Aversion and Ambiguity: On the Robustness of the Macroeconomic Uncertainty Measure Framework

Abstract

The economic literature has focused on the role of uncertainty in the real economy, employing both measures of risk aversion and ambiguity aversion in structural models. In this connection, concerns about the measures for VIX and EPU, have been raised about whether or not they both measure and identify similar type of uncertainty. Using a structural vector autoregressive (SVAR) approach, we examine the relationship between VIX and EPU, their impact on the real economy and whether, and under which conditions, they can be distinguished between measures of risk aversion and ambiguity aversion. Specifically, we analyse the impact of uncertainty shocks of VIX and EPU on the industrial production, unemployment, and consumer credit in the US. Our main finding is that given their fundamental differences, the two measures are capturing different dimensions of uncertainty, VIX is a measure of risk aversion and EPU is a measure of ambiguity aversion. As such, our results are very important in terms of trading decision strategies to be implemented by investors and portfolio managers as it may help explain the two central behavioural traits affecting economic lifecycle problems, such as production, unemployment and consummation.

Keywords: Ambiguity aversion; Risk aversion; Industrial Production; Unemployment rate; Consumer credit; SVAR-test framework

JEL Codes: D91, G11, J17

1. Introduction

In behavioural economics, the term “uncertainty” has been largely misinterpreted due to its polysemous nature and conceptual inclusion of a diverse range of nuances corresponding to various economic consequences (Bloom, 2014). Since the time of the Great depression, scholars started decomposing the concept, and its influence on the behaviour of the economic agents or their sentiment related actions (Brunnermeier and Pedersen, 2009; Abedin et al., 2023; Bouteska et al., 2023a), and the real economy at large (Baker et al., 2020; Kumar et al., 2023), such as output growth, exchange rates, unemployment, and business cycle (Fernández-Villaverde and Guerrón-Quintana, 2020). The theoretical framework on how the economy reacts to uncertainty shocks flourished in economic literature of the early 1980s (e.g., Bernanke, 1983). Voluminous attempts to measure the nature and magnitude of uncertainty in real economy, mainly financial markets, took place in the Millenium eras (e.g., Beber and Brandt, 2008; David 2008; Anderson et al., 2009; Buraschi et al., 2013; Aramonte, 2014; Bali et al., 2014, 2017; David and Veronesi, 2014; Sharif et al., 2015; Bali and Zhou, 2016; Kelly et al., 2016; Xyngis, 2017; Bouteska et al., 2023a, 2023b, 2023c; Chen et al., 2023; Yadav et al. 2023). Due to topical importance of the time related to volatility in the digital currency, research on cryptocurrencies started gaining popularity recently (e.g., Luo et al., 2021; Lucey et al., 2022; Wang et al., 2022). In common, the growing influence of uncertainty on decision making of the economic agents has been evident in all these studies, given its real irreversibilities in investment or partial irreversibility and undesirability in credit creation due to financial frictions that impede the borrowing power of individuals and corporations (Gulen and Ion, 2015; Kim and Kung, 2017; Valencia, 2017; Chow et al., 2018; David and Veronesi, 2022). Following a significant decline in the volatility in business cycles during the “Great Moderation period”, the emergence of the recent Black Swan events (Taleb, 2007; Yousaf et al., 2022), i.e., the COVID-19 pandemic (Albulescu, 2020; Bouteska et al., 2023c; Sharif et al., 2020), and the Russia-Ukraine conflict (Chen et al., 2023), have sharply elevated uncertainty and hence deepened scholars’ interest in measuring uncertainty and its transmissions to the economy (Szafranek et al., 2023). Nonetheless, given that various dimensions of uncertainty exert diverse influence on investors’ decision-making process in a real economy, extant literature on structural models still lacks reliable gauges to quantify with greater precision the implication of the shocks arising from various dimensions of uncertainty (Fernández-Villaverde and Guerrón-Quintana, 2020).

