   2.64381  10.48875   2892.3 < 3e-04 ***
# life                                      -6.99846 -15.23854   0.85251   1508.1 0.07055 .
# drugs                                     -9.19871 -14.32258  -3.59913   1156.3 < 3e-04 ***
# physical                                   2.19807  -2.59098   7.18762   2113.7 0.37428
# emotion                                    1.54600  -2.45487   5.47318   3599.5 0.44333
# self                                     -27.90316 -39.21135 -16.39462    709.9 < 3e-04 ***
# think                                     10.40967   4.12983  16.99035   1513.0 < 3e-04 ***
# attitude                                   7.46415  -1.84720  16.94411   3997.0 0.11559
# change                                    17.31457   6.84207  27.38253   1303.0 < 3e-04 ***
# G_ageFirst13 to 17 years                  14.17181 -12.13032  38.43889   3145.3 0.24869
# I_Seriousness2                           -31.54723 -50.26978 -13.83019    541.3 < 3e-04 ***
# FTE:time                                 -11.25257 -19.20095  -4.64871    536.6 < 3e-04 ***
# FTE:live                                  -6.17638 -16.42788   4.14934   2163.7 0.23017
# time:live                                 -0.87303  -1.94967   0.10321   1845.5 0.07656 .
# FTE:relation                             -12.47750 -27.35222  -0.25586    619.8 0.03703 *
# time:relation                             -2.73476  -4.48587  -1.13791   1479.6 < 3e-04 ***
# FTE:ete                                   -1.19977 -10.03975   7.49297   3771.4 0.77758
# time:ete                                   0.99208  -0.01728   2.05502   3192.6 0.05054 .
# FTE:where                                -24.25489 -38.27035 -10.52519    527.7 < 3e-04 ***
# time:where                                -1.17454  -1.93655  -0.38984   2249.4 0.00050 ***
# FTE:life                                  22.28468   8.04872  35.72338    843.7 < 3e-04 ***
# time:life                                  0.87700  -0.64423   2.46893   2284.6 0.24869
# FTE:drugs                                 -3.07929 -11.98473   6.46785   3593.8 0.50238
# time:drugs                                 2.16706   0.98851   3.32302   1019.8 < 3e-04 ***
# FTE:physical                               4.75004  -7.03414  16.32528   1743.2 0.41981
# time:physical                             -0.24577  -1.19010   0.67903   3403.4 0.62497
# FTE:emotion                               -5.54420 -14.07013   2.41049   1383.3 0.16612
# time:emotion                              -1.58783  -2.91597  -0.31037    714.4 0.00550 **
# FTE:self                                   0.42014  -8.75807  10.31026   2849.7 0.91268
# time:self                                  6.45773   3.99228   9.08888    531.3 < 3e-04 ***
# FTE:think                                 -5.94536 -14.98144   3.01889   3335.1 0.19965
# time:think                                -0.50773  -1.55967   0.55633   4404.7 0.35427
# FTE:attitude                              -8.42247 -17.17194  -0.31079   3061.7 0.03953 *
# time:attitude                             -2.04614  -3.62134  -0.49384   1836.5 0.00550 **
# FTE:change                                13.01145   1.16935  24.50985   3373.7 0.02152 *
# time:change                               -2.57358  -4.38725  -0.89461   1775.2 0.00050 ***
# time:G_ageFirst13 to 17 years             -3.44781  -6.71331  -0.08289   2878.9 0.04203 *
# live:G_ageFirst13 to 17 years             10.97390   2.26640  20.20982    887.0 0.00450 **
# relation:G_ageFirst13 to 17 years        -18.28276 -28.01374  -8.57907   1642.7 0.00050 ***
# ete:G_ageFirst13 to 17 years               2.56777  -4.43618   8.72230   3680.0 0.42732
# where:G_ageFirst13 to 17 years             0.04583  -7.65008   7.06614   3367.4 0.99074
# life:G_ageFirst13 to 17 years              4.49353  -6.29788  14.79465   2718.7 0.41831
# drugs:G_ageFirst13 to 17 years            -7.55413 -15.79449   0.58356    810.7 0.04253 *
# physical:G_ageFirst13 to 17 years        -10.57770 -20.71514  -1.72729   1038.1 0.01001 *
# emotion:G_ageFirst13 to 17 years          -2.56672  -8.14127   3.03106   3997.0 0.36227
# self:G_ageFirst13 to 17 years             32.39376  18.72654  45.74511    840.7 < 3e-04 ***
# think:G_ageFirst13 to 17 years            -0.67342  -8.31531   7.56652   3498.5 0.84213
# attitude:G_ageFirst13 to 17 years         -2.23790 -13.87357   8.24089   3997.0 0.68752
# change:G_ageFirst13 to 17 years          -14.42706 -25.66251  -2.82619   3165.4 0.01451 *
# time:I_Seriousness2                        3.98261   1.92625   6.15862    629.1 < 3e-04 ***
# live:I_Seriousness2                       -2.99281  -6.48954   0.17488    733.0 0.04754 *
# relation:I_Seriousness2                    9.94485   3.83403  17.21775    419.6 < 3e-04 ***
# ete:I_Seriousness2                         0.69141  -1.86077   3.52406   1619.0 0.58794
# where:I_Seriousness2                       1.30345  -1.14932   3.90015   1570.2 0.30923
# life:I_Seriousness2                       -0.37537  -5.32372   4.06987   1898.0 0.90668
# drugs:I_Seriousness2                      10.81189   5.71745  16.60012    475.0 < 3e-04 ***
# physical:I_Seriousness2                   -2.65002  -6.95829   0.78216   2454.7 0.16562
# emotion:I_Seriousness2                     0.04520  -2.10683   2.10756   3997.0 0.97823
# self:I_Seriousness2                        5.84416   1.52108  10.02360    931.7 0.00200 **
# think:I_Seriousness2                      -2.82096  -6.49552   0.60500   2574.1 0.11008
# attitude:I_Seriousness2                   -0.85787  -4.30518   2.81751   3997.0 0.61046
# change:I_Seriousness2                     -7.30257 -12.58698  -2.67145   1312.6 0.00050 ***
# FTE:G_ageFirst13 to 17 years              14.18845 -24.19119  53.26583   3488.9 0.44633
# FTE:I_Seriousness2                        14.27908   3.76326  26.13142    686.2 0.00100 **
# G_ageFirst13 to 17 years:I_Seriousness2   -2.40635 -13.34167   6.97468   4065.9 0.63147
# FTE:time:live                             -1.59230  -3.86018   0.65088   1681.5 0.14961
# FTE:time:relation                          2.34144  -0.31363   5.02442    739.4 0.06705 .
# FTE:time:ete                               3.49084   0.82962   6.33672   1115.8 0.00300 **
# FTE:time:where                             2.81407   0.84091   4.73530    898.4 < 3e-04 ***
# FTE:time:life                             -3.47073  -6.42030  -0.59878   1131.9 0.01051 *
# FTE:time:drugs                             2.04837   0.05852   4.05554   1548.8 0.03403 *
```

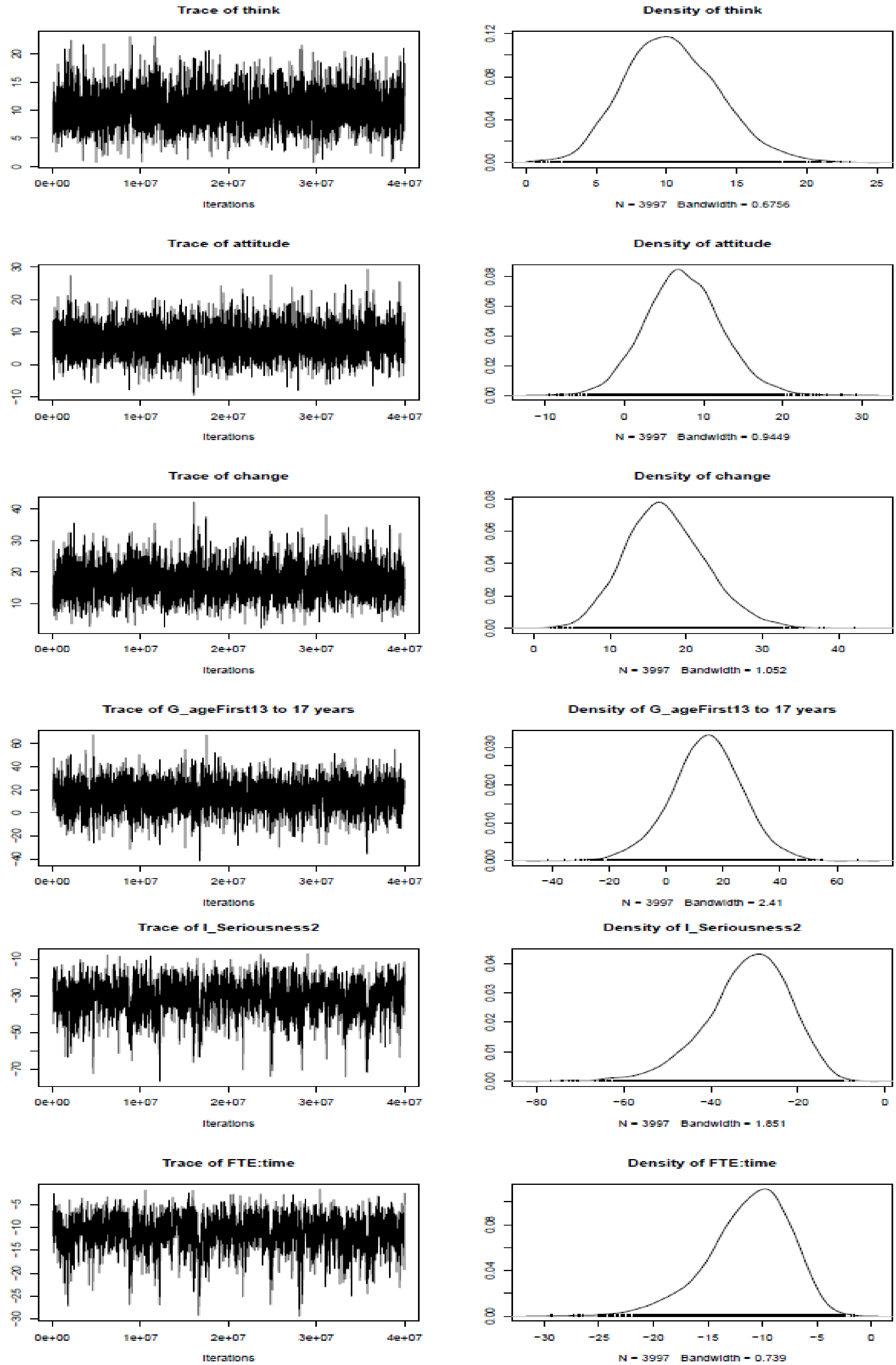
```
# FTE:time:physical                      -2.95480  -5.83783  -0.12907   1084.5 0.02402 *
# FTE:time:emotion                        1.34895  -0.55633   3.54408   1146.6 0.17263
# FTE:time:self                          -2.35135  -4.49134  -0.46138   2054.3 0.01351 *
# FTE:time:think                          3.46294   1.39021   5.74296   1477.1 0.00200 **
# FTE:time:attitude                       3.25390   0.84810   5.63711   1506.0 0.00300 **
# FTE:time:change                        -3.97620  -6.72157  -1.59653   1525.8 0.00050 ***
# time:live:G_ageFirst13 to 17 years      0.34392  -1.19373   1.91147   3706.7 0.64548
# time:relation:G_ageFirst13 to 17 years  4.47329   2.22524   7.00095   1084.0 < 3e-04 ***
# time:ete:G_ageFirst13 to 17 years      -1.60184  -3.06051  -0.15718   1600.6 0.01951 *
# time:where:G_ageFirst13 to 17 years     1.21788  -0.05278   2.49143   2555.6 0.04704 *
# time:life:G_ageFirst13 to 17 years     -1.22858  -3.56421   1.22935   1548.4 0.31273
# time:drugs:G_ageFirst13 to 17 years     0.23279  -1.20777   1.63325   1521.6 0.77758
# time:physical:G_ageFirst13 to 17 years  2.08098   0.12354   4.18215   1670.9 0.03152 *
# time:emotion:G_ageFirst13 to 17 years   0.22451  -1.46971   1.85745   3731.6 0.78459
# time:self:G_ageFirst13 to 17 years     -6.06324  -8.64022  -3.62061    787.3 < 3e-04 ***
# time:think:G_ageFirst13 to 17 years    -2.47983  -4.77106  -0.39856    739.1 0.00650 **
# time:attitude:G_ageFirst13 to 17 years  0.13003  -2.06392   2.37716   3997.0 0.90368
# time:change:G_ageFirst13 to 17 years    3.54531   1.29420   5.81436   1062.3 < 3e-04 ***
# time:live:I_Seriousness2                0.66666  -0.07011   1.49509    834.8 0.05954 .
# time:relation:I_Seriousness2           -1.46424  -2.53489  -0.58127    512.5 < 3e-04 ***
# time:ete:I_Seriousness2                -0.25098  -0.81699   0.26491   3997.0 0.34926
# time:where:I_Seriousness2              -0.76809  -1.43169  -0.08569    894.8 0.00751 **
# time:life:I_Seriousness2               -0.11589  -1.00059   0.81179   1999.2 0.77208
# time:drugs:I_Seriousness2              -1.72829  -2.70404  -0.84203    457.1 < 3e-04 ***
# time:physical:I_Seriousness2            1.69601   0.54017   2.95686    732.2 < 3e-04 ***
# time:emotion:I_Seriousness2             1.14757   0.45166   1.82450    777.6 < 3e-04 ***
# time:self:I_Seriousness2               -1.50970  -2.62397  -0.55308    730.3 < 3e-04 ***
# time:think:I_Seriousness2               0.34914  -0.26626   0.98427   2485.3 0.26220
# time:attitude:I_Seriousness2           -0.33866  -1.22446   0.56367   2179.5 0.46385
# time:change:I_Seriousness2              1.42789   0.48066   2.30370   2275.0 0.00100 **
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Trace Plots and Posterior Density Plots

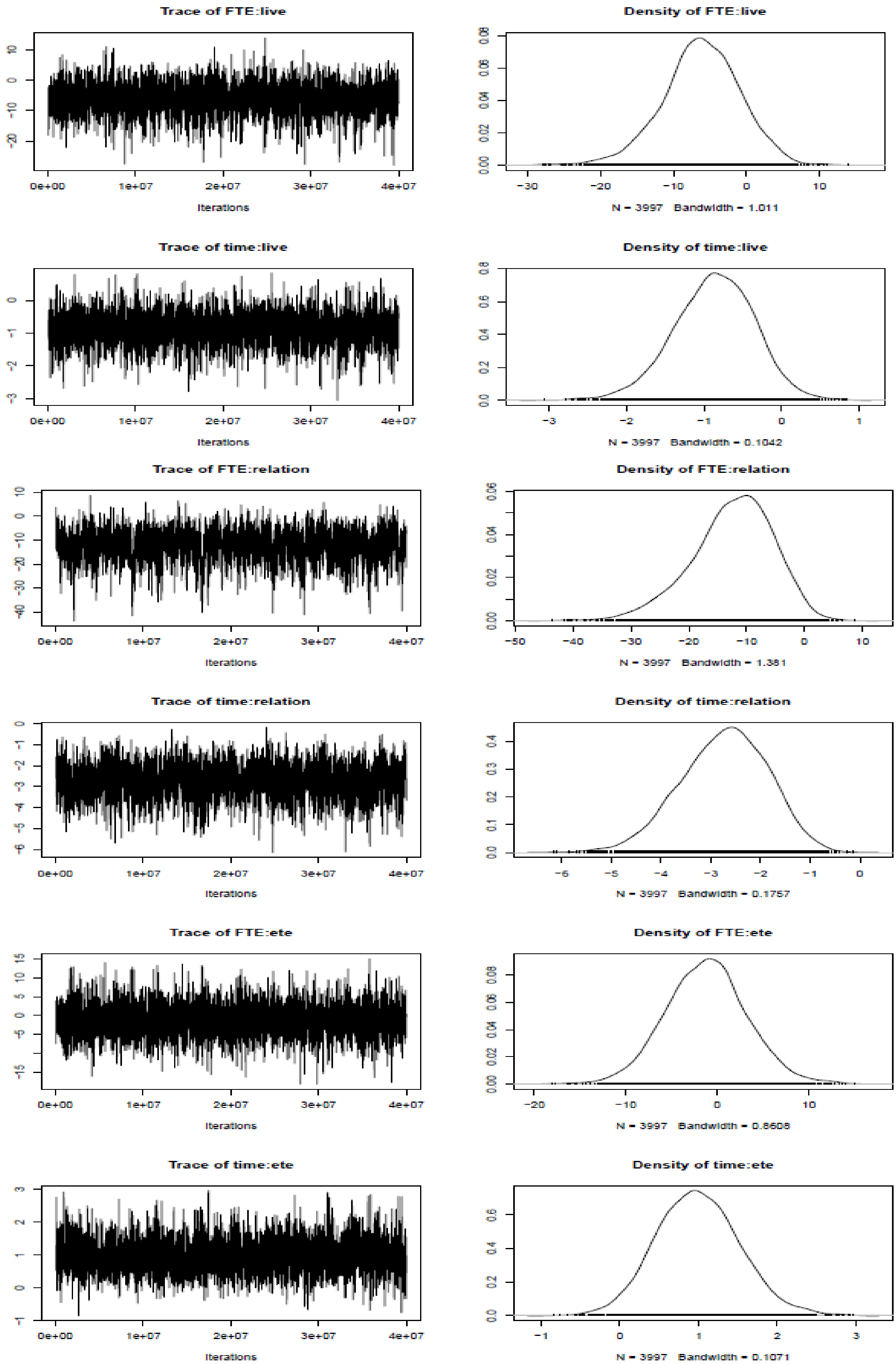
Fixed Effects

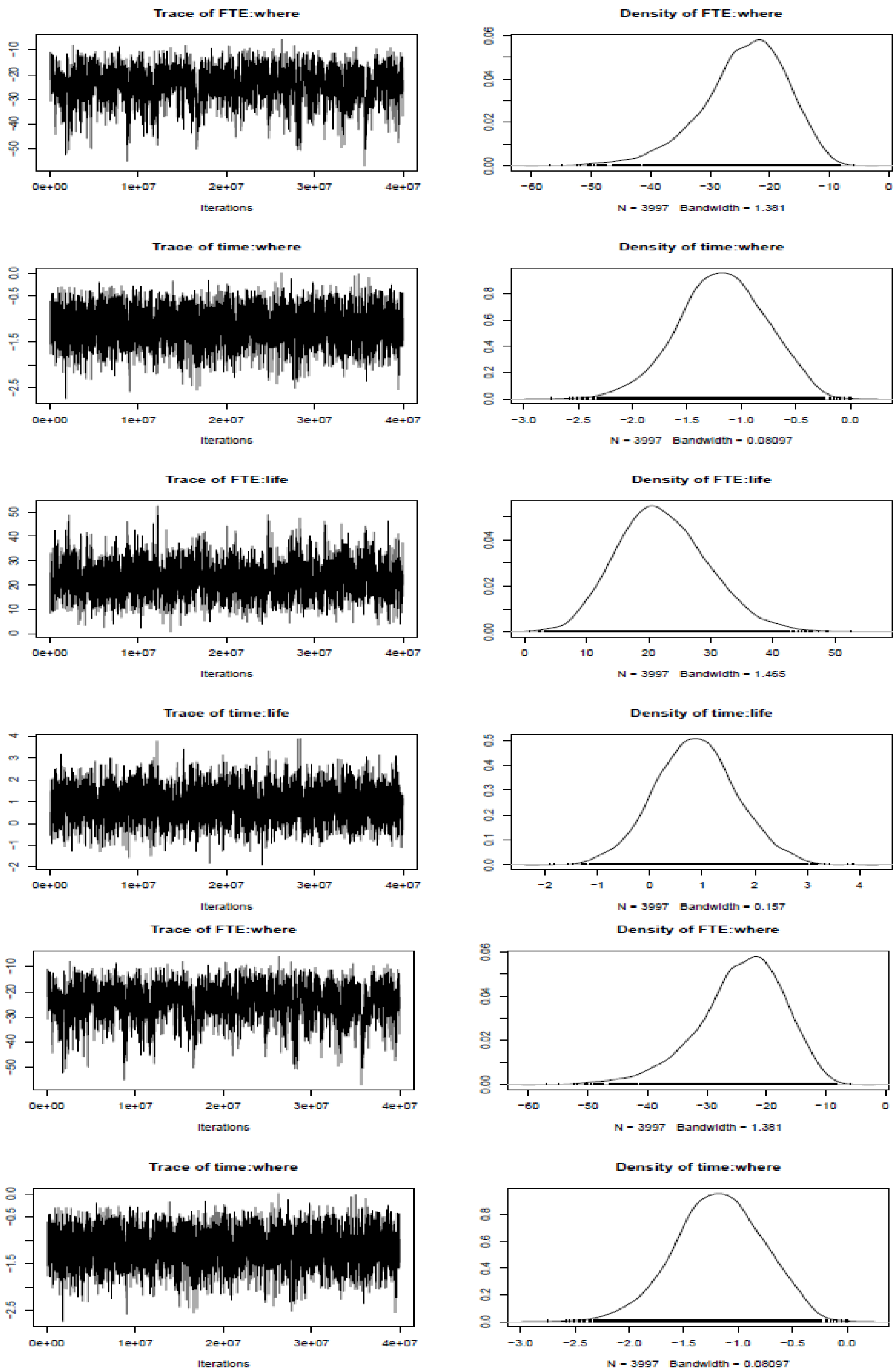


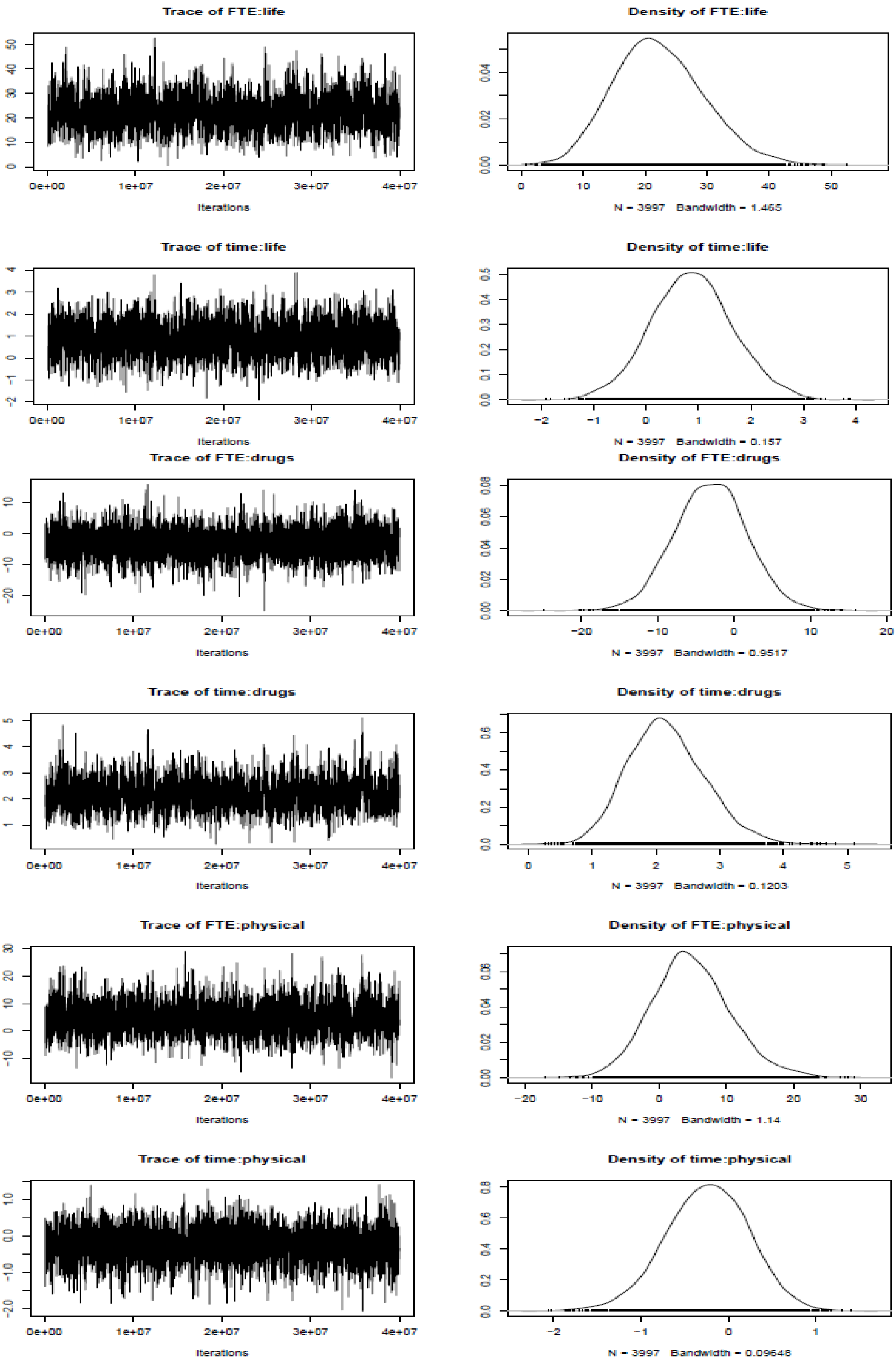

Trace of where
Iterations
Density of where
N = 3997 Bandwidth = 0.4116
Trace of life
Iterations
Density of life
N = 3997 Bandwidth = 0.8022
Trace of drugs
Iterations
Density of drugs
N = 3997 Bandwidth = 0.543
Trace of physical
Iterations
Density of physical
N = 3997 Bandwidth = 0.4924
Trace of emotion
Iterations
Density of emotion
N = 3997 Bandwidth = 0.4099
Trace of self
Iterations
Density of self
N = 3997 Bandwidth = 1.204

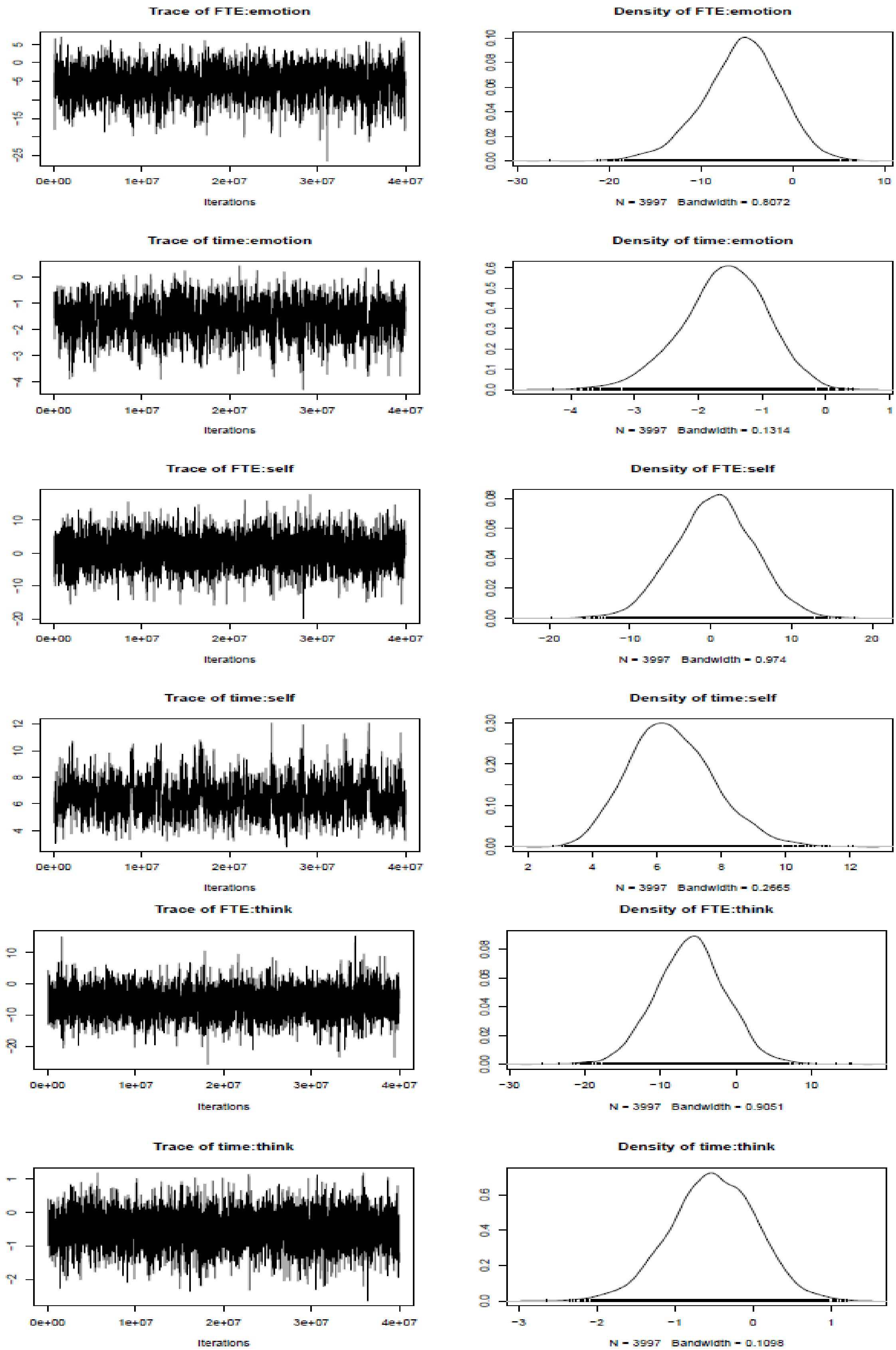


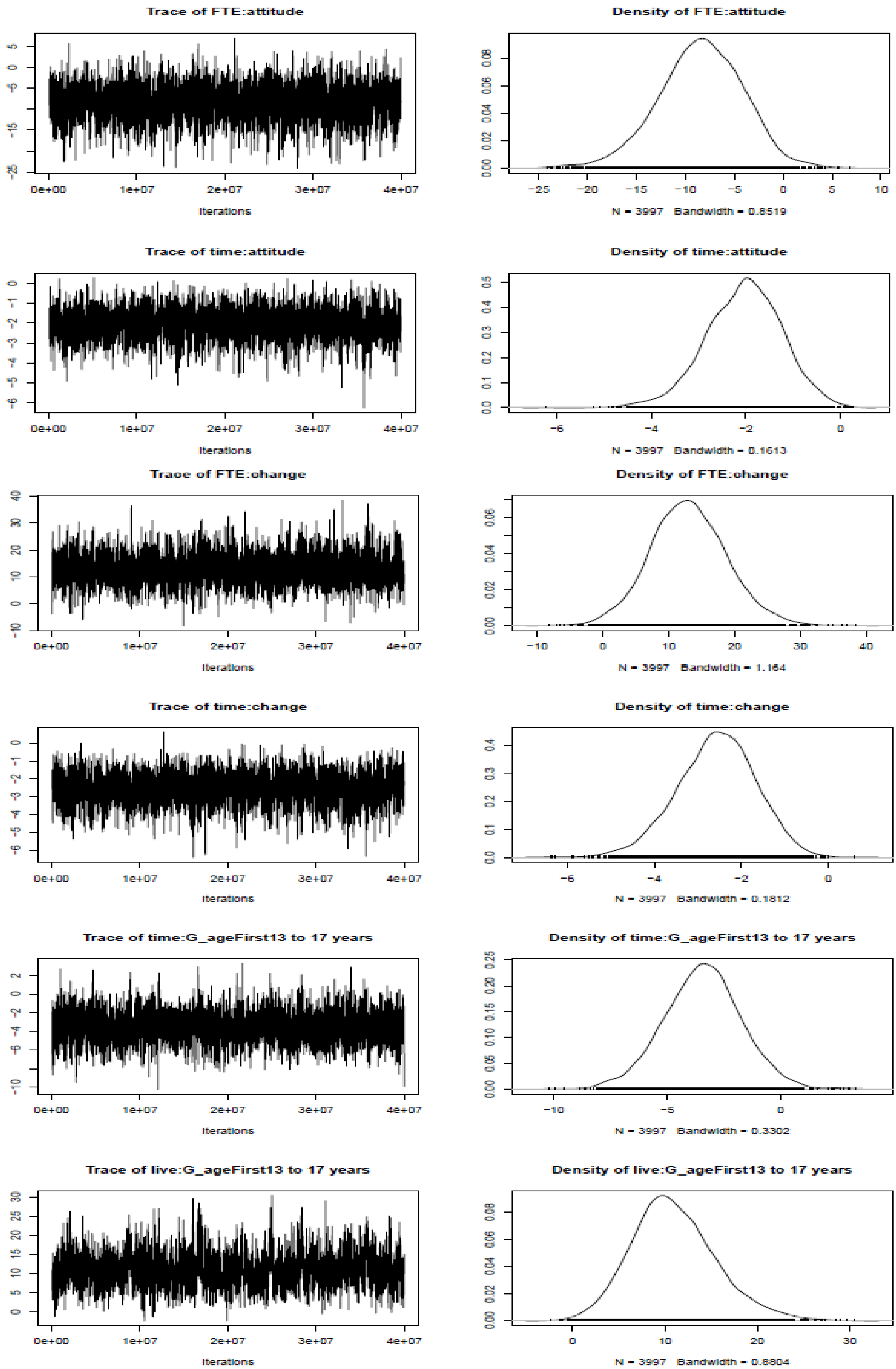
Trace of think
Density of think
N = 3997 Bandwidth = 0.6756
Trace of attitude
Density of attitude
N = 3997 Bandwidth = 0.9449
Trace of change
Density of change
N = 3997 Bandwidth = 1.052
Trace of G_ageFirst13 to 17 years
Density of G_ageFirst13 to 17 years
N = 3997 Bandwidth = 2.41
Trace of I_Seriousness2
Density of I_Seriousness2
N = 3997 Bandwidth = 1.851
Trace of FTE:time
Density of FTE:time
N = 3997 Bandwidth = 0.739
Iterations


Trace of FTE:live
Iterations
Density of FTE:live
N = 3997 Bandwidth = 1.011
Trace of time:live
Iterations
Density of time:live
N = 3997 Bandwidth = 0.1042
Trace of FTE:relation
Iterations
Density of FTE:relation
N = 3997 Bandwidth = 1.381
Trace of time:relation
Iterations
Density of time:relation
N = 3997 Bandwidth = 0.1757
Trace of FTE:ete
Iterations
Density of FTE:ete
N = 3997 Bandwidth = 0.8608
Trace of time:ete
Iterations
Density of time:ete
N = 3997 Bandwidth = 0.1071

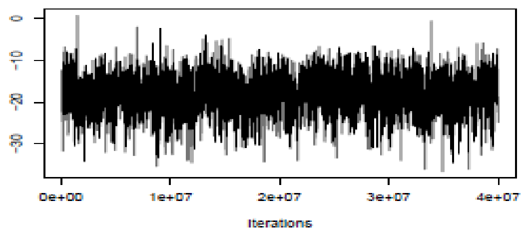

Trace of FTE:where
Iterations
Density of FTE:where
N = 3997 Bandwidth = 1.381
Trace of time:where
Iterations
Density of time:where
N = 3997 Bandwidth = 0.08097
Trace of FTE:life
Iterations
Density of FTE:life
N = 3997 Bandwidth = 1.465
Trace of time:life
Iterations
Density of time:life
N = 3997 Bandwidth = 0.157
Trace of FTE:where
Iterations
Density of FTE:where
N = 3997 Bandwidth = 1.381
Trace of time:where
Iterations
Density of time:where
N = 3997 Bandwidth = 0.08097


Trace of FTE:life
Iterations
Density of FTE:life
N = 3997 Bandwidth = 1.465
Trace of time:life
Iterations
Density of time:life
N = 3997 Bandwidth = 0.157
Trace of FTE:drugs
Iterations
Density of FTE:drugs
N = 3997 Bandwidth = 0.9517
Trace of time:drugs
Iterations
Density of time:drugs
N = 3997 Bandwidth = 0.1203
Trace of FTE:physical
Iterations
Density of FTE:physical
N = 3997 Bandwidth = 1.14
Trace of time:physical
Iterations
Density of time:physical
N = 3997 Bandwidth = 0.09648

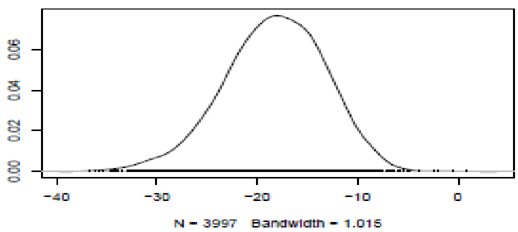

Trace of FTE:emotion
Iterations
Density of FTE:emotion
N = 3997 Bandwidth = 0.8072
Trace of time:emotion
Iterations
Density of time:emotion
N = 3997 Bandwidth = 0.1314
Trace of FTE:self
Iterations
Density of FTE:self
N = 3997 Bandwidth = 0.974
Trace of time:self
Iterations
Density of time:self
N = 3997 Bandwidth = 0.2665
Trace of FTE:think
Iterations
Density of FTE:think
N = 3997 Bandwidth = 0.9051
Trace of time:think
Iterations
Density of time:think
N = 3997 Bandwidth = 0.1098


Trace of FTE:attitude
Iterations
Density of FTE:attitude
N = 3997 Bandwidth = 0.8519
Trace of time:attitude
Iterations
Density of time:attitude
N = 3997 Bandwidth = 0.1613
Trace of FTE:change
Iterations
Density of FTE:change
N = 3997 Bandwidth = 1.164
Trace of time:change
Iterations
Density of time:change
N = 3997 Bandwidth = 0.1812
Trace of time:G_ageFirst13 to 17 years
Iterations
Density of time:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.3302
Trace of live:G_ageFirst13 to 17 years
Iterations
Density of live:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.8804

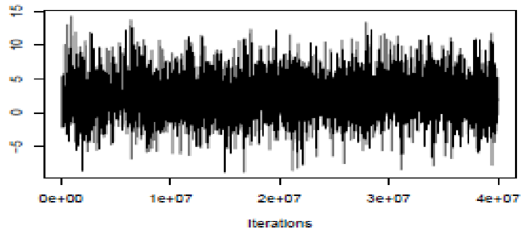
Trace of relation:G_ageFirst13 to 17 years



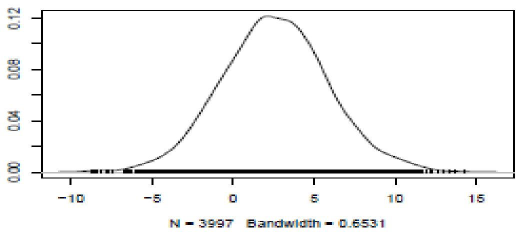
Density of relation:G_ageFirst13 to 17 years



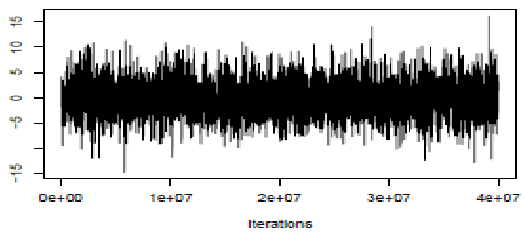
Trace of ete:G_ageFirst13 to 17 years



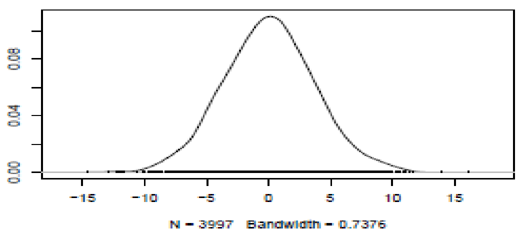
Density of ete:G_ageFirst13 to 17 years



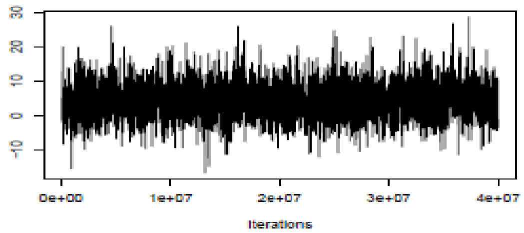
Trace of where:G_ageFirst13 to 17 years



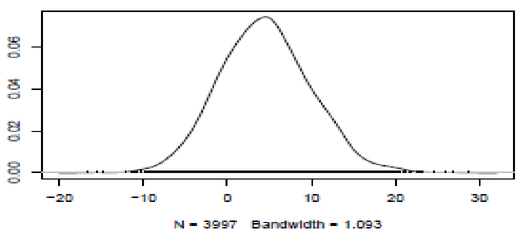
Density of where:G_ageFirst13 to 17 years



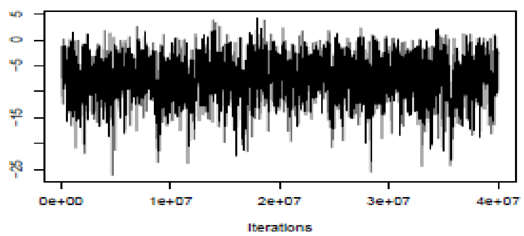
Trace of life:G_ageFirst13 to 17 years



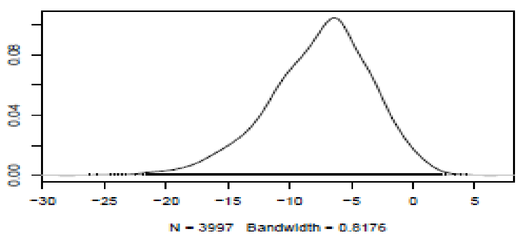
Density of life:G_ageFirst13 to 17 years



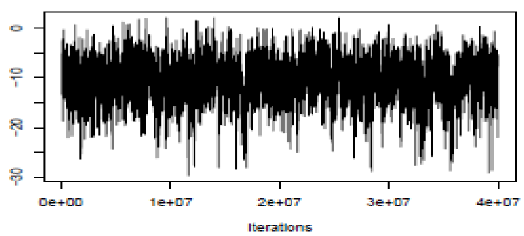
Trace of drugs:G_ageFirst13 to 17 years



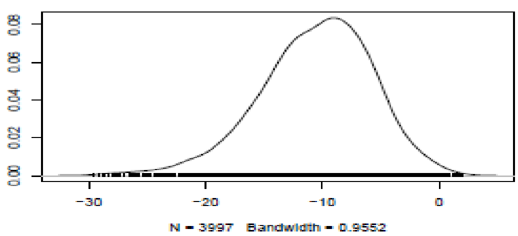
Density of drugs:G_ageFirst13 to 17 years



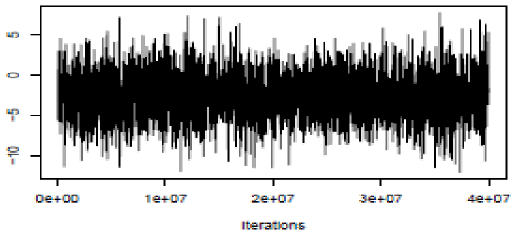
Trace of physical:G_ageFirst13 to 17 years



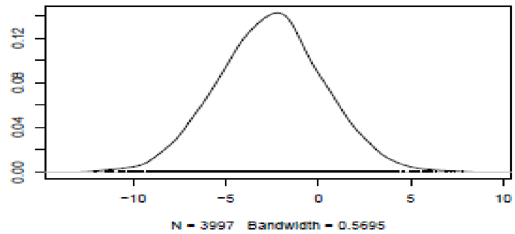
Density of physical:G_ageFirst13 to 17 years



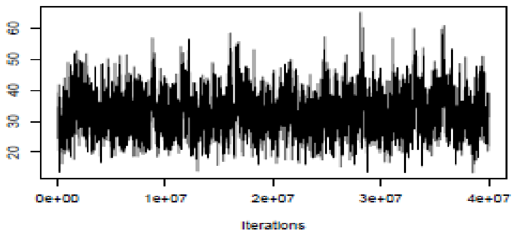
Trace of emotion:G_ageFirst13 to 17 years



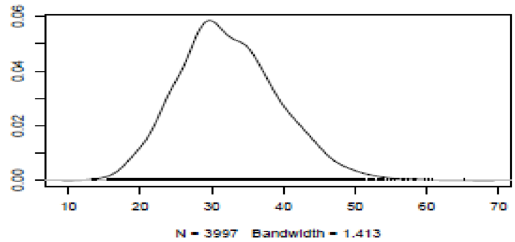
Density of emotion:G_ageFirst13 to 17 years



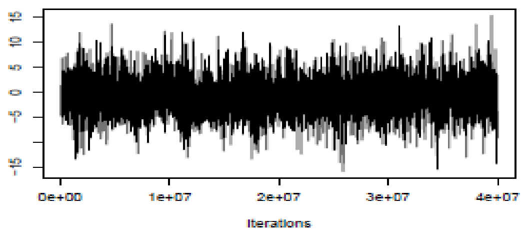
Trace of self:G_ageFirst13 to 17 years



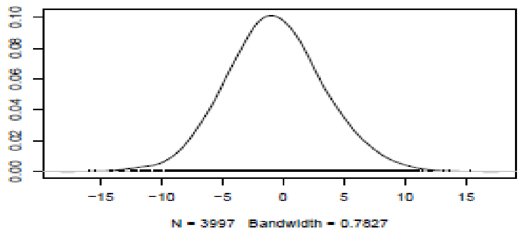
Density of self:G_ageFirst13 to 17 years



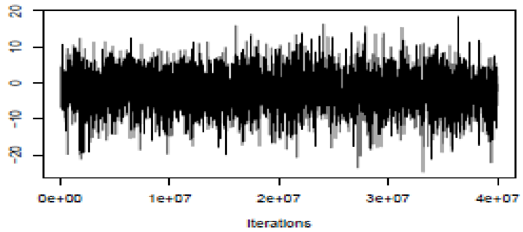
Trace of think:G_ageFirst13 to 17 years



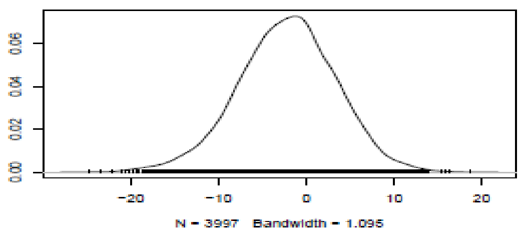
Density of think:G_ageFirst13 to 17 years



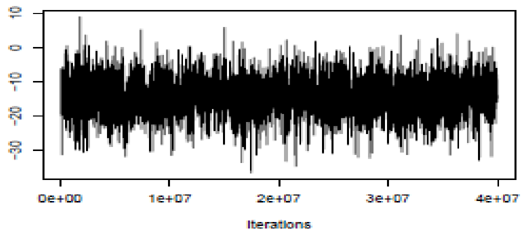
Trace of attitude:G_ageFirst13 to 17 years



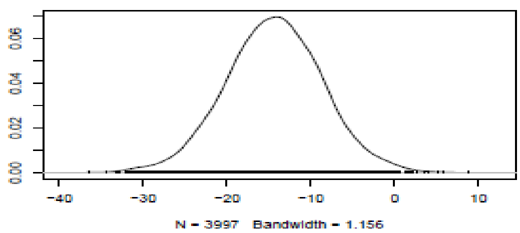
Density of attitude:G_ageFirst13 to 17 years



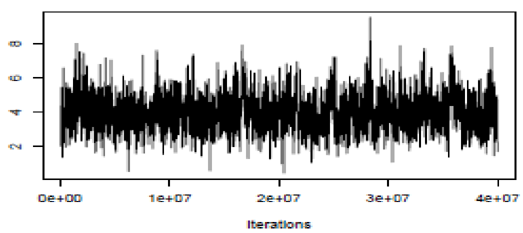
Trace of change:G_ageFirst13 to 17 years



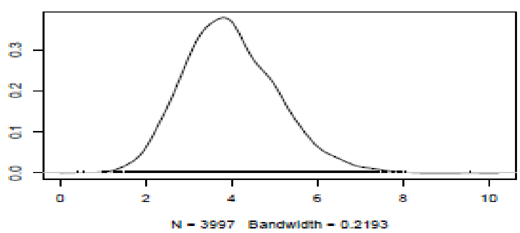
Density of change:G_ageFirst13 to 17 years

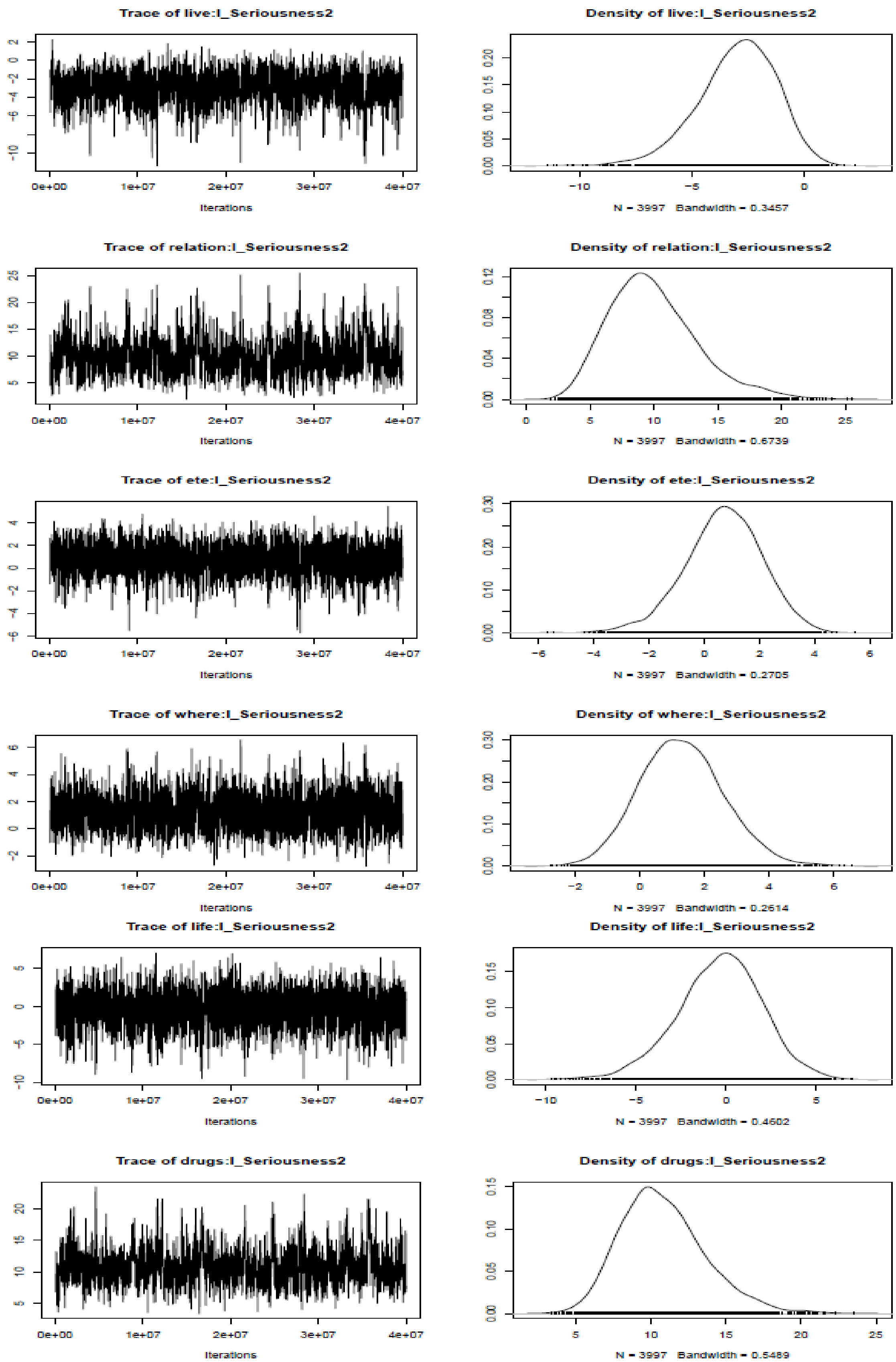


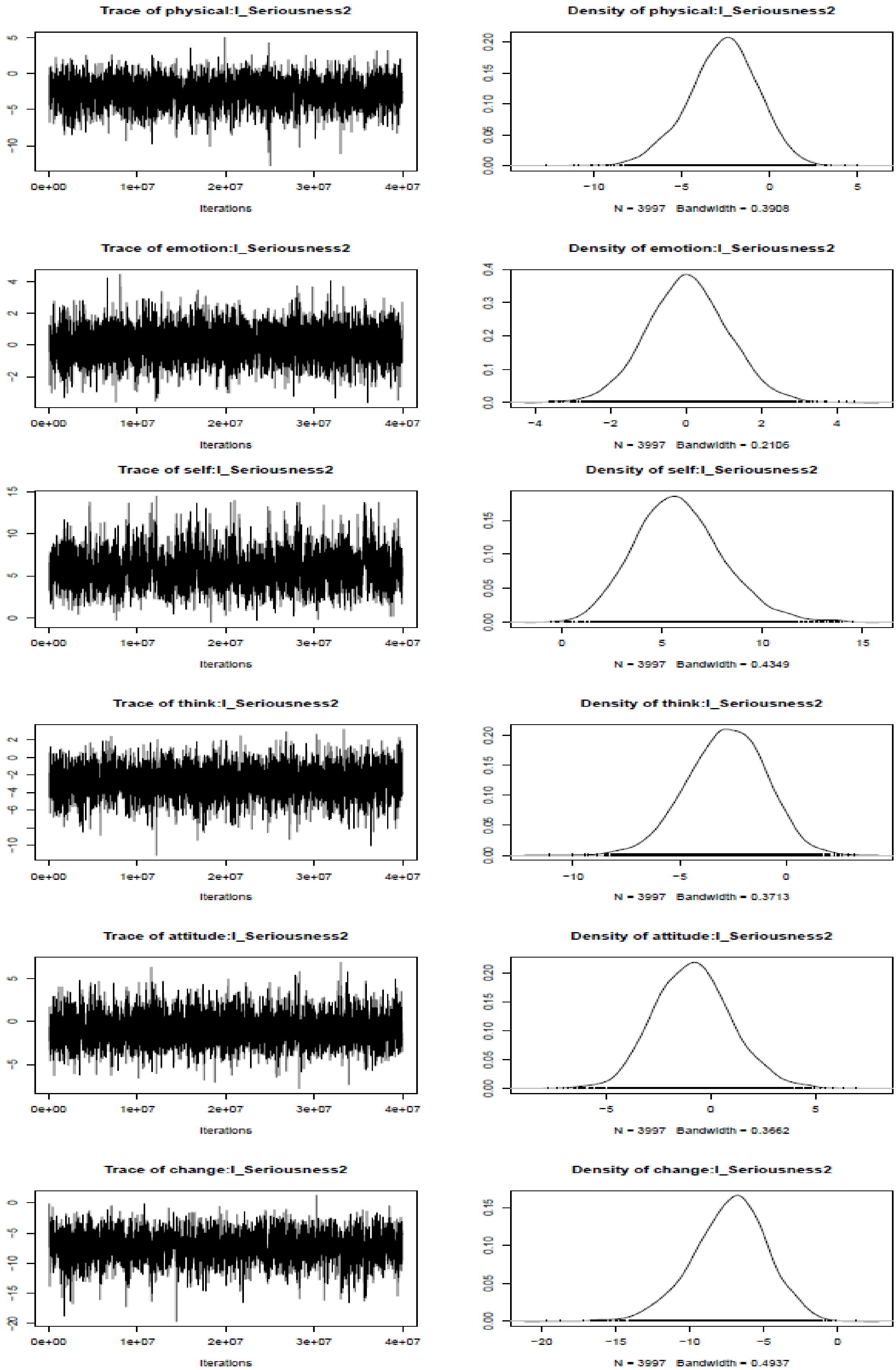
Trace of time:I_Seriousness2

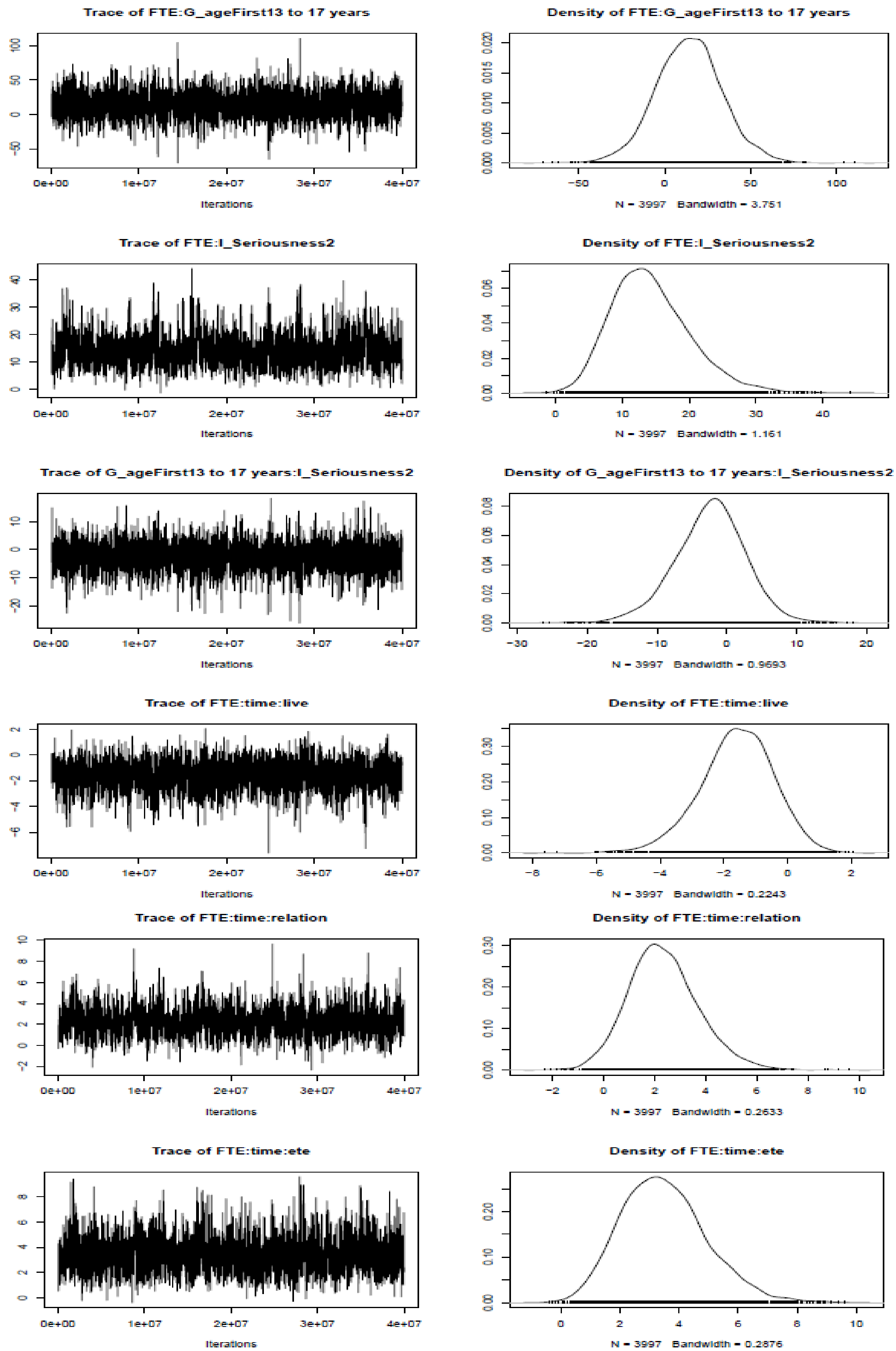


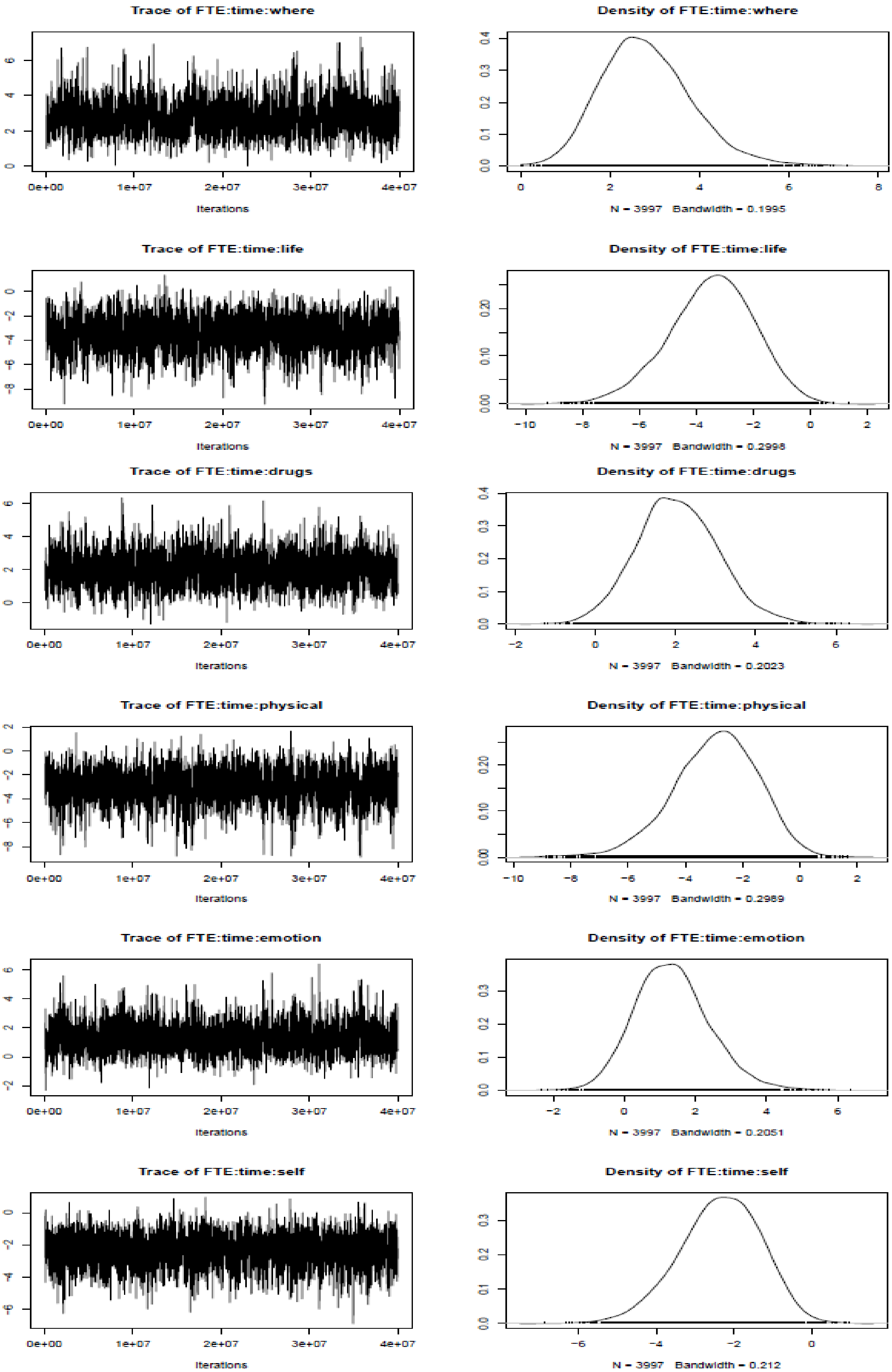
Density of time:I_Seriousness2

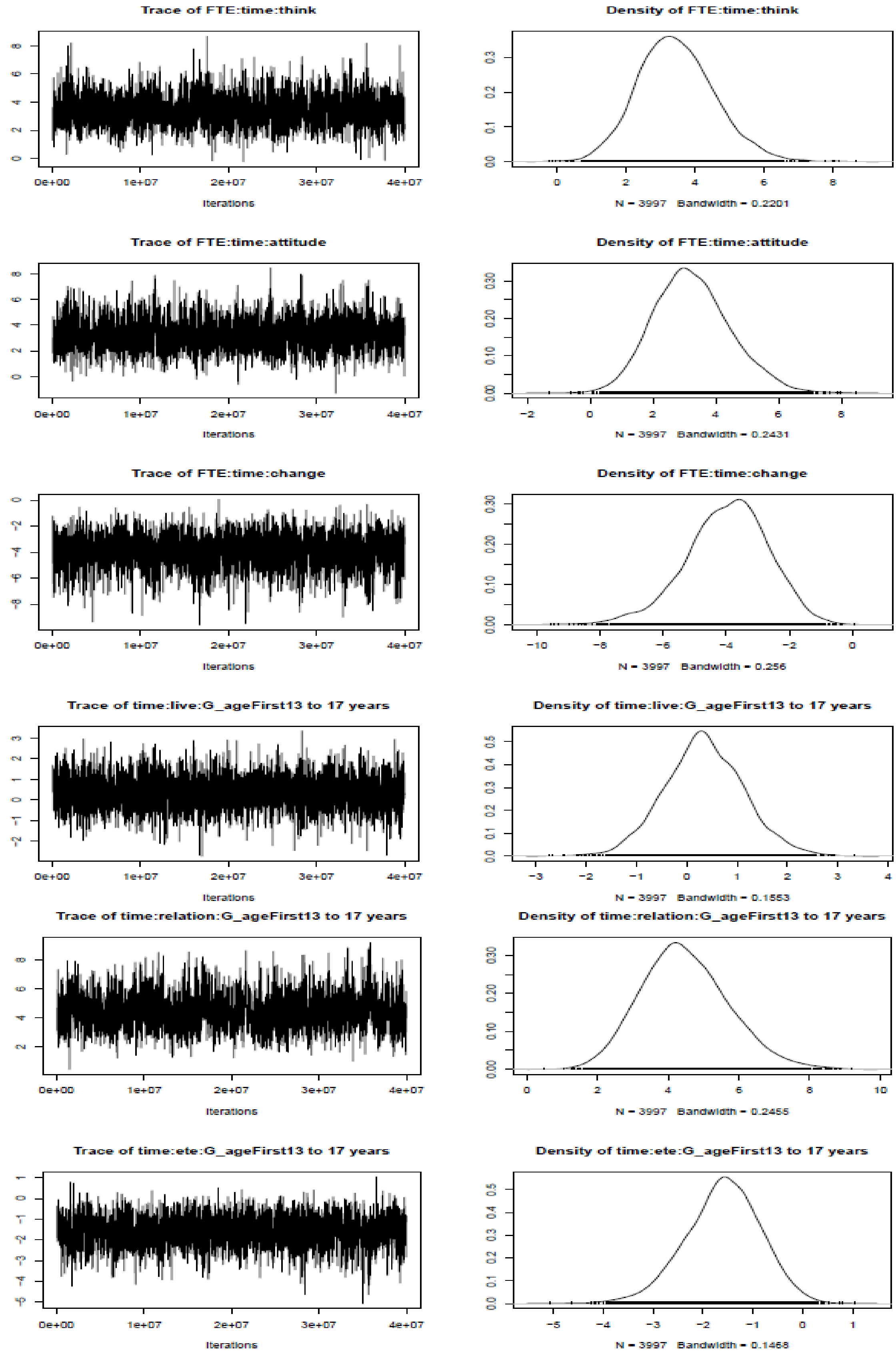


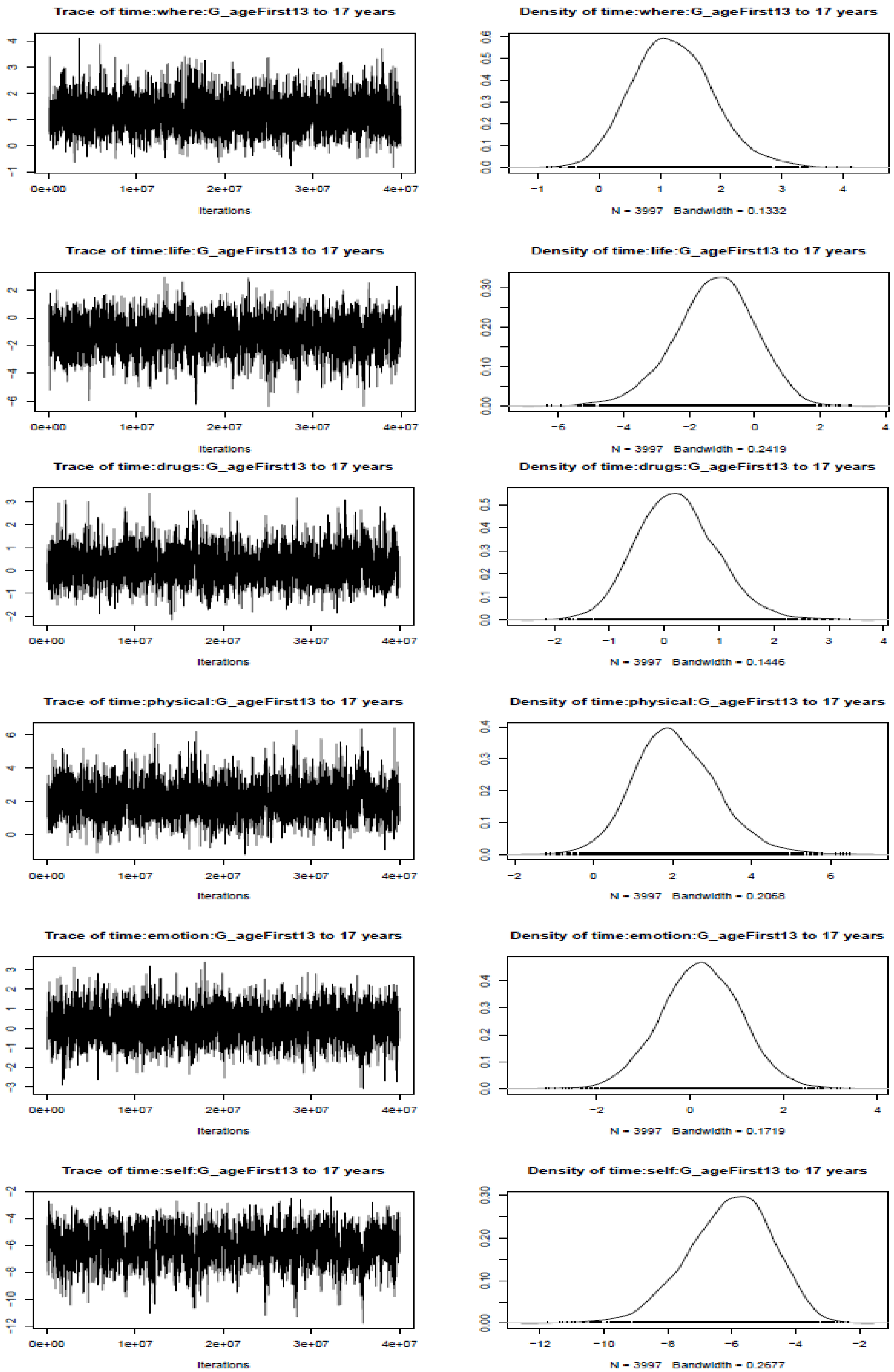

Trace of live:I_Seriousness2
Iterations
Density of live:I_Seriousness2
N = 3997 Bandwidth = 0.3457
Trace of relation:I_Seriousness2
Iterations
Density of relation:I_Seriousness2
N = 3997 Bandwidth = 0.6739
Trace of ete:I_Seriousness2
Iterations
Density of ete:I_Seriousness2
N = 3997 Bandwidth = 0.2705
Trace of where:I_Seriousness2
Iterations
Density of where:I_Seriousness2
N = 3997 Bandwidth = 0.2614
Trace of life:I_Seriousness2
Iterations
Density of life:I_Seriousness2
N = 3997 Bandwidth = 0.4602
Trace of drugs:I_Seriousness2
Iterations
Density of drugs:I_Seriousness2
N = 3997 Bandwidth = 0.5489


Trace of physical:I_Seriousness2
Iterations
Density of physical:I_Seriousness2
N = 3997 Bandwidth = 0.3908
Trace of emotion:I_Seriousness2
Iterations
Density of emotion:I_Seriousness2
N = 3997 Bandwidth = 0.2106
Trace of self:I_Seriousness2
Iterations
Density of self:I_Seriousness2
N = 3997 Bandwidth = 0.4349
Trace of think:I_Seriousness2
Iterations
Density of think:I_Seriousness2
N = 3997 Bandwidth = 0.3713
Trace of attitude:I_Seriousness2
Iterations
Density of attitude:I_Seriousness2
N = 3997 Bandwidth = 0.3662
Trace of change:I_Seriousness2
Iterations
Density of change:I_Seriousness2
N = 3997 Bandwidth = 0.4937

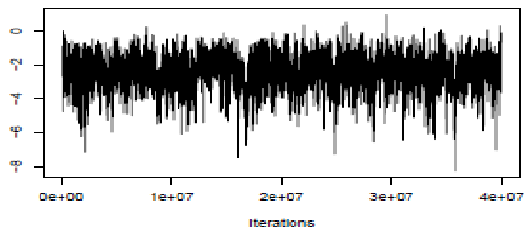

Trace of FTE:G_ageFirst13 to 17 years
Iterations
Density of FTE:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 3.751
Trace of FTE:I_Seriousness2
Iterations
Density of FTE:I_Seriousness2
N = 3997 Bandwidth = 1.161
Trace of G_ageFirst13 to 17 years:I_Seriousness2
Iterations
Density of G_ageFirst13 to 17 years:I_Seriousness2
N = 3997 Bandwidth = 0.9693
Trace of FTE:time:live
Iterations
Density of FTE:time:live
N = 3997 Bandwidth = 0.2243
Trace of FTE:time:relation
Iterations
Density of FTE:time:relation
N = 3997 Bandwidth = 0.2633
Trace of FTE:time:ete
Iterations
Density of FTE:time:ete
N = 3997 Bandwidth = 0.2876


Trace of FTE:time:where
Iterations
Density of FTE:time:where
N = 3997 Bandwidth = 0.1995
Trace of FTE:time:life
Iterations
Density of FTE:time:life
N = 3997 Bandwidth = 0.2998
Trace of FTE:time:drugs
Iterations
Density of FTE:time:drugs
N = 3997 Bandwidth = 0.2023
Trace of FTE:time:physical
Iterations
Density of FTE:time:physical
N = 3997 Bandwidth = 0.2989
Trace of FTE:time:emotion
Iterations
Density of FTE:time:emotion
N = 3997 Bandwidth = 0.2051
Trace of FTE:time:self
Iterations
Density of FTE:time:self
N = 3997 Bandwidth = 0.212

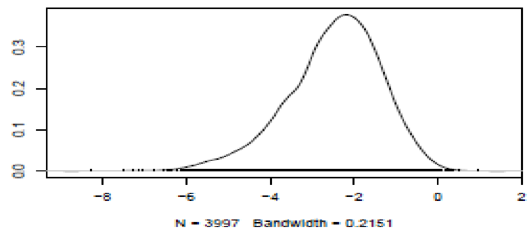

Trace of FTE:time:think
Iterations
Density of FTE:time:think
N = 3997 Bandwidth = 0.2201
Trace of FTE:time:attitude
Iterations
Density of FTE:time:attitude
N = 3997 Bandwidth = 0.2431
Trace of FTE:time:change
Iterations
Density of FTE:time:change
N = 3997 Bandwidth = 0.256
Trace of time:live:G_ageFirst13 to 17 years
Iterations
Density of time:live:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.1553
Trace of time:relation:G_ageFirst13 to 17 years
Iterations
Density of time:relation:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.2455
Trace of time:ete:G_ageFirst13 to 17 years
Iterations
Density of time:ete:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.1468


Trace of time:where:G_ageFirst13 to 17 years
Iterations
Density of time:where:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.1332
Trace of time:life:G_ageFirst13 to 17 years
Iterations
Density of time:life:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.2419
Trace of time:drugs:G_ageFirst13 to 17 years
Iterations
Density of time:drugs:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.1446
Trace of time:physical:G_ageFirst13 to 17 years
Iterations
Density of time:physical:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.2068
Trace of time:emotion:G_ageFirst13 to 17 years
Iterations
Density of time:emotion:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.1719
Trace of time:self:G_ageFirst13 to 17 years
Iterations
Density of time:self:G_ageFirst13 to 17 years
N = 3997 Bandwidth = 0.2677

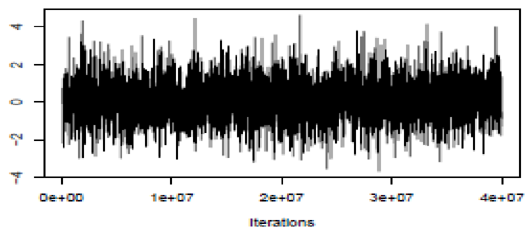
Trace of time:think:G_ageFirst13 to 17 years



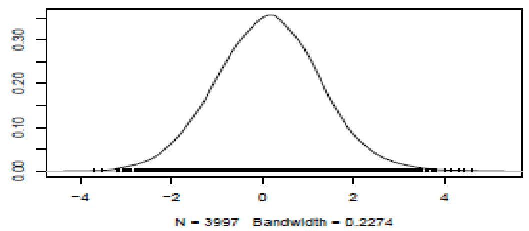
Density of time:think:G_ageFirst13 to 17 years



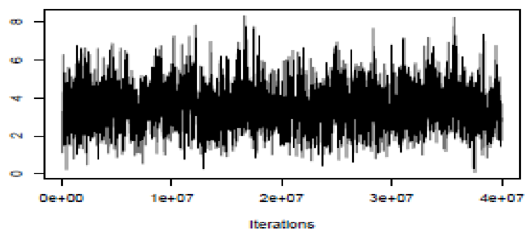
Trace of time:attitude:G_ageFirst13 to 17 years



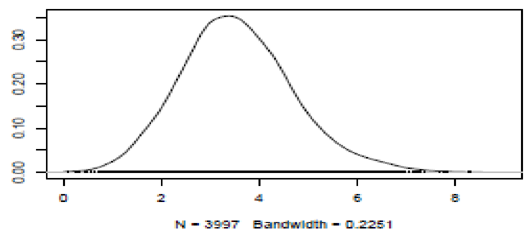
Density of time:attitude:G_ageFirst13 to 17 years



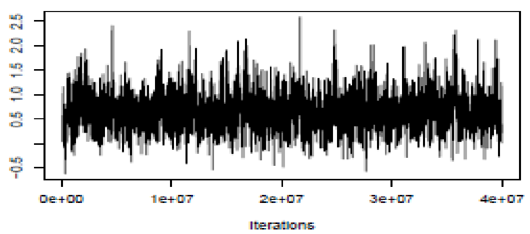
Trace of time:change:G_ageFirst13 to 17 years



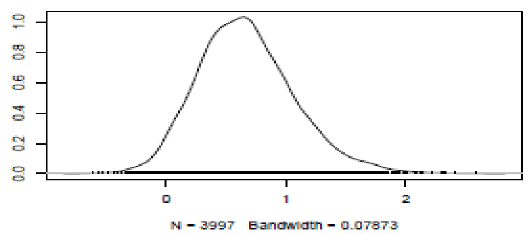
Density of time:change:G_ageFirst13 to 17 years



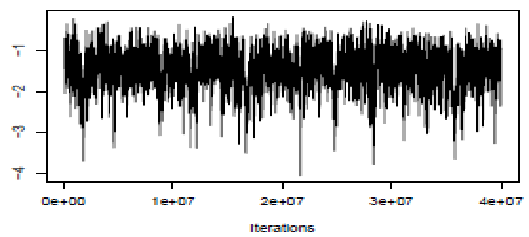
Trace of time:live:I_Seriousness2



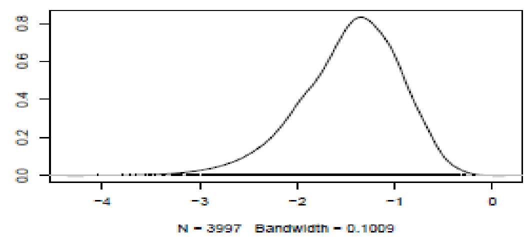
Density of time:live:I_Seriousness2



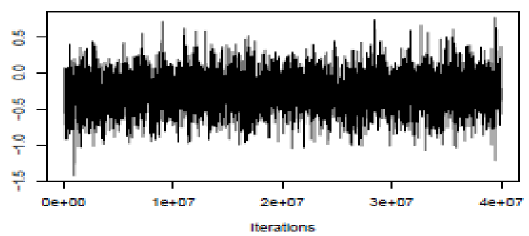
Trace of time:relation:I_Seriousness2



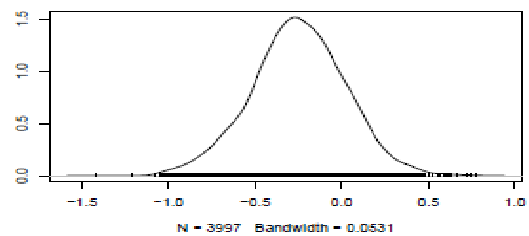
Density of time:relation:I_Seriousness2

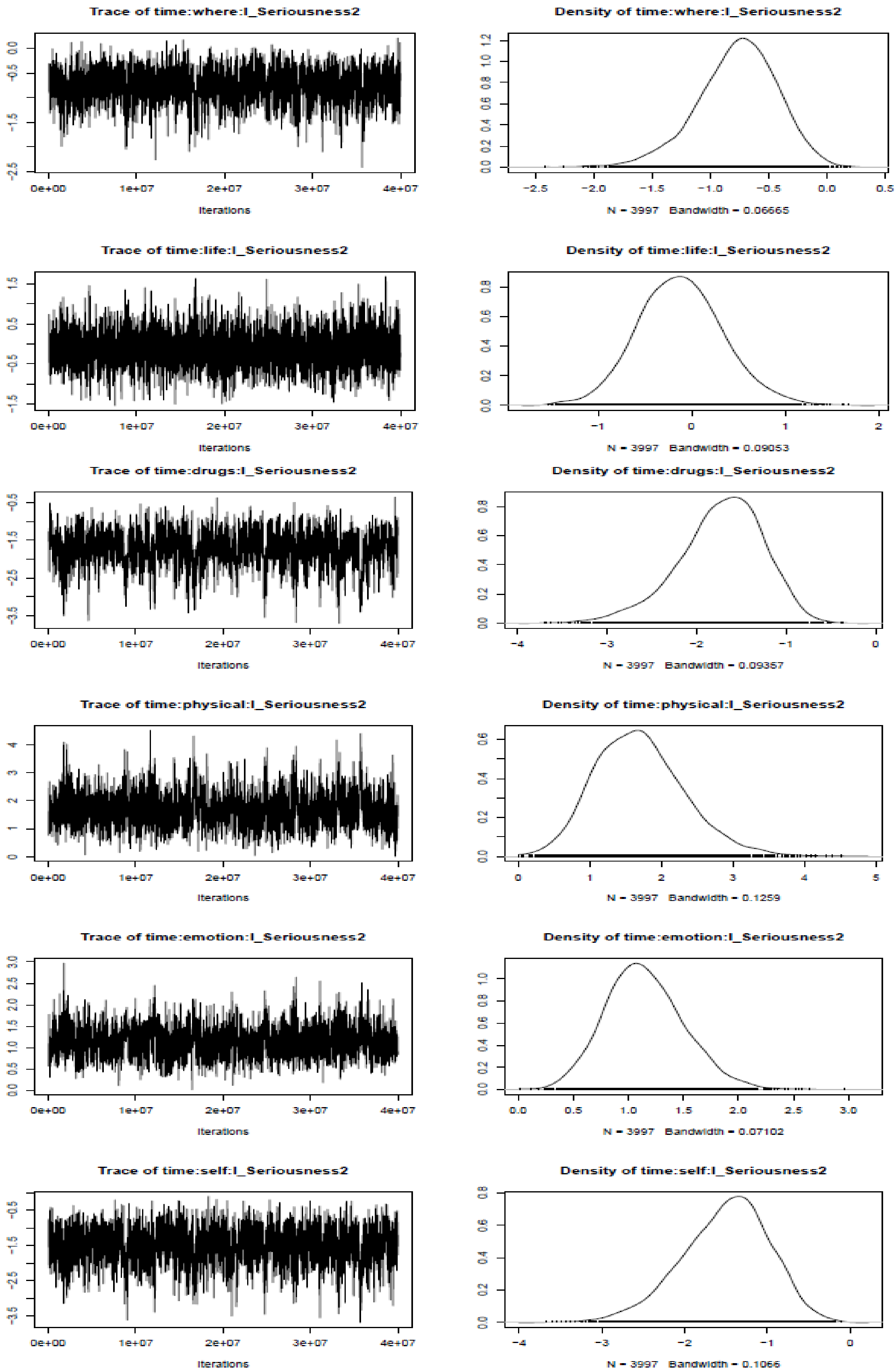


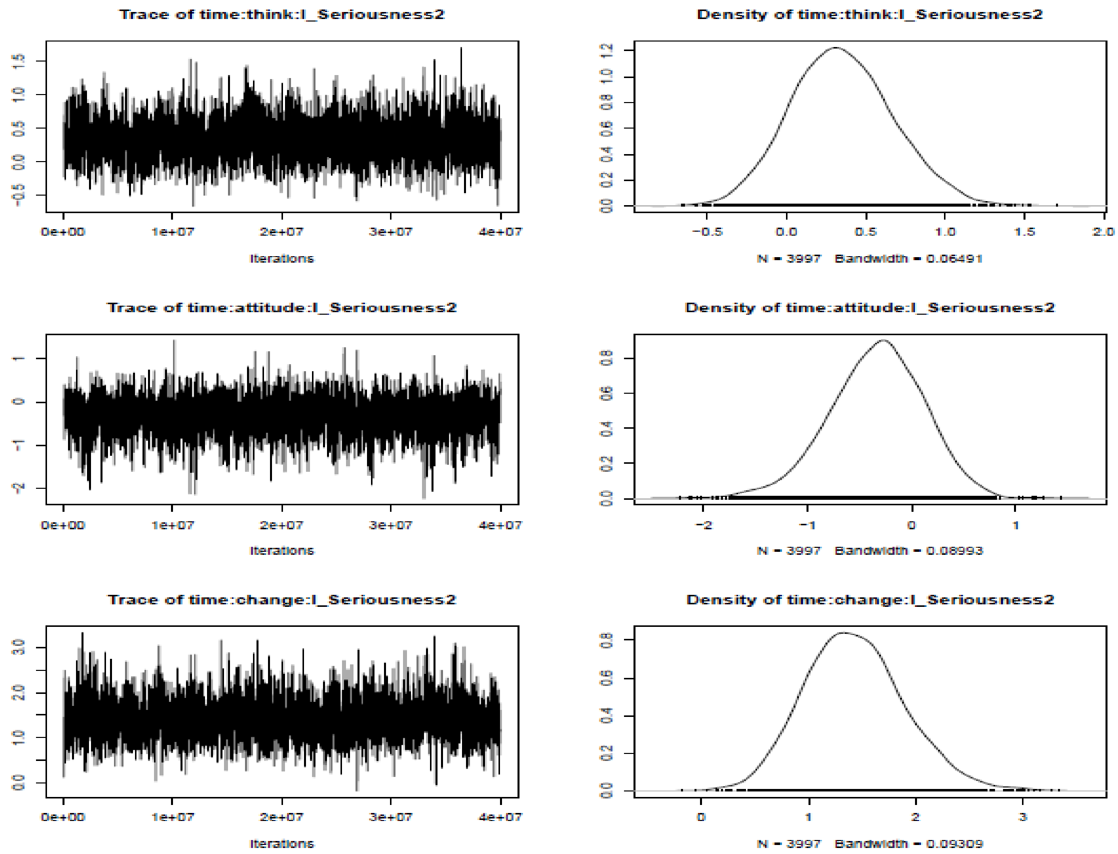
Trace of time:ete:I_Seriousness2



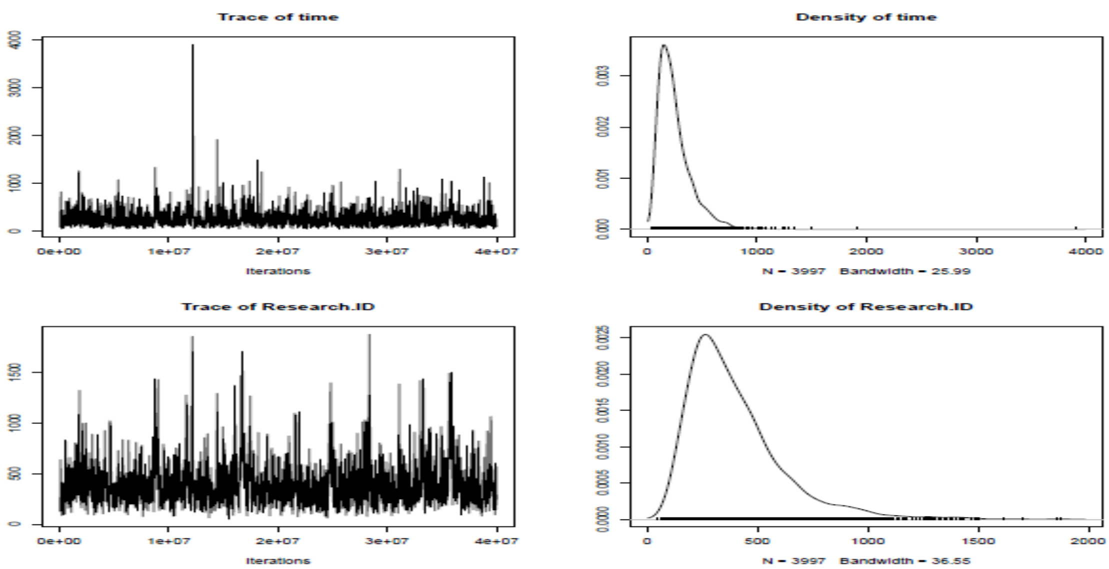
Density of time:ete:I_Seriousness2




Trace of time:where:I_Seriousness2
Iterations
Density of time:where:I_Seriousness2
N = 3997 Bandwidth = 0.06665
Trace of time:life:I_Seriousness2
Iterations
Density of time:life:I_Seriousness2
N = 3997 Bandwidth = 0.09053
Trace of time:drugs:I_Seriousness2
Iterations
Density of time:drugs:I_Seriousness2
N = 3997 Bandwidth = 0.09357
Trace of time:physical:I_Seriousness2
Iterations
Density of time:physical:I_Seriousness2
N = 3997 Bandwidth = 0.1259
Trace of time:emotion:I_Seriousness2
Iterations
Density of time:emotion:I_Seriousness2
N = 3997 Bandwidth = 0.07102
Trace of time:self:I_Seriousness2
Iterations
Density of time:self:I_Seriousness2
N = 3997 Bandwidth = 0.1066



Random Effects



The Combined Model involving Offending History: Version 2a

Bayesian Model (BDm3G_cc12)

Define the Model

```
BDm3G_cc12 <- MCMCglmm(FO.bin~G_ageFirst*time*live +
G_ageFirst*time*relation + G_ageFirst*time*ete +
G_ageFirst*time*where + G_ageFirst*time*life + G_ageFirst*time*drugs +
G_ageFirst*time*physical + G_ageFirst*time*emotion +
G_ageFirst*time*self + G_ageFirst*time*think + G_ageFirst*time*attitude
+ G_ageFirst*time*change +
FTE*time*live + FTE*time*relation + FTE*time*ete +
FTE*time*where + FTE*time*life + FTE*time*drugs +
FTE*time*physical + FTE*time*emotion + FTE*time*self +
FTE*time*think + FTE*time*attitude + FTE*time*change +
G_ageFirst*FTE,                        ,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
nitt=20000000, thin=5000, burnin=3000)
```

Checks for suitable convergence

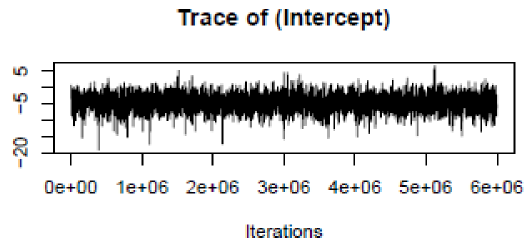
```
raftery.diag(BDm3G_cc12a$VCV)
heidel.diag(BDm3G_cc12a$VCV)

# > raftery.diag(BDm3G_cc12a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total    Lower bound  Dependence
#              (M)      (N)      (Nmin)       factor (I)
# time         10000    19730000 3746         5270
# Research.ID  10000    18935000 3746         5050
# units        <NA>     <NA>     3746           NA

# > heidel.diag(BDm3G_cc12a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed         1        0.280
# Research.ID  passed         1        0.613
# units        failed       NA            NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    11.82 0.283
# Research.ID  passed     5.77 0.102
# units        <NA>         NA    NA

autocorr(BDm3G_cc12a$VCV)
autocorr(BDm3G_cc12a$Sol)   # not included here
summary(BDm3G_cc12a)
```

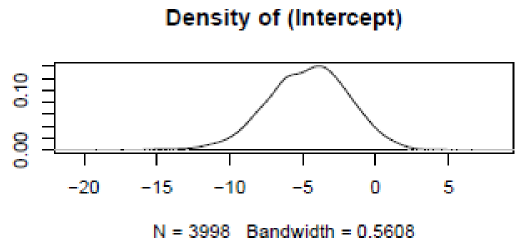
```
# > autocorr(BDm3G_cc12a$VCV)
# , , time
#
#                    time Research.ID units
# Lag 0       1.000000000  0.25414524   NaN
# Lag 5000    0.021491274  0.04637041   NaN
# Lag 25000  -0.004033681  0.01837104   NaN
# Lag 50000   0.011864825  0.02625236   NaN
# Lag 250000 -0.011464257  0.01628681   NaN
#
# , , Research.ID
#
#                    time  Research.ID units
# Lag 0       0.254145242  1.000000000   NaN
# Lag 5000    0.007662382  0.024729140   NaN
# Lag 25000   0.015071632  0.017639024   NaN
# Lag 50000  -0.013319793 -0.012933252   NaN
# Lag 250000 -0.019841085  0.005466752   NaN

# > summary(BDm3G_cc12a)
#
# Iterations = 3001:19998001
# Thinning interval  = 5000
# Sample size  = 4000
#
# DIC: 391.1588
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     11.82    1.704    28.45     3945
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID     5.772    0.912    11.95     3806
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageFirst * time * live + G_ageFirst *
time * relation + G_ageFirst * time * ete + G_ageFirst * time * where +
G_ageFirst * time * life + G_ageFirst * time * drugs + G_ageFirst * time
* physical + G_ageFirst * time * emotion + G_ageFirst * time * self +
G_ageFirst * time * think + G_ageFirst * time * attitude + G_ageFirst *
time * change + FTE * time * live + FTE * time * relation + FTE * time *
ete + FTE * time * where + FTE * time * life + FTE * time * drugs + FTE
* time * physical + FTE * time * emotion + FTE * time * self + FTE *
time * think + FTE * time * attitude + FTE * time * change + G_ageFirst
* FTE
#
#                                           post.mean  l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept)                               -4.702640 -10.205000   0.313114     4000 0.0710 .
# G_ageFirst13 to 17 years                   4.430101  -1.067301  10.788480     4000 0.1290
# time                                       0.231764  -0.646595   1.139908     4007 0.6190
# live                                      -0.547642  -2.168070   1.022266     4000 0.5085
# relation                                   2.510645   0.411304   4.551425     4000 0.0095 **
# ete                                       -0.975567  -2.434322   0.484326     3140 0.1835
# where                                      0.500875  -0.720161   1.769561     4417 0.4390
# life                                       2.572099   0.294232   4.966155     3742 0.0310 *
# drugs                                     -0.585368  -2.212467   0.918795     4000 0.4555
# physical                                  -1.264506  -2.903797   0.389825     4000 0.1285
```