“Uncertainty is inherently a latent variable. Consequently, it cannot be precisely measured and must be approximated” (Szafranek et al., 2023, p.2). Due to the vagueness in capturing various nuances/dimensions constituting the concept of uncertainty (Cascaldi-Garcia et al., 2020), structural models in economic literature have commonly used general measures of quantifying uncertainty, sidelining a vital but complex task of empirically differentiating between risk and ambiguity – the two key dimensions of uncertainty (Golman et al., 2021; Moore, 2017). Extant literature dating back to the past two decades has documented multiple measures of risk, uncertainty, and volatility in real economy. Among all, “the most popular methods to measure economic uncertainty are based on pure financial market prices (such as volatility), structural approaches based on macroeconomic fundamental data as well as market prices, textual based, or survey based” (David and Veronesi, 2022, p.440), and, based on the nature of coverage of issues of relevance, the implied volatility index (VIX) and the economic policy uncertainty (EPU) are recognised as the more popular indices of measuring uncertainty (Białkowski et al., 2022). The VIX was introduced by the Chicago Board Options Exchange (CBOE) in 1993, and later popularised by Bloom (2009) as a finance-based measure of uncertainty. Often referred to as the fear index, the VIX measures the level of portfolio protection in the financial market by assessing the 30-day volatility implied in the price of the S&P500 index at the money options. As a more direct proxy of uncertainty, Baker et al. (2016) proposed to construct EPU index by aggregating three news-based proxies (components) of uncertainty, e.g., fiscal matters, government spending, and general elections (Al-Thaqeb et al., 2020), related to a specific nuance of the concept of uncertainty, i.e., ambiguity. Since higher frequency in articles is indicative of the perceived ambiguity of the general public caused by lack and/or weak interpretation of information (Williams et al., 2022), the EPU index is able to capture the ambiguity aversion behaviour of the investors (Bouteska et al., 2023a). In terms of facing-off between the VIX and the EPU, the structural models in the extant literature have shown preferance to make an interchangeable use of these measures, due to their high level of correlations (David and Veronesi, 2022). On the contrary, the correlation between these two measures decoupled drastically in specific periods since mid-2010 with a puzzlingly low VIX and a sky-rocketting S&P 500 index and EPU, following the 2015 UK general election, the BREXIT referendum and the 2016 US presidential election (Białkowski et al., 2022; David and Veronesi, 2022). This backdrop implies the possibility of the repeats of a low VIX index and a high EPU index during uncertain periods, leading to a confusing behaviour of investors due to their difficulties in interpreting ambiguous political signals, and raises concerns regarding the closeness of VIX and EPU in measuring similar type of uncertainty (Pastor & Veronesi, 2017; Tiwari et al., 2019). We anticipate a similar scenario in connection with the emergence of the very recent Black Swan events, and therefore consider the task of venturing into the conceptual and measurement black box related to uncertainty of paramount importance.

Given the above backdrop, we build on the works by Pastor and Veronesi (2013, 2017), and argue that investors show a responsive behaviour to the ambiguity of the information received, and accordingly aim to examine the relationship between VIX and EPU, their impact on the real economy and their potential distinctiveness as measures of risk and ambiguity aversions, respectively. We follow an unpublished work of Melany (2019) and make an opening for an investigation on the distinctions between VIX and EPU in a decoupling manner, in connection with industrial output, unemployment rate and consumer credit in the US during the January 1994 – February 2023 period. Overall, the empirical outcomes of this study reveal the countervailing nature of the VIX index and the EPU index, which can induce recessions. It implies that a shock in these measures is associated to a fall in industrial production (IP) and consumer credit (CC), and an increase in unemployment rate (UR), thus evidencing the influence of both measures on the US business cycle. This paper empirically demonstrates that the EPU index captures a slightly different dimension of uncertainty than just risk, and this finding could be extended to all news-based measures. In particular, the results show that there is weak empirical evidence that VIX is a measure of risk aversion and EPU is a measure of ambiguity aversion, given the fundamental differences between these two uncertainty proxies. Thus, we emphasise the importance of checking the robustness of results by using different uncertainty measures.

It is evident that many research works in the post Millennium eras have examined the relation between VIX and EPU (Deutsche Bank Research, 2018; Shaikh, 2019) and produced mixed outcomes in various country contexts whereas a few of them endeavored to explain the measurement puzzle associated with the decoupling of VIX and EPU indices (e.g., Pastor and Veronesi, 2017; Tiwari et al., 2019). For instance, in the developed market context, the VIX has evolved to be the most instrumental uncertainty measuring index, followed by the EPU. In Brazil and India, the co-movements between oil and stock prices have appeared to be more sensitive to the VIX whereas the same in China is found to be more susceptible to the EPU (Chen, 2023). Although both are equally valued as measures of uncertainty in behavioural finance, the VIX has earned recognition to be a more popular and dominant measure than the EPU (Gong et al., 2022). However, we argue in this study that they are conceptually different and they may capture different aspects of uncertainty, i.e., risk and ambiguity, as pinpointed in our review of literature below. In this connection, the originality of this study is reflected through the novel attempt of elucidating the distinctions between the aforementioned indexes using the notion of ambiguity aversion, which is sparse in the extant literature.

The rest of this paper is structured as follows. In Section 2, we review the definition of uncertainty, and we detail the differences among VIX and EPU. We describe the sample of data and the structural vector autoregressive (SVAR) approach used in our analysis in Section 3. In Section 4, we present and discuss the empirical results. Finally, we conclude in Section 5, where we also discuss some policy implications.

2. Literature review

Over the last half-century, the notion of "uncertainty" has evolved with multiple dimensions (Bradley and Drechsler, 2014), ensueing developments of numerous frameworks, typologies and taxonomies to understand and analyse uncertainty associated with large, complex, societally-coupled problems in many disciplines (Bevan, 2022). The pioneering contribution in understanding the concept of uncertainty comes from the seminal studies of Keynes (1921) and Knight (1921), who for the first time attempted to explain and analyse uncertainty from two distinct standpoints, namely, risk and ambiguity. The popularly known 'Knightian Risk' (Knight, 1921) postulated uncertainty to be both measurable and unmeasurable concept, exposing investors to a choice between known and unknown risks, respectively (Luo et al., 2021). Measurable group of uncertainties implies economic actors' awareness of all likely consequences of an uncertainty, and their ability to imagine a probability of each of the expected consequences using numbers and eliminate the risk using insurance market. On the contrary, the unmeasurable type implies economic actors' lack of knowledge or availability of information regarding the possibility of a likely occurrence related to uncertainty, and difficulty to eliminate the risks. Ramsey (1926) and Savage (1954) came up with the subjective probability theory, and argued that economic agents are able to use their professional judgements and hence develop some confidence to infer a numeric probability of occurrence. For example, professional gamblers show their subjective numerical probability distribution of events by placing a bet on the possible occurrence of a particular event. According to this stream of literature, "the beliefs of a decision-maker are captured by a well-defined probability distribution of possible outcomes", influencing economic agents on displaying almost indifferent behaviour to risky or uncertain events (Luo et al., 2021, p.2).

Ellsberg (1961) reinterpreted uncertainty by establishing links of the measurable and unmeasurable categories with the notions of ambiguity and ambiguity aversion, based on a famously known experiment, namely, "Two-Urns Ellsberg Paradox". The experiment set four bets of arbitrarily picking a ball from two urns that contained 100 red and black colour balls. In the first urn, colours were distributed without any particular order whereas red and black balls were equally allocated in the second urn. Bets B1 and B2 required drawing of a red ball from urns 1 and 2 respectively. Likewise, bets B3 and B4 required drawing of a black ball from urns 1 and 2 respectively. Although individuals displayed indifferent behaviour of drawing associated with each urn, i.e., urn