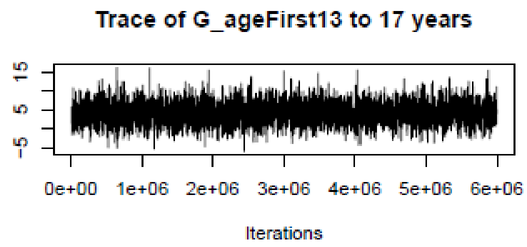
```
# emotion                                 -0.484623  -1.829558   1.012913     4000 0.5115
# self                                    -6.460357  -9.678682  -3.215738     4000 <3e-04 ***
# think                                    1.669118  -0.704790   4.095740     4000 0.1660
# attitude                                 2.817919  -0.291587   5.805046     4000 0.0670 .
# change                                   0.819301  -1.721556   3.439919     4000 0.5390
# FTE                                     -4.847546 -13.561338   4.455934     4000 0.2825
# G_ageFirst13 to 17 years:time           -0.641117  -1.928313   0.690669     4000 0.3330
# G_ageFirst13 to 17 years:live            1.115740  -1.127051   3.368384     4000 0.3365
# time:live                               -0.155139  -0.537235   0.203420     4000 0.4020
# G_ageFirst13 to 17 years:relation       -3.813922  -6.698231  -1.011309     4000 0.0050 **
# time:relation                           -0.509886  -1.007874  -0.058906     4000 0.0260 *
# G_ageFirst13 to 17 years:ete             0.389873  -1.441920   2.215190     4000 0.6745
# time:ete                                 0.190172  -0.106355   0.518690     4000 0.2355
# G_ageFirst13 to 17 years:where           1.213332  -0.736476   3.183052     4000 0.2150
# time:where                              -0.197742  -0.480357   0.060532     4469 0.1390
# G_ageFirst13 to 17 years:life           -2.511732  -5.852417   0.716128     4000 0.1330
# time:life                               -0.521940  -1.037114   0.056250     4000 0.0600 .
# G_ageFirst13 to 17 years:drugs           0.445641  -1.513650   2.612982     4000 0.6515
# time:drugs                               0.344492   0.025170   0.676704     3821 0.0340 *
# G_ageFirst13 to 17 years:physical       -0.844165  -3.195825   1.625114     4000 0.4850
# time:physical                            0.366109  -0.040479   0.764650     4000 0.0760 .
# G_ageFirst13 to 17 years:emotion         0.053954  -2.038371   1.919305     4000 0.9370
# time:emotion                             0.360413   0.062408   0.675211     4000 0.0160 *
# G_ageFirst13 to 17 years:self            7.612935   3.848314  11.422412     4000 <3e-04 ***
# time:self                                1.420245   0.789232   2.065964     4000 <3e-04 ***
# G_ageFirst13 to 17 years:think          -0.458755  -3.267825   2.433660     3333 0.7490
# time:think                              -0.349783  -0.776270   0.105242     4000 0.1160
# G_ageFirst13 to 17 years:attitude       -0.366802  -4.182706   3.041417     4000 0.8350
# time:attitude                           -0.825983  -1.392150  -0.299298     4000 0.0025 **
# G_ageFirst13 to 17 years:change         -2.899528  -6.146631   0.327787     4000 0.0715 .
# time:change                              0.122425  -0.378120   0.613728     4000 0.6315
# time:FTE                                -0.892885  -2.355309   0.574030     4000 0.2150
# live:FTE                                 1.071579  -1.487255   4.144556     4417 0.4535
# relation:FTE                            -0.089557  -2.834016   2.612893     4000 0.9580
# ete:FTE                                  1.041621  -1.109479   3.288448     4180 0.3315
# where:FTE                               -4.046171  -6.642584  -1.544356     4000 <3e-04 ***
# life:FTE                                 2.175587  -0.976327   5.629425     4000 0.1745
# drugs:FTE                               -0.780049  -3.309279   1.702972     4000 0.5345
# physical:FTE                             1.036036  -1.514445   3.824026     4000 0.4405
# emotion:FTE                             -0.453750  -2.452381   1.701031     4475 0.6665
# self:FTE                                 2.172313  -0.528967   4.841978     4368 0.0970 .
# think:FTE                               -2.247786  -4.958328   0.372087     4000 0.0880 .
# attitude:FTE                            -3.612875  -6.506613  -1.077648     4000 0.0055 **
# change:FTE                               3.066947   0.281370   6.043277     4251 0.0370 *
# G_ageFirst13 to 17 years:FTE             4.855018  -3.669784  13.759253     4216 0.2680
# G_ageFirst13 to 17 years:time:live       0.308343  -0.289208   0.865401     4543 0.2910
# G_ageFirst13 to 17 years:time:relation   1.030753   0.325518   1.699486     4000 0.0015 **
# G_ageFirst13 to 17 years:time:ete       -0.283843  -0.772463   0.195819     4000 0.2495
# G_ageFirst13 to 17 years:time:where      0.032733  -0.364398   0.451480     4413 0.8830
# G_ageFirst13 to 17 years:time:life       0.367604  -0.411213   1.212240     4000 0.3705
# G_ageFirst13 to 17 years:time:drugs     -0.622412  -1.118620  -0.106981     3909 0.0130 *
# G_ageFirst13 to 17 years:time:physical   0.451169  -0.294234   1.210187     4000 0.2265
# G_ageFirst13 to 17 years:time:emotion   -0.552947  -1.172558   0.010831     4000 0.0610 .
# G_ageFirst13 to 17 years:time:self      -1.495552  -2.288632  -0.728005     4000 <3e-04 ***
# G_ageFirst13 to 17 years:time:think     -0.105656  -0.761886   0.540139     3666 0.7600
# G_ageFirst13 to 17 years:time:attitude   0.071999  -0.744118   0.831351     4000 0.8540
# G_ageFirst13 to 17 years:time:change     0.598472  -0.117981   1.367059     4000 0.1025
# time:live:FTE                           -0.548858  -1.293485   0.119208     4234 0.1070
# time:relation:FTE                       -0.095832  -0.806058   0.570128     4000 0.7755
# time:ete:FTE                             0.422807  -0.184195   1.054467     4041 0.1710
# time:where:FTE                           0.571166   0.102918   1.033199     3752 0.0090 **
# time:life:FTE                           -0.497196  -1.356102   0.283092     4000 0.2230
# time:drugs:FTE                           0.655910   0.097017   1.267469     4000 0.0215 *
# time:physical:FTE                       -0.856352  -1.701723  -0.001359     4000 0.0380 *
# time:emotion:FTE                         0.452900  -0.160053   1.079197     4000 0.1425
# time:self:FTE                           -0.771919  -1.398545  -0.135649     4000 0.0085 **
# time:think:FTE                           0.753242   0.106954   1.468762     4000 0.0250 *
# time:attitude:FTE                        1.065784   0.339676   1.868700     4000 0.0050 **
# time:change:FTE                         -0.949386  -1.738856  -0.210314     4186 0.0135 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

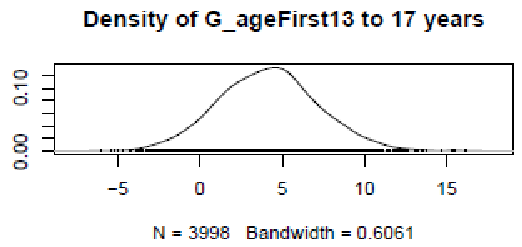
Trace Plots and Posterior Density Plots

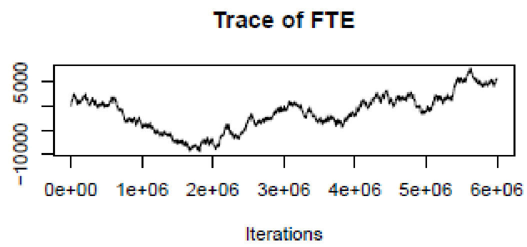
<u>Fixed Effects</u>

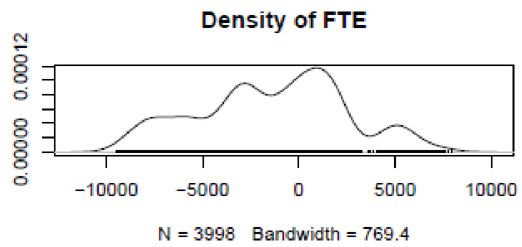


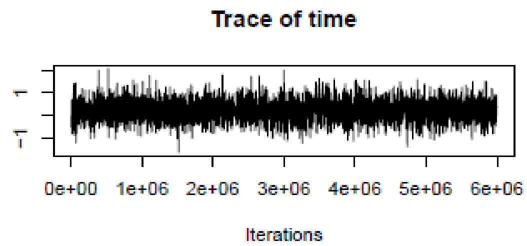


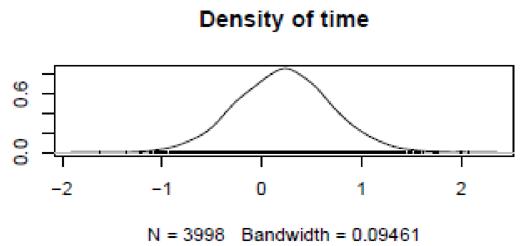


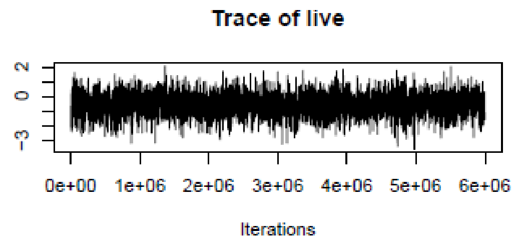


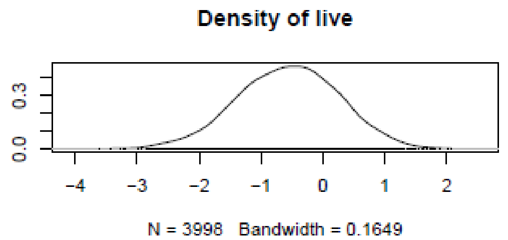


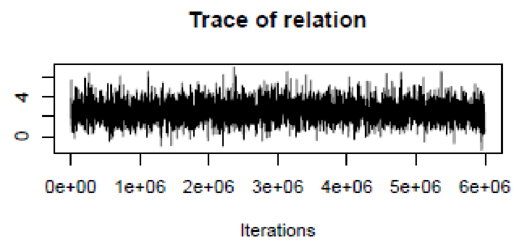


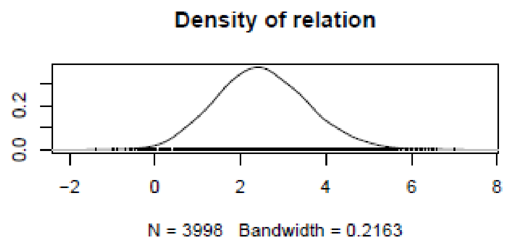


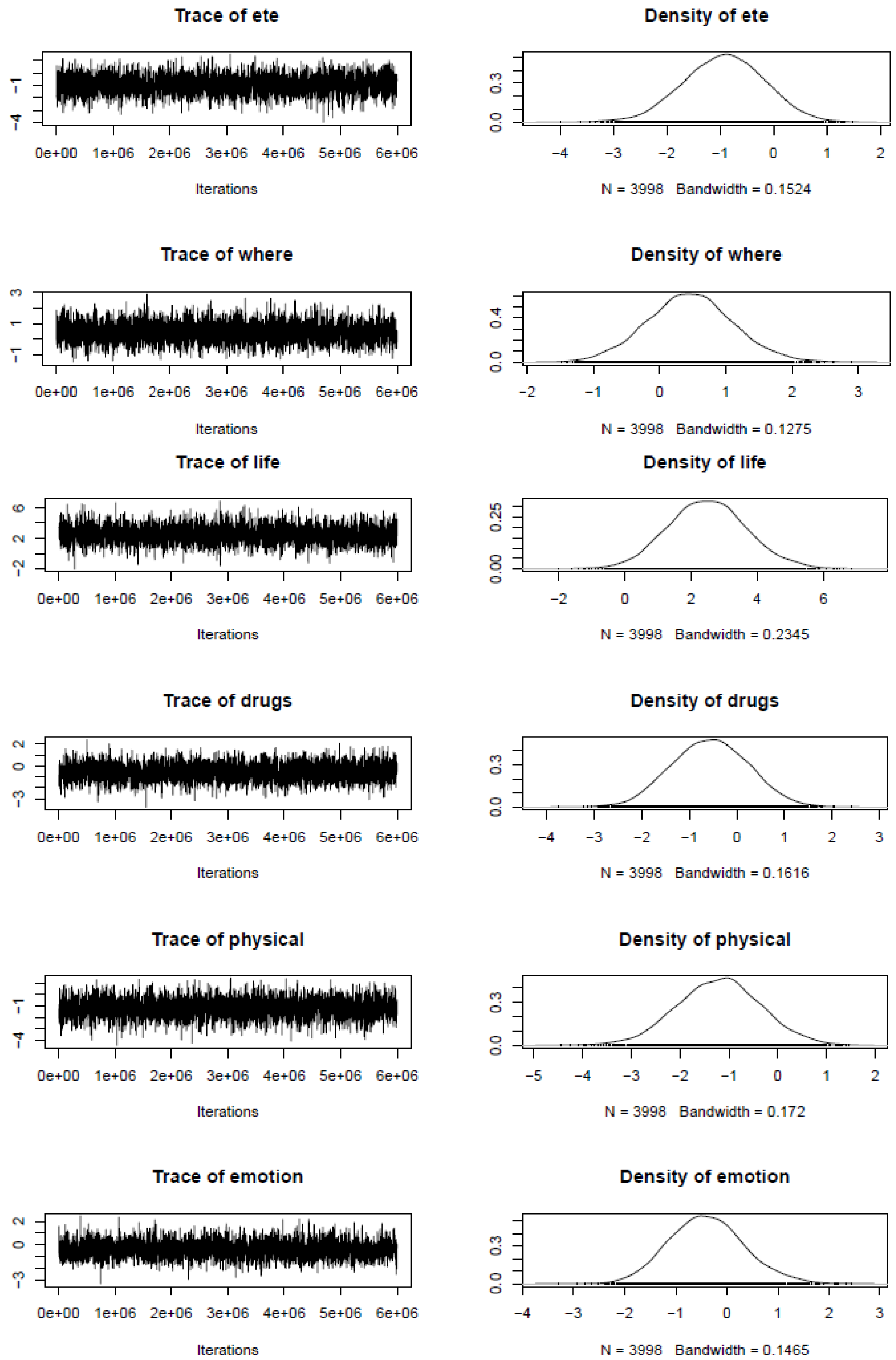


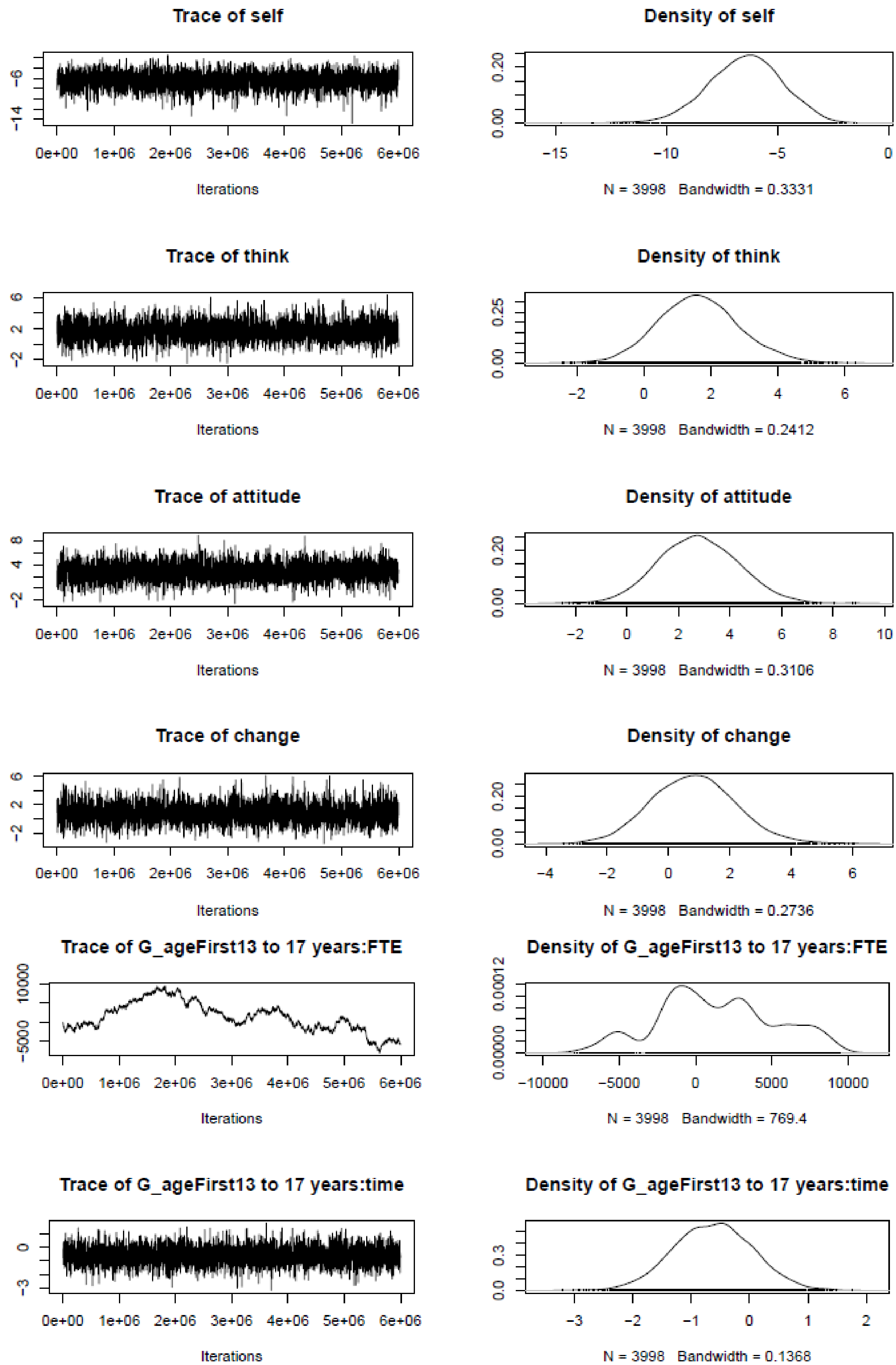


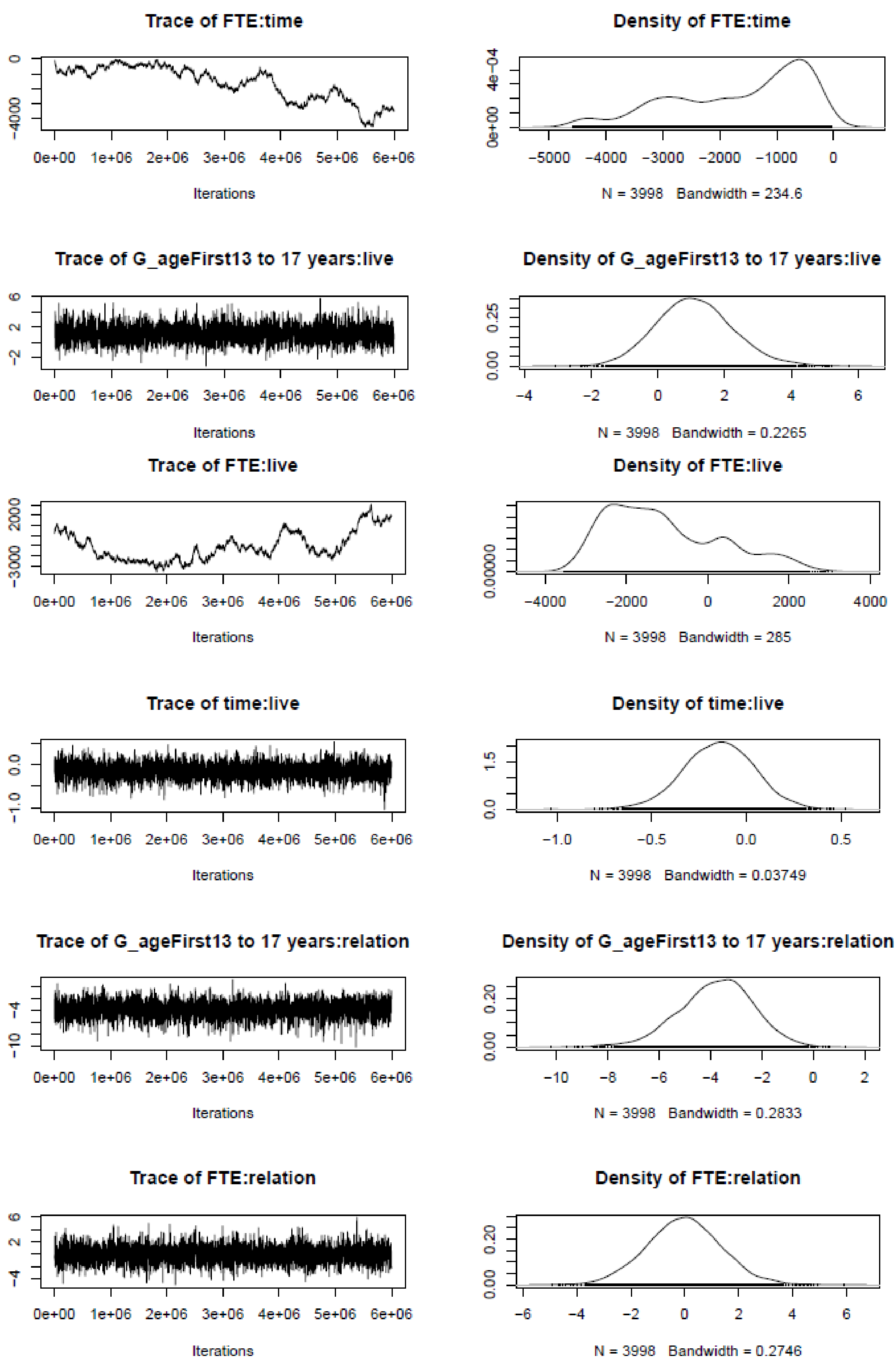


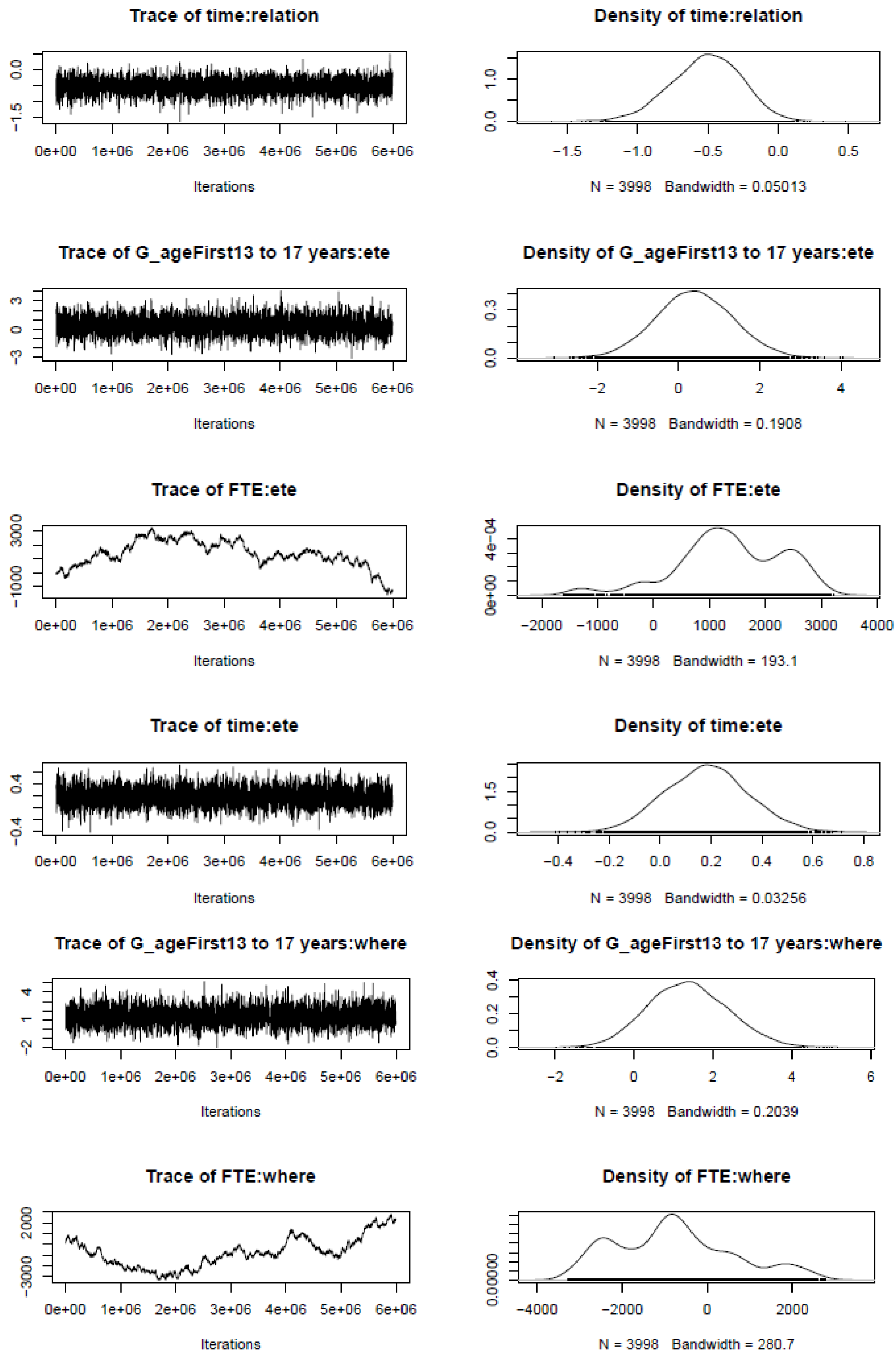


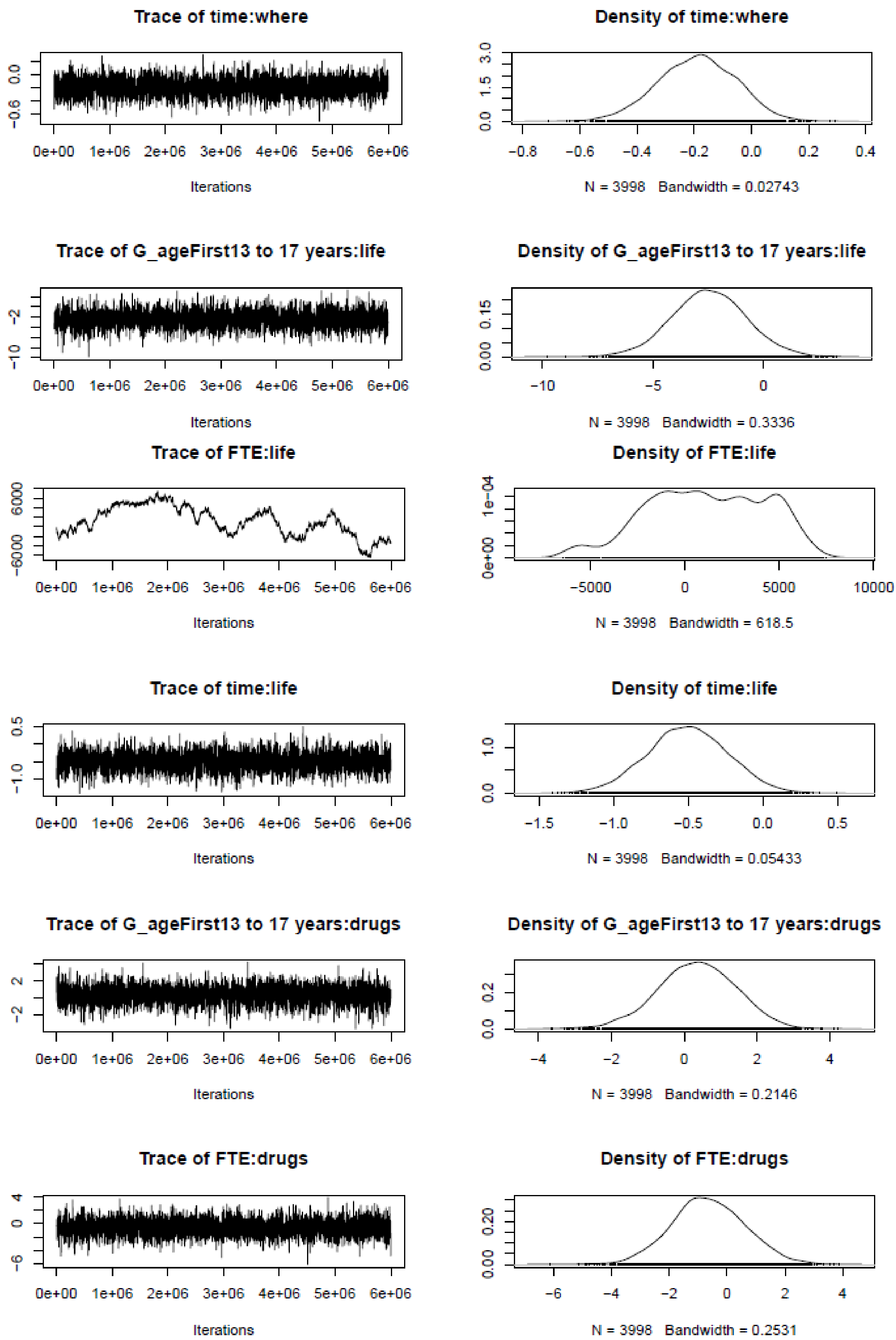


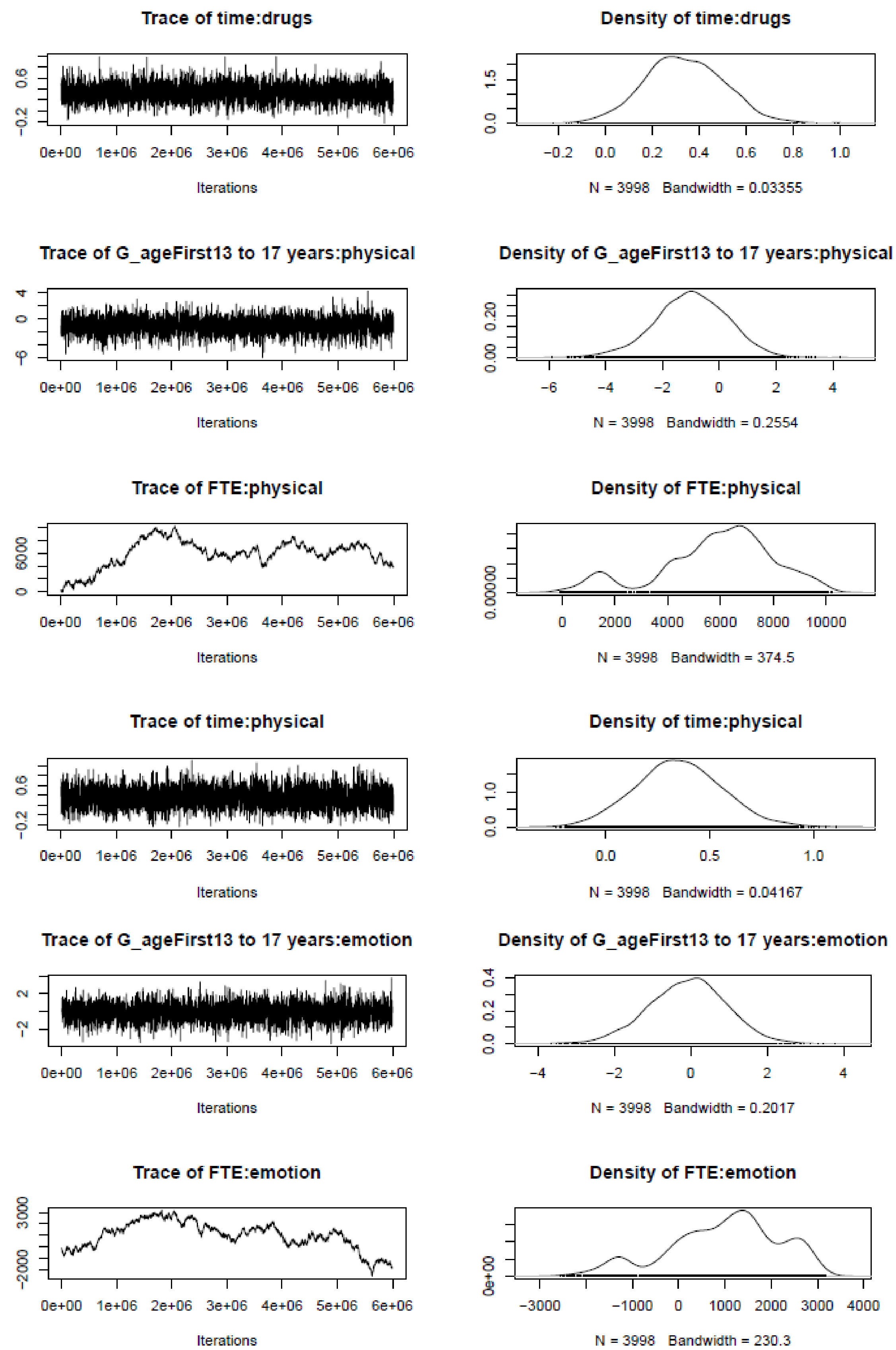

Trace of ete
Density of ete
Iterations
N = 3998 Bandwidth = 0.1524
Trace of where
Density of where
Iterations
N = 3998 Bandwidth = 0.1275
Trace of life
Density of life
Iterations
N = 3998 Bandwidth = 0.2345
Trace of drugs
Density of drugs
Iterations
N = 3998 Bandwidth = 0.1616
Trace of physical
Density of physical
Iterations
N = 3998 Bandwidth = 0.172
Trace of emotion
Density of emotion
Iterations
N = 3998 Bandwidth = 0.1465

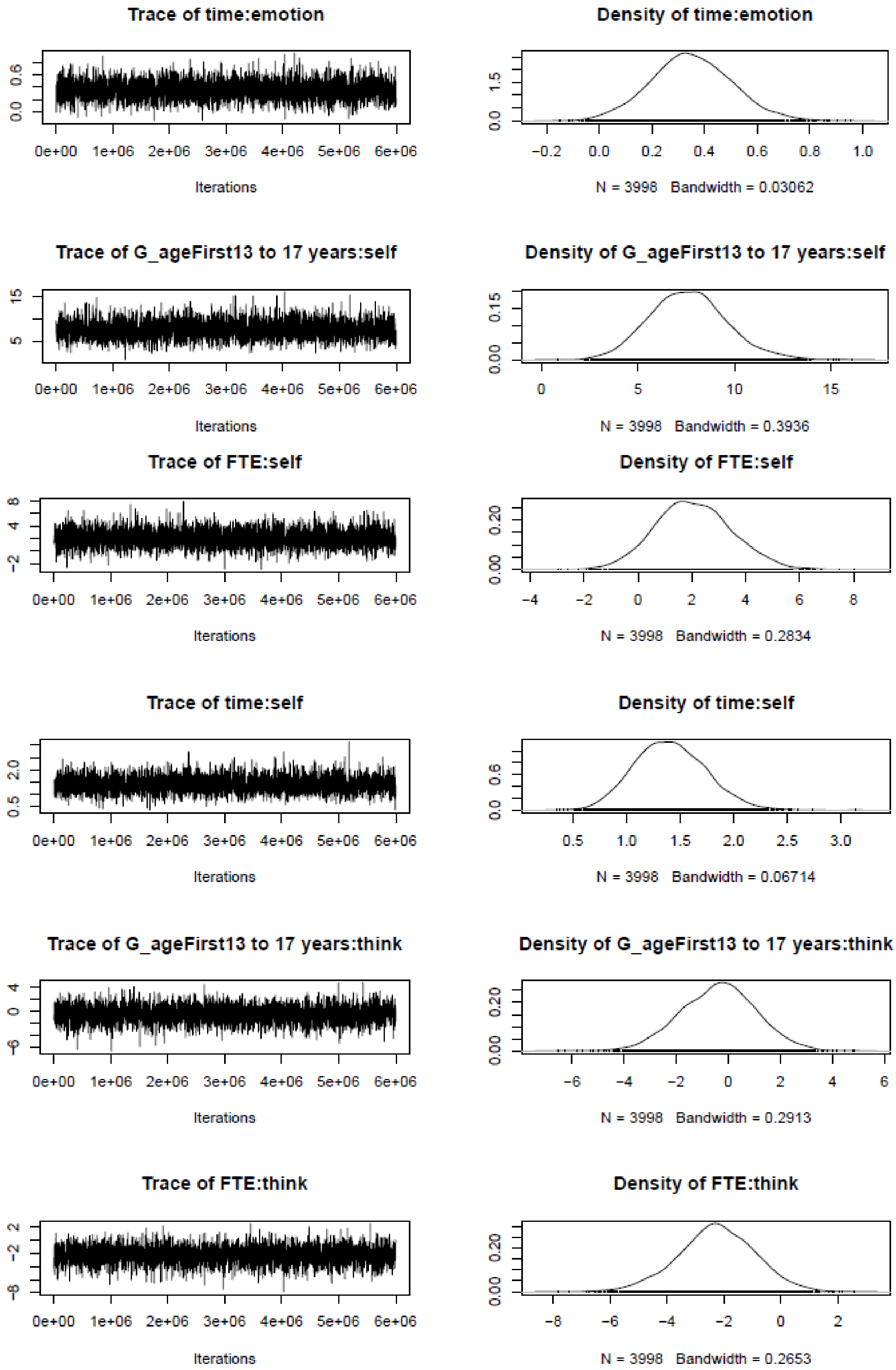

Trace of self
Iterations
Density of self
N = 3998 Bandwidth = 0.3331
Trace of think
Iterations
Density of think
N = 3998 Bandwidth = 0.2412
Trace of attitude
Iterations
Density of attitude
N = 3998 Bandwidth = 0.3106
Trace of change
Iterations
Density of change
N = 3998 Bandwidth = 0.2736
Trace of G_ageFirst13 to 17 years:FTE
Iterations
Density of G_ageFirst13 to 17 years:FTE
N = 3998 Bandwidth = 769.4
Trace of G_ageFirst13 to 17 years:time
Iterations
Density of G_ageFirst13 to 17 years:time
N = 3998 Bandwidth = 0.1368

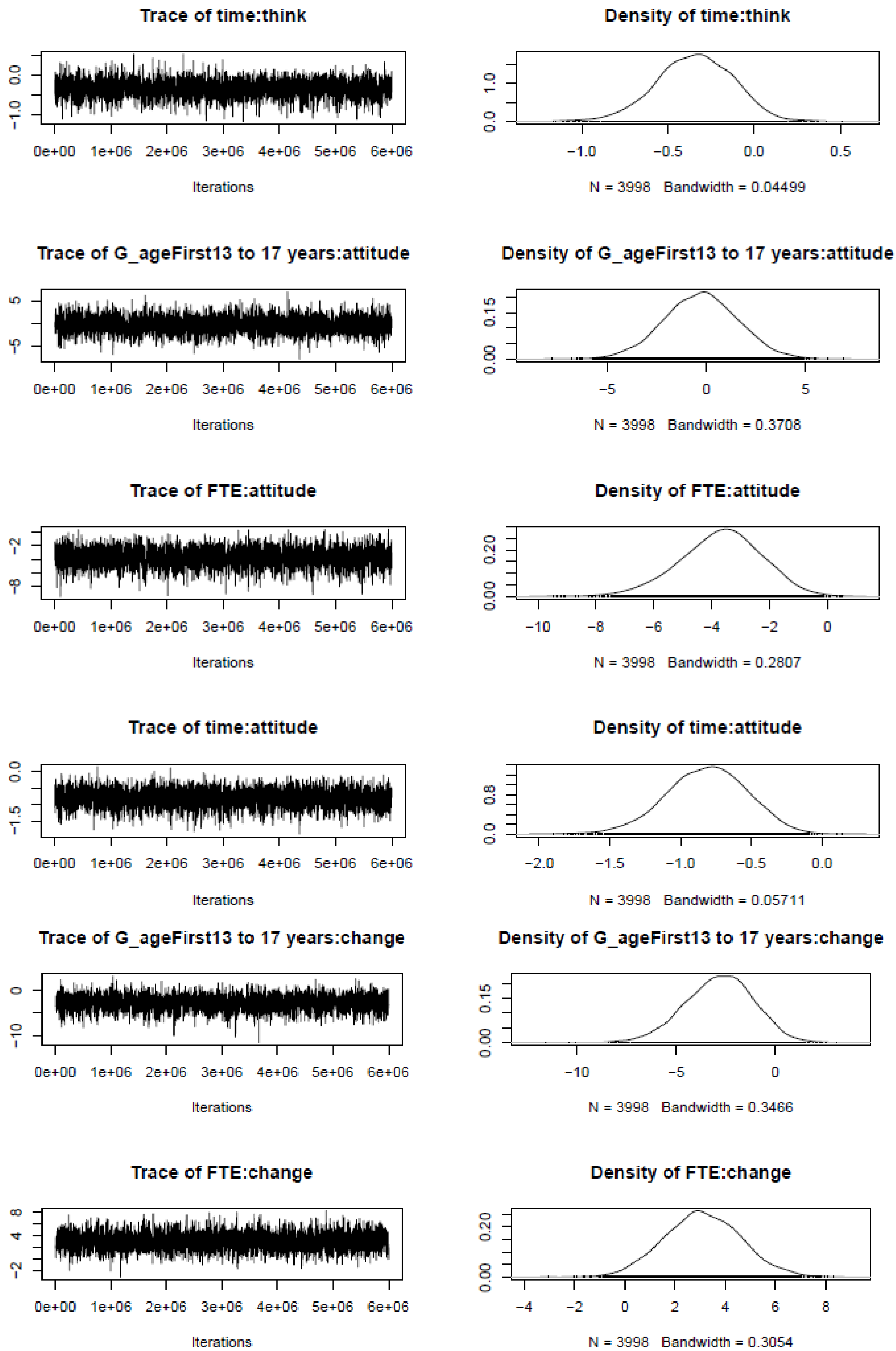

Trace of FTE:time
Iterations
Density of FTE:time
N = 3998 Bandwidth = 234.6
Trace of G_ageFirst13 to 17 years:live
Iterations
Density of G_ageFirst13 to 17 years:live
N = 3998 Bandwidth = 0.2265
Trace of FTE:live
Iterations
Density of FTE:live
N = 3998 Bandwidth = 285
Trace of time:live
Iterations
Density of time:live
N = 3998 Bandwidth = 0.03749
Trace of G_ageFirst13 to 17 years:relation
Iterations
Density of G_ageFirst13 to 17 years:relation
N = 3998 Bandwidth = 0.2833
Trace of FTE:relation
Iterations
Density of FTE:relation
N = 3998 Bandwidth = 0.2746

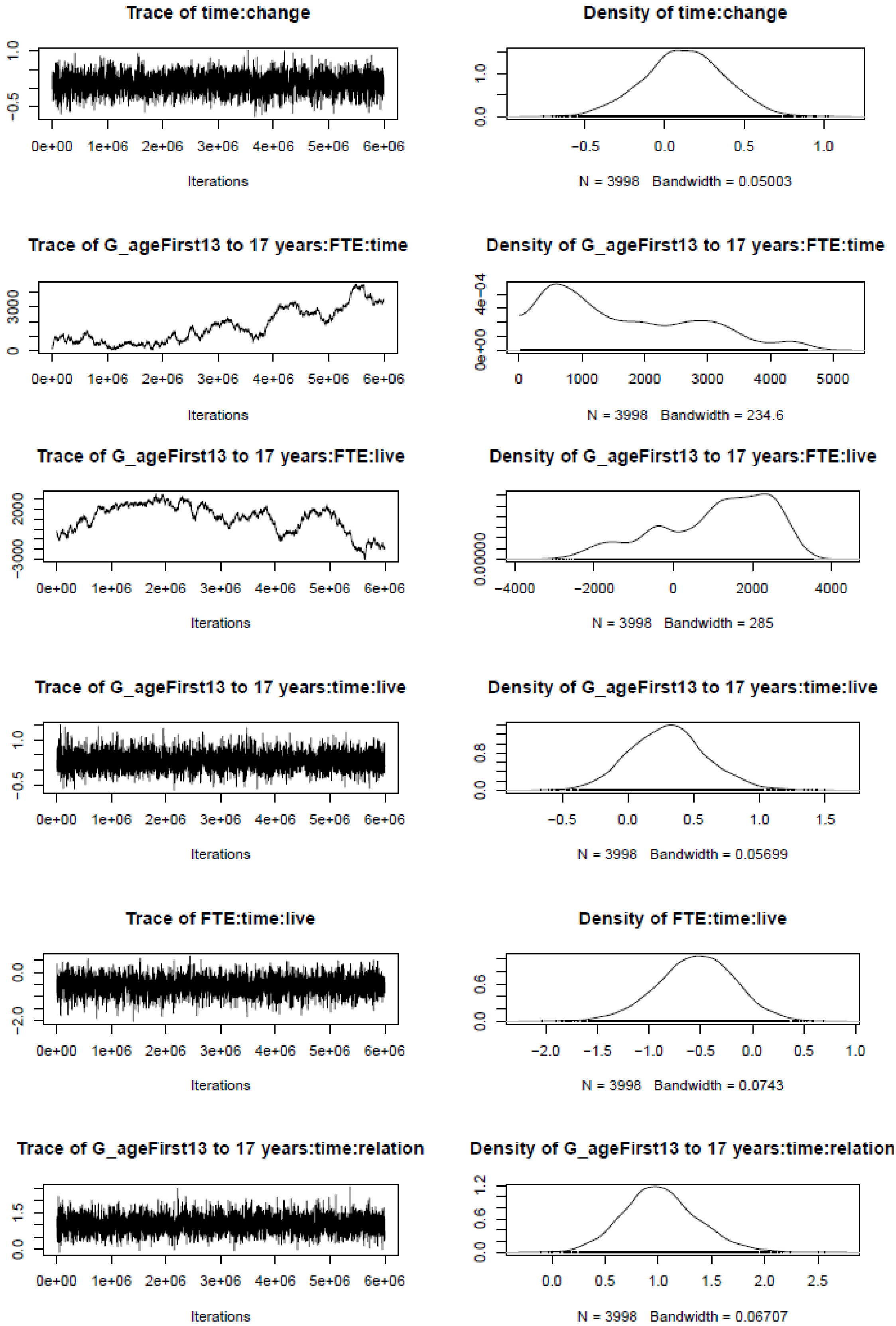

Trace of time:relation
Iterations
Density of time:relation
N = 3998 Bandwidth = 0.05013
Trace of G_ageFirst13 to 17 years:ete
Iterations
Density of G_ageFirst13 to 17 years:ete
N = 3998 Bandwidth = 0.1908
Trace of FTE:ete
Iterations
Density of FTE:ete
N = 3998 Bandwidth = 193.1
Trace of time:ete
Iterations
Density of time:ete
N = 3998 Bandwidth = 0.03256
Trace of G_ageFirst13 to 17 years:where
Iterations
Density of G_ageFirst13 to 17 years:where
N = 3998 Bandwidth = 0.2039
Trace of FTE:where
Iterations
Density of FTE:where
N = 3998 Bandwidth = 280.7

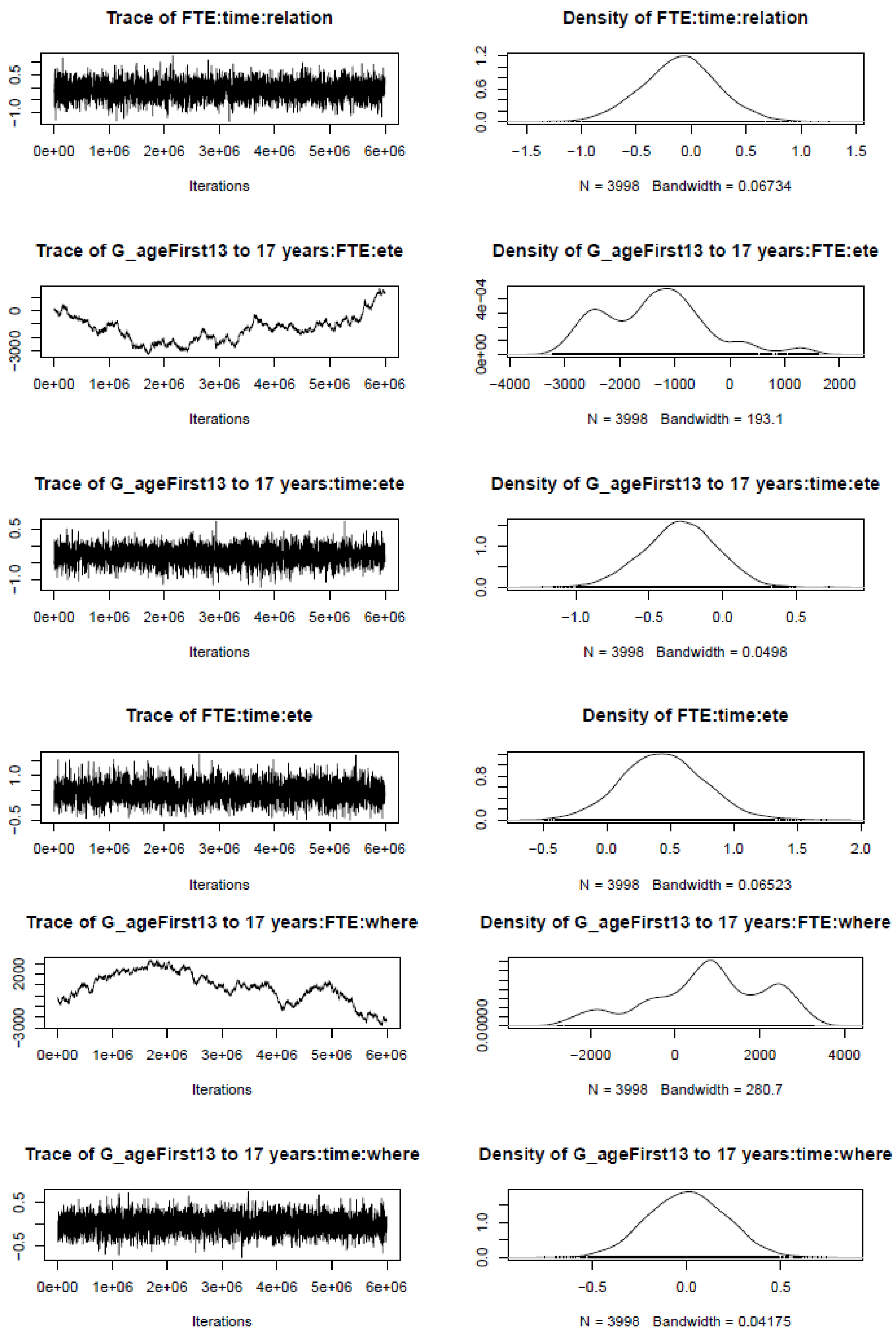

Trace of time:where
Iterations
Density of time:where
N = 3998 Bandwidth = 0.02743
Trace of G_ageFirst13 to 17 years:life
Iterations
Density of G_ageFirst13 to 17 years:life
N = 3998 Bandwidth = 0.3336
Trace of FTE:life
Iterations
Density of FTE:life
N = 3998 Bandwidth = 618.5
Trace of time:life
Iterations
Density of time:life
N = 3998 Bandwidth = 0.05433
Trace of G_ageFirst13 to 17 years:drugs
Iterations
Density of G_ageFirst13 to 17 years:drugs
N = 3998 Bandwidth = 0.2146
Trace of FTE:drugs
Iterations
Density of FTE:drugs
N = 3998 Bandwidth = 0.2531

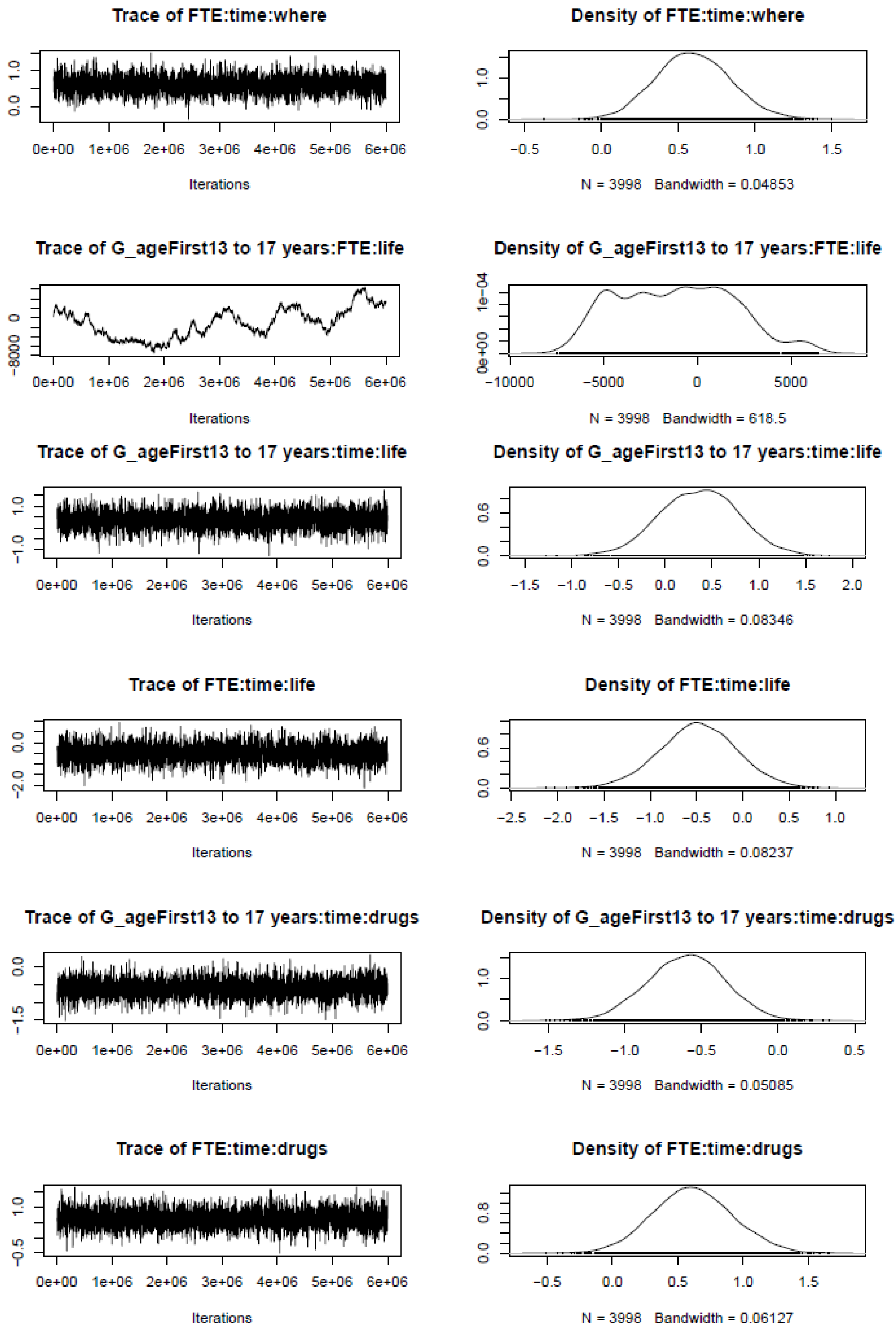

Trace of time:drugs
Iterations
Density of time:drugs
N = 3998 Bandwidth = 0.03355
Trace of G_ageFirst13 to 17 years:physical
Iterations
Density of G_ageFirst13 to 17 years:physical
N = 3998 Bandwidth = 0.2554
Trace of FTE:physical
Iterations
Density of FTE:physical
N = 3998 Bandwidth = 374.5
Trace of time:physical
Iterations
Density of time:physical
N = 3998 Bandwidth = 0.04167
Trace of G_ageFirst13 to 17 years:emotion
Iterations
Density of G_ageFirst13 to 17 years:emotion
N = 3998 Bandwidth = 0.2017
Trace of FTE:emotion
Iterations
Density of FTE:emotion
N = 3998 Bandwidth = 230.3

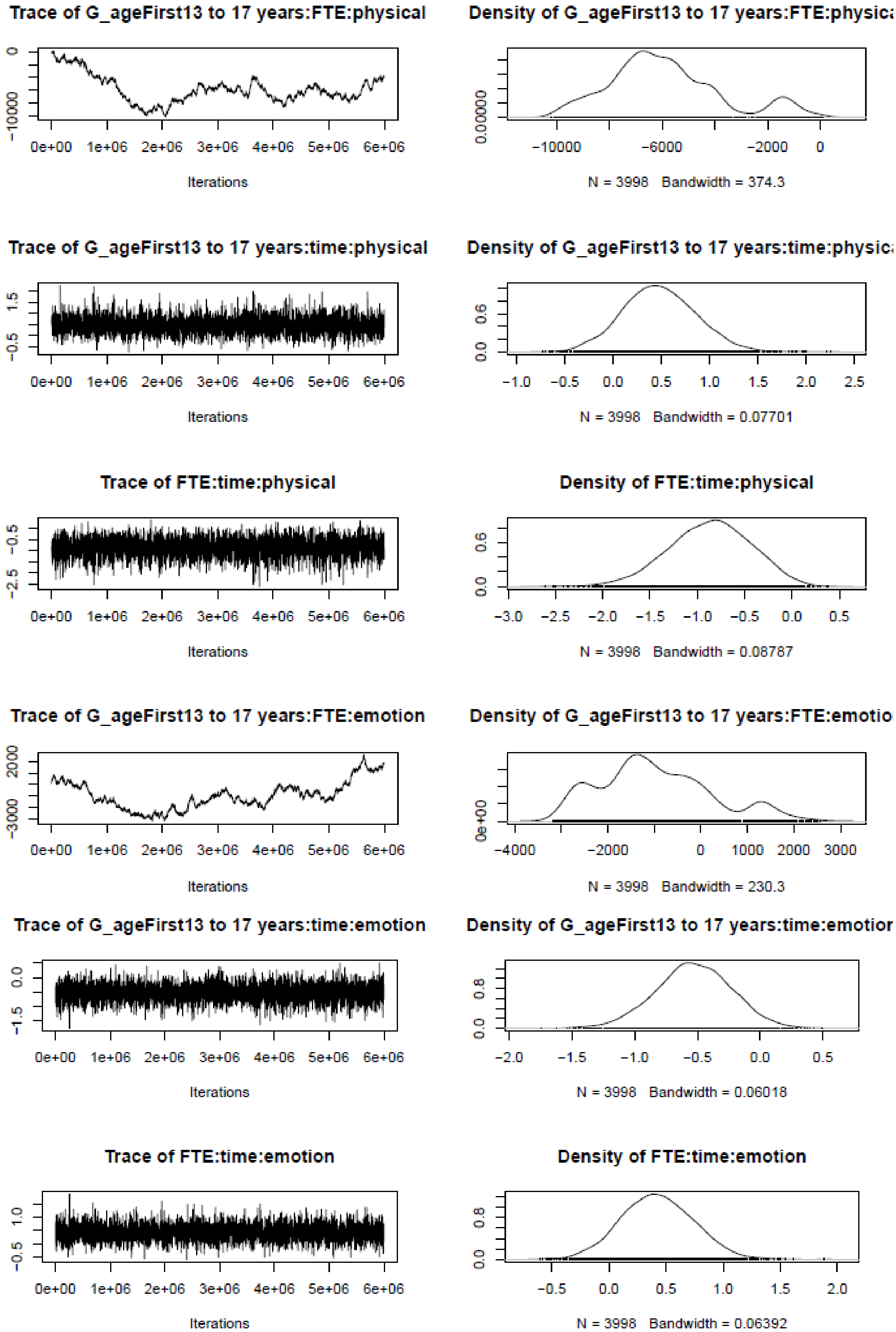

Trace of time:emotion
0.0
0.6
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Iterations
Density of time:emotion
0.0
1.5
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
N = 3998 Bandwidth = 0.03062
Trace of G_ageFirst13 to 17 years:self
5
15
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Iterations
Density of G_ageFirst13 to 17 years:self
0.00
0.15
0
5
10
15
N = 3998 Bandwidth = 0.3936
Trace of FTE:self
−2
4
8
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Iterations
Density of FTE:self
0.00
0.20
−4
−2
0
2
4
6
8
N = 3998 Bandwidth = 0.2834
Trace of time:self
0.5
2.0
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Iterations
Density of time:self
0.0
0.6
0.5
1.0
1.5
2.0
2.5
3.0
N = 3998 Bandwidth = 0.06714
Trace of G_ageFirst13 to 17 years:think
−6
0
4
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Iterations
Density of G_ageFirst13 to 17 years:think
0.00
0.20
−6
−4
−2
0
2
4
6
N = 3998 Bandwidth = 0.2913
Trace of FTE:think
−8
−2
2
0e+00
1e+06
2e+06
3e+06
4e+06
5e+06
6e+06
Iterations
Density of FTE:think
0.00
0.20
−8
−6
−4
−2
0
2
N = 3998 Bandwidth = 0.2653

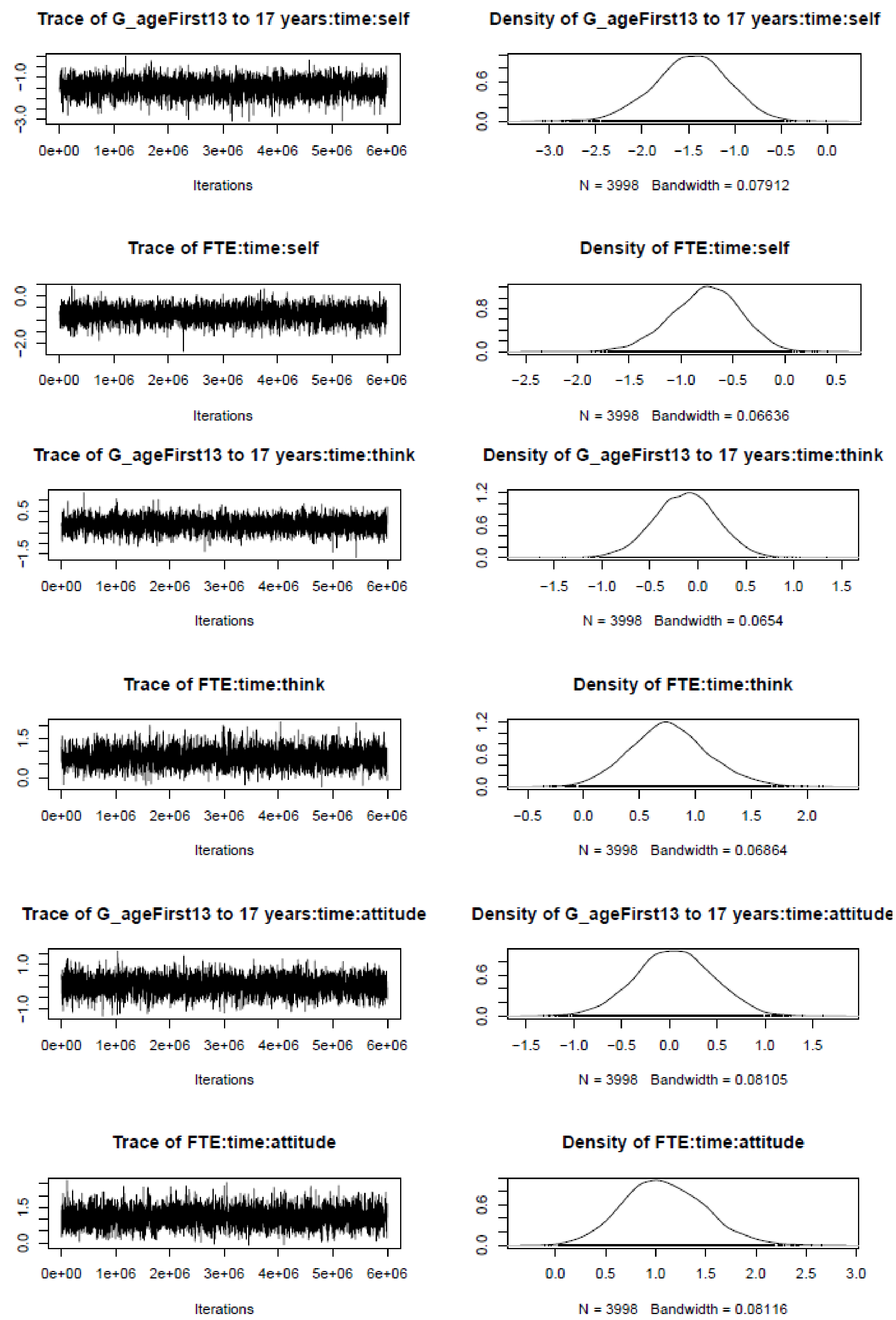

Trace of time:think
Density of time:think
Iterations
N = 3998 Bandwidth = 0.04499
Trace of G_ageFirst13 to 17 years:attitude
Density of G_ageFirst13 to 17 years:attitude
Iterations
N = 3998 Bandwidth = 0.3708
Trace of FTE:attitude
Density of FTE:attitude
Iterations
N = 3998 Bandwidth = 0.2807
Trace of time:attitude
Density of time:attitude
Iterations
N = 3998 Bandwidth = 0.05711
Trace of G_ageFirst13 to 17 years:change
Density of G_ageFirst13 to 17 years:change
Iterations
N = 3998 Bandwidth = 0.3466
Trace of FTE:change
Density of FTE:change
Iterations
N = 3998 Bandwidth = 0.3054

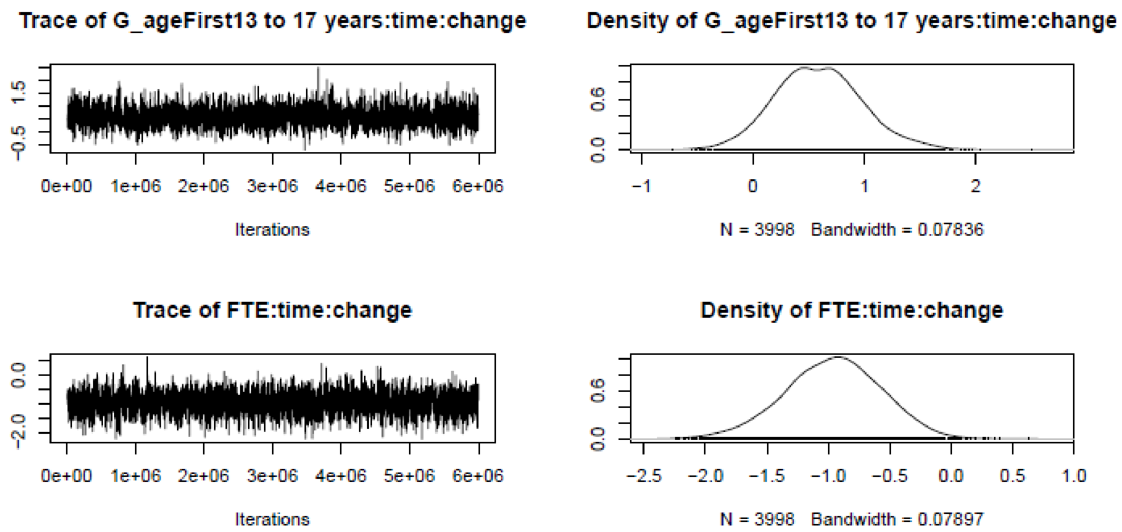

Trace of time:change
Iterations
Density of time:change
N = 3998 Bandwidth = 0.05003
Trace of G_ageFirst13 to 17 years:FTE:time
Iterations
Density of G_ageFirst13 to 17 years:FTE:time
N = 3998 Bandwidth = 234.6
Trace of G_ageFirst13 to 17 years:FTE:live
Iterations
Density of G_ageFirst13 to 17 years:FTE:live
N = 3998 Bandwidth = 285
Trace of G_ageFirst13 to 17 years:time:live
Iterations
Density of G_ageFirst13 to 17 years:time:live
N = 3998 Bandwidth = 0.05699
Trace of FTE:time:live
Iterations
Density of FTE:time:live
N = 3998 Bandwidth = 0.0743
Trace of G_ageFirst13 to 17 years:time:relation
Iterations
Density of G_ageFirst13 to 17 years:time:relation
N = 3998 Bandwidth = 0.06707


Trace of FTE:time:relation
Iterations
Density of FTE:time:relation
N = 3998 Bandwidth = 0.06734
Trace of G_ageFirst13 to 17 years:FTE:ete
Iterations
Density of G_ageFirst13 to 17 years:FTE:ete
N = 3998 Bandwidth = 193.1
Trace of G_ageFirst13 to 17 years:time:ete
Iterations
Density of G_ageFirst13 to 17 years:time:ete
N = 3998 Bandwidth = 0.0498
Trace of FTE:time:ete
Iterations
Density of FTE:time:ete
N = 3998 Bandwidth = 0.06523
Trace of G_ageFirst13 to 17 years:FTE:where
Iterations
Density of G_ageFirst13 to 17 years:FTE:where
N = 3998 Bandwidth = 280.7
Trace of G_ageFirst13 to 17 years:time:where
Iterations
Density of G_ageFirst13 to 17 years:time:where
N = 3998 Bandwidth = 0.04175

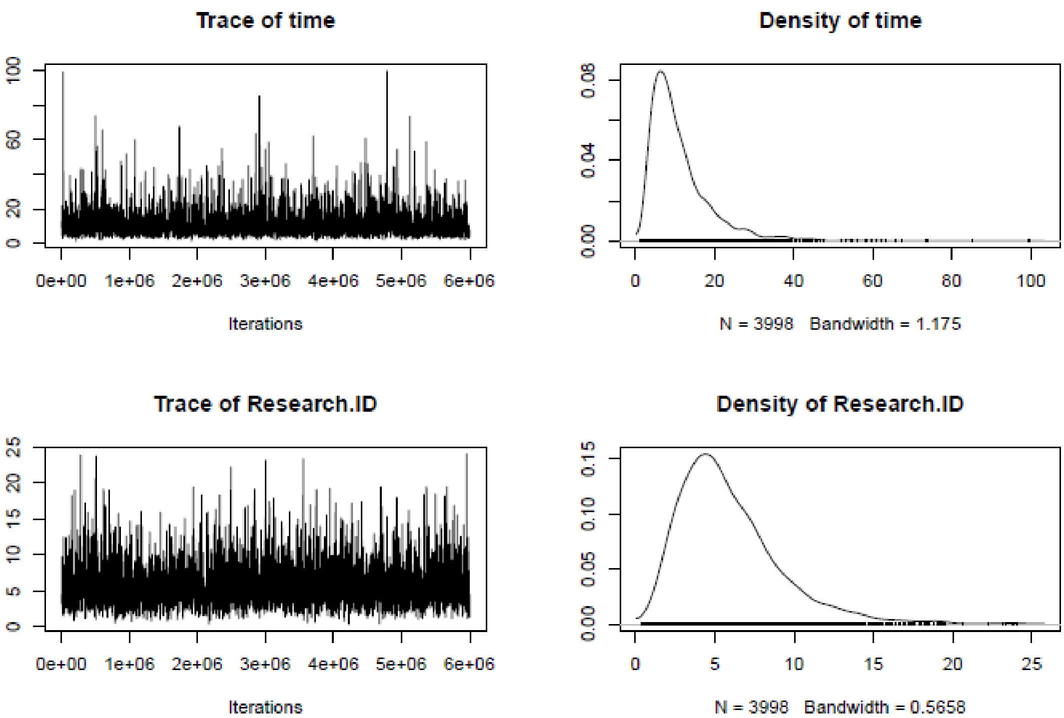

Trace of FTE:time:where
Iterations
Density of FTE:time:where
N = 3998 Bandwidth = 0.04853
Trace of G_ageFirst13 to 17 years:FTE:life
Iterations
Density of G_ageFirst13 to 17 years:FTE:life
N = 3998 Bandwidth = 618.5
Trace of G_ageFirst13 to 17 years:time:life
Iterations
Density of G_ageFirst13 to 17 years:time:life
N = 3998 Bandwidth = 0.08346
Trace of FTE:time:life
Iterations
Density of FTE:time:life
N = 3998 Bandwidth = 0.08237
Trace of G_ageFirst13 to 17 years:time:drugs
Iterations
Density of G_ageFirst13 to 17 years:time:drugs
N = 3998 Bandwidth = 0.05085
Trace of FTE:time:drugs
Iterations
Density of FTE:time:drugs
N = 3998 Bandwidth = 0.06127


Trace of G_ageFirst13 to 17 years:FTE:physical
Iterations
Density of G_ageFirst13 to 17 years:FTE:physic
N = 3998 Bandwidth = 374.3
Trace of G_ageFirst13 to 17 years:time:physical
Iterations
Density of G_ageFirst13 to 17 years:time:physic
N = 3998 Bandwidth = 0.07701
Trace of FTE:time:physical
Iterations
Density of FTE:time:physical
N = 3998 Bandwidth = 0.08787
Trace of G_ageFirst13 to 17 years:FTE:emotion
Iterations
Density of G_ageFirst13 to 17 years:FTE:emotio
N = 3998 Bandwidth = 230.3
Trace of G_ageFirst13 to 17 years:time:emotion
Iterations
Density of G_ageFirst13 to 17 years:time:emotior
N = 3998 Bandwidth = 0.06018
Trace of FTE:time:emotion
Iterations
Density of FTE:time:emotion
N = 3998 Bandwidth = 0.06392


Trace of G_ageFirst13 to 17 years:time:self
Iterations
Density of G_ageFirst13 to 17 years:time:self
N = 3998 Bandwidth = 0.07912
Trace of FTE:time:self
Iterations
Density of FTE:time:self
N = 3998 Bandwidth = 0.06636
Trace of G_ageFirst13 to 17 years:time:think
Iterations
Density of G_ageFirst13 to 17 years:time:think
N = 3998 Bandwidth = 0.0654
Trace of FTE:time:think
Iterations
Density of FTE:time:think
N = 3998 Bandwidth = 0.06864
Trace of G_ageFirst13 to 17 years:time:attitude
Iterations
Density of G_ageFirst13 to 17 years:time:attitude
N = 3998 Bandwidth = 0.08105
Trace of FTE:time:attitude
Iterations
Density of FTE:time:attitude
N = 3998 Bandwidth = 0.08116



Random Effects



The Combined Model involving Offending History: Version 2b

Bayesian Model (BDm3G_cc1o2a)

Define the Model

```
BDm3_cc1o2a <- MCMCglmm(FO.bin~FTE*time*live + FTE*time*relation +
FTE*time*ete + FTE*time*where + FTE*time*life + FTE*time*drugs +
FTE*time*physical + FTE*time*emotion + FTE*time*self +
FTE*time*think + FTE*time*attitude + FTE*time*change +
I_Seriousness2*time*live + I_Seriousness2*time*relation +
I_Seriousness2*time*ete + I_Seriousness2*time*where +
I_Seriousness2*time*life + I_Seriousness2*time*drugs +
I_Seriousness2*time*physical + I_Seriousness2*time*emotion +
I_Seriousness2*time*self + I_Seriousness2*time*think +
I_Seriousness2*time*attitude + I_Seriousness2*time*change +
FTE*I_Seriousness2, random=~time+Research.ID, data=data3,
family="ordinal", prior=priorD,nitt=4500000, thin=1000, burnin=3000)
```

Checks for suitable convergence

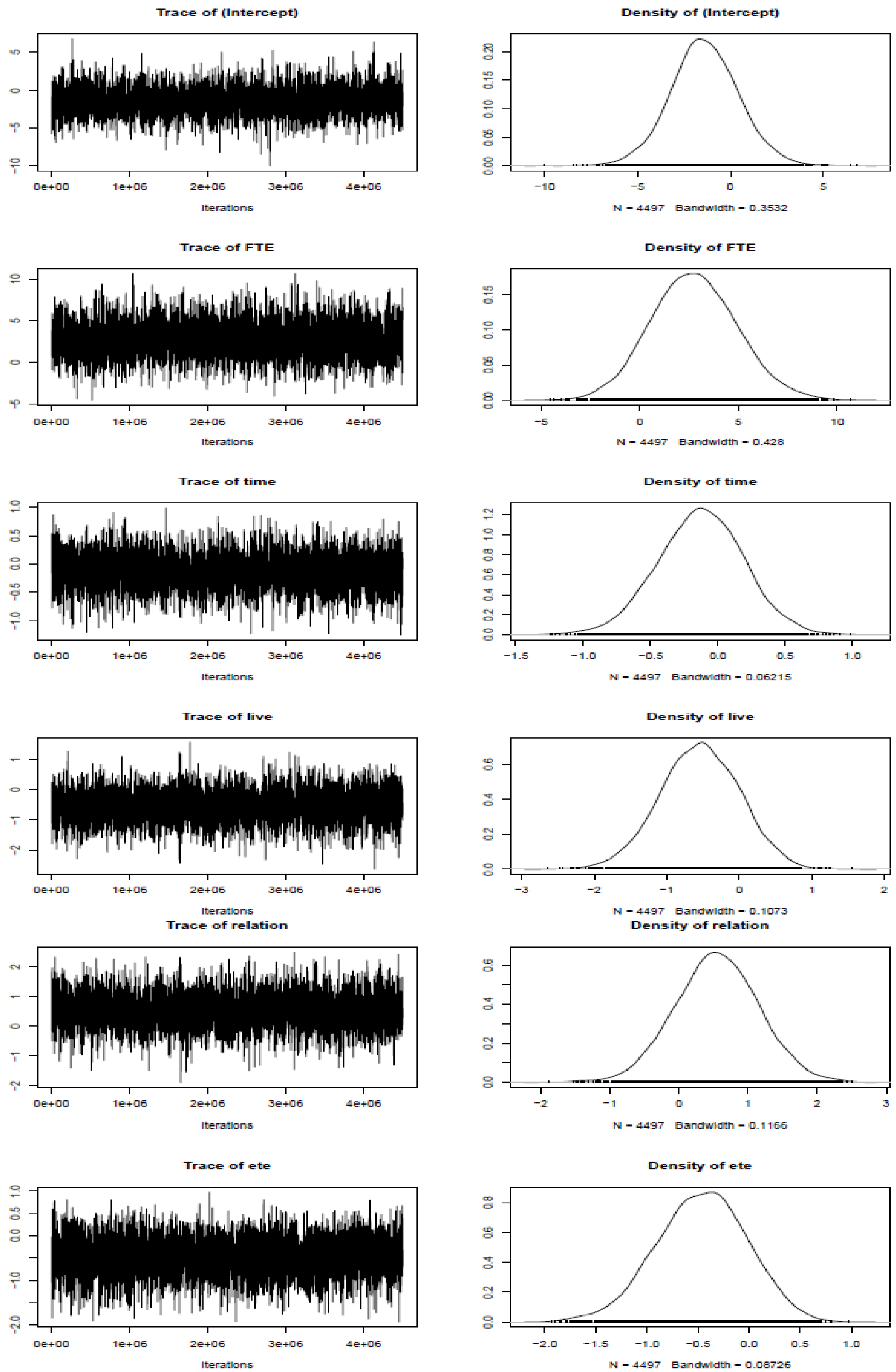
```
raftery.diag(BDm3_cc1o2a$VCV)
heidel.diag(BDm3_cc1o2a$VCV)

# > raftery.diag(BDm3_cc1o2a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total   Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# time         2000     3918000 3746         1050
# Research.ID  2000     3710000 3746          990
# units        <NA>     <NA>    3746           NA
#
# > heidel.diag(BDm3_cc1o2a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.195
# Research.ID  passed        1        0.246
# units        failed       NA           NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    6.41 0.1930
# Research.ID  passed    3.52 0.0669
# units        <NA>        NA     NA

autocorr(BDm3_cc1o2a$VCV)
autocorr(BDm3_cc1o2a$Sol)   # not included here
summary(BDm3_cc1o2a)
```

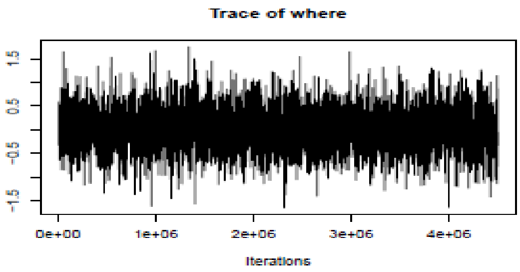
```
# > autocorr(BDm3_cc1o2a$VCV)
# , , time
#
#                  time   Research.ID units
# Lag 0     1.00000000  0.2655765954   NaN
# Lag 1000  0.12543179  0.0852781985   NaN
# Lag 5000  0.03636260 -0.0009314978   NaN
# Lag 10000 0.01275812  0.0178013003   NaN
# Lag 50000 0.01116559  0.0143540097   NaN
#
# , , Research.ID
#
#                    time Research.ID units
# Lag 0      0.265576595 1.000000000   NaN
# Lag 1000   0.077014038 0.146761169   NaN
# Lag 5000   0.007185990 0.003276287   NaN
# Lag 10000 -0.003770812 0.016470959   NaN
# Lag 50000  0.010617757 0.026723732   NaN

# > summary(BDm3_cc1o2a)
#
# Iterations = 3001:4499001
# Thinning interval  = 1000
# Sample size  = 4497
#
# DIC: 432.8018
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     6.411   0.8444    14.46     1835
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID     3.516   0.3999    7.399     3345
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ FTE * time * live + FTE * time * relation + FTE * time
* ete + FTE * time * where + FTE * time * life + FTE * time * drugs + FTE * time *
physical + FTE * time * emotion + FTE * time * self + FTE * time * think + FTE *
time * attitude + FTE * time * change + I_Seriousness2 * time * live +
I_Seriousness2 * time * relation + I_Seriousness2 * time * ete + I_Seriousness2 *
time * where + I_Seriousness2 * time * life + I_Seriousness2 * time * drugs +
I_Seriousness2 * time * physical + I_Seriousness2 * time * emotion + I_Seriousness2
* time * self + I_Seriousness2 * time * think + I_Seriousness2 * time * attitude +
I_Seriousness2 * time * change + FTE * I_Seriousness2
#
#                           post.mean  l-95% CI  u-95% CI eff.samp    pMCMC
# (Intercept)               -1.382300 -4.833474  2.494213     4497 0.443851
# FTE                        2.748099 -1.608198  6.993117     4497 0.199244
# time                      -0.129602 -0.807832  0.452541     4497 0.692906
# live                      -0.542898 -1.592684  0.520890     4497 0.323771
# relation                   0.548669 -0.559609  1.771618     4497 0.361574
# ete                       -0.466017 -1.325266  0.390343     4497 0.290861
# where                      0.018254 -0.868579  0.919770     4497 0.960196
# life                       0.400091 -1.289867  2.018508     4497 0.638648
# drugs                     -0.206436 -1.294152  0.769899     4497 0.703135
# physical                  -0.381602 -1.434258  0.747978     4497 0.482099
# emotion                    0.086101 -0.811179  1.013282     4497 0.853013
```

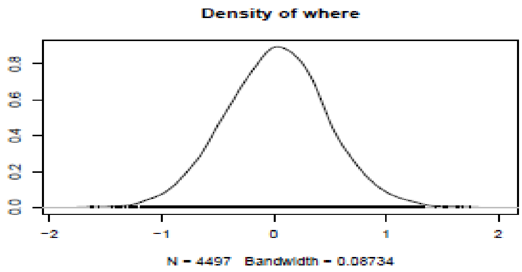
```
# self                          -0.342930 -1.925782  1.066532     4497 0.646209
# think                          0.216209 -1.005404  1.498252     4235 0.736936
# attitude                       0.238029 -1.342149  1.561904     4497 0.733378
# change                         1.223136 -0.242999  2.738791     4497 0.096064 .
# I_Seriousness2                -2.253587 -4.370716 -0.048567     4049 0.027129 *
# FTE:time                      -1.660161 -2.842567 -0.585947     4097 0.001334 **
# FTE:live                       1.135370 -0.975041  3.189806     4497 0.267289
# time:live                      0.104465 -0.131132  0.321750     4497 0.357572
# FTE:relation                  -2.358624 -4.491019 -0.394325     4118 0.021792 *
# time:relation                  0.089489 -0.228527  0.401815     4497 0.585724
# FTE:ete                        0.247655 -1.489445  2.016588     4169 0.788970
# time:ete                       0.025860 -0.182562  0.245143     4497 0.814765
# FTE:where                     -3.055754 -5.234707 -1.165322     4025 0.000445 ***
# time:where                     0.126564 -0.046067  0.314463     4497 0.169002
# FTE:life                       1.907104 -0.732942  4.403817     4276 0.131199
# time:life                     -0.016182 -0.354350  0.348589     4741 0.913943
# FTE:drugs                     -0.965043 -2.807518  0.961111     4497 0.301090
# time:drugs                     0.015186 -0.230314  0.252018     4310 0.925951
# FTE:physical                  -0.707541 -2.961240  1.375536     4497 0.511007
# time:physical                  0.068348 -0.255334  0.357237     4993 0.640872
# FTE:emotion                   -1.537741 -3.216871  0.010309     3804 0.048922 *
# time:emotion                  -0.253510 -0.517977  0.001654     4497 0.048477 *
# FTE:self                       3.475428  1.239732  5.661227     4497 0.000889 ***
# time:self                      0.075353 -0.217569  0.356569     4497 0.619969
# FTE:think                     -0.634879 -2.831293  1.265667     4072 0.545697
# time:think                     0.025417 -0.260386  0.308615     4240 0.841450
# FTE:attitude                  -1.436785 -3.241776  0.749092     4746 0.149433
# time:attitude                 -0.079201 -0.383948  0.247747     4497 0.620414
# FTE:change                     1.643750 -0.807792  3.701927     4497 0.145875
# time:change                   -0.277032 -0.599596  0.023732     4497 0.079609 .
# time:I_Seriousness2            0.257480 -0.152208  0.646677     4497 0.194352
# live:I_Seriousness2            0.162427 -0.437151  0.820362     4497 0.604848
# relation:I_Seriousness2        0.542614 -0.137583  1.338979     4178 0.137870
# ete:I_Seriousness2             0.038391 -0.511244  0.540541     4368 0.879253
# where:I_Seriousness2           0.340200 -0.181482  0.930463     4497 0.226373
# life:I_Seriousness2            0.056096 -0.844746  0.965582     4497 0.902824
# drugs:I_Seriousness2           0.462739 -0.198586  1.102590     4085 0.146320
# physical:I_Seriousness2       -0.061651 -0.875632  0.688354     4497 0.869913
# emotion:I_Seriousness2         0.282737 -0.306169  0.868801     4771 0.354459
# self:I_Seriousness2           -0.120144 -0.829189  0.640971     4497 0.720036
# think:I_Seriousness2          -0.047151 -0.928193  0.736806     4257 0.917056
# attitude:I_Seriousness2        0.253458 -0.539994  1.003869     4801 0.512342
# change:I_Seriousness2         -1.090915 -2.070497 -0.104056     4085 0.023571 *
# FTE:I_Seriousness2             1.210039 -0.034627  2.557973     4251 0.051145 .
# FTE:time:live                 -0.263340 -0.751909  0.230959     4127 0.293529
# FTE:time:relation              0.584765  0.123945  1.094246     4079 0.016900 *
# FTE:time:ete                   0.419638 -0.126208  0.928547     4230 0.112519
# FTE:time:where                 0.436195  0.024574  0.806203     4498 0.018679 *
# FTE:time:life                 -0.663469 -1.266730 -0.054756     4049 0.026684 *
# FTE:time:drugs                 0.375388 -0.071661  0.827867     3537 0.097398 .
# FTE:time:physical             -0.013302 -0.560279  0.540833     4855 0.994441
# FTE:time:emotion               0.331637 -0.044422  0.740836     4497 0.087169 .
# FTE:time:self                 -0.937199 -1.491810 -0.440383     4267  < 2e-04 ***
# FTE:time:think                 0.305740 -0.134129  0.763320     4293 0.171670
# FTE:time:attitude              0.372506 -0.153163  0.898032     4497 0.167223
# FTE:time:change               -0.362468 -0.918849  0.190889     4965 0.192128
# time:live:I_Seriousness2       0.004346 -0.133557  0.153397     4497 0.964643
# time:relation:I_Seriousness2 -0.231991 -0.414573 -0.041742     4176 0.005337 **
# time:ete:I_Seriousness2        0.030451 -0.116756  0.164473     4497 0.676451
# time:where:I_Seriousness2     -0.162123 -0.302361 -0.024723     4497 0.014232 *
# time:life:I_Seriousness2       0.005614 -0.184254  0.206578     4497 0.956638
# time:drugs:I_Seriousness2     -0.073027 -0.211623  0.056374     4086 0.283745
# time:physical:I_Seriousness2  0.055819 -0.159365  0.274706     4240 0.616411
# time:emotion:I_Seriousness2    0.153052  0.006180  0.293244     4497 0.032911 *
# time:self:I_Seriousness2       0.019499 -0.155689  0.178772     4497 0.809873
# time:think:I_Seriousness2     -0.052948 -0.229350  0.131690     4237 0.557260
# time:attitude:I_Seriousness2 -0.065910 -0.261099  0.136127     4497 0.521681
# time:change:I_Seriousness2     0.251913  0.062418  0.454085     4497 0.008450 **
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

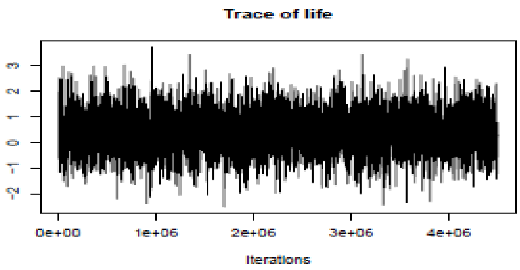
Trace Plots and Posterior Density Plots

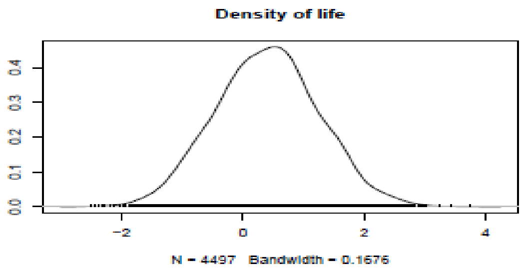
Fixed Effects

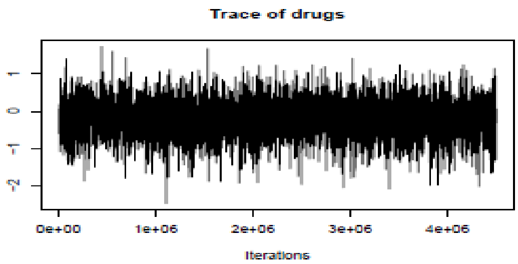


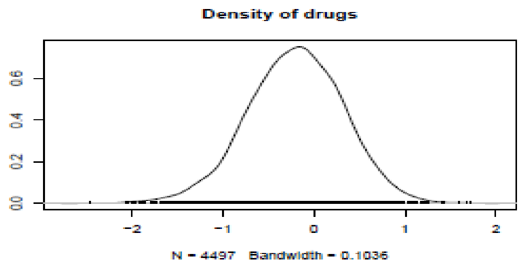

Trace of where
Iterations

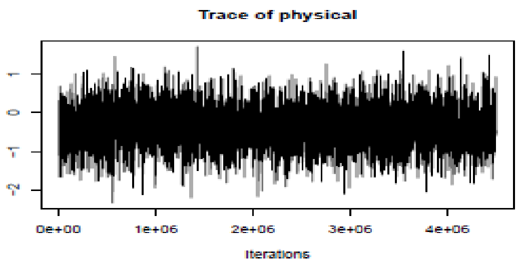

Density of where
N = 4497   Bandwidth = 0.08734

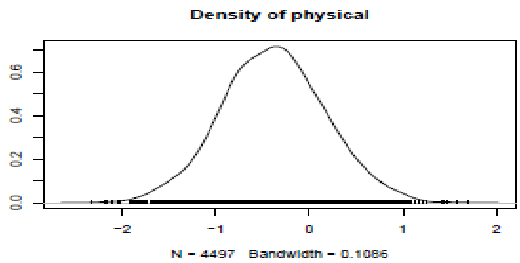

Trace of life
Iterations

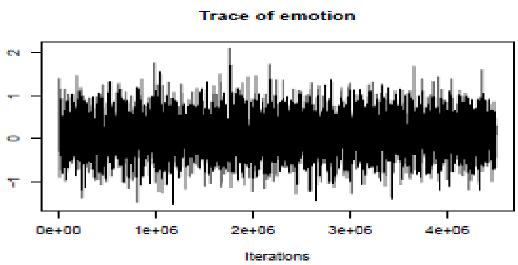

Density of life
N = 4497   Bandwidth = 0.1676

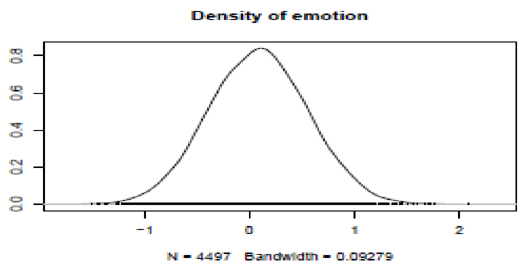

Trace of drugs
Iterations


Density of drugs
N = 4497   Bandwidth = 0.1036

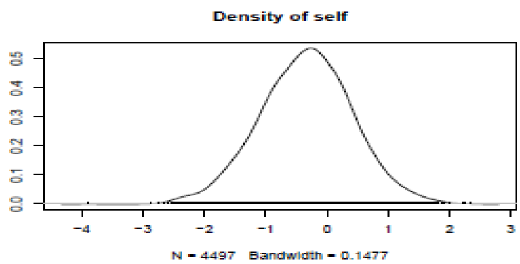

Trace of physical
Iterations

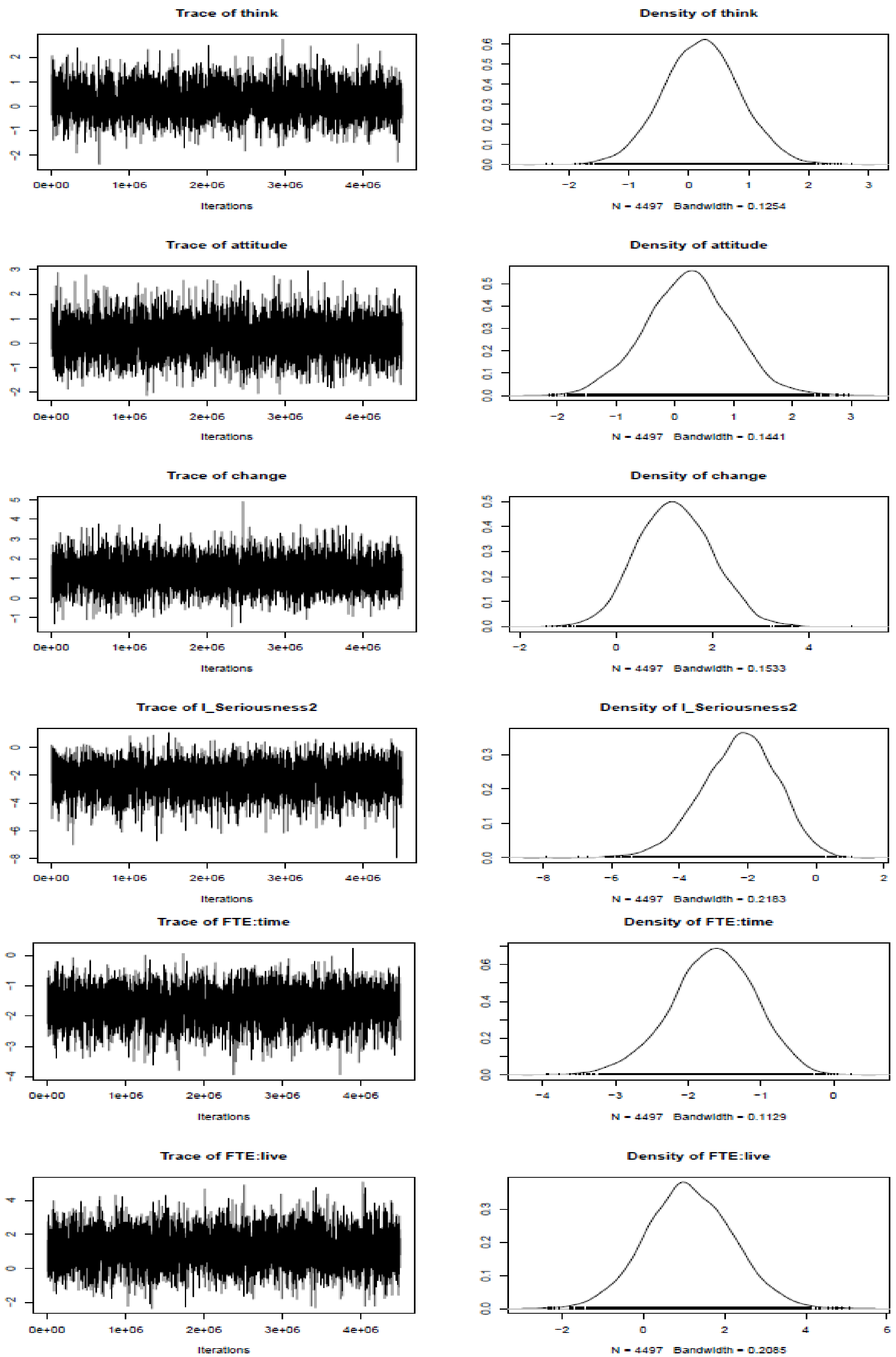

Density of physical
N = 4497   Bandwidth = 0.1066

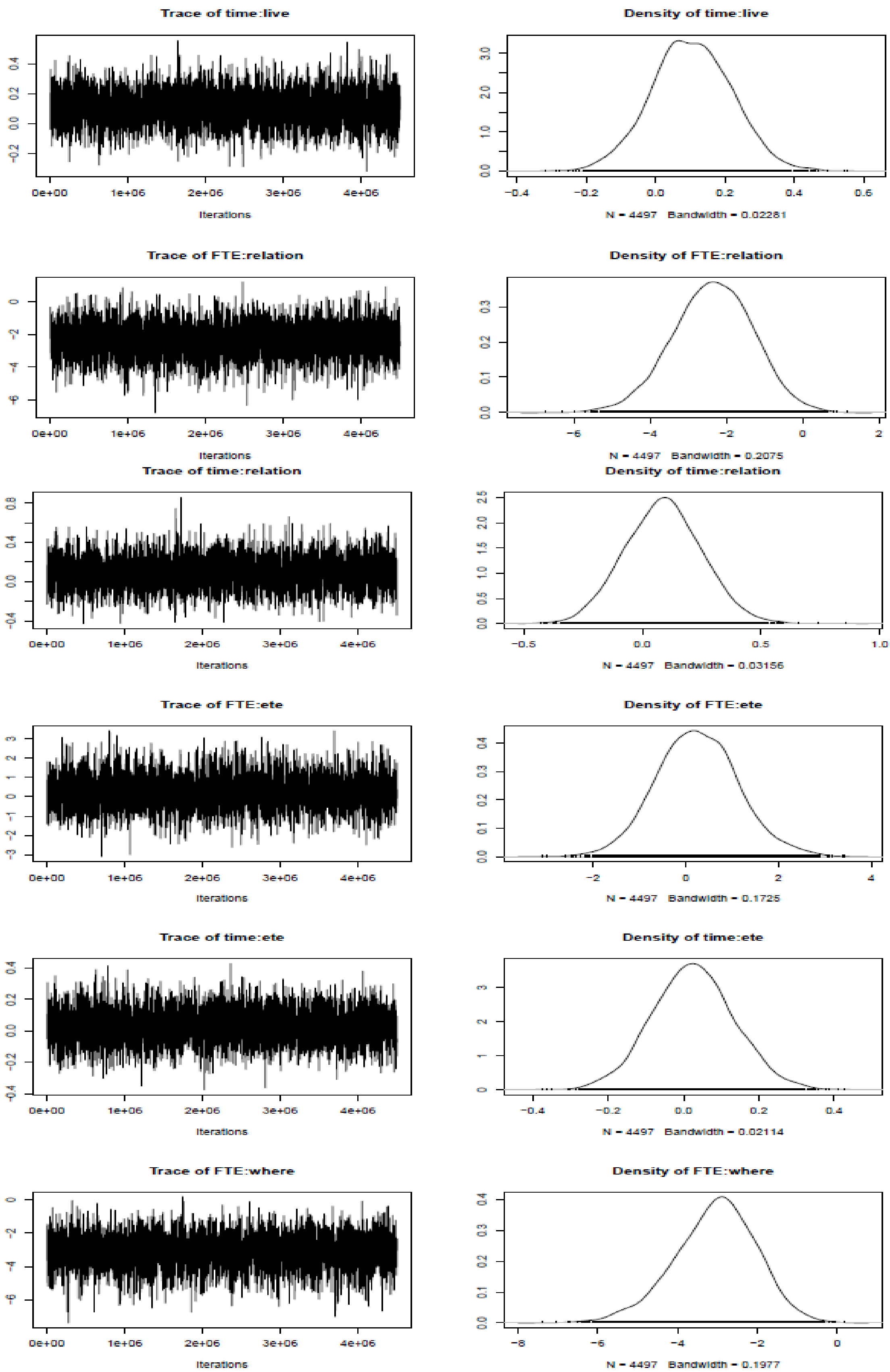

Trace of emotion
Iterations

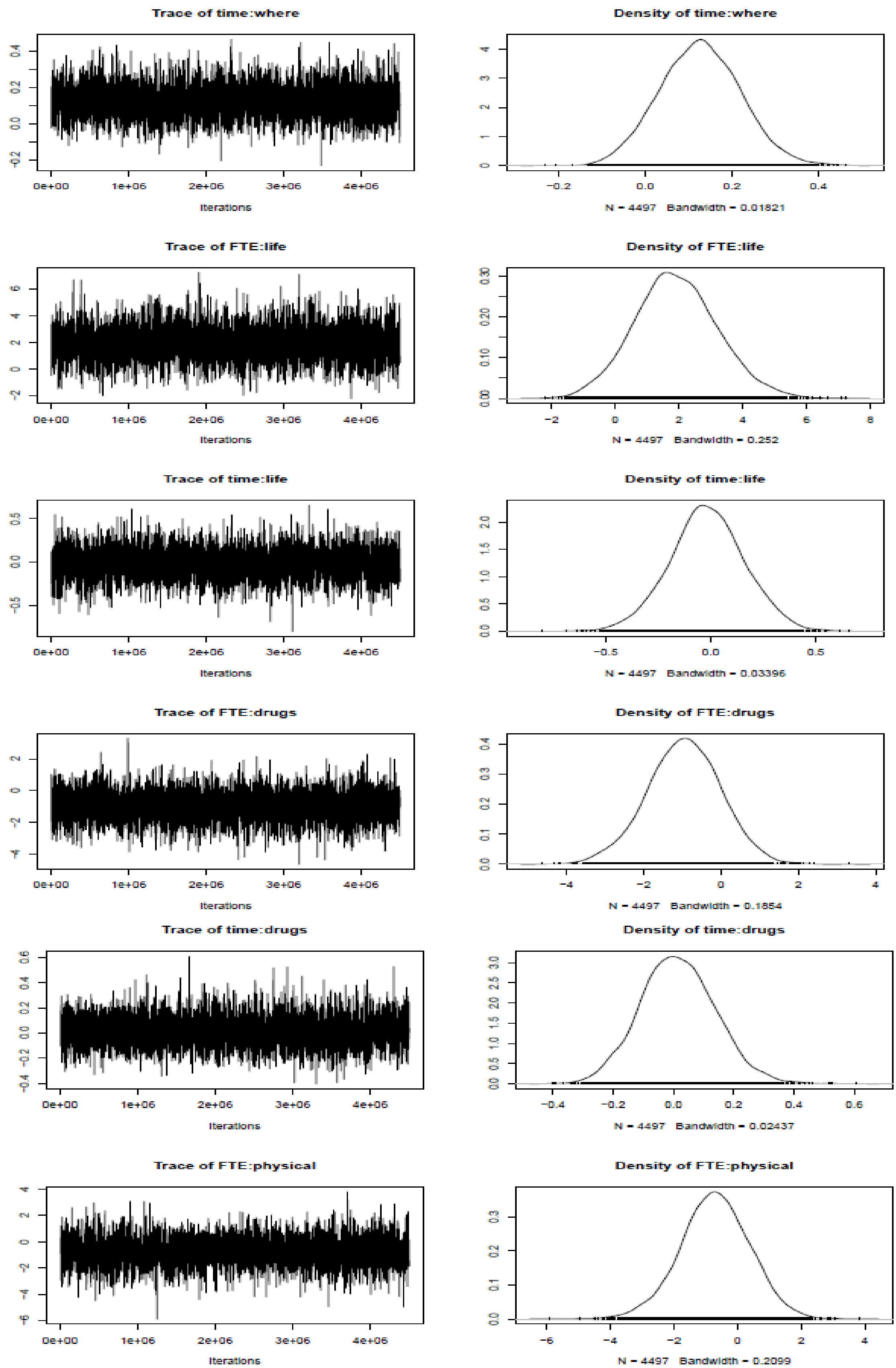

Density of emotion
N = 4497   Bandwidth = 0.09279

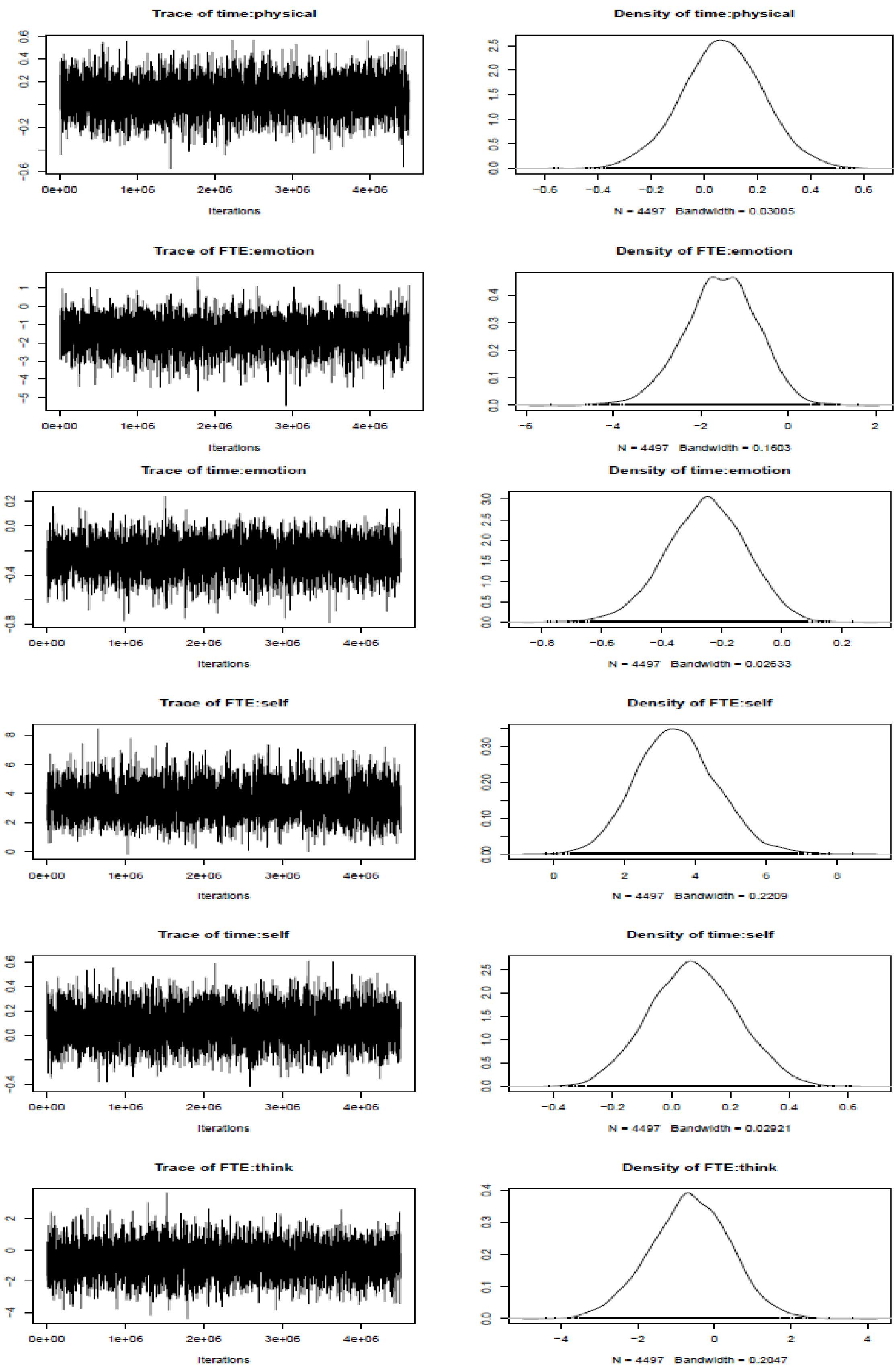

Trace of self
Iterations

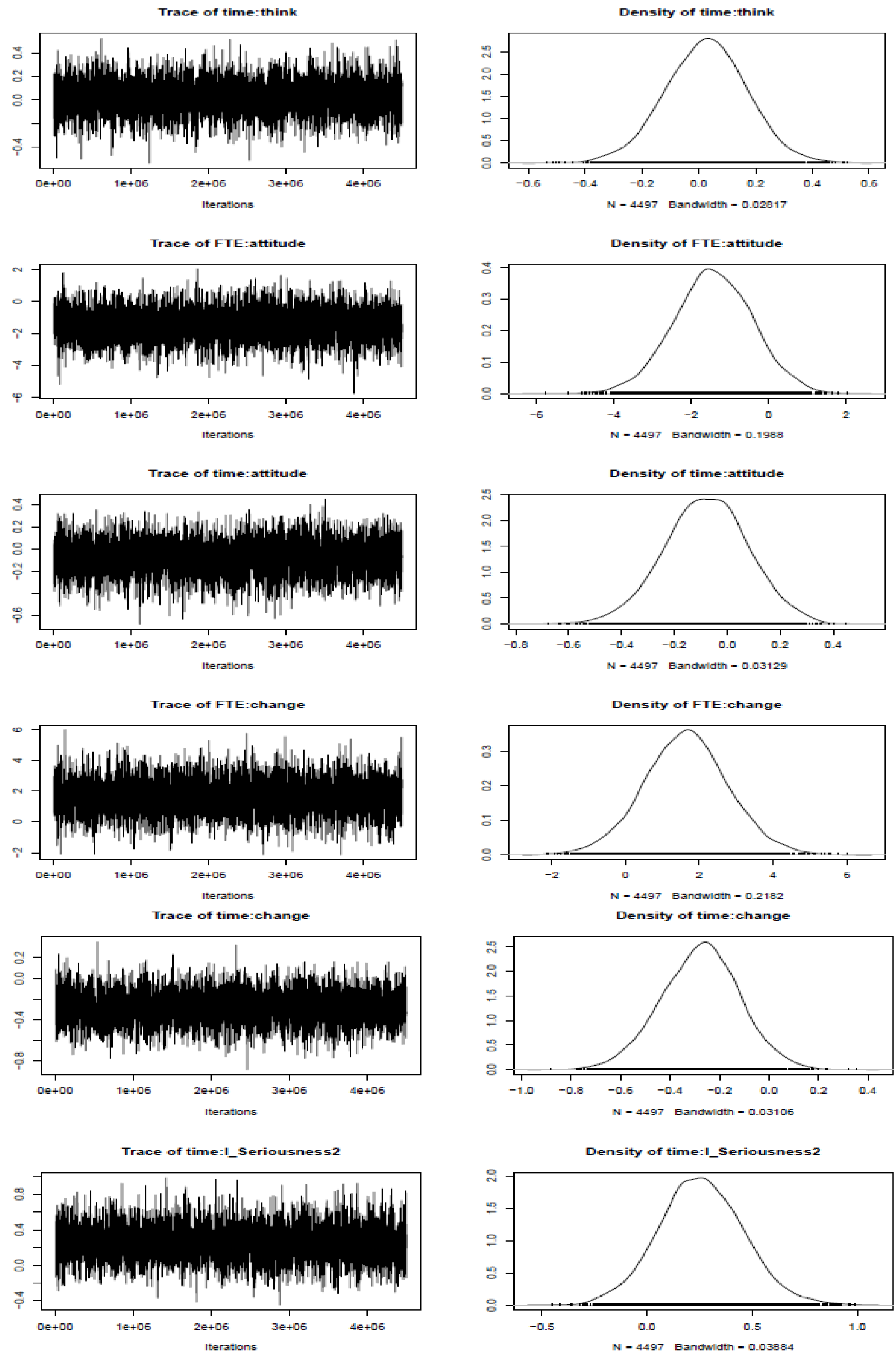

Density of self
N = 4497   Bandwidth = 0.1477

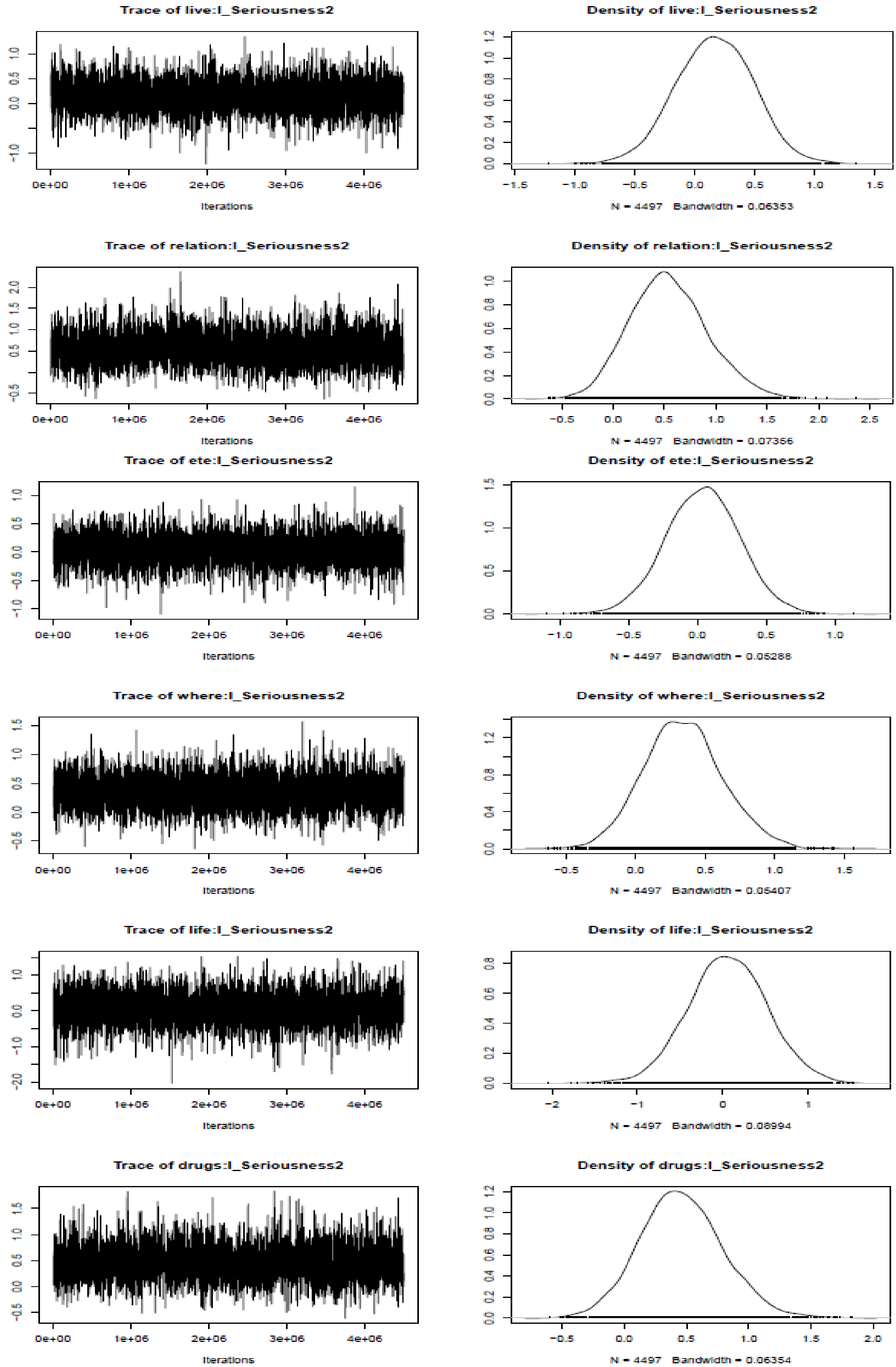

Trace of think
Density of think
Iterations
N = 4497 Bandwidth = 0.1254
Trace of attitude
Density of attitude
Iterations
N = 4497 Bandwidth = 0.1441
Trace of change
Density of change
Iterations
N = 4497 Bandwidth = 0.1533
Trace of I_Seriousness2
Density of I_Seriousness2
Iterations
N = 4497 Bandwidth = 0.2163
Trace of FTE:time
Density of FTE:time
Iterations
N = 4497 Bandwidth = 0.1129
Trace of FTE:live
Density of FTE:live
Iterations
N = 4497 Bandwidth = 0.2085