1 corresponding to B1 and B3 and urn 2 corresponding to B2 and B4, they eventually showed an inclination to place bets on urn 2 that contained an equal number of balls. This tendency was indicative of an "ambiguity aversion" behaviour of the individuals' to remain in the comfort zone having a certain degree of probability. Ellsberg (1961) also pinpointed the presence of "ambiguity of information" in ambiguous situations that affects an economic agent's poise to predict the likelihood of an occurrence. Following Ellsberg (1961), a number of succeeding researchers (e.g., Lawson, 1985; Runde, 1990) interpreted ambiguity based on the "degree of completeness of information". For example, Bradley and Drechsler (2014) explored the degree of knowledge or awareness of market situations and concluded that an individual is: (a) not able to make any judgement at all (*ignorance*), (b) make fractional judgement (*severe uncertainty*), (c) make a possible judgement (*mild uncertainty*), or (d) make a judgement which has known outcome (*certainty*).

Literature documents numerous contemporary studies on ambiguity, mainly related to equity markets (e.g., Anderson et al., 2009; Ulrich, 2013; Antoniou et al., 2015; Williams, 2015; Brenner and Izhakian, 2018; Bianchi and Tallon, 2019). For instance, Epstein and Schneider (2008) examined the influence of the quality of information on investors' decision making and suggested that ambiguity-averse investors show a tendency to respond strongly to negative information and react mildly to the positive ones. Kelsey et al. (2011) revealed that investors in momentum trading react differently to past winners and losers and hence create an asymmetric momentum impact while facing ambiguity. Antoniou et al. (2015) recorded an increase in the outflows of investments when equity markets bear ambiguity of information. In the context of the US stock markets, Brenner and Izhakian (2018) noted demand of the ambiguity-averse investors for a premium for facing ambiguity. Driouchi et al. (2018) scrutinised volatility of stock markets during the 2006–2008 subprime crisis, and noted a significant contribution of ambiguity to the rising volatility. Bianchi and Tallon (2019) documented higher mobility of ambiguity averse investors to the domestic stock market (home bias) and a poor inclination to diversification, and as a consequence getting exposed to higher risk. Among the meagre volume of studies on cryptocurrency markets, the contribution of Luo et al. (2021) is worth mentioning. The authors followed the methodological approach of Brenner and Izhakian (2018) and employed the asset price models, suggesting: an increasing aversive behaviour of Bitcoin investors to ambiguity, and insignificance of the risk premium during periods of high ambiguity. Despite all these findings, as Snow (2010) and

Cavatorta and Schröder (2019) stressed, due to deficiency of information in ambiguous situations, decision-makers beliefs on the probabilities of outcomes are unknown.

As an amorphous concept, measuring uncertainty has always been complicated (Fernández-Villaverde & Guerrón-Quintana, 2020). The measures or indicators of uncertainty that researchers have developed in the past years can be classified broadly into three groups (Bontempi et al., 2016), namely, finance-based measures, forecasts-based measures, and news-based measures. The first group is based on the stock market volatility, corresponding to future uncertainties that investors face. The VIX index is one such measure that is popularly used for estimating uncertainty observed by investors, who are known to be a restricted group of economic agents. The second group of measures are based on the notion that the uncertainty is basically represented by the difficulty of forecasting the future. Therefore, as a proxy of the difficulty to predict the future, i.e., uncertainty, they measure the divergence amid various professional forecasts. The third group assumes media as an instrument through which uncertainty can be captured by the perception of the general public, and hence focuses on counting the frequency of publication of newspaper articles with certain words related to uncertainty. The reasoning behind this approach is that a high frequency of news with regard to a specific incidence is a reflective measure of how much the general public is worried about that matter. The EPU index is a renowned measure that belongs to the third group, as suggested by Baker et al. (2016). It tallies newspaper coverage of uncertainty arising from an economic policy change. One way of measuring such coverage is to count the number of individuals' internet searches using certain words corresponding to consequences of macro- and non-macro-related issues (Donadelli, 2014; Donadelli & Gerotto, 2019). Huang and Luk (2020) adopted the methodological approach of Baker et al. (2016) and investigated sensitive news related to uncertainty in ten most prominent newspapers in China.

It is evident that uncertainty is an unobservable phenomenon and the measures of uncertainty clearly manifest the absence of an objective way of measuring uncertainty, and this indicates the need of using a proxy in economic models. However, assessing the adequacy of a proxy is always difficult as some proxies are noisy and hence fail to capture the phenomenon in question. Given the above background, one way of judging a new measure of uncertainty in research is to look at its association with other renowned and popularly used measures. Indeed, due to the high correlation amid measures for the same phenomenon and their tendency to move together (Forbes, 2016), structural models are observed to use these measures in an interchangeable manner. However, given that the correlation of different measures of uncertainty with various macroeconomic variables varies depending on the type of measure chosen (Forbes, 2016), the interchangeably used measures in structural models might capture various aspects of uncertainty having different effect on the real economy. This observation justifies the reason why interest has grown in investigating what these indicators are actually capturing. For example, the rationale behind the interchangeable use of the VIX and EPU indices in structural models is their usual display of a high level of correlation. Evidence (Figure A, Appendix 1) suggests that the VIX and the EPU have tended to co-move, showing a correlation of about 45% from January 1994 to February 2023. During this period, volatility caused by uncertainty associated with economic policy change compelled investors to manage their distress by insuring their portfolios, resulting in a rise in the level of VIX. This corroborated the outcome of the implication of a model developed by Pastor and Veronesi (2013), which revealed the response of the financial markets to news covering economic policy-related uncertainty and argued for determining a risk premium on higher stock market volatility.

On the contrary, in the post-2010 period, the usual high correlation among the VIX and the EPU decoupled, diminishing drastically in three specific periods. In the first period that lasted till mid-2011, the time when the debt ceiling crisis happened, the correlation of the VIX with the EPU was estimated to be approximately -14%. In both the second period that ended in January 2013, the time when the fiscal cliff took place, and the third period that started after Trump's election in November 2016, the correlations of the VIX with the EPU were recorded to be approximately 7%. Likewise, the EPU and the VIX indices showed a persistently low asset price-based measures of financial market uncertainty in the UK, despite the rocketing rise in economic policy uncertainty in the months after the general election and the BREXIT referendum in 2016 (ECB, 2017). In general, all these periods highlighted the co-existence of a high degree of policy-related uncertainty (proxied by the EPU) and a low market volatility (measured by the VIX). The above theoretical and empirical face-off implies a puzzling decoupling scenario for the economic theory. In order to further explain the decoupling phenomenon, Pastor and Veronesi (2017) used the concept of precision of political signals, that provide an impression of the government's future course of action(s), as indicated by the sensitivity and the informative nature of the news. The authors postulated market volatility not only as a function of political uncertainty but also of the level of accuracy of political signals. For instance, in case of a higher accuracy of the political signals, investors are able to make better anticipations regarding government's future actions and the likely direction of the market, and act accordingly in making feasible decisions. On the contrary, in case of a lower accuracy of the political signals, investors struggle to interpret the information asymmetry in the news, and hence fail to renew their market perception, causing little impact on market volatility. An important insight of Pastor and Veronesi's (2017) interpretation is that investors' give rational reactions to the political signals, based on its levels of precisions investors can sense from news coverages.