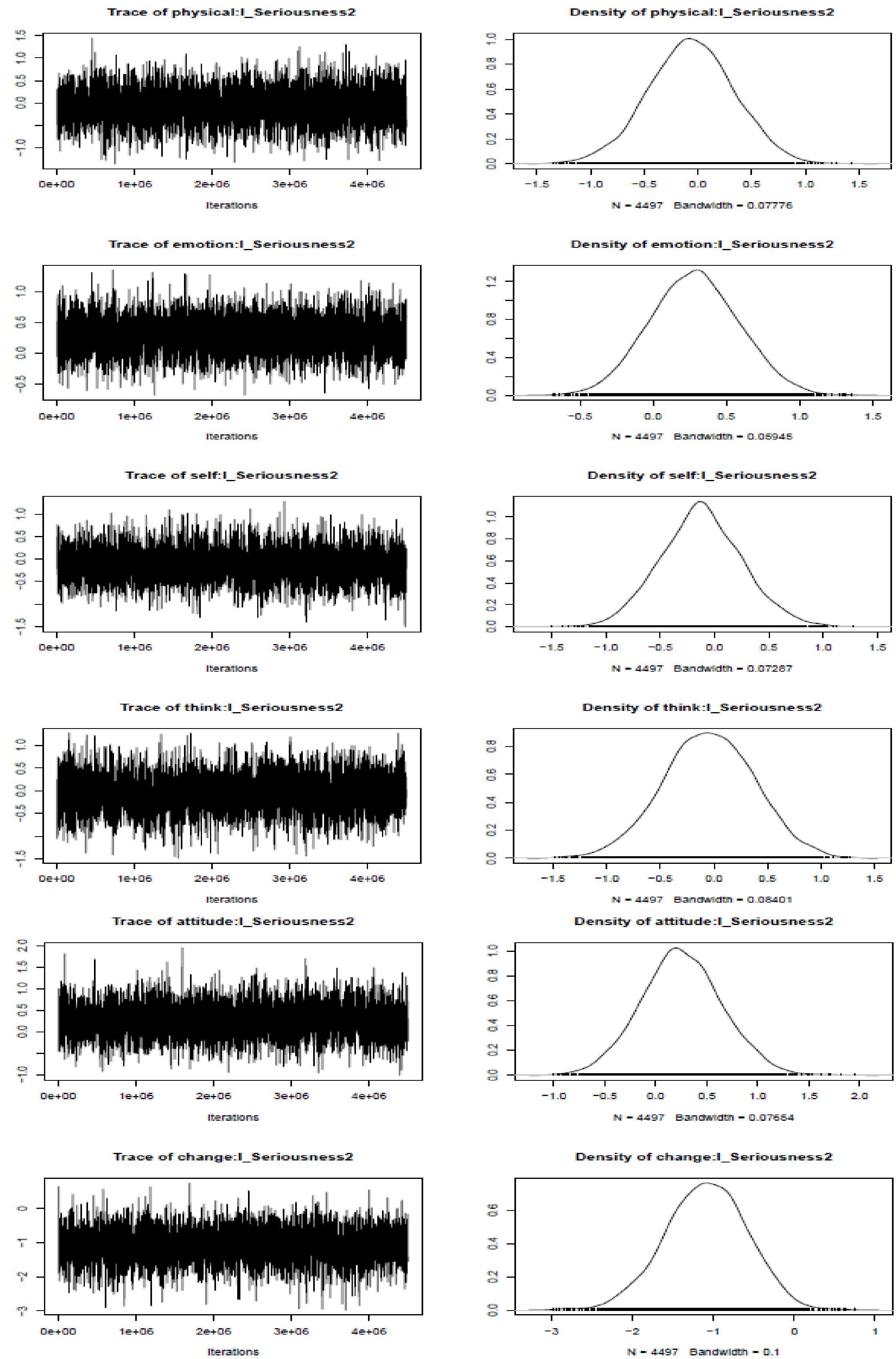

Trace of time:live
Iterations
Density of time:live
N = 4497 Bandwidth = 0.02281
Trace of FTE:relation
Iterations
Density of FTE:relation
N = 4497 Bandwidth = 0.2075
Trace of time:relation
Iterations
Density of time:relation
N = 4497 Bandwidth = 0.03156
Trace of FTE:ete
Iterations
Density of FTE:ete
N = 4497 Bandwidth = 0.1725
Trace of time:ete
Iterations
Density of time:ete
N = 4497 Bandwidth = 0.02114
Trace of FTE:where
Iterations
Density of FTE:where
N = 4497 Bandwidth = 0.1977

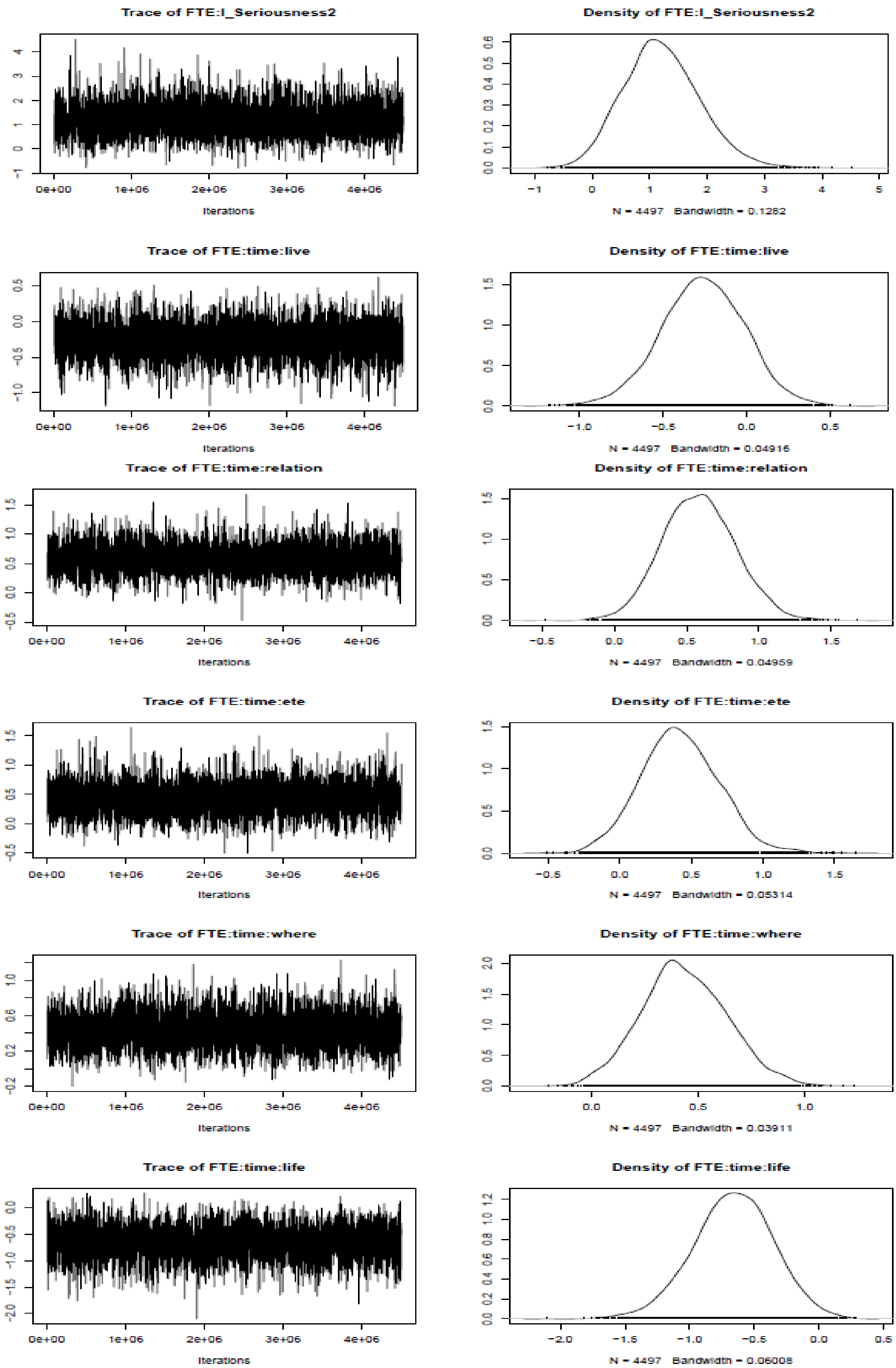

Trace of time:where
Iterations
Density of time:where
N = 4497 Bandwidth = 0.01821
Trace of FTE:life
Iterations
Density of FTE:life
N = 4497 Bandwidth = 0.252
Trace of time:life
Iterations
Density of time:life
N = 4497 Bandwidth = 0.03396
Trace of FTE:drugs
Iterations
Density of FTE:drugs
N = 4497 Bandwidth = 0.1854
Trace of time:drugs
Iterations
Density of time:drugs
N = 4497 Bandwidth = 0.02437
Trace of FTE:physical
Iterations
Density of FTE:physical
N = 4497 Bandwidth = 0.2099

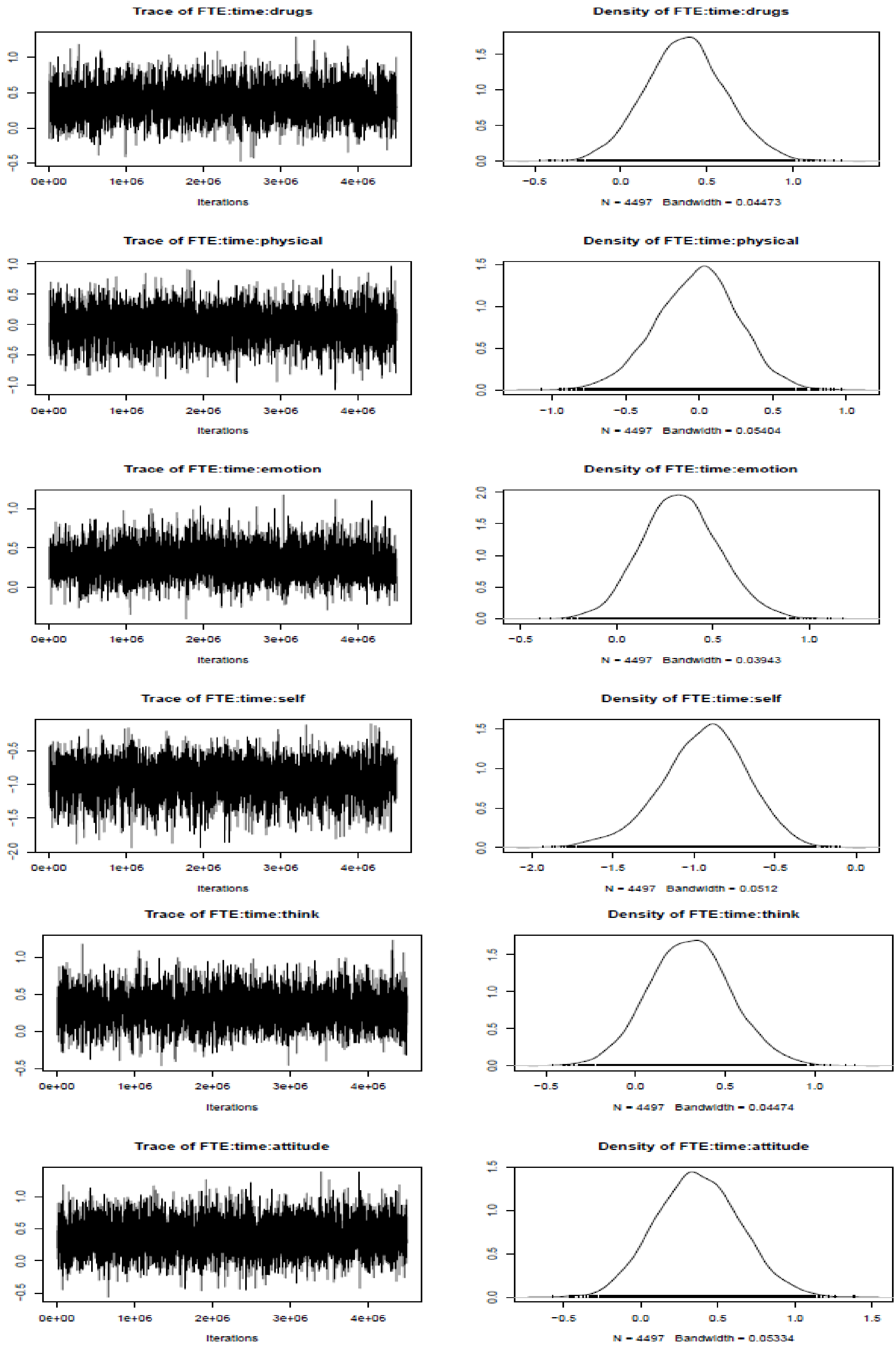

Trace of time:physical
Iterations
Density of time:physical
N = 4497 Bandwidth = 0.03005
Trace of FTE:emotion
Iterations
Density of FTE:emotion
N = 4497 Bandwidth = 0.1603
Trace of time:emotion
Iterations
Density of time:emotion
N = 4497 Bandwidth = 0.02633
Trace of FTE:self
Iterations
Density of FTE:self
N = 4497 Bandwidth = 0.2209
Trace of time:self
Iterations
Density of time:self
N = 4497 Bandwidth = 0.02921
Trace of FTE:think
Iterations
Density of FTE:think
N = 4497 Bandwidth = 0.2047

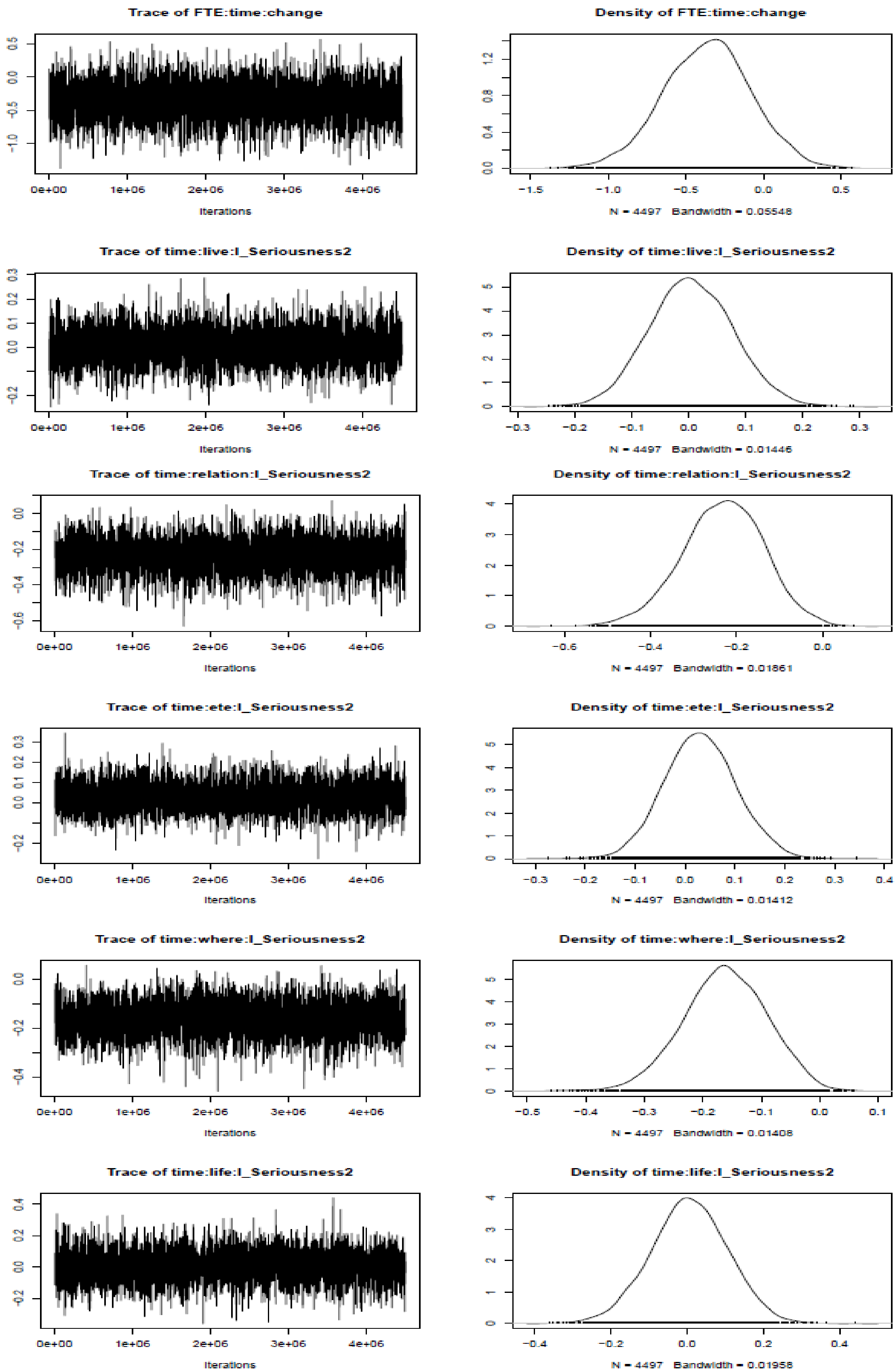

Trace of time:think
Iterations
Density of time:think
N = 4497 Bandwidth = 0.02817
Trace of FTE:attitude
Iterations
Density of FTE:attitude
N = 4497 Bandwidth = 0.1988
Trace of time:attitude
Iterations
Density of time:attitude
N = 4497 Bandwidth = 0.03129
Trace of FTE:change
Iterations
Density of FTE:change
N = 4497 Bandwidth = 0.2182
Trace of time:change
Iterations
Density of time:change
N = 4497 Bandwidth = 0.03106
Trace of time:I_Seriousness2
Iterations
Density of time:I_Seriousness2
N = 4497 Bandwidth = 0.03884

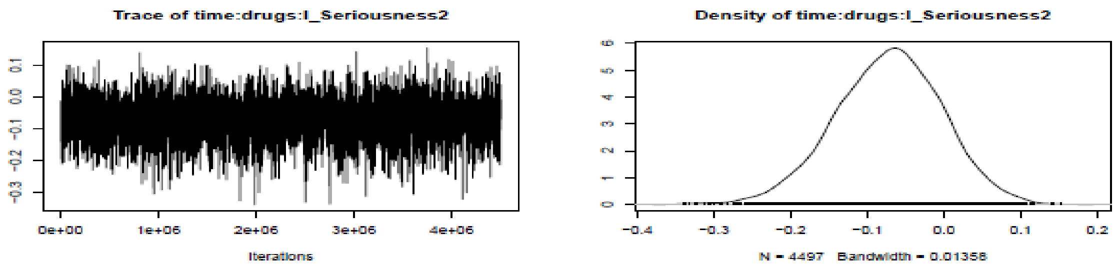

Trace of live:I_Seriousness2
Iterations
Density of live:I_Seriousness2
N = 4497 Bandwidth = 0.06353
Trace of relation:I_Seriousness2
Iterations
Density of relation:I_Seriousness2
N = 4497 Bandwidth = 0.07356
Trace of ete:I_Seriousness2
Iterations
Density of ete:I_Seriousness2
N = 4497 Bandwidth = 0.05288
Trace of where:I_Seriousness2
Iterations
Density of where:I_Seriousness2
N = 4497 Bandwidth = 0.05407
Trace of life:I_Seriousness2
Iterations
Density of life:I_Seriousness2
N = 4497 Bandwidth = 0.08994
Trace of drugs:I_Seriousness2
Iterations
Density of drugs:I_Seriousness2
N = 4497 Bandwidth = 0.06354

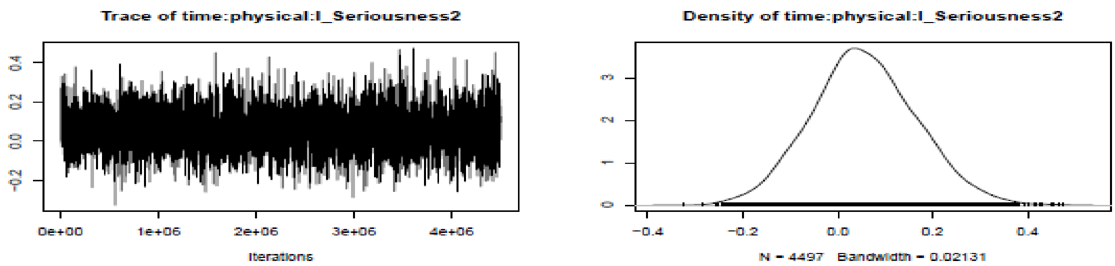

Trace of physical:I_Seriousness2
Iterations
Density of physical:I_Seriousness2
N = 4497 Bandwidth = 0.07776
Trace of emotion:I_Seriousness2
Iterations
Density of emotion:I_Seriousness2
N = 4497 Bandwidth = 0.06945
Trace of self:I_Seriousness2
Iterations
Density of self:I_Seriousness2
N = 4497 Bandwidth = 0.07267
Trace of think:I_Seriousness2
Iterations
Density of think:I_Seriousness2
N = 4497 Bandwidth = 0.08401
Trace of attitude:I_Seriousness2
Iterations
Density of attitude:I_Seriousness2
N = 4497 Bandwidth = 0.07654
Trace of change:I_Seriousness2
Iterations
Density of change:I_Seriousness2
N = 4497 Bandwidth = 0.1

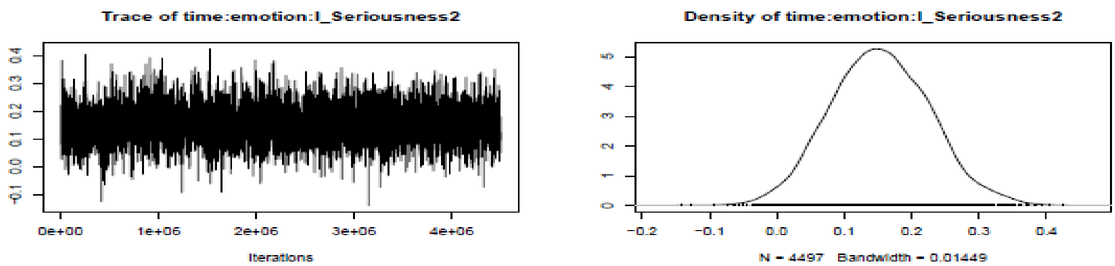

Trace of FTE:I_Seriousness2
Iterations
Density of FTE:I_Seriousness2
N = 4497 Bandwidth = 0.1282
Trace of FTE:time:live
Iterations
Density of FTE:time:live
N = 4497 Bandwidth = 0.04916
Trace of FTE:time:relation
Iterations
Density of FTE:time:relation
N = 4497 Bandwidth = 0.04959
Trace of FTE:time:ete
Iterations
Density of FTE:time:ete
N = 4497 Bandwidth = 0.05314
Trace of FTE:time:where
Iterations
Density of FTE:time:where
N = 4497 Bandwidth = 0.03911
Trace of FTE:time:life
Iterations
Density of FTE:time:life
N = 4497 Bandwidth = 0.06008

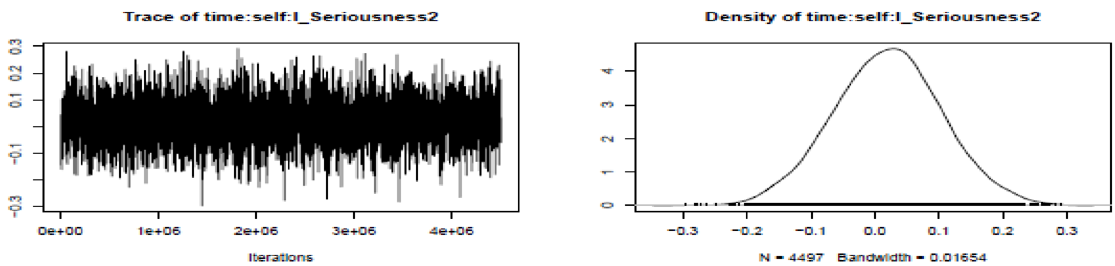

Trace of FTE:time:drugs
Iterations
Density of FTE:time:drugs
N = 4497 Bandwidth = 0.04473
Trace of FTE:time:physical
Iterations
Density of FTE:time:physical
N = 4497 Bandwidth = 0.05404
Trace of FTE:time:emotion
Iterations
Density of FTE:time:emotion
N = 4497 Bandwidth = 0.03943
Trace of FTE:time:self
Iterations
Density of FTE:time:self
N = 4497 Bandwidth = 0.0512
Trace of FTE:time:think
Iterations
Density of FTE:time:think
N = 4497 Bandwidth = 0.04474
Trace of FTE:time:attitude
Iterations
Density of FTE:time:attitude
N = 4497 Bandwidth = 0.05334

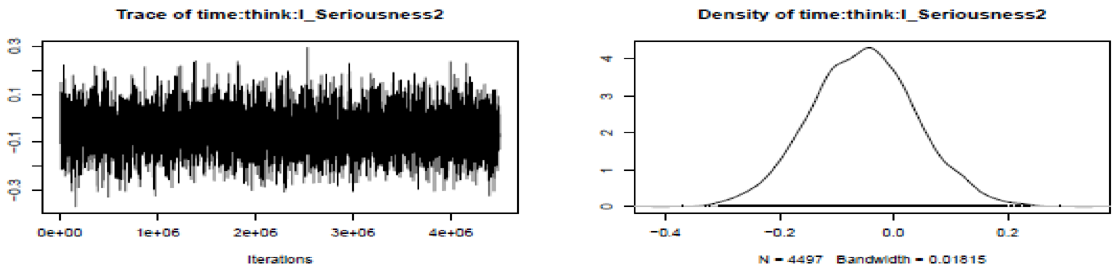

Trace of FTE:time:change
Iterations
Density of FTE:time:change
N = 4497 Bandwidth = 0.05548
Trace of time:live:I_Seriousness2
Iterations
Density of time:live:I_Seriousness2
N = 4497 Bandwidth = 0.01446
Trace of time:relation:I_Seriousness2
Iterations
Density of time:relation:I_Seriousness2
N = 4497 Bandwidth = 0.01861
Trace of time:ete:I_Seriousness2
Iterations
Density of time:ete:I_Seriousness2
N = 4497 Bandwidth = 0.01412
Trace of time:where:I_Seriousness2
Iterations
Density of time:where:I_Seriousness2
N = 4497 Bandwidth = 0.01408
Trace of time:life:I_Seriousness2
Iterations
Density of time:life:I_Seriousness2
N = 4497 Bandwidth = 0.01958

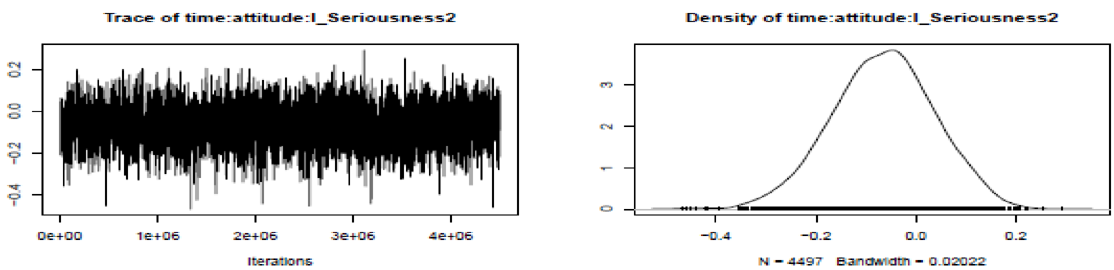

Trace of time:drugs:l_Seriousness2
Iterations
Density of time:drugs:l_Seriousness2
N = 4497 Bandwidth = 0.01358

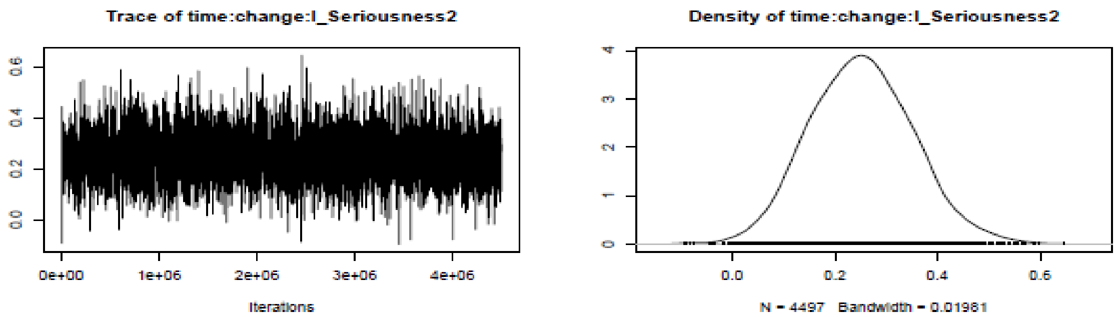

Trace of time:physical:l_Seriousness2
Iterations
Density of time:physical:l_Seriousness2
N = 4497 Bandwidth = 0.02131


Trace of time:emotion:l_Seriousness2
Iterations
Density of time:emotion:l_Seriousness2
N = 4497 Bandwidth = 0.01449

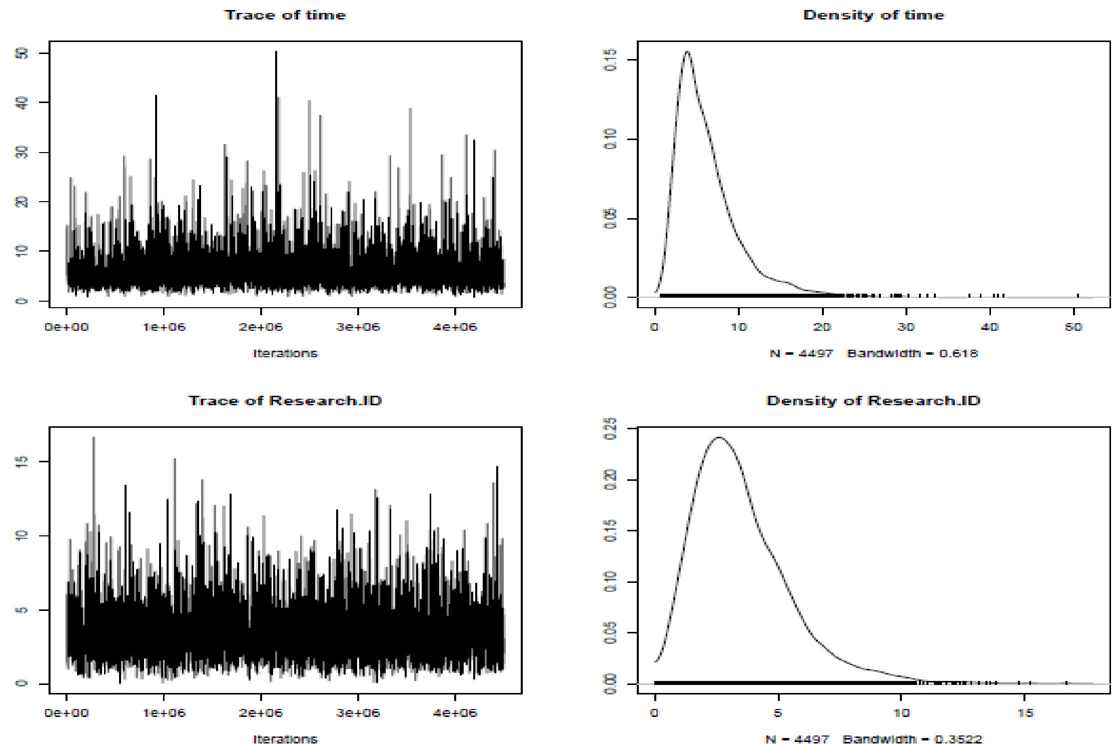

Trace of time:self:l_Seriousness2
Iterations
Density of time:self:l_Seriousness2
N = 4497 Bandwidth = 0.01654


Trace of time:think:l_Seriousness2
Iterations
Density of time:think:l_Seriousness2
N = 4497 Bandwidth = 0.01815


Trace of time:attitude:l_Seriousness2
Iterations
Density of time:attitude:l_Seriousness2
N = 4497 Bandwidth = 0.02022



Random Effects



The Combined Model involving Offending History: Version 2c

Bayesian Model (BDm3G_cc2o2a)

Define the Model

```
BDm3G_cc2o2a <- MCMCglmm(FO.bin~G_ageFirst*time*live +
G_ageFirst*time*relation + G_ageFirst*time*ete + G_ageFirst*time*where +
G_ageFirst*time*life + G_ageFirst*time*drugs + G_ageFirst*time*physical
+ G_ageFirst*time*emotion + G_ageFirst*time*self +
G_ageFirst*time*think + G_ageFirst*time*attitude +
G_ageFirst*time*change +
I_Seriousness2*time*live + I_Seriousness2*time*relation +
I_Seriousness2*time*ete + I_Seriousness2*time*where +
I_Seriousness2*time*life + I_Seriousness2*time*drugs +
I_Seriousness2*time*physical + I_Seriousness2*time*emotion +
I_Seriousness2*time*self + I_Seriousness2*time*think +
I_Seriousness2*time*attitude + I_Seriousness2*time*change +
G_ageFirst*I_Seriousness2,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
nitt=4500000, thin=1000, burnin=3000)
```

Checks for suitable convergence

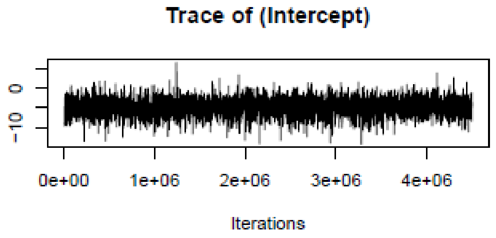
```
raftery.diag(BDm3G_cc2o2a$VCV)
heidel.diag(BDm3G_cc2o2a$VCV)

# > raftery.diag(BDm3G_cc2o2a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total   Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# time         3000     4064000 3746         1080
# Research.ID 2000      3848000 3746         1030
# units        <NA>     <NA>    3746           NA

# > heidel.diag(BDm3G_cc2o2a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         failed       NA        0.000316
# Research.ID passed         1        0.100507
# units        failed       NA              NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         <NA>        NA      NA
# Research.ID passed     2.11 0.0524
# units        <NA>        NA      NA

autocorr(BDm3G_cc2o2a$VCV)
autocorr(BDm3G_cc2o2a$Sol)    # not included here
summary(BDm3G_cc2o2a)
```

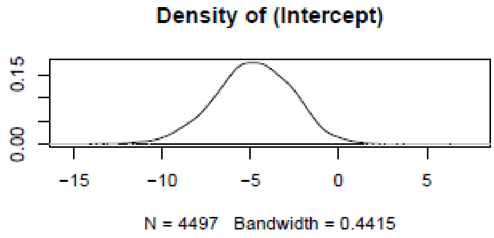
```
# > autocorr(BDm3G_cc2o2a$VCV)
# , , time
#
#                 time  Research.ID units
# Lag 0     1.00000000 0.3392759501   NaN
# Lag 1000  0.13957788 0.1072370561   NaN
# Lag 5000  0.03778720 0.0002832768   NaN
# Lag 10000 0.01280715 0.0189695102   NaN
# Lag 50000 0.02101734 0.0379747325   NaN
#
# , , Research.ID
#
#                  time  Research.ID units
# Lag 0     0.339275950 1.0000000000   NaN
# Lag 1000  0.127822079 0.1590234777   NaN
# Lag 5000  0.012350794 0.0002041186   NaN
# Lag 10000 0.034435999 0.0037686874   NaN
# Lag 50000 0.004613751 0.0261747138   NaN

# > summary(BDm3G_cc2o2a)
#
# Iterations = 3001:4499001
# Thinning interval  = 1000
# Sample size  = 4497
#
# DIC: 434.8735
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     6.884    1.222    16.12     2456
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID     2.109 1.086e-07    5.009     3076
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageFirst * time * live + G_ageFirst * time * relation + G_ageFirst * time * ete + G_ageFirst * time * where + G_ageFirst * time * life + G_ageFirst * time * drugs + G_ageFirst * time * physical + G_ageFirst * time * emotion + G_ageFirst * time * self + G_ageFirst * time * think + G_ageFirst * time * attitude + G_ageFirst * time * change + I_Seriousness2 * time * live + I_Seriousness2 * time * relation + I_Seriousness2 * time * ete + I_Seriousness2 * time * where + I_Seriousness2 * time * life + I_Seriousness2 * time * drugs + I_Seriousness2 * time * physical + I_Seriousness2 * time * emotion + I_Seriousness2 * time * self + I_Seriousness2 * time * think + I_Seriousness2 * time * attitude + I_Seriousness2 * time * change + G_ageFirst * I_Seriousness2
#
#                                     post.mean  l-95% CI  u-95% CI eff.samp   pMCMC
# (Intercept)                         -4.845208 -9.365473 -0.665058     4497 0.02446 *
# G_ageFirst13 to 17 years             5.313879  0.941231  9.655146     3947 0.00934 **
# time                                 0.554102 -0.368083  1.459198     5250 0.22815
# live                                -1.041962 -2.750049  0.582561     4497 0.22415
# relation                             2.036595 -0.094746  4.056710     4180 0.05248 .
# ete                                 -0.465963 -1.941047  1.027089     4497 0.54570
# where                                0.525625 -0.753246  1.893029     4497 0.41005
# life                                 1.987958 -0.621675  4.376215     4497 0.11741
# drugs                               -0.745039 -2.308510  0.777867     4497 0.33800
# physical                            -0.530613 -2.124111  0.919352     4497 0.49544
# emotion                             -0.408780 -1.659853  1.009559     4787 0.55948
# self                                -4.850418 -7.664600 -2.035409     3509 < 2e-04 ***
```

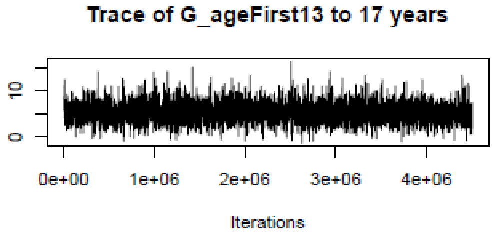
```
# think                                     1.531073 -0.837077  3.798752     4086 0.19924
# attitude                                  1.648651 -0.857748  4.245089     4497 0.19524
# change                                    1.561624 -0.834507  3.837416     4497 0.18813
# I_Seriousness2                           -0.529703 -2.293308  1.160746     4497 0.55281
# G_ageFirst13 to 17 years:time            -1.019994 -2.033596 -0.158709     4232 0.03336 *
# G_ageFirst13 to 17 years:live             0.274137 -1.550578  2.034567     4497 0.77919
# time:live                                -0.095794 -0.503263  0.276487     4497 0.63509
# G_ageFirst13 to 17 years:relation        -2.523551 -4.862332 -0.345153     3994 0.02135 *
# time:relation                            -0.293833 -0.895886  0.227693     4497 0.30909
# G_ageFirst13 to 17 years:ete              0.035873 -1.571953  1.591780     4497 0.99755
# time:ete                                  0.031108 -0.352049  0.414621     4497 0.87169
# G_ageFirst13 to 17 years:where           -0.751577 -2.340717  0.746703     4497 0.32155
# time:where                               -0.173479 -0.453938  0.105196     4497 0.21570
# G_ageFirst13 to 17 years:life            -2.222948 -4.733746  0.293226     4497 0.08761 .
# time:life                                -0.439546 -1.037985  0.179820     4334 0.14499
# G_ageFirst13 to 17 years:drugs            0.943723 -0.691234  2.423550     4497 0.23927
# time:drugs                                0.436618  0.062899  0.824812     4309 0.01868 *
# G_ageFirst13 to 17 years:physical        -0.432504 -2.345595  1.461063     4497 0.66222
# time:physical                             0.127947 -0.314793  0.576081     4497 0.60040
# G_ageFirst13 to 17 years:emotion         -0.424059 -1.862574  1.091487     4823 0.57950
# time:emotion                              0.103187 -0.296401  0.481579     5133 0.59017
# G_ageFirst13 to 17 years:self             7.274862  4.174170 10.584677     3539 < 2e-04 ***
# time:self                                 1.149899  0.529328  1.819848     3762 < 2e-04 ***
# G_ageFirst13 to 17 years:think           -0.818664 -3.148625  1.532716     4071 0.51101
# time:think                               -0.157131 -0.588816  0.316864     4261 0.51768
# G_ageFirst13 to 17 years:attitude        -1.373094 -4.366109  1.290830     4497 0.33533
# time:attitude                            -0.690845 -1.205314 -0.192087     4209 0.00400 **
# G_ageFirst13 to 17 years:change          -1.271744 -3.840756  1.180617     4497 0.31710
# time:change                              -0.126111 -0.634886  0.379490     4497 0.63598
# time:I_Seriousness2                       0.068583 -0.267104  0.411008     4497 0.70758
# live:I_Seriousness2                       0.729438  0.056152  1.375594     4278 0.02757 *
# relation:I_Seriousness2                   0.105349 -0.539488  0.764591     4497 0.77074
# ete:I_Seriousness2                        0.030777 -0.486260  0.617603     4497 0.90994
# where:I_Seriousness2                      0.152915 -0.343264  0.696599     4497 0.55771
# life:I_Seriousness2                       0.579917 -0.310903  1.419792     4497 0.17790
# drugs:I_Seriousness2                      0.198894 -0.324971  0.814341     3510 0.52791
# physical:I_Seriousness2                  -0.016765 -0.754021  0.707431     4497 0.94908
# emotion:I_Seriousness2                   -0.115152 -0.739543  0.445747     4497 0.72359
# self:I_Seriousness2                      -0.057963 -0.820255  0.627269     4499 0.85479
# think:I_Seriousness2                     -0.584045 -1.555725  0.337977     4497 0.19924
# attitude:I_Seriousness2                  -0.117701 -0.959506  0.681988     4497 0.76051
# change:I_Seriousness2                    -0.516985 -1.567937  0.491443     4497 0.33178
# G_ageFirst13 to 17 years:I_Seriousness2 -0.333040 -1.280756  0.664171     4497 0.48299
# G_ageFirst13 to 17 years:time:live        0.307286 -0.107757  0.712230     4497 0.14454
# G_ageFirst13 to 17 years:time:relation    0.502973 -0.061281  1.019482     4497 0.06404 .
# G_ageFirst13 to 17 years:time:ete         0.021505 -0.321508  0.394904     4996 0.89304
# G_ageFirst13 to 17 years:time:where       0.273128 -0.038278  0.599362     4497 0.08584 .
# G_ageFirst13 to 17 years:time:life        0.447158 -0.111649  1.028163     4497 0.12586
# G_ageFirst13 to 17 years:time:drugs      -0.469318 -0.835467 -0.095394     4497 0.01423 *
# G_ageFirst13 to 17 years:time:physical    0.115366 -0.355544  0.651551     4497 0.66489
# G_ageFirst13 to 17 years:time:emotion    -0.056832 -0.439570  0.337727     5266 0.76851
# G_ageFirst13 to 17 years:time:self       -1.624014 -2.342584 -0.973356     3830 < 2e-04 ***
# G_ageFirst13 to 17 years:time:think       0.251063 -0.192669  0.737697     4497 0.27485
# G_ageFirst13 to 17 years:time:attitude    0.401481 -0.185685  1.042453     4497 0.19391
# G_ageFirst13 to 17 years:time:change      0.047039 -0.483663  0.562252     4497 0.86769
# time:live:I_Seriousness2                 -0.100628 -0.258226  0.058768     3713 0.20102
# time:relation:I_Seriousness2             -0.124871 -0.309567  0.060818     3646 0.18145
# time:ete:I_Seriousness2                   0.080462 -0.083779  0.240542     4497 0.34334
# time:where:I_Seriousness2                -0.061447 -0.185911  0.060174     4497 0.32733
# time:life:I_Seriousness2                 -0.112723 -0.321087  0.104006     4497 0.30064
# time:drugs:I_Seriousness2                -0.043295 -0.177969  0.096658     4250 0.54792
# time:physical:I_Seriousness2             -0.034524 -0.217524  0.153743     4497 0.70669
# time:emotion:I_Seriousness2               0.166970  0.008951  0.329542     4226 0.02846 *
# time:self:I_Seriousness2                 -0.003704 -0.193680  0.162753     4497 0.98866
# time:think:I_Seriousness2                -0.051042 -0.249519  0.155564     4497 0.61552
# time:attitude:I_Seriousness2              0.125413 -0.088931  0.356560     4497 0.26507
# time:change:I_Seriousness2                0.127453 -0.096407  0.357011     4497 0.27574
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

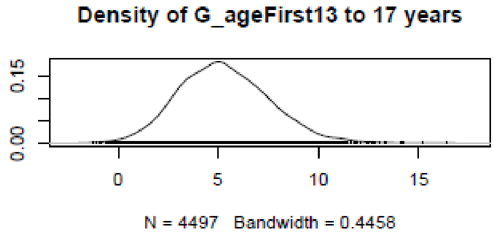
Trace Plots and Posterior Density Plots

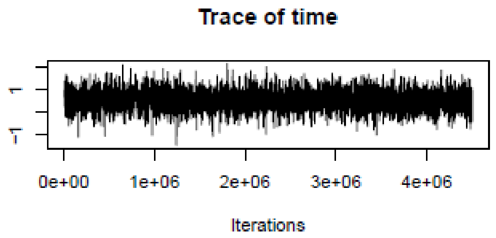
Fixed Effects

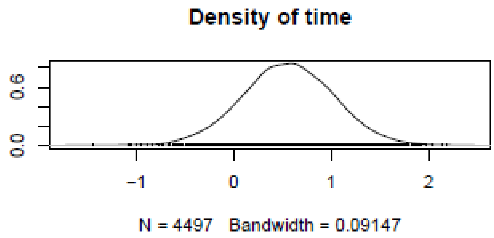


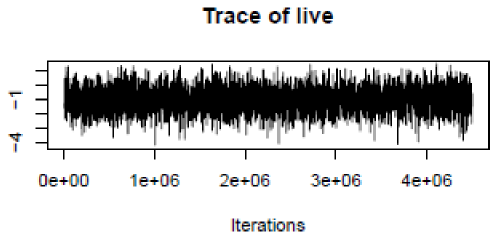


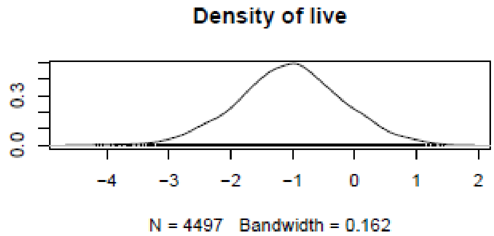


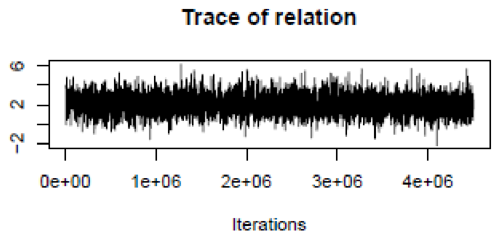


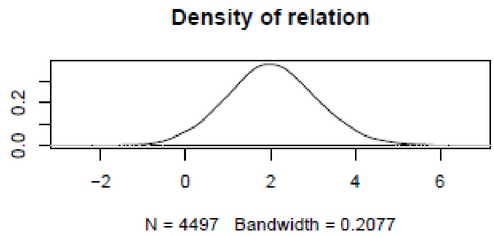


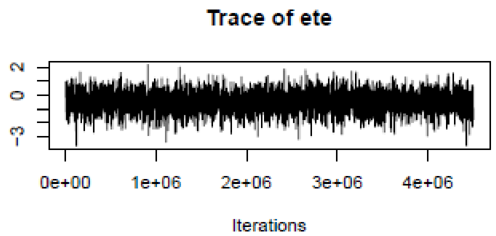


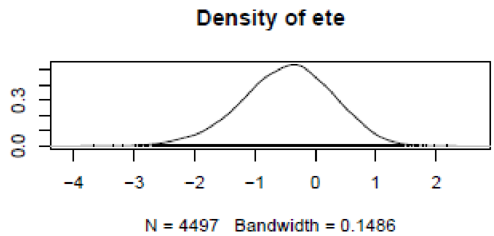


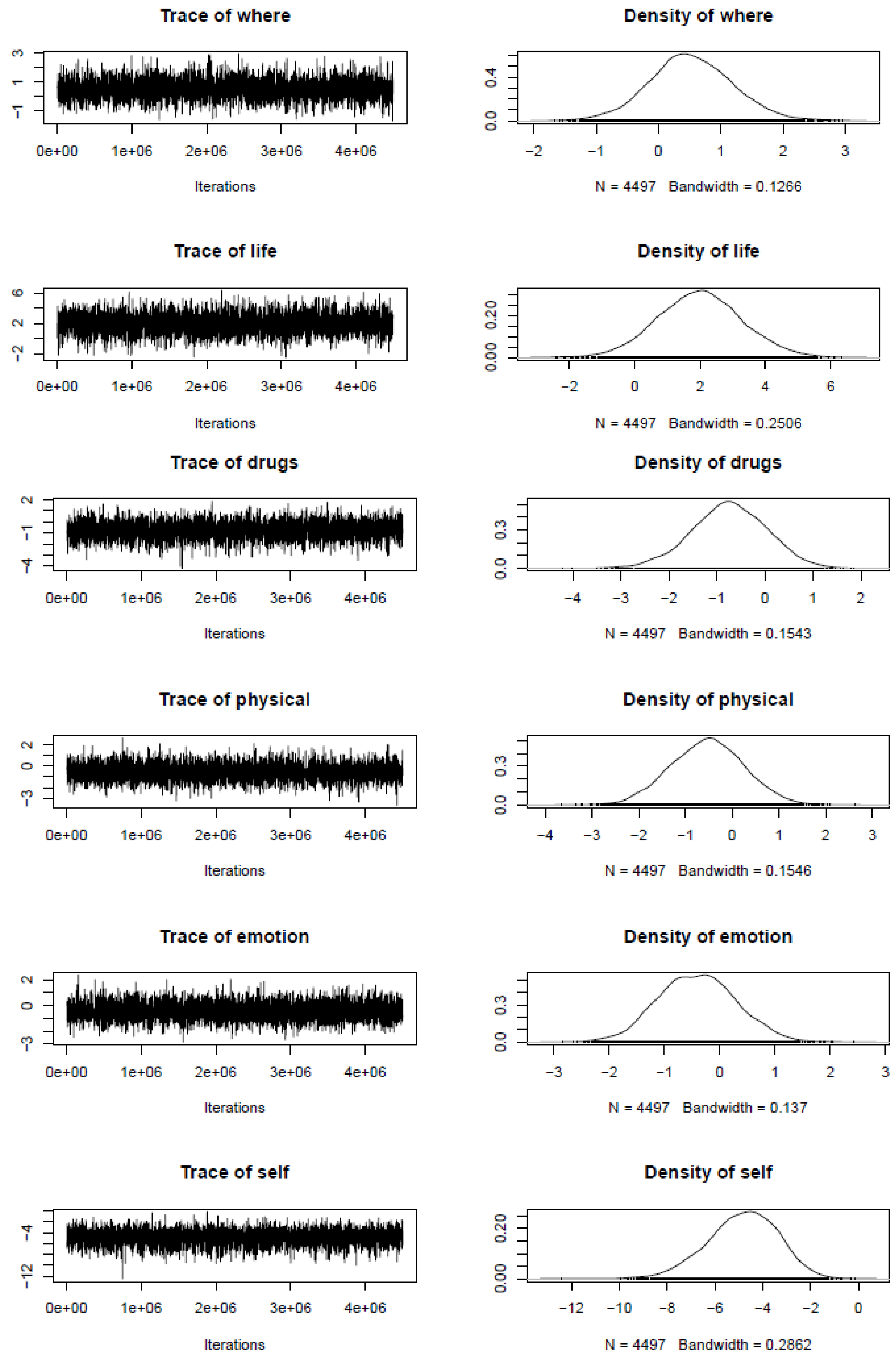


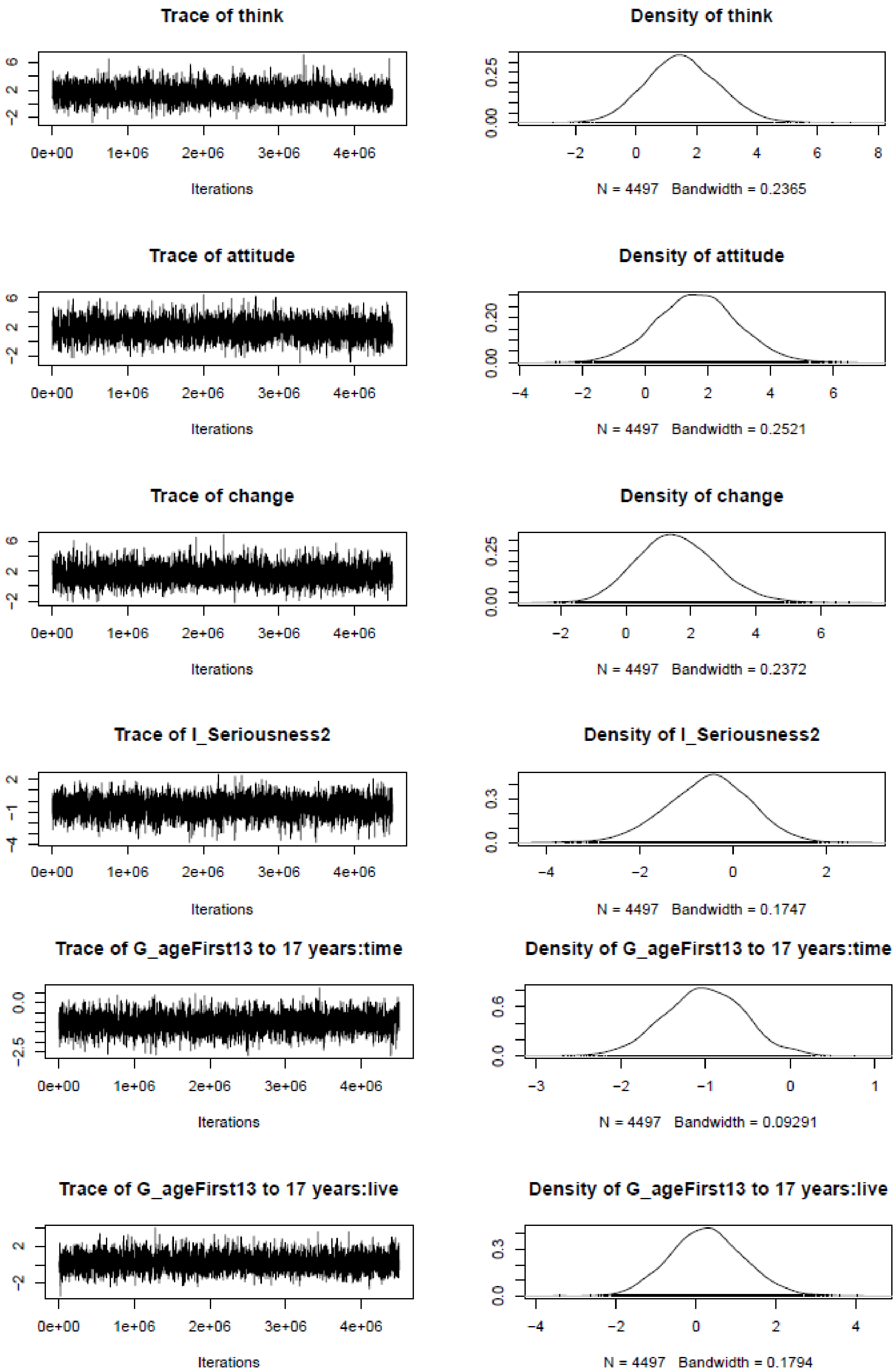


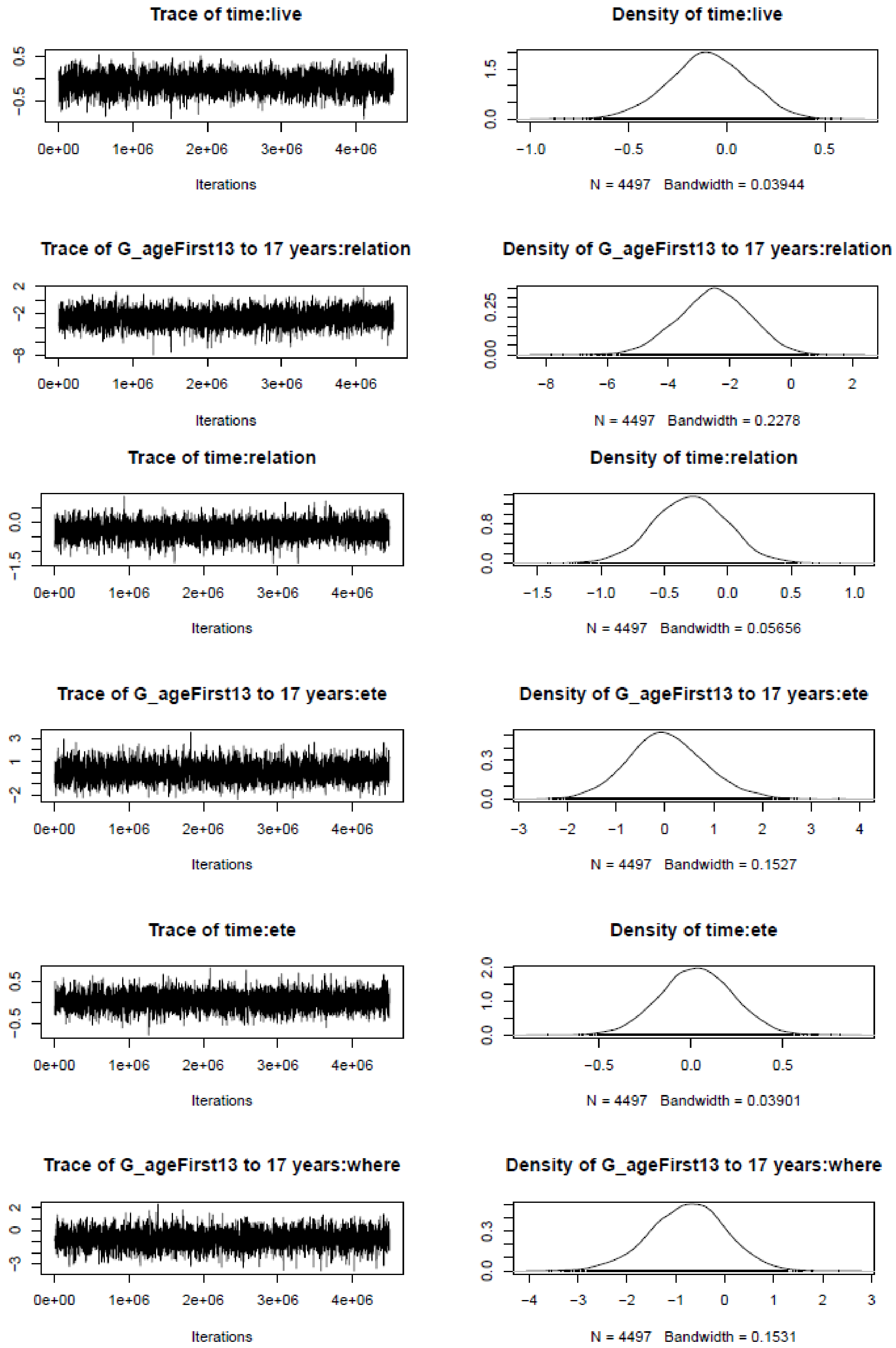




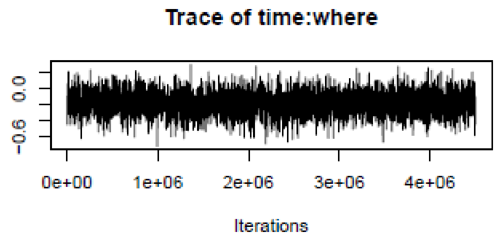


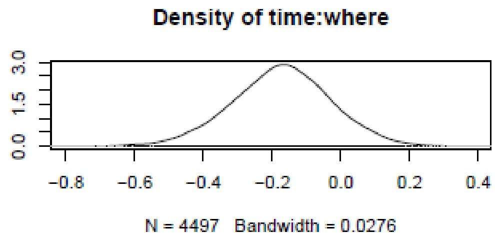

Trace of where
Iterations
Density of where
N = 4497 Bandwidth = 0.1266
Trace of life
Iterations
Density of life
N = 4497 Bandwidth = 0.2506
Trace of drugs
Iterations
Density of drugs
N = 4497 Bandwidth = 0.1543
Trace of physical
Iterations
Density of physical
N = 4497 Bandwidth = 0.1546
Trace of emotion
Iterations
Density of emotion
N = 4497 Bandwidth = 0.137
Trace of self
Iterations
Density of self
N = 4497 Bandwidth = 0.2862

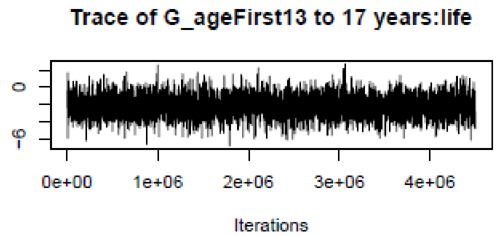

Trace of think
Iterations
Density of think
N = 4497 Bandwidth = 0.2365
Trace of attitude
Iterations
Density of attitude
N = 4497 Bandwidth = 0.2521
Trace of change
Iterations
Density of change
N = 4497 Bandwidth = 0.2372
Trace of I_Seriousness2
Iterations
Density of I_Seriousness2
N = 4497 Bandwidth = 0.1747
Trace of G_ageFirst13 to 17 years:time
Iterations
Density of G_ageFirst13 to 17 years:time
N = 4497 Bandwidth = 0.09291
Trace of G_ageFirst13 to 17 years:live
Iterations
Density of G_ageFirst13 to 17 years:live
N = 4497 Bandwidth = 0.1794

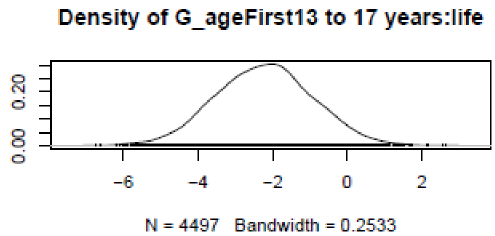


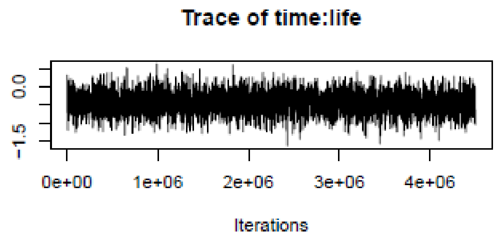
Trace of time:live
Iterations
Density of time:live
N = 4497 Bandwidth = 0.03944
Trace of G_ageFirst13 to 17 years:relation
Iterations
Density of G_ageFirst13 to 17 years:relation
N = 4497 Bandwidth = 0.2278
Trace of time:relation
Iterations
Density of time:relation
N = 4497 Bandwidth = 0.05656
Trace of G_ageFirst13 to 17 years:ete
Iterations
Density of G_ageFirst13 to 17 years:ete
N = 4497 Bandwidth = 0.1527
Trace of time:ete
Iterations
Density of time:ete
N = 4497 Bandwidth = 0.03901
Trace of G_ageFirst13 to 17 years:where
Iterations
Density of G_ageFirst13 to 17 years:where
N = 4497 Bandwidth = 0.1531

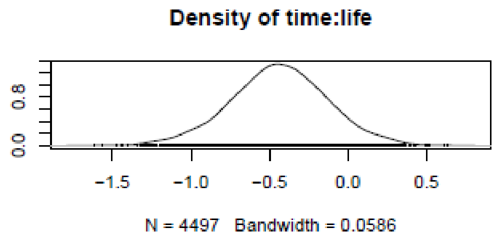

Trace of time:where
0.0
-0.6
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

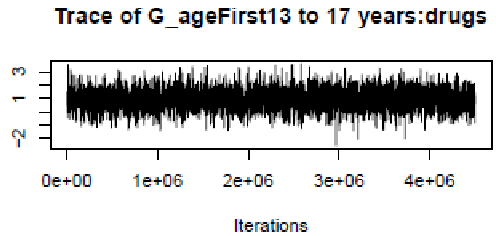

Density of time:where
3.0
1.5
0.0
-0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4
N = 4497 Bandwidth = 0.0276

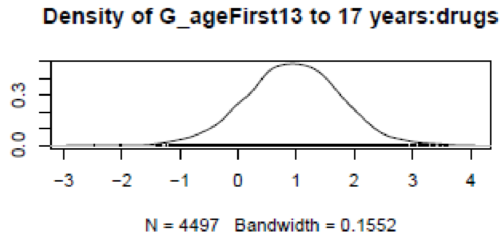

Trace of G_ageFirst13 to 17 years:life
0
-6
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

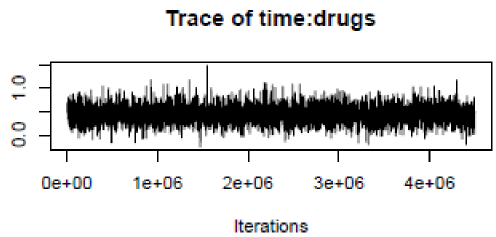

Density of G_ageFirst13 to 17 years:life
0.20
0.00
-6 -4 -2 0 2
N = 4497 Bandwidth = 0.2533

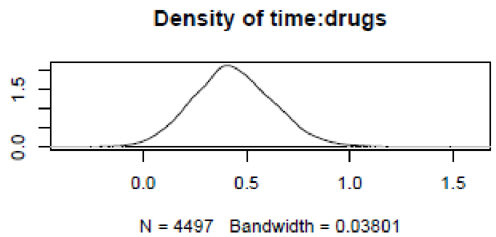

Trace of time:life
0.0
-1.5
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

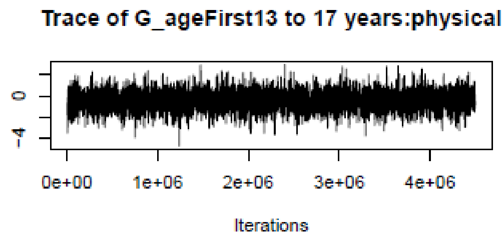

Density of time:life
0.8
0.0
-1.5 -1.0 -0.5 0.0 0.5
N = 4497 Bandwidth = 0.0586

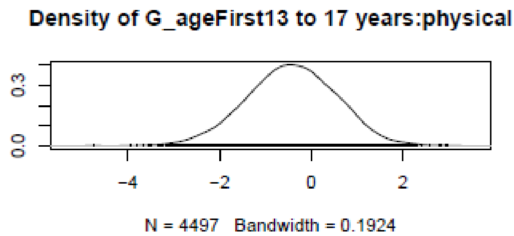

Trace of G_ageFirst13 to 17 years:drugs
3
1
-2
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

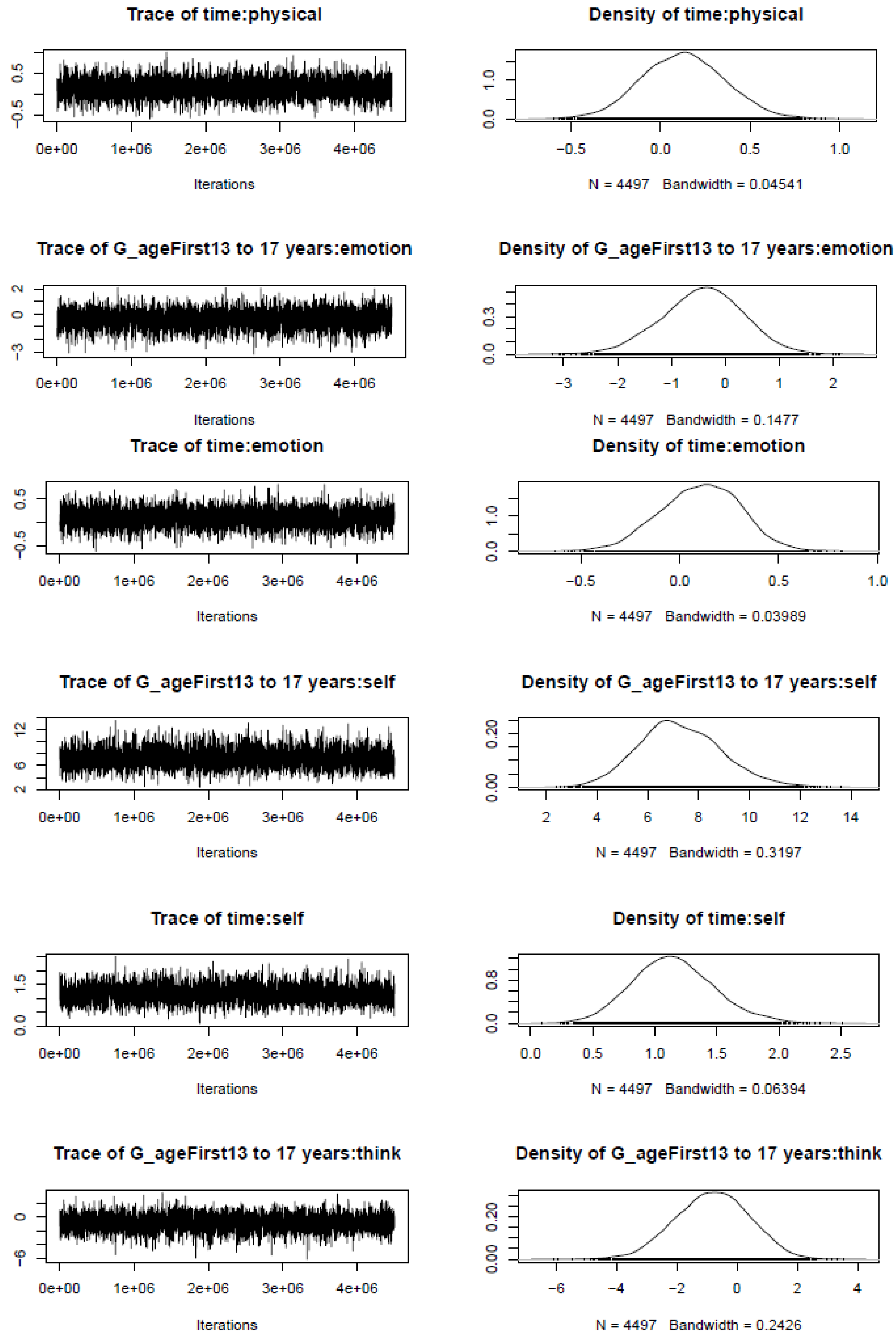

Density of G_ageFirst13 to 17 years:drugs
0.3
0.0
-3 -2 -1 0 1 2 3 4
N = 4497 Bandwidth = 0.1552

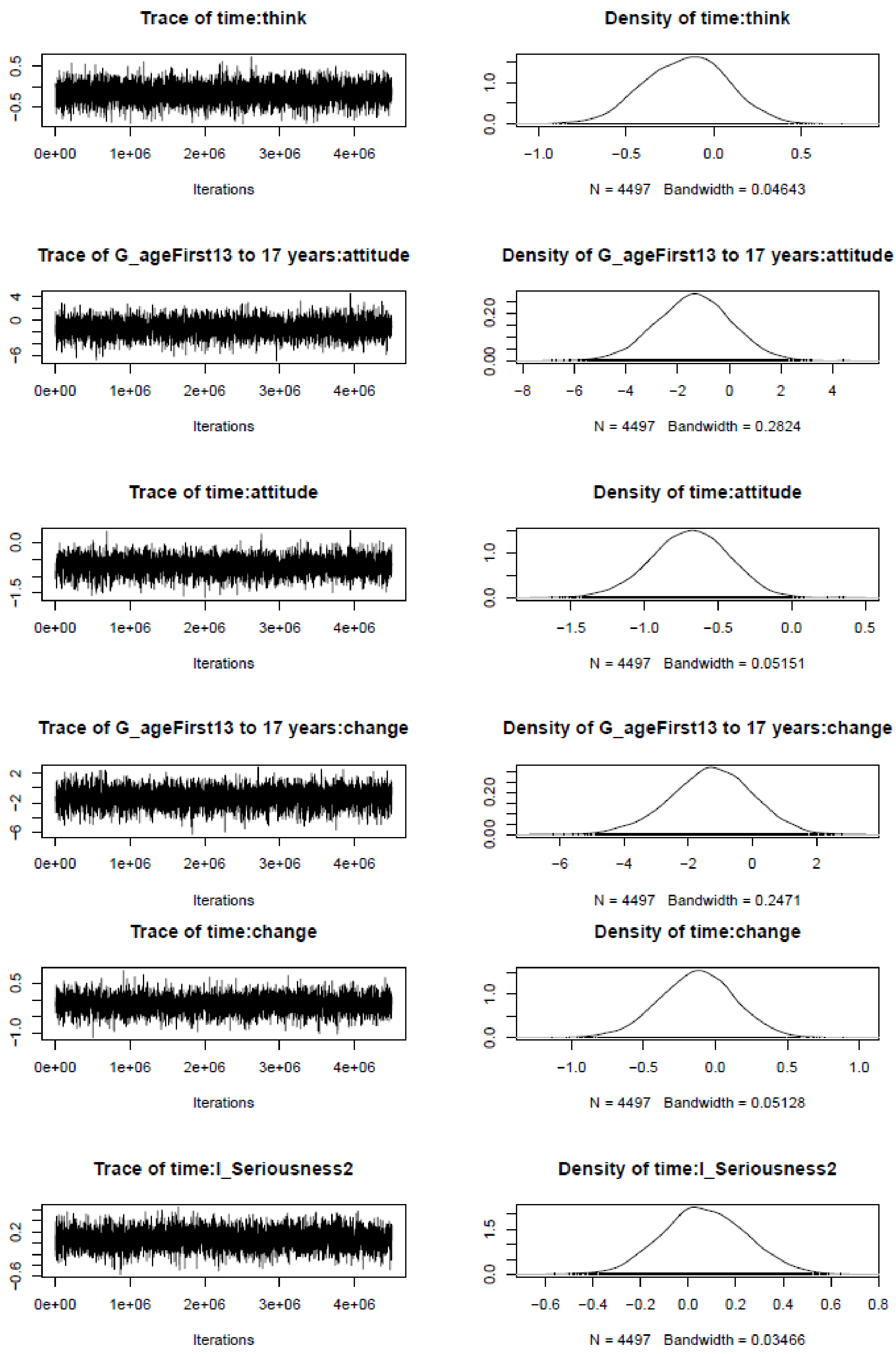

Trace of time:drugs
1.0
0.0
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

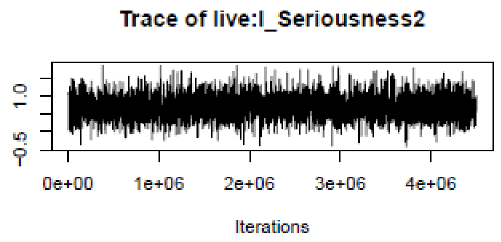

Density of time:drugs
1.5
0.0
0.0 0.5 1.0 1.5
N = 4497 Bandwidth = 0.03801

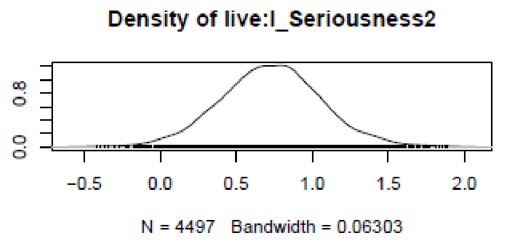

Trace of G_ageFirst13 to 17 years:physical
0
-4
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

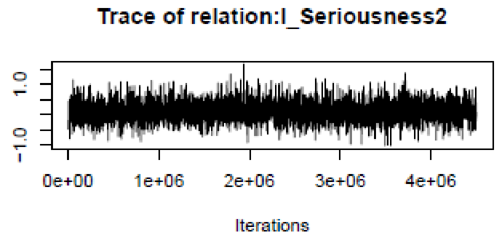

Density of G_ageFirst13 to 17 years:physical
0.3
0.0
-4 -2 0 2
N = 4497 Bandwidth = 0.1924

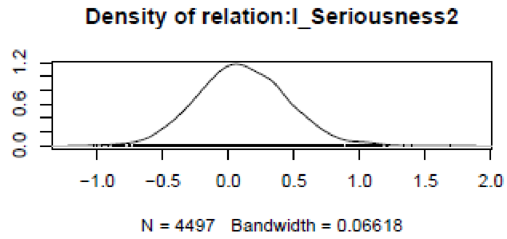

Trace of time:physical
Iterations
Density of time:physical
N = 4497 Bandwidth = 0.04541
Trace of G_ageFirst13 to 17 years:emotion
Iterations
Density of G_ageFirst13 to 17 years:emotion
N = 4497 Bandwidth = 0.1477
Trace of time:emotion
Iterations
Density of time:emotion
N = 4497 Bandwidth = 0.03989
Trace of G_ageFirst13 to 17 years:self
Iterations
Density of G_ageFirst13 to 17 years:self
N = 4497 Bandwidth = 0.3197
Trace of time:self
Iterations
Density of time:self
N = 4497 Bandwidth = 0.06394
Trace of G_ageFirst13 to 17 years:think
Iterations
Density of G_ageFirst13 to 17 years:think
N = 4497 Bandwidth = 0.2426

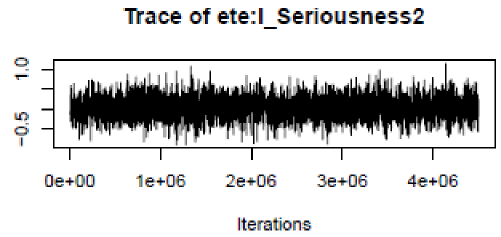

Trace of time:think
Density of time:think
N = 4497 Bandwidth = 0.04643
Trace of G_ageFirst13 to 17 years:attitude
Density of G_ageFirst13 to 17 years:attitude
N = 4497 Bandwidth = 0.2824
Trace of time:attitude
Density of time:attitude
N = 4497 Bandwidth = 0.05151
Trace of G_ageFirst13 to 17 years:change
Density of G_ageFirst13 to 17 years:change
N = 4497 Bandwidth = 0.2471
Trace of time:change
Density of time:change
N = 4497 Bandwidth = 0.05128
Trace of time:I_Seriousness2
Density of time:I_Seriousness2
N = 4497 Bandwidth = 0.03466
Iterations

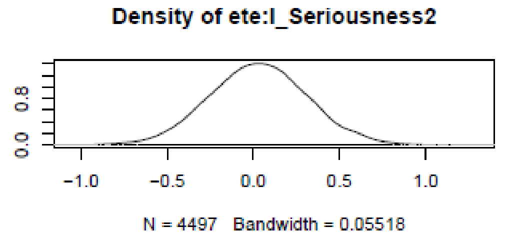

Trace of live:I_Seriousness2
-0.5
1.0
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

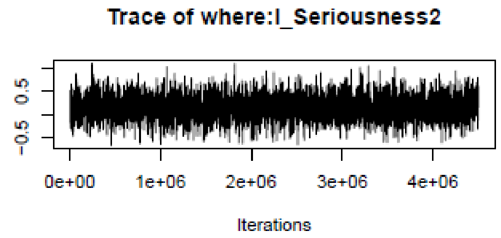

Density of live:I_Seriousness2
0.0
0.8
-0.5 0.0 0.5 1.0 1.5 2.0
N = 4497 Bandwidth = 0.06303

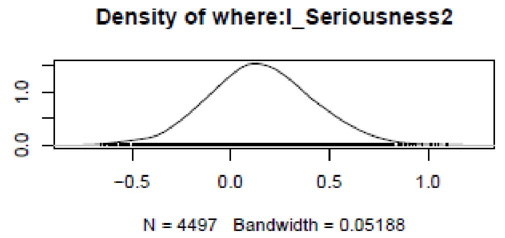

Trace of relation:I_Seriousness2
-1.0
1.0
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

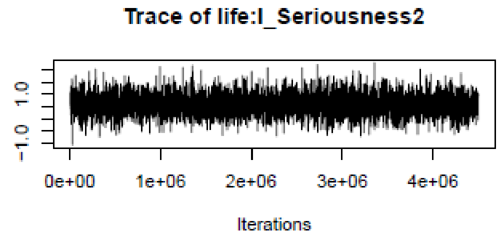

Density of relation:I_Seriousness2
0.0 0.6 1.2
-1.0 -0.5 0.0 0.5 1.0 1.5 2.0
N = 4497 Bandwidth = 0.06618

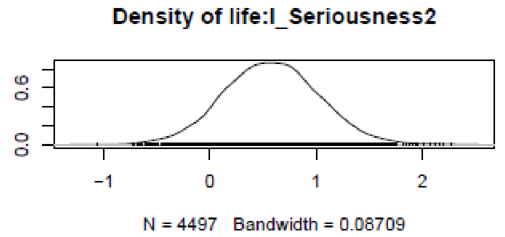

Trace of ete:I_Seriousness2
-0.5
1.0
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

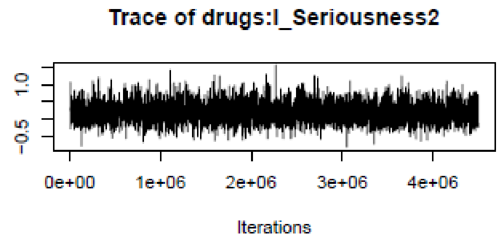

Density of ete:I_Seriousness2
0.0
0.8
-1.0 -0.5 0.0 0.5 1.0
N = 4497 Bandwidth = 0.05518

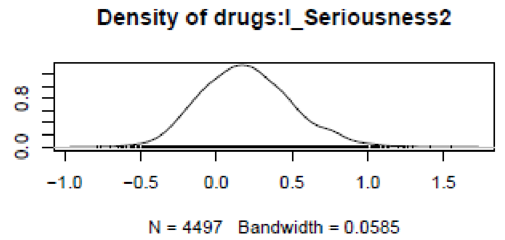

Trace of where:I_Seriousness2
-0.5
0.5
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

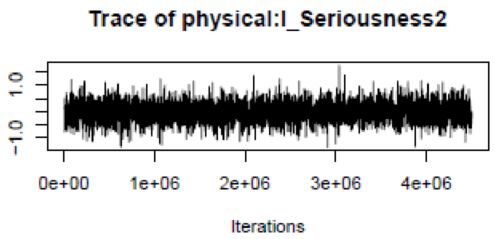

Density of where:I_Seriousness2
0.0
1.0
-0.5 0.0 0.5 1.0
N = 4497 Bandwidth = 0.05188

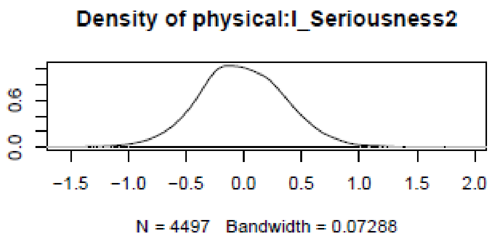

Trace of life:I_Seriousness2
-1.0
1.0
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

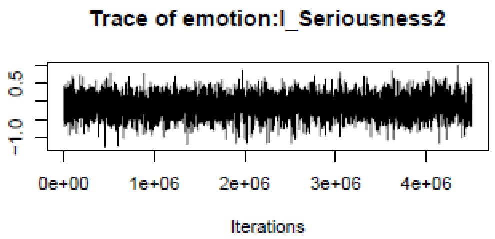

Density of life:I_Seriousness2
0.0
0.6
-1 0 1 2
N = 4497 Bandwidth = 0.08709

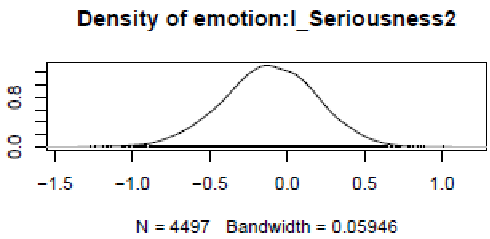

Trace of drugs:I_Seriousness2
-0.5
1.0
0e+00 1e+06 2e+06 3e+06 4e+06
Iterations

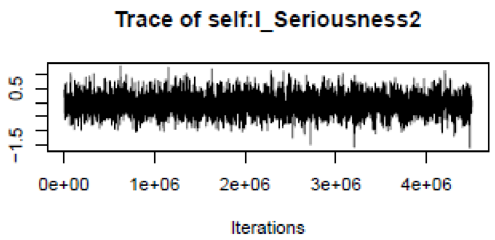

Density of drugs:I_Seriousness2
0.0
0.8
-1.0 -0.5 0.0 0.5 1.0 1.5
N = 4497 Bandwidth = 0.0585

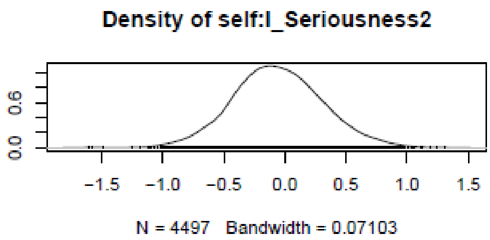

Trace of physical:I_Seriousness2
Iterations


Density of physical:I_Seriousness2
N = 4497 Bandwidth = 0.07288

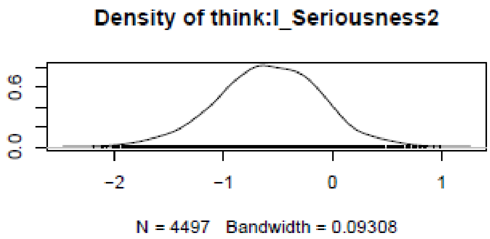

Trace of emotion:I_Seriousness2
Iterations

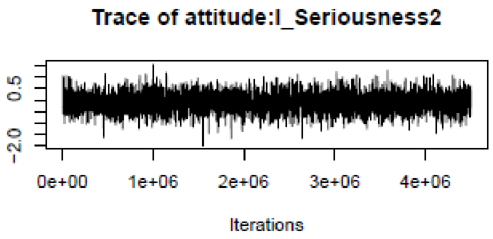

Density of emotion:I_Seriousness2
N = 4497 Bandwidth = 0.05946

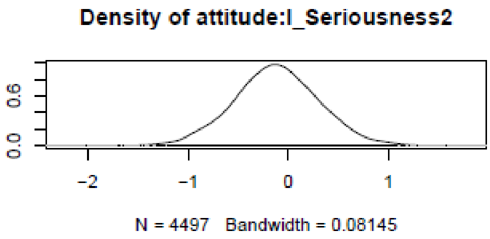

Trace of self:I_Seriousness2
Iterations

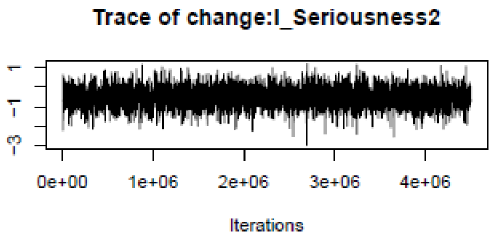

Density of self:I_Seriousness2
N = 4497 Bandwidth = 0.07103

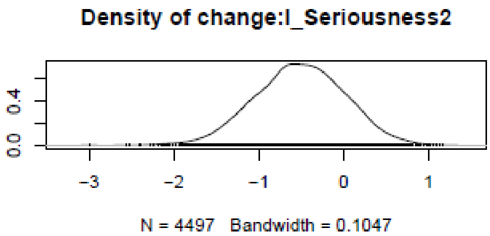

Trace of think:I_Seriousness2
Iterations

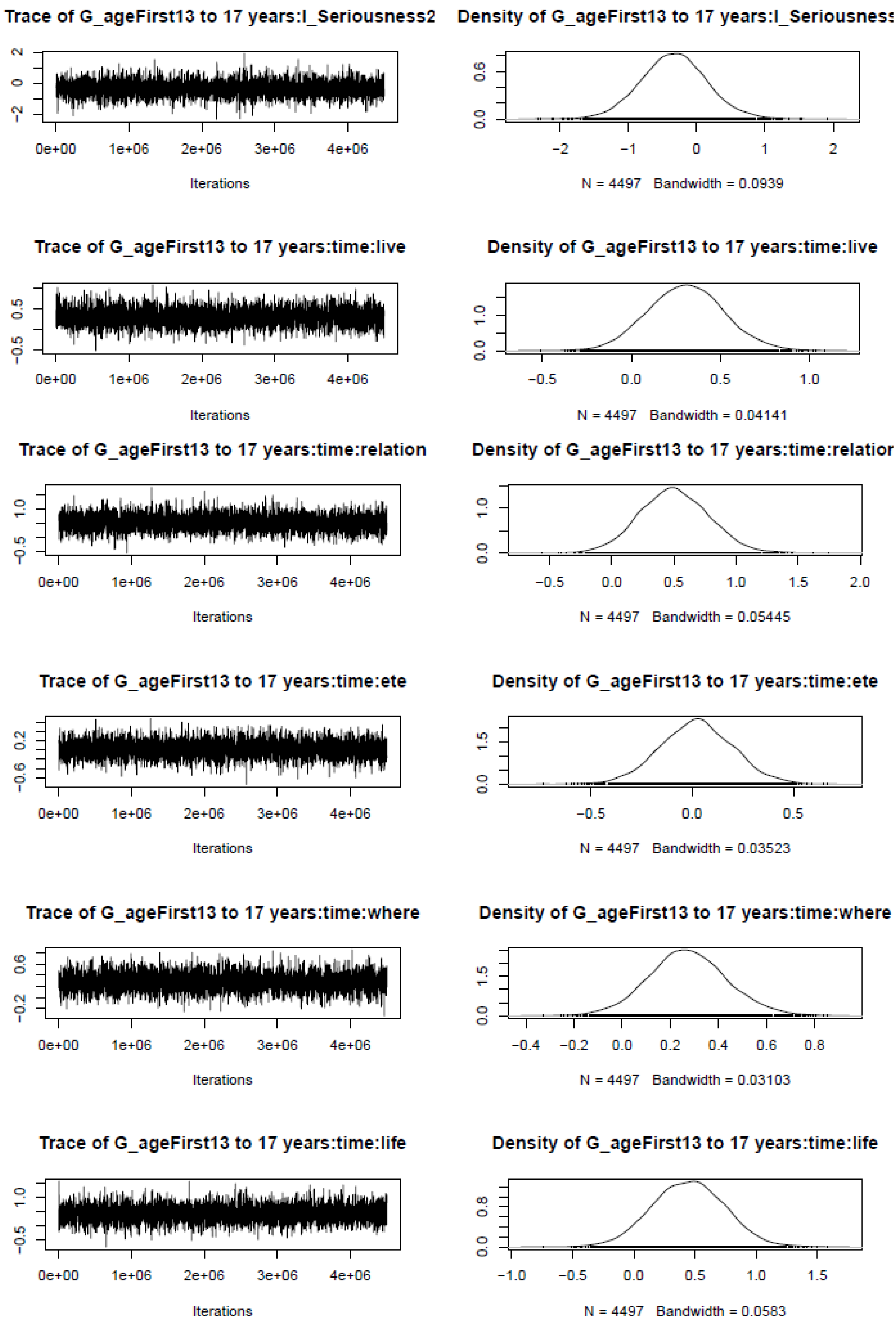

Density of think:I_Seriousness2
N = 4497 Bandwidth = 0.09308

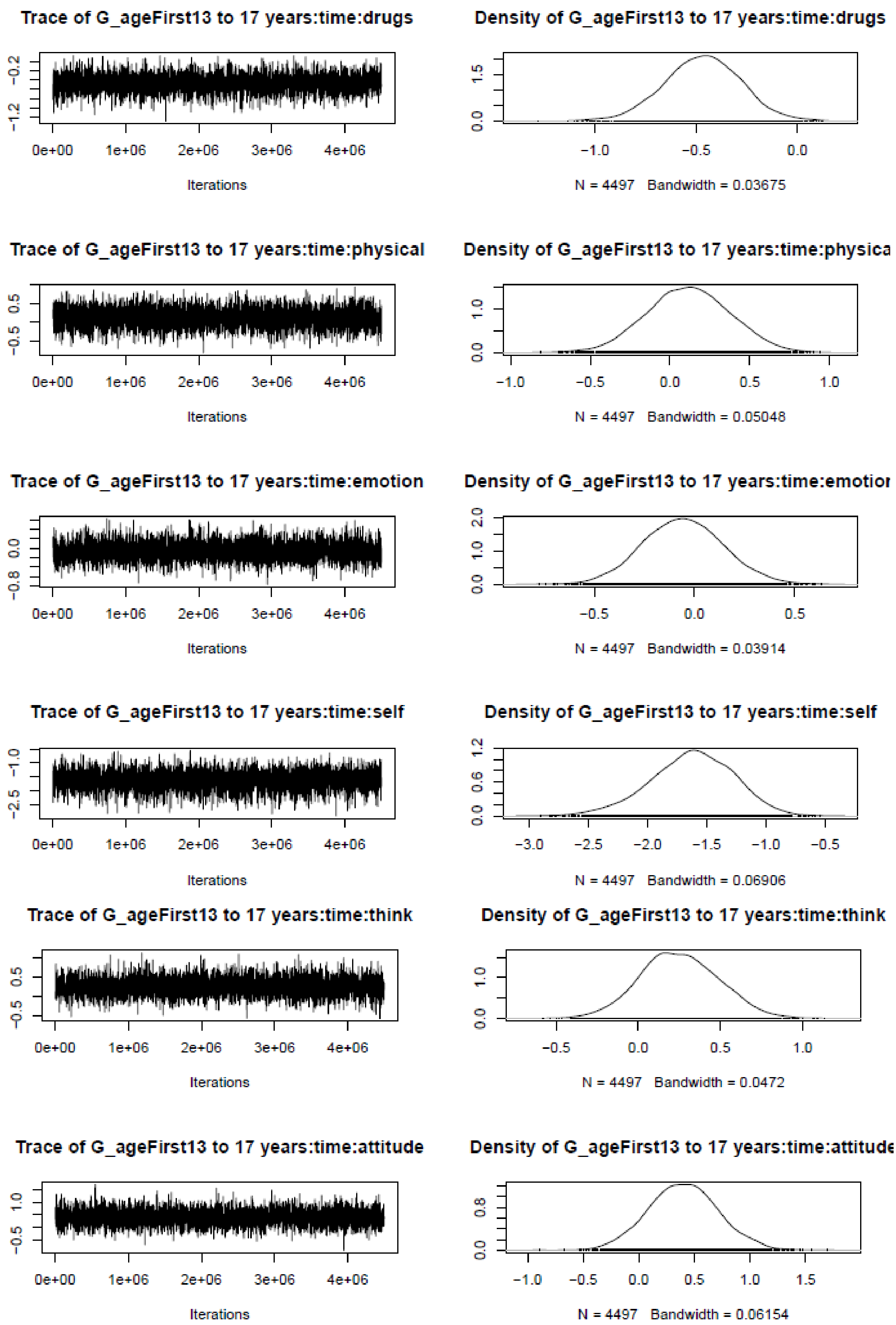

Trace of attitude:I_Seriousness2
Iterations


Density of attitude:I_Seriousness2
N = 4497 Bandwidth = 0.08145


Trace of change:I_Seriousness2
Iterations

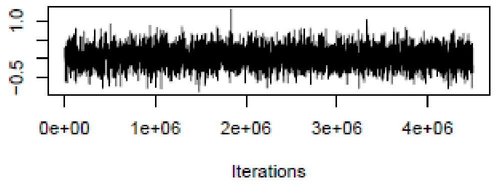

Density of change:I_Seriousness2
N = 4497 Bandwidth = 0.1047


Trace of G_ageFirst13 to 17 years:I_Seriousness2
Iterations
Density of G_ageFirst13 to 17 years:I_Seriousness
N = 4497 Bandwidth = 0.0939
Trace of G_ageFirst13 to 17 years:time:live
Iterations
Density of G_ageFirst13 to 17 years:time:live
N = 4497 Bandwidth = 0.04141
Trace of G_ageFirst13 to 17 years:time:relation
Iterations
Density of G_ageFirst13 to 17 years:time:relatior
N = 4497 Bandwidth = 0.05445
Trace of G_ageFirst13 to 17 years:time:ete
Iterations
Density of G_ageFirst13 to 17 years:time:ete
N = 4497 Bandwidth = 0.03523
Trace of G_ageFirst13 to 17 years:time:where
Iterations
Density of G_ageFirst13 to 17 years:time:where
N = 4497 Bandwidth = 0.03103
Trace of G_ageFirst13 to 17 years:time:life
Iterations
Density of G_ageFirst13 to 17 years:time:life
N = 4497 Bandwidth = 0.0583

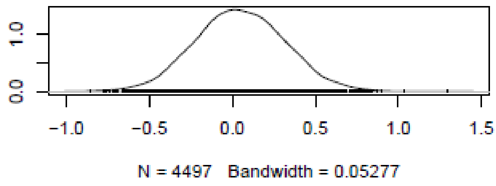


Trace of G_ageFirst13 to 17 years:time:drugs
Iterations
Density of G_ageFirst13 to 17 years:time:drugs
N = 4497 Bandwidth = 0.03675
Trace of G_ageFirst13 to 17 years:time:physical
Iterations
Density of G_ageFirst13 to 17 years:time:physica
N = 4497 Bandwidth = 0.05048
Trace of G_ageFirst13 to 17 years:time:emotion
Iterations
Density of G_ageFirst13 to 17 years:time:emotior
N = 4497 Bandwidth = 0.03914
Trace of G_ageFirst13 to 17 years:time:self
Iterations
Density of G_ageFirst13 to 17 years:time:self
N = 4497 Bandwidth = 0.06906
Trace of G_ageFirst13 to 17 years:time:think
Iterations
Density of G_ageFirst13 to 17 years:time:think
N = 4497 Bandwidth = 0.0472
Trace of G_ageFirst13 to 17 years:time:attitude
Iterations
Density of G_ageFirst13 to 17 years:time:attitude
N = 4497 Bandwidth = 0.06154

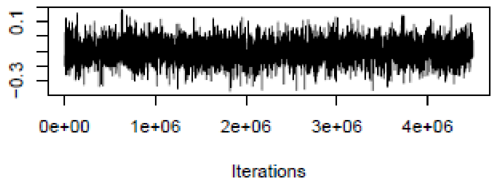
Trace of G_ageFirst13 to 17 years:time:change



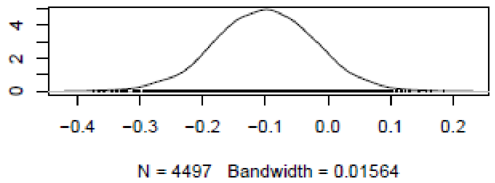
Density of G_ageFirst13 to 17 years:time:change



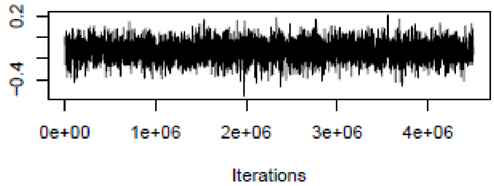
Trace of time:live:l_Seriousness2



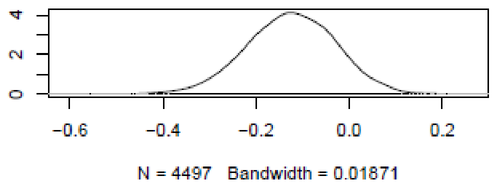
Density of time:live:l_Seriousness2



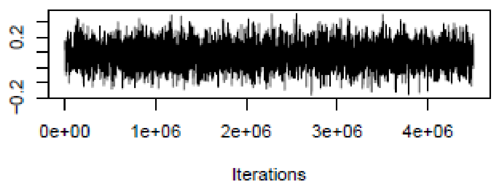
Trace of time:relation:l_Seriousness2



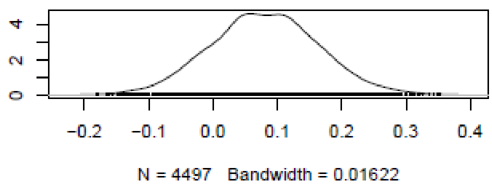
Density of time:relation:l_Seriousness2



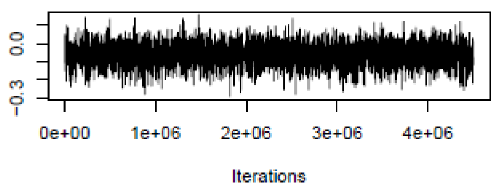
Trace of time:ete:l_Seriousness2



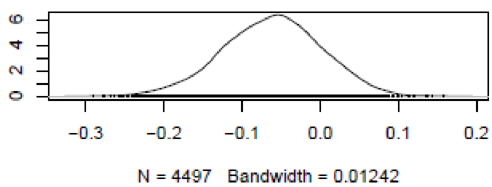
Density of time:ete:l_Seriousness2



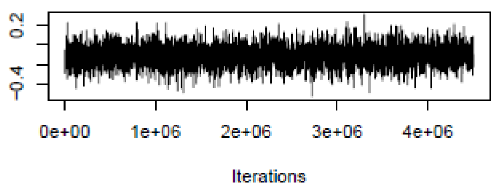
Trace of time:where:l_Seriousness2



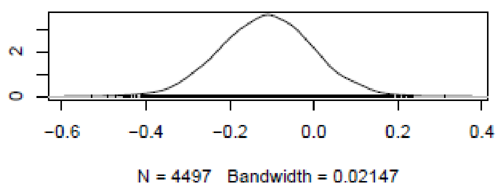
Density of time:where:l_Seriousness2

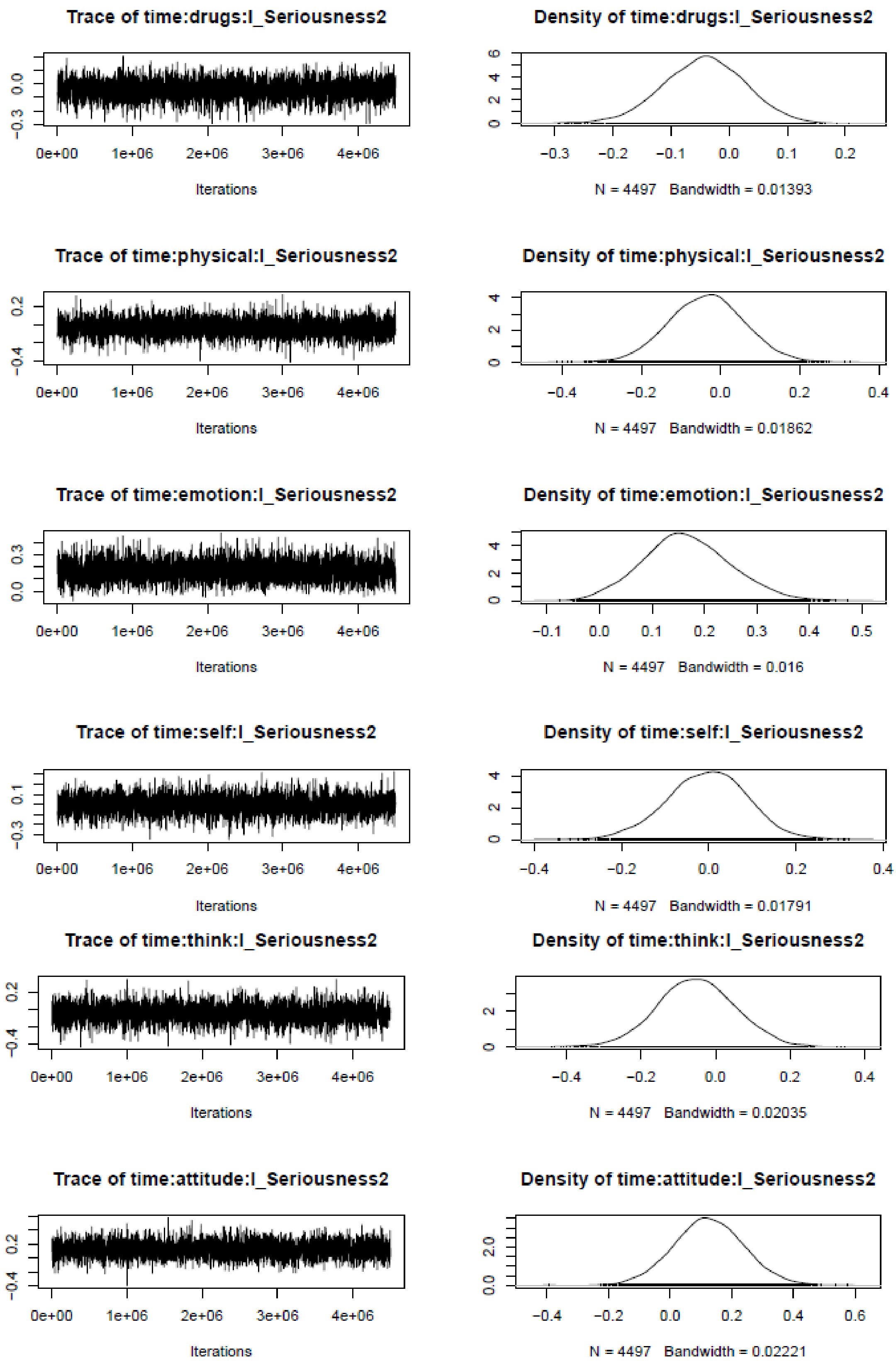


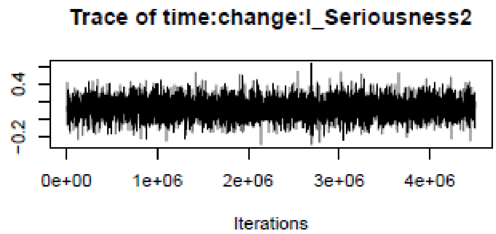
Trace of time:life:l_Seriousness2

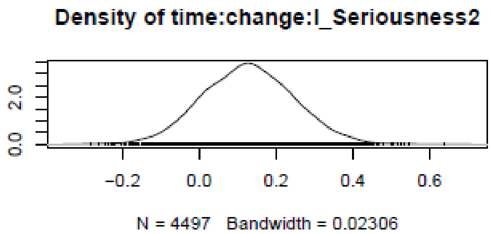


Density of time:life:l_Seriousness2

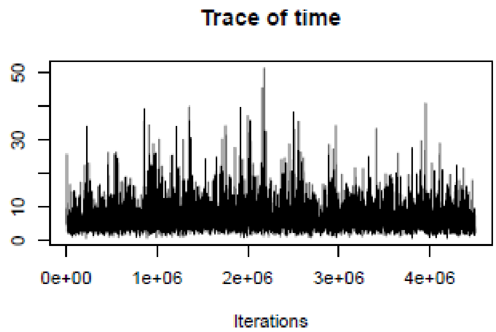


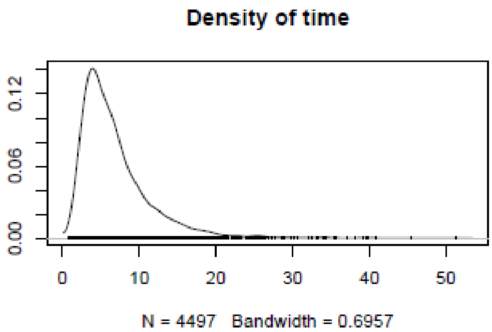

Trace of time:drugs:l_Seriousness2
Iterations
Density of time:drugs:l_Seriousness2
N = 4497 Bandwidth = 0.01393
Trace of time:physical:l_Seriousness2
Iterations
Density of time:physical:l_Seriousness2
N = 4497 Bandwidth = 0.01862
Trace of time:emotion:l_Seriousness2
Iterations
Density of time:emotion:l_Seriousness2
N = 4497 Bandwidth = 0.016
Trace of time:self:l_Seriousness2
Iterations
Density of time:self:l_Seriousness2
N = 4497 Bandwidth = 0.01791
Trace of time:think:l_Seriousness2
Iterations
Density of time:think:l_Seriousness2
N = 4497 Bandwidth = 0.02035
Trace of time:attitude:l_Seriousness2
Iterations
Density of time:attitude:l_Seriousness2
N = 4497 Bandwidth = 0.02221

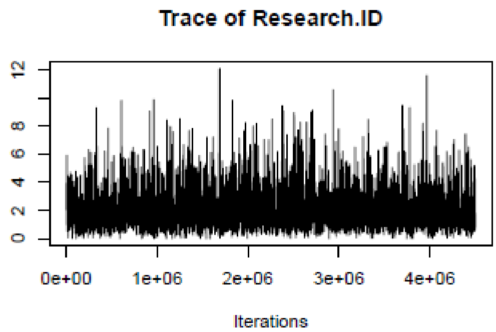


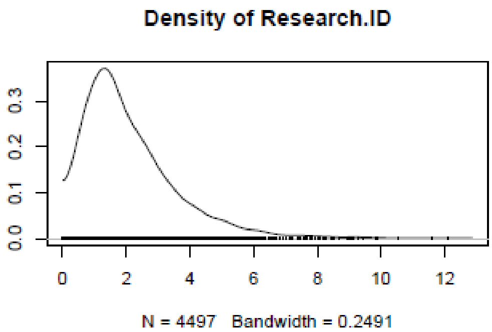


Random Effects









Dynamic Model 3 (Table 6.20)

Bayesian Model (BDm3G_cc12ao2a)

Define the model