In summary, the formulation of the aim of this study is influenced by the contributions of multiple studies, such as Knight (1921), Ellsberg (1961), Epstein and Schneider (2008), Antoniou et al. (2015), Pastor and Veronesi (2013, 2017), and so on. The Two-Urns experiment (Ellsberg, 1961) indicated investors' inclination to react to changes, based on the clarity of market information and their awareness of a likelihood (e.g., equally distributed red and black balls in run 2). Investors are influenced by the level of ambiguity of information (Epstein & Schneider, 2008), and accordingly react (Pastor & Veronesi, 2013, 2017) and change the degree of their involvement in the financial markets (Antoniou et al., 2015). Altogether, in ambiguous situations, "an agent's subjective knowledge about the likelihoods of contingent events is consistent with multiple probability distributions" which the agent is not usually aware of and, on the contrary, a unique probability distribution represents the perceived likelihoods of events in case of risky market conditions (Luo et al., 2021, p. 2). During the periods when the VIX and the EPU decoupled, i.e., the period immediately preceding the debt ceiling crisis of 2011, the period immediately preceding the fiscal cliff of January 2013, and the period immediately preceding Trump's election of November 2016, they coincide with periods of possibly high ambiguity of information. During these periods, a high EPU was followed by a low VIX, implying that investors were considering the consequences of an uncertainty as an outcome of ambiguity and not as a risk. Given that the latter can be and the former cannot be reduced using insurance market (Knight, 1921), e.g., the S&P500 option market, investors displayed an expected behaviour of not inclining to safeguard their portfolios through insurance, eventually producing a low impact on volatility. In view of the "decoupling" phenomenon of two variables losing their continued high correlation after 2010, this study focuses on investigating whether the VIX and EPU indices measure risk and ambiguity aversions respectively.

3. Data and methodology

This section presents the variables used in this study and briefly describes the SVAR model, used for the empirical analysis.

3.1 Methods

In this paper, we examine the implied volatility index (VIX) of the CBOE and the economic policy uncertainty (EPU) indices, which are used as a proxy for general uncertainty. Following Gong et al. (2022), we consider the accessibility of high-frequency data and accordingly employ the VIX, i.e., known to be a measure of the market anticipations about potential volatility in the coming 30 days. The VIX has been used not only as a popular measure of uncertainty (Wang et al., 2020; Megaritis et al., 2021) but also as a useful tool of knowing investor sentiment (Deeney et al., 2015; Gong et al., 2022). Moreover, the method of construction implies the VIX as a measure of anticipated volatilities, reflecting both the panic of falling prices and the prospect of witnessing rises. In case of a possible fall in price, investors will be inclined to use the insurance market and buy some S&P put options targeting a future sell at an agreed price. In this connection, since more worries of a price drop will result in more use of the insurance market, causing a further rise in the VIX, Whaley (2009) called the VIX a measure of the price of safeguarding portfolio. Given that the VIX captures risk averse attitude of investors to measurable uncertainty, associated with subsequent inclination of reducing the risk using the insurance market, we follow Knight's (1921) interpretation of risk and select the VIX index as a method of measuring risk aversion.

Like the above, we consider the accessibility of high-frequency data and accordingly employ the EPU, i.e., used by scholars to investigate the impact that economic policy uncertainty may have on large and strong global economies such as the US, the UK, and China (Gong et al., 2022). As introduced first by Baker (2016), the EPU index is built of three constituents. The first type covered the occurrence of the publication of updates or information associated with economy (E), policy (P), and uncertainty (U) in 10 prominent newspapers in the US. The suggestive keywords to search related to these three categories (E, P, and U) could be uncertain or uncertainty, economic or economy, and congress, regulation, white house, legislation, deficit or federal reserve. Huang and Luk (2020) followed the same approach to investigate 10 top-selling newspapers in the mainland China. The second constituent / component is associated with the uncertainty arising from the expiring federal tax code provisions in a decade whereas the third type measures uncertainty arising from changes in macroeconomic variables, proxied for example by CPI, public spending, and so on. A number of studies (e.g., Aldy and Viscusi, 2014; Liu and Zhang, 2015; Li et al., 2020) ensued Baker (2016) and the EPU index earned growing popularity due to its widely recognised links with economic variables. This study examines the possibility of it capturing ambiguity aversion due to the consideration that the EPU index is typically a news-based measure that focuses not only on the frequency of newspaper articles related to uncertainty but also captures other characteristics of news, such as being ambiguous in certain periods.