```
BDm3G_cc12ao2 <- MCMCglmm(FO.bin~G_ageFirst*time*live +
G_ageFirst*time*relation + G_ageFirst*time*ete +
G_ageFirst*time*where + G_ageFirst*time*life + G_ageFirst*time*drugs +
G_ageFirst*time*physical + G_ageFirst*time*emotion +
G_ageFirst*time*self + G_ageFirst*time*think + G_ageFirst*time*attitude
+ G_ageFirst*time*change +
FTE*time*live + FTE*time*relation + FTE*time*ete +
FTE*time*where + FTE*time*life + FTE*time*drugs + FTE*time*physical +
FTE*time*emotion + FTE*time*self + FTE*time*think + FTE*time*attitude +
FTE*time*change +
I_Seriousness2*time + G_ageFirst*I_Seriousness2 + FTE*I_Seriousness2 +
G_ageFirst*FTE,                          ,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
nitt=8000000, thin=2000, burnin=5000)
```

Checks for suitable convergence

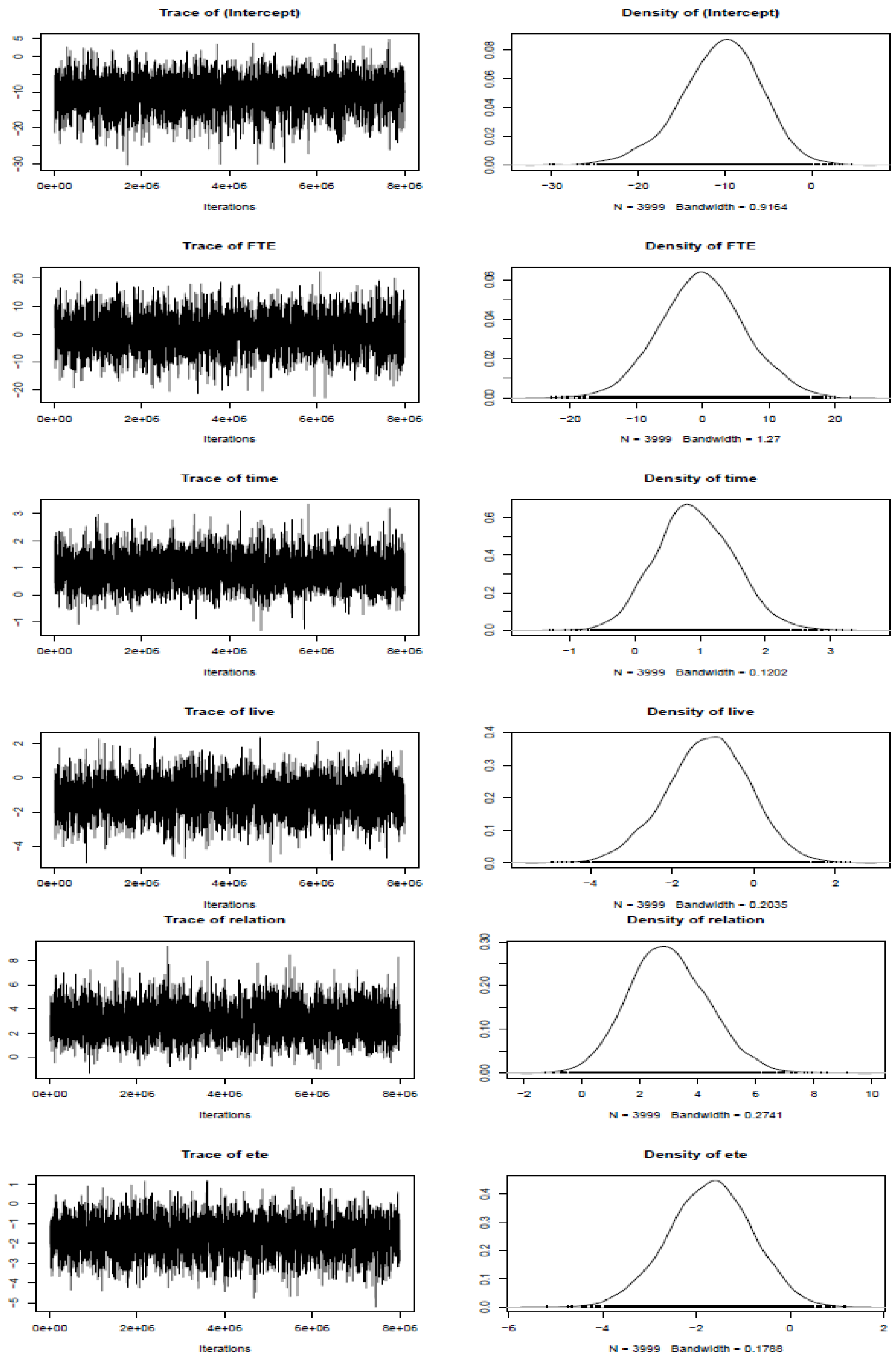
```
raftery.diag(BDm3G_cc12ao2$VCV)
heidel.diag(BDm3G_cc12ao2$VCV)

# > raftery.diag(BDm3G_cc12ao2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total   Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# time         4000     7578000 3746         2020
# Research.ID  4000     7896000 3746         2110
# units        <NA>     <NA>    3746           NA

# > heidel.diag(BDm3G_cc12ao2$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.872
# Research.ID  passed        1         0.855
# units        failed       NA            NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    13.28 0.387
# Research.ID  passed     7.37 0.143
# units        <NA>         NA    NA

autocorr(BDm3G_cc12ao2$VCV)
autocorr(BDm3G_cc12ao2$Sol)    # not included here
summary(BDm3G_cc12ao2)
```

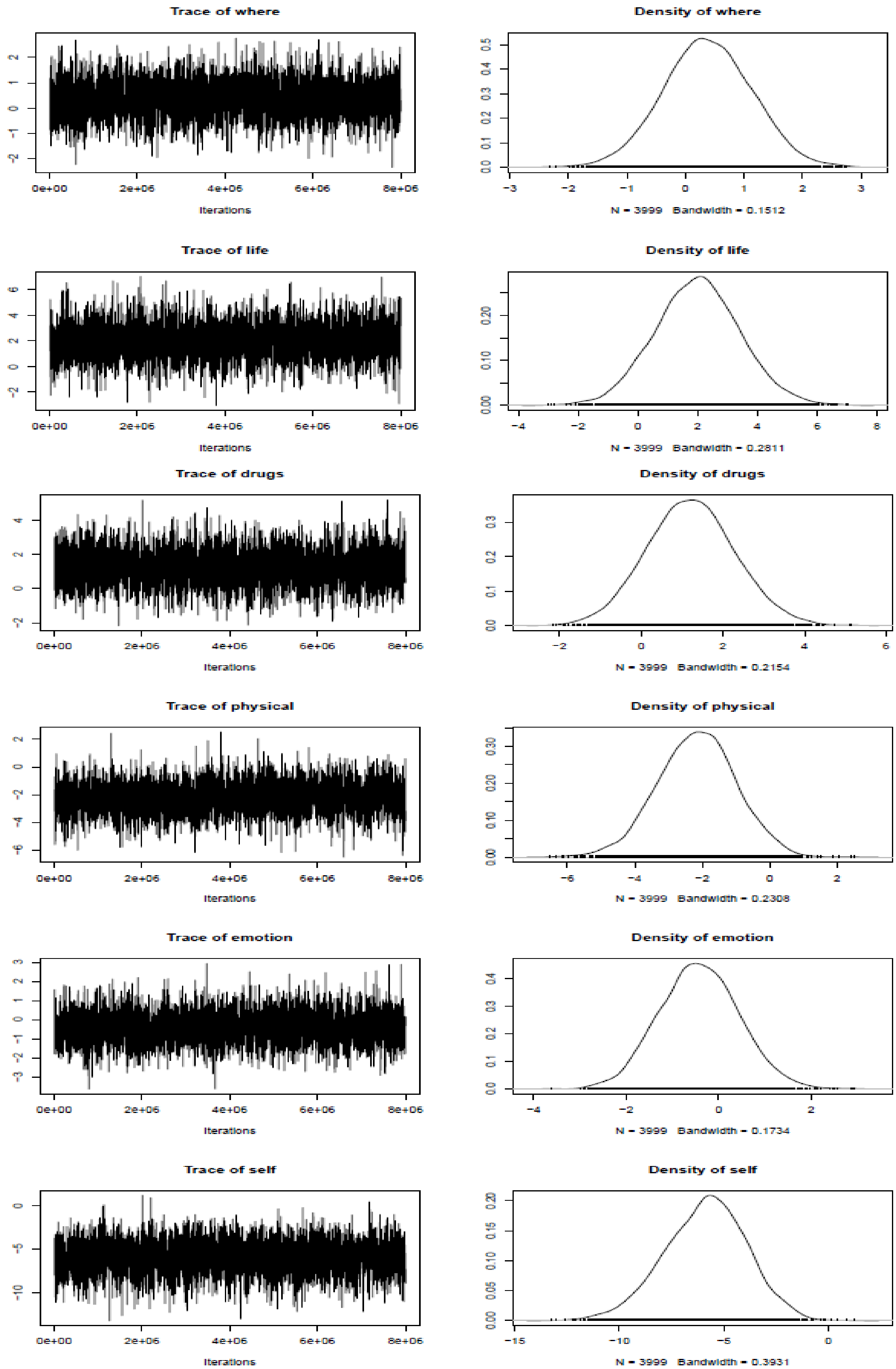
```
# > autocorr(BDm3G_cc12ao2$VCV)
# , , time
#
#                    time Research.ID units
# Lag 0      1.000000000  0.32180895   NaN
# Lag 2000   0.155041248  0.12458222   NaN
# Lag 10000  0.002024459  0.00451892   NaN
# Lag 20000 -0.040775461 -0.03777498   NaN
# Lag 1e+05  0.026504630  0.03270567   NaN
#
# , , Research.ID
#
#                    time  Research.ID units
# Lag 0      0.321808946  1.000000000   NaN
# Lag 2000   0.094812615  0.128935470   NaN
# Lag 10000 -0.005005904 -0.022869389   NaN
# Lag 20000 -0.031319928 -0.022133728   NaN
# Lag 1e+05  0.013504824  0.006847859   NaN

# > summary(BDm3G_cc12ao2)
#
# Iterations = 5001:7999001
# Thinning interval  = 2000
# Sample size  = 3998
#
# DIC: 387.8933
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     13.28    1.636    31.54     2688
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID     7.371    1.133    15.09     2923
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageFirst * time * live + G_ageFirst *
time * relation + G_ageFirst * time * ete + G_ageFirst * time * where +
G_ageFirst * time * life + G_ageFirst * time * drugs + G_ageFirst * time
* physical + G_ageFirst * time * emotion + G_ageFirst * time * self +
G_ageFirst * time * think + G_ageFirst * time * attitude + G_ageFirst *
time * change + FTE * time * live + FTE * time * relation + FTE * time *
ete + FTE * time * where + FTE * time * life + FTE * time * drugs + FTE
* time * physical + FTE * time * emotion + FTE * time * self + FTE *
time * think + FTE * time * attitude + FTE * time * change +
I_Seriousness2 * time + G_ageFirst * I_Seriousness2 + FTE *
I_Seriousness2 + G_ageFirst * FTE
#
#                                          post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept)                              -5.150972 -11.164018   0.570215     3808 0.0730 .
# G_ageFirst13 to 17 years                  5.144254  -1.234317  11.585239     3998 0.0975 .
# time                                      0.201232  -0.724955   1.139300     3998 0.6563
# live                                     -0.673757  -2.386204   0.979445     3998 0.4457
# relation                                  2.670993   0.383865   4.839662     3976 0.0110 *
# ete                                      -1.092417  -2.650211   0.442562     3998 0.1536
# where                                     0.480067  -0.870381   1.758244     3712 0.4777
# life                                      2.513456   0.199280   4.967693     3998 0.0395 *
# drugs                                    -0.446668  -2.008858   1.269984     4241 0.5873
```

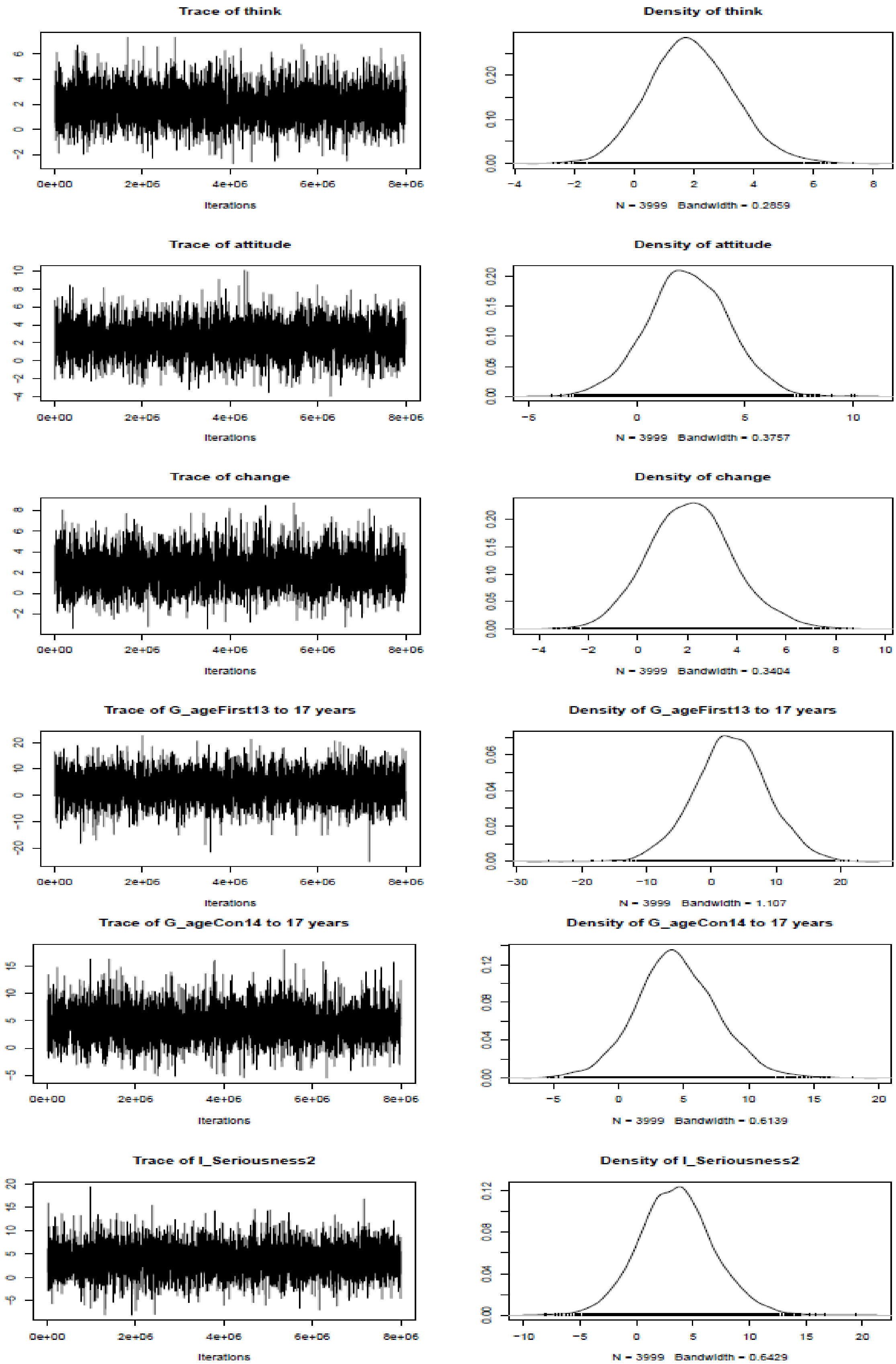
```
# physical                               -1.159918  -2.987216   0.610702     3808 0.1956
# emotion                                -0.471944  -1.888879   1.008432     3669 0.5103
# self                                   -6.735600 -10.170844  -3.456450     3485 <3e-04 ***
# think                                   1.839929  -0.618378   4.405593     3800 0.1321
# attitude                                2.818820  -0.321225   6.040191     3998 0.0740 .
# change                                  1.065015  -1.535402   3.995168     3998 0.4522
# FTE                                    -4.720378 -14.577722   4.547239     3998 0.3212
# I_Seriousness2                          0.084943  -1.265054   1.478074     3998 0.9110
# G_ageFirst13 to 17 years:time          -0.587150  -1.873360   0.828290     3998 0.3892
# G_ageFirst13 to 17 years:live           1.273958  -1.151754   3.454466     3998 0.2846
# time:live                              -0.142900  -0.516844   0.257516     3998 0.4587
# G_ageFirst13 to 17 years:relation      -4.089522  -7.297931  -1.259992     3605 0.0040 **
# time:relation                          -0.518666  -1.013080  -0.012912     3998 0.0265 *
# G_ageFirst13 to 17 years:ete            0.332241  -1.547266   2.373488     3640 0.7209
# time:ete                                0.207592  -0.113639   0.528399     3998 0.2061
# G_ageFirst13 to 17 years:where          1.477620  -0.590788   3.578961     3391 0.1526
# time:where                             -0.193267  -0.461103   0.084899     3998 0.1661
# G_ageFirst13 to 17 years:life          -2.415914  -5.929684   0.776649     3792 0.1596
# time:life                              -0.527517  -1.055041   0.038999     3998 0.0570 .
# G_ageFirst13 to 17 years:drugs          0.357525  -1.859566   2.530974     4253 0.7224
# time:drugs                              0.339848   0.020407   0.700737     3998 0.0435 *
# G_ageFirst13 to 17 years:physical      -1.259509  -3.939164   1.430843     3704 0.3517
# time:physical                           0.326911  -0.118426   0.756309     3730 0.1376
# G_ageFirst13 to 17 years:emotion        0.170452  -1.771077   2.322582     3776 0.8724
# time:emotion                            0.372673   0.075528   0.675698     3998 0.0120 *
# G_ageFirst13 to 17 years:self           8.071152   4.000871  12.024510     3558 <3e-04 ***
# time:self                               1.471754   0.820258   2.191141     3342 <3e-04 ***
# G_ageFirst13 to 17 years:think         -0.318265  -3.185917   2.640217     3998 0.8499
# time:think                             -0.366022  -0.842472   0.068409     3998 0.1051
# G_ageFirst13 to 17 years:attitude      -0.362018  -4.096083   3.346858     3998 0.8619
# time:attitude                          -0.859489  -1.421434  -0.282483     3624 0.0010 **
# G_ageFirst13 to 17 years:change        -3.296657  -6.840479   0.087031     3305 0.0520 .
# time:change                             0.099450  -0.413371   0.604584     3998 0.7084
# time:FTE                               -1.046247  -2.577325   0.473854     3548 0.1661
# live:FTE                                1.079842  -1.841439   4.082608     3998 0.4617
# relation:FTE                           -0.024719  -2.810608   2.747417     4631 0.9760
# ete:FTE                                 1.228447  -1.146733   3.681512     3757 0.3052
# where:FTE                              -4.412089  -7.223455  -1.938864     3201 <3e-04 ***
# life:FTE                                2.333735  -1.050389   5.869065     3768 0.1861
# drugs:FTE                              -0.963615  -3.504742   1.834314     3998 0.4497
# physical:FTE                            1.310114  -1.555944   4.123877     3590 0.3647
# emotion:FTE                            -0.686621  -2.926955   1.532065     3998 0.5288
# self:FTE                                2.151453  -0.631508   4.936126     3998 0.1306
# think:FTE                              -2.604403  -5.332442   0.131680     3543 0.0520 .
# attitude:FTE                           -3.706076  -6.714992  -1.076466     3446 0.0065 **
# change:FTE                              3.256467   0.291315   6.520936     3998 0.0415 *
# time:I_Seriousness2                     0.041573  -0.080143   0.161113     3608 0.5063
# G_ageFirst13 to 17 years:I_Seriousness2  -0.672519  -2.240818   0.841369     4188 0.3732
# FTE:I_Seriousness2                      0.509346  -0.708681   1.935971     3998 0.4337
# G_ageFirst13 to 17 years:FTE            4.642491  -4.262667  13.741457     3998 0.3067
# G_ageFirst13 to 17 years:time:live      0.325173  -0.282989   0.940236     3998 0.2916
# G_ageFirst13 to 17 years:time:relation    1.049072   0.391227   1.773237     4198 <3e-04 ***
# G_ageFirst13 to 17 years:time:ete      -0.308003  -0.806831   0.198059     3686 0.2181
# G_ageFirst13 to 17 years:time:where    -0.003797  -0.432438   0.432732     3630 0.9835
# G_ageFirst13 to 17 years:time:life      0.357633  -0.464132   1.197844     3760 0.4097
# G_ageFirst13 to 17 years:time:drugs    -0.622083  -1.203937  -0.150852     3998 0.0200 *
# G_ageFirst13 to 17 years:time:physical    0.554315  -0.232537   1.365315     3691 0.1671
# G_ageFirst13 to 17 years:time:emotion  -0.592757  -1.182620  -0.023141     4308 0.0390 *
# G_ageFirst13 to 17 years:time:self     -1.561500  -2.373767  -0.739141     3484 <3e-04 ***
# G_ageFirst13 to 17 years:time:think    -0.162584  -0.820154   0.494323     3998 0.6433
# G_ageFirst13 to 17 years:time:attitude    0.106286  -0.694704   0.907729     3904 0.8069
# G_ageFirst13 to 17 years:time:change    0.653849  -0.128593   1.402211     3531 0.0820 .
# time:live:FTE                          -0.593345  -1.353827   0.138757     3356 0.1121
# time:relation:FTE                      -0.083004  -0.805392   0.602084     3998 0.8089
# time:ete:FTE                            0.434190  -0.226843   1.115738     3652 0.1921
# time:where:FTE                          0.606103   0.102222   1.064802     3610 0.0080 **
# time:life:FTE                          -0.525872  -1.400477   0.338078     3998 0.2426
# time:drugs:FTE                          0.695160   0.065938   1.285142     3566 0.0200 *
# time:physical:FTE                      -0.920443  -1.851233  -0.108412     3241 0.0305 *
# time:emotion:FTE                        0.498393  -0.121621   1.134819     3611 0.1206
# time:self:FTE                          -0.807315  -1.496655  -0.160331     3998 0.0115 *
# time:think:FTE                          0.853626   0.141123   1.529417     4153 0.0105 *
# time:attitude:FTE                       1.087005   0.331429   1.921780     3550 0.0060 **
# time:change:FTE                        -0.987037  -1.798955  -0.236410     3614 0.0110 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

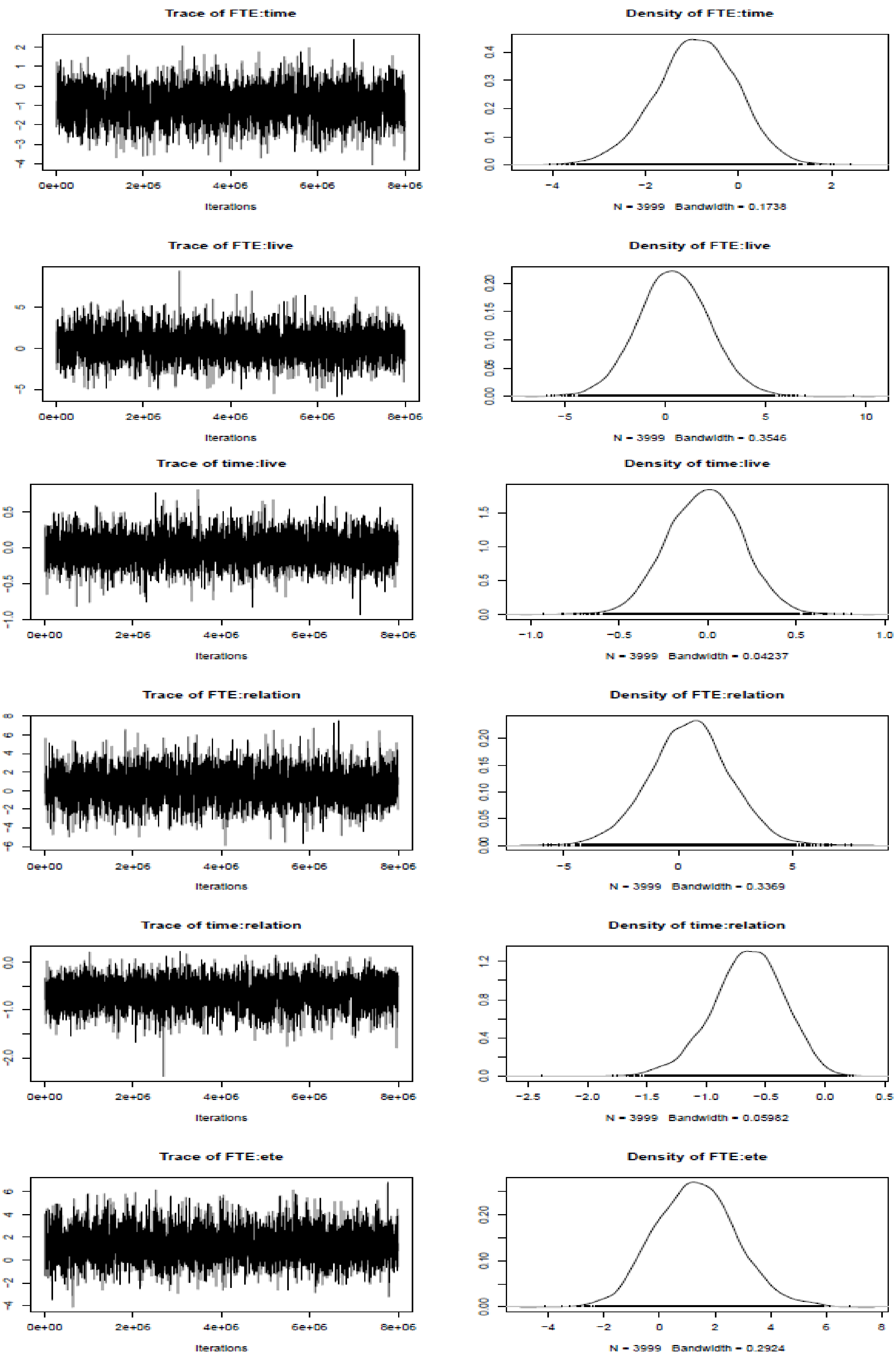
Trace Plots and Posterior Density Plots

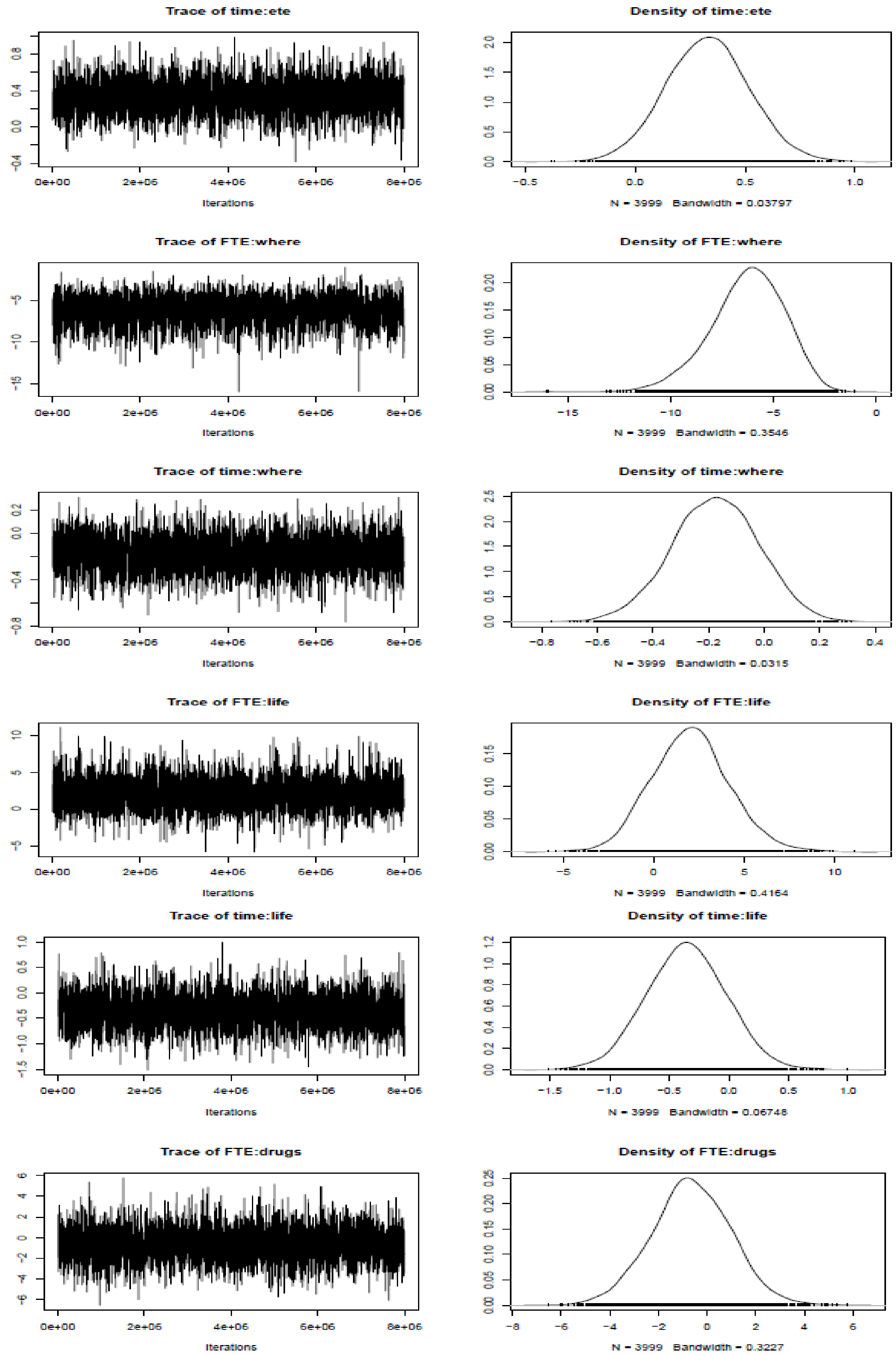
Fixed Effects

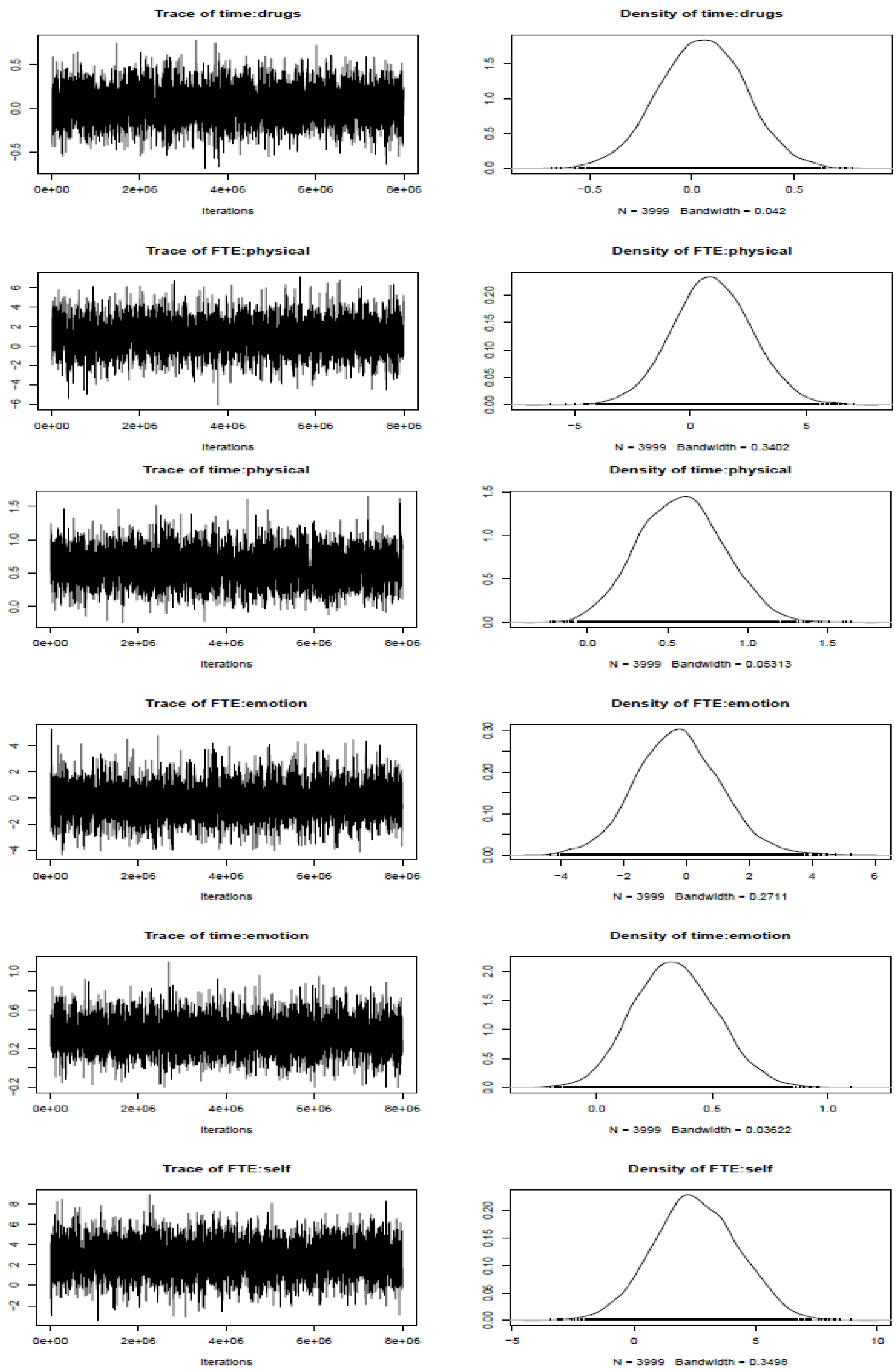


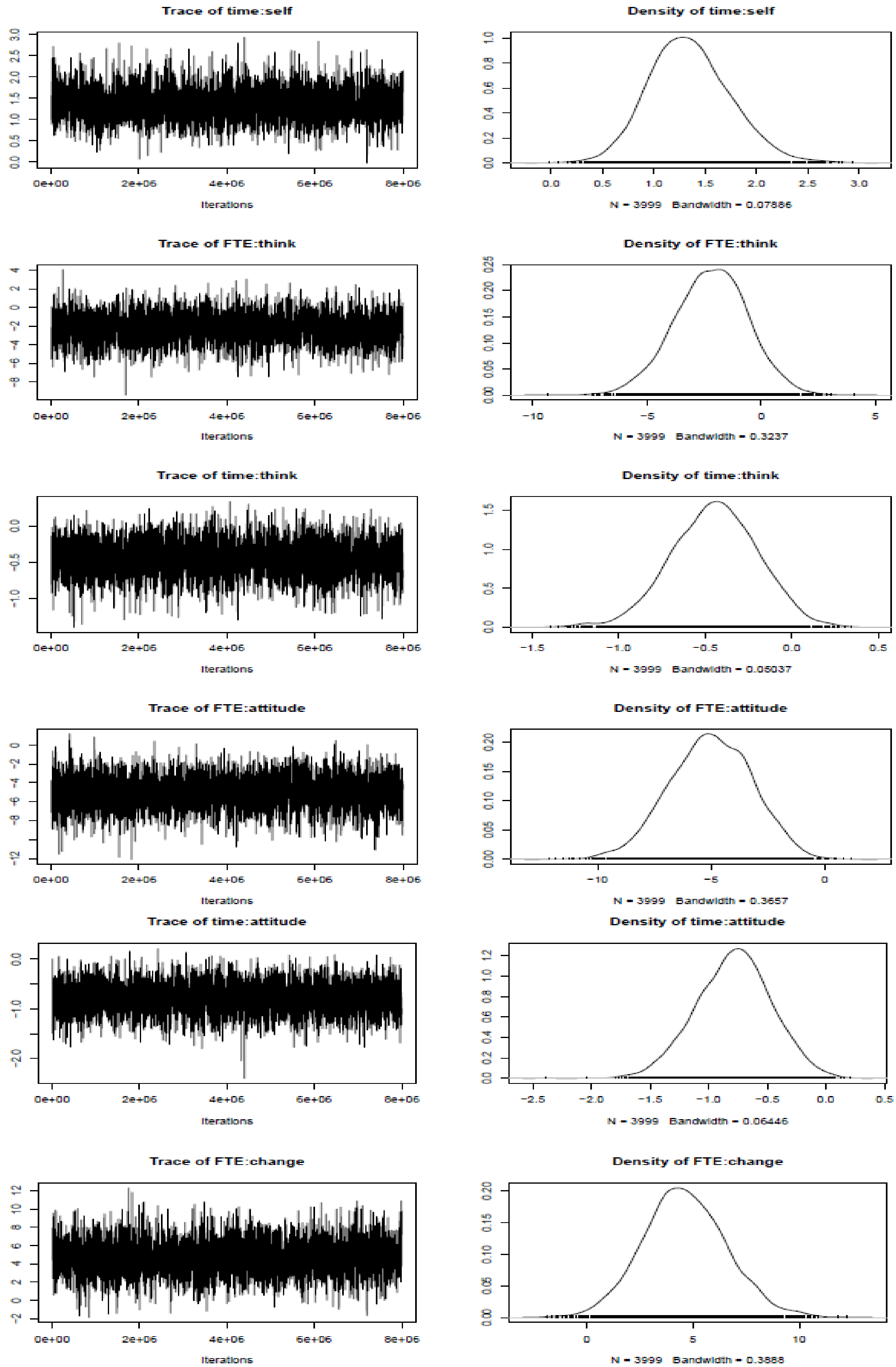

Trace of where
Iterations
Density of where
N = 3999 Bandwidth = 0.1512
Trace of life
Iterations
Density of life
N = 3999 Bandwidth = 0.2811
Trace of drugs
Iterations
Density of drugs
N = 3999 Bandwidth = 0.2154
Trace of physical
Iterations
Density of physical
N = 3999 Bandwidth = 0.2308
Trace of emotion
Iterations
Density of emotion
N = 3999 Bandwidth = 0.1734
Trace of self
Iterations
Density of self
N = 3999 Bandwidth = 0.3931

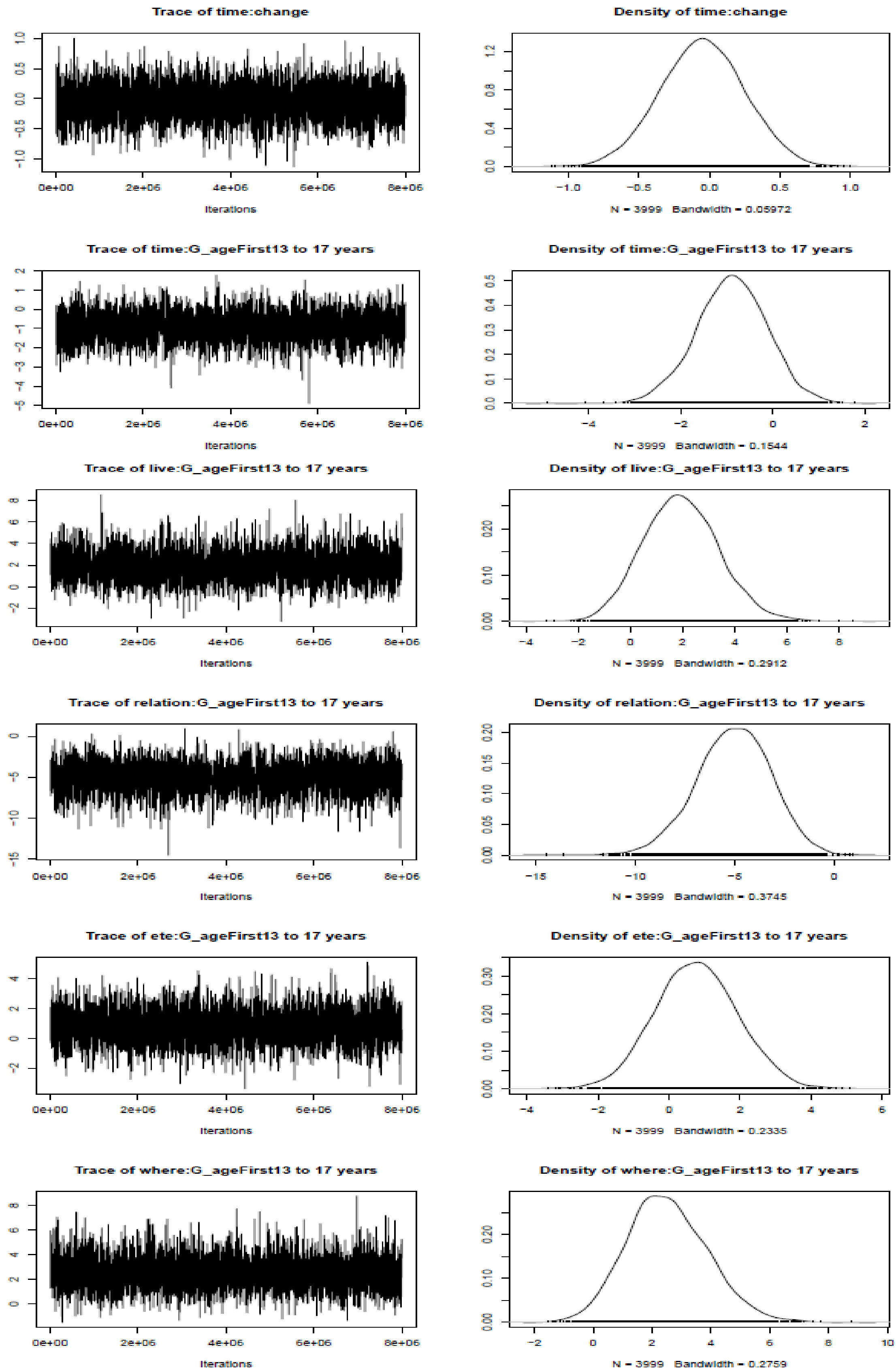

Trace of think
Iterations
Density of think
N = 3999 Bandwidth = 0.2859
Trace of attitude
Iterations
Density of attitude
N = 3999 Bandwidth = 0.3757
Trace of change
Iterations
Density of change
N = 3999 Bandwidth = 0.3404
Trace of G_ageFirst13 to 17 years
Iterations
Density of G_ageFirst13 to 17 years
N = 3999 Bandwidth = 1.107
Trace of G_ageCon14 to 17 years
Iterations
Density of G_ageCon14 to 17 years
N = 3999 Bandwidth = 0.6139
Trace of I_Seriousness2
Iterations
Density of I_Seriousness2
N = 3999 Bandwidth = 0.6429

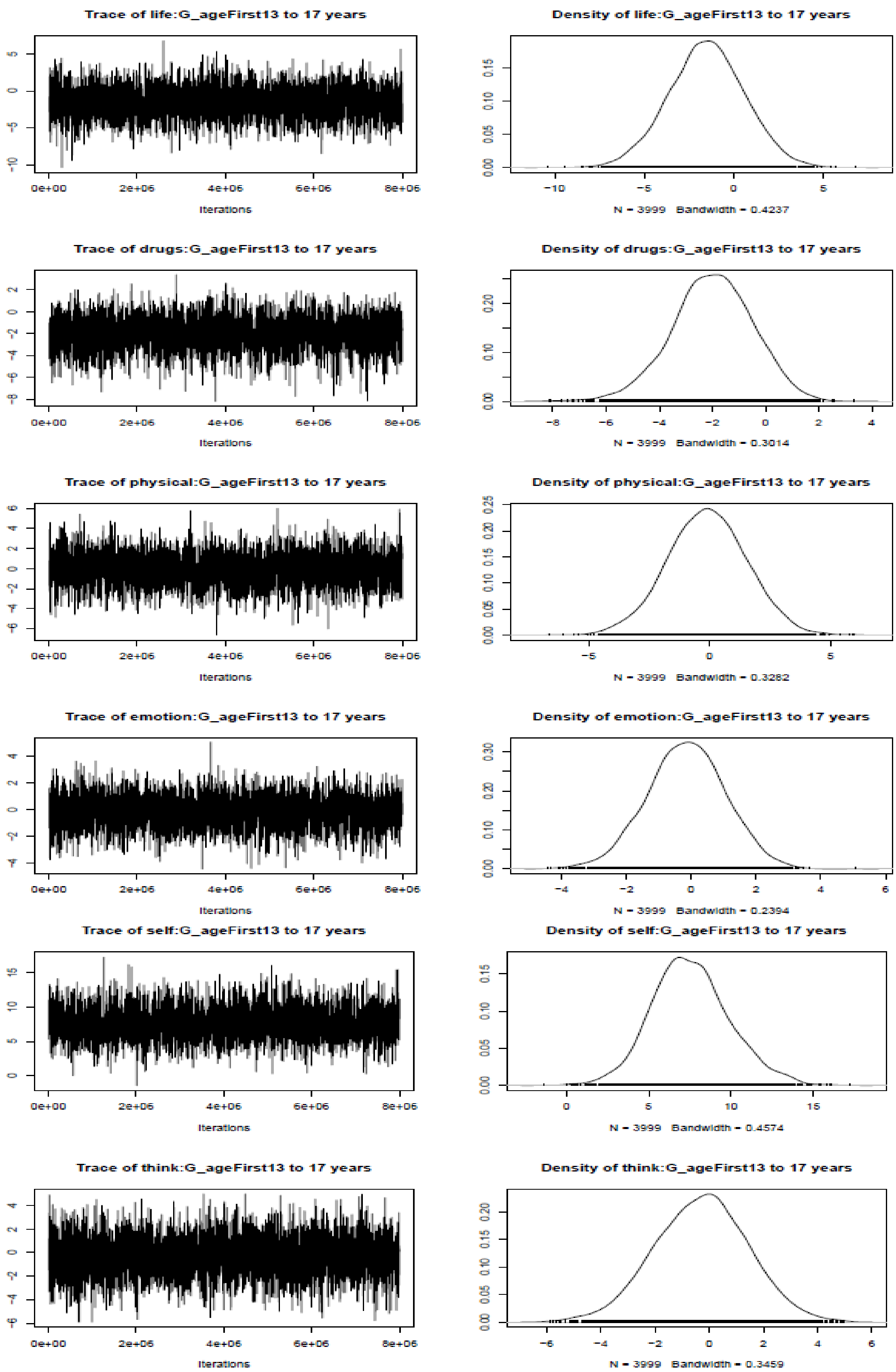

Trace of FTE:time
Iterations
Density of FTE:time
N = 3999 Bandwidth = 0.1738
Trace of FTE:live
Iterations
Density of FTE:live
N = 3999 Bandwidth = 0.3546
Trace of time:live
Iterations
Density of time:live
N = 3999 Bandwidth = 0.04237
Trace of FTE:relation
Iterations
Density of FTE:relation
N = 3999 Bandwidth = 0.3369
Trace of time:relation
Iterations
Density of time:relation
N = 3999 Bandwidth = 0.05982
Trace of FTE:ete
Iterations
Density of FTE:ete
N = 3999 Bandwidth = 0.2924

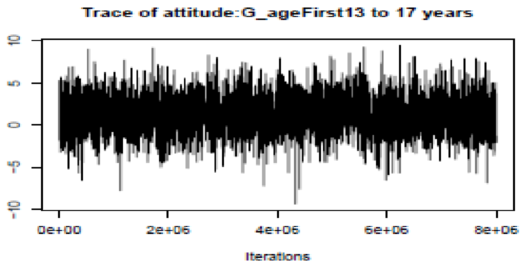

Trace of time:ete
Iterations
Density of time:ete
N = 3999 Bandwidth = 0.03797
Trace of FTE:where
Iterations
Density of FTE:where
N = 3999 Bandwidth = 0.3546
Trace of time:where
Iterations
Density of time:where
N = 3999 Bandwidth = 0.0315
Trace of FTE:life
Iterations
Density of FTE:life
N = 3999 Bandwidth = 0.4164
Trace of time:life
Iterations
Density of time:life
N = 3999 Bandwidth = 0.06748
Trace of FTE:drugs
Iterations
Density of FTE:drugs
N = 3999 Bandwidth = 0.3227

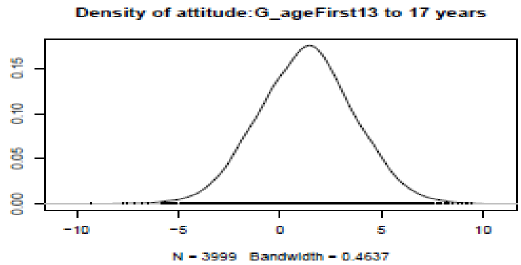

Trace of time:drugs
Iterations
Density of time:drugs
N = 3999 Bandwidth = 0.042
Trace of FTE:physical
Iterations
Density of FTE:physical
N = 3999 Bandwidth = 0.3402
Trace of time:physical
Iterations
Density of time:physical
N = 3999 Bandwidth = 0.05313
Trace of FTE:emotion
Iterations
Density of FTE:emotion
N = 3999 Bandwidth = 0.2711
Trace of time:emotion
Iterations
Density of time:emotion
N = 3999 Bandwidth = 0.03622
Trace of FTE:self
Iterations
Density of FTE:self
N = 3999 Bandwidth = 0.3498

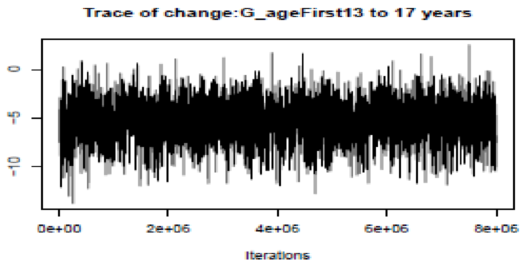

Trace of time:self
Iterations
Density of time:self
N = 3999 Bandwidth = 0.07886
Trace of FTE:think
Iterations
Density of FTE:think
N = 3999 Bandwidth = 0.3237
Trace of time:think
Iterations
Density of time:think
N = 3999 Bandwidth = 0.05037
Trace of FTE:attitude
Iterations
Density of FTE:attitude
N = 3999 Bandwidth = 0.3657
Trace of time:attitude
Iterations
Density of time:attitude
N = 3999 Bandwidth = 0.06446
Trace of FTE:change
Iterations
Density of FTE:change
N = 3999 Bandwidth = 0.3888

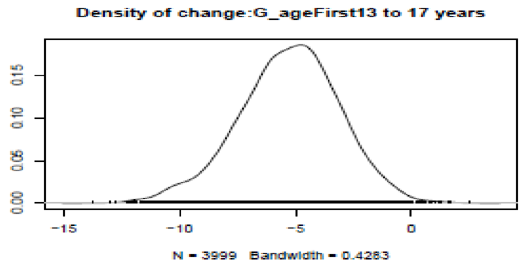

Trace of time:change
Iterations
Density of time:change
N = 3999 Bandwidth = 0.05972
Trace of time:G_ageFirst13 to 17 years
Iterations
Density of time:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.1544
Trace of live:G_ageFirst13 to 17 years
Iterations
Density of live:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.2912
Trace of relation:G_ageFirst13 to 17 years
Iterations
Density of relation:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.3745
Trace of ete:G_ageFirst13 to 17 years
Iterations
Density of ete:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.2335
Trace of where:G_ageFirst13 to 17 years
Iterations
Density of where:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.2759

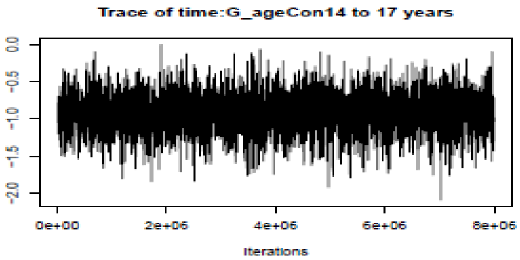

Trace of life:G_ageFirst13 to 17 years
Iterations
Density of life:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.4237
Trace of drugs:G_ageFirst13 to 17 years
Iterations
Density of drugs:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.3014
Trace of physical:G_ageFirst13 to 17 years
Iterations
Density of physical:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.3282
Trace of emotion:G_ageFirst13 to 17 years
Iterations
Density of emotion:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.2394
Trace of self:G_ageFirst13 to 17 years
Iterations
Density of self:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.4574
Trace of think:G_ageFirst13 to 17 years
Iterations
Density of think:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.3459

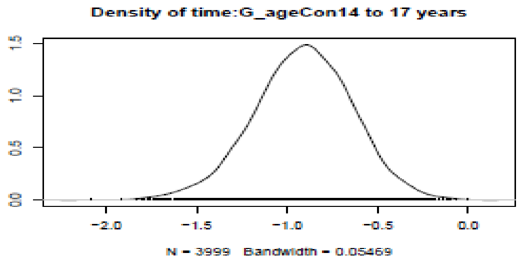

Trace of attitude:G_ageFirst13 to 17 years
Iterations

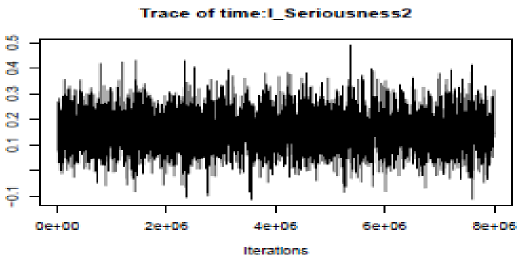

Density of attitude:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.4637

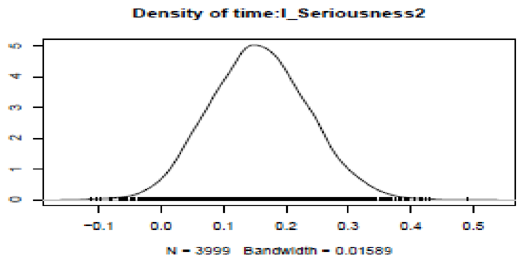

Trace of change:G_ageFirst13 to 17 years
Iterations

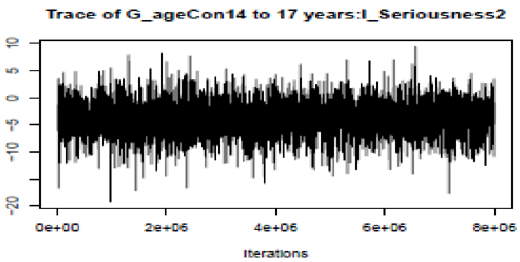

Density of change:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.4283

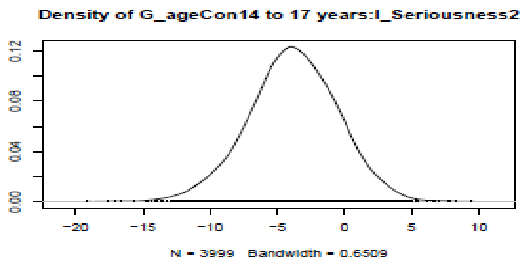

Trace of time:G_ageCon14 to 17 years
Iterations

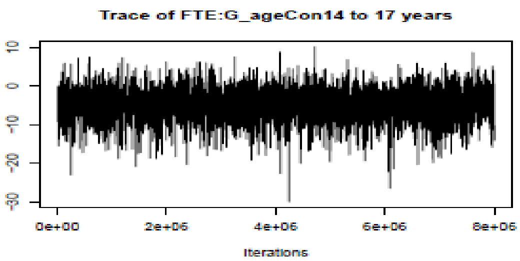

Density of time:G_ageCon14 to 17 years
N = 3999 Bandwidth = 0.05469

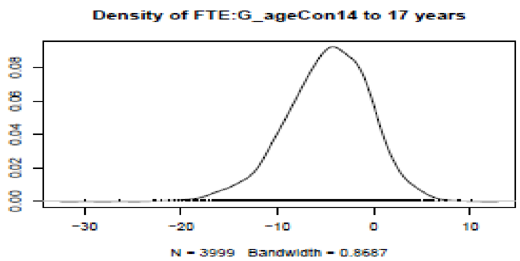

Trace of time:I_Seriousness2
Iterations

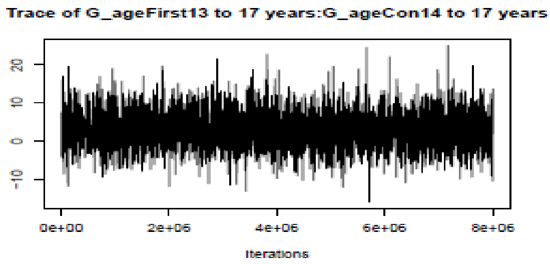

Density of time:I_Seriousness2
N = 3999 Bandwidth = 0.01589

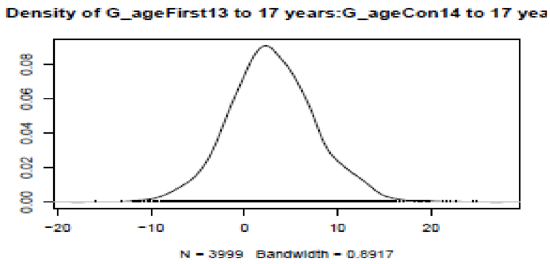

Trace of G_ageCon14 to 17 years:I_Seriousness2
Iterations

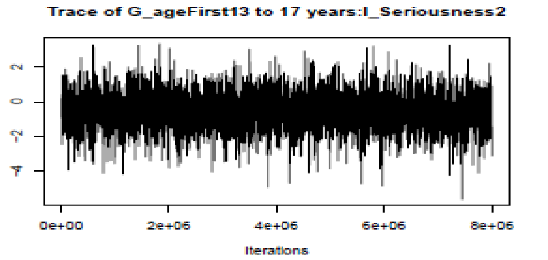

Density of G_ageCon14 to 17 years:I_Seriousness2
N = 3999 Bandwidth = 0.6509

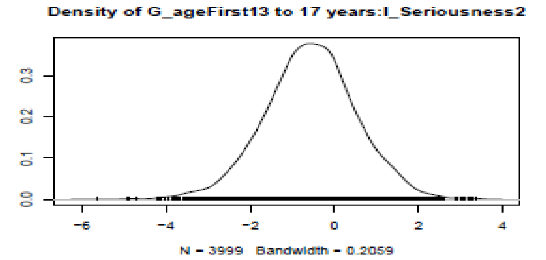

Trace of FTE:G_ageCon14 to 17 years
Iterations

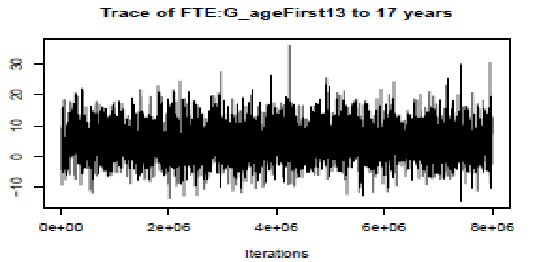

Density of FTE:G_ageCon14 to 17 years
N = 3999 Bandwidth = 0.8687

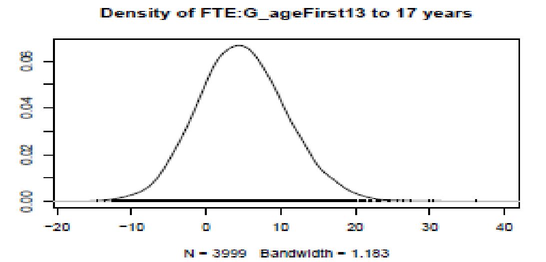

Trace of G_ageFirst13 to 17 years:G_ageCon14 to 17 years
Iterations

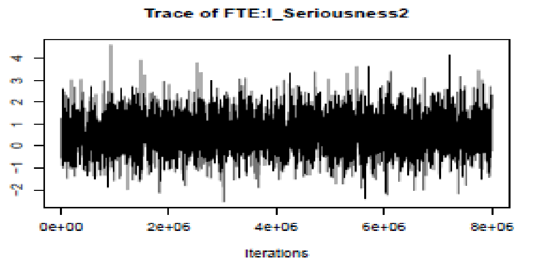

Density of G_ageFirst13 to 17 years:G_ageCon14 to 17 yea
N = 3999 Bandwidth = 0.6917

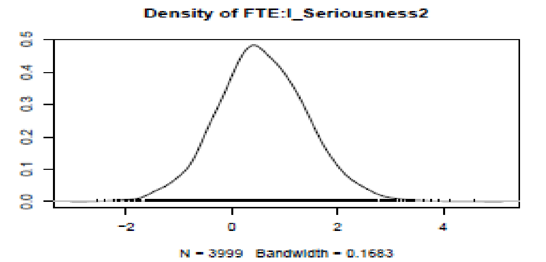

Trace of G_ageFirst13 to 17 years:I_Seriousness2
Iterations

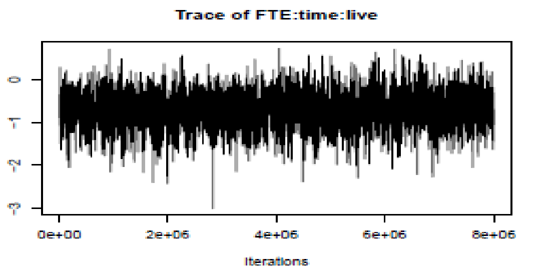

Density of G_ageFirst13 to 17 years:I_Seriousness2
N = 3999 Bandwidth = 0.2059

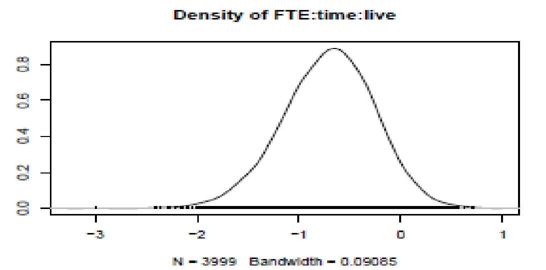

Trace of FTE:G_ageFirst13 to 17 years
Iterations

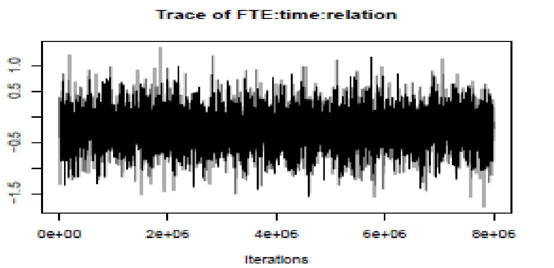

Density of FTE:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 1.183

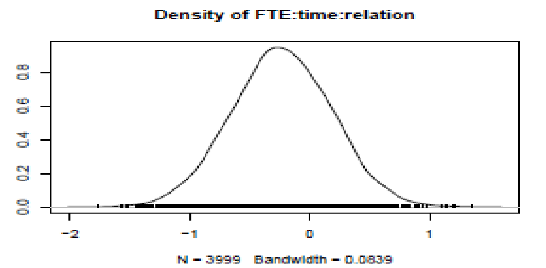

Trace of FTE:I_Seriousness2
Iterations

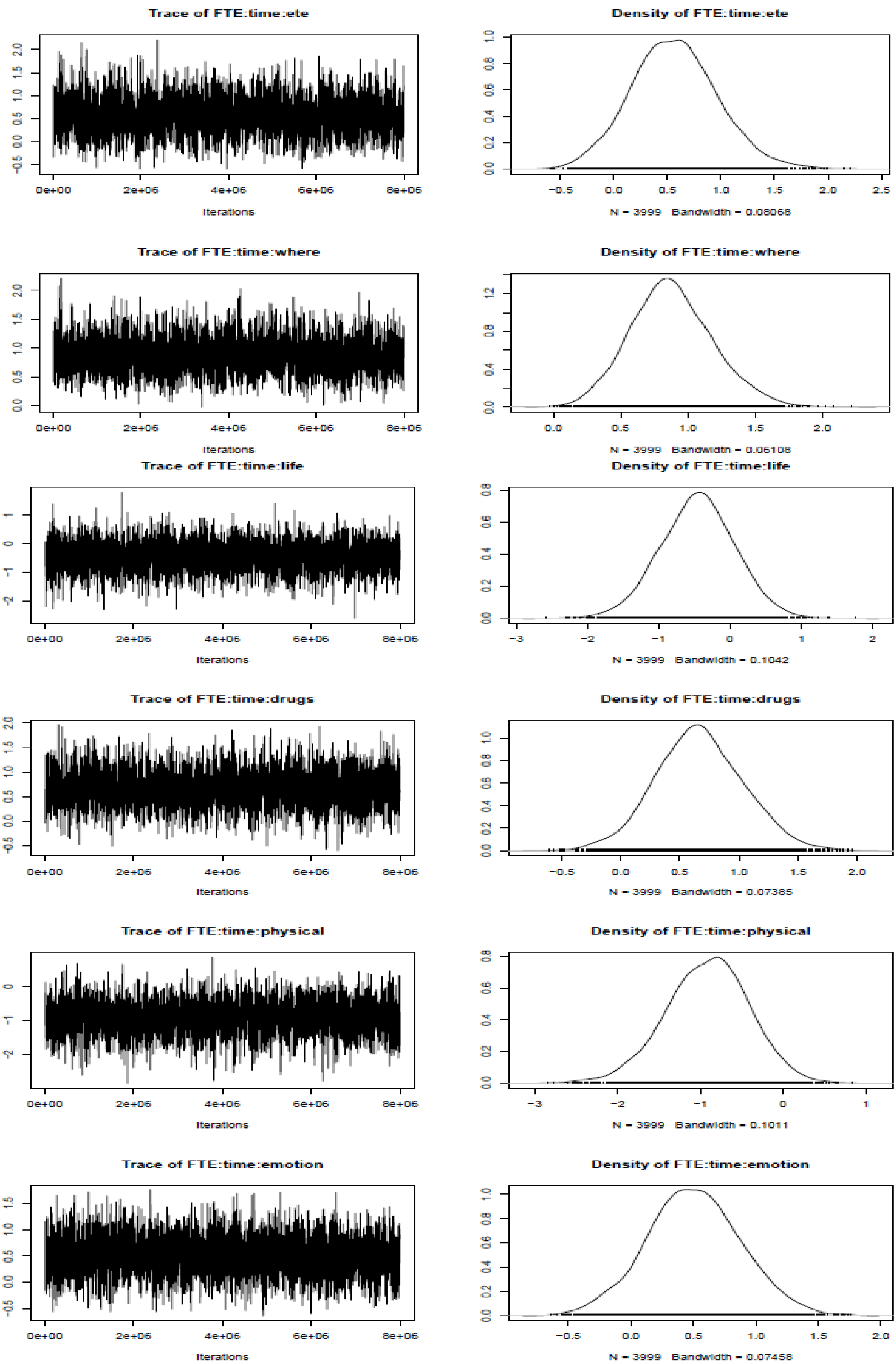

Density of FTE:I_Seriousness2
N = 3999 Bandwidth = 0.1683

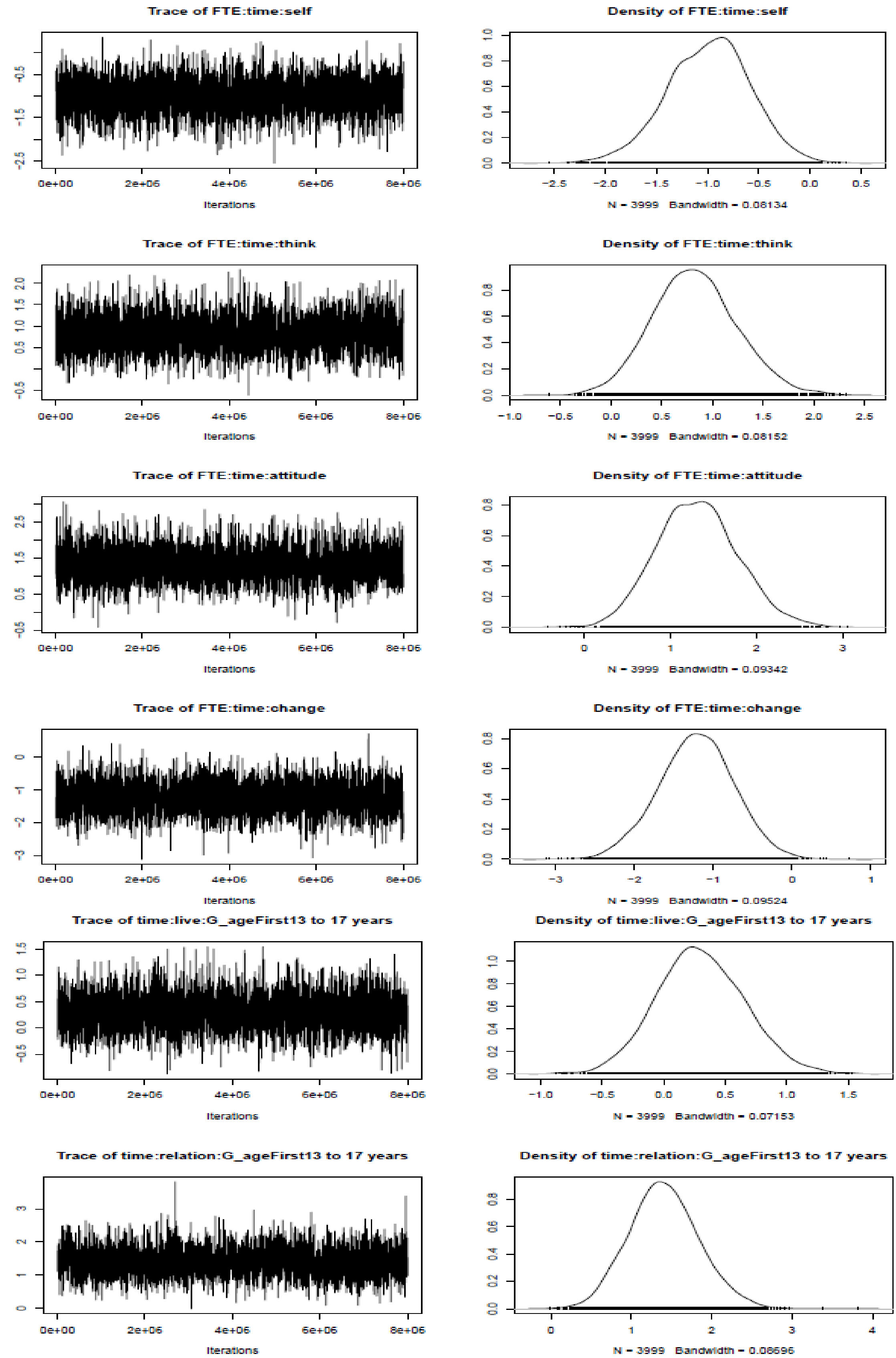

Trace of FTE:time:live
Iterations

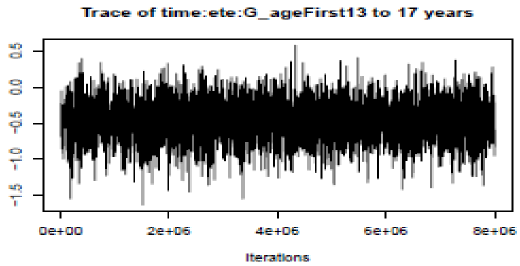

Density of FTE:time:live
N = 3999 Bandwidth = 0.09085

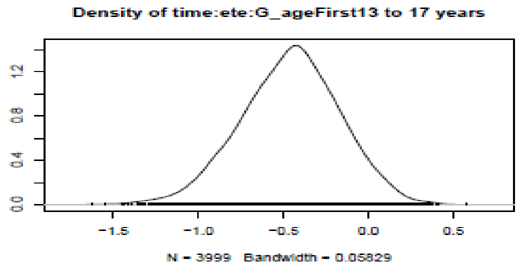

Trace of FTE:time:relation
Iterations

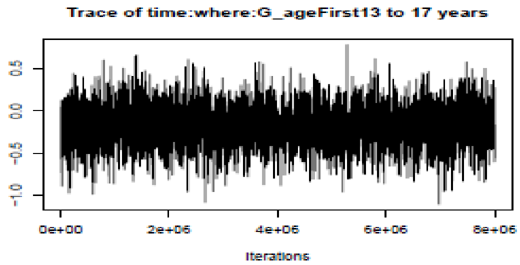

Density of FTE:time:relation
N = 3999 Bandwidth = 0.0839

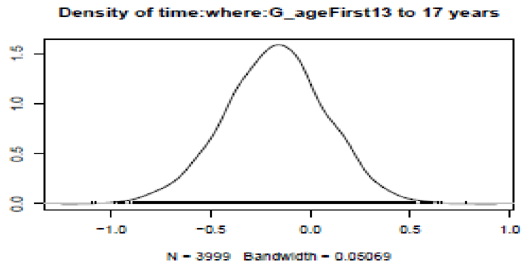

Trace of FTE:time:ete
Iterations
Density of FTE:time:ete
N = 3999 Bandwidth = 0.06068
Trace of FTE:time:where
Iterations
Density of FTE:time:where
N = 3999 Bandwidth = 0.06108
Trace of FTE:time:life
Iterations
Density of FTE:time:life
N = 3999 Bandwidth = 0.1042
Trace of FTE:time:drugs
Iterations
Density of FTE:time:drugs
N = 3999 Bandwidth = 0.07385
Trace of FTE:time:physical
Iterations
Density of FTE:time:physical
N = 3999 Bandwidth = 0.1011
Trace of FTE:time:emotion
Iterations
Density of FTE:time:emotion
N = 3999 Bandwidth = 0.07458

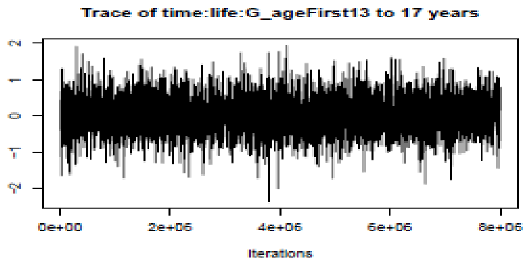

Trace of FTE:time:self
Iterations
Density of FTE:time:self
N = 3999 Bandwidth = 0.08134
Trace of FTE:time:think
Iterations
Density of FTE:time:think
N = 3999 Bandwidth = 0.08152
Trace of FTE:time:attitude
Iterations
Density of FTE:time:attitude
N = 3999 Bandwidth = 0.09342
Trace of FTE:time:change
Iterations
Density of FTE:time:change
N = 3999 Bandwidth = 0.09524
Trace of time:live:G_ageFirst13 to 17 years
Iterations
Density of time:live:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.07153
Trace of time:relation:G_ageFirst13 to 17 years
Iterations
Density of time:relation:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.08696

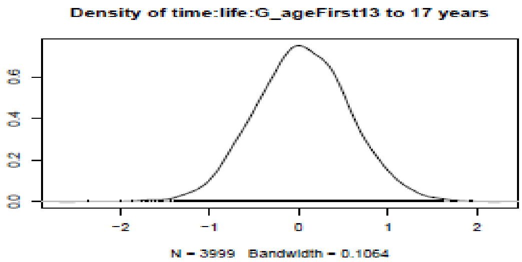

Trace of time:ete:G_ageFirst13 to 17 years
Iterations

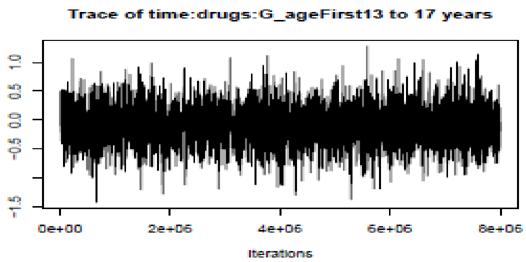

Density of time:ete:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.05829

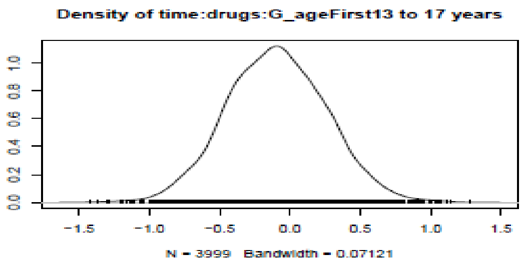

Trace of time:where:G_ageFirst13 to 17 years
Iterations

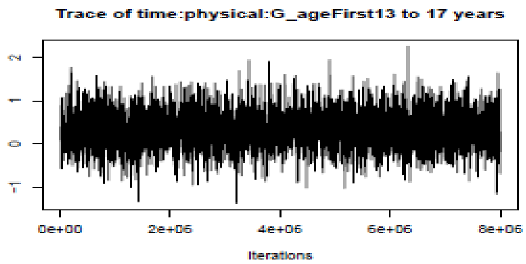

Density of time:where:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.05069

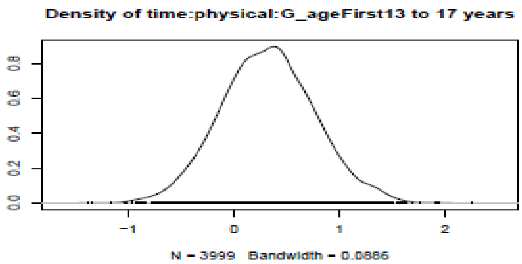

Trace of time:life:G_ageFirst13 to 17 years
Iterations

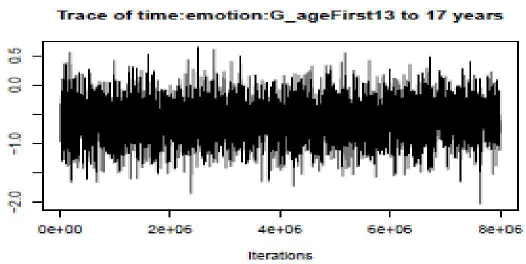

Density of time:life:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.1064

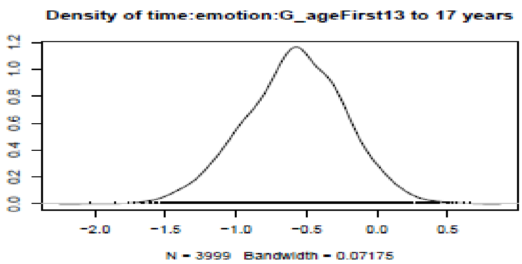

Trace of time:drugs:G_ageFirst13 to 17 years
Iterations

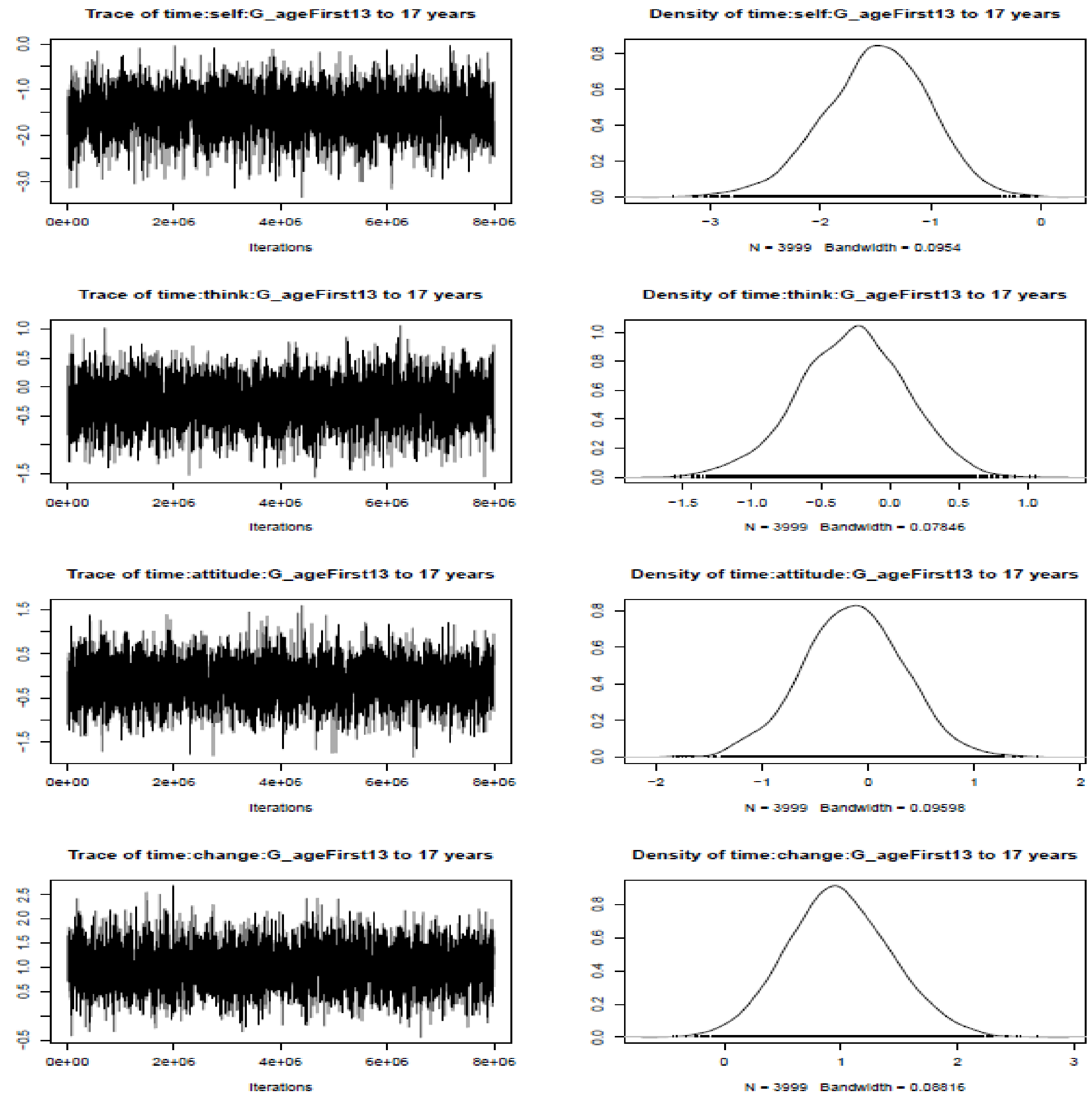

Density of time:drugs:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.07121


Trace of time:physical:G_ageFirst13 to 17 years
Iterations

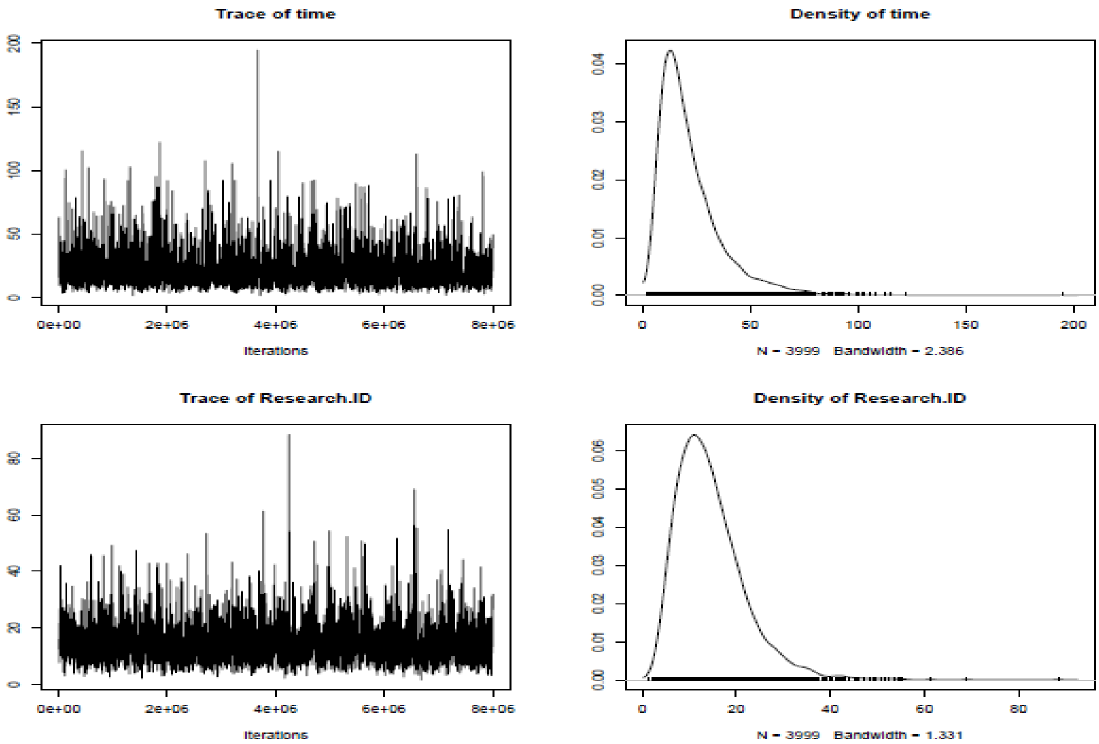

Density of time:physical:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.0886


Trace of time:emotion:G_ageFirst13 to 17 years
Iterations


Density of time:emotion:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.07175


Trace of time:self:G_ageFirst13 to 17 years
Iterations
Density of time:self:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.0954
Trace of time:think:G_ageFirst13 to 17 years
Iterations
Density of time:think:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.07846
Trace of time:attitude:G_ageFirst13 to 17 years
Iterations
Density of time:attitude:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.09598
Trace of time:change:G_ageFirst13 to 17 years
Iterations
Density of time:change:G_ageFirst13 to 17 years
N = 3999 Bandwidth = 0.08816

Random Effects



Dynamic Model involving Age at First Offence (Table 6.21)

Bayesian Model (BDm3_cc2)

Define the model

```
BDm3_cc2 <- MCMCglmm(FO.bin ~ ageFirst_10*time*live +
ageFirst_10*time*relation + ageFirst_10*time*ete +
ageFirst_10*time*where + ageFirst_10*time*life + ageFirst_10*time*drugs
+ ageFirst_10*time*physical + ageFirst_10*time*emotion +
ageFirst_10*time*self + ageFirst_10*time*think +
ageFirst_10*time*attitude + ageFirst_10*time*change,
random=~time+Research.ID, data=data, family="ordinal", prior=priorD,
slice=TRUE, nitt=610000, thin=50, burnin=3000)
```

Checks for suitable convergence

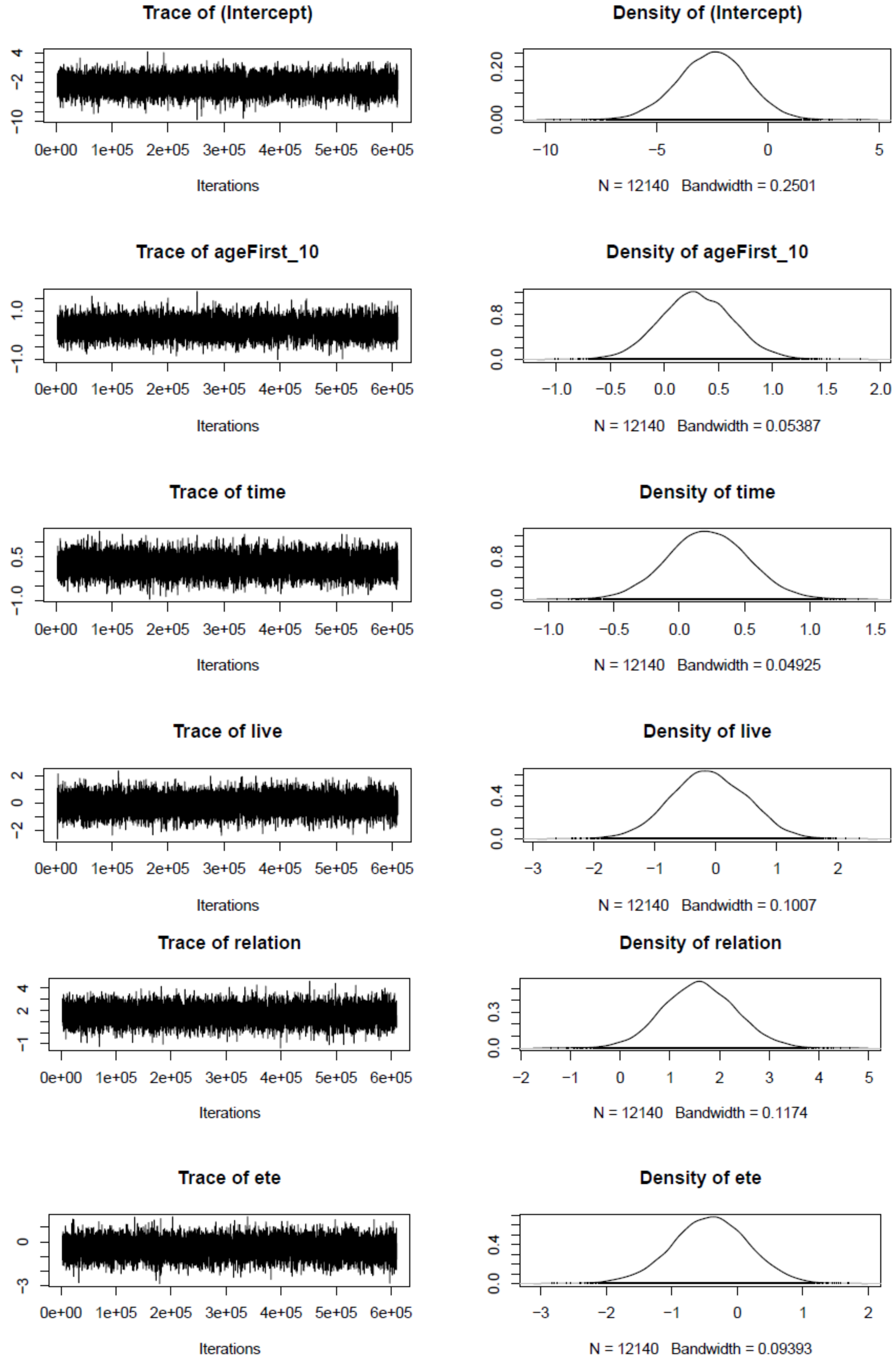
```
raftery.diag(BDm3_cc2$VCV)
heidel.diag(BDm3_cc2$VCV)

# > raftery.diag(BDm3_cc2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      192050 3746         51.3
# Research.ID  150      222900 3746         59.5
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm3_cc2$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.311
# Research.ID  passed        1        0.409
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    2.768 0.0614
# Research.ID  passed    0.662 0.0120
# units        <NA>         NA     NA

autocorr(BDm3_cc2$VCV)
autocorr(BDm3_cc2$Sol)    # Output not included here
summary(BDm3_cc2)

# > autocorr(BDm3_cc2$VCV)
# , , time
#
#                 time Research.ID units
# Lag 0    1.00000000  0.19334515   NaN
# Lag 50   0.19448863  0.11769285   NaN
# Lag 250  0.06418957  0.01236136   NaN
# Lag 500  0.04726820  0.01911098   NaN
# Lag 2500 0.01935262 -0.01541798   NaN
```

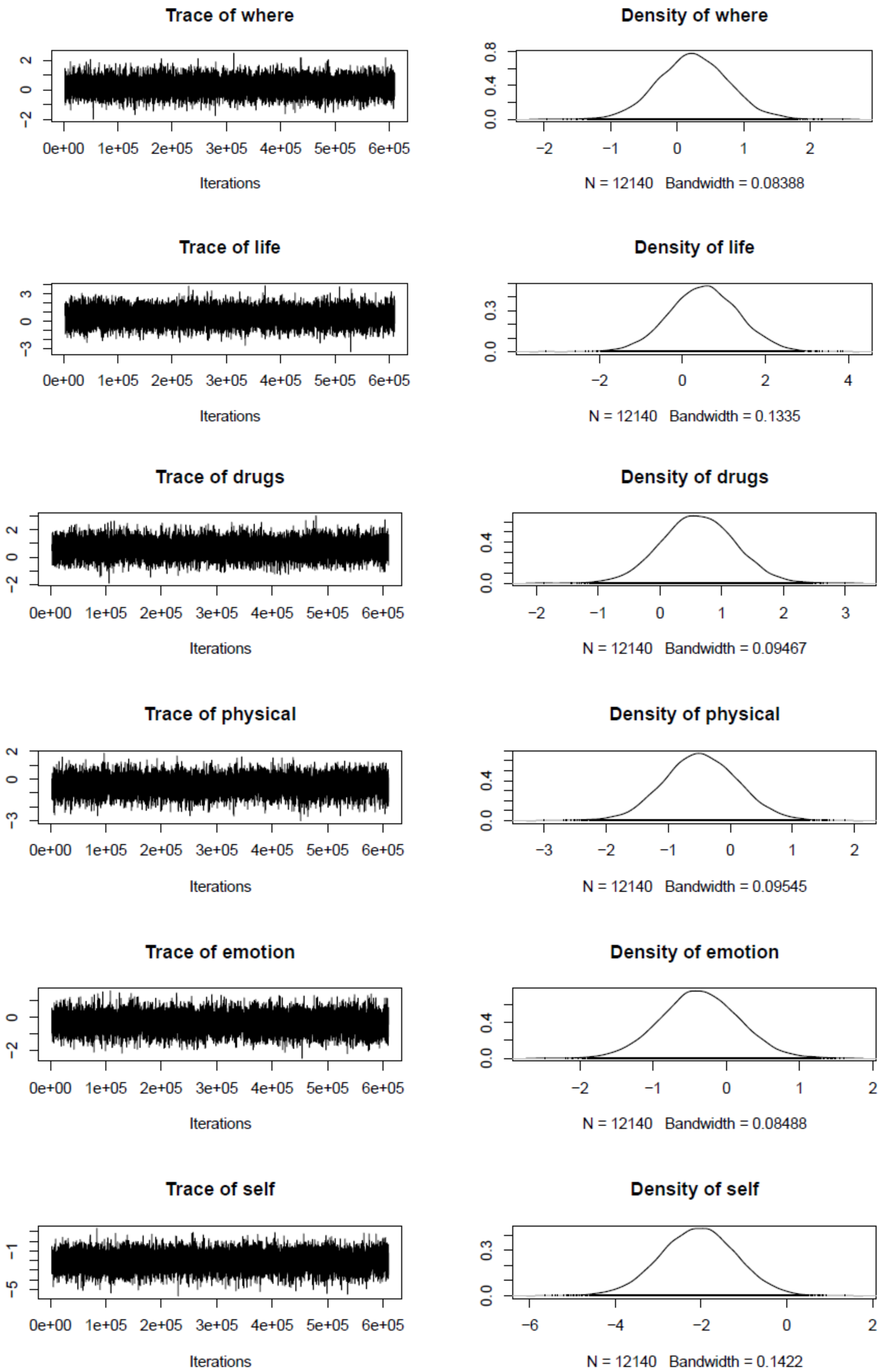
```
# , , Research.ID
#
#                   time Research.ID units
# Lag 0     0.193345147  1.00000000   NaN
# Lag 50    0.095167869  0.29080023   NaN
# Lag 250   0.006980513  0.03427083   NaN
# Lag 500   0.006088558  0.01053880   NaN
# Lag 2500 -0.005030420  0.01011263   NaN

# > summary(BDm3_cc2)
#
# Iterations = 3001:609951
# Thinning interval  = 50
# Sample size  = 12140
#
# DIC: 465.2738
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.768   0.5756    5.972     3221
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.6618 6.913e-07    1.528     5472
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ ageFirst_10 * time * live + ageFirst_10 * time * relation + ageFirst_10 * time * ete + ageFirst_10 * time * where + ageFirst_10 * time * life + ageFirst_10 * time * drugs + ageFirst_10 * time * physical + ageFirst_10 * time * emotion + ageFirst_10 * time * self + ageFirst_10 * time * think + ageFirst_10 * time * attitude + ageFirst_10 * time * change

#                          post.mean  l-95% CI  u-95% CI eff.samp    pMCMC
# (Intercept)              -2.530000 -5.687846  0.408050    10640 0.100824
# ageFirst_10               0.297198 -0.368490  0.938716    10718 0.377595
# time                      0.220691 -0.396946  0.807179    10728 0.470675
# live                     -0.109482 -1.405698  1.076946    12140 0.866886
# relation                  1.606528  0.206527  3.021811    11669 0.025865 *
# ete                      -0.409371 -1.571403  0.718282    11590 0.475453
# where                     0.251670 -0.766253  1.219090    11364 0.621252
# life                      0.536263 -1.115136  2.141893    12017 0.520593
# drugs                     0.606402 -0.578611  1.692365    11630 0.287809
# physical                 -0.473916 -1.602006  0.702729    11677 0.423394
# emotion                  -0.360726 -1.404536  0.672859    11098 0.494399
# self                     -2.082001 -3.783864 -0.323285    11180 0.013839 *
# think                     0.351036 -1.241713  1.997439    11535 0.679242
# attitude                  0.445100 -1.324734  2.280710    12140 0.629489
# change                    0.169732 -1.430469  1.821562    12140 0.837891
# ageFirst_10:time         -0.140295 -0.312066  0.025096    11216 0.097529 .
# ageFirst_10:live          0.026597 -0.289357  0.365958    12140 0.875288
# time:live                -0.075220 -0.350869  0.196760    12140 0.586820
# ageFirst_10:relation     -0.364494 -0.717212 -0.012033    11574 0.042010 *
# time:relation            -0.361232 -0.703048 -0.020496    11136 0.034102 *
# ageFirst_10:ete           0.020860 -0.262475  0.315496    12140 0.899012
# time:ete                  0.008325 -0.253992  0.269855    11752 0.957002
# ageFirst_10:where        -0.045942 -0.319690  0.207531    11453 0.732455
```

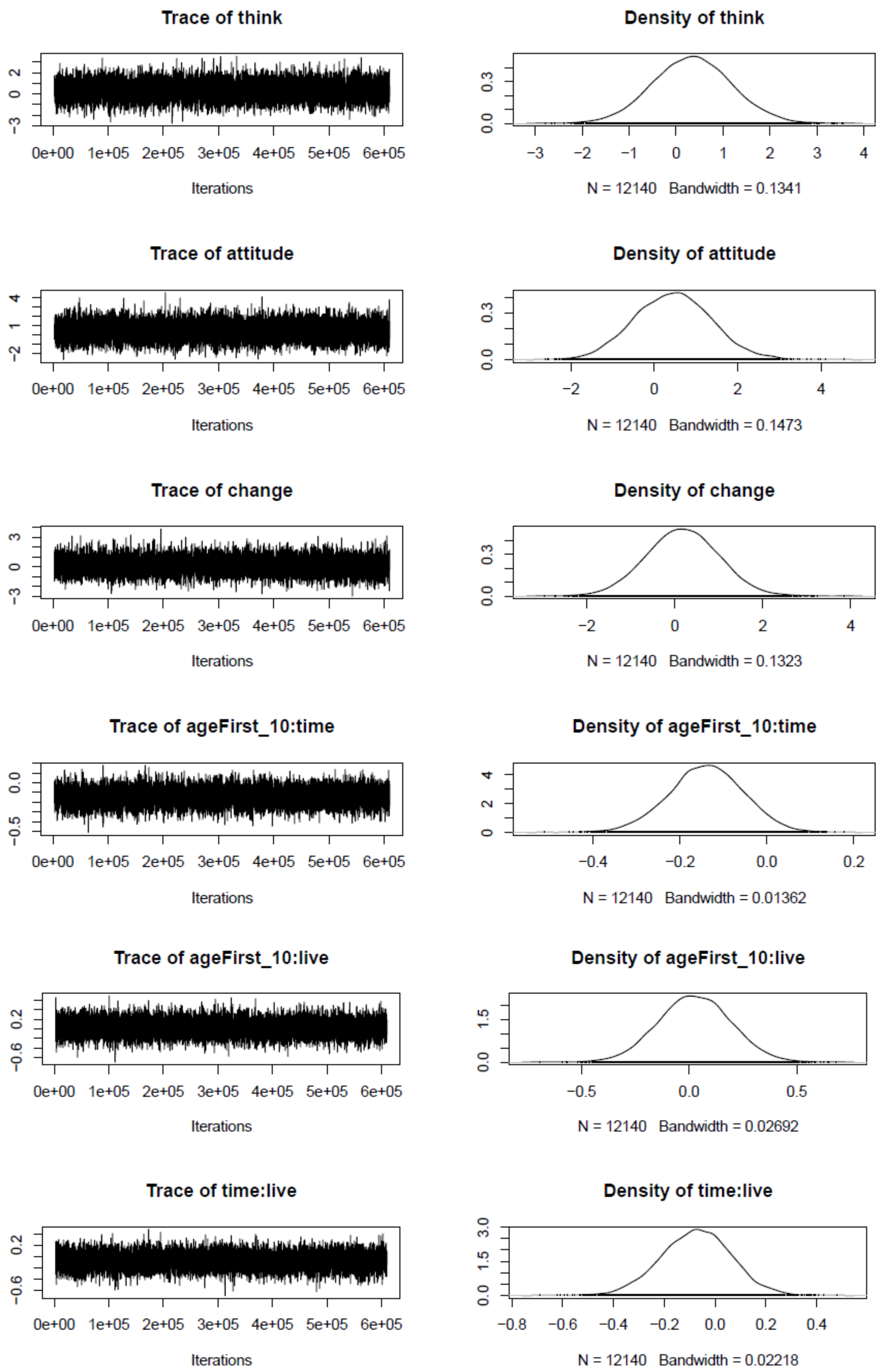
```
# time:where                -0.042589 -0.245877  0.167784    11620 0.680066
# ageFirst_10:life          -0.052279 -0.458204  0.369826    11623 0.807249
# time:life                  0.014039 -0.353171  0.401648    10456 0.954201
# ageFirst_10:drugs         -0.085978 -0.375990  0.195714    11802 0.554201
# time:drugs                -0.114764 -0.380707  0.117230    11412 0.366886
# ageFirst_10:physical      -0.047447 -0.363590  0.258750    11793 0.768369
# time:physical              0.232502 -0.063816  0.517579    11473 0.114992
# ageFirst_10:emotion        0.005864 -0.265216  0.291699    11329 0.967710
# time:emotion               0.114801 -0.125499  0.361792    11152 0.350906
# ageFirst_10:self           0.666313  0.237757  1.116004    10864 0.001318 **
# time:self                  0.514624  0.153033  0.902988    10932 0.004778 **
# ageFirst_10:think         -0.122879 -0.543053  0.267296    12140 0.547776
# time:think                -0.156506 -0.482053  0.169959    11690 0.336079
# ageFirst_10:attitude      -0.019507 -0.470902  0.421149    11273 0.942834
# time:attitude             -0.096444 -0.451299  0.251643    12140 0.601647
# ageFirst_10:change         0.013744 -0.448135  0.451297    12140 0.948270
# time:change                0.070945 -0.277724  0.424002    12999 0.683361
# ageFirst_10:time:live      0.030960 -0.048252  0.104150    11702 0.427018
# ageFirst_10:time:relation  0.093347 -0.002207  0.181162    10891 0.044316 *
# ageFirst_10:time:ete       0.032027 -0.044399  0.113027    11189 0.427018
# ageFirst_10:time:where     0.018543 -0.038420  0.076280    11455 0.532290
# ageFirst_10:time:life     -0.023736 -0.129972  0.085828    11090 0.670181
# ageFirst_10:time:drugs     0.030245 -0.044580  0.104906    11593 0.428830
# ageFirst_10:time:physical -0.018817 -0.101539  0.064733    11448 0.658320
# ageFirst_10:time:emotion   0.001546 -0.072904  0.076484    11101 0.970675
# ageFirst_10:time:self     -0.182721 -0.293139 -0.083412    10297 0.000494 ***
# ageFirst_10:time:think     0.040274 -0.045860  0.127252    11716 0.353542
# ageFirst_10:time:attitude -0.008130 -0.109456  0.091971    12140 0.872817
# ageFirst_10:time:change   -0.015731 -0.116063  0.089730    12140 0.754036
---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

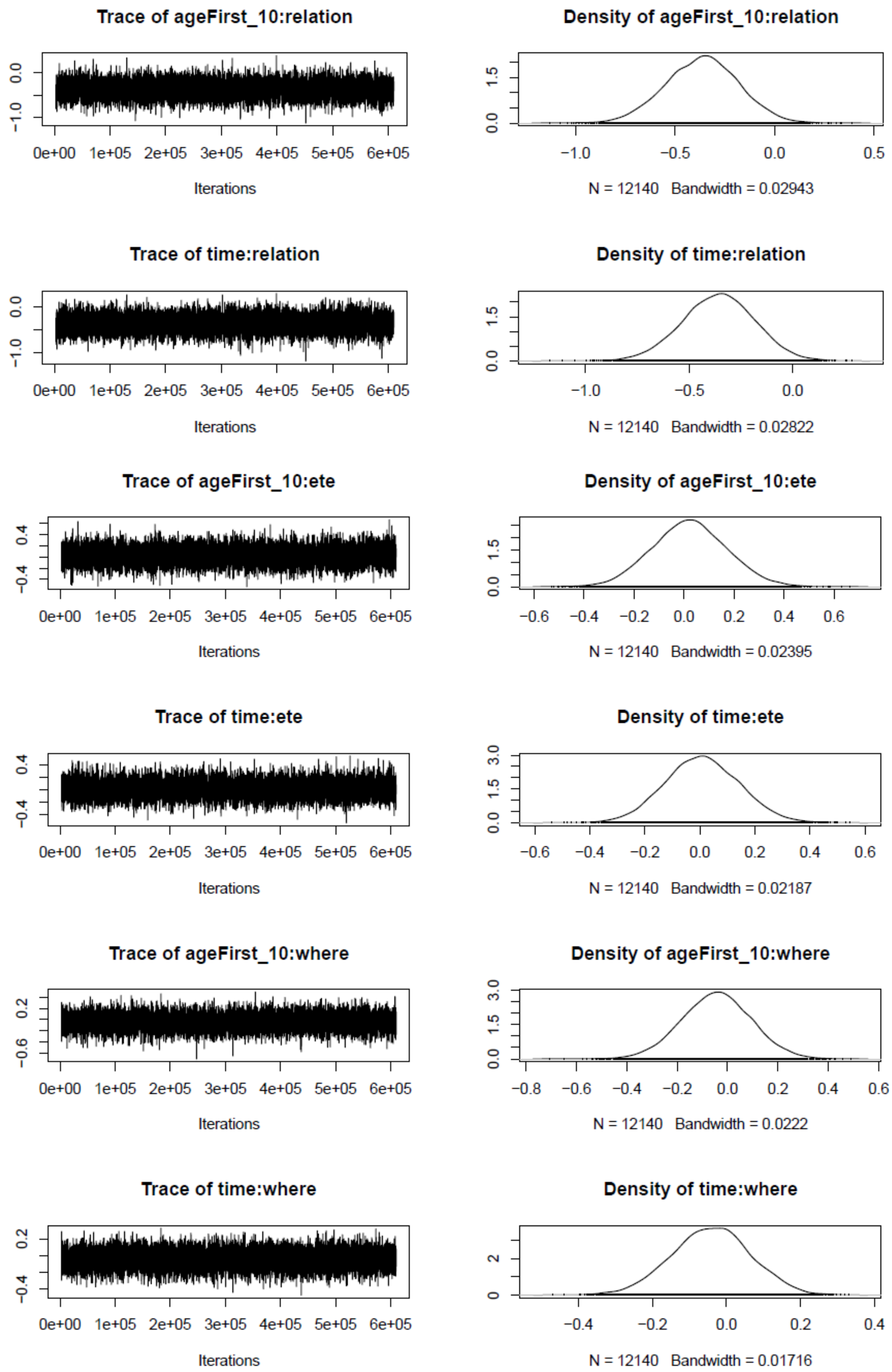
Trace Plots and Posterior Density Plots

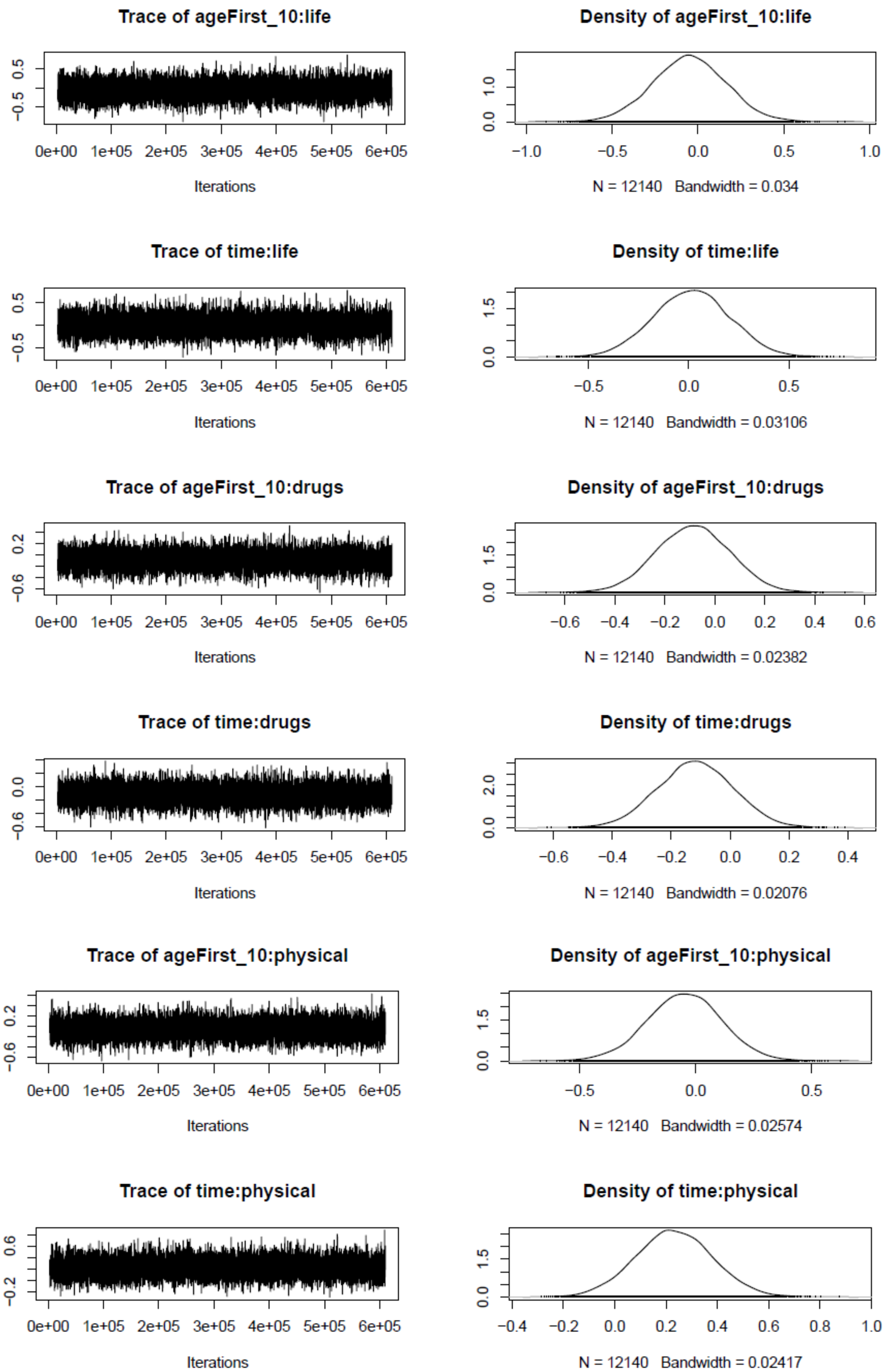
<u>Fixed Effects</u>

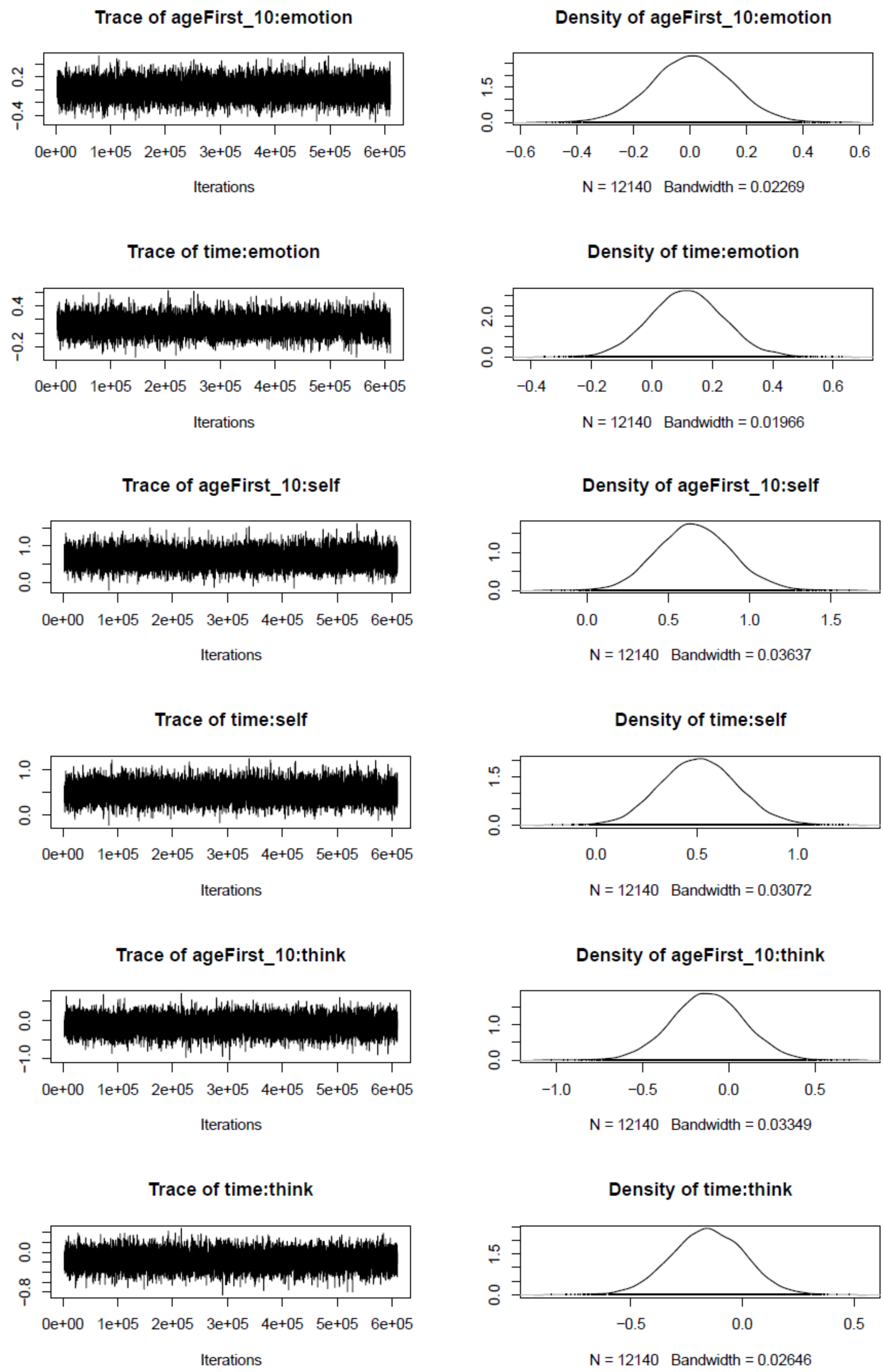


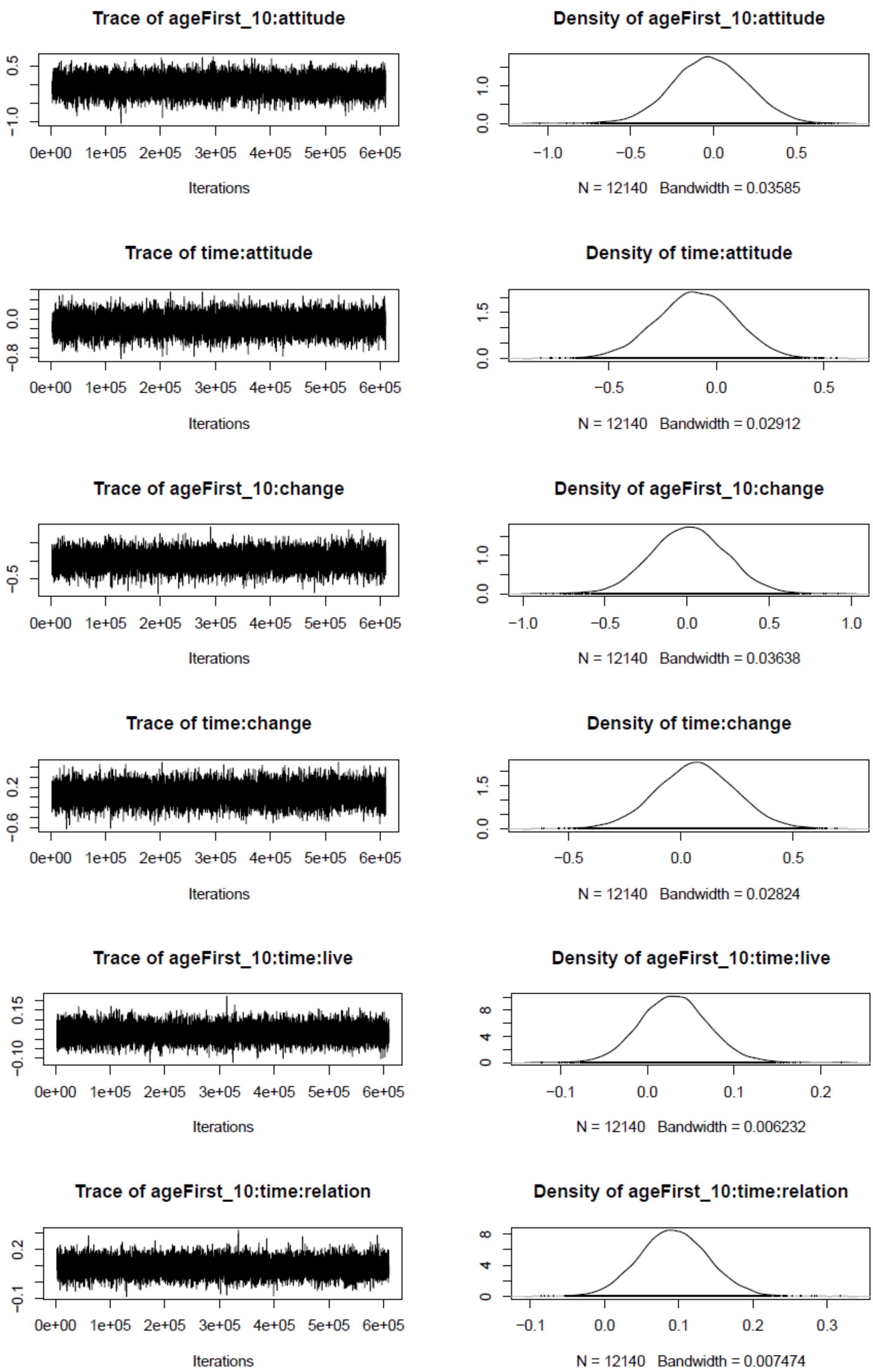

Trace of where
Density of where
N = 12140 Bandwidth = 0.08388
Trace of life
Density of life
N = 12140 Bandwidth = 0.1335
Trace of drugs
Density of drugs
N = 12140 Bandwidth = 0.09467
Trace of physical
Density of physical
N = 12140 Bandwidth = 0.09545
Trace of emotion
Density of emotion
N = 12140 Bandwidth = 0.08488
Trace of self
Density of self
N = 12140 Bandwidth = 0.1422
Iterations
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05

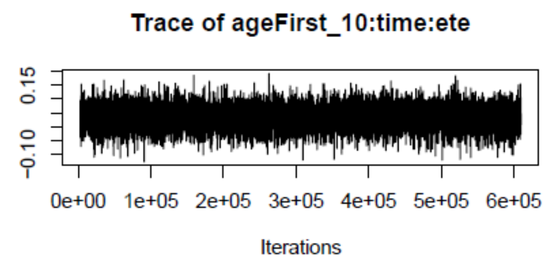

Trace of think
Iterations
Density of think
N = 12140 Bandwidth = 0.1341
Trace of attitude
Iterations
Density of attitude
N = 12140 Bandwidth = 0.1473
Trace of change
Iterations
Density of change
N = 12140 Bandwidth = 0.1323
Trace of ageFirst_10:time
Iterations
Density of ageFirst_10:time
N = 12140 Bandwidth = 0.01362
Trace of ageFirst_10:live
Iterations
Density of ageFirst_10:live
N = 12140 Bandwidth = 0.02692
Trace of time:live
Iterations
Density of time:live
N = 12140 Bandwidth = 0.02218

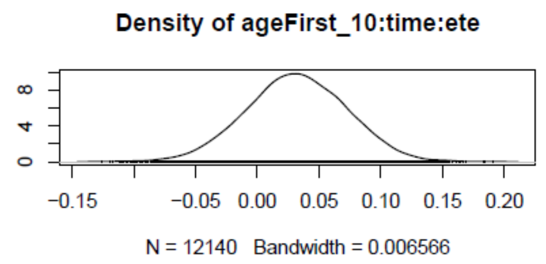

Trace of ageFirst_10:relation
Iterations
Density of ageFirst_10:relation
N = 12140 Bandwidth = 0.02943
Trace of time:relation
Iterations
Density of time:relation
N = 12140 Bandwidth = 0.02822
Trace of ageFirst_10:ete
Iterations
Density of ageFirst_10:ete
N = 12140 Bandwidth = 0.02395
Trace of time:ete
Iterations
Density of time:ete
N = 12140 Bandwidth = 0.02187
Trace of ageFirst_10:where
Iterations
Density of ageFirst_10:where
N = 12140 Bandwidth = 0.0222
Trace of time:where
Iterations
Density of time:where
N = 12140 Bandwidth = 0.01716

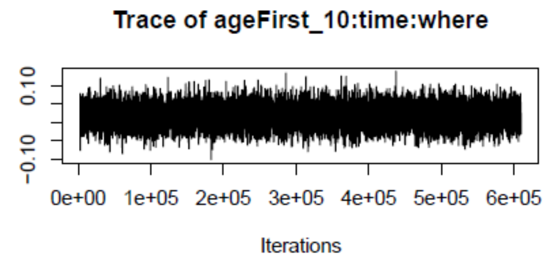

Trace of ageFirst_10:life
Iterations
Density of ageFirst_10:life
N = 12140 Bandwidth = 0.034
Trace of time:life
Iterations
Density of time:life
N = 12140 Bandwidth = 0.03106
Trace of ageFirst_10:drugs
Iterations
Density of ageFirst_10:drugs
N = 12140 Bandwidth = 0.02382
Trace of time:drugs
Iterations
Density of time:drugs
N = 12140 Bandwidth = 0.02076
Trace of ageFirst_10:physical
Iterations
Density of ageFirst_10:physical
N = 12140 Bandwidth = 0.02574
Trace of time:physical
Iterations
Density of time:physical
N = 12140 Bandwidth = 0.02417

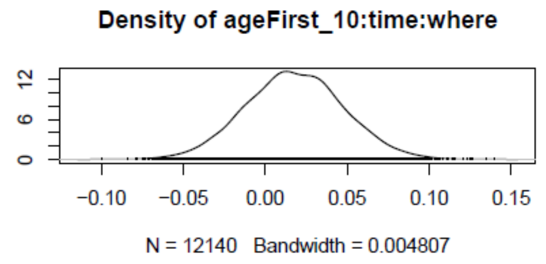

Trace of ageFirst_10:emotion
Iterations
Density of ageFirst_10:emotion
N = 12140 Bandwidth = 0.02269
Trace of time:emotion
Iterations
Density of time:emotion
N = 12140 Bandwidth = 0.01966
Trace of ageFirst_10:self
Iterations
Density of ageFirst_10:self
N = 12140 Bandwidth = 0.03637
Trace of time:self
Iterations
Density of time:self
N = 12140 Bandwidth = 0.03072
Trace of ageFirst_10:think
Iterations
Density of ageFirst_10:think
N = 12140 Bandwidth = 0.03349
Trace of time:think
Iterations
Density of time:think
N = 12140 Bandwidth = 0.02646

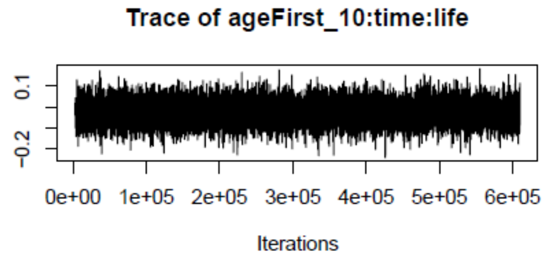

Trace of ageFirst_10:attitude
Iterations
Density of ageFirst_10:attitude
N = 12140 Bandwidth = 0.03585
Trace of time:attitude
Iterations
Density of time:attitude
N = 12140 Bandwidth = 0.02912
Trace of ageFirst_10:change
Iterations
Density of ageFirst_10:change
N = 12140 Bandwidth = 0.03638
Trace of time:change
Iterations
Density of time:change
N = 12140 Bandwidth = 0.02824
Trace of ageFirst_10:time:live
Iterations
Density of ageFirst_10:time:live
N = 12140 Bandwidth = 0.006232
Trace of ageFirst_10:time:relation
Iterations
Density of ageFirst_10:time:relation
N = 12140 Bandwidth = 0.007474

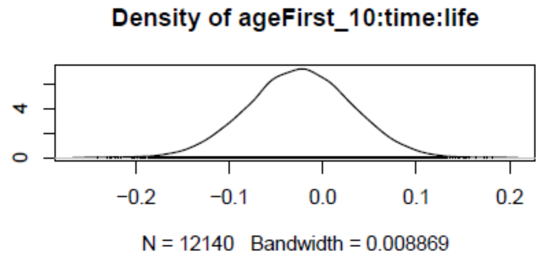

Trace of ageFirst_10:time:ete
−0.10 0.15
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05
Iterations

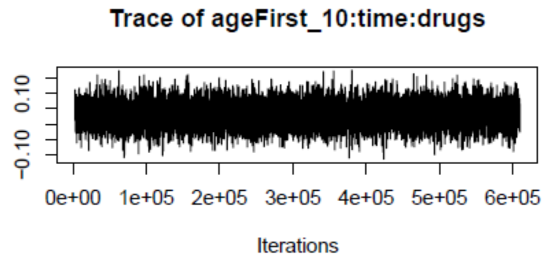

Density of ageFirst_10:time:ete
0 4 8
−0.15 −0.05 0.00 0.05 0.10 0.15 0.20
N = 12140 Bandwidth = 0.006566

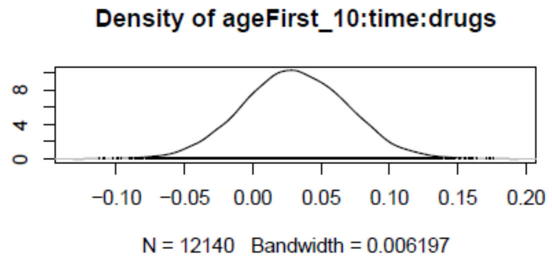

Trace of ageFirst_10:time:where
−0.10 0.10
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05
Iterations

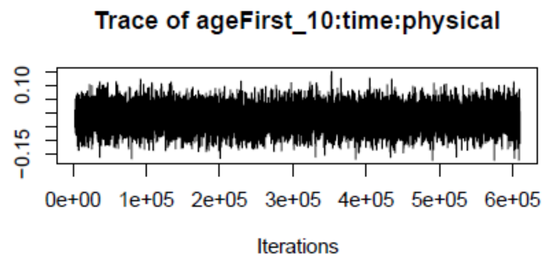

Density of ageFirst_10:time:where
0 6 12
−0.10 −0.05 0.00 0.05 0.10 0.15
N = 12140 Bandwidth = 0.004807

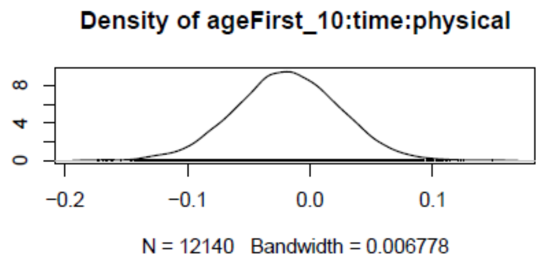

Trace of ageFirst_10:time:life
−0.2 0.1
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05
Iterations

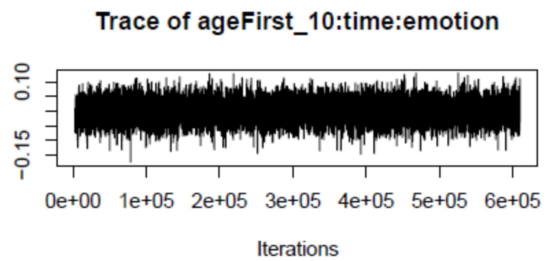

Density of ageFirst_10:time:life
0 4
−0.2 −0.1 0.0 0.1 0.2
N = 12140 Bandwidth = 0.008869

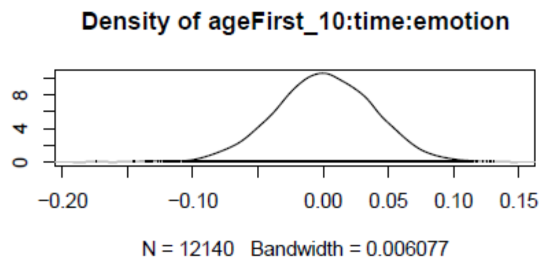

Trace of ageFirst_10:time:drugs
−0.10 0.10
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05
Iterations

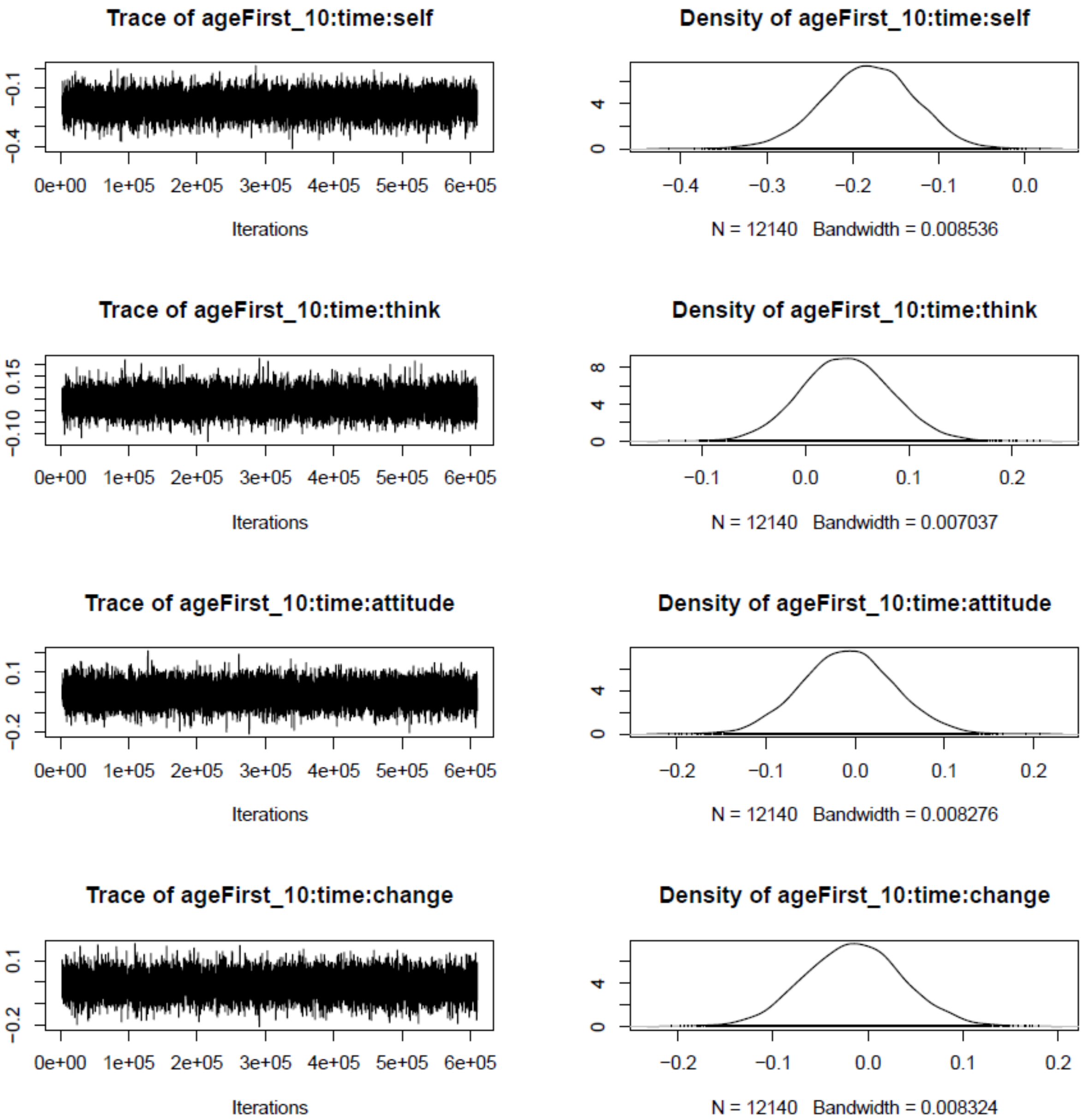

Density of ageFirst_10:time:drugs
0 4 8
−0.10 −0.05 0.00 0.05 0.10 0.15 0.20
N = 12140 Bandwidth = 0.006197


Trace of ageFirst_10:time:physical
−0.15 0.10
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05
Iterations

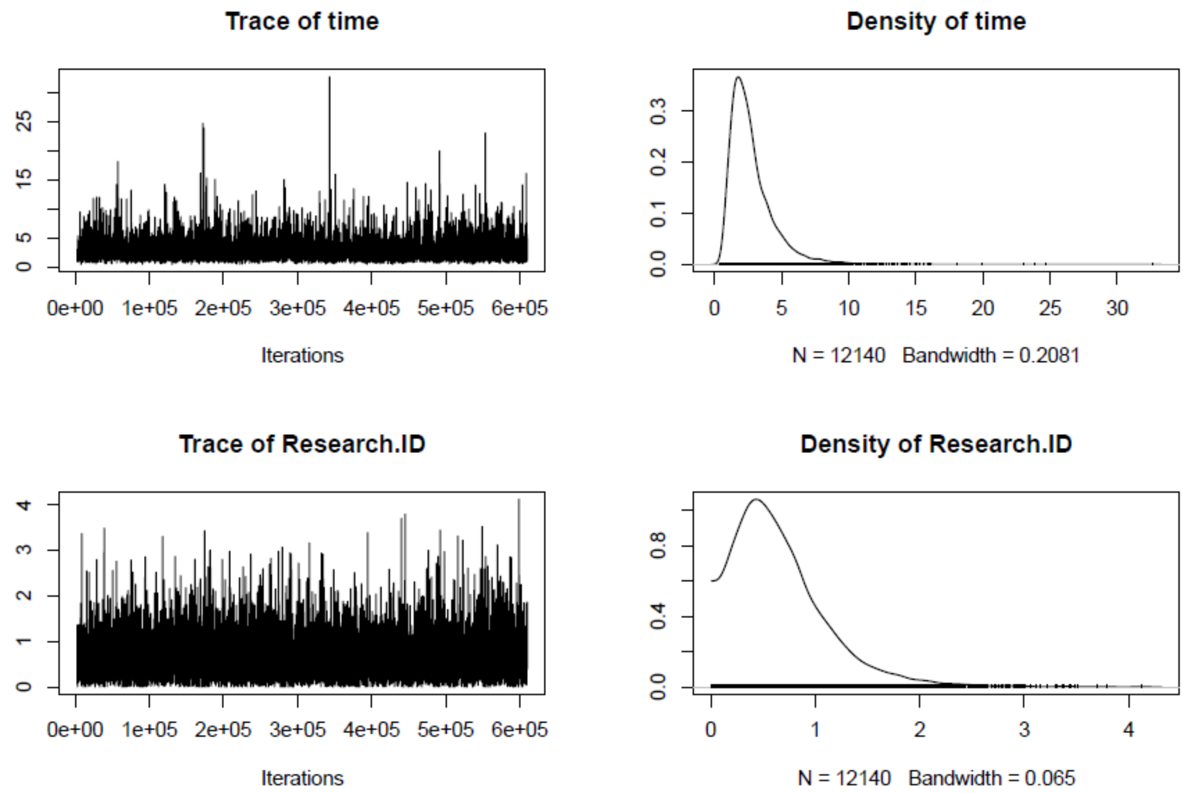

Density of ageFirst_10:time:physical
0 4 8
−0.2 −0.1 0.0 0.1
N = 12140 Bandwidth = 0.006778


Trace of ageFirst_10:time:emotion
−0.15 0.10
0e+00 1e+05 2e+05 3e+05 4e+05 5e+05 6e+05
Iterations


Density of ageFirst_10:time:emotion
0 4 8
−0.20 −0.10 0.00 0.05 0.10 0.15
N = 12140 Bandwidth = 0.006077


Trace of ageFirst_10:time:self
Iterations
Density of ageFirst_10:time:self
N = 12140 Bandwidth = 0.008536
Trace of ageFirst_10:time:think
Iterations
Density of ageFirst_10:time:think
N = 12140 Bandwidth = 0.007037
Trace of ageFirst_10:time:attitude
Iterations
Density of ageFirst_10:time:attitude
N = 12140 Bandwidth = 0.008276
Trace of ageFirst_10:time:change
Iterations
Density of ageFirst_10:time:change
N = 12140 Bandwidth = 0.008324

Random Effects



Model 1.11 – Basic Model + Grouped YJB Offence Category and YJB Gravity Score (Table 6.23)

Bayesian Model (Bm1G_o12a)

Define the model

```
Bm1G_o12a <- MCMCglmm(FO.bin ~ I_Seriousness*as.factor(I_Cat2) +
live + relation + ete + where + life + drugs + physical + emotion + self
+ think + attitude + change + time,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
slice=TRUE, nitt=600000, thin=150, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1G_o12a$VCV)
heidel.diag(Bm1G_o12a$VCV)


# > raftery.diag(Bm1G_o12a$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         300      570750 3746         152
# Research.ID 300      570750 3746         152
# units        <NA>     <NA>   3746          NA

# > heidel.diag(Bm1G_o12a$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.282
# Research.ID passed        1        0.707
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.607 0.03544
# Research.ID passed    0.287 0.00705
# units        <NA>         NA      NA

autocorr(Bm1G_o12$VCV)
autocorr(Bm1G_o12$Sol)  # Output not included here
summary(Bm1G_o12)

# > autocorr(Bm1G_o12$VCV)
# , , time
#
#                     time  Research.ID units
# Lag 0     1.0000000000  0.112623998   NaN
# Lag 150   0.0619593340  0.032790926   NaN
# Lag 750   0.0193524510 -0.004381124   NaN
# Lag 1500  0.0001532138  0.037330727   NaN
# Lag 7500 -0.0176424934 -0.005286949   NaN
```

```
# , , Research.ID
#
#                  time   Research.ID units
# Lag 0     0.11262400  1.0000000000   NaN
# Lag 150  -0.00448042  0.0019148765   NaN
# Lag 750   0.01569912  0.0099305191   NaN
# Lag 1500 -0.02236655  0.0007982283   NaN
# Lag 7500 -0.01292781 -0.0240287431   NaN

# > summary(Bm1G_o12)
#
# Iterations = 3001:599851
# Thinning interval  = 150
# Sample size  = 3980
#
# DIC: 473.5603
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.607    0.376    3.364     2760
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID     0.287 1.219e-07   0.7204     3980
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ I_Seriousness * as.factor(I_Cat2) + live +
relation + ete + where + life + drugs + physical + emotion + self +
think + attitude + change + time
#
#                                  post.mean l-95% CI u-95% CI eff.samp  pMCMC
# (Intercept)                        -1.22897 -3.38974  0.78085     3980 0.2387
# I_Seriousness                      -0.01504 -0.66258  0.58735     3980 0.9693
# as.factor(I_Cat2)SAC                0.86537 -1.91093  3.48102     3980 0.5216
# as.factor(I_Cat2)VAP                1.31331 -1.08666  4.06724     3980 0.3201
# live                                0.04705 -0.24070  0.31471     3589 0.7322
# relation                            0.25337 -0.05464  0.57548     3980 0.1121
# ete                                 0.06530 -0.19364  0.33957     3980 0.6302
# where                               0.06361 -0.19037  0.28770     3980 0.5940
# life                                0.04906 -0.32127  0.41142     3980 0.7789
# drugs                               0.20675 -0.03886  0.48597     3980 0.1166
# physical                           -0.11537 -0.42220  0.19214     3792 0.4704
# emotion                             0.02217 -0.22895  0.28214     3980 0.8864
# self                               -0.14196 -0.49589  0.17846     3980 0.4035
# think                              -0.16577 -0.52064  0.17425     4220 0.3548
# attitude                            0.02861 -0.34279  0.39135     3980 0.8709
# change                              0.21311 -0.13912  0.56722     3980 0.2457
# time                               -0.17680 -0.32401 -0.02488     3980 0.0191
*
# I_Seriousness:as.factor(I_Cat2)SAC  -0.13034 -0.91010  0.62262     3980 0.7221
# I_Seriousness:as.factor(I_Cat2)VAP  -0.31632 -1.15510  0.56211     3980 0.4698
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1G_o12)

```
M1G_o12 <- glmer(FO.bin ~ as.factor(offence2)*serious + live +
relation + ete + where + life + drugs + physical + emotion + self
+ think + attitude + change + time + (time|Individual),
data=data3, family=binomial)
summary(m1G_o12)
vcomps.icc(m1G_o12)
```

```
Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv,  :
  Model failed to converge with max|grad| = 0.0838951 (tol = 0.001, comp
onent 1)
```

```
# > summary(m1G_o12)
# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) ['glmerMod']
# Family: binomial  ( logit )
# Formula: FO.bin ~ as.factor(offence2) * serious + live + relation +
ete +
where + life + drugs + physical + emotion + self + think + attitude +
change + time + (time | Individual)
# Data: data3
#
#   AIC      BIC   logLik deviance df.resid
# 646.0    740.6   -301.0    602.0      523
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.7879 -0.6770 -0.3498  0.7989  3.5821
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.06322  0.2514
#            time        0.05717  0.2391   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#                              Estimate Std. Error z value Pr(>|z|)
# (Intercept)                 -0.757028   0.777884  -0.973   0.3305
# as.factor(offence2)SAC       2.428571   1.498682   1.620   0.1051
# as.factor(offence2)VAP       1.022173   1.165583   0.877   0.3805
# serious                     -0.018072   0.269937  -0.067   0.9466
# live                        -0.071944   0.145404  -0.495   0.6208
# relation                     0.160063   0.161383   0.992   0.3213
# ete                         -0.009224   0.133606  -0.069   0.9450
# where                        0.164115   0.130202   1.260   0.2075
# life                         0.028159   0.191385   0.147   0.8830
# drugs                        0.278690   0.135790   2.052   0.0401 *
# physical                    -0.184251   0.153491  -1.200   0.2300
# emotion                     -0.020927   0.135564  -0.154   0.8773
# self                        -0.103220   0.182711  -0.565   0.5721
# think                        0.119956   0.190876   0.628   0.5297
# attitude                    -0.033456   0.195116  -0.171   0.8639
# change                       0.188303   0.182865   1.030   0.3031
# time                          -0.453716   0.102335  -4.434 9.27e-06
***
# as.factor(offence2)SAC:serious -0.435889   0.367585  -1.186   0.2357
# as.factor(offence2)VAP:serious -0.243067   0.372505  -0.653   0.5141
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# convergence code: 0
# Model failed to converge with max|grad| = 0.0838951 (tol = 0.001,
component 1)

# > vcomps.icc(m1G_o12)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.063         0.057         1.000         0.525

# > anova(m1,m1G_o12)
# Data: data3
# Models:
# m1: FO.bin ~ live + relation + ete + where + life + drugs + physical +
#   m1:     emotion + self + think + attitude + change + time + (time |
#   m1:     Individual)
# m1G_o12: FO.bin ~ as.factor(offence2) * serious + live + relation + ete +
#   m1G_o12:     where + life + drugs + physical + emotion + self + think +
#   m1G_o12:     attitude + change + time + (time | Individual)
#         Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1      17 640.59 713.70 -303.29   606.59
# m1G_o12 22 645.96 740.58 -300.98   601.96 4.6249      5     0.4633
```

Chapter Seven – System Contact

Dynamic Model 4 (Table 7.1)

Bayesian Model (BDm4G_cc2_ch)

Define the model

```
BDm4G_cc2_ch <- MCMCglmm(FO.bin~G_ageFirst*time*live +
G_ageFirst*time*relation + G_ageFirst*time*ete +
G_ageFirst*time*where + G_ageFirst*time*life + G_ageFirst*time*drugs +
G_ageFirst*time*physical + G_ageFirst*time*emotion +
G_ageFirst*time*self + G_ageFirst*time*think + G_ageFirst*time*attitude
+ G_ageFirst*time*change + careExp*time*live + careExp*time*relation +
careExp*time*ete + careExp*time*where + careExp*time*life +
careExp*time*drugs + careExp*time*physical + careExp*time*emotion +
careExp*time*self + careExp*time*think + careExp*time*attitude +
careExp*time*change + G_ageFirst*careExp,                        ,
random=~time+Research.ID, data=data3, family="ordinal", prior=priorD,
nitt=12000000, thin=2500, burnin=3000)
```

Checks for suitable convergence

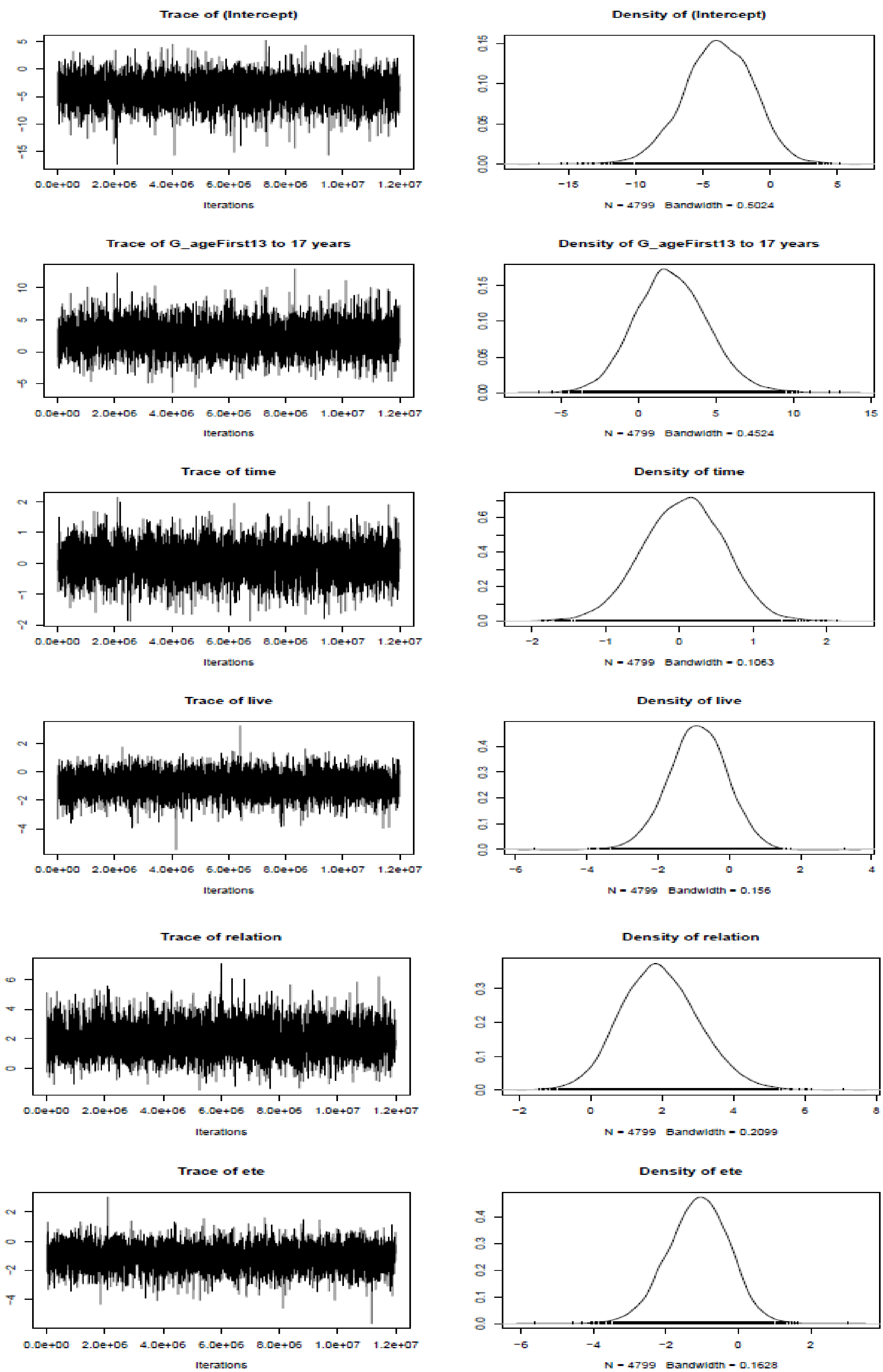
```
raftery.diag(BDm4G_cc2_ch$VCV)
heidel.diag(BDm4G_cc2_ch$VCV)

# > raftery.diag(BDm4G_cc2_ch$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total    Lower bound  Dependence
#              (M)      (N)      (Nmin)       factor (I)
# time         5000     9057500  3746         2420
# Research.ID  7500     10040000 3746         2680
# units        <NA>     <NA>     3746           NA

# > heidel.diag(BDm4G_cc2_ch$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed       481       0.203
# Research.ID  passed         1       0.143
# units        failed        NA          NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    5.28 0.1121
# Research.ID  passed    3.21 0.0632
# units        <NA>        NA     NA

autocorr(BDm4G_cc2_ch$VCV)
autocorr(BDm4G_cc2_ch$Sol)    # not included here
summary(BDm4G_cc2_ch)
```

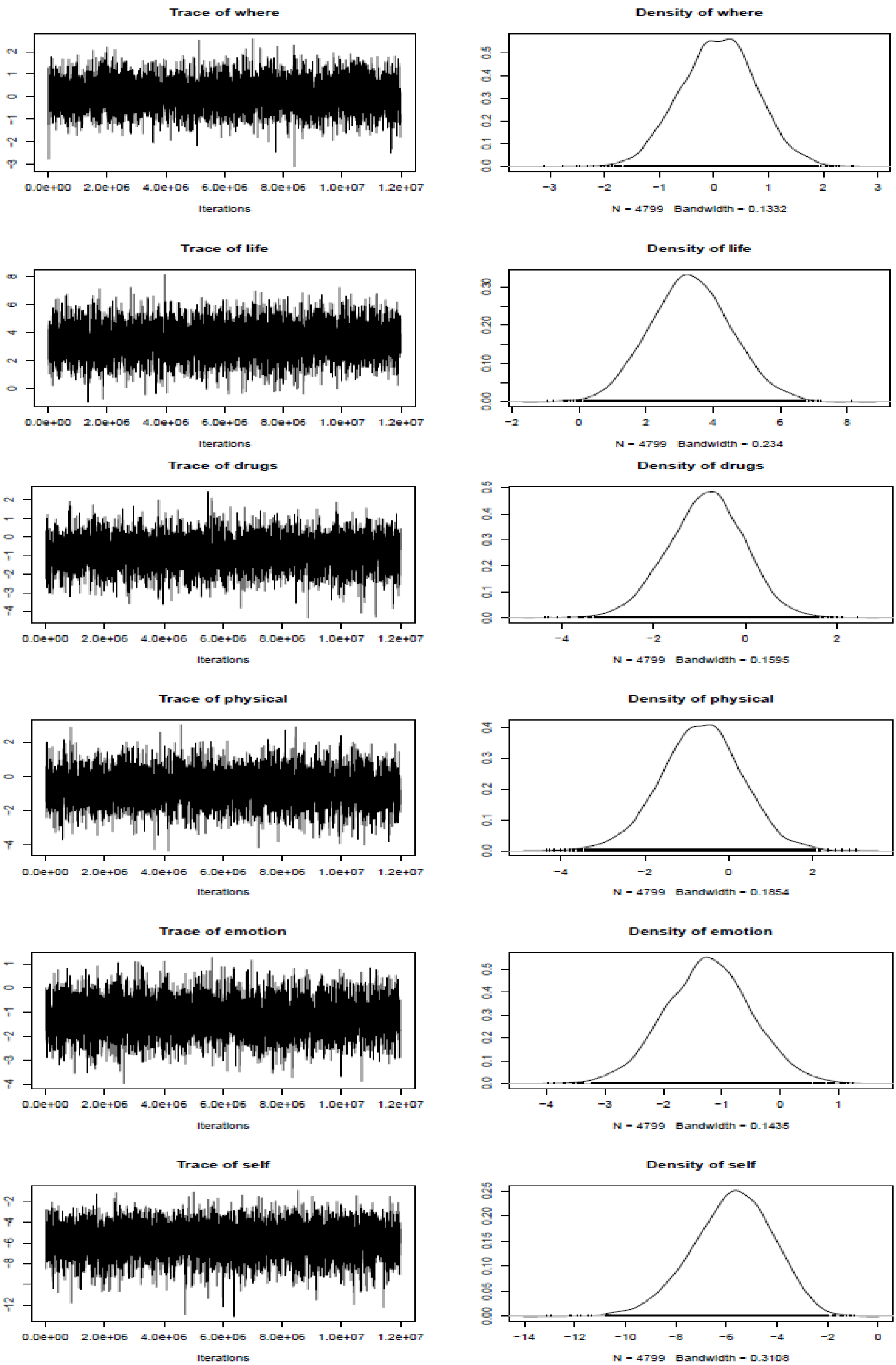
```
# > autocorr(BDm4G_cc2_ch$VCV)
# , , time
#
#                   time Research.ID units
# Lag 0       1.000000000  0.38253815   NaN
# Lag 2500    0.012396756  0.02358538   NaN
# Lag 12500  -0.028482146 -0.01014160   NaN
# Lag 25000   0.007411605  0.01826704   NaN
# Lag 125000  0.005003184 -0.02420582   NaN
#
# , , Research.ID
#
#                   time  Research.ID units
# Lag 0       0.382538149  1.000000000   NaN
# Lag 2500    0.038182399  0.067708692   NaN
# Lag 12500  -0.014780601 -0.006171341   NaN
# Lag 25000  -0.022565125 -0.026737873   NaN
# Lag 125000  0.006617778  0.012066333   NaN

# > summary(BDm4G_cc2_ch)
#
# Iterations = 3001:11998001
# Thinning interval  = 2500
# Sample size  = 4799
#
# DIC: 425.9019
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     5.241   0.7786    12.17     4799
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID     3.206   0.3054     7.46     4189
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ G_ageFirst * time * live + G_ageFirst * time * relation + G_ageFirst * time * ete + G_ageFirst * time * where + G_ageFirst * time * life + G_ageFirst * time * drugs + G_ageFirst * time * physical + G_ageFirst * time * emotion + G_ageFirst * time * self + G_ageFirst * time * think + G_ageFirst * time * attitude + G_ageFirst * time * change + careExp * time * live + careExp * time * relation + careExp * time * ete + careExp * time * where + careExp * time * life + careExp * time * drugs + careExp * time * physical + careExp * time * emotion + careExp * time * self + careExp * time * think + careExp * time * attitude + careExp * time * change + G_ageFirst * careExp
#
#                                  post.mean  l-95% CI  u-95% CI eff.samp   pMCMC
# (Intercept)                      -3.872339 -8.997951  0.955015     4799 0.11211
# G_ageFirst13 to 17 years          2.134798 -2.229657  6.924747     4799 0.35799
# time                              0.057013 -0.986196  1.101141     4799 0.90727
# live                             -0.889110 -2.550817  0.637703     4799 0.27047
# relation                          1.941504 -0.204575  3.994280     4799 0.05793 .
# ete                              -1.103249 -2.870131  0.387791     4548 0.16837
# where                             0.085476 -1.247643  1.378829     4464 0.89310
# life                              3.333665  1.001727  5.708019     4799 0.00625 **
# drugs                            -0.852275 -2.457521  0.820185     4799 0.29673
# physical                         -0.654261 -2.717206  1.082287     4860 0.49302
```

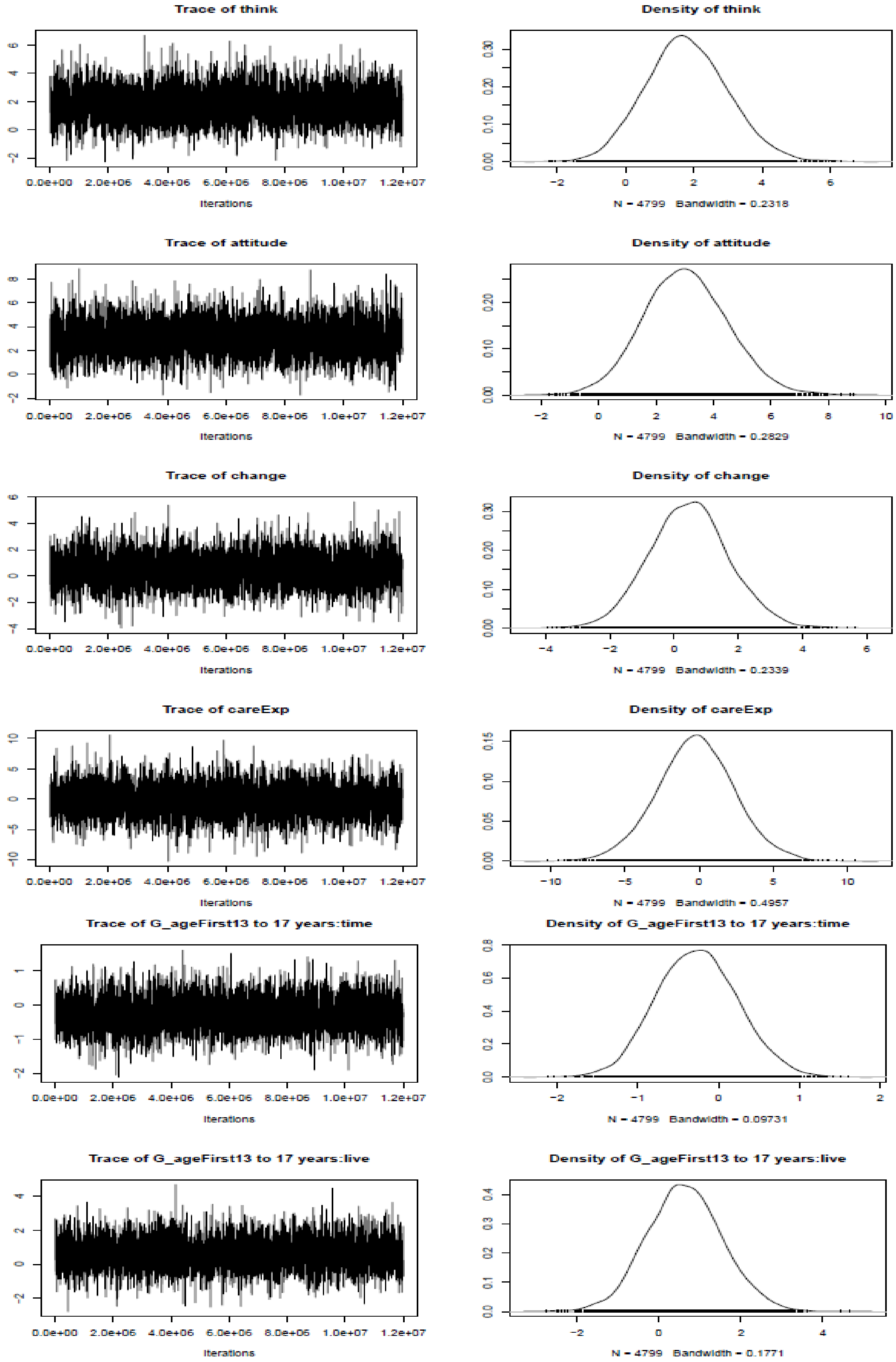
```
# emotion                              -1.227014 -2.673822  0.252411     4799 0.09794 .
# self                                 -5.759757 -8.832532 -2.634739     4799 < 2e-04 ***
# think                                 1.797935 -0.471976  4.183234     4799 0.13086
# attitude                              3.033604  0.211281  5.908489     4799 0.03251 *
# change                                0.467332 -1.929188  2.911647     4799 0.70890
# careExp                              -0.228025 -5.271780  5.155326     4917 0.93478
# G_ageFirst13 to 17 years:time        -0.263512 -1.194770  0.725694     4799 0.58721
# G_ageFirst13 to 17 years:live         0.631514 -1.052351  2.535050     4799 0.48385
# time:live                            -0.239882 -0.624241  0.127367     4799 0.21088
# G_ageFirst13 to 17 years:relation    -1.886166 -4.096080  0.329907     4799 0.08418 .
# time:relation                        -0.411429 -0.862590  0.057267     4799 0.07001 .
# G_ageFirst13 to 17 years:ete          0.947751 -0.688462  2.781769     4799 0.27047
# time:ete                              0.185148 -0.148967  0.511745     5221 0.26714
# G_ageFirst13 to 17 years:where       -0.084367 -1.548711  1.334312     4799 0.91186
# time:where                           -0.230428 -0.504518  0.078273     4799 0.12003
# G_ageFirst13 to 17 years:life        -2.566938 -5.159708  0.005613     4799 0.04543 *
# time:life                            -0.621558 -1.171776 -0.100854     4364 0.02626 *
# G_ageFirst13 to 17 years:drugs        1.200262 -0.500819  2.914296     4799 0.16295
# time:drugs                            0.479659  0.117203  0.837792     4799 0.00750 **
# G_ageFirst13 to 17 years:physical     0.654892 -1.418091  2.663817     4878 0.51386
# time:physical                         0.314691 -0.228012  0.821034     4799 0.21880
# G_ageFirst13 to 17 years:emotion     -0.204765 -1.844180  1.463089     4577 0.81517
# time:emotion                          0.396577  0.070341  0.720360     4799 0.01167 *
# G_ageFirst13 to 17 years:self         6.720708  3.484180 10.099387     4799 < 2e-04 ***
# time:self                             1.497034  0.916763  2.226787     4799 < 2e-04 ***
# G_ageFirst13 to 17 years:think       -1.033804 -3.532620  1.418097     4799 0.42009
# time:think                           -0.437461 -0.925407  0.012309     4799 0.06210 .
# G_ageFirst13 to 17 years:attitude    -2.351456 -5.354870  0.683452     4799 0.12961
# time:attitude                        -0.952729 -1.518737 -0.418043     4799 < 2e-04 ***
# G_ageFirst13 to 17 years:change      -1.599914 -4.253427  1.068217     4799 0.23463
# time:change                           0.288514 -0.280780  0.807395     4799 0.30090
# time:careExp                         -0.074282 -1.013078  0.758561     4799 0.87101
# live:careExp                          1.024483 -0.689049  2.680836     4799 0.22796
# relation:careExp                     -0.405719 -2.258436  1.661162     4799 0.69973
# ete:careExp                           0.053004 -1.458192  1.546695     4799 0.95020
# where:careExp                         0.434813 -0.985248  1.842742     4799 0.55470
# life:careExp                         -1.018860 -3.178350  1.297538     4799 0.36383
# drugs:careExp                         0.140209 -1.247198  1.583807     4799 0.84684
# physical:careExp                     -1.778954 -3.693988  0.284462     4799 0.06543 .
# emotion:careExp                       1.582138 -0.022036  3.174495     4799 0.04668 *
# self:careExp                          1.492924 -0.856122  3.921866     4799 0.21338
# think:careExp                        -1.937133 -4.050339  0.118227     4799 0.06543 .
# attitude:careExp                     -0.277645 -2.230124  1.610904     4799 0.77433
# change:careExp                        0.460460 -1.800147  2.657094     4799 0.67097
# G_ageFirst13 to 17 years:careExp      2.550140 -0.513954  5.636276     4799 0.08377 .
# G_ageFirst13 to 17 years:time:live     0.324585 -0.114959  0.783763     4462 0.14295
# G_ageFirst13 to 17 years:time:relation  0.374828 -0.139287  0.892689     4799 0.14128
# G_ageFirst13 to 17 years:time:ete     -0.217400 -0.611978  0.161938     5218 0.26297
# G_ageFirst13 to 17 years:time:where    0.136712 -0.163324  0.441435     4799 0.37675
# G_ageFirst13 to 17 years:time:life     0.490657 -0.090900  1.056123     4799 0.10294
# G_ageFirst13 to 17 years:time:drugs   -0.390639 -0.772823 -0.024585     4799 0.03542 *
# G_ageFirst13 to 17 years:time:physical -0.435456 -0.979248  0.039765     4799 0.08043 .
# G_ageFirst13 to 17 years:time:emotion  -0.159673 -0.558997  0.217374     4799 0.42259
# G_ageFirst13 to 17 years:time:self    -1.643284 -2.358392 -0.984504     4799 < 2e-04 ***
# G_ageFirst13 to 17 years:time:think    0.326859 -0.181477  0.829892     4799 0.20129
# G_ageFirst13 to 17 years:time:attitude  0.570583 -0.067273  1.216288     4799 0.07418 .
# G_ageFirst13 to 17 years:time:change   0.164517 -0.407990  0.739970     4504 0.58846
# time:live:careExp                     0.019327 -0.373352  0.442100     4799 0.93811
# time:relation:careExp                 0.009034 -0.450543  0.424516     4799 0.97020
# time:ete:careExp                      0.163132 -0.143513  0.498032     4799 0.31840
# time:where:careExp                    0.198704 -0.110234  0.468676     4799 0.17337
# time:life:careExp                     0.021968 -0.430367  0.434656     4799 0.91269
# time:drugs:careExp                   -0.169615 -0.533720  0.156080     4799 0.32632
# time:physical:careExp                 0.165546 -0.301081  0.617280     4799 0.48718
# time:emotion:careExp                 -0.154553 -0.525639  0.192321     4799 0.39800
# time:self:careExp                    -0.546273 -1.018585 -0.069081     4799 0.01750 *
# time:think:careExp                    0.451540  0.002091  0.899078     4799 0.04668 *
# time:attitude:careExp                 0.293294 -0.196383  0.801338     4799 0.24088
# time:change:careExp                  -0.389711 -0.861326  0.090797     4799 0.10210
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Trace Plots and Posterior Density Plots

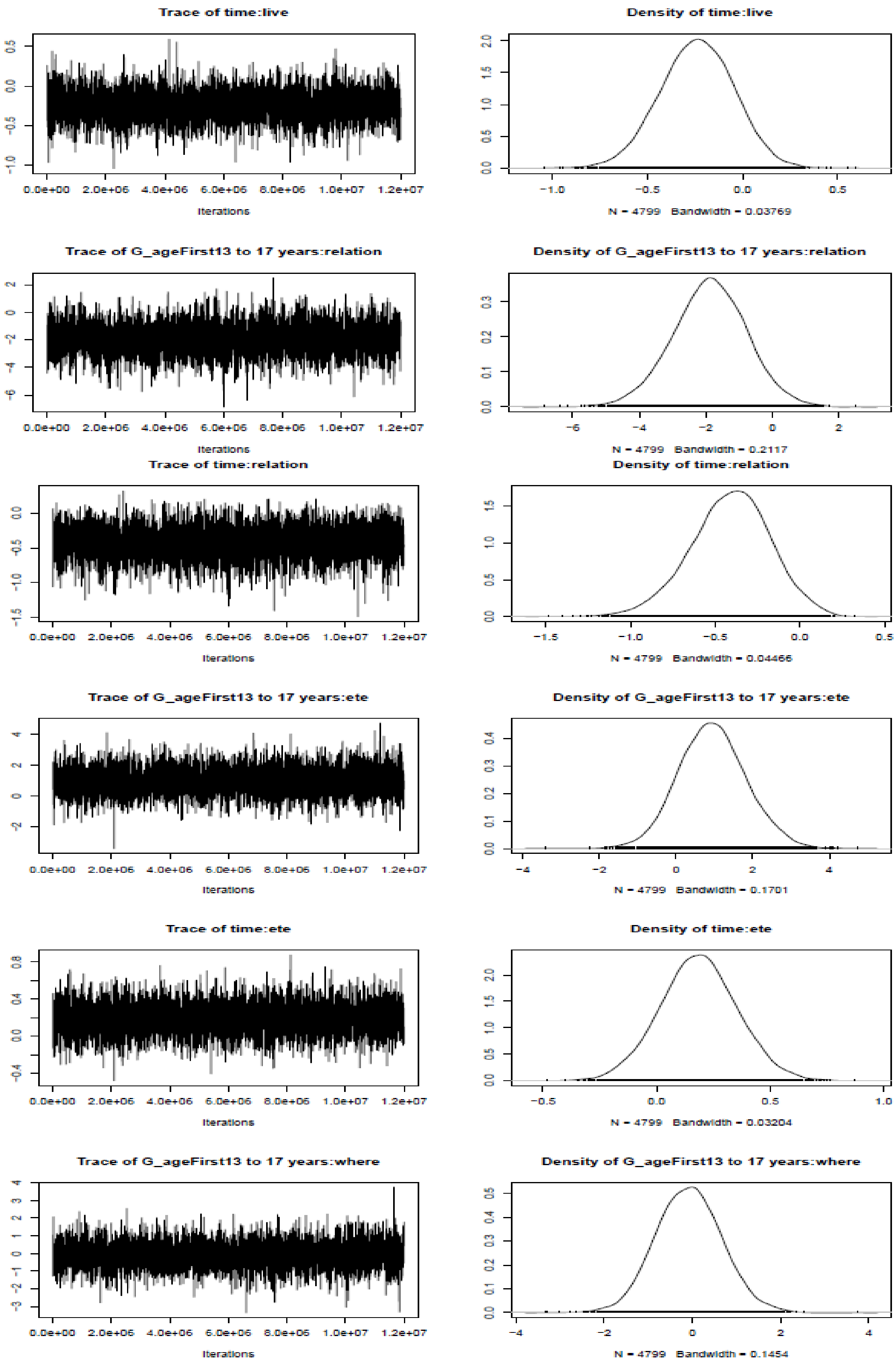
<u>Fixed Effects</u>

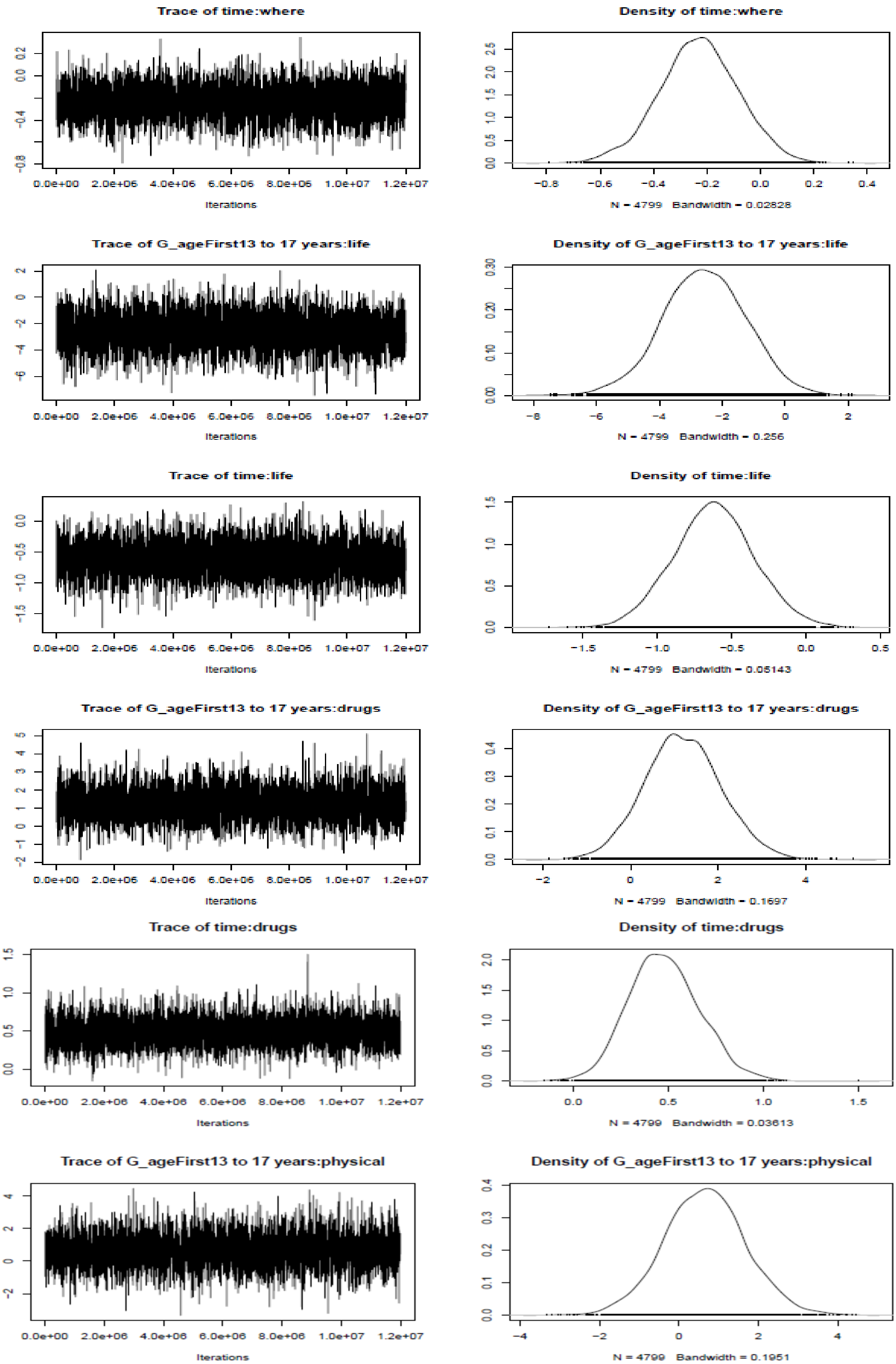


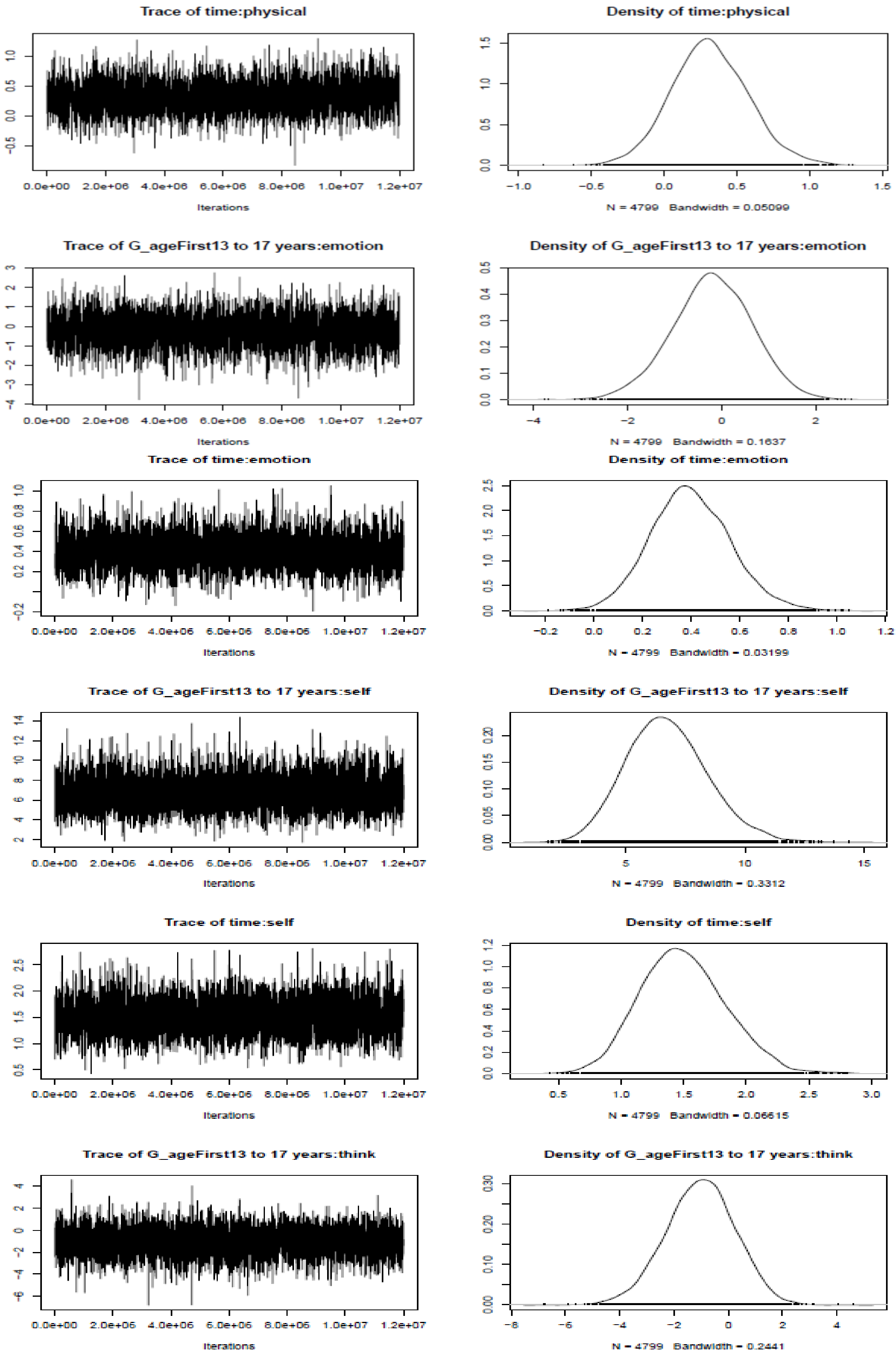

Trace of where
Iterations
Density of where
N = 4799 Bandwidth = 0.1332
Trace of life
Iterations
Density of life
N = 4799 Bandwidth = 0.234
Trace of drugs
Iterations
Density of drugs
N = 4799 Bandwidth = 0.1595
Trace of physical
Iterations
Density of physical
N = 4799 Bandwidth = 0.1854
Trace of emotion
Iterations
Density of emotion
N = 4799 Bandwidth = 0.1435
Trace of self
Iterations
Density of self
N = 4799 Bandwidth = 0.3108

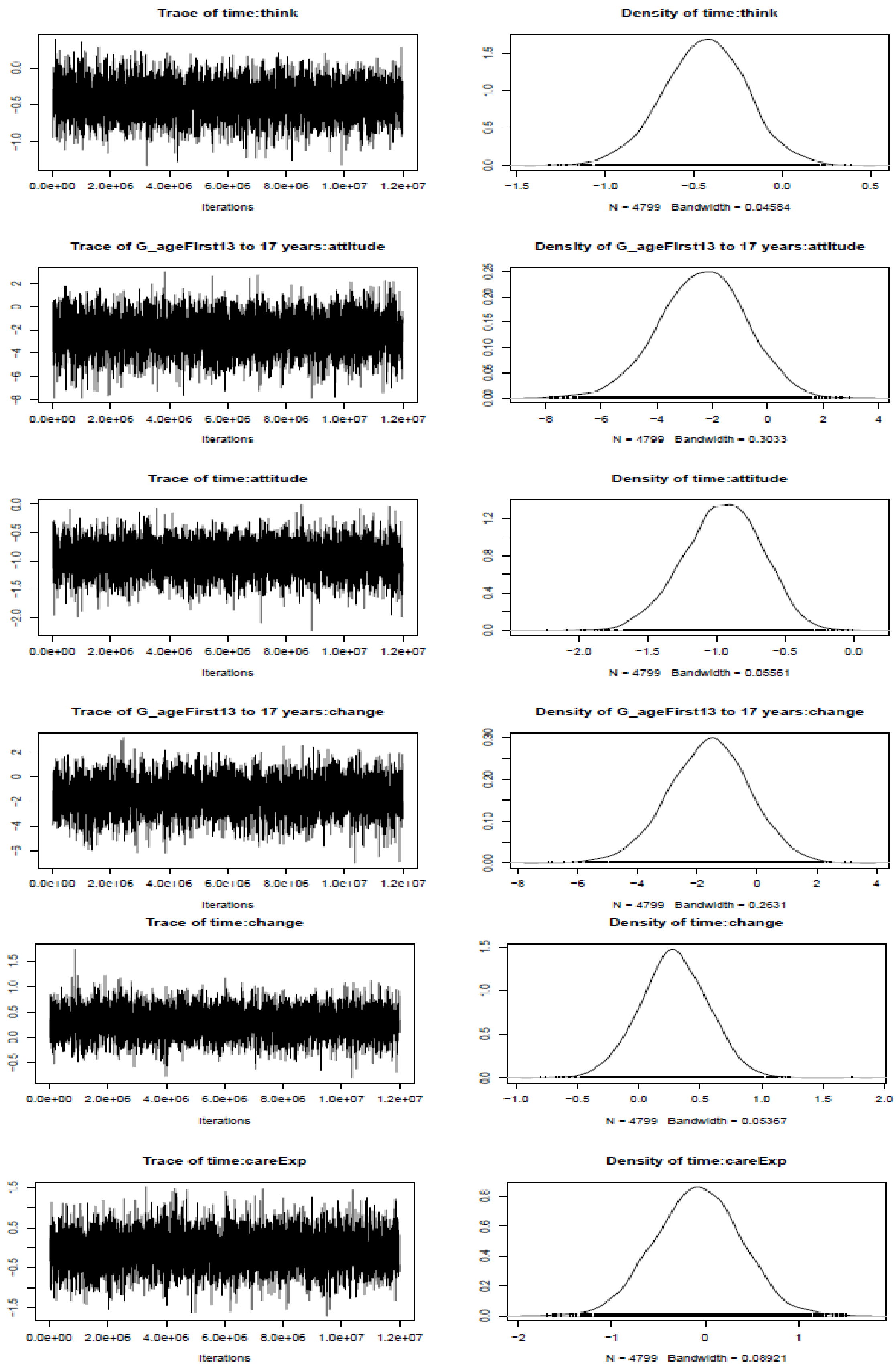


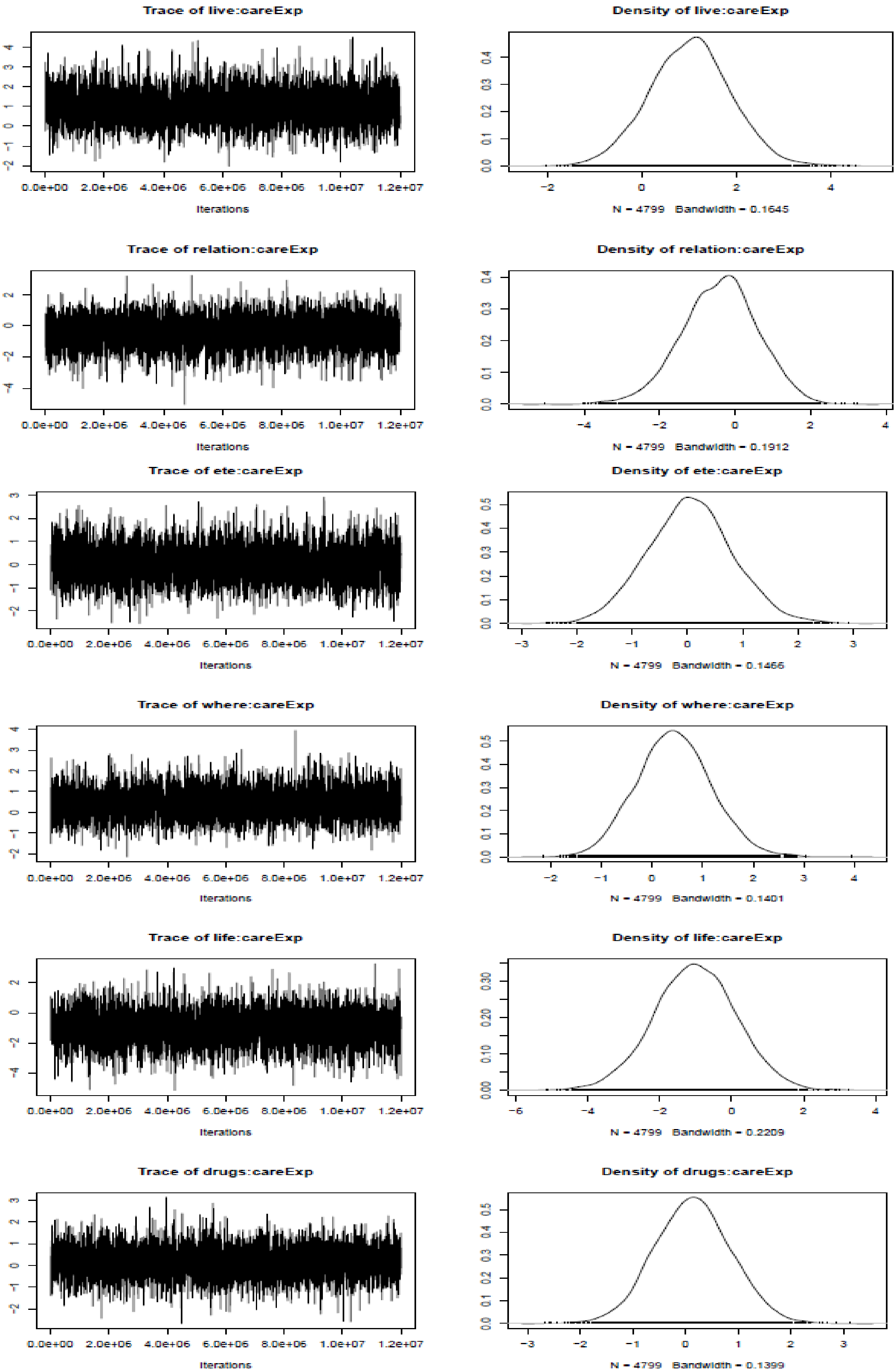
Trace of think
Iterations
Density of think
N = 4799 Bandwidth = 0.2318
Trace of attitude
Iterations
Density of attitude
N = 4799 Bandwidth = 0.2829
Trace of change
Iterations
Density of change
N = 4799 Bandwidth = 0.2339
Trace of careExp
Iterations
Density of careExp
N = 4799 Bandwidth = 0.4957
Trace of G_ageFirst13 to 17 years:time
Iterations
Density of G_ageFirst13 to 17 years:time
N = 4799 Bandwidth = 0.09731
Trace of G_ageFirst13 to 17 years:live
Iterations
Density of G_ageFirst13 to 17 years:live
N = 4799 Bandwidth = 0.1771

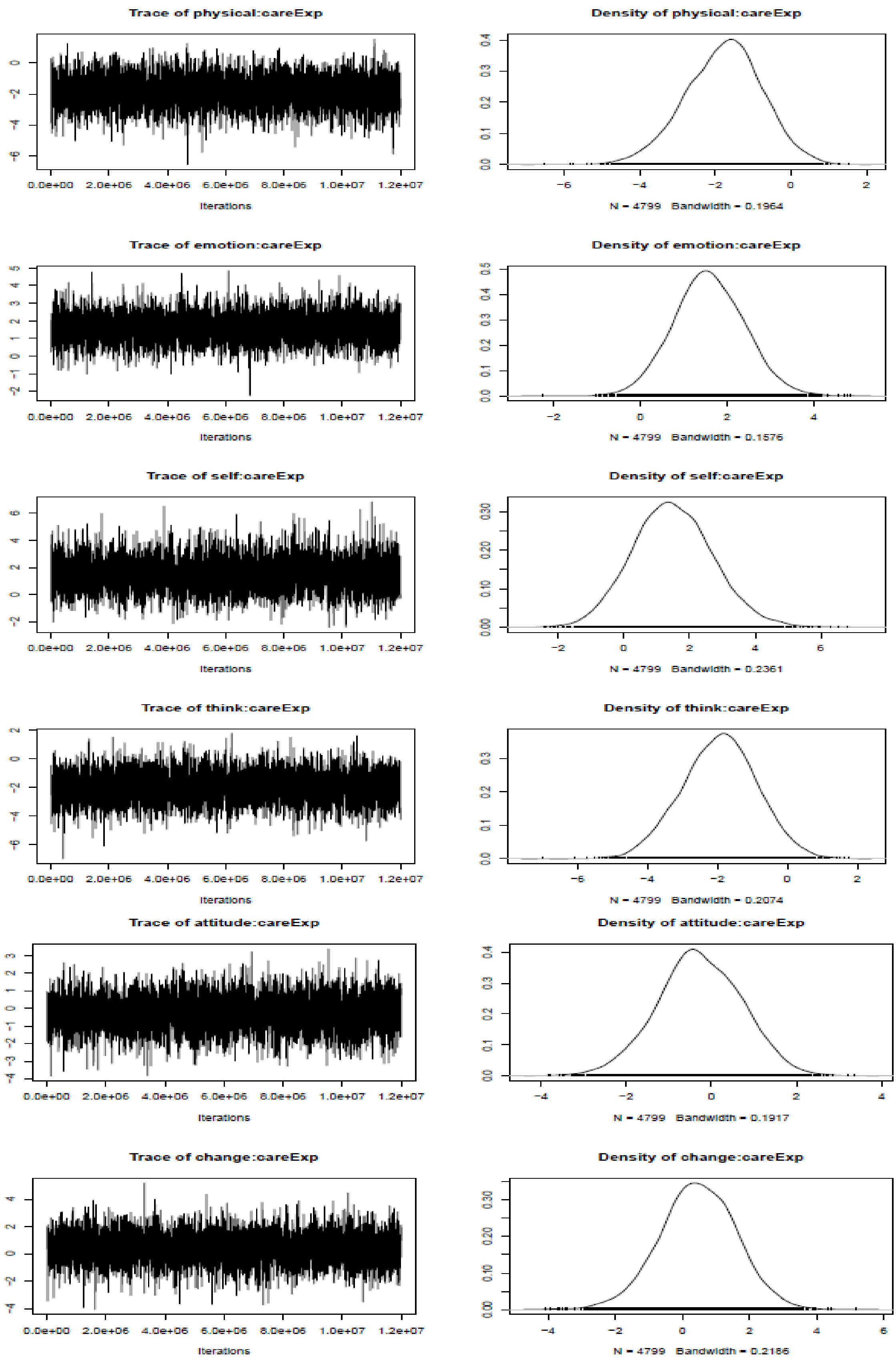

Trace of time:live
Density of time:live
Iterations
N = 4799 Bandwidth = 0.03769
Trace of G_ageFirst13 to 17 years:relation
Density of G_ageFirst13 to 17 years:relation
Iterations
N = 4799 Bandwidth = 0.2117
Trace of time:relation
Density of time:relation
Iterations
N = 4799 Bandwidth = 0.04466
Trace of G_ageFirst13 to 17 years:ete
Density of G_ageFirst13 to 17 years:ete
Iterations
N = 4799 Bandwidth = 0.1701
Trace of time:ete
Density of time:ete
Iterations
N = 4799 Bandwidth = 0.03204
Trace of G_ageFirst13 to 17 years:where
Density of G_ageFirst13 to 17 years:where
Iterations
N = 4799 Bandwidth = 0.1454

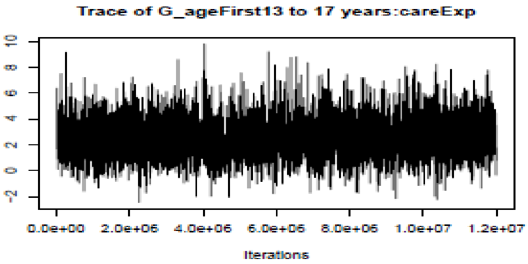

Trace of time:where
Iterations
Density of time:where
N = 4799 Bandwidth = 0.02828
Trace of G_ageFirst13 to 17 years:life
Iterations
Density of G_ageFirst13 to 17 years:life
N = 4799 Bandwidth = 0.256
Trace of time:life
Iterations
Density of time:life
N = 4799 Bandwidth = 0.05143
Trace of G_ageFirst13 to 17 years:drugs
Iterations
Density of G_ageFirst13 to 17 years:drugs
N = 4799 Bandwidth = 0.1697
Trace of time:drugs
Iterations
Density of time:drugs
N = 4799 Bandwidth = 0.03613
Trace of G_ageFirst13 to 17 years:physical
Iterations
Density of G_ageFirst13 to 17 years:physical
N = 4799 Bandwidth = 0.1951

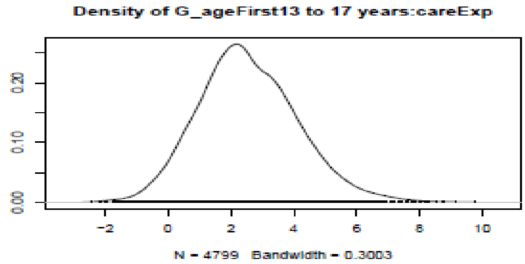

Trace of time:physical
Iterations
Density of time:physical
N = 4799 Bandwidth = 0.05099
Trace of G_ageFirst13 to 17 years:emotion
Iterations
Density of G_ageFirst13 to 17 years:emotion
N = 4799 Bandwidth = 0.1637
Trace of time:emotion
Iterations
Density of time:emotion
N = 4799 Bandwidth = 0.03199
Trace of G_ageFirst13 to 17 years:self
Iterations
Density of G_ageFirst13 to 17 years:self
N = 4799 Bandwidth = 0.3312
Trace of time:self
Iterations
Density of time:self
N = 4799 Bandwidth = 0.06615
Trace of G_ageFirst13 to 17 years:think
Iterations
Density of G_ageFirst13 to 17 years:think
N = 4799 Bandwidth = 0.2441

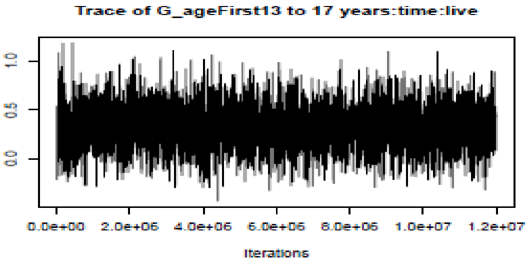

Trace of time:think
Iterations
Density of time:think
N = 4799 Bandwidth = 0.04584
Trace of G_ageFirst13 to 17 years:attitude
Iterations
Density of G_ageFirst13 to 17 years:attitude
N = 4799 Bandwidth = 0.3033
Trace of time:attitude
Iterations
Density of time:attitude
N = 4799 Bandwidth = 0.05561
Trace of G_ageFirst13 to 17 years:change
Iterations
Density of G_ageFirst13 to 17 years:change
N = 4799 Bandwidth = 0.2631
Trace of time:change
Iterations
Density of time:change
N = 4799 Bandwidth = 0.05367
Trace of time:careExp
Iterations
Density of time:careExp
N = 4799 Bandwidth = 0.08921

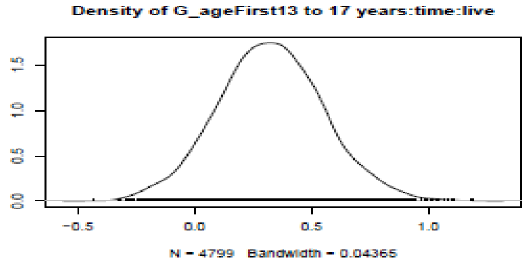

Trace of live:careExp
Iterations
Density of live:careExp
N = 4799 Bandwidth = 0.1645
Trace of relation:careExp
Iterations
Density of relation:careExp
N = 4799 Bandwidth = 0.1912
Trace of ete:careExp
Iterations
Density of ete:careExp
N = 4799 Bandwidth = 0.1466
Trace of where:careExp
Iterations
Density of where:careExp
N = 4799 Bandwidth = 0.1401
Trace of life:careExp
Iterations
Density of life:careExp
N = 4799 Bandwidth = 0.2209
Trace of drugs:careExp
Iterations
Density of drugs:careExp
N = 4799 Bandwidth = 0.1399

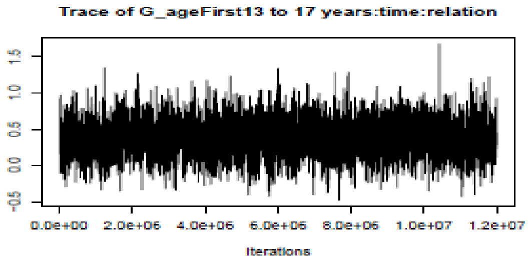

Trace of physical:careExp
Iterations
Density of physical:careExp
N = 4799 Bandwidth = 0.1964
Trace of emotion:careExp
Iterations
Density of emotion:careExp
N = 4799 Bandwidth = 0.1576
Trace of self:careExp
Iterations
Density of self:careExp
N = 4799 Bandwidth = 0.2361
Trace of think:careExp
Iterations
Density of think:careExp
N = 4799 Bandwidth = 0.2074
Trace of attitude:careExp
Iterations
Density of attitude:careExp
N = 4799 Bandwidth = 0.1917
Trace of change:careExp
Iterations
Density of change:careExp
N = 4799 Bandwidth = 0.2186

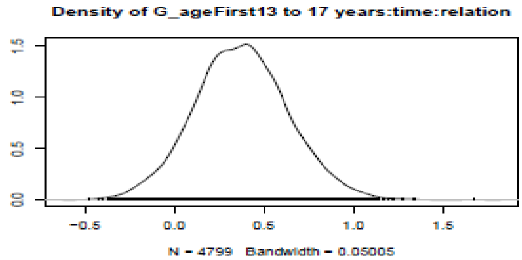

Trace of G_ageFirst13 to 17 years:careExp
Iterations

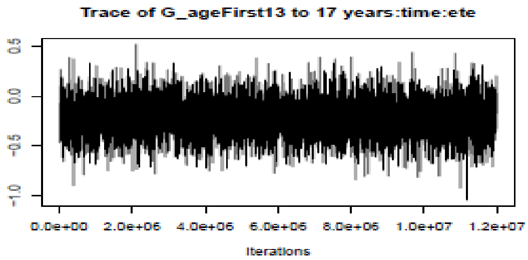

Density of G_ageFirst13 to 17 years:careExp
N = 4799 Bandwidth = 0.3003

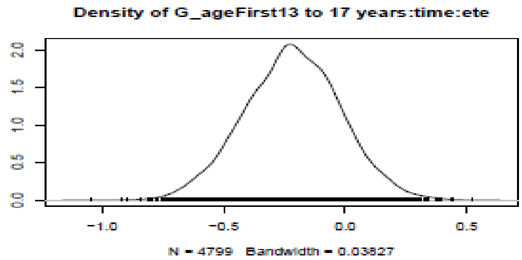

Trace of G_ageFirst13 to 17 years:time:live
Iterations

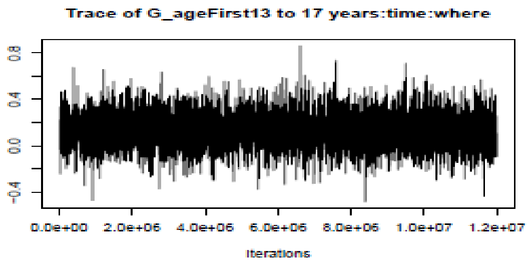

Density of G_ageFirst13 to 17 years:time:live
N = 4799 Bandwidth = 0.04365

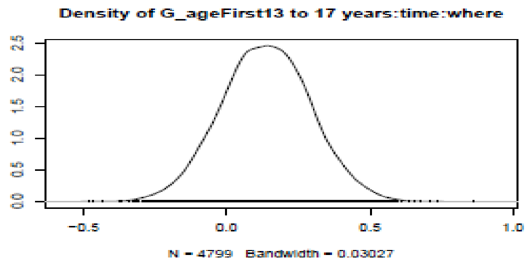

Trace of G_ageFirst13 to 17 years:time:relation
Iterations

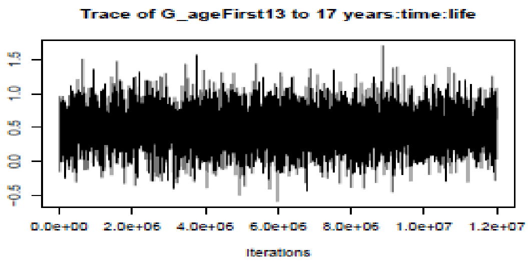

Density of G_ageFirst13 to 17 years:time:relation
N = 4799 Bandwidth = 0.05005

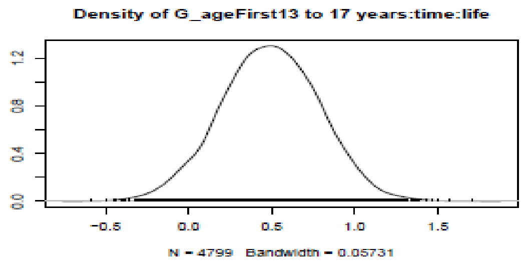

Trace of G_ageFirst13 to 17 years:time:ete
Iterations

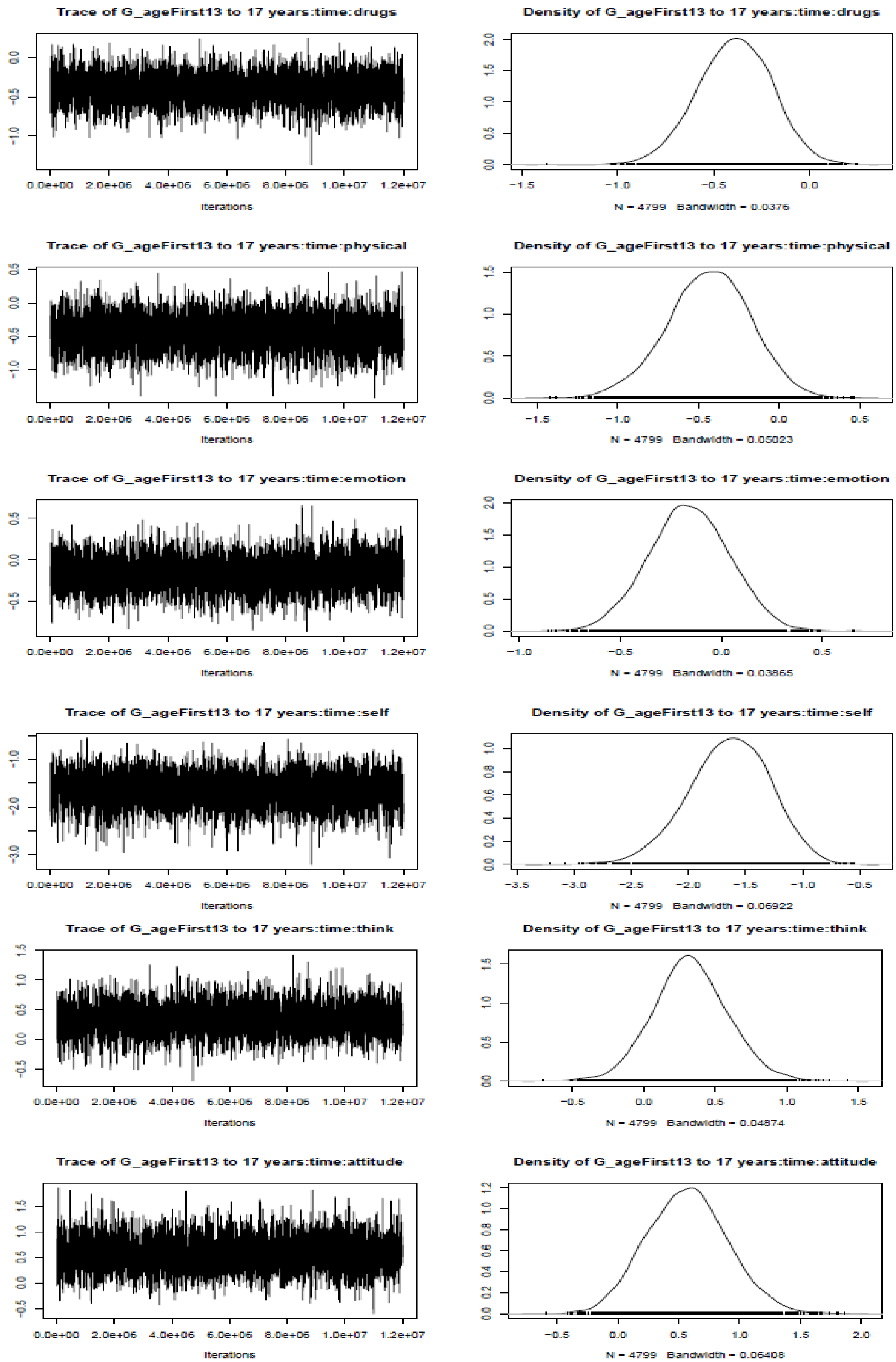

Density of G_ageFirst13 to 17 years:time:ete
N = 4799 Bandwidth = 0.03827

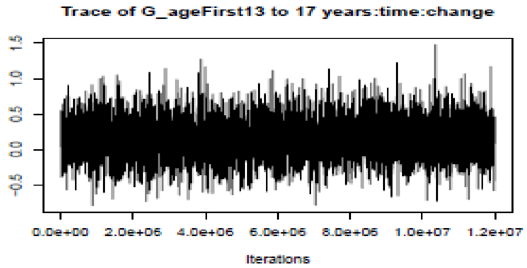

Trace of G_ageFirst13 to 17 years:time:where
Iterations

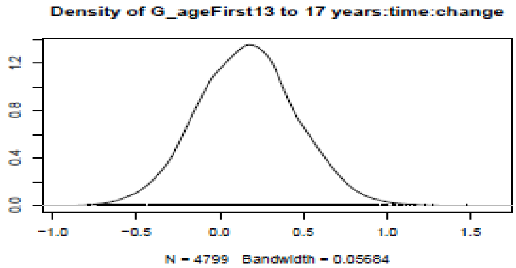

Density of G_ageFirst13 to 17 years:time:where
N = 4799 Bandwidth = 0.03027

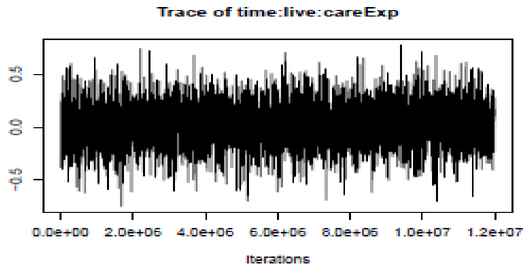

Trace of G_ageFirst13 to 17 years:time:life
Iterations

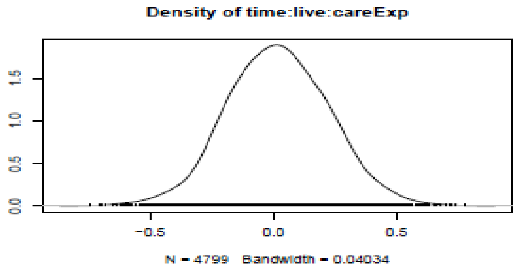

Density of G_ageFirst13 to 17 years:time:life
N = 4799 Bandwidth = 0.05731

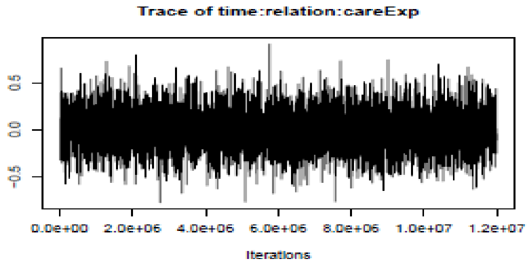

Trace of G_ageFirst13 to 17 years:time:drugs
Iterations
Density of G_ageFirst13 to 17 years:time:drugs
N = 4799 Bandwidth = 0.0376
Trace of G_ageFirst13 to 17 years:time:physical
Iterations
Density of G_ageFirst13 to 17 years:time:physical
N = 4799 Bandwidth = 0.05023
Trace of G_ageFirst13 to 17 years:time:emotion
Iterations
Density of G_ageFirst13 to 17 years:time:emotion
N = 4799 Bandwidth = 0.03865
Trace of G_ageFirst13 to 17 years:time:self
Iterations
Density of G_ageFirst13 to 17 years:time:self
N = 4799 Bandwidth = 0.06922
Trace of G_ageFirst13 to 17 years:time:think
Iterations
Density of G_ageFirst13 to 17 years:time:think
N = 4799 Bandwidth = 0.04874
Trace of G_ageFirst13 to 17 years:time:attitude
Iterations
Density of G_ageFirst13 to 17 years:time:attitude
N = 4799 Bandwidth = 0.06408

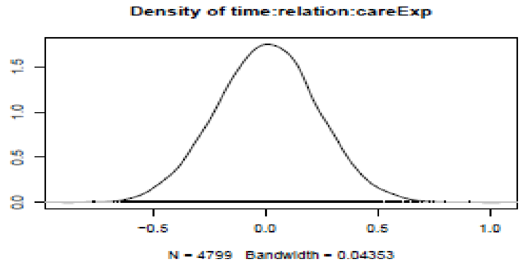

Trace of G_ageFirst13 to 17 years:time:change
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations

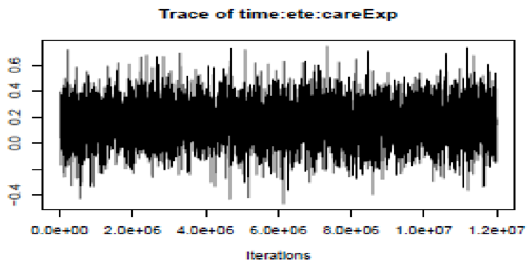

Density of G_ageFirst13 to 17 years:time:change
N = 4799 Bandwidth = 0.05684

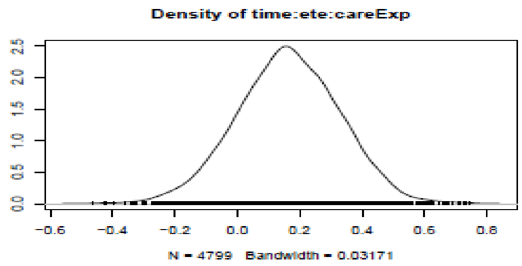

Trace of time:live:careExp
Iterations

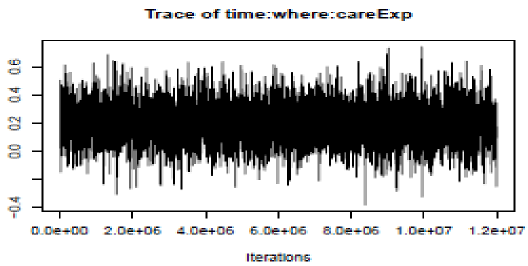

Density of time:live:careExp
N = 4799 Bandwidth = 0.04034

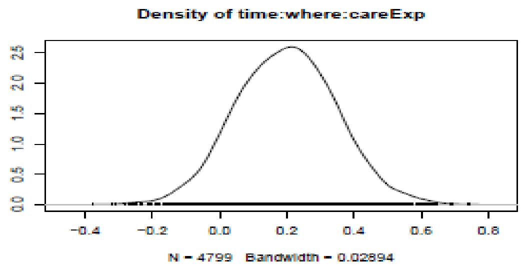

Trace of time:relation:careExp
Iterations

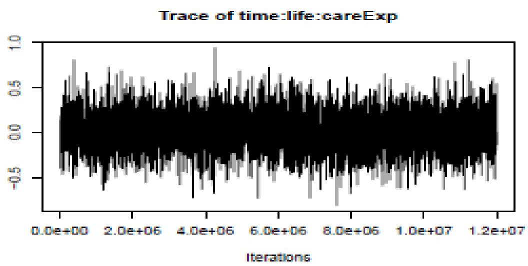

Density of time:relation:careExp
N = 4799 Bandwidth = 0.04353

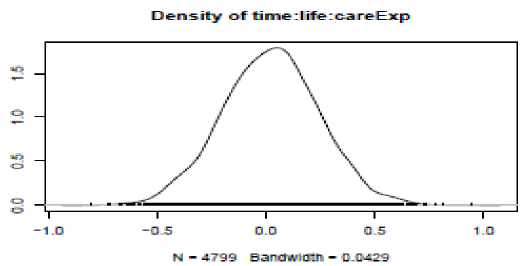

Trace of time:ete:careExp
Iterations

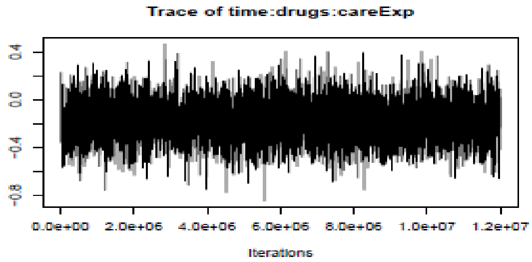

Density of time:ete:careExp
N = 4799 Bandwidth = 0.03171

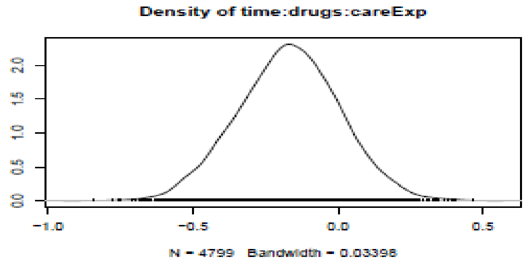

Trace of time:where:careExp
Iterations

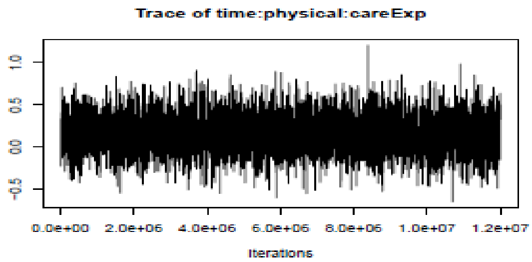

Density of time:where:careExp
N = 4799 Bandwidth = 0.02894

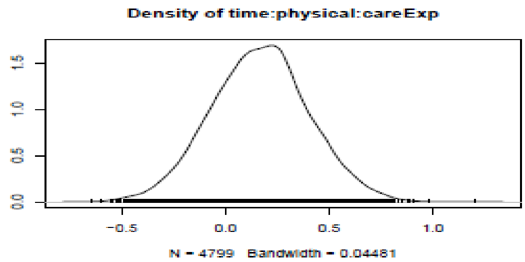

Trace of time:life:careExp
Iterations

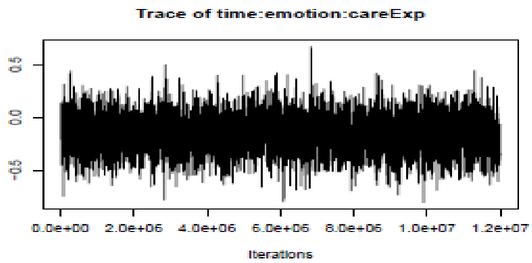

Density of time:life:careExp
N = 4799 Bandwidth = 0.0429

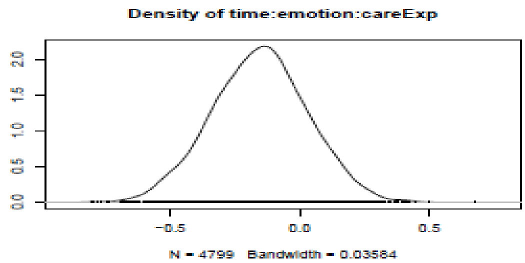

Trace of time:drugs:careExp
0.4
0.0
-0.4
-0.8
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations

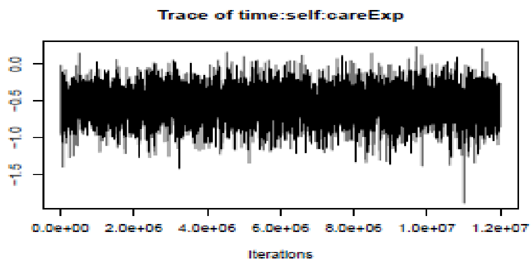

Density of time:drugs:careExp
2.0
1.5
1.0
0.5
0.0
-1.0 -0.5 0.0 0.5
N = 4799 Bandwidth = 0.03398

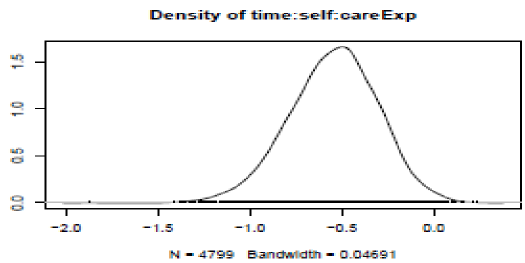

Trace of time:physical:careExp
1.0
0.5
0.0
-0.5
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations

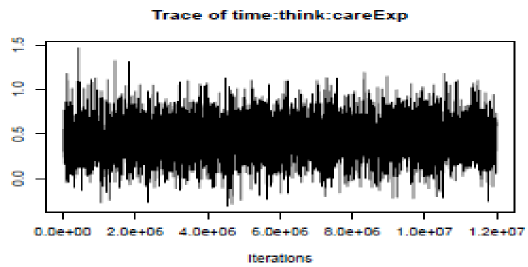

Density of time:physical:careExp
1.5
1.0
0.5
0.0
-0.5 0.0 0.5 1.0
N = 4799 Bandwidth = 0.04481

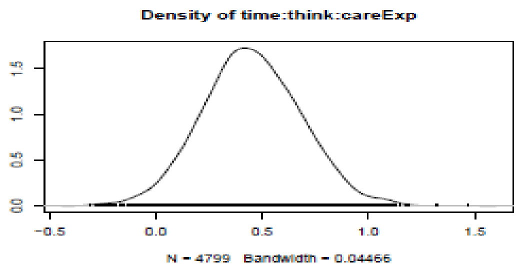

Trace of time:emotion:careExp
0.5
0.0
-0.5
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations

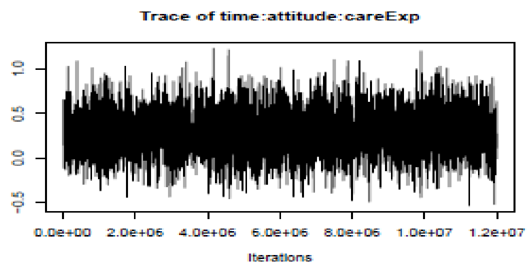

Density of time:emotion:careExp
2.0
1.5
1.0
0.5
0.0
-0.5 0.0 0.5
N = 4799 Bandwidth = 0.03584

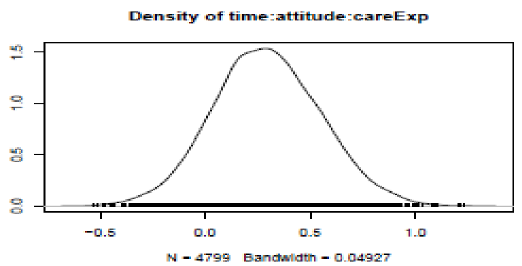

Trace of time:self:careExp
0.0
-0.5
-1.0
-1.5
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations

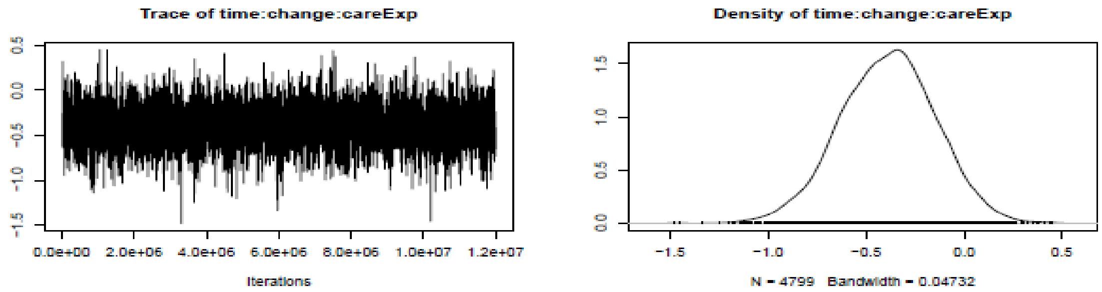

Density of time:self:careExp
1.5
1.0
0.5
0.0
-2.0 -1.5 -1.0 -0.5 0.0
N = 4799 Bandwidth = 0.04691


Trace of time:think:careExp
1.5
1.0
0.5
0.0
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations

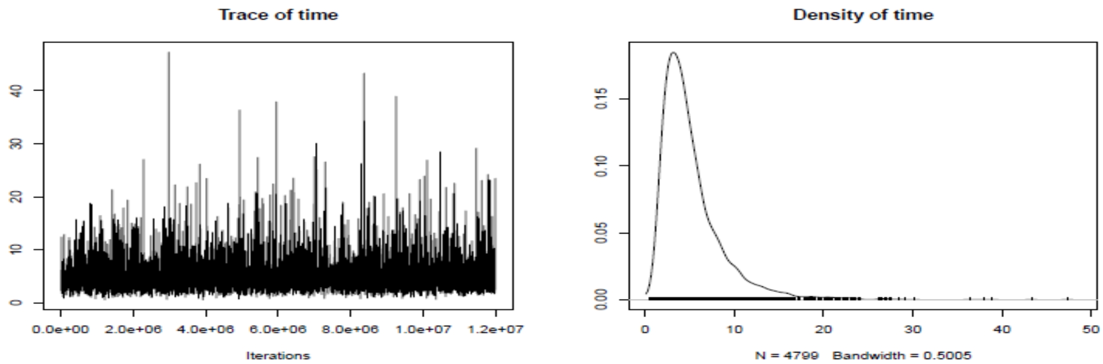

Density of time:think:careExp
1.5
1.0
0.5
0.0
-0.5 0.0 0.5 1.0 1.5
N = 4799 Bandwidth = 0.04466

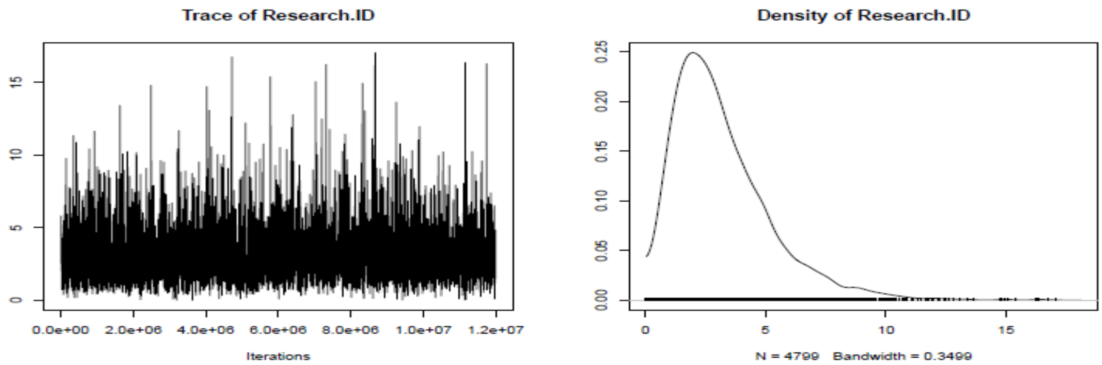

Trace of time:attitude:careExp
1.0
0.5
0.0
-0.5
0.0e+00 2.0e+06 4.0e+06 6.0e+06 8.0e+06 1.0e+07 1.2e+07
Iterations


Density of time:attitude:careExp
1.5
1.0
0.5
0.0
-0.5 0.0 0.5 1.0
N = 4799 Bandwidth = 0.04927



Random Effects





Model 1.12 – Basic Model + Breach (Table 7.4)

Bayesian Model (Bm1_cj1)

Define the model

```
Bm1_cj1 <- MCMCglmm(FO.bin~breach + live + relation + ete + where + life
+ drugs + physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=250000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_cj1$VCV)
heidel.diag(Bm1_cj1$VCV)

# > raftery.diag(Bm1_cj1$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         40       77580  3746         20.7
# Research.ID 200       252400 3746         67.4
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_cj1$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed       9881      0.112
# Research.ID passed          1       0.111
# units        failed        NA          NA
#
#              Halfwidth Mean   Halfwidth
#              test
# time         passed    1.2810 0.02154
# Research.ID passed     0.0999 0.00768
# units        <NA>         NA       NA

autocorr(Bm1_cj1$VCV)
autocorr(Bm1_cj1$Sol)  # Output not included here
summary(Bm1_cj1)

# > autocorr(Bm1_cj1$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0    1.000000000 0.103649294   NaN
# Lag 10   0.248515487 0.099750398   NaN
# Lag 50   0.088724977 0.079092374   NaN
# Lag 100  0.026723071 0.049852767   NaN
# Lag 500 -0.007684639 0.002891446   NaN


# , , Research.ID
#
#                  time Research.ID units
```

```
# Lag 0    0.103649294  1.00000000   NaN
# Lag 10   0.108245162  0.83607711   NaN
# Lag 50   0.080586342  0.54074414   NaN
# Lag 100  0.046786548  0.34939104   NaN
# Lag 500 -0.002504076  0.04449408   NaN

# > summary(Bm1_cj1)
#
# Iterations = 3001:249991
# Thinning interval  = 10
# Sample size  = 24700
#
# DIC: 476.7263
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.262    0.344    2.612     7457
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID   0.09992 0.0001634     0.37     1140
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ breach + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time
#
#             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -1.143198 -2.387365  0.070878    15937 0.0672 .
# breach       0.189913 -0.396895  0.772496    10720 0.5206
# live         0.030526 -0.229645  0.289499    10303 0.8221
# relation     0.266898 -0.033854  0.546650    10099 0.0754 .
# ete          0.093581 -0.157631  0.336024     8727 0.4441
# where        0.046496 -0.172852  0.263872    10369 0.6825
# life         0.007227 -0.341841  0.354041     9938 0.9670
# drugs        0.158319 -0.078550  0.395885     9323 0.1883
# physical    -0.111773 -0.391918  0.168199     8906 0.4343
# emotion      0.005892 -0.240734  0.245167    10233 0.9662
# self        -0.144495 -0.460061  0.166368     9551 0.3634
# think       -0.155733 -0.488951  0.167837    10135 0.3485
# attitude     0.041321 -0.303440  0.387206    10696 0.8262
# change       0.235704 -0.107660  0.574600    10294 0.1733
# time        -0.153975 -0.290119 -0.024314    10766 0.0207 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_cj1)

```
m1_cj1 <- glmer(FO.bin ~ breach + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_cj1)
vcomps.icc(m1_cj1)
anova(m1,m1_cj1)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ breach + live + relation + ete + where + life +
drugs +
#   physical + emotion + self + think + attitude + change + time +
#   (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 640.7    718.1   -302.3    604.7      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.7384 -0.6690 -0.3725  0.7822  3.6742
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.04335  0.2082
#            time        0.04670  0.2161   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.792459   0.317652  -2.495   0.0126 *
# breach       0.442068   0.319427   1.384   0.1664
# live        -0.060001   0.141244  -0.425   0.6710
# relation     0.187198   0.156865   1.193   0.2327
# ete          0.004197   0.129354   0.032   0.9741
# where        0.142099   0.127302   1.116   0.2643
# life        -0.013208   0.190978  -0.069   0.9449
# drugs        0.259464   0.132621   1.956   0.0504 .
# physical    -0.226642   0.148879  -1.522   0.1279
# emotion     -0.024953   0.133092  -0.187   0.8513
# self        -0.082077   0.174963  -0.469   0.6390
# think        0.131034   0.185670   0.706   0.4804
# attitude    -0.078593   0.189352  -0.415   0.6781
# change       0.223828   0.180563   1.240   0.2151
# time        -0.418857   0.102937  -4.069 4.72e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.039008 (tol = 0.001,
component 1)

# vcomps.icc(m1_cj1)
# Var (Level 2) Var (Level 1)          ICC          <NA>
#         0.043         0.047        1.000         0.481
```

```
# anova(m1,m1_cj1)
# Data: data
# Models:
#   m1: FO.bin ~ time + live + relation + ete + where + life + drugs +
#    m1:      physical + emotion + self + think + attitude + change +
(time |
#   m1:     Individual)
# m1_cj1: FO.bin ~ breach + live + relation + ete + where + life + drugs
+
#   m1_cj1:     physical + emotion + self + think + attitude + change +
#   m1_cj1:     time + (time | Individual)
#        Df    AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1     17 640.59 713.7 -303.29   606.59
# m1_cj1 18 640.68 718.1 -302.34   604.68 1.9039      1     0.1676
```

Model 1.13 – Basic Model + Court Appearance (Table 7.4)

Bayesian Model (Bm1_cj2)

Define the model

```
Bm1_cj2 <- MCMCglmm(FO.bin~appear + live + relation + ete + where + life
+ drugs + physical + emotion + self + think + attitude + change + time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=250000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_cj2$VCV)
heidel.diag(Bm1_cj2$VCV)

# > raftery.diag(Bm1_cj2$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         30       43650  3746         11.7
# Research.ID 160       204200 3746         54.5
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_cj2$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.247
# Research.ID passed         1         0.543
# units        failed       NA            NA
#
#              Halfwidth Mean   Halfwidth
#              test
# time         passed     0.8240 0.00966
# Research.ID passed      0.0347 0.00276
# units        <NA>          NA      NA

autocorr(Bm1_cj2$VCV)
autocorr(Bm1_cj2$Sol)    # Output not included here
summary(Bm1_cj2)

# > autocorr(Bm1_cj2$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0   1.000000000  0.06303838   NaN
# Lag 10  0.229599633  0.05994002   NaN
# Lag 50  0.060463139  0.04032790   NaN
# Lag 100 0.010917155  0.02941136   NaN
# Lag 500 0.004131155  0.01336416   NaN
```

```
# , , Research.ID
#
#                  time Research.ID units
# Lag 0    0.063038377  1.00000000   NaN
# Lag 10   0.065281168  0.82698191   NaN
# Lag 50   0.046247787  0.46247083   NaN
# Lag 100  0.012278791  0.24768914   NaN
# Lag 500 -0.005866268  0.01992502   NaN

# > summary(Bm1_cj2)
#
# Iterations = 3001:249991
# Thinning interval  = 10
# Sample size  = 24700
#
# DIC: 429.5509
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     0.824   0.1645    1.722     9834
#
# ~Research.ID
#
#             post.mean l-95% CI u-95% CI eff.samp
# Research.ID   0.03473 0.000147   0.1493     1753
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ appear + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time
#
#             post.mean  l-95% CI  u-95% CI eff.samp   pMCMC
# (Intercept) -1.832973 -2.925032 -0.719776    12252 0.00251 **
# appear       1.658946  1.206336  2.111629     8677 < 4e-05 ***
# live         0.021979 -0.244022  0.288987     9050 0.86842
# relation     0.270502 -0.015933  0.573147     9522 0.07085 .
# ete          0.044851 -0.203873  0.289202     9551 0.72389
# where        0.049833 -0.172716  0.268289     9254 0.65895
# life        -0.123259 -0.471322  0.232500     9101 0.48907
# drugs        0.103203 -0.135168  0.345968     9081 0.40178
# physical     0.010420 -0.275408  0.303215     8854 0.93514
# emotion      0.014290 -0.229637  0.263633     9377 0.91142
# self        -0.216061 -0.553666  0.100963     9125 0.18874
# think       -0.155727 -0.488393  0.187828     9774 0.36777
# attitude     0.031774 -0.323476  0.386118     9195 0.86283
# change       0.281691 -0.077648  0.626029     8580 0.11579
# time        -0.125358 -0.243626 -0.009813    11711 0.03344 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_cj2)

```
m1_cj2 <- glmer(FO.bin ~ appear + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_cj2)
vcomps.icc(m1_cj2)
anova(m1,m1_cj2)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ appear + live + relation + ete + where + life +
drugs +
#   physical + emotion + self + think + attitude + change + time +
#   (time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 533.1    610.5   -248.6    497.1      527
#
# Scaled residuals:
#     Min      1Q  Median      3Q     Max
# -1.7861 -0.4465 -0.2578  0.6134  9.4408
#
# Random effects:
#   Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.038220 0.19550
#            time        0.006282 0.07926  -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -2.034945   0.369552  -5.507 3.66e-08 ***
# appear       2.567946   0.276842   9.276  < 2e-16 ***
# live         0.004493   0.151039   0.030    0.976
# relation     0.228351   0.164675   1.387    0.166
# ete         -0.006867   0.141854  -0.048    0.961
# where        0.036791   0.127525   0.288    0.773
# life        -0.137637   0.201059  -0.685    0.494
# drugs        0.077222   0.138560   0.557    0.577
# physical     0.031244   0.164426   0.190    0.849
# emotion     -0.012031   0.139123  -0.086    0.931
# self        -0.178852   0.183423  -0.975    0.330
# think       -0.042394   0.195604  -0.217    0.828
# attitude    -0.067963   0.204140  -0.333    0.739
# change       0.315790   0.196219   1.609    0.108
# time        -0.227312   0.050609  -4.492 7.07e-06 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


# convergence code: 0
# Model failed to converge with max|grad| = 0.0132078 (tol = 0.001,
component 1)

# vcomps.icc(m1_cj2)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.038         0.006         1.000         0.859
```

```
# anova(m1,m1_cj2)
# Data: data
# Models:
#   m1: FO.bin ~ time + live + relation + ete + where + life + drugs +
#    m1:      physical + emotion + self + think + attitude + change +
(time |
#   m1:     Individual)
# m1_cj2: FO.bin ~ appear + live + relation + ete + where + life + drugs
+
#   m1_cj2:     physical + emotion + self + think + attitude + change +
#   m1_cj2:     time + (time | Individual)
#        Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1     17 640.59 713.70 -303.29   606.59
# m1_cj2 18 533.13 610.55 -248.57   497.13 109.46      1  < 2.2e-16 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model 1.14 – Basic Model + Custody (Table 7.4)

Bayesian Model (Bm1_cj3)

Define the model

```
Bm1_cj3 <- MCMCglmm(FO.bin~custody + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time,
random=~time+Research.ID, data=data, family="ordinal", prior=prior2,
nitt=210000, thin=10, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(Bm1_cj3$VCV)
heidel.diag(Bm1_cj3$VCV)

# > raftery.diag(Bm1_cj3$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         30       41110  3746         11.0
# Research.ID 160       214000 3746         57.1
# units        <NA>     <NA>   3746           NA

# > heidel.diag(Bm1_cj3$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.801
# Research.ID passed         1         0.782
# units        failed       NA           NA
#
#              Halfwidth Mean   Halfwidth
#              test
# time         passed    1.2977 0.01587
# Research.ID passed     0.0737 0.00652
# units        <NA>          NA       NA

autocorr(Bm1_cj3$VCV)
autocorr(Bm1_cj3$Sol)   # Output not included here
summary(Bm1_cj3)

# > autocorr(Bm1_cj3$VCV)
# , , time
#
#                  time Research.ID units
# Lag 0    1.000000000 0.079310373   NaN
# Lag 10   0.220706976 0.077769729   NaN
# Lag 50   0.062883138 0.056309552   NaN
# Lag 100  0.020306536 0.019986447   NaN
# Lag 500 -0.001485739 0.004142412   NaN
```

```
# , , Research.ID
#
#                 time Research.ID units
# Lag 0   0.079310373 1.000000000   NaN
# Lag 10  0.078214070 0.836523345   NaN
# Lag 50  0.056574852 0.515825732   NaN
# Lag 100 0.041492172 0.323822539   NaN
# Lag 500 0.008023129 0.003847498   NaN

# > summary(Bm1_cj3)
#
# Iterations = 3001:209991
# Thinning interval  = 10
# Sample size  = 20700
#
# DIC: 475.1556
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.298   0.3423    2.654     7640
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID   0.07374 0.0001701   0.2898     1020
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ custody + live + relation + ete + where +
life + drugs + physical + emotion + self + think + attitude + change +
time
#
#             post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept) -1.213521 -2.462275  0.055519    13105 0.0583 .
# custody     -0.528193 -1.203653  0.131148     6951 0.1176
# live         0.036122 -0.215179  0.291650     8128 0.7738
# relation     0.247137 -0.040860  0.542565     8413 0.0948 .
# ete          0.091922 -0.154852  0.331762     7972 0.4658
# where        0.053267 -0.158767  0.274517     9128 0.6304
# life         0.018177 -0.320078  0.353798     8791 0.9219
# drugs        0.155519 -0.067949  0.399989     7956 0.1912
# physical    -0.119075 -0.417798  0.147153     8631 0.4088
# emotion      0.021660 -0.218204  0.265390     8380 0.8598
# self        -0.132997 -0.441251  0.186738     8269 0.3963
# think       -0.143539 -0.459601  0.192432     9019 0.3871
# attitude     0.097292 -0.242608  0.459287     8681 0.5764
# change       0.207908 -0.122006  0.549357     8133 0.2254
# time        -0.143892 -0.278642 -0.009512     8037 0.0297 *
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Frequentist Model (m1_cj3)

```
m1_cj3 <- glmer(FO.bin ~ custody + live + relation + ete + where + life
+ drugs + physical + emotion + self + think + attitude + change + time +
(time|Individual), data=data, family=binomial)
summary(m1_cj3)
vcomps.icc(m1_cj3)
anova(m1,m1_cj3)

# Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
# Family: binomial  ( logit )
# Formula: FO.bin ~ custody + live + relation + ete + where + life +
drugs + physical + emotion + self + think + attitude + change + time +
(time | Individual)
# Data: data
#
#   AIC      BIC   logLik deviance df.resid
# 640.9    718.3   -302.4    604.9      527
#
# Scaled residuals:
#   Min      1Q  Median      3Q     Max
# -1.5349 -0.6740 -0.3647  0.8268  3.6153
#
# Random effects:
# Groups     Name        Variance Std.Dev. Corr
# Individual (Intercept) 0.05443  0.2333
#            time        0.04983  0.2232   -1.00
# Number of obs: 545, groups:  Individual, 87
#
# Fixed effects:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept) -0.83923    0.31976  -2.625  0.00868 **
# custody     -0.51348    0.40397  -1.271  0.20370
# live        -0.06426    0.14132  -0.455  0.64930
# relation     0.17819    0.15718   1.134  0.25692
# ete         -0.01002    0.12981  -0.077  0.93845
# where        0.15435    0.12706   1.215  0.22445
# life         0.01938    0.18950   0.102  0.91853
# drugs        0.26113    0.13230   1.974  0.04841 *
# physical    -0.22867    0.14800  -1.545  0.12235
# emotion     -0.01811    0.13294  -0.136  0.89165
# self        -0.05755    0.17441  -0.330  0.74143
# think        0.12745    0.18509   0.689  0.49108
# attitude    -0.01983    0.19142  -0.104  0.91749
# change       0.20201    0.18019   1.121  0.26226
# time        -0.42369    0.10439  -4.059 4.94e-05 ***
#   ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# convergence code: 0
# Model failed to converge with max|grad| = 0.15032 (tol = 0.001,
component 1)

# vcomps.icc(m1_cj3)
# Var (Level 2) Var (Level 1)           ICC          <NA>
#         0.054         0.050         1.000         0.522
```

```
# anova(m1,m1_cj3)
# Data: data
# Models:
#   m1: FO.bin ~ time + live + relation + ete + where + life + drugs +
#   m1:     physical + emotion + self + think + attitude + change + (time |
#   m1:     Individual)
# m1_cj3: FO.bin ~ custody + live + relation + ete + where + life + drugs +
#   m1_cj3:  physical + emotion + self + think + attitude + change + time +
#   m1_cj3:  (time | Individual)
#        Df    AIC   BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
# m1     17 640.59 713.7 -303.29   606.59
# m1_cj3 18 640.89 718.3 -302.44   604.89 1.7028      1     0.1919
```

Dynamic Model 5: Breaches (Table 7.5)

Bayesian Model (BDm5_B)

Define the model

```
BDm5_B <- MCMCglmm(FO.bin ~ breach*time*live + breach*time*relation +
breach*time*ete + breach*time*where + breach*time*life +
breach*time*drugs + breach*time*physical + breach*time*emotion +
breach*time*self + breach*time*think + breach*time*attitude +
breach*time*change,
random=~time+Research.ID, data=data,
family="ordinal",prior=priorD,slice=TRUE,
nitt=250000, thin=50, burnin=3000)
```

Checks for suitable convergence

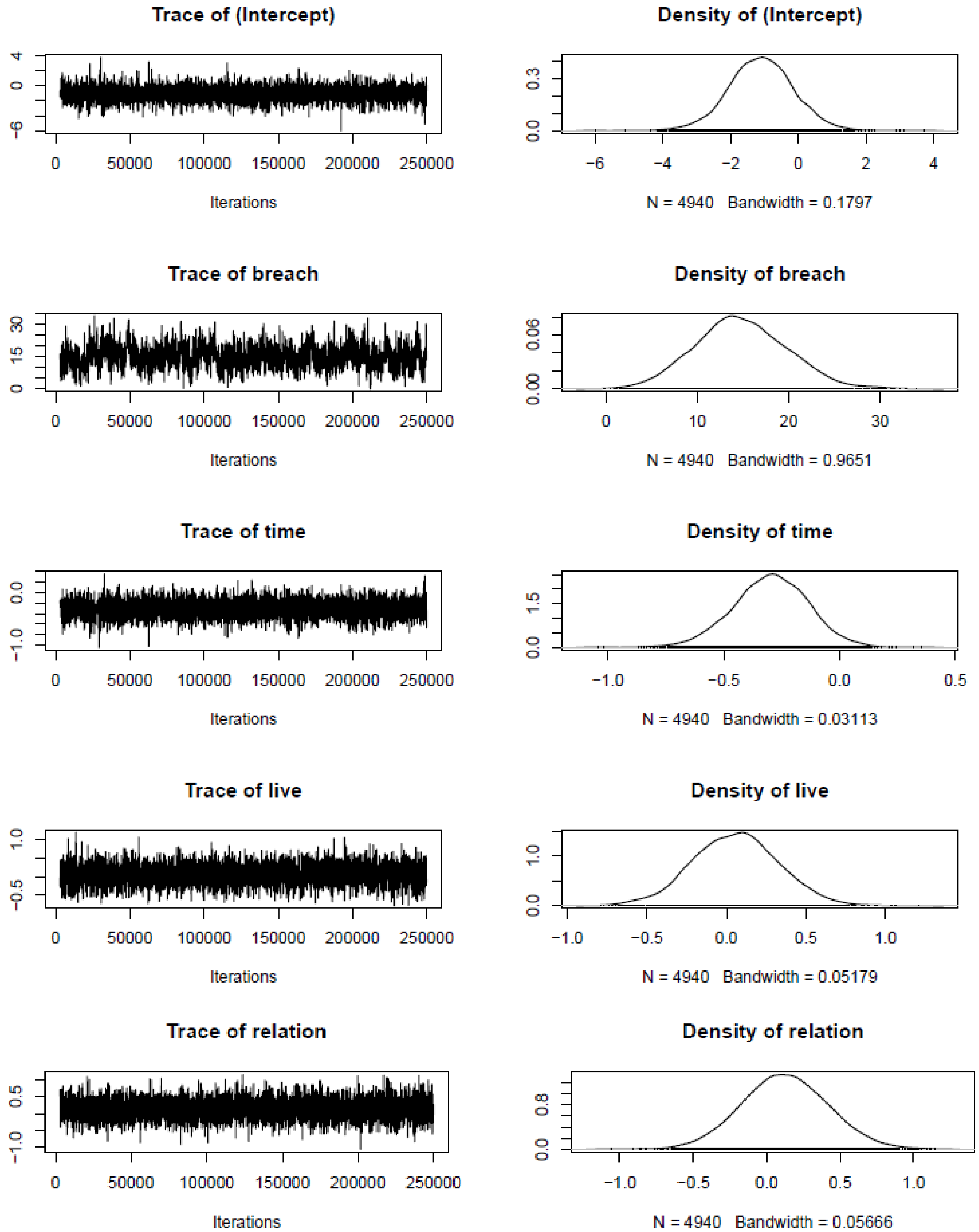
```
raftery.diag(BDm5_B$VCV)
heidel.diag(BDm5_B$VCV)

# > raftery.diag(BDm5_B$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         150      207800 3746         55.5
# Research.ID  150      225450 3746         60.2
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm5_B$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1        0.0816
# Research.ID  passed        1        0.2340
# units        failed       NA            NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    2.273 0.0825
# Research.ID  passed    0.582 0.0161
# units        <NA>         NA     NA

autocorr(BDm5_B$VCV)
autocorr(BDm5_B$Sol)    # Output not included here
summary(BDm5_B)

# > autocorr(BDm5_B$VCV)
# , , time
#
#                 time    Research.ID units
# Lag 0      1.000000000  0.1599752675   NaN
# Lag 50     0.254621015  0.1187341416   NaN
# Lag 250    0.093256091  0.0003990827   NaN
# Lag 500    0.063648167  0.0179645105   NaN
# Lag 2500  -0.006828798 -0.0138586856   NaN
```

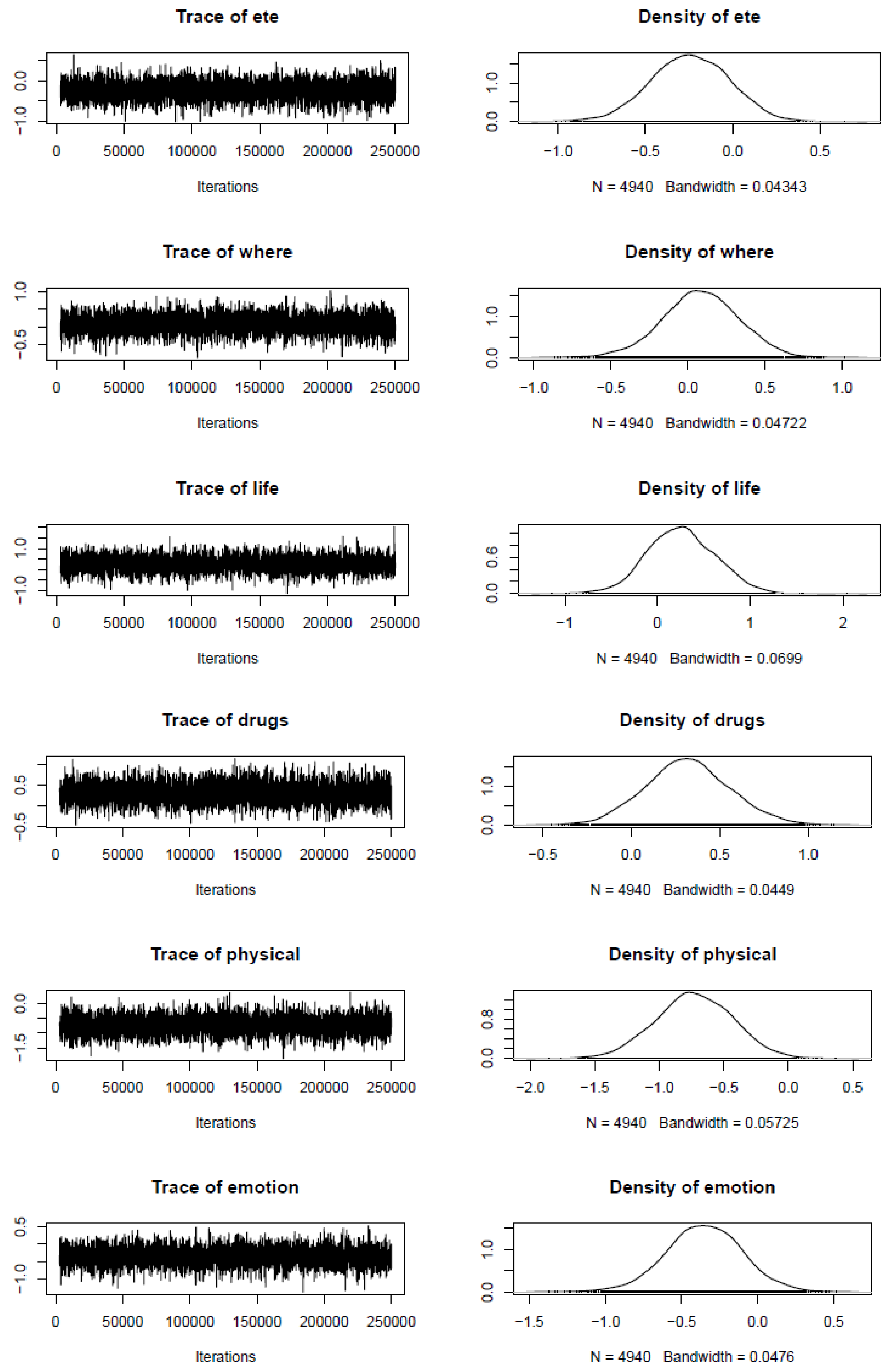
```
# , , Research.ID
#
#                   time Research.ID units
# Lag 0     0.1599752675 1.000000000   NaN
# Lag 50    0.0834747144 0.267174128   NaN
# Lag 250   0.0213318057 0.038551223   NaN
# Lag 500  -0.0001986719 0.020659719   NaN
# Lag 2500 -0.0137814783 0.007258196   NaN

# > summary(BDm5_B)
#
# Iterations = 3001:249951
# Thinning interval  = 50
# Sample size  = 4940
#
# DIC: 449.9071
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.273   0.4518    4.976     1114
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.5825 2.885e-05    1.315     2420
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ breach * time * live + breach * time * relation + breach * time * ete + breach * time * where + breach * time * life + breach * time * drugs + breach * time * physical + breach * time * emotion + breach * time * self + breach * time * think + breach * time * attitude + breach * time * change
#
#                     post.mean   l-95% CI   u-95% CI eff.samp    pMCMC
# (Intercept)          -1.092748  -2.930658   0.834432  4940.00 0.240081
# breach               14.801449   5.234311  24.736125   362.15 0.000810 ***
# time                 -0.298138  -0.613198   0.016410  4940.00 0.058300 .
# live                  0.058455  -0.453282   0.593657  4626.62 0.832389
# relation              0.125021  -0.454329   0.690887  4940.00 0.667611
# ete                  -0.244007  -0.686458   0.175185  4706.15 0.274494
# where                 0.081875  -0.361439   0.621169  4940.00 0.731579
# life                  0.257191  -0.447425   0.955128  4279.27 0.484211
# drugs                 0.319144  -0.115835   0.806025  4886.16 0.179757
# physical             -0.729767  -1.312297  -0.166009  4696.91 0.010121 *
# emotion              -0.352560  -0.844414   0.141348  4940.00 0.146964
# self                  0.270251  -0.370997   0.931962  4148.94 0.406478
# think                 0.071285  -0.528186   0.750377  4940.00 0.834413
# attitude              0.139984  -0.477380   0.825853  4940.00 0.682591
# change                0.387295  -0.298924   1.019775  4940.00 0.239271
# breach:time          -6.005245  -9.873236  -2.505929   123.81  < 2e-04 ***
# breach:live         -10.355569 -15.968279  -4.400889   170.51  < 2e-04 ***
# time:live            -0.004365  -0.113495   0.112126  4641.29 0.940081
# breach:relation      15.298721   7.366613  23.776054   206.77  < 2e-04 ***
# time:relation         0.028008  -0.112302   0.164322  4625.52 0.677733
# breach:ete          -10.431193 -16.322042  -5.104512   136.62  < 2e-04 ***
# time:ete              0.088991  -0.018666   0.198256  4534.84 0.108097
# breach:where         -0.793638  -2.868679   1.164735  1575.01 0.448583
# time:where            0.015250  -0.075528   0.111604  4940.00 0.744939
```

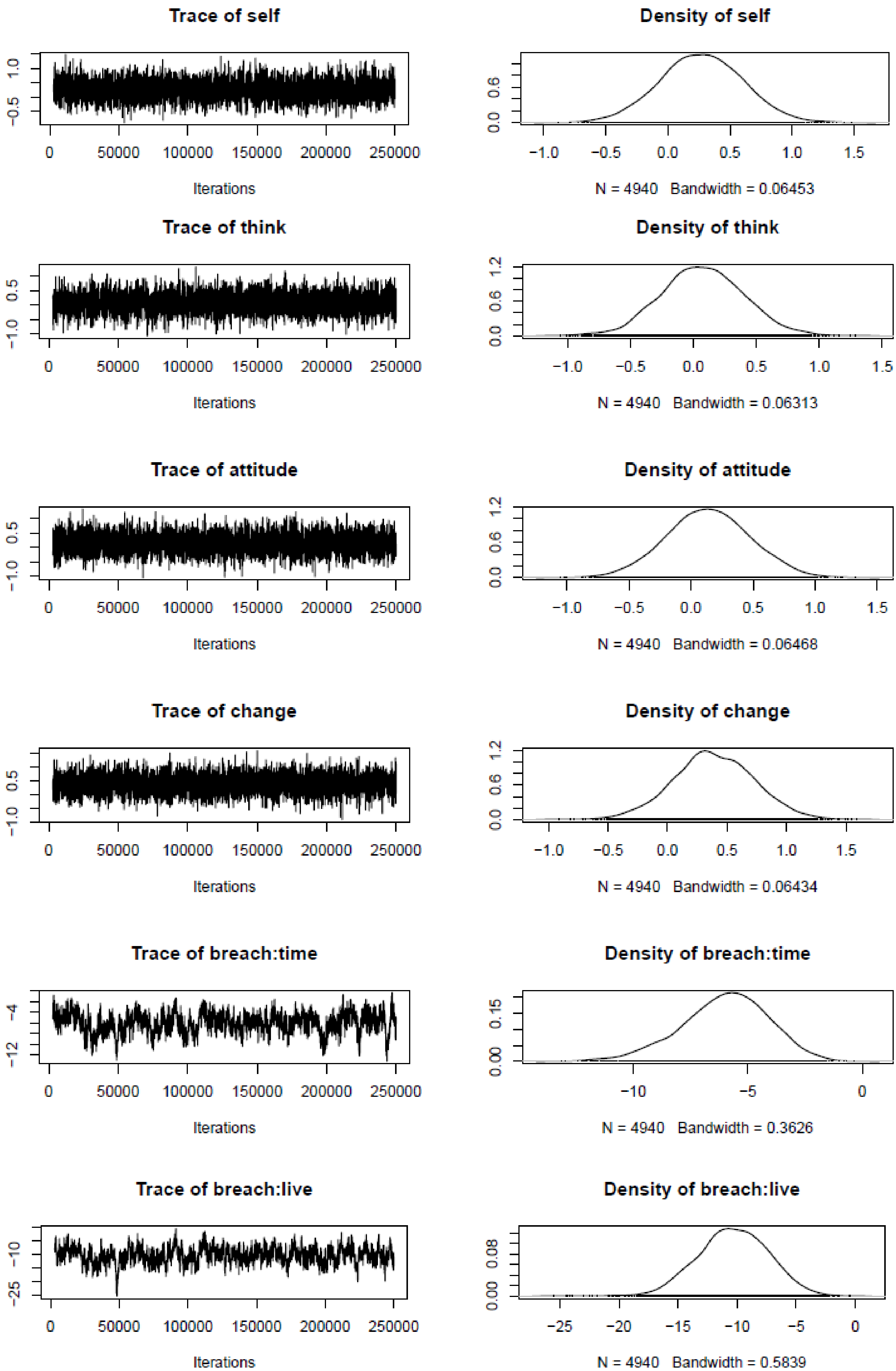
```
# breach:life           4.784246  -0.907616  10.398429   529.71 0.087854 .
# time:life            -0.056880  -0.204665   0.093713  4421.70 0.455870
# breach:drugs         -3.050524  -6.599359   0.048901   966.40 0.059919 .
# time:drugs           -0.020533  -0.120113   0.087057  4940.00 0.689474
# breach:physical       4.932068   1.218155   9.212560   540.35 0.002834 **
# time:physical         0.151894   0.019748   0.291163  4940.00 0.034818 *
# breach:emotion        7.798455   3.609135  12.234344   171.73  < 2e-04 ***
# time:emotion          0.118724   0.002507   0.233172  4644.83 0.037247 *
# breach:self           6.533446   1.588917  11.396637   429.82 0.004453 **
# time:self            -0.096029  -0.229016   0.037262  4940.00 0.163968
# breach:think        -19.325248 -29.823146  -7.733745   173.07  < 2e-04 ***
# time:think           -0.046171  -0.190511   0.090131  4940.00 0.533603
# breach:attitude      -4.250730  -9.508121   0.888145  1153.11 0.104453
# time:attitude        -0.052438  -0.212348   0.109017  4940.00 0.514980
# breach:change        10.737254   4.120036  17.668559   262.35 0.000810 ***
# time:change          -0.034837  -0.192263   0.104689  4940.00 0.642915
# breach:time:live      1.101463   0.091651   2.150812   300.08 0.029960 *
# breach:time:relation  -0.704305  -2.248936   0.773791   439.33 0.362348
# breach:time:ete       2.291268   0.896505   3.973414   122.44  < 2e-04 ***
# breach:time:where    -1.073262  -1.857900  -0.243072   167.08 0.006478 **
# breach:time:life      1.490473  -0.087001   3.071252   268.38 0.052632 .
# breach:time:drugs     1.377608   0.641775   2.217526   312.88  < 2e-04 ***
# breach:time:physical  -1.865093  -3.357332  -0.635078   165.28 0.001215 **
# breach:time:emotion  -2.807474  -4.446609  -1.452383    94.71  < 2e-04 ***
# breach:time:self     -1.364682  -2.244127  -0.504141   271.59 0.000405 ***
# breach:time:think     2.389414   0.680819   4.157169   251.71 0.002024 **
# breach:time:attitude   1.432577   0.346706   2.469320   227.02 0.003239 **
# breach:time:change   -3.625822  -5.677445  -1.557652   102.97  < 2e-04 ***
  ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Trace Plots and Posterior Density Plots

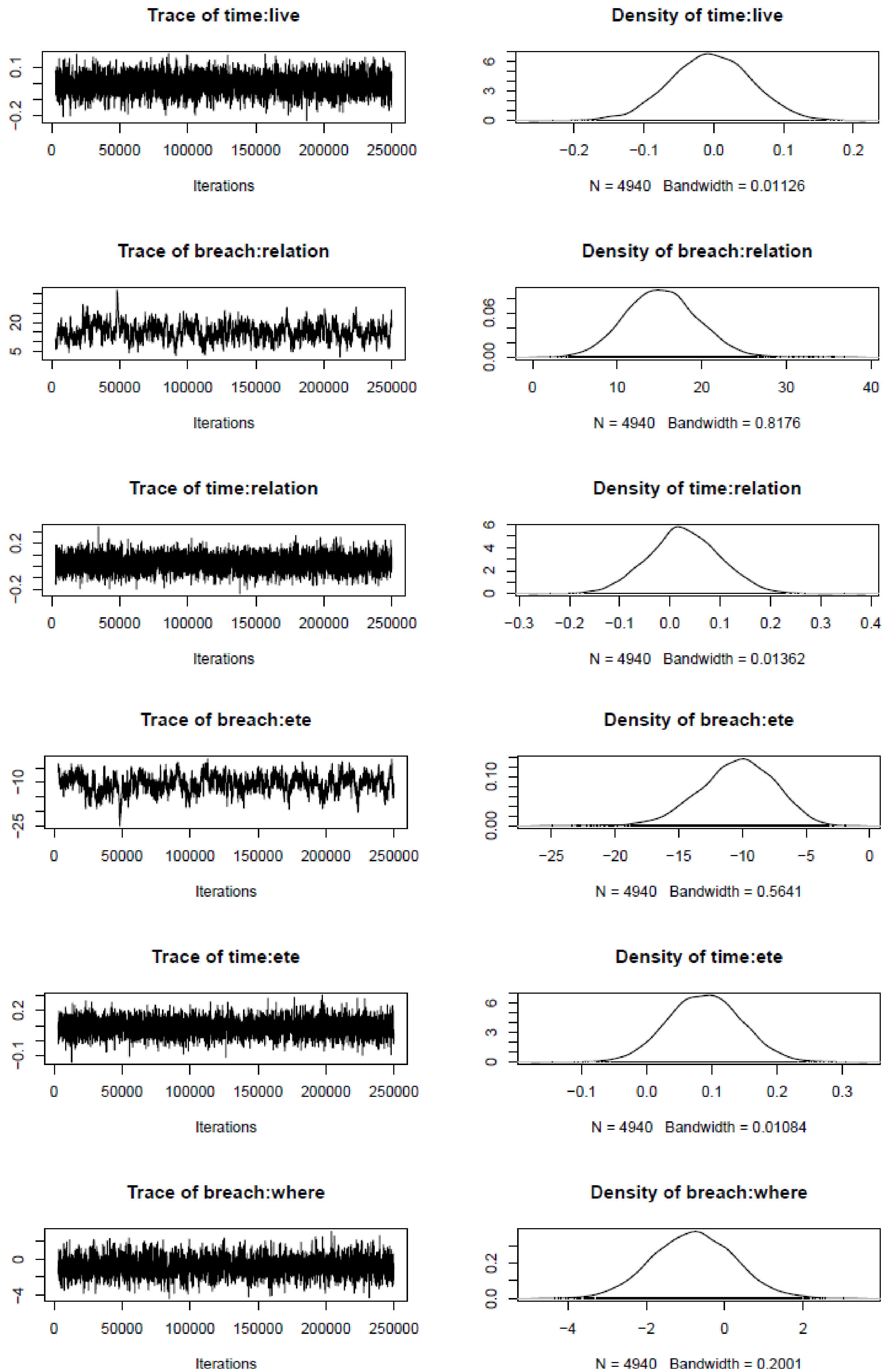
<u>Fixed Effects</u>

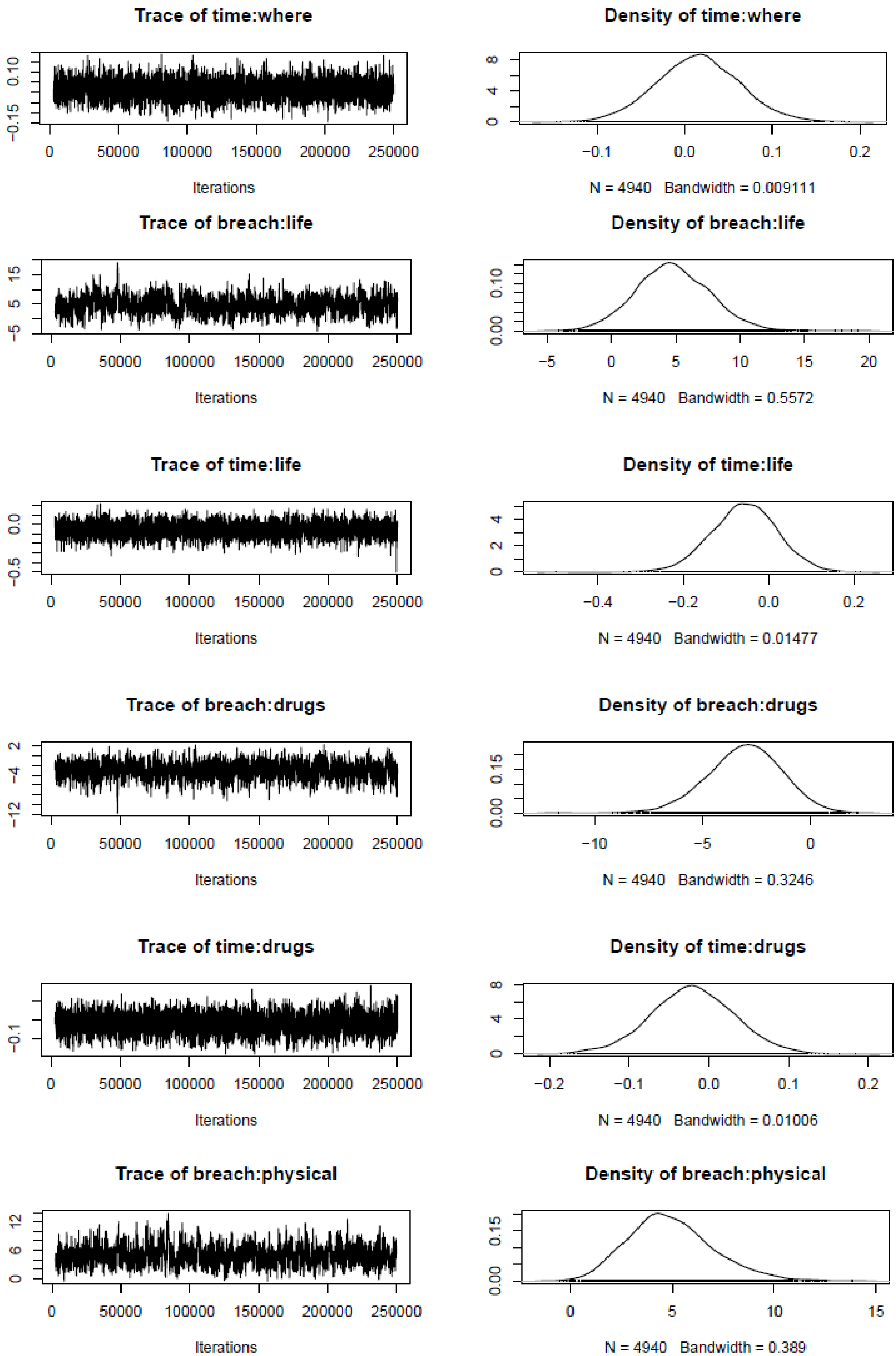


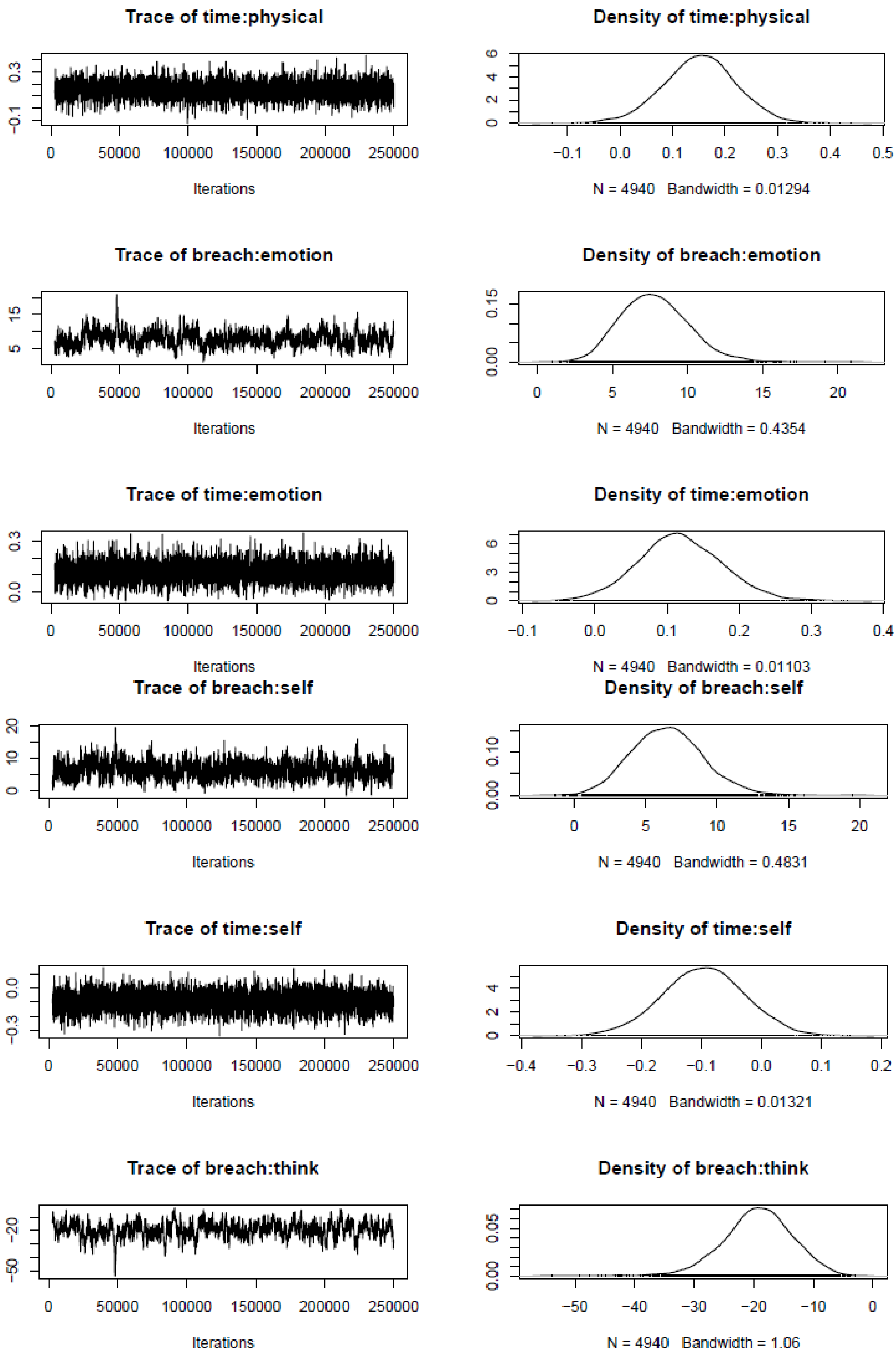

Trace of ete
Iterations
Density of ete
N = 4940 Bandwidth = 0.04343
Trace of where
Iterations
Density of where
N = 4940 Bandwidth = 0.04722
Trace of life
Iterations
Density of life
N = 4940 Bandwidth = 0.0699
Trace of drugs
Iterations
Density of drugs
N = 4940 Bandwidth = 0.0449
Trace of physical
Iterations
Density of physical
N = 4940 Bandwidth = 0.05725
Trace of emotion
Iterations
Density of emotion
N = 4940 Bandwidth = 0.0476

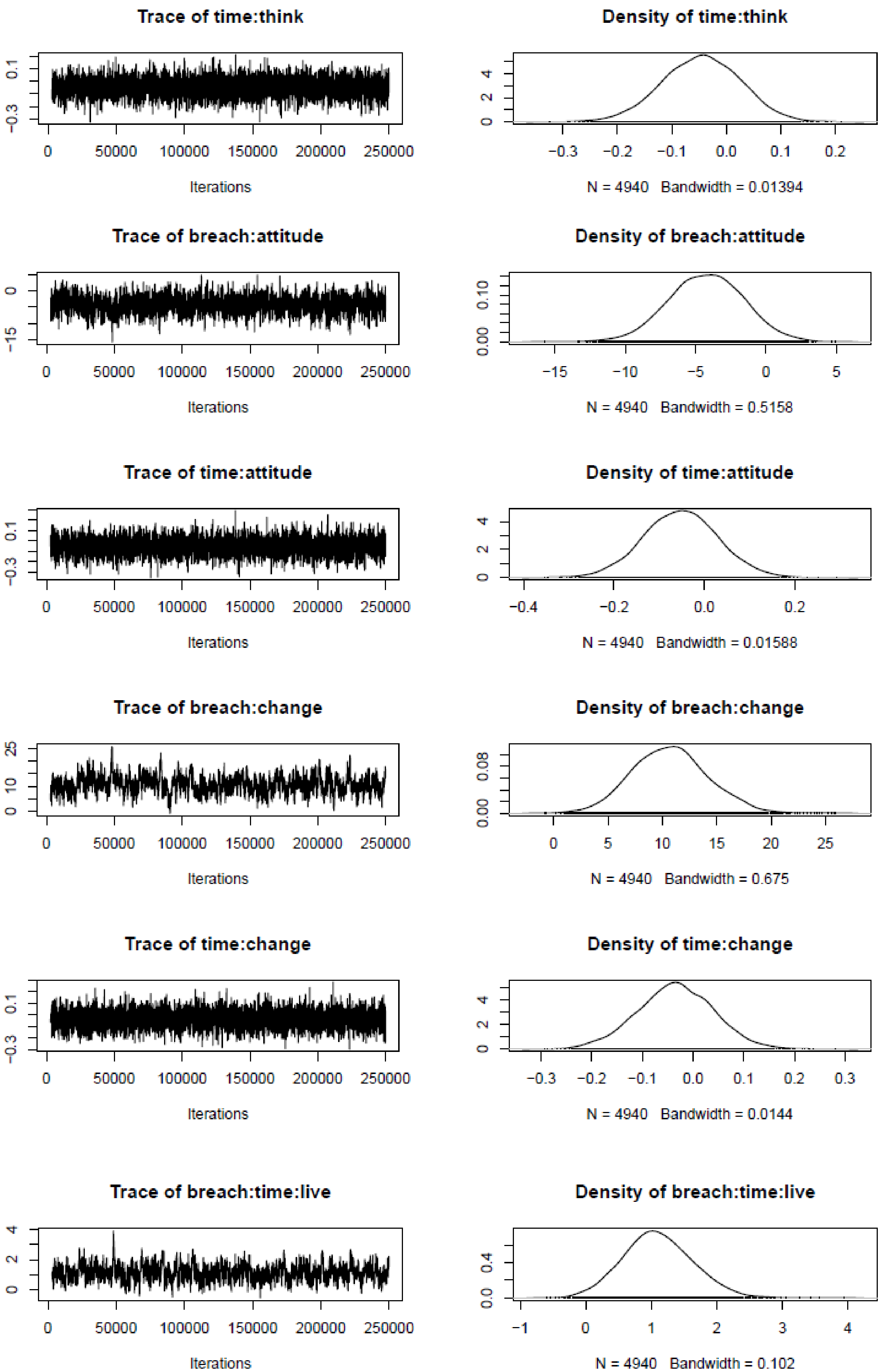


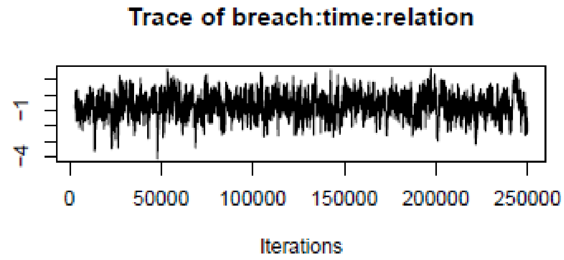
Trace of self
1.0
−0.5
0 50000 100000 150000 200000 250000
Iterations
Density of self
0.6
0.0
−1.0 −0.5 0.0 0.5 1.0 1.5
N = 4940 Bandwidth = 0.06453
Trace of think
0.5
−1.0
0 50000 100000 150000 200000 250000
Iterations
Density of think
1.2
0.6
0.0
−1.0 −0.5 0.0 0.5 1.0 1.5
N = 4940 Bandwidth = 0.06313
Trace of attitude
0.5
−1.0
0 50000 100000 150000 200000 250000
Iterations
Density of attitude
1.2
0.6
0.0
−1.0 −0.5 0.0 0.5 1.0 1.5
N = 4940 Bandwidth = 0.06468
Trace of change
0.5
−1.0
0 50000 100000 150000 200000 250000
Iterations
Density of change
1.2
0.6
0.0
−1.0 −0.5 0.0 0.5 1.0 1.5
N = 4940 Bandwidth = 0.06434
Trace of breach:time
−4
−12
0 50000 100000 150000 200000 250000
Iterations
Density of breach:time
0.15
0.00
−10 −5 0
N = 4940 Bandwidth = 0.3626
Trace of breach:live
−10
−25
0 50000 100000 150000 200000 250000
Iterations
Density of breach:live
0.08
0.00
−25 −20 −15 −10 −5 0
N = 4940 Bandwidth = 0.5839

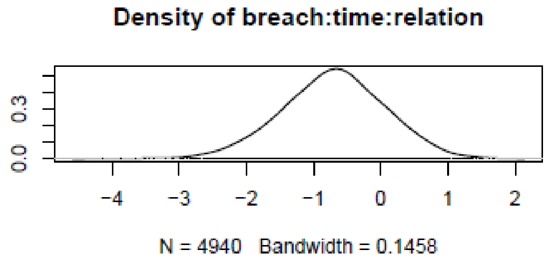

Trace of time:live
Iterations
Density of time:live
N = 4940 Bandwidth = 0.01126
Trace of breach:relation
Iterations
Density of breach:relation
N = 4940 Bandwidth = 0.8176
Trace of time:relation
Iterations
Density of time:relation
N = 4940 Bandwidth = 0.01362
Trace of breach:ete
Iterations
Density of breach:ete
N = 4940 Bandwidth = 0.5641
Trace of time:ete
Iterations
Density of time:ete
N = 4940 Bandwidth = 0.01084
Trace of breach:where
Iterations
Density of breach:where
N = 4940 Bandwidth = 0.2001

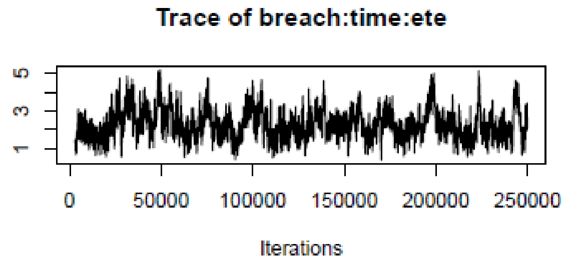

Trace of time:where
Iterations
Density of time:where
N = 4940 Bandwidth = 0.009111
Trace of breach:life
Iterations
Density of breach:life
N = 4940 Bandwidth = 0.5572
Trace of time:life
Iterations
Density of time:life
N = 4940 Bandwidth = 0.01477
Trace of breach:drugs
Iterations
Density of breach:drugs
N = 4940 Bandwidth = 0.3246
Trace of time:drugs
Iterations
Density of time:drugs
N = 4940 Bandwidth = 0.01006
Trace of breach:physical
Iterations
Density of breach:physical
N = 4940 Bandwidth = 0.389

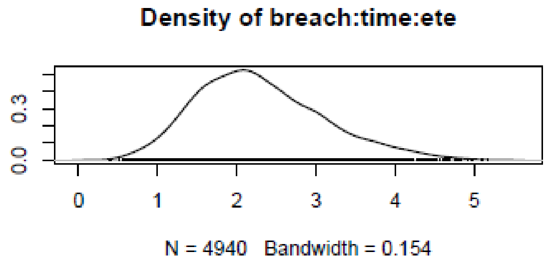

Trace of time:physical
Iterations
Density of time:physical
N = 4940 Bandwidth = 0.01294
Trace of breach:emotion
Iterations
Density of breach:emotion
N = 4940 Bandwidth = 0.4354
Trace of time:emotion
Iterations
Density of time:emotion
N = 4940 Bandwidth = 0.01103
Trace of breach:self
Iterations
Density of breach:self
N = 4940 Bandwidth = 0.4831
Trace of time:self
Iterations
Density of time:self
N = 4940 Bandwidth = 0.01321
Trace of breach:think
Iterations
Density of breach:think
N = 4940 Bandwidth = 1.06

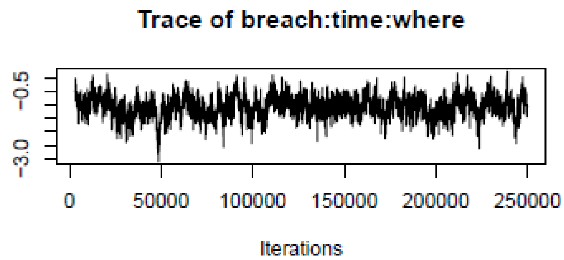

Trace of time:think
Iterations
Density of time:think
N = 4940 Bandwidth = 0.01394
Trace of breach:attitude
Iterations
Density of breach:attitude
N = 4940 Bandwidth = 0.5158
Trace of time:attitude
Iterations
Density of time:attitude
N = 4940 Bandwidth = 0.01588
Trace of breach:change
Iterations
Density of breach:change
N = 4940 Bandwidth = 0.675
Trace of time:change
Iterations
Density of time:change
N = 4940 Bandwidth = 0.0144
Trace of breach:time:live
Iterations
Density of breach:time:live
N = 4940 Bandwidth = 0.102

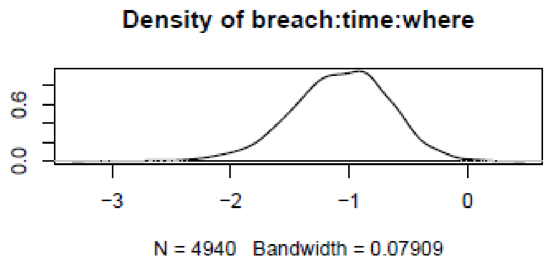

Trace of breach:time:relation
-1
-4
0 50000 100000 150000 200000 250000
Iterations

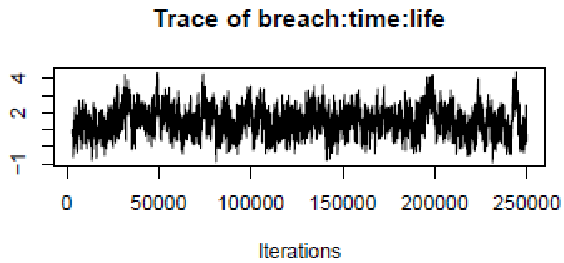

Density of breach:time:relation
0.3
0.0
-4 -3 -2 -1 0 1 2
N = 4940 Bandwidth = 0.1458

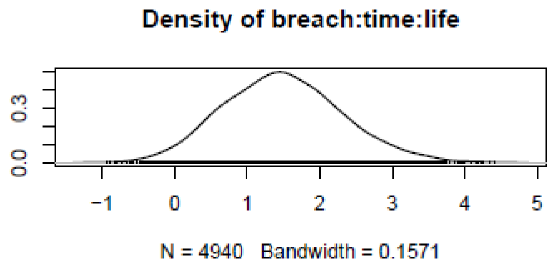

Trace of breach:time:ete
5
3
1
0 50000 100000 150000 200000 250000
Iterations

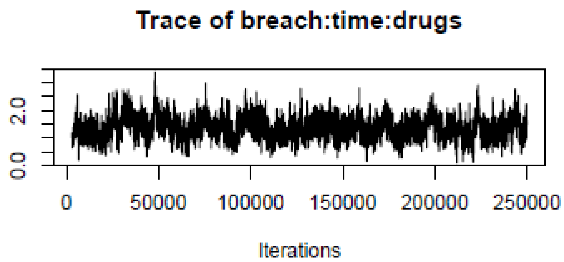

Density of breach:time:ete
0.3
0.0
0 1 2 3 4 5
N = 4940 Bandwidth = 0.154

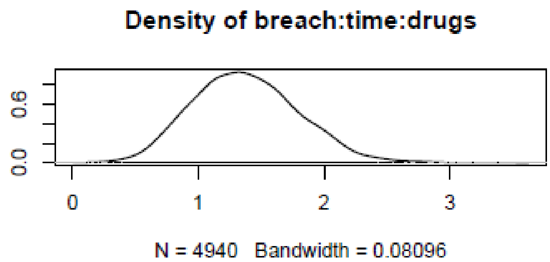

Trace of breach:time:where
-0.5
-3.0
0 50000 100000 150000 200000 250000
Iterations

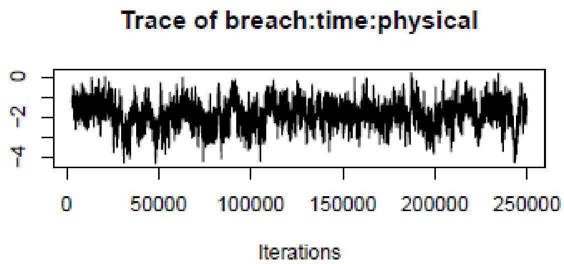

Density of breach:time:where
0.6
0.0
-3 -2 -1 0
N = 4940 Bandwidth = 0.07909

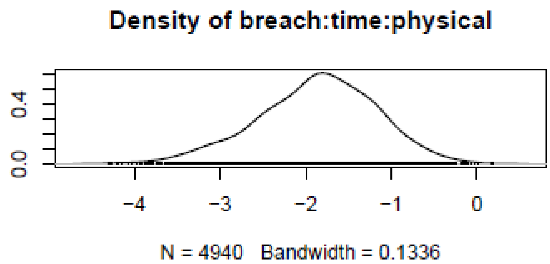

Trace of breach:time:life
4
2
-1
0 50000 100000 150000 200000 250000
Iterations

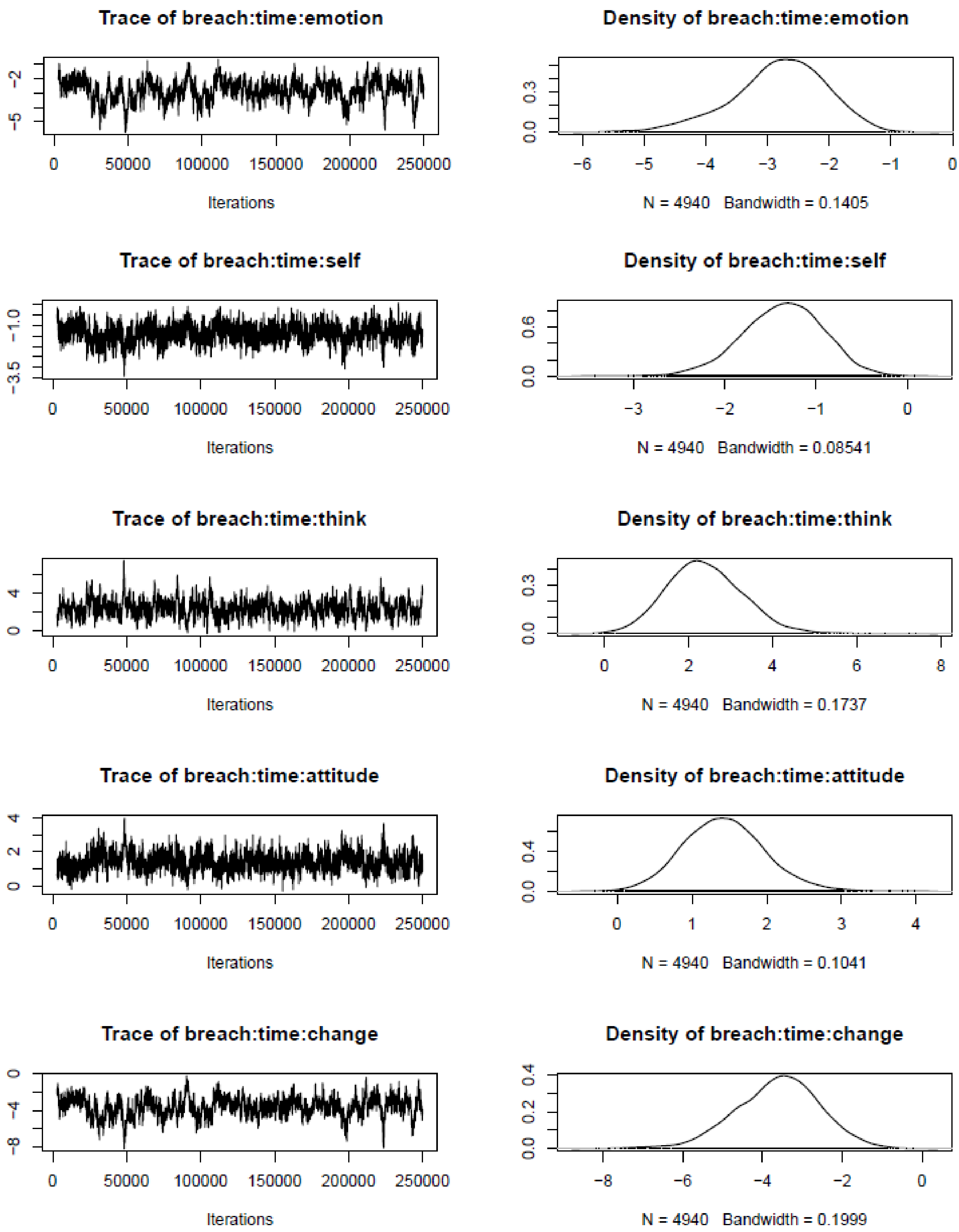

Density of breach:time:life
0.3
0.0
-1 0 1 2 3 4 5
N = 4940 Bandwidth = 0.1571


Trace of breach:time:drugs
2.0
0.0
0 50000 100000 150000 200000 250000
Iterations

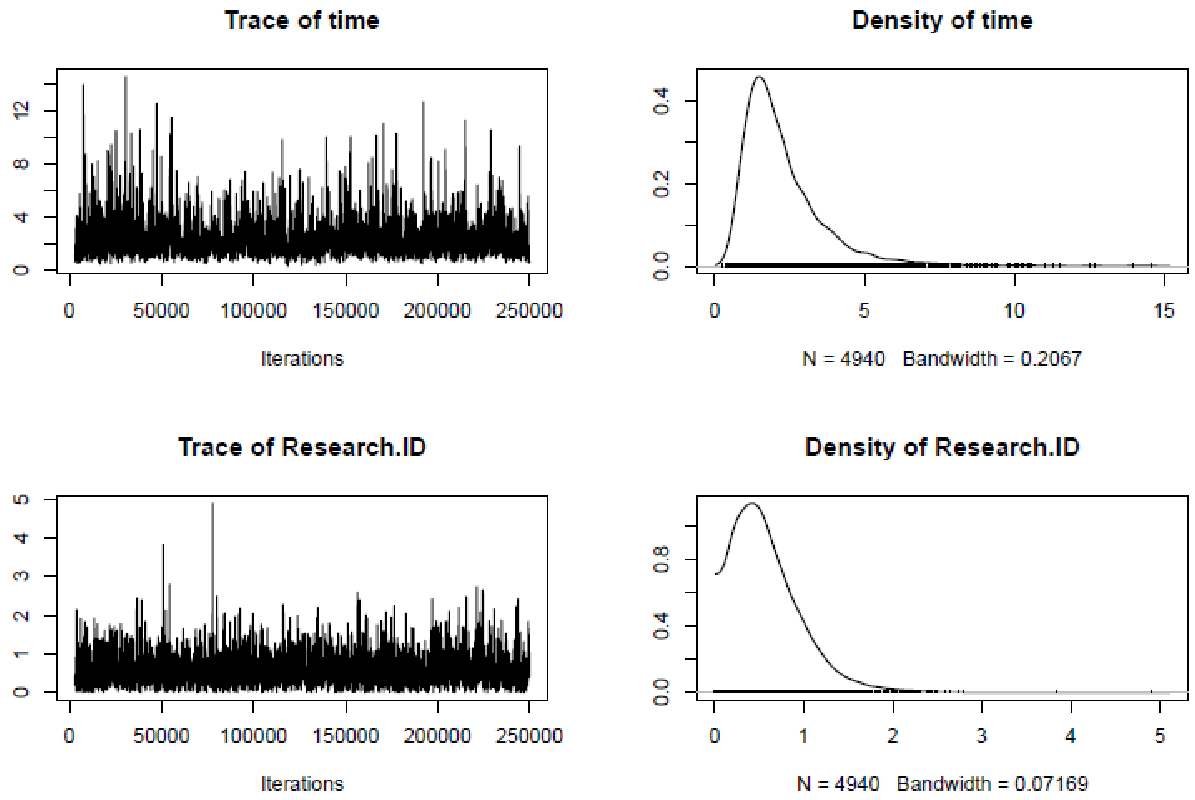

Density of breach:time:drugs
0.6
0.0
0 1 2 3
N = 4940 Bandwidth = 0.08096


Trace of breach:time:physical
0
-2
-4
0 50000 100000 150000 200000 250000
Iterations


Density of breach:time:physical
0.4
0.0
-4 -3 -2 -1 0
N = 4940 Bandwidth = 0.1336


Trace of breach:time:emotion
Iterations
Density of breach:time:emotion
N = 4940 Bandwidth = 0.1405
Trace of breach:time:self
Iterations
Density of breach:time:self
N = 4940 Bandwidth = 0.08541
Trace of breach:time:think
Iterations
Density of breach:time:think
N = 4940 Bandwidth = 0.1737
Trace of breach:time:attitude
Iterations
Density of breach:time:attitude
N = 4940 Bandwidth = 0.1041
Trace of breach:time:change
Iterations
Density of breach:time:change
N = 4940 Bandwidth = 0.1999

Random Effects



Dynamic Model 5: Court Appearances (Table 7.7)

Bayesian Model (BDm5_A)

Define the model

```
BDm5_A <- MCMCglmm(FO.bin ~ appear*time*live + appear*time*relation +
appear*time*ete + appear*time*where + appear*time*life +
appear*time*drugs + appear*time*physical + appear*time*emotion +
appear*time*self + appear*time*think + appear*time*attitude +
appear*time*change,
random=~time+Research.ID, data=data,
family="ordinal",prior=priorD,slice=TRUE,
nitt=200000, thin=50, burnin=3000)
```

Checks for suitable convergence

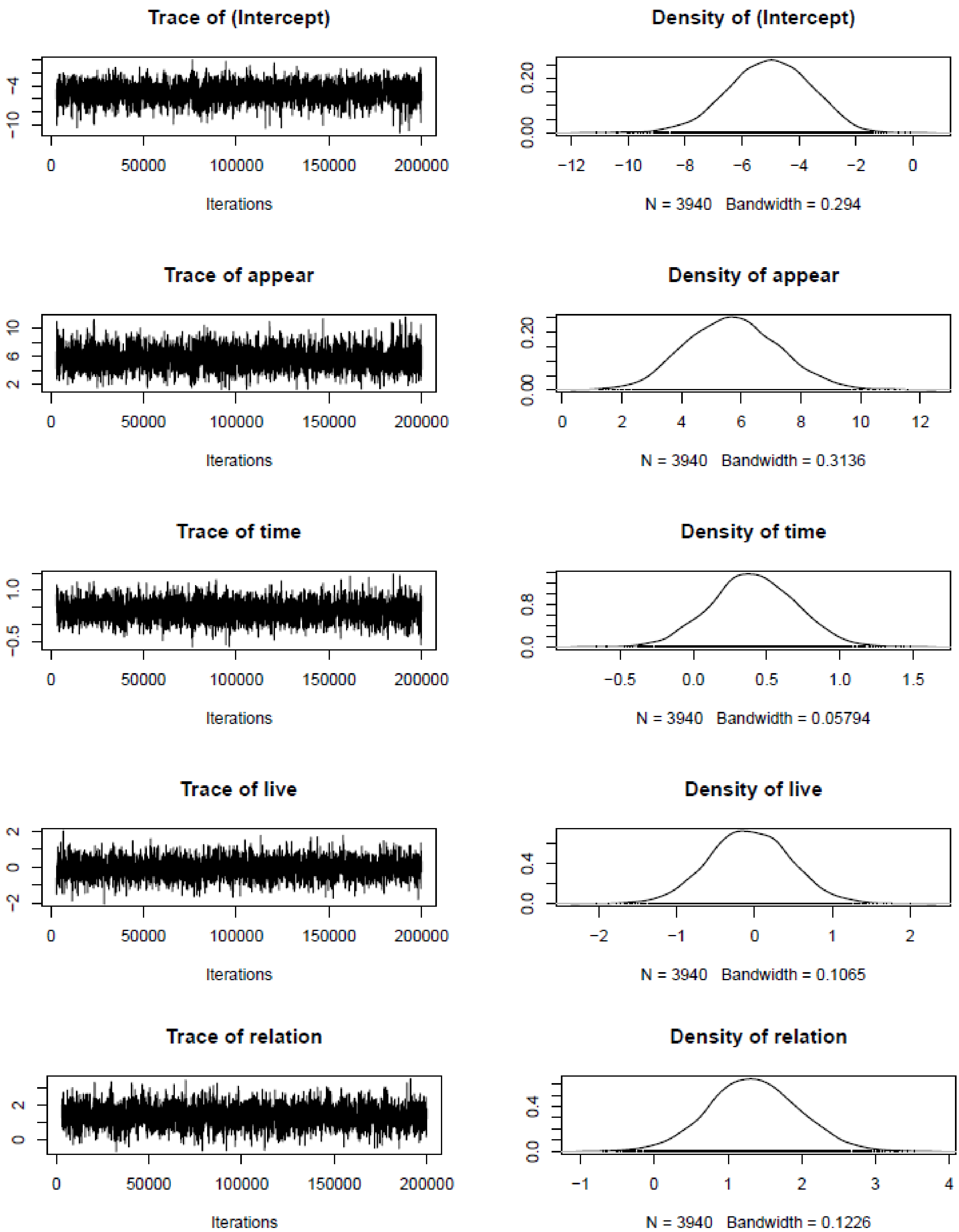
```
raftery.diag(BDm5_A$VCV)
heidel.diag(BDm5_A$VCV)

# > raftery.diag(BDm5_A$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      194350 3746         51.9
# Research.ID  100      186450 3746         49.8
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm5_A$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.274
# Research.ID  passed        1         0.446
# units        failed       NA            NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    1.219 0.04111
# Research.ID  passed    0.164 0.00854
# units        <NA>         NA      NA

autocorr(BDm5_A$VCV)
autocorr(BDm5_A$Sol)    # Output not included here
summary(BDm5_A)

# > autocorr(BDm5_A$VCV)
# , , time
#
#                 time Research.ID units
# Lag 0    1.000000000 0.134106370   NaN
# Lag 50   0.216052151 0.093558094   NaN
# Lag 250  0.070465361 0.035240076   NaN
# Lag 500  0.030070498 0.014683513   NaN
# Lag 2500 0.006862207 0.008138861   NaN
```

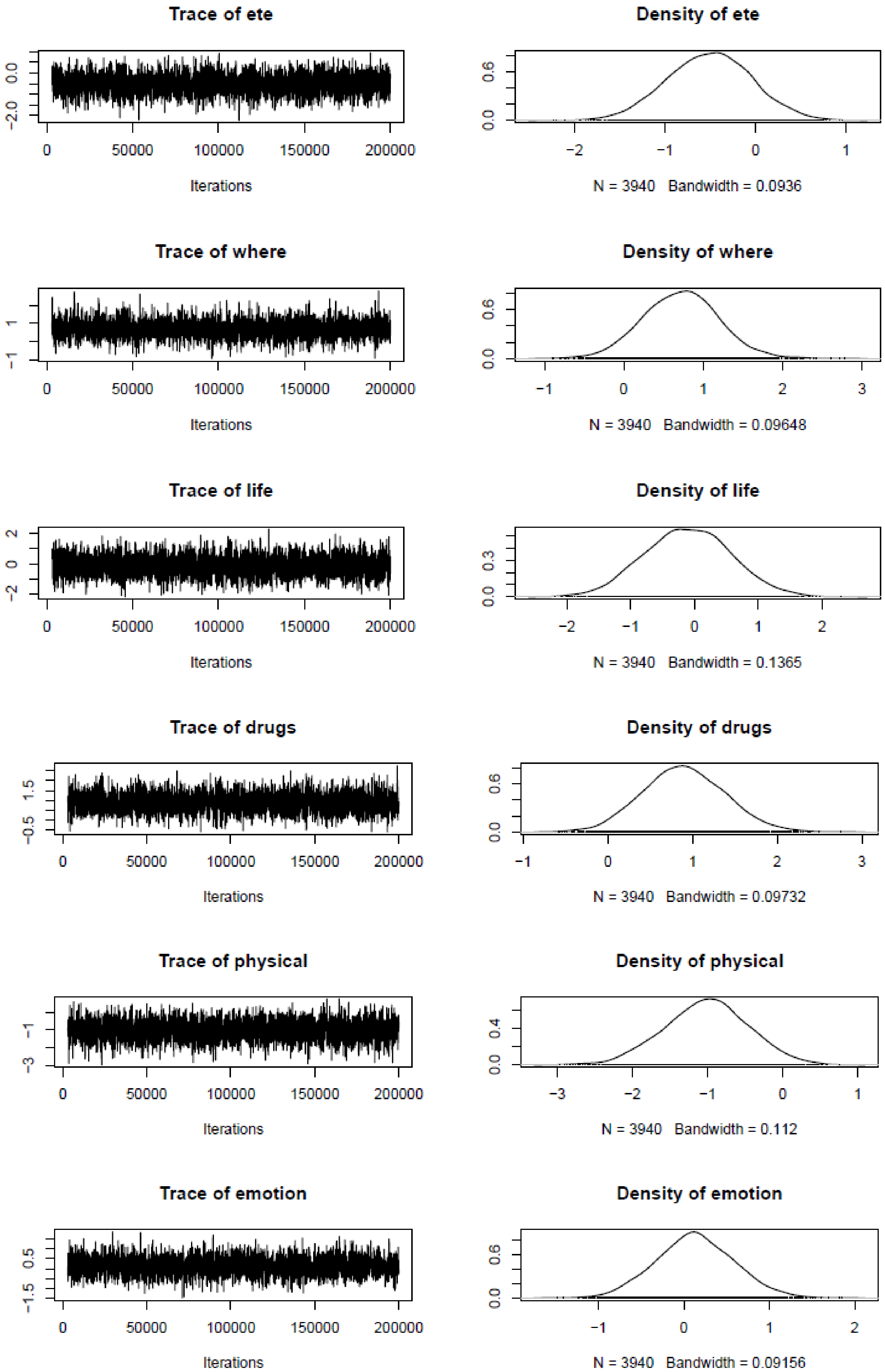
```
# , , Research.ID
#
#                   time   Research.ID units
# Lag 0    0.1341063697  1.000000e+00   NaN
# Lag 50   0.0747624789  2.670853e-01   NaN
# Lag 250  0.0003551421  2.174553e-02   NaN
# Lag 500  0.0193296689  5.038358e-05   NaN
# Lag 2500 0.0248573319 -9.386622e-03   NaN

# > summary(BDm5_A)
#
# Iterations = 3001:199951
# Thinning interval  = 50
# Sample size  = 3940
#
# DIC: 445.9102
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.219   0.2207    2.817     1488
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.1638 3.303e-08   0.5877     2278
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ appear * time * live + appear * time *
relation + appear * time * ete + appear * time * where + appear * time *
life + appear * time * drugs + appear * time * physical + appear * time
* emotion + appear * time * self + appear * time * think + appear * time
* attitude + appear * time * change
#
#                       post.mean  l-95% CI  u-95% CI eff.samp  pMCMC
# (Intercept)           -5.053216 -7.814806 -2.256873     2598 <3e-04 ***
# appear                 5.709747  2.913240  8.884383     2712 <3e-04 ***
# time                   0.409634 -0.133462  0.977064     3259 0.1584
# live                  -0.066079 -1.035330  1.023152     3444 0.8954
# relation               1.349109  0.126732  2.513781     2925 0.0305 *
# ete                   -0.509749 -1.380245  0.419549     3262 0.2579
# where                  0.719173 -0.227844  1.656956     3214 0.1345
# life                  -0.106326 -1.452579  1.172606     3631 0.8817
# drugs                  0.896422 -0.059803  1.807681     3474 0.0533 .
# physical              -1.016692 -2.169174  0.008143     3170 0.0640 .
# emotion                0.132507 -0.803379  0.989279     3144 0.7685
# self                   0.157173 -1.156008  1.483759     3461 0.8234
# think                  0.091031 -1.153416  1.382282     3598 0.9066
# attitude               0.121500 -1.078481  1.424181     3162 0.8553
# change                -0.216185 -1.720649  1.220924     3321 0.7777
# appear:time           -0.805110 -1.432310 -0.165684     3436 0.0102 *
# appear:live            0.052916 -1.074673  1.262578     3499 0.9294
# time:live             -0.119871 -0.365843  0.126170     3181 0.3462
# appear:relation       -1.045124 -2.363965  0.302689     3055 0.1239
# time:relation         -0.256998 -0.555523  0.032408     3072 0.0919 .
# appear:ete             0.330202 -0.661883  1.337067     3874 0.5299
```

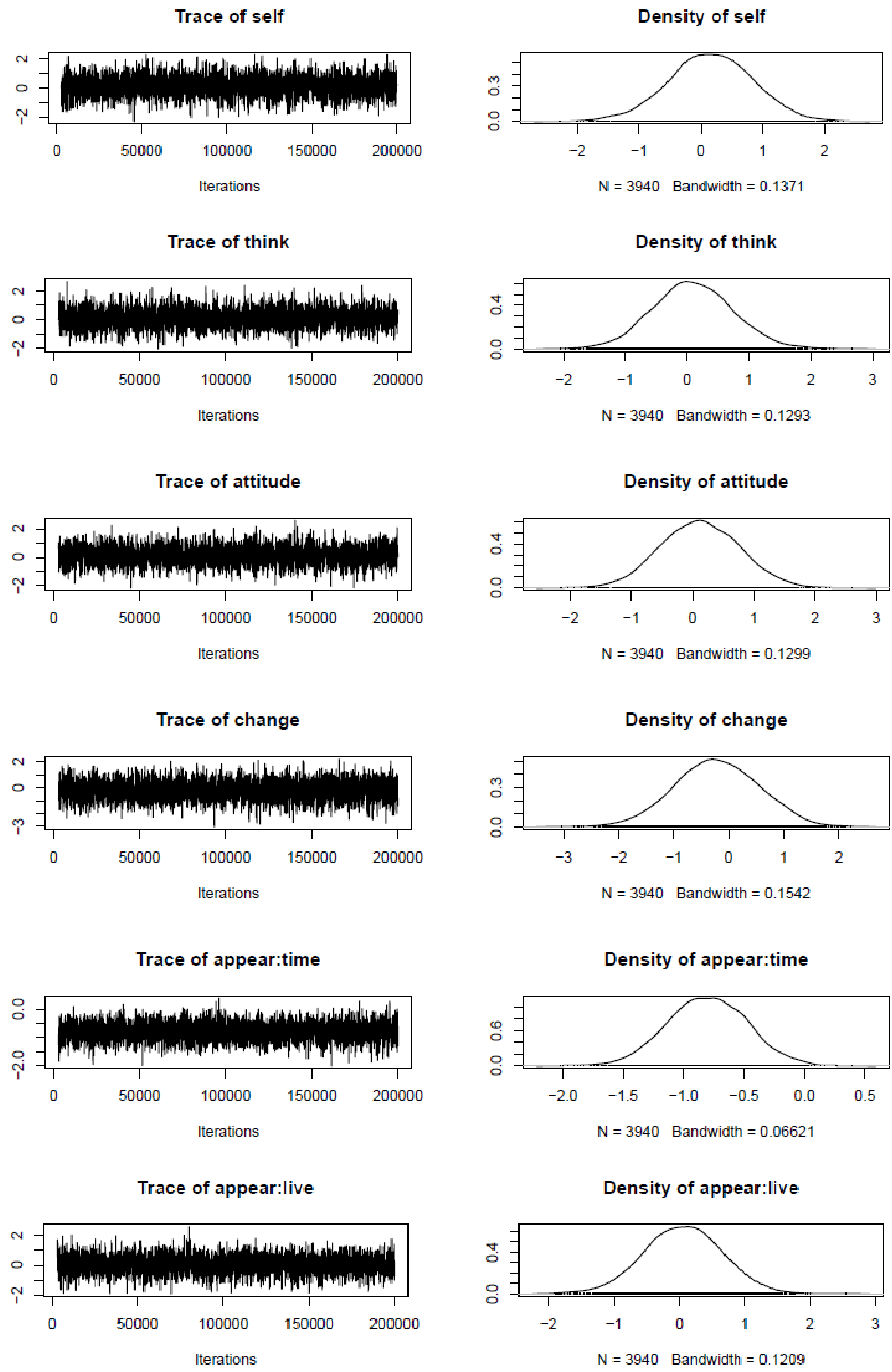
```
# time:ete              0.098178 -0.114627  0.303793     3587 0.3477
# appear:where         -0.794658 -1.853522  0.226605     3163 0.1254
# time:where           -0.013168 -0.181236  0.169508     3390 0.8599
# appear:life           0.107449 -1.362381  1.656022     3067 0.9015
# time:life             0.028882 -0.244569  0.348722     3321 0.8594
# appear:drugs         -0.789434 -1.796985  0.247185     3638 0.1447
# time:drugs           -0.115975 -0.302226  0.079546     3424 0.2421
# appear:physical       0.801711 -0.438474  2.019193     3410 0.1914
# time:physical         0.196196 -0.066303  0.447562     2968 0.1345
# appear:emotion       -0.185342 -1.265025  0.800439     3308 0.7355
# time:emotion          0.052920 -0.171298  0.273318     2590 0.6462
# appear:self          -0.244089 -1.696440  1.253640     3599 0.7619
# time:self            -0.057703 -0.318252  0.216022     3391 0.6701
# appear:think         -0.378711 -1.787579  1.044519     3610 0.6178
# time:think            0.012472 -0.283208  0.308774     3201 0.9162
# appear:attitude      -0.126793 -1.495381  1.352345     3335 0.8909
# time:attitude        -0.110925 -0.439534  0.211836     2798 0.5036
# appear:change         0.666199 -1.005825  2.151904     3170 0.4102
# time:change           0.070520 -0.243854  0.378299     2860 0.6675
# appear:time:live      0.188389 -0.077190  0.469990     3290 0.1731
# appear:time:relation  0.226057 -0.083488  0.563344     3149 0.1751
# appear:time:ete      -0.042766 -0.274674  0.201501     4098 0.7269
# appear:time:where     0.003518 -0.200224  0.186757     3450 0.9579
# appear:time:life     -0.046350 -0.379604  0.286693     3077 0.7980
# appear:time:drugs     0.107363 -0.092609  0.340177     3509 0.3279
# appear:time:physical -0.094817 -0.388504  0.197698     3412 0.5325
# appear:time:emotion  -0.035068 -0.279783  0.211832     2841 0.7848
# appear:time:self      0.010078 -0.278015  0.313944     3483 0.9533
# appear:time:think    -0.007101 -0.336114  0.328611     3267 0.9584
# appear:time:attitude  0.143184 -0.203426  0.505483     2984 0.4371
# appear:time:change   -0.094426 -0.421831  0.256820     2867 0.5888
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

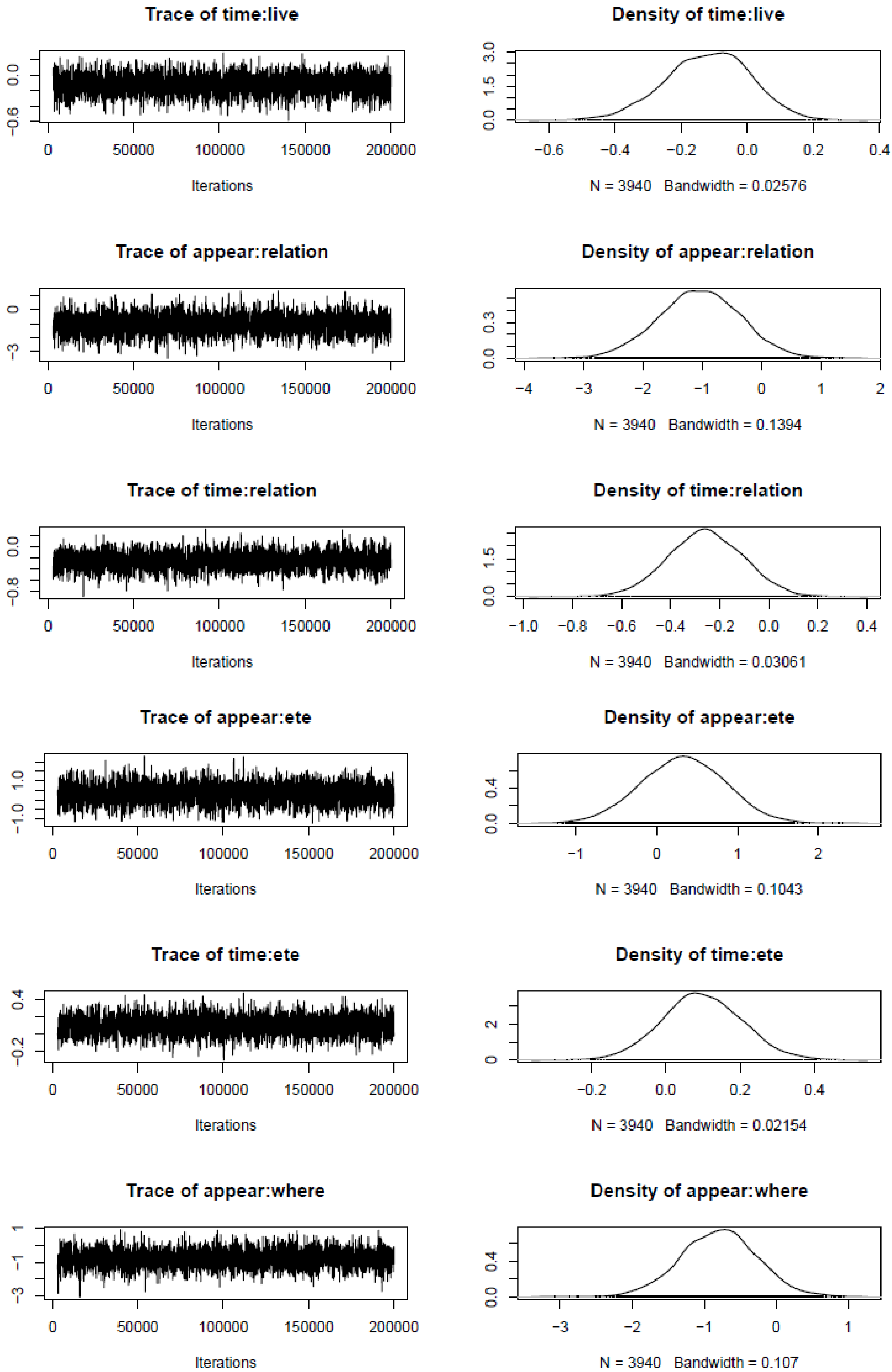
Trace Plots and Posterior Density Plots

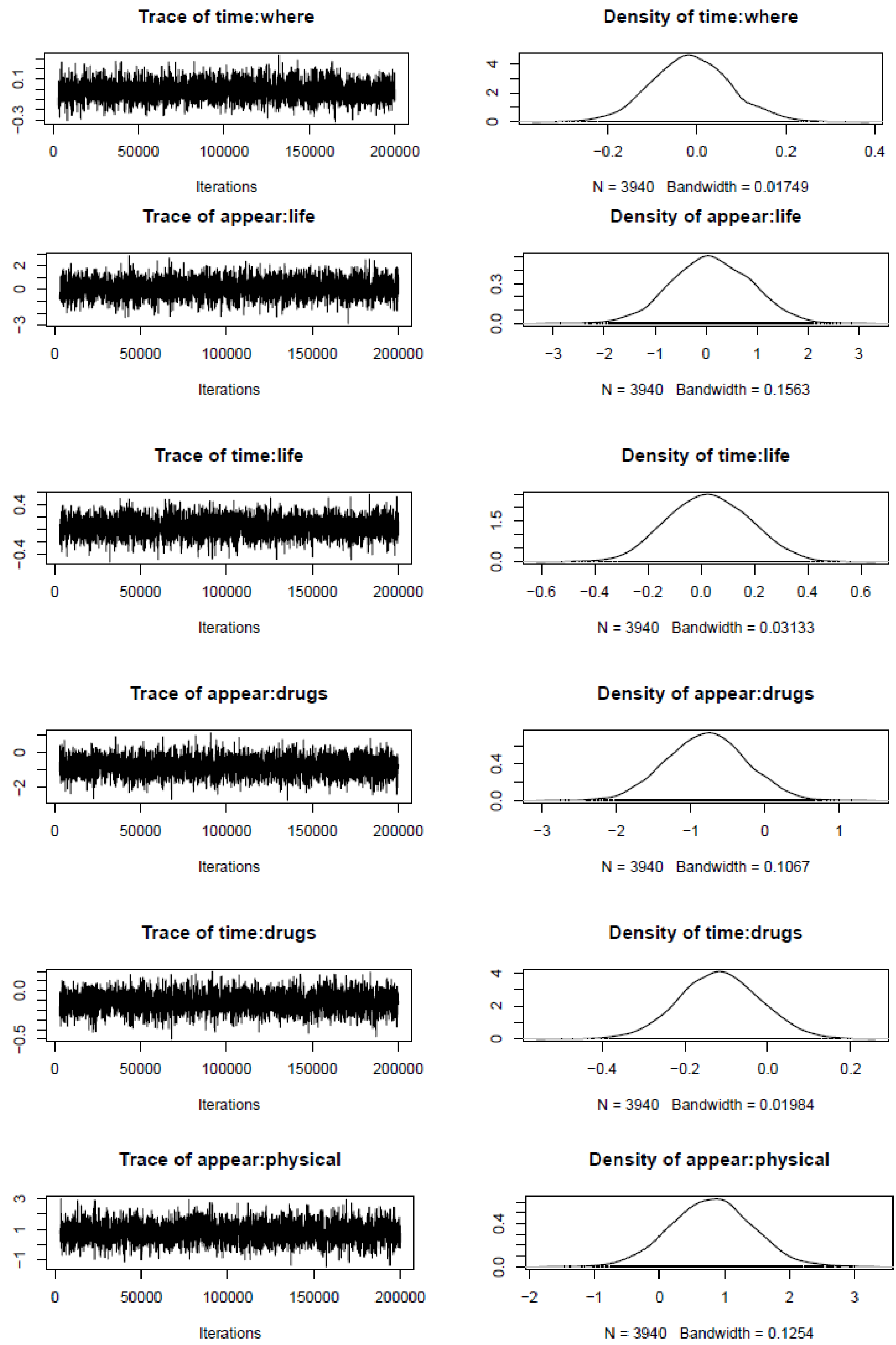
<u>Fixed Effects</u>

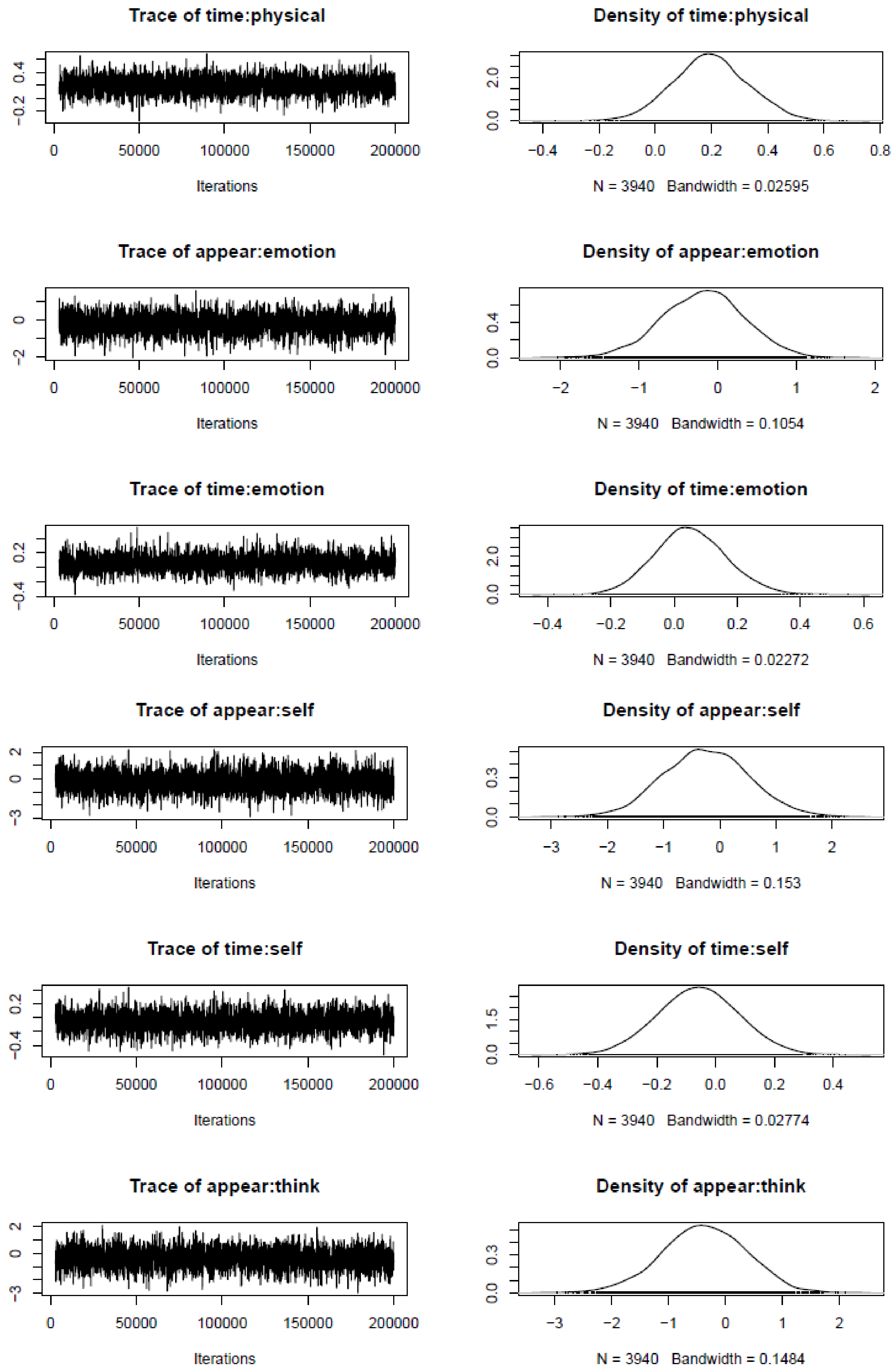


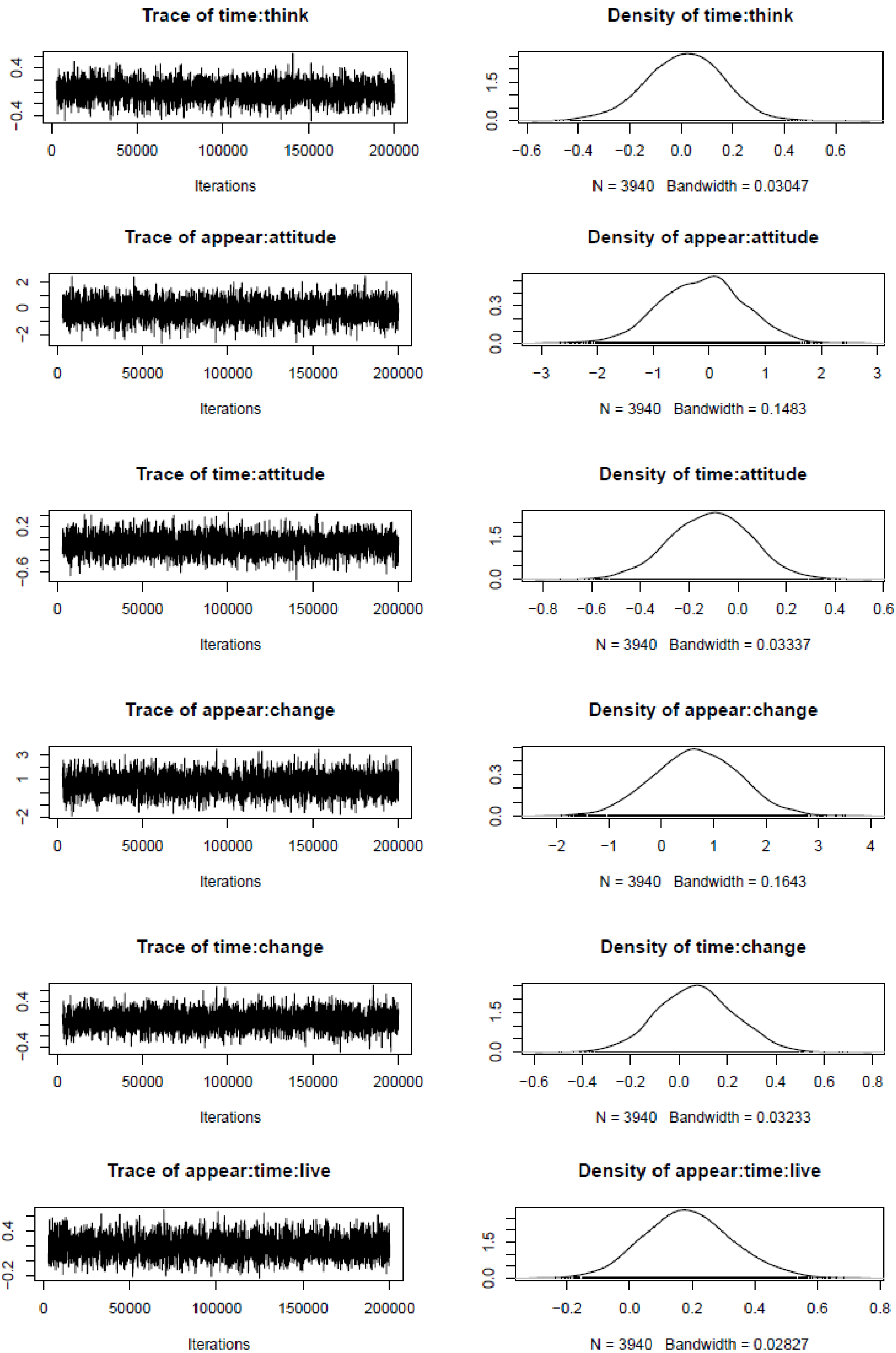

Trace of ete
Iterations
Density of ete
N = 3940 Bandwidth = 0.0936
Trace of where
Iterations
Density of where
N = 3940 Bandwidth = 0.09648
Trace of life
Iterations
Density of life
N = 3940 Bandwidth = 0.1365
Trace of drugs
Iterations
Density of drugs
N = 3940 Bandwidth = 0.09732
Trace of physical
Iterations
Density of physical
N = 3940 Bandwidth = 0.112
Trace of emotion
Iterations
Density of emotion
N = 3940 Bandwidth = 0.09156

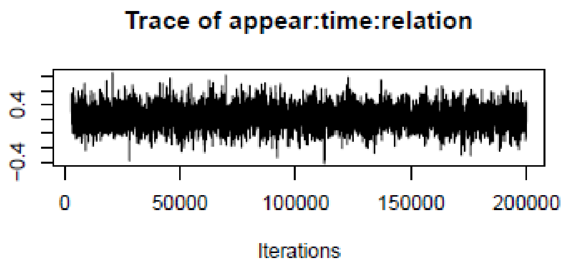

Trace of self
Iterations
Density of self
N = 3940 Bandwidth = 0.1371
Trace of think
Iterations
Density of think
N = 3940 Bandwidth = 0.1293
Trace of attitude
Iterations
Density of attitude
N = 3940 Bandwidth = 0.1299
Trace of change
Iterations
Density of change
N = 3940 Bandwidth = 0.1542
Trace of appear:time
Iterations
Density of appear:time
N = 3940 Bandwidth = 0.06621
Trace of appear:live
Iterations
Density of appear:live
N = 3940 Bandwidth = 0.1209

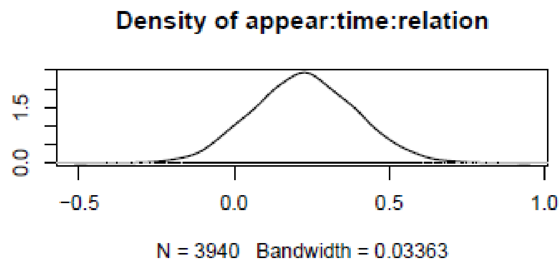

Trace of time:live
0.0
−0.6
0
50000
100000
150000
200000
Iterations
Density of time:live
3.0
1.5
0.0
−0.6
−0.4
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.02576
Trace of appear:relation
0
−3
0
50000
100000
150000
200000
Iterations
Density of appear:relation
0.3
0.0
−4
−3
−2
−1
0
1
2
N = 3940 Bandwidth = 0.1394
Trace of time:relation
0.0
−0.8
0
50000
100000
150000
200000
Iterations
Density of time:relation
1.5
0.0
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.03061
Trace of appear:ete
1.0
−1.0
0
50000
100000
150000
200000
Iterations
Density of appear:ete
0.4
0.0
−1
0
1
2
N = 3940 Bandwidth = 0.1043
Trace of time:ete
0.4
−0.2
0
50000
100000
150000
200000
Iterations
Density of time:ete
2
0
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.02154
Trace of appear:where
1
−1
−3
0
50000
100000
150000
200000
Iterations
Density of appear:where
0.4
0.0
−3
−2
−1
0
1
N = 3940 Bandwidth = 0.107

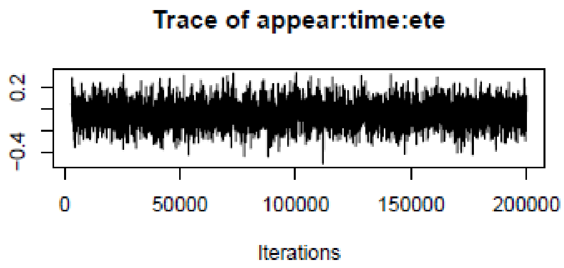

Trace of time:where
Iterations
Density of time:where
N = 3940 Bandwidth = 0.01749
Trace of appear:life
Iterations
Density of appear:life
N = 3940 Bandwidth = 0.1563
Trace of time:life
Iterations
Density of time:life
N = 3940 Bandwidth = 0.03133
Trace of appear:drugs
Iterations
Density of appear:drugs
N = 3940 Bandwidth = 0.1067
Trace of time:drugs
Iterations
Density of time:drugs
N = 3940 Bandwidth = 0.01984
Trace of appear:physical
Iterations
Density of appear:physical
N = 3940 Bandwidth = 0.1254

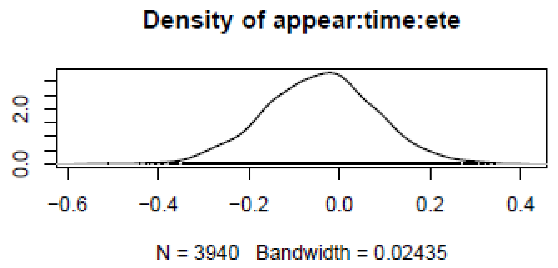

Trace of time:physical
Iterations
Density of time:physical
N = 3940 Bandwidth = 0.02595
Trace of appear:emotion
Iterations
Density of appear:emotion
N = 3940 Bandwidth = 0.1054
Trace of time:emotion
Iterations
Density of time:emotion
N = 3940 Bandwidth = 0.02272
Trace of appear:self
Iterations
Density of appear:self
N = 3940 Bandwidth = 0.153
Trace of time:self
Iterations
Density of time:self
N = 3940 Bandwidth = 0.02774
Trace of appear:think
Iterations
Density of appear:think
N = 3940 Bandwidth = 0.1484

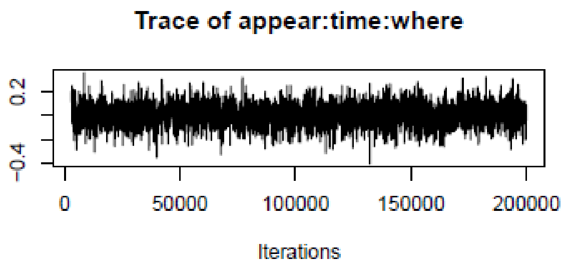

Trace of time:think
Iterations
Density of time:think
N = 3940 Bandwidth = 0.03047
Trace of appear:attitude
Iterations
Density of appear:attitude
N = 3940 Bandwidth = 0.1483
Trace of time:attitude
Iterations
Density of time:attitude
N = 3940 Bandwidth = 0.03337
Trace of appear:change
Iterations
Density of appear:change
N = 3940 Bandwidth = 0.1643
Trace of time:change
Iterations
Density of time:change
N = 3940 Bandwidth = 0.03233
Trace of appear:time:live
Iterations
Density of appear:time:live
N = 3940 Bandwidth = 0.02827

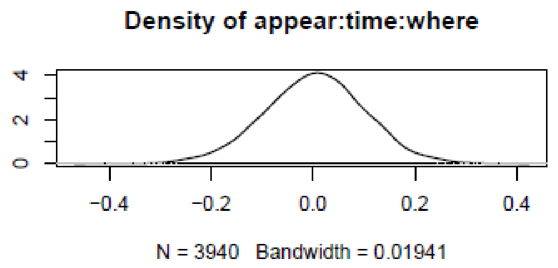

Trace of appear:time:relation
0.4
−0.4
0
50000
100000
150000
200000
Iterations

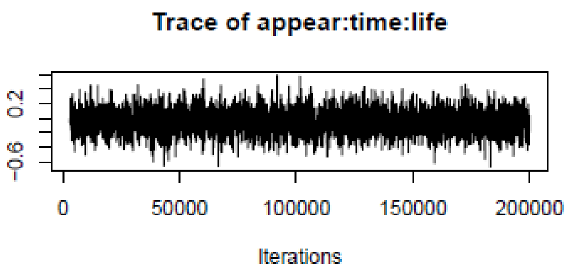

Density of appear:time:relation
1.5
0.0
−0.5
0.0
0.5
1.0
N = 3940 Bandwidth = 0.03363

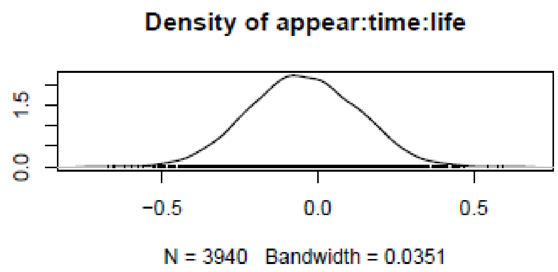

Trace of appear:time:ete
0.2
−0.4
0
50000
100000
150000
200000
Iterations

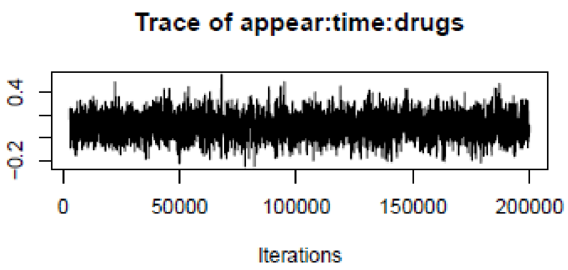

Density of appear:time:ete
2.0
0.0
−0.6
−0.4
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.02435

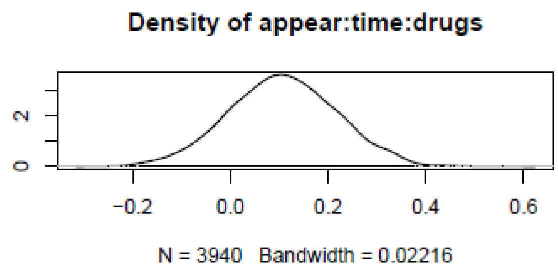

Trace of appear:time:where
0.2
−0.4
0
50000
100000
150000
200000
Iterations

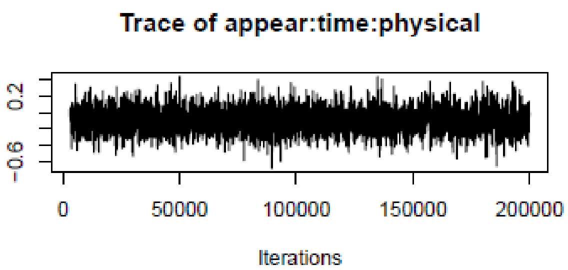

Density of appear:time:where
4
2
0
−0.4
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.01941

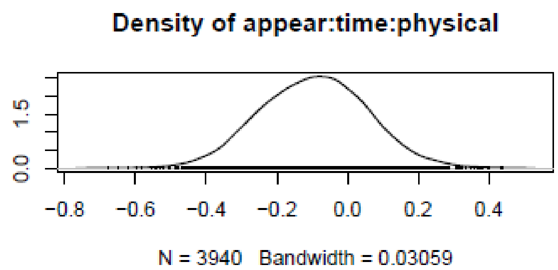

Trace of appear:time:life
0.2
−0.6
0
50000
100000
150000
200000
Iterations

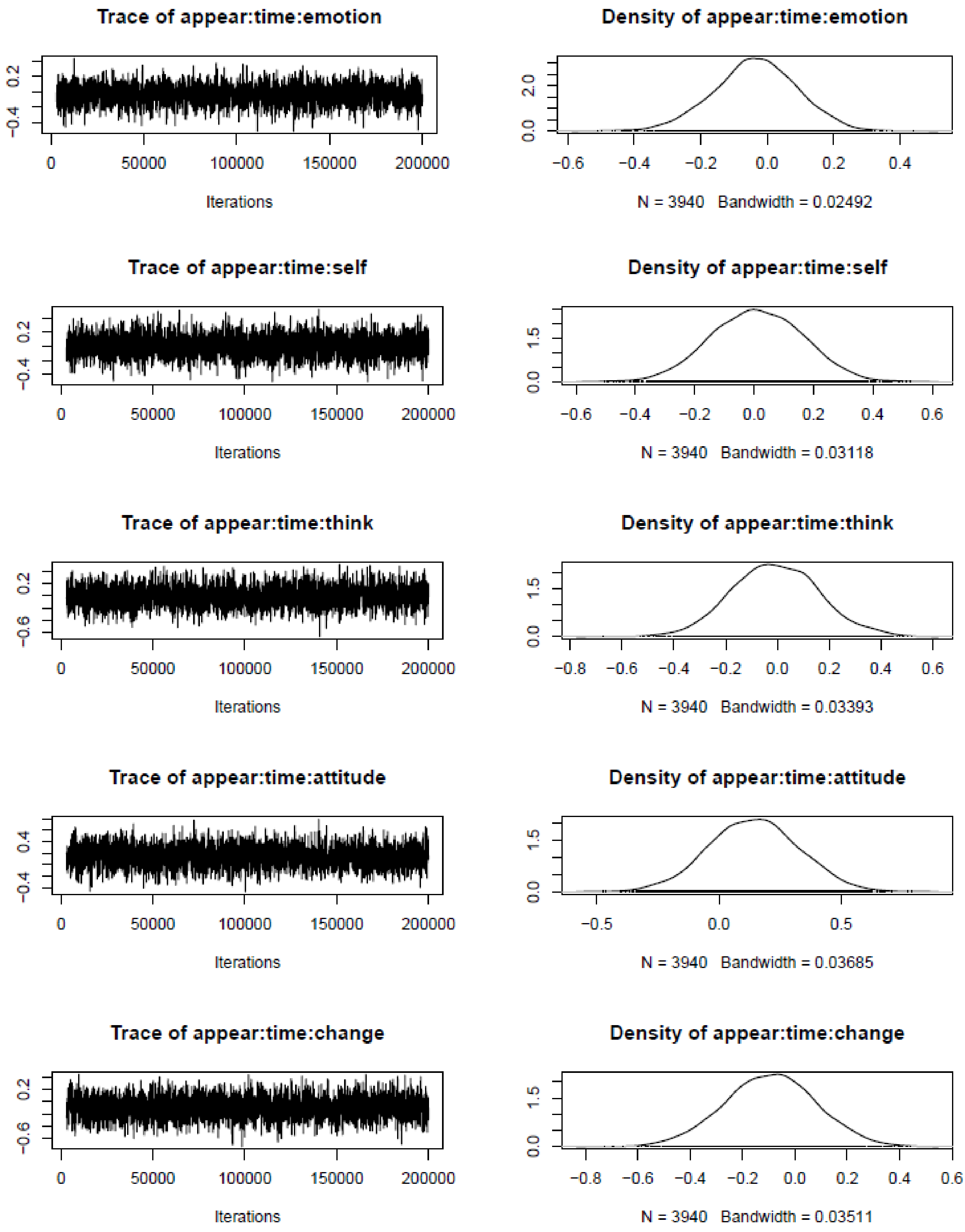

Density of appear:time:life
1.5
0.0
−0.5
0.0
0.5
N = 3940 Bandwidth = 0.0351


Trace of appear:time:drugs
0.4
−0.2
0
50000
100000
150000
200000
Iterations

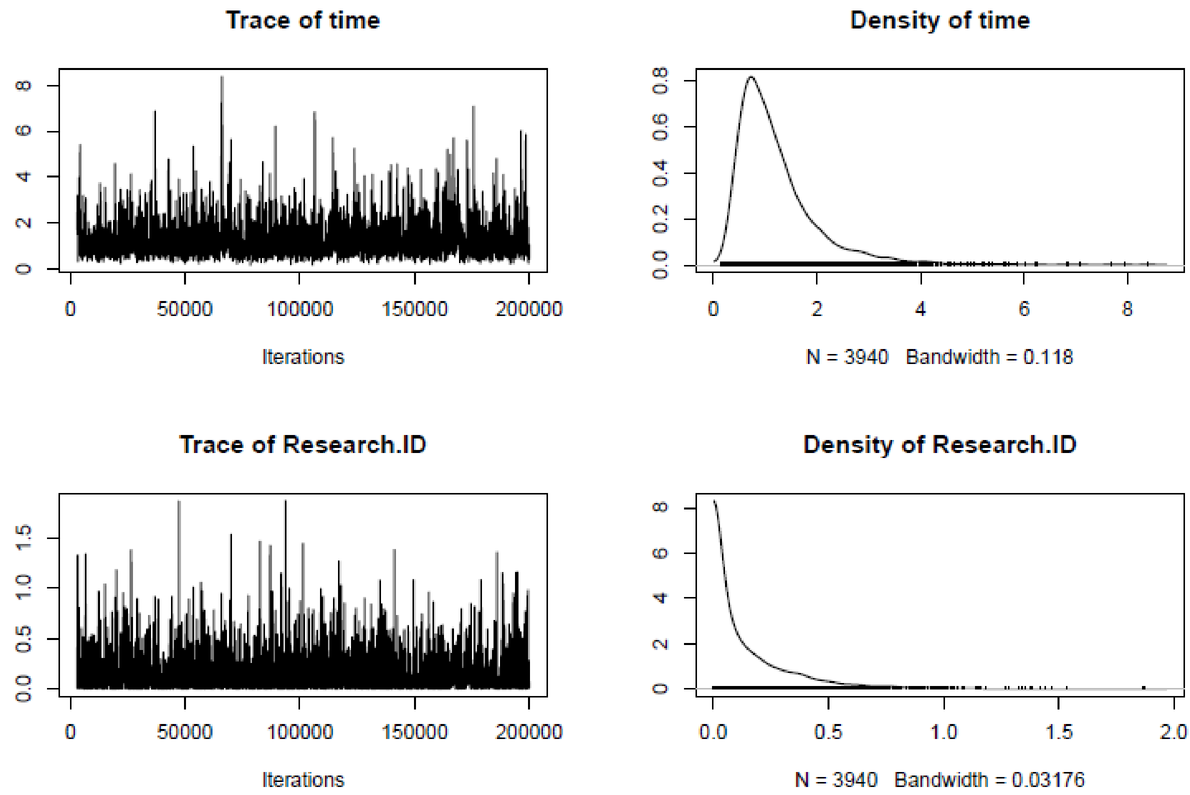

Density of appear:time:drugs
2
0
−0.2
0.0
0.2
0.4
0.6
N = 3940 Bandwidth = 0.02216


Trace of appear:time:physical
0.2
−0.6
0
50000
100000
150000
200000
Iterations


Density of appear:time:physical
1.5
0.0
−0.8
−0.6
−0.4
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.03059


Trace of appear:time:emotion
0.2
−0.4
0
50000
100000
150000
200000
Iterations
Density of appear:time:emotion
2.0
0.0
−0.6
−0.4
−0.2
0.0
0.2
0.4
N = 3940 Bandwidth = 0.02492
Trace of appear:time:self
0.2
−0.4
0
50000
100000
150000
200000
Iterations
Density of appear:time:self
1.5
0.0
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
N = 3940 Bandwidth = 0.03118
Trace of appear:time:think
0.2
−0.6
0
50000
100000
150000
200000
Iterations
Density of appear:time:think
1.5
0.0
−0.8
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
N = 3940 Bandwidth = 0.03393
Trace of appear:time:attitude
0.4
−0.4
0
50000
100000
150000
200000
Iterations
Density of appear:time:attitude
1.5
0.0
−0.5
0.0
0.5
N = 3940 Bandwidth = 0.03685
Trace of appear:time:change
0.2
−0.6
0
50000
100000
150000
200000
Iterations
Density of appear:time:change
1.5
0.0
−0.8
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
N = 3940 Bandwidth = 0.03511

Random Effects



Dynamic Model 5: Custody (Table 7.9)

Bayesian Model (BDm5_C)

Define the model

```
BDm5_C <- MCMCglmm(FO.bin ~ custody*time*live + custody*time*relation +
custody*time*ete + custody*time*where + custody*time*life +
custody*time*drugs + custody*time*physical + custody*time*emotion +
custody*time*self + custody*time*think + custody*time*attitude +
custody*time*change,
random=~time+Research.ID, data=data,
family="ordinal",prior=priorD,slice=TRUE,
nitt=250000, thin=50, burnin=3000)
```

Checks for suitable convergence

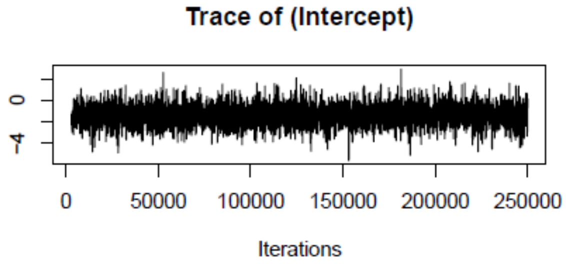
```
raftery.diag(BDm5_C$VCV)
heidel.diag(BDm5_C$VCV)

# > raftery.diag(BDm5_C$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total  Lower bound  Dependence
#              (M)      (N)    (Nmin)       factor (I)
# time         100      190950 3746         51.0
# Research.ID  100      194150 3746         51.8
# units        <NA>     <NA>   3746           NA

# > heidel.diag(BDm5_C$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.721
# Research.ID  passed        1         0.155
# units        failed       NA           NA
#
#              Halfwidth Mean  Halfwidth
#              test
# time         passed    2.654 0.11435
# Research.ID  passed    0.215 0.00871
# units        <NA>         NA      NA

autocorr(BDm5_C$VCV)
autocorr(BDm5_C$Sol)    # Output not included here
summary(BDm5_C)

# > autocorr(BDm5_C$VCV)
# , , time
#
#                 time   Research.ID units
# Lag 0     1.00000000  0.0871660800   NaN
# Lag 50    0.23620797  0.0272492892   NaN
# Lag 250   0.12878080  0.0176358926   NaN
# Lag 500   0.06333346  0.0183311208   NaN
# Lag 2500  0.01664997 -0.0005900159   NaN
```

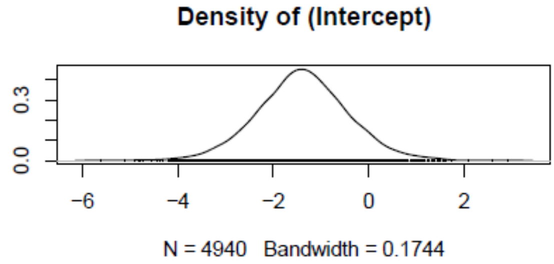
```
# , , Research.ID
#
#                    time  Research.ID units
# Lag 0     0.0871660800  1.000000000   NaN
# Lag 50    0.0500118215  0.259413028   NaN
# Lag 250  -0.0126014597  0.001184461   NaN
# Lag 500   0.0098867986 -0.008114468   NaN
# Lag 2500  0.0005961371 -0.025819025   NaN

# > summary(BDm5_C)
#
# Iterations = 3001:249951
# Thinning interval  = 50
# Sample size  = 4940
#
# DIC: 477.985
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     2.654   0.5019    6.329     1094
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID    0.2145 9.571e-08   0.6694     2774
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ custody * time * live + custody * time * relation + custody * time * ete + custody * time * where + custody * time * life + custody * time * drugs + custody * time * physical + custody * time * emotion + custody * time * self + custody * time * think + custody * time * attitude + custody * time * change
#
#                       post.mean   l-95% CI   u-95% CI eff.samp    pMCMC
# (Intercept)           -1.379656  -3.256386   0.545191   5272.1 0.142915
# custody                8.295420 -10.669796  26.221315    428.2 0.370850
# time                  -0.142098  -0.451409   0.148728   4940.0 0.350607
# live                  -0.059373  -0.547953   0.414147   4733.2 0.809717
# relation               0.393335  -0.123009   0.940111   4940.0 0.138057
# ete                   -0.303748  -0.688524   0.100034   4940.0 0.135223
# where                  0.189650  -0.232106   0.575585   5087.0 0.363968
# life                   0.251329  -0.388619   0.921616   4740.6 0.459514
# drugs                  0.366745  -0.046526   0.803472   4940.0 0.086235 .
# physical              -0.587958  -1.135892  -0.080866   4940.0 0.030364 *
# emotion               -0.157274  -0.572677   0.269487   4940.0 0.450607
# self                   0.185773  -0.418474   0.799549   4940.0 0.557895
# think                 -0.138637  -0.742762   0.456898   4940.0 0.635628
# attitude              -0.081002  -0.702606   0.501733   4940.0 0.805668
# change                 0.436215  -0.174042   0.999689   4940.0 0.145344
# custody:time          -4.947159  -8.971323  -1.293376    203.2 0.000405 ***
# custody:live           1.741380  -2.684320   6.317678    652.2 0.444130
# time:live              0.026285  -0.079452   0.135039   4673.9 0.616194
# custody:relation       0.299667 -10.651162  11.070578    485.9 0.957895
# time:relation         -0.043494  -0.163754   0.089453   4940.0 0.493117
# custody:ete           -0.710068  -7.560245   5.366095    769.6 0.853036
# time:ete               0.102222   0.012122   0.201674   4445.7 0.031984 *
# custody:where         -0.907380  -6.603257   4.644491    573.7 0.732794
# time:where            -0.029368  -0.114372   0.055343   4940.0 0.522672
# custody:life          -7.233647 -13.231076  -0.957334    784.5 0.018623 *
```

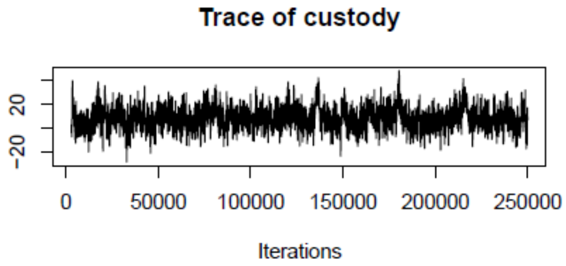
```
# time:life               -0.031307  -0.173771   0.104467   4723.0 0.675304
# custody:drugs           -1.733850  -7.218663   3.397332    624.3 0.519433
# time:drugs              -0.054709  -0.146487   0.035063   4940.0 0.250607
# custody:physical        -1.560205  -6.103669   2.726212    937.4 0.488259
# time:physical            0.123609  -0.014393   0.257073   4940.0 0.072065 .
# custody:emotion          2.791973  -8.356890  14.398819    545.2 0.658704
# time:emotion             0.056767  -0.038385   0.148771   4940.0 0.225101
# custody:self             0.659167  -8.023239   9.339297    280.2 0.866802
# time:self               -0.082914  -0.206727   0.039614   4730.4 0.189474
# custody:think            1.833132  -9.165312  13.882505    374.5 0.780162
# time:think               0.001207  -0.139149   0.130715   4705.9 0.991498
# custody:attitude         7.785652  -4.112593  20.235339    681.3 0.200405
# time:attitude            0.018583  -0.112816   0.152234   4940.0 0.777328
# custody:change          -8.794357 -24.027253   6.464864    439.0 0.263968
# time:change             -0.052021  -0.190441   0.076872   4940.0 0.433198
# custody:time:live       -0.781755  -1.750338   0.132218    248.9 0.085020 .
# custody:time:relation  -0.359860  -1.713474   1.060900    590.7 0.639271
# custody:time:ete         0.940456  -0.578471   2.380562    622.8 0.196356
# custody:time:where       0.902648   0.094271   1.709943    317.5 0.018219 *
# custody:time:life        0.907317  -0.440528   2.229964    466.6 0.176923
# custody:time:drugs       0.988711  -0.022727   1.912290    526.5 0.028340 *
# custody:time:physical    0.812469  -0.051338   1.712480    444.2 0.050607 .
# custody:time:emotion    -0.285715  -1.736301   1.166276    628.1 0.714980
# custody:time:self        0.050467  -1.714904   1.804351    250.3 0.973684
# custody:time:think      -0.331905  -2.214339   1.370768    366.4 0.742510
# custody:time:attitude  -1.338827  -3.096636   0.214132    997.8 0.090688 .
# custody:time:change      0.868017  -1.457904   3.101199    390.9 0.461134
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

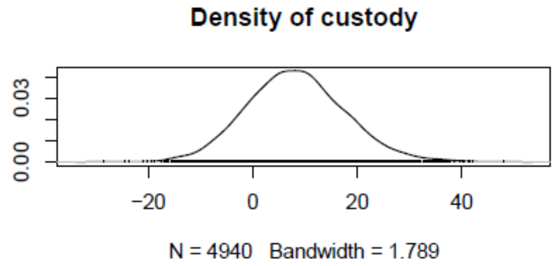
Trace Plots and Posterior Density Plots

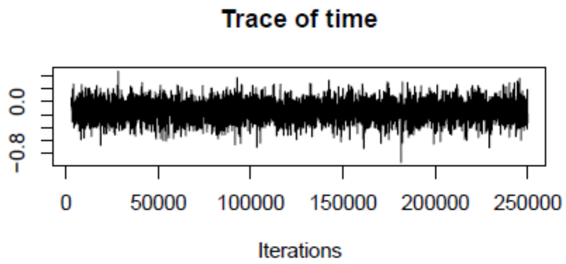
<u>Fixed Effects</u>

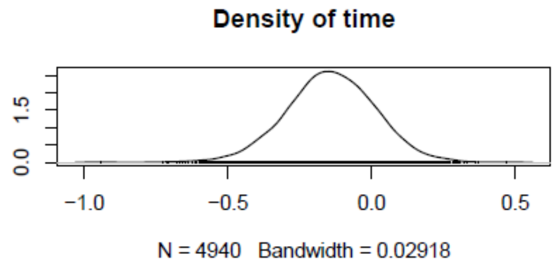


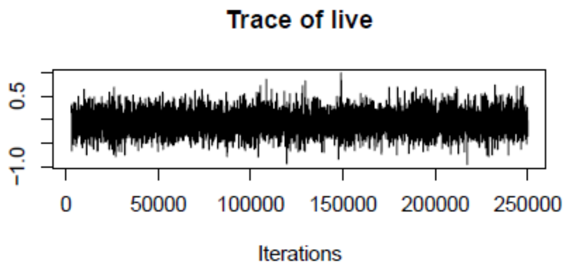


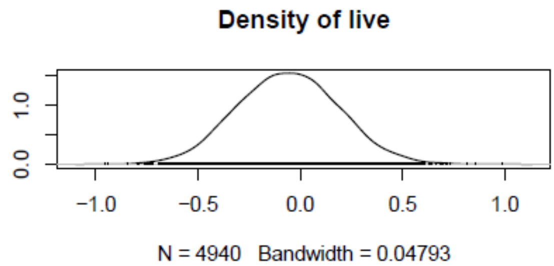


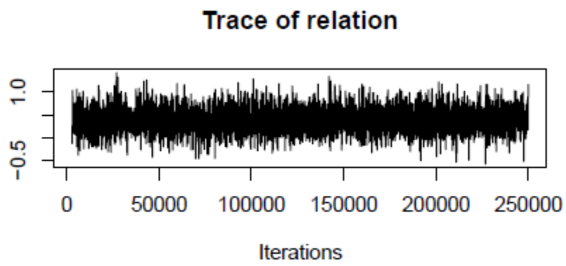


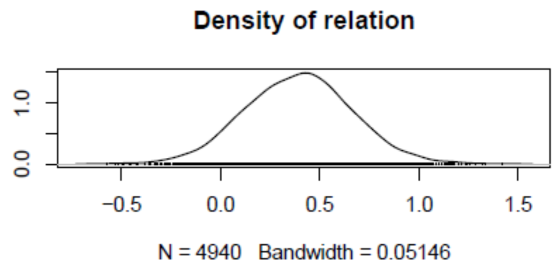


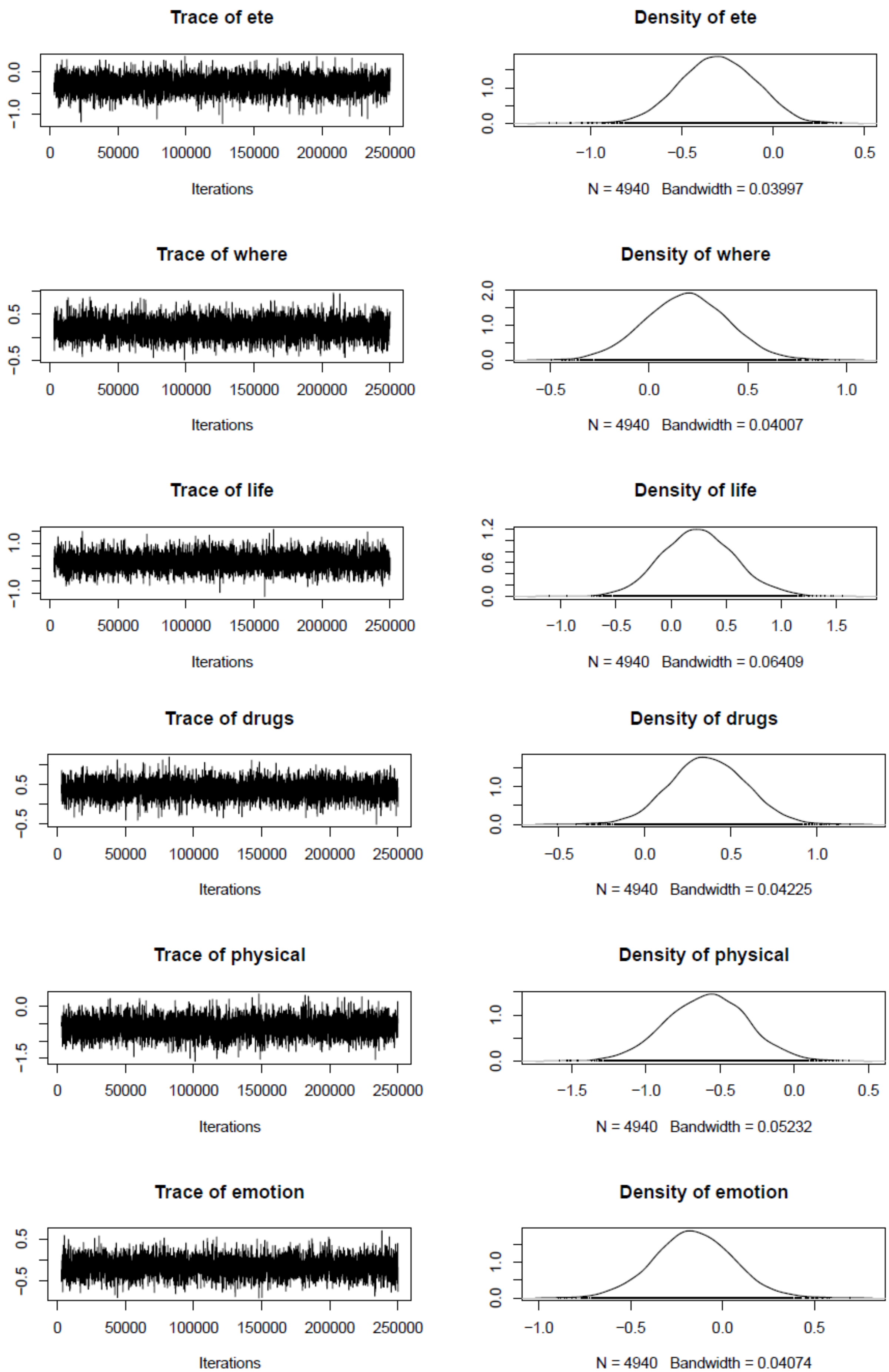


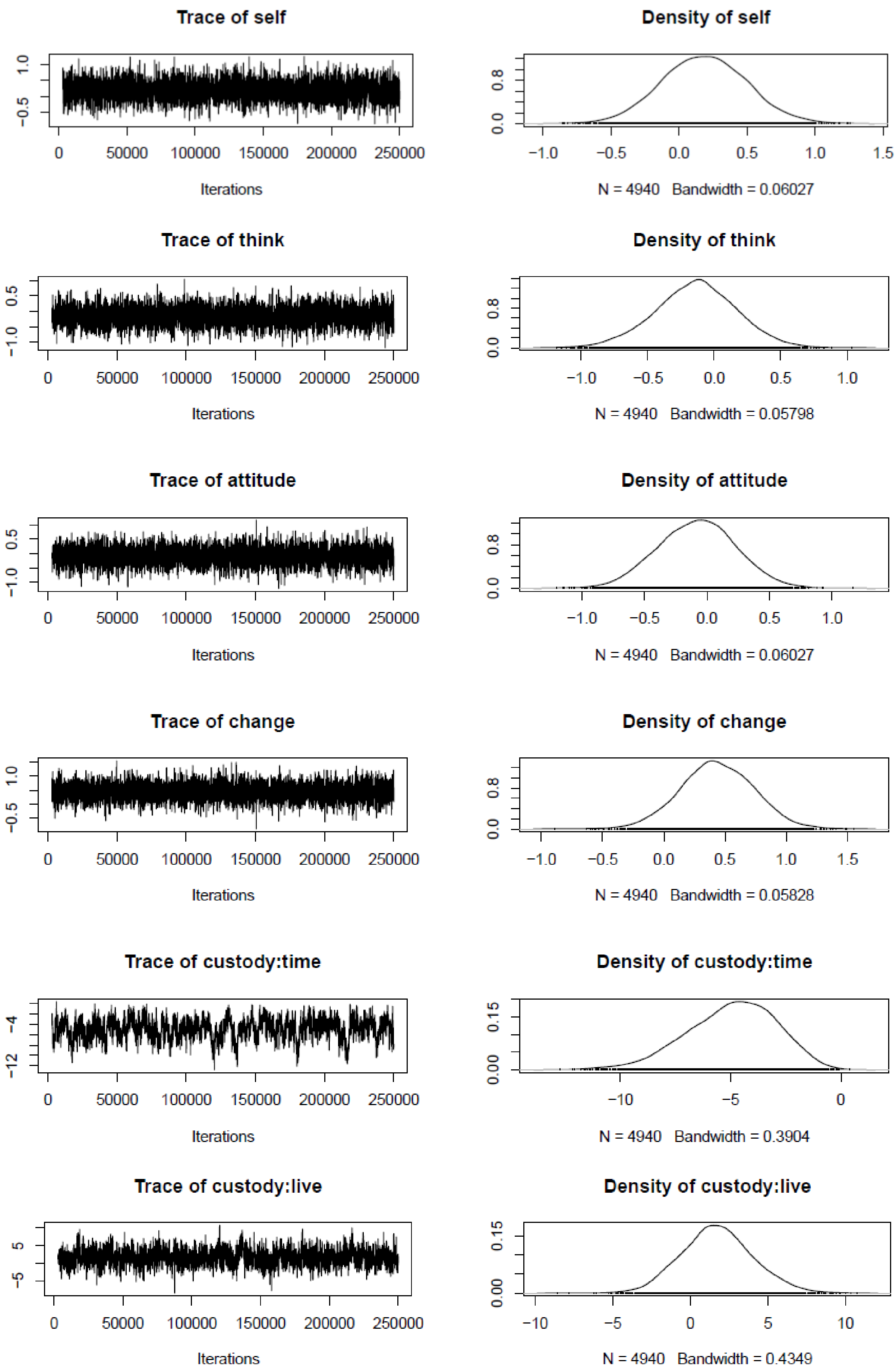


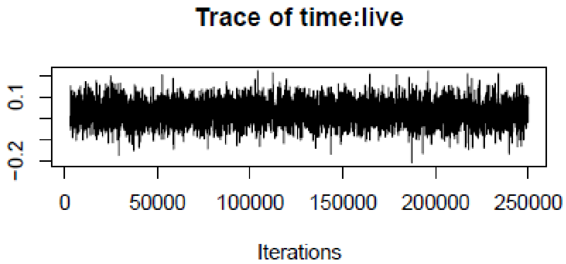


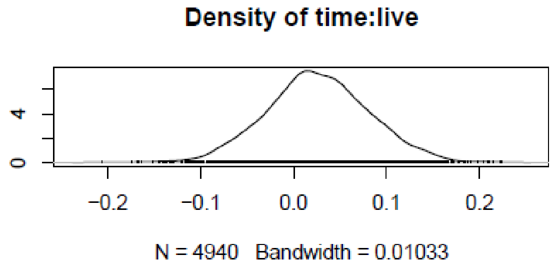


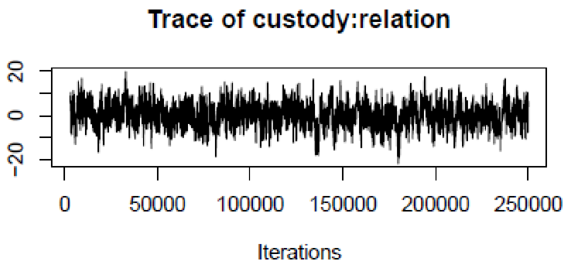


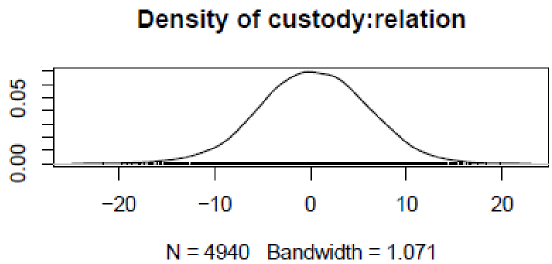

Trace of ete
Iterations
Density of ete
N = 4940 Bandwidth = 0.03997
Trace of where
Iterations
Density of where
N = 4940 Bandwidth = 0.04007
Trace of life
Iterations
Density of life
N = 4940 Bandwidth = 0.06409
Trace of drugs
Iterations
Density of drugs
N = 4940 Bandwidth = 0.04225
Trace of physical
Iterations
Density of physical
N = 4940 Bandwidth = 0.05232
Trace of emotion
Iterations
Density of emotion
N = 4940 Bandwidth = 0.04074

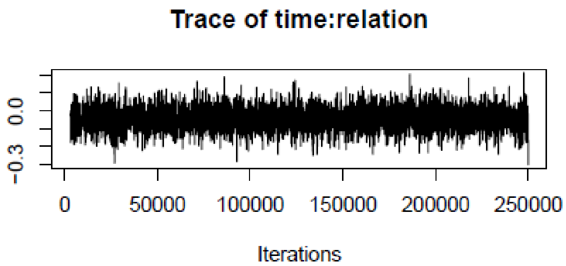

Trace of self
Iterations
Density of self
N = 4940 Bandwidth = 0.06027
Trace of think
Iterations
Density of think
N = 4940 Bandwidth = 0.05798
Trace of attitude
Iterations
Density of attitude
N = 4940 Bandwidth = 0.06027
Trace of change
Iterations
Density of change
N = 4940 Bandwidth = 0.05828
Trace of custody:time
Iterations
Density of custody:time
N = 4940 Bandwidth = 0.3904
Trace of custody:live
Iterations
Density of custody:live
N = 4940 Bandwidth = 0.4349

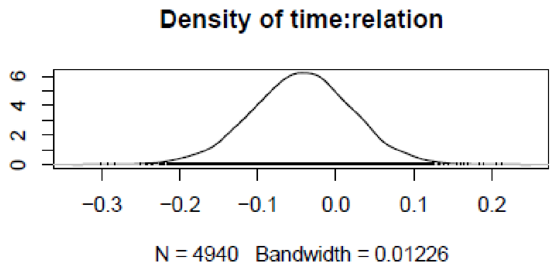

Trace of time:live
-0.2
0.1
0
50000
100000
150000
200000
250000
Iterations

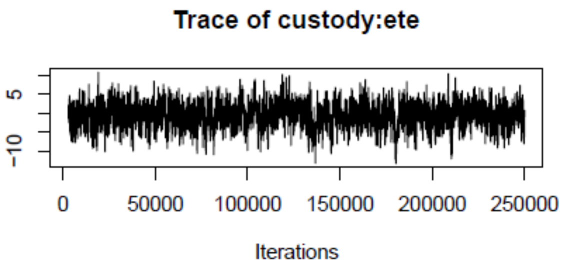

Density of time:live
0
4
-0.2
-0.1
0.0
0.1
0.2
N = 4940 Bandwidth = 0.01033

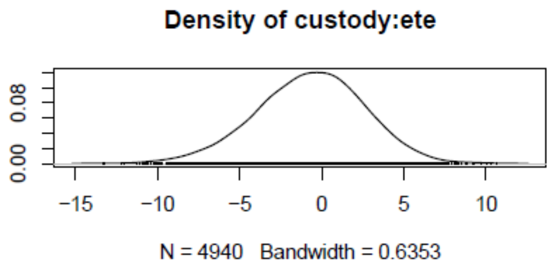

Trace of custody:relation
-20
0
20
0
50000
100000
150000
200000
250000
Iterations

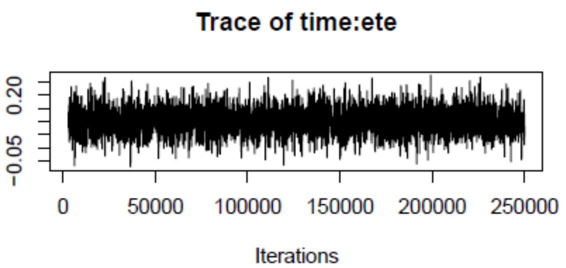

Density of custody:relation
0.00
0.05
-20
-10
0
10
20
N = 4940 Bandwidth = 1.071

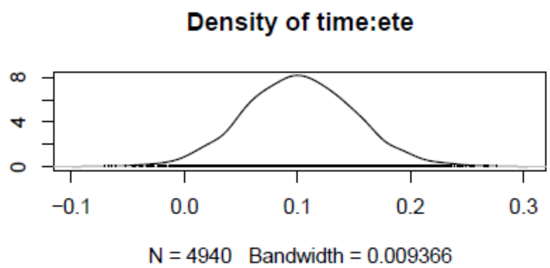

Trace of time:relation
-0.3
0.0
0
50000
100000
150000
200000
250000
Iterations

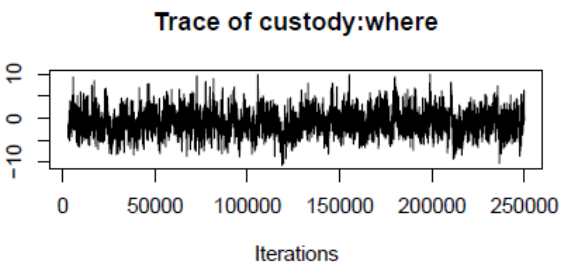

Density of time:relation
0
2
4
6
-0.3
-0.2
-0.1
0.0
0.1
0.2
N = 4940 Bandwidth = 0.01226

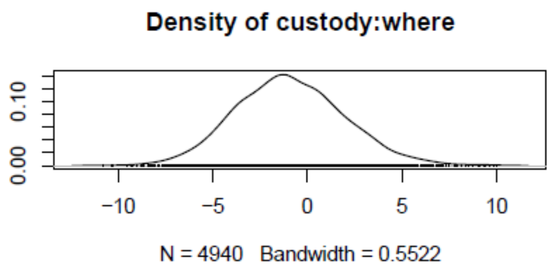

Trace of custody:ete
-10
5
0
50000
100000
150000
200000
250000
Iterations

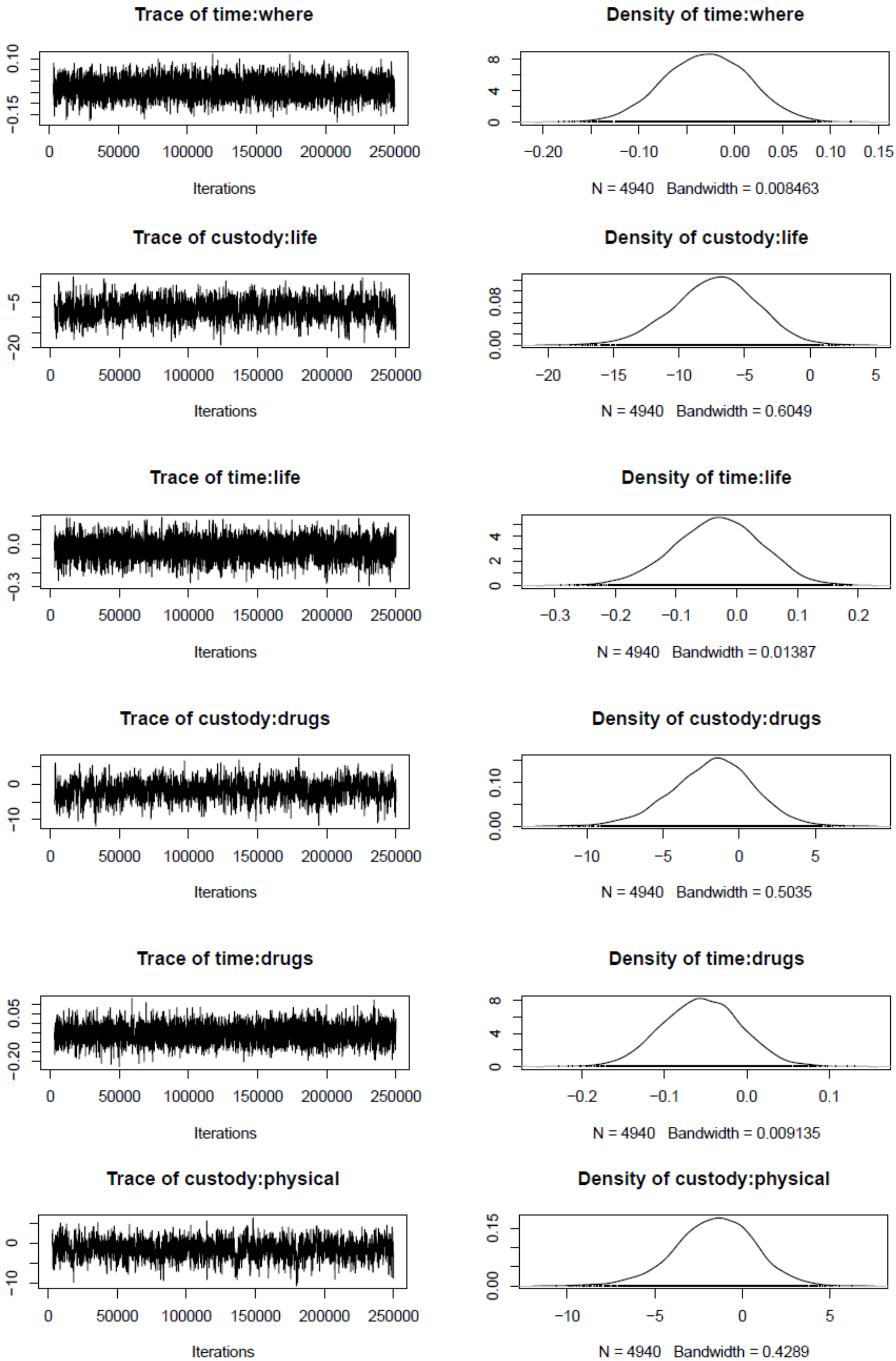

Density of custody:ete
0.00
0.08
-15
-10
-5
0
5
10
N = 4940 Bandwidth = 0.6353

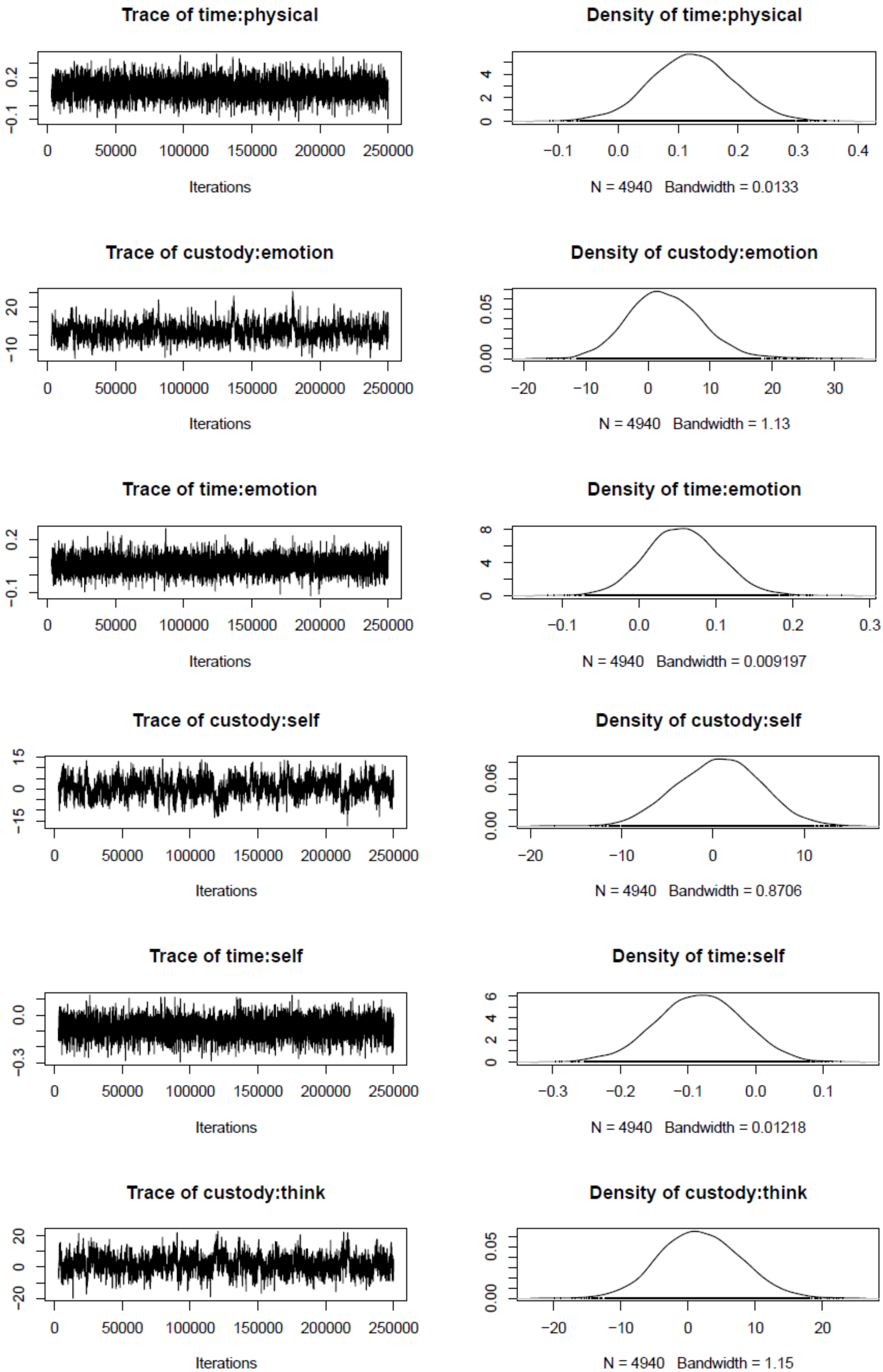

Trace of time:ete
-0.05
0.20
0
50000
100000
150000
200000
250000
Iterations

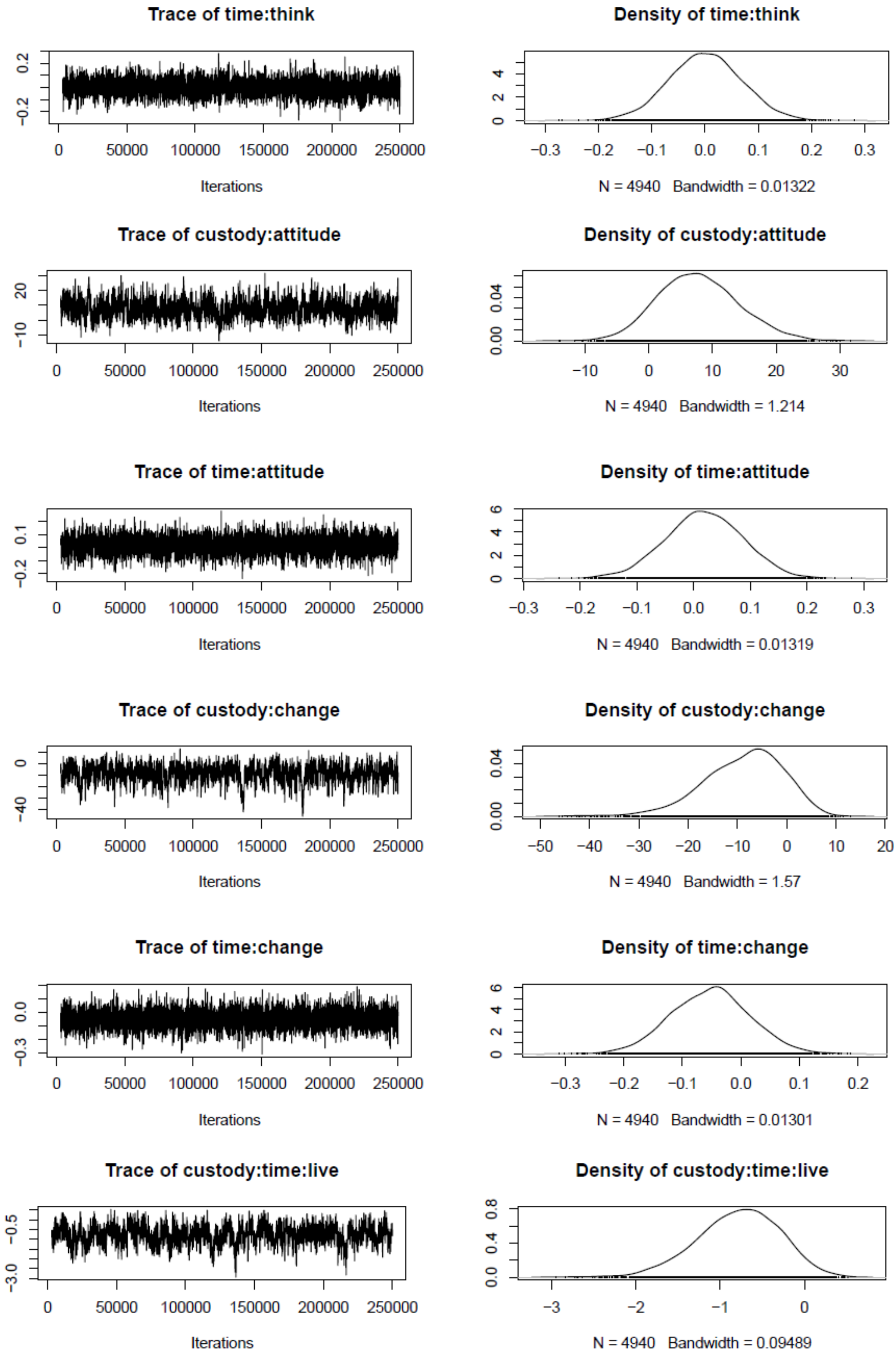

Density of time:ete
0
4
8
-0.1
0.0
0.1
0.2
0.3
N = 4940 Bandwidth = 0.009366


Trace of custody:where
-10
0
10
0
50000
100000
150000
200000
250000
Iterations

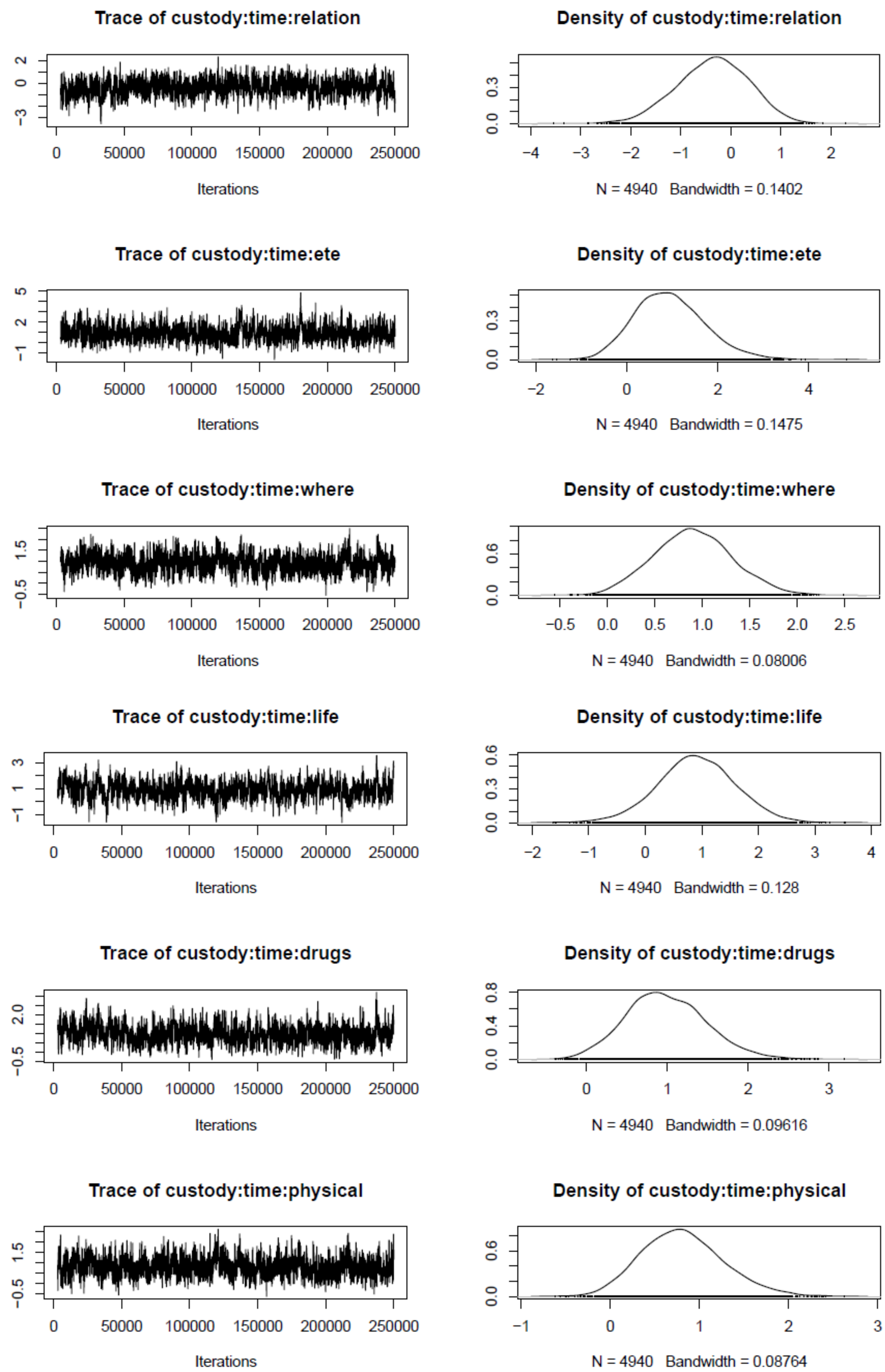

Density of custody:where
0.00
0.10
-10
-5
0
5
10
N = 4940 Bandwidth = 0.5522

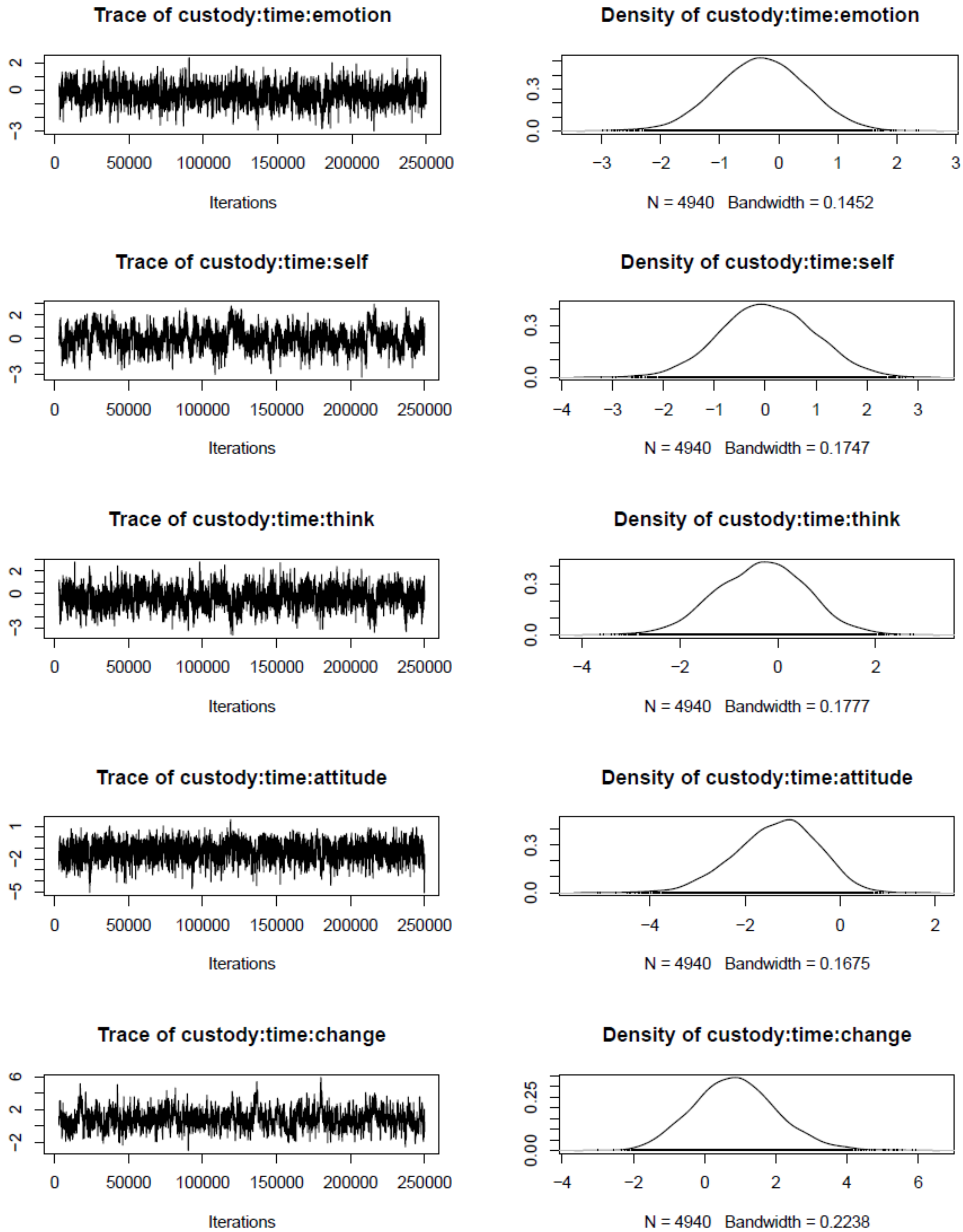

Trace of time:where
Iterations
Density of time:where
N = 4940 Bandwidth = 0.008463
Trace of custody:life
Iterations
Density of custody:life
N = 4940 Bandwidth = 0.6049
Trace of time:life
Iterations
Density of time:life
N = 4940 Bandwidth = 0.01387
Trace of custody:drugs
Iterations
Density of custody:drugs
N = 4940 Bandwidth = 0.5035
Trace of time:drugs
Iterations
Density of time:drugs
N = 4940 Bandwidth = 0.009135
Trace of custody:physical
Iterations
Density of custody:physical
N = 4940 Bandwidth = 0.4289


Trace of time:physical
Iterations
Density of time:physical
N = 4940 Bandwidth = 0.0133
Trace of custody:emotion
Iterations
Density of custody:emotion
N = 4940 Bandwidth = 1.13
Trace of time:emotion
Iterations
Density of time:emotion
N = 4940 Bandwidth = 0.009197
Trace of custody:self
Iterations
Density of custody:self
N = 4940 Bandwidth = 0.8706
Trace of time:self
Iterations
Density of time:self
N = 4940 Bandwidth = 0.01218
Trace of custody:think
Iterations
Density of custody:think
N = 4940 Bandwidth = 1.15

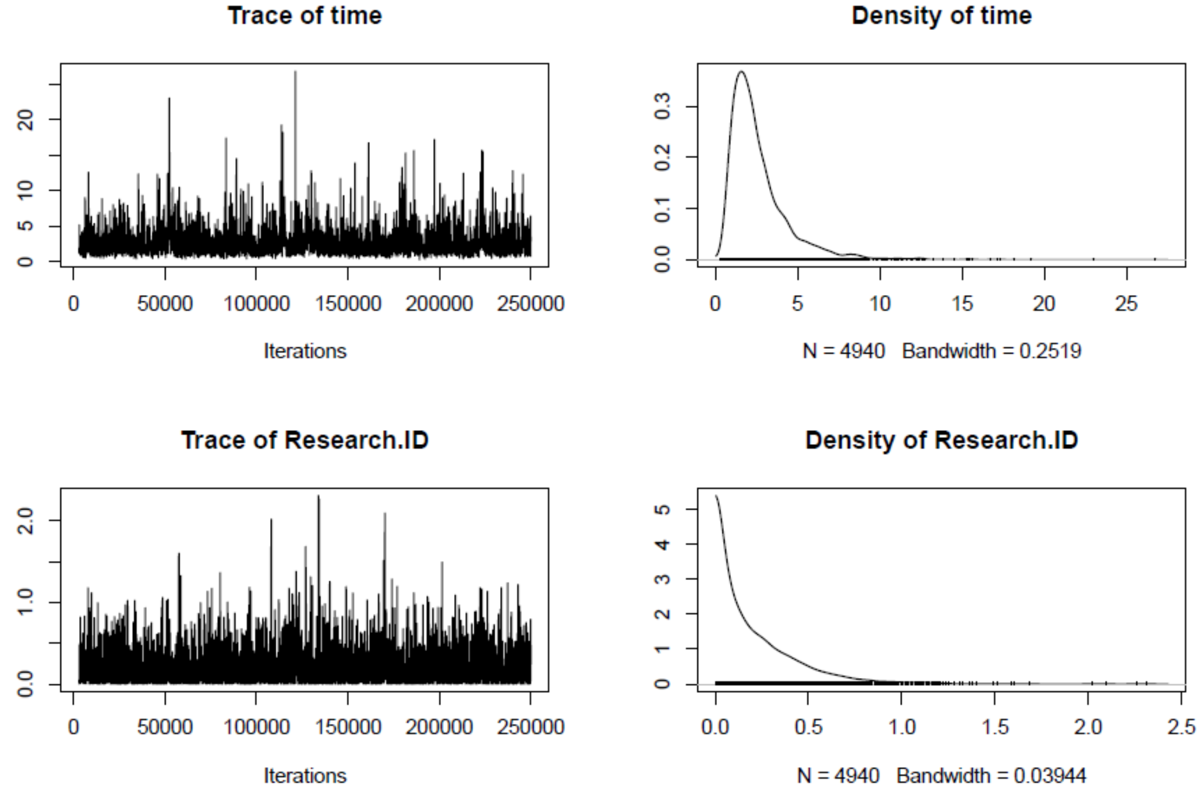


Trace of time:think
Iterations
Density of time:think
N = 4940 Bandwidth = 0.01322
Trace of custody:attitude
Iterations
Density of custody:attitude
N = 4940 Bandwidth = 1.214
Trace of time:attitude
Iterations
Density of time:attitude
N = 4940 Bandwidth = 0.01319
Trace of custody:change
Iterations
Density of custody:change
N = 4940 Bandwidth = 1.57
Trace of time:change
Iterations
Density of time:change
N = 4940 Bandwidth = 0.01301
Trace of custody:time:live
Iterations
Density of custody:time:live
N = 4940 Bandwidth = 0.09489


Trace of custody:time:relation
Iterations
Density of custody:time:relation
N = 4940 Bandwidth = 0.1402
Trace of custody:time:ete
Iterations
Density of custody:time:ete
N = 4940 Bandwidth = 0.1475
Trace of custody:time:where
Iterations
Density of custody:time:where
N = 4940 Bandwidth = 0.08006
Trace of custody:time:life
Iterations
Density of custody:time:life
N = 4940 Bandwidth = 0.128
Trace of custody:time:drugs
Iterations
Density of custody:time:drugs
N = 4940 Bandwidth = 0.09616
Trace of custody:time:physical
Iterations
Density of custody:time:physical
N = 4940 Bandwidth = 0.08764


Trace of custody:time:emotion
Iterations
Density of custody:time:emotion
N = 4940 Bandwidth = 0.1452
Trace of custody:time:self
Iterations
Density of custody:time:self
N = 4940 Bandwidth = 0.1747
Trace of custody:time:think
Iterations
Density of custody:time:think
N = 4940 Bandwidth = 0.1777
Trace of custody:time:attitude
Iterations
Density of custody:time:attitude
N = 4940 Bandwidth = 0.1675
Trace of custody:time:change
Iterations
Density of custody:time:change
N = 4940 Bandwidth = 0.2238

Random Effects



Dynamic Model 6 (Table 7.11)

Bayesian Model (BDm6)

Define the Model

```
BDm6 <- MCMCglmm(FO.bin ~ careExp*time*live +
careExp*time*relation + careExp*time*ete + careExp*time*where +
careExp*time*life + careExp*time*drugs + careExp*time*physical +
careExp*time*emotion + careExp*time*self + careExp*time*think +
careExp*time*attitude + careExp*time*change + time*appear*live +
time*appear*relation + time*appear*ete + time*appear*where +
time*appear*life + time*appear*drugs + time*appear*physical +
time*appear*emotion + time*appear*self + time*appear*think +
time*appear*attitude + time*appear*change + careExp*appear*time +
careExp*breach*time + careExp*custody*time,
slice=TRUE, random=~time+Research.ID, data=data, family="ordinal",
prior=priorD, pl=TRUE, nitt=5000000, thin=750, burnin=3000)
```

Checks for suitable convergence

```
raftery.diag(BDm6VCV)
heidel.diag(BDm6$VCV)

# > raftery.diag(BDm6$VCV)
#
# Quantile (q) = 0.025
# Accuracy (r) = +/- 0.005
# Probability (s) = 0.95
#
#              Burn-in  Total   Lower bound  Dependence
#              (M)      (N)     (Nmin)       factor (I)
# time         1500     2847000 3746         760
# Research.ID 1500     2953500 3746         788
# units        <NA>     <NA>    3746          NA

# > heidel.diag(BDm6$VCV)
#
#              Stationarity start     p-value
#              test         iteration
# time         passed        1         0.109
# Research.ID passed        1         0.283
# units        failed       NA            NA
#
#              Halfwidth Mean Halfwidth
#              test
# time         passed    1.98 0.0455
# Research.ID passed    1.79 0.0518
# units        <NA>        NA      NA

autocorr(BDm6$VCV)
autocorr(BDm6$Sol) # not included here
summary(BDm6)
```

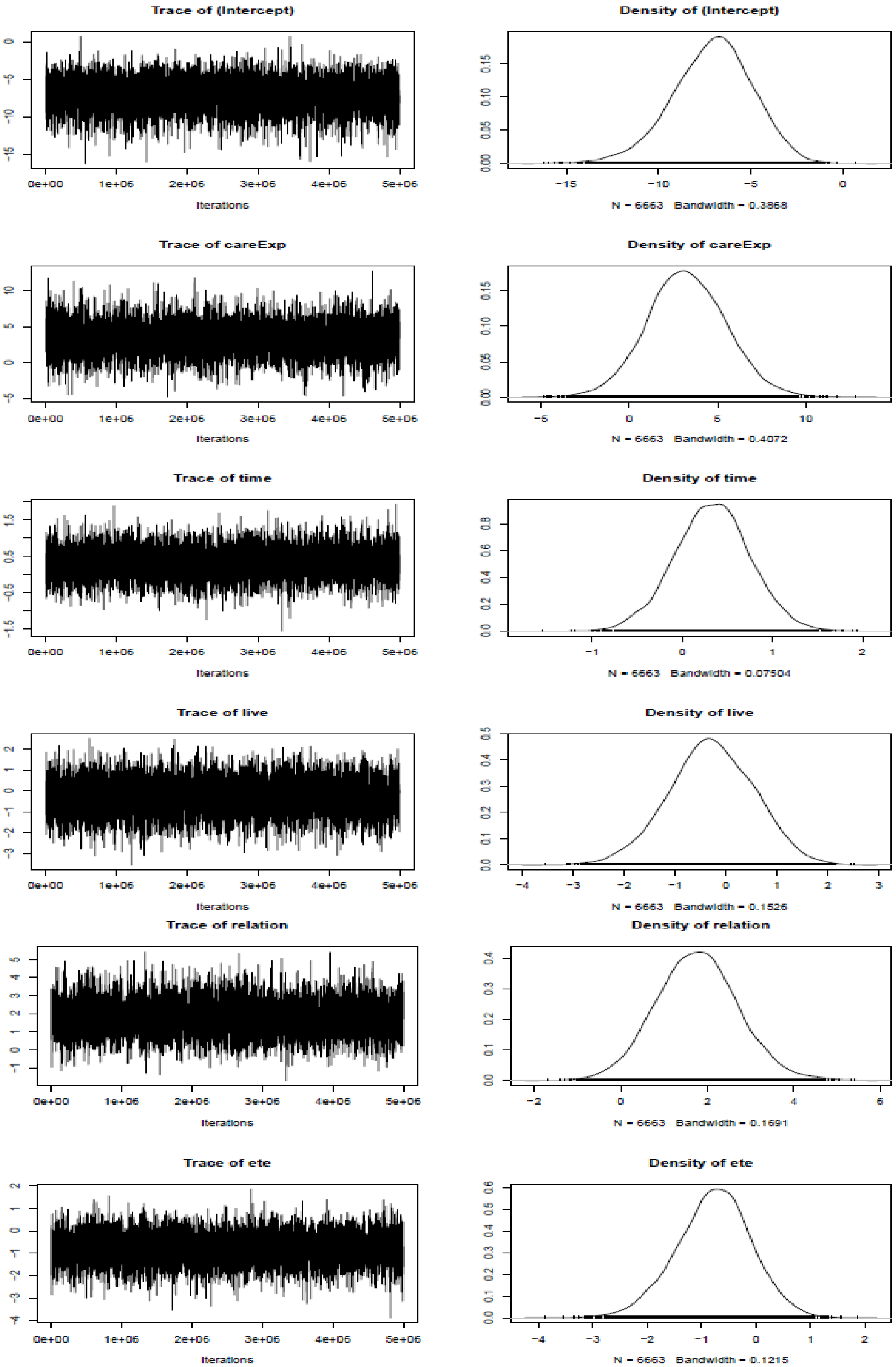
```
# > autocorr(BDm6$VCV)
# , , time
#
#                    time  Research.ID units
# Lag 0      1.000000000  0.304610860   NaN
# Lag 750    0.100077459  0.137060037   NaN
# Lag 3750   0.006134726  0.010565395   NaN
# Lag 7500  -0.010029548 -0.016649565   NaN
# Lag 37500 -0.004563689 -0.006864169   NaN
#
# , , Research.ID
#
#                    time  Research.ID units
# Lag 0      0.304610860  1.000000000   NaN
# Lag 750    0.125263231  0.290590014   NaN
# Lag 3750   0.021014062  0.028036514   NaN
# Lag 7500  -0.015314869 -0.030992706   NaN
# Lag 37500 -0.005895889 -0.006377321   NaN

# > summary(BDm6)
#
# Iterations = 3001:4999501
# Thinning interval  = 750
# Sample size  = 6663
#
# DIC: 433.6397
#
# G-structure:  ~time
#
#      post.mean l-95% CI u-95% CI eff.samp
# time     1.982   0.2349    4.818     4874
#
# ~Research.ID
#
#             post.mean  l-95% CI u-95% CI eff.samp
# Research.ID     1.795 1.559e-07    4.759     3436
#
# R-structure:  ~units
#
#       post.mean l-95% CI u-95% CI eff.samp
# units         1        1        1        0
#
# Location effects: FO.bin ~ careExp * time * live + careExp * time *
relation + careExp * time * ete + careExp * time * where + careExp *
time * life + careExp * time * drugs + careExp * time * physical +
careExp * time * emotion + careExp * time * self + careExp * time *
think + careExp * time * attitude + careExp * time * change + time *
appear * live + time * appear * relation + time * appear * ete + time *
appear * where + time * appear * life + time * appear * drugs + time *
appear * physical + time * appear * emotion + time * appear * self +
time * appear * think + time * appear * attitude + time * appear *
change + careExp * appear * time + careExp * breach * time + careExp *
custody * time
#
#                        post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
# (Intercept)            -7.069773 -11.138043  -2.705344     6434 0.0006 ***
# careExp                 3.260213  -1.267726   7.552579     6663 0.1420
# time                    0.331863  -0.507611   1.136140     7020 0.4262
# live                   -0.287627  -1.899358   1.365220     6663 0.7360
# relation                1.767157  -0.149945   3.563469     5900 0.0576 .
# ete                    -0.775876  -2.187265   0.503696     6171 0.2395
# where                   0.867531  -0.525859   2.177561     6663 0.2014
```

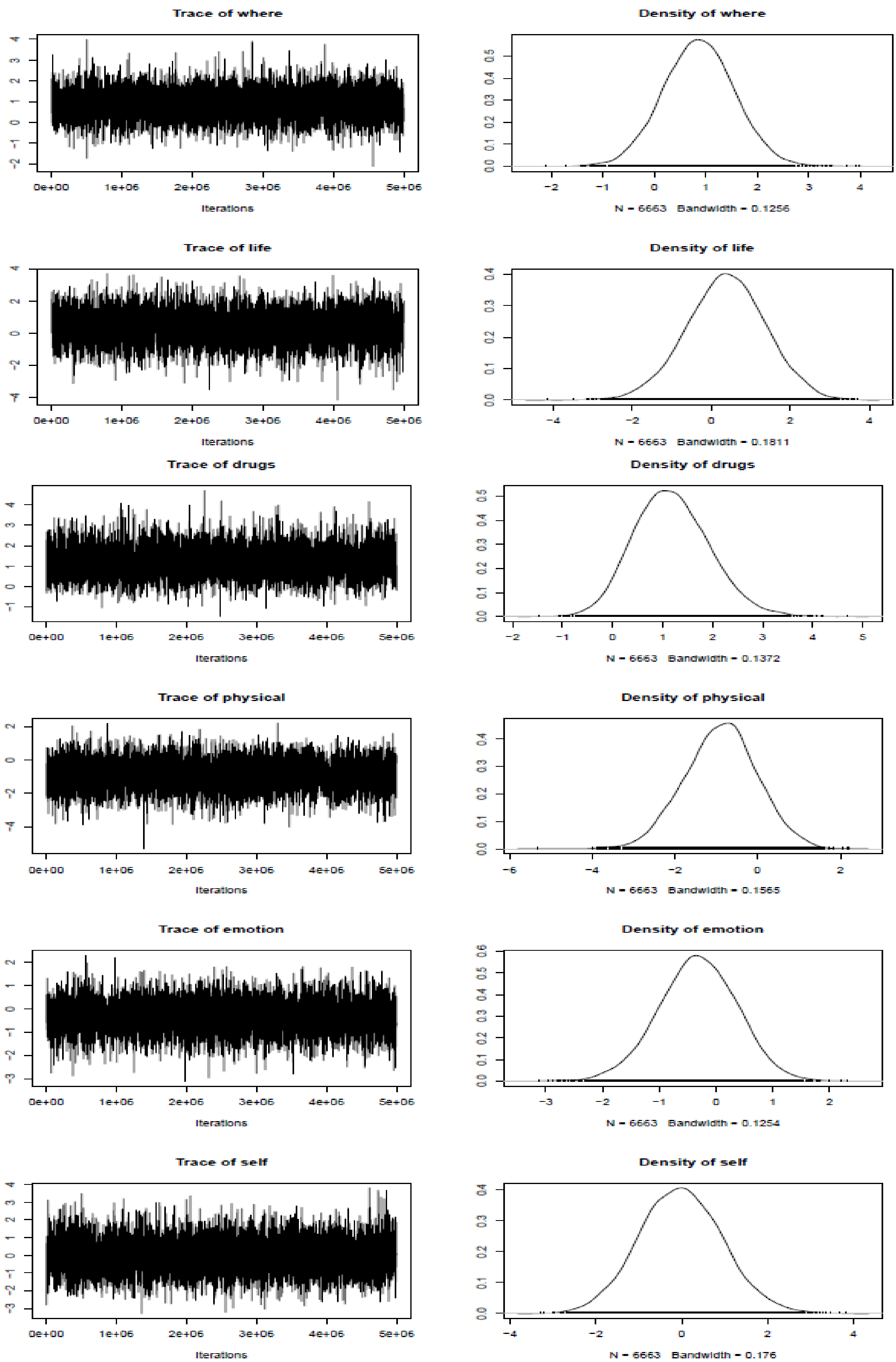
```
# life                    0.372869  -1.585451   2.356092     6663 0.6931
# drugs                   1.181383  -0.291584   2.625191     6192 0.0946 .
# physical               -0.891114  -2.529983   0.889509     6418 0.3080
# emotion                -0.322118  -1.716649   0.989895     6663 0.6472
# self                   -0.018944  -1.884595   1.903803     6252 0.9770
# think                   0.122643  -1.597343   1.875663     6663 0.8945
# attitude                1.127322  -0.758501   3.071044     6235 0.2440
# change                 -1.059619  -3.278459   1.200687     6663 0.3482
# appear                  7.794157   3.530560  12.264003     5892 <2e-04 ***
# breach                 -0.844272  -2.462815   0.825309     6663 0.3071
# custody                -2.095157  -5.608333   1.259246     6315 0.2245
# careExp:time           -0.256468  -1.153023   0.611332     7040 0.5529
# careExp:live            0.590978  -0.839235   2.048854     6308 0.4154
# time:live              -0.282406  -0.650934   0.121267     6663 0.1447
# careExp:relation       -0.174758  -1.881731   1.452648     6055 0.8450
# time:relation          -0.264438  -0.688532   0.149294     6364 0.2176
# careExp:ete             0.303300  -1.098171   1.635024     5939 0.6892
# time:ete                0.143663  -0.170727   0.465593     6365 0.3857
# careExp:where          -0.420173  -1.708939   1.025917     6663 0.5307
# time:where              0.018767  -0.263015   0.280434     6384 0.8954
# careExp:life           -0.888157  -2.923987   1.115263     6663 0.3983
# time:life              -0.043381  -0.483801   0.421280     6387 0.8351
# careExp:drugs          -0.072159  -1.344496   1.155148     6663 0.9092
# time:drugs             -0.010502  -0.314882   0.273770     6663 0.9248
# careExp:physical       -1.271230  -3.167270   0.529821     5226 0.1645
# time:physical          -0.003127  -0.436091   0.460065     5851 0.9869
# careExp:emotion         0.900807  -0.488686   2.244614     6663 0.1831
# time:emotion            0.161373  -0.171611   0.521928     6293 0.3629
# careExp:self            1.197236  -0.765456   3.069938     6312 0.2164
# time:self               0.134553  -0.268570   0.499689     6197 0.4959
# careExp:think          -1.347197  -3.490857   0.725898     6663 0.1906
# time:think              0.001250  -0.394505   0.394539     6382 0.9944
# careExp:attitude       -0.923892  -2.767796   1.040479     6432 0.3410
# time:attitude          -0.512440  -1.040872  -0.021488     5675 0.0402 *
# careExp:change          1.168776  -0.859737   3.318136     6663 0.2644
# time:change             0.395286  -0.102352   0.923894     5903 0.1153
# time:appear            -1.271619  -2.173961  -0.375232     6102 0.0036 **
# live:appear             0.153104  -1.509407   1.842144     6663 0.8618
# relation:appear        -1.536024  -3.393707   0.398265     6304 0.1057
# ete:appear              0.354532  -1.100483   1.733333     6663 0.6210
# where:appear           -0.999517  -2.416960   0.412507     6303 0.1624
# life:appear             0.232217  -1.702384   2.492338     6663 0.8378
# drugs:appear           -1.025345  -2.551426   0.378932     6133 0.1573
# physical:appear         1.166195  -0.531644   2.960384     6378 0.1846
# emotion:appear         -0.206991  -1.581978   1.265101     6394 0.7591
# self:appear            -0.561546  -2.678006   1.491274     5654 0.6048
# think:appear            0.136416  -1.874819   2.072368     6663 0.8975
# attitude:appear        -1.143949  -3.125126   0.900308     6275 0.2488
# change:appear           1.419226  -0.889532   3.805548     6320 0.2137
# careExp:appear         -0.746077  -3.411035   1.979120     5718 0.5862
# careExp:breach          2.540442  -0.440962   5.565652     6663 0.0897 .
# time:breach             0.116760  -0.204543   0.436506     6663 0.4785
# careExp:custody         1.191969  -2.724786   5.286302     6377 0.5694
# time:custody           -0.010910  -0.520199   0.492816     6663 0.9656
# careExp:time:live       0.079988  -0.212344   0.390760     6663 0.6069
# careExp:time:relation  -0.136614  -0.532904   0.251202     6663 0.5034
# careExp:time:ete        0.012872  -0.287829   0.318472     7082 0.9272
# careExp:time:where      0.237487  -0.022518   0.513509     6663 0.0825 .
# careExp:time:life      -0.039832  -0.458574   0.351293     6663 0.8411
# careExp:time:drugs     -0.106310  -0.402127   0.197201     6663 0.4824
# careExp:time:physical   0.403861  -0.004666   0.825532     6100 0.0507 .
# careExp:time:emotion   -0.116206  -0.459221   0.199775     6663 0.4848
# careExp:time:self      -0.630780  -1.068681  -0.196131     5548 0.0012 **
# careExp:time:think      0.436539   0.031344   0.898404     5991 0.0348 *
# careExp:time:attitude   0.379641  -0.064960   0.817040     6663 0.0903 .
# careExp:time:change    -0.409267  -0.841456   0.017104     6663 0.0543 .
# time:live:appear        0.272084  -0.112738   0.653737     6663 0.1474
# time:relation:appear    0.324026  -0.104088   0.764841     6663 0.1432
```

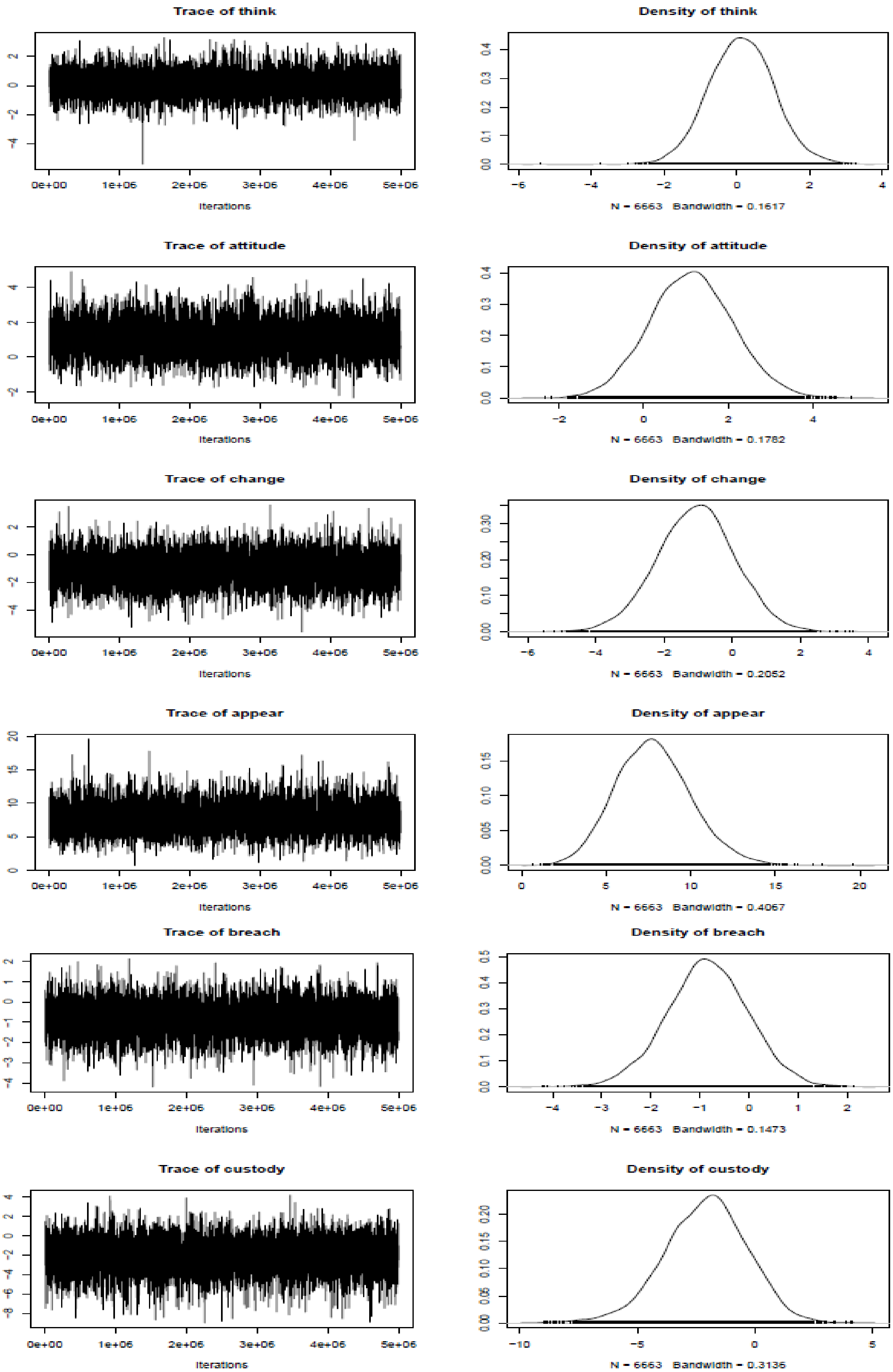
```
# time:ete:appear        -0.122960  -0.455313   0.216137     6663 0.4770
# time:where:appear      -0.115755  -0.399078   0.172582     6357 0.4436
# time:life:appear        0.066307  -0.405193   0.554893     6663 0.7792
# time:drugs:appear       0.108021  -0.191315   0.420726     6648 0.4941
# time:physical:appear   -0.176126  -0.615083   0.251586     5611 0.4286
# time:emotion:appear    -0.048471  -0.410514   0.315329     6268 0.7975
# time:self:appear        0.091462  -0.353513   0.496388     5866 0.6910
# time:think:appear      -0.173315  -0.607257   0.275383     6385 0.4460
# time:attitude:appear    0.424585  -0.067991   0.908028     5925 0.0783 .
# time:change:appear     -0.229760  -0.742272   0.239993     6308 0.3683
# careExp:time:appear     0.435027  -0.172613   1.074508     5786 0.1693
# careExp:time:breach    -0.668934  -1.225926  -0.055823     6663 0.0177 *
# careExp:time:custody    0.093250  -0.555543   0.700844     6663 0.7588
# ---
#   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

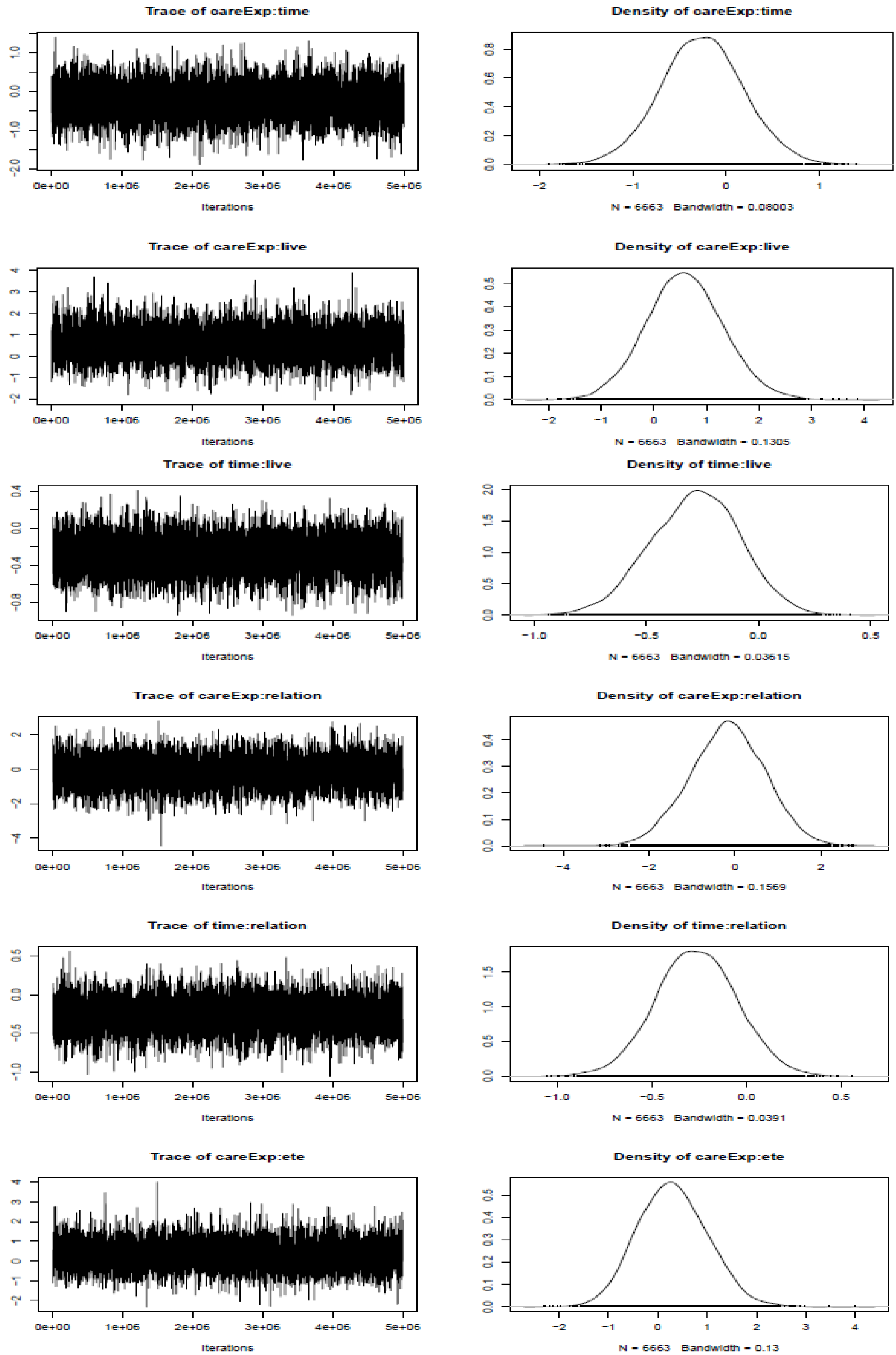
Trace Plots and Posterior Density Plots

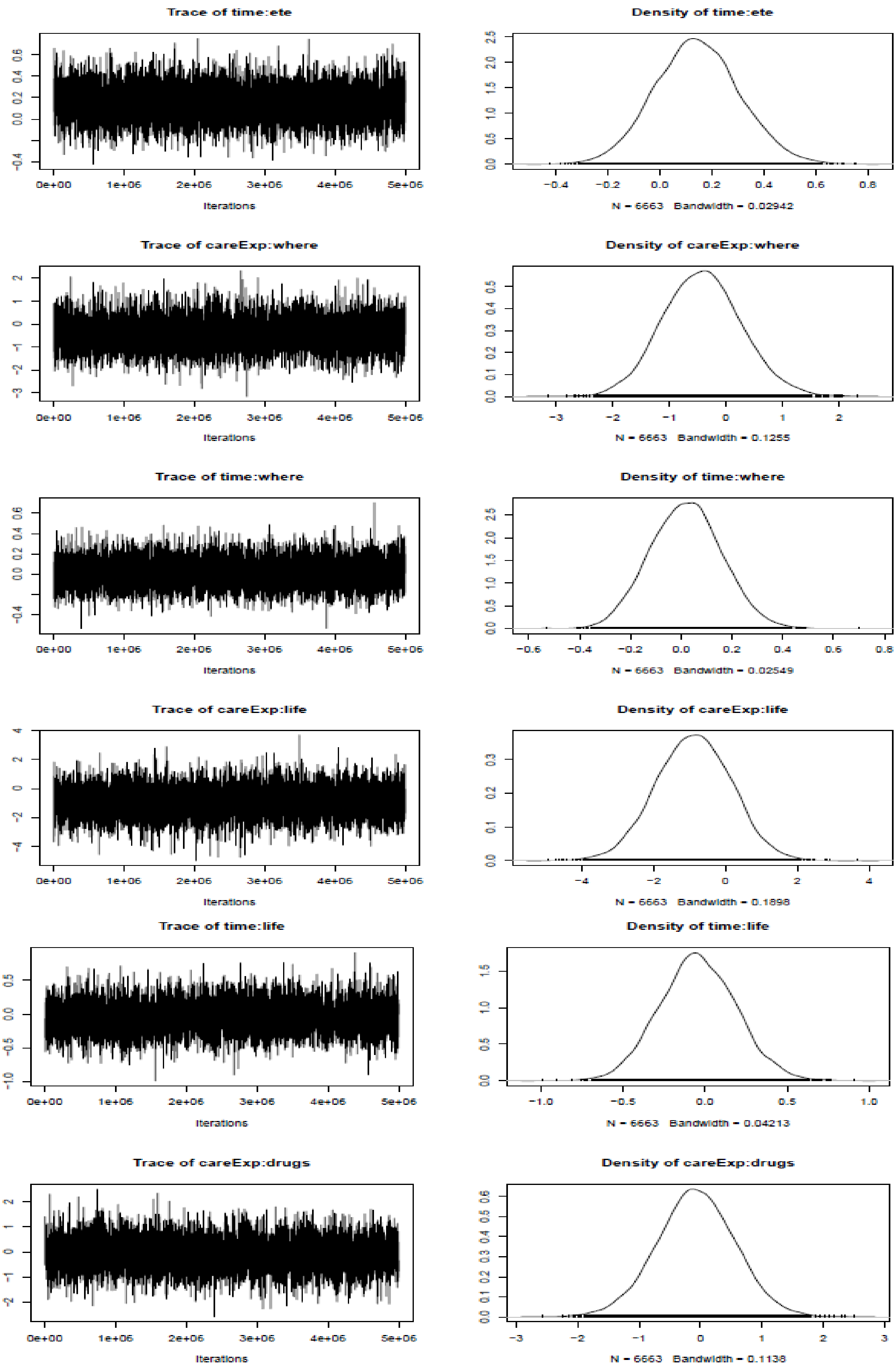
Fixed Effects

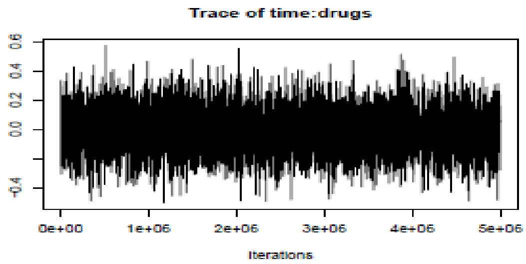
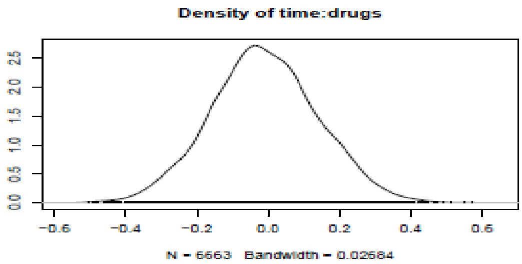
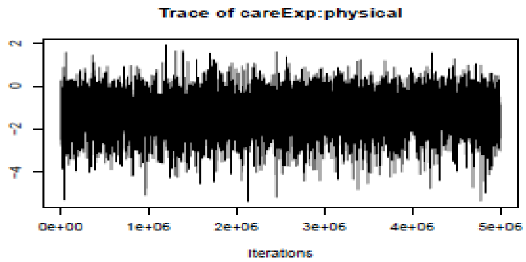
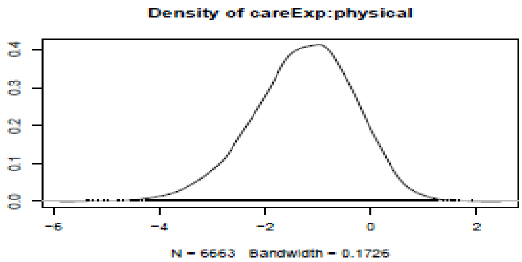
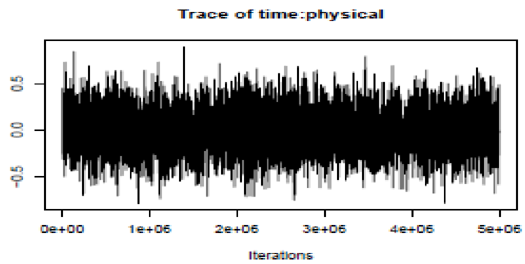
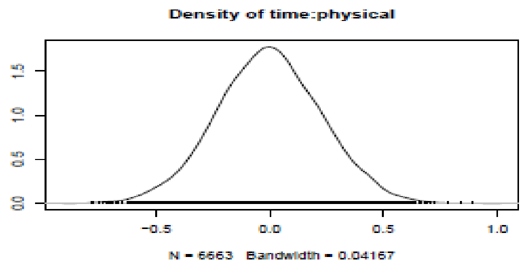
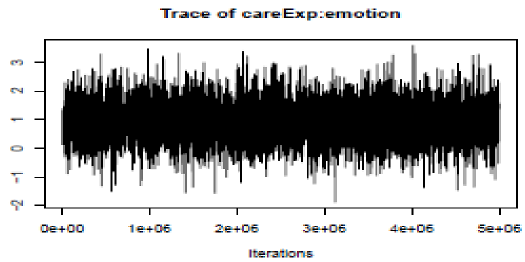
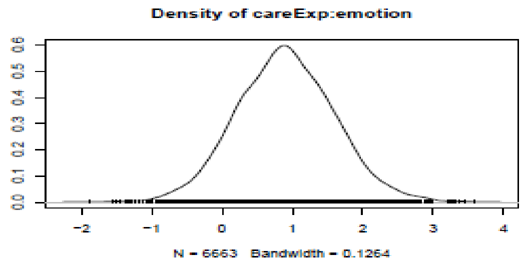
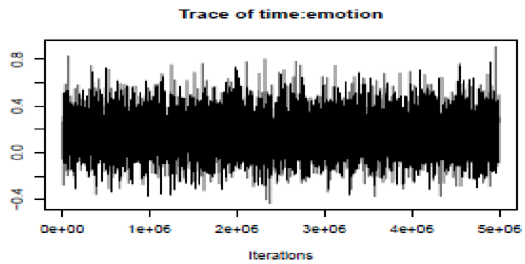
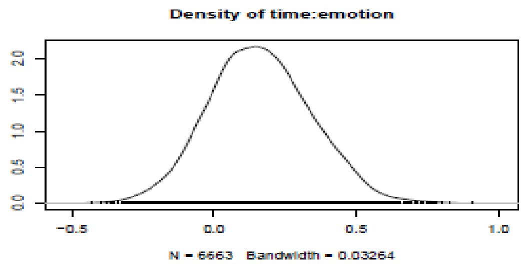
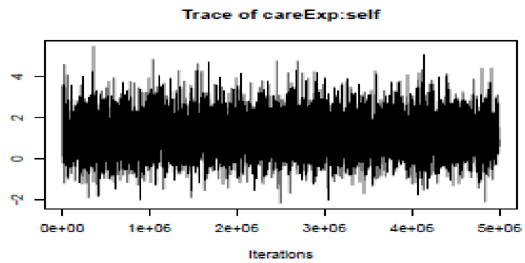
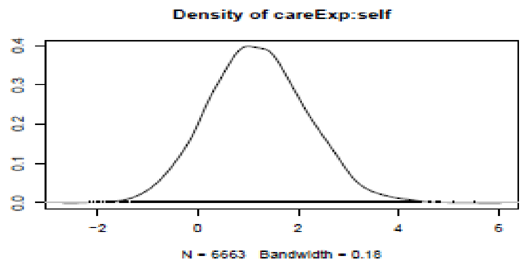


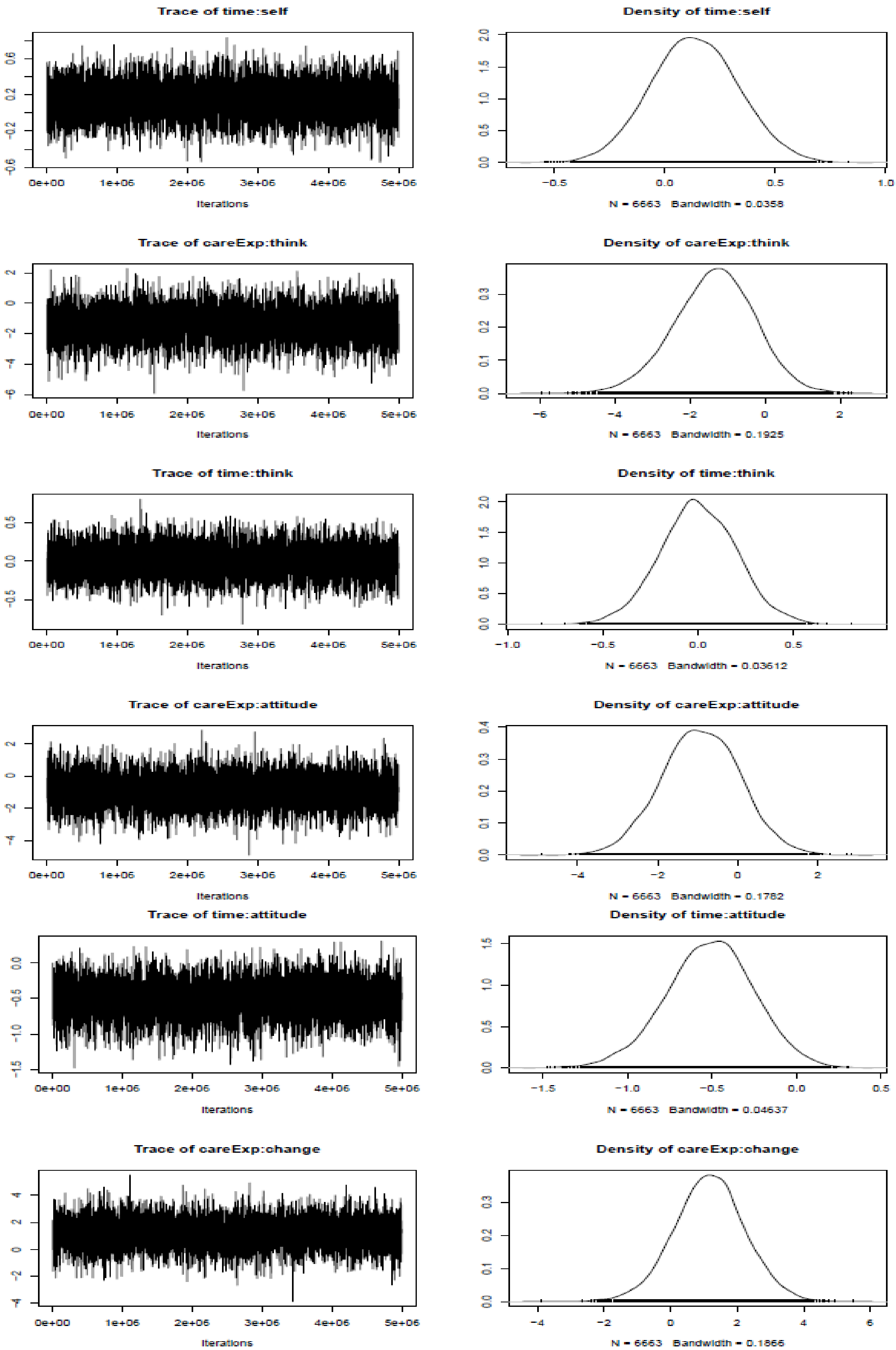

Trace of where
Iterations
Density of where
N = 6663 Bandwidth = 0.1256
Trace of life
Iterations
Density of life
N = 6663 Bandwidth = 0.1811
Trace of drugs
Iterations
Density of drugs
N = 6663 Bandwidth = 0.1372
Trace of physical
Iterations
Density of physical
N = 6663 Bandwidth = 0.1565
Trace of emotion
Iterations
Density of emotion
N = 6663 Bandwidth = 0.1254
Trace of self
Iterations
Density of self
N = 6663 Bandwidth = 0.176

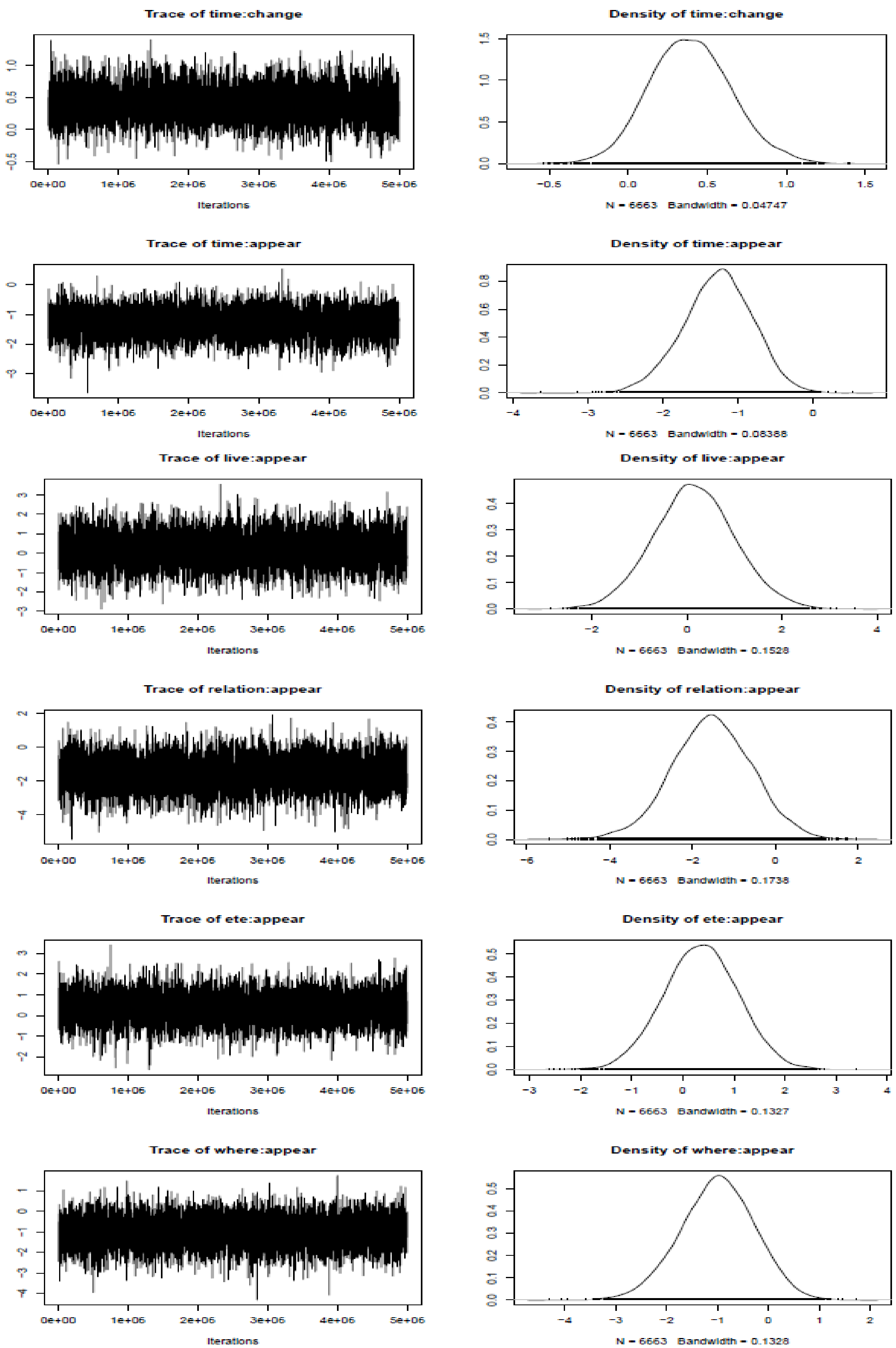

Trace of think
Iterations
Density of think
N = 6663 Bandwidth = 0.1617
Trace of attitude
Iterations
Density of attitude
N = 6663 Bandwidth = 0.1782
Trace of change
Iterations
Density of change
N = 6663 Bandwidth = 0.2052
Trace of appear
Iterations
Density of appear
N = 6663 Bandwidth = 0.4067
Trace of breach
Iterations
Density of breach
N = 6663 Bandwidth = 0.1473
Trace of custody
Iterations
Density of custody
N = 6663 Bandwidth = 0.3136

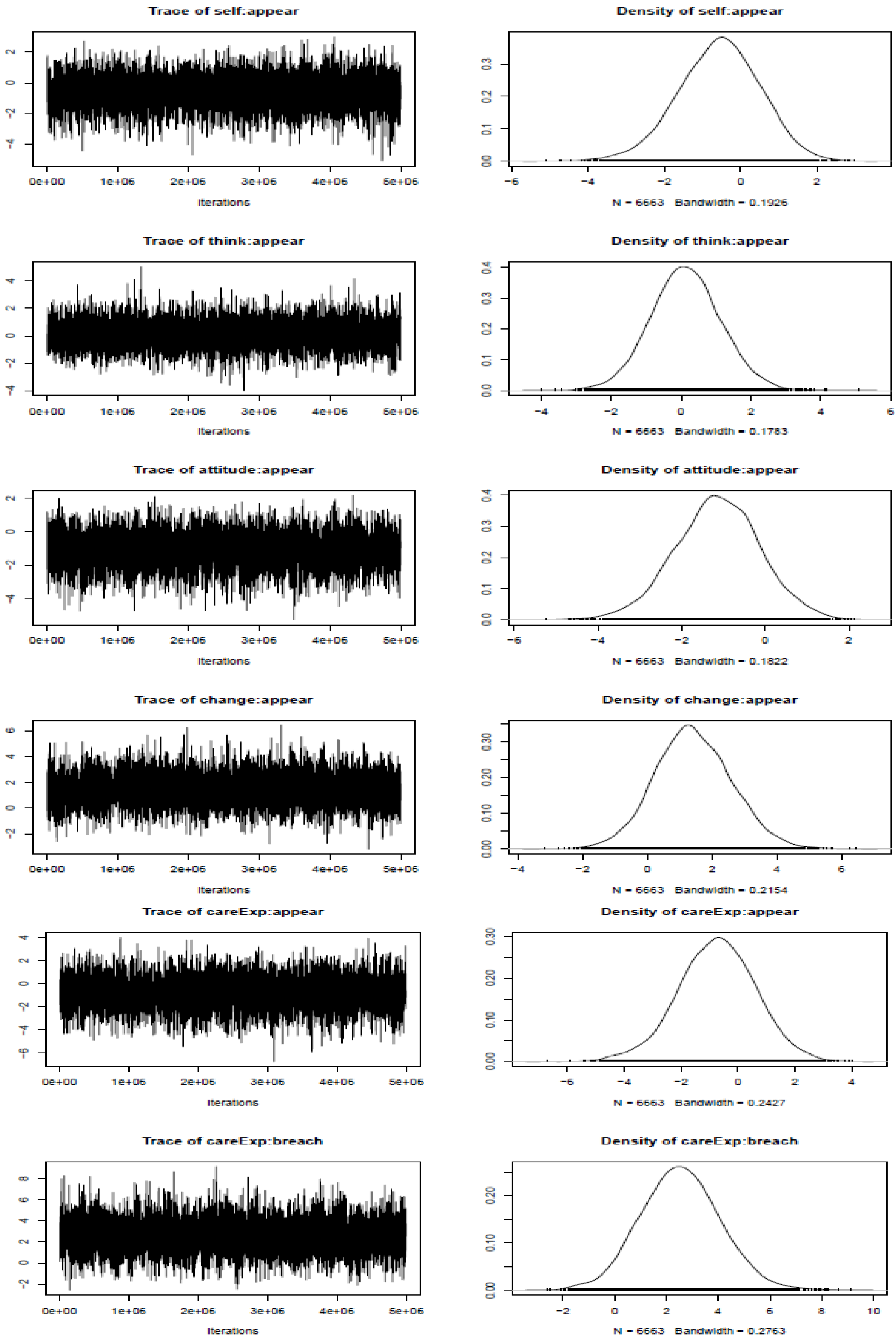

Trace of careExp:time
Iterations
Density of careExp:time
N = 6663 Bandwidth = 0.08003
Trace of careExp:live
Iterations
Density of careExp:live
N = 6663 Bandwidth = 0.1305
Trace of time:live
Iterations
Density of time:live
N = 6663 Bandwidth = 0.03615
Trace of careExp:relation
Iterations
Density of careExp:relation
N = 6663 Bandwidth = 0.1569
Trace of time:relation
Iterations
Density of time:relation
N = 6663 Bandwidth = 0.0391
Trace of careExp:ete
Iterations
Density of careExp:ete
N = 6663 Bandwidth = 0.13

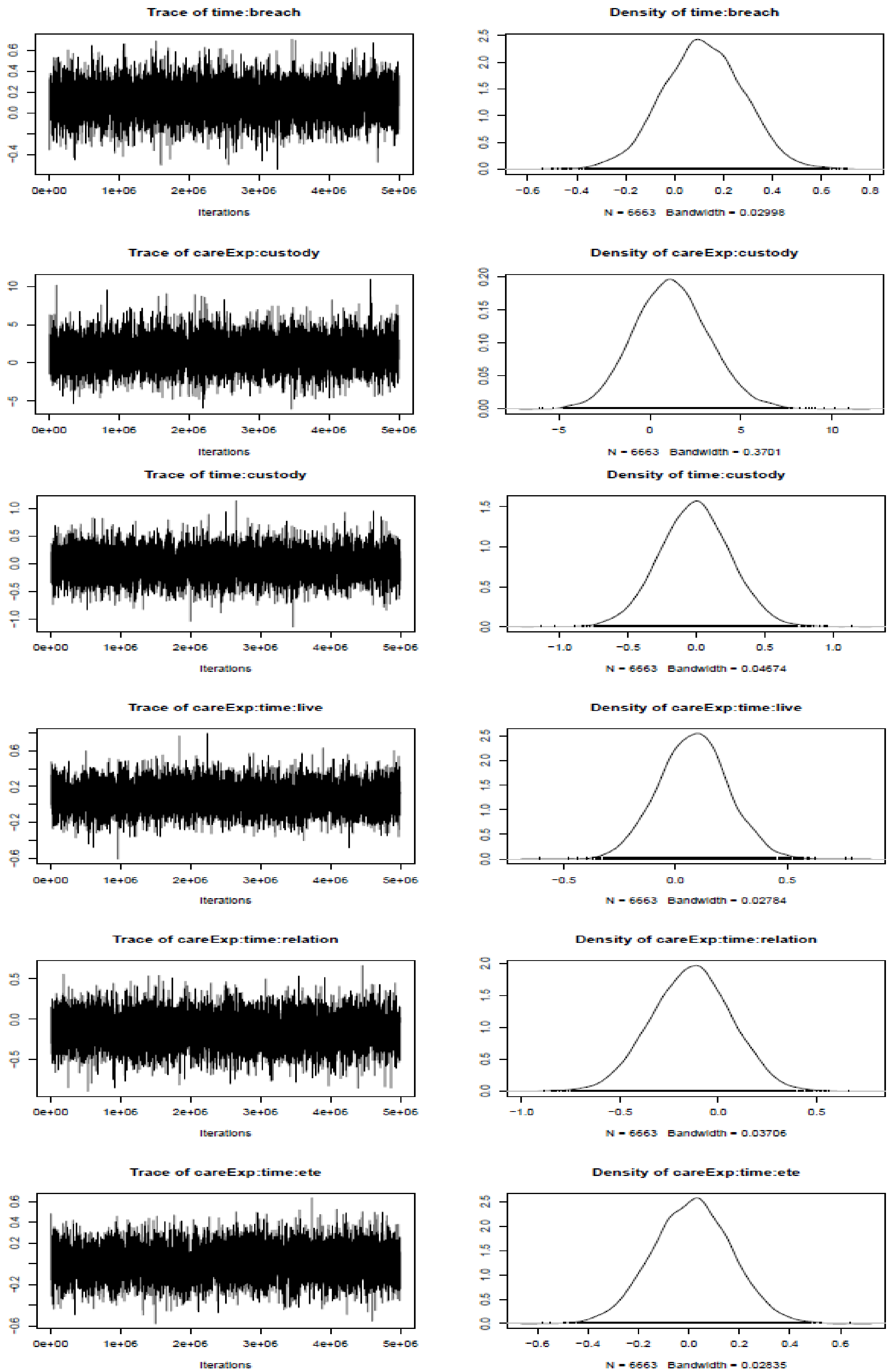

Trace of time:ete
Iterations
Density of time:ete
N = 6663 Bandwidth = 0.02942
Trace of careExp:where
Iterations
Density of careExp:where
N = 6663 Bandwidth = 0.1255
Trace of time:where
Iterations
Density of time:where
N = 6663 Bandwidth = 0.02549
Trace of careExp:life
Iterations
Density of careExp:life
N = 6663 Bandwidth = 0.1898
Trace of time:life
Iterations
Density of time:life
N = 6663 Bandwidth = 0.04213
Trace of careExp:drugs
Iterations
Density of careExp:drugs
N = 6663 Bandwidth = 0.1138

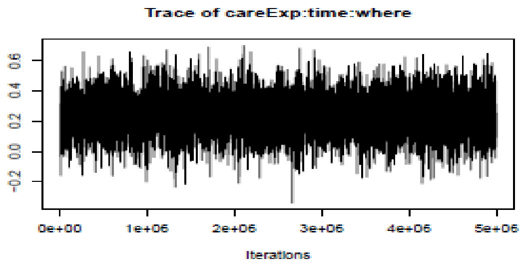

Trace of time:drugs
Iterations

Density of time:drugs
N = 6663 Bandwidth = 0.02684

Trace of careExp:physical
Iterations

Density of careExp:physical
N = 6663 Bandwidth = 0.1726

Trace of time:physical
Iterations

Density of time:physical
N = 6663 Bandwidth = 0.04167

Trace of careExp:emotion
Iterations

Density of careExp:emotion
N = 6663 Bandwidth = 0.1264

Trace of time:emotion
Iterations

Density of time:emotion
N = 6663 Bandwidth = 0.03264

Trace of careExp:self
Iterations

Density of careExp:self
N = 6663 Bandwidth = 0.18

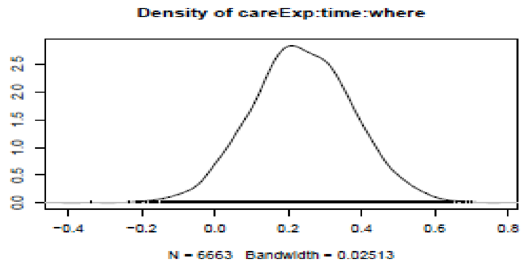

Trace of time:self
Iterations
Density of time:self
N = 6663 Bandwidth = 0.0358
Trace of careExp:think
Iterations
Density of careExp:think
N = 6663 Bandwidth = 0.1925
Trace of time:think
Iterations
Density of time:think
N = 6663 Bandwidth = 0.03612
Trace of careExp:attitude
Iterations
Density of careExp:attitude
N = 6663 Bandwidth = 0.1782
Trace of time:attitude
Iterations
Density of time:attitude
N = 6663 Bandwidth = 0.04637
Trace of careExp:change
Iterations
Density of careExp:change
N = 6663 Bandwidth = 0.1866

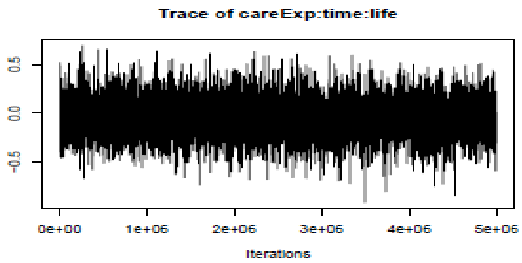

Trace of time:change
Iterations
Density of time:change
N = 6663 Bandwidth = 0.04747
Trace of time:appear
Iterations
Density of time:appear
N = 6663 Bandwidth = 0.08388
Trace of live:appear
Iterations
Density of live:appear
N = 6663 Bandwidth = 0.1528
Trace of relation:appear
Iterations
Density of relation:appear
N = 6663 Bandwidth = 0.1738
Trace of ete:appear
Iterations
Density of ete:appear
N = 6663 Bandwidth = 0.1327
Trace of where:appear
Iterations
Density of where:appear
N = 6663 Bandwidth = 0.1328

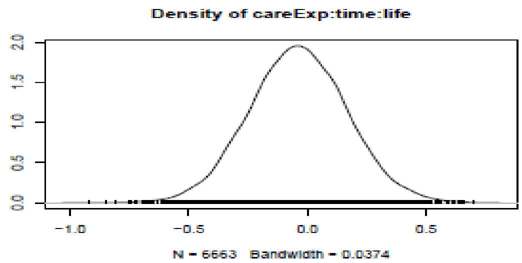

Trace of self:appear
Iterations
Density of self:appear
N = 6663 Bandwidth = 0.1926
Trace of think:appear
Iterations
Density of think:appear
N = 6663 Bandwidth = 0.1783
Trace of attitude:appear
Iterations
Density of attitude:appear
N = 6663 Bandwidth = 0.1822
Trace of change:appear
Iterations
Density of change:appear
N = 6663 Bandwidth = 0.2154
Trace of careExp:appear
Iterations
Density of careExp:appear
N = 6663 Bandwidth = 0.2427
Trace of careExp:breach
Iterations
Density of careExp:breach
N = 6663 Bandwidth = 0.2763

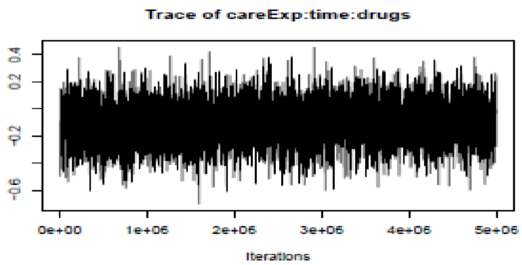

Trace of time:breach
Iterations
Density of time:breach
N = 6663 Bandwidth = 0.02998
Trace of careExp:custody
Iterations
Density of careExp:custody
N = 6663 Bandwidth = 0.3701
Trace of time:custody
Iterations
Density of time:custody
N = 6663 Bandwidth = 0.04674
Trace of careExp:time:live
Iterations
Density of careExp:time:live
N = 6663 Bandwidth = 0.02784
Trace of careExp:time:relation
Iterations
Density of careExp:time:relation
N = 6663 Bandwidth = 0.03706
Trace of careExp:time:ete
Iterations
Density of careExp:time:ete
N = 6663 Bandwidth = 0.02835

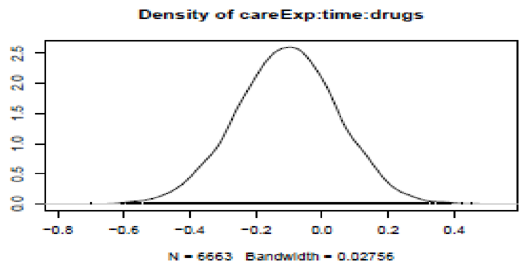

Trace of careExp:time:where
Iterations

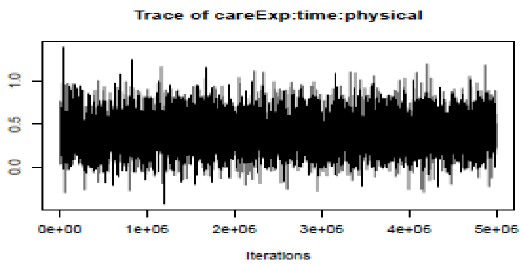

Density of careExp:time:where
N = 6663 Bandwidth = 0.02513

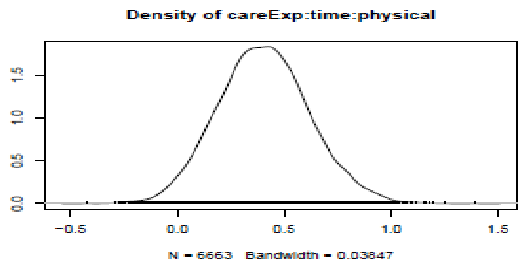

Trace of careExp:time:life
Iterations

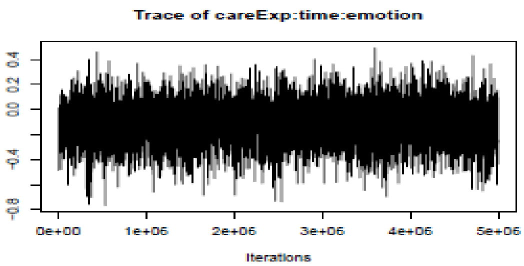

Density of careExp:time:life
N = 6663 Bandwidth = 0.0374

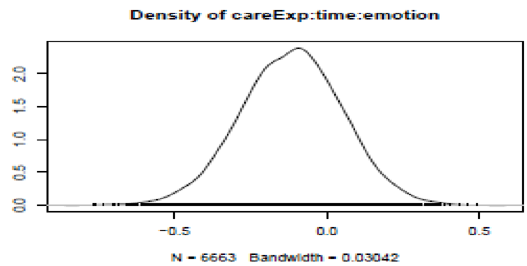

Trace of careExp:time:drugs
Iterations

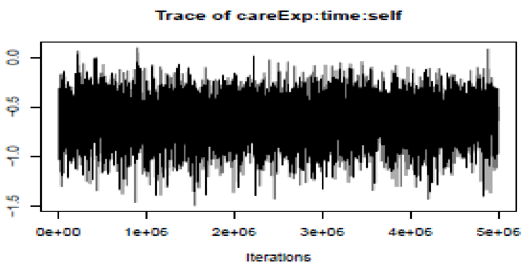

Density of careExp:time:drugs
N = 6663 Bandwidth = 0.02756

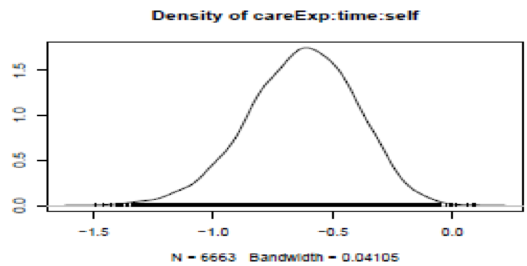

Trace of careExp:time:physical
Iterations

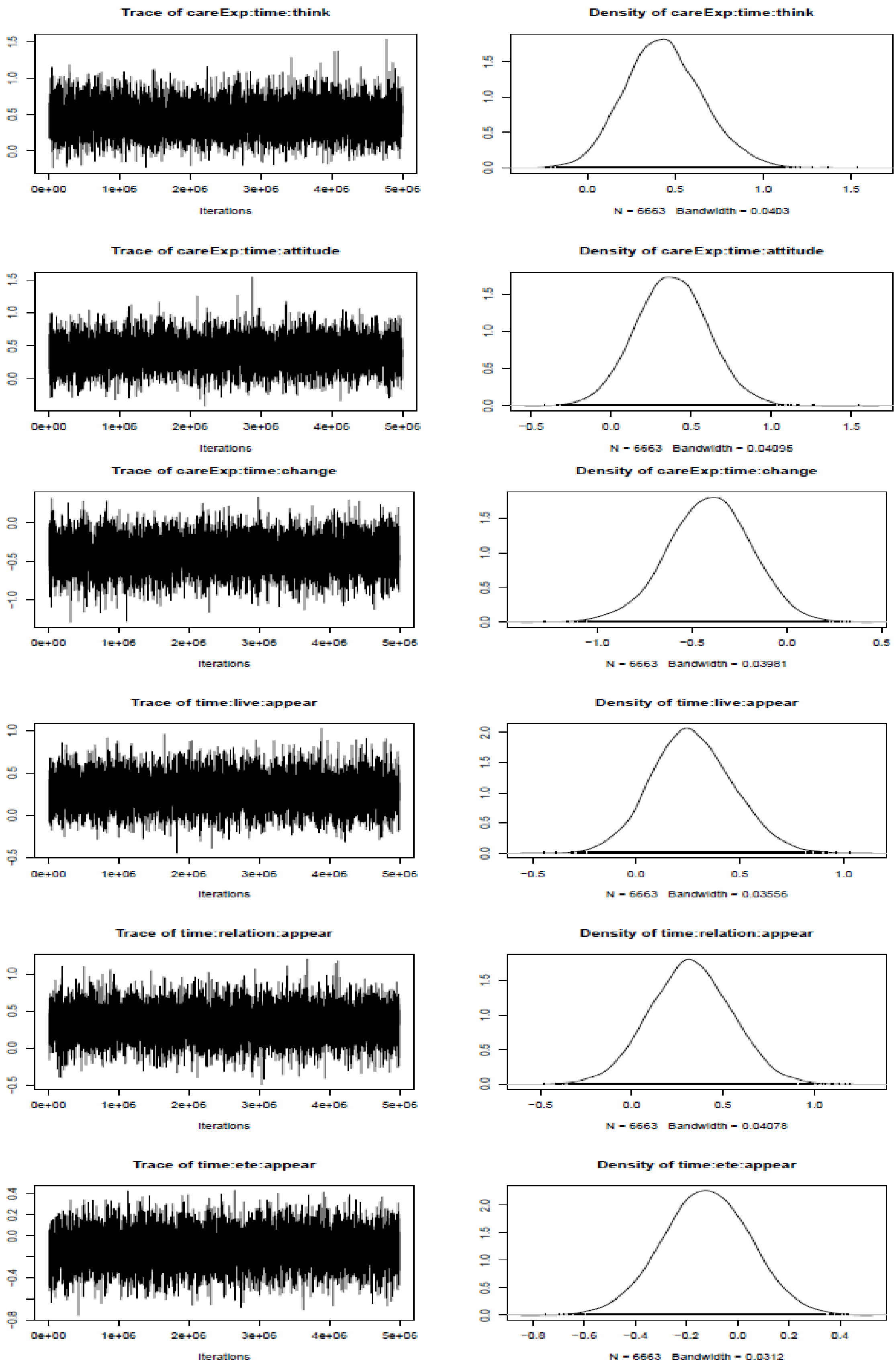

Density of careExp:time:physical
N = 6663 Bandwidth = 0.03847

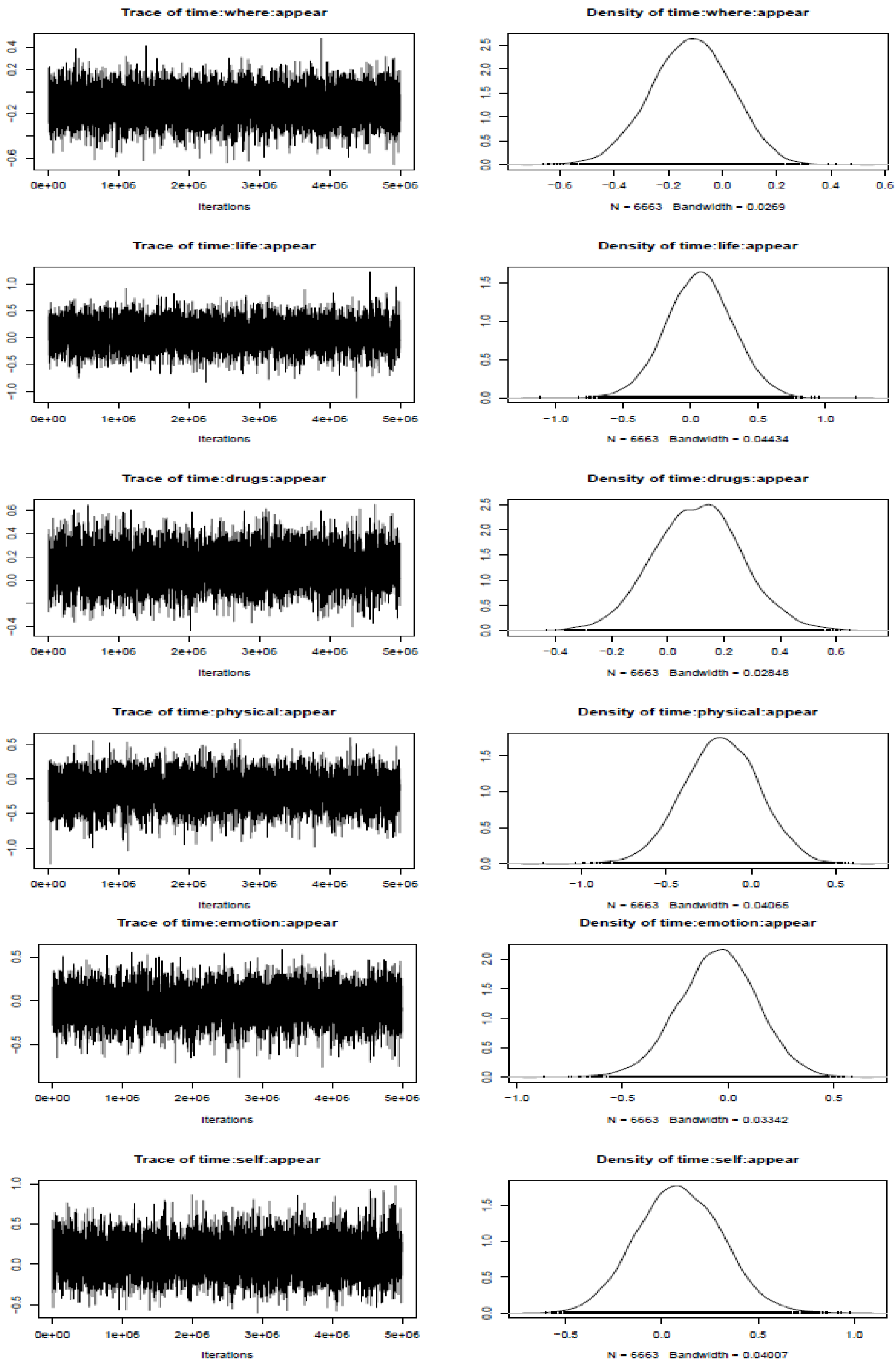

Trace of careExp:time:emotion
Iterations

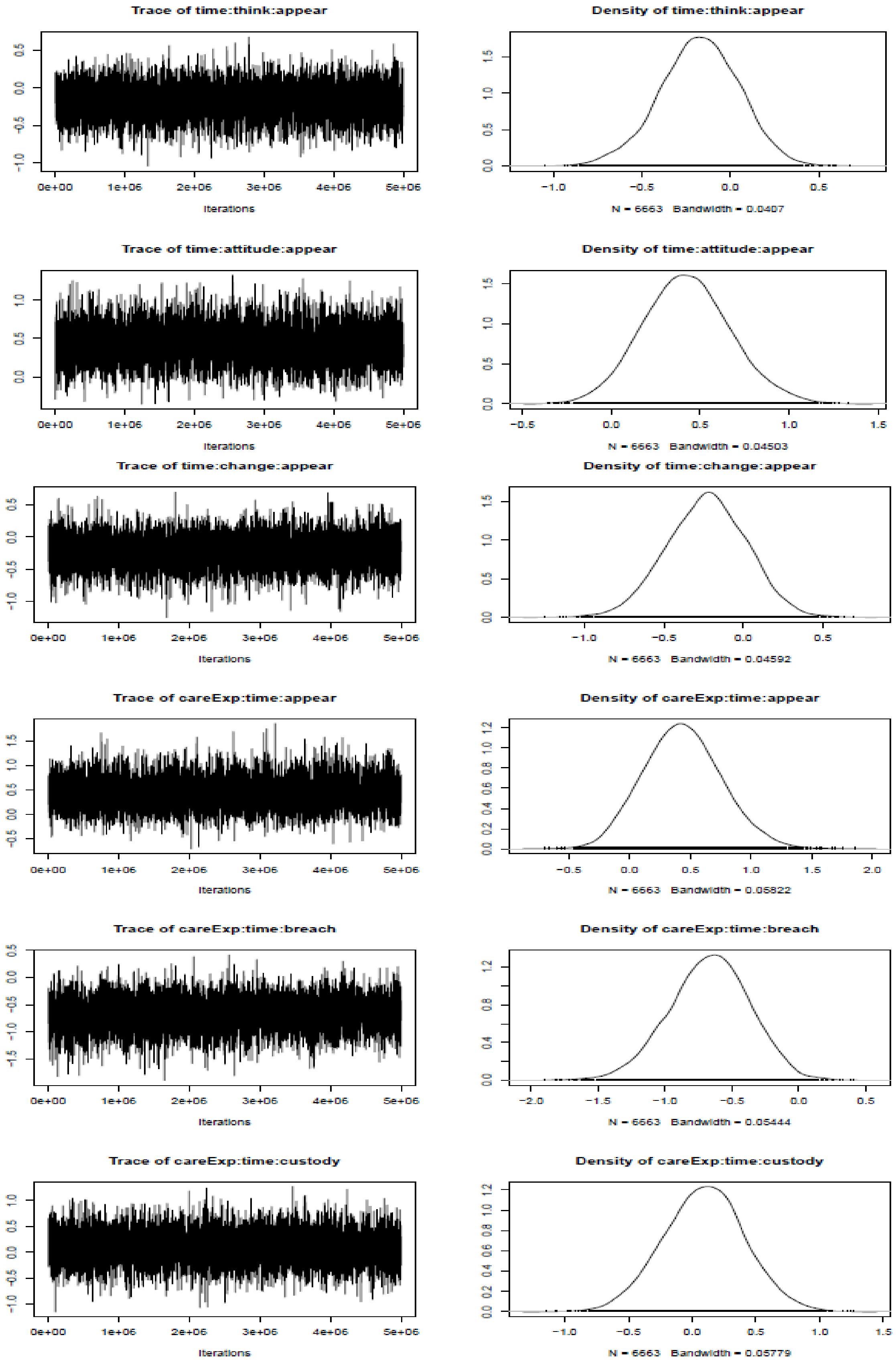

Density of careExp:time:emotion
N = 6663 Bandwidth = 0.03042


Trace of careExp:time:self
Iterations

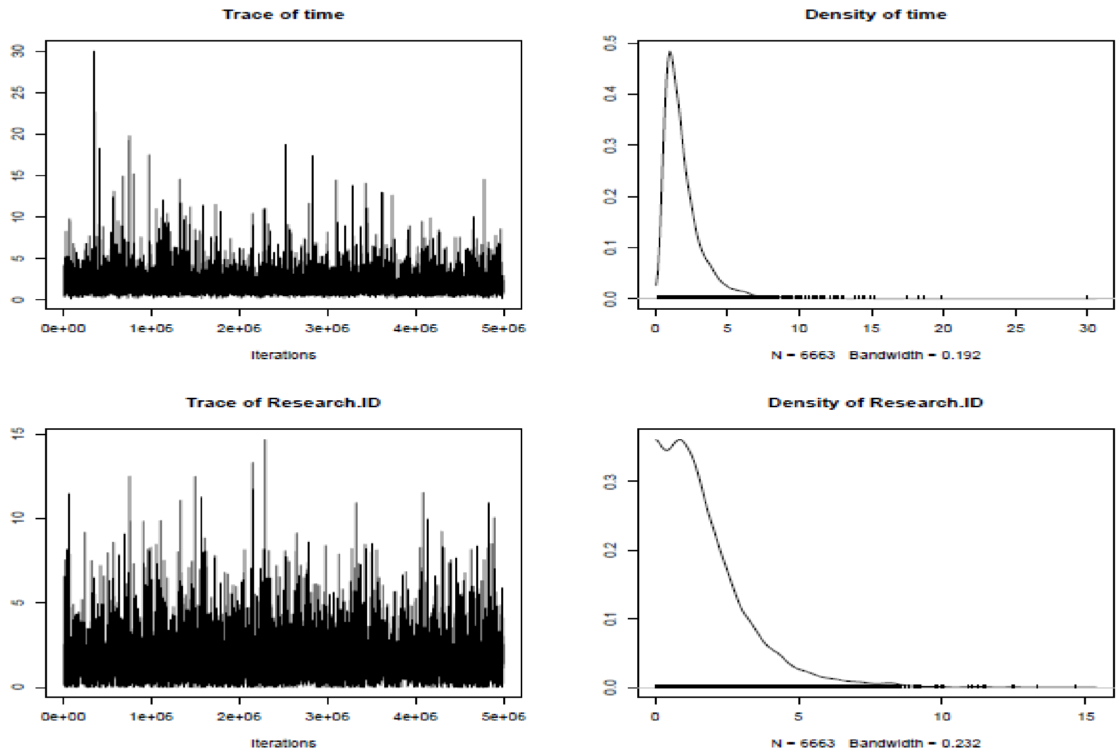

Density of careExp:time:self
N = 6663 Bandwidth = 0.04105


Trace of careExp:time:think
Iterations
Density of careExp:time:think
N = 6663 Bandwidth = 0.0403
Trace of careExp:time:attitude
Iterations
Density of careExp:time:attitude
N = 6663 Bandwidth = 0.04095
Trace of careExp:time:change
Iterations
Density of careExp:time:change
N = 6663 Bandwidth = 0.03981
Trace of time:live:appear
Iterations
Density of time:live:appear
N = 6663 Bandwidth = 0.03556
Trace of time:relation:appear
Iterations
Density of time:relation:appear
N = 6663 Bandwidth = 0.04078
Trace of time:ete:appear
Iterations
Density of time:ete:appear
N = 6663 Bandwidth = 0.0312


Trace of time:where:appear
Iterations
Density of time:where:appear
N = 6663 Bandwidth = 0.0269
Trace of time:life:appear
Iterations
Density of time:life:appear
N = 6663 Bandwidth = 0.04434
Trace of time:drugs:appear
Iterations
Density of time:drugs:appear
N = 6663 Bandwidth = 0.02848
Trace of time:physical:appear
Iterations
Density of time:physical:appear
N = 6663 Bandwidth = 0.04065
Trace of time:emotion:appear
Iterations
Density of time:emotion:appear
N = 6663 Bandwidth = 0.03342
Trace of time:self:appear
Iterations
Density of time:self:appear
N = 6663 Bandwidth = 0.04007


Trace of time:think:appear
Density of time:think:appear
Iterations
N = 6663 Bandwidth = 0.0407
Trace of time:attitude:appear
Density of time:attitude:appear
Iterations
N = 6663 Bandwidth = 0.04503
Trace of time:change:appear
Density of time:change:appear
Iterations
N = 6663 Bandwidth = 0.04592
Trace of careExp:time:appear
Density of careExp:time:appear
Iterations
N = 6663 Bandwidth = 0.05822
Trace of careExp:time:breach
Density of careExp:time:breach
Iterations
N = 6663 Bandwidth = 0.05444
Trace of careExp:time:custody
Density of careExp:time:custody
Iterations
N = 6663 Bandwidth = 0.05779

Random Effects



7. References

Finch WH, Bolin JE and Kelley K. (2014) *Multilevel Modeling Using R,* Boca Raton, FL: CRC Press.

Youth Justice Board. (2008a) *Asset Core Profile - Guidance*. Available at: https://www.gov.uk/government/publications/asset-documents. (Accessed 31/1/18).

Youth Justice Board. (2008b) *Asset Core Profile - Introduction*. Available at: https://www.gov.uk/government/publications/asset-documents. (Accessed 31/1/18).