3.2 Data and variables

As mentioned above, we employ the implied volatility index (VIX) and economic policy uncertainty (EPU) indices as measures of uncertainty. We study the period from January 1994 to February 2023, at a monthly frequency, which matches the highest shocks frequency available for the economy in our sample. Our sample starts in 1994, which is one year after Chicago Board Options Exchange (CBOE) started reporting their uncertainty measure under the VIX. Our sample ends in February 2023, which corresponds to the period of the global outbreak of the COVID-19 pandemic and the Russia-Ukraine war that led regulators to adopt a series of temporary adjustments in the implementation of the capital requirements and in the protection of the economy. Following Liu and Zhang (2015) and Li et al. (2020) we adopt three macroeconomic indicators of the US real economy, i.e., the Industrial Production index (IP), the Unemployment Rate (UR) and the Consumer Credit (CC) in order to understand the impact of the economic shocks in VIX and EPU. The IP is a measure of the real output of various industrial sectors in the US, e.g., manufacturing, mining, electricity and gas. The UR encompasses the US residents of age 16 or more, who are part of the labour force, actively looking for jobs, and not part of any institutional facilities (e.g., legal/prison or mental health). The CC refers to personal and securitised credits provided to the clients living permanently in the US. Monthly data from January 1994 to February 2023 of the VIX and EPU indices as well as all the three US macroeconomic variables (i.e., IP, UR, CC) are collected from the Federal Reserve Bank of St. Louis database (FRED).

3.2 Structural vector autoregressive (SVAR) framework

Since the pioneering work of Sims (1980), the SVAR modelling has emerged as a well-known model for understanding the dynamic relation among various variables (Volpicella, 2022) and also as one of the most flexible means to illuminate underlying causal relationships in time series data (Bose et al., 2017). The SVAR modelling is an extension of the univariate autoregressive model to the multivariate form. Each variable included in the system is regressed on p lags of itself and of all the other variables in the model, giving rise to a system of multiple regressions. Therefore, an optimum number of lags is selected (Lütkepohl, 2005) using the three most recurrently applied information benchmarks of Akaike (AIC), Schwarz Bayesian (BIC) and Hannan-Quinn (HQC) (Lütkepohl, 2005; Vrieze, 2012). The VAR methodology is generally employed in structural analysis as it helps explaining the dynamic behaviour of various variables during time (Zivot and Wang, 2006). More precisely, The SVAR(p) modelling is written as follows:

$$A_0 Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + B\varepsilon_t \qquad \text{with } t = 1, \cdots, T \tag{1}$$

where Y_t is a $(N \times 1)$ vector composed by time-series variables; A_0 is a matrix of contemporaneous coefficients, which captures the immediate impact of the variables on each other; A_i are $(N \times N)$ coefficient matrices for the lags of the endogenous variables; B is a matrix that transforms the reduced-form errors into structural shocks; and ε_t is the vector of residuals with noise error terms. The SVAR modelling is sensitive to the order of the variables that enforces a recursive structure, implying that in the vector $Y_t = (y_1, y_2, y_3, y_4)$, the variable y_2 has a contemporaneous impact on the variables on its right y_3 and y_4, and a lagged impact on the variables on its left y_1. For this reason, the ordering is vital in a SVAR model, which should be supported by theory and the robustness of the outcomes tested.

Following some of the prominent studies (e.g., Alexopoulos and Cohen, 2009; Bloom, 2009) that studied the uncertainty shocks, we employ two key instruments, i.e., the structural Impulse Response Functions (IRFs) and the structural Forecast Error Variance Decomposition (FEVD) to infer the dynamic behaviour of variables in the SVAR analysis. The structural IRF, one of the most applied tools for interpreting the SVAR model, describes the dynamic reaction of a variable to a one time shock in another endogenous variable (Volpicella, 2022). With the term shock we commonly refer to an unexpected increase in a variable. In our analysis, the impact of one standard deviation (SD) shocks is examined, indicating the significance of the unanticipated rise is one SD in connection with the mean value of the variable under analysis. Structural IRFs are generally demonstrated by a plot that comprises confidence bands to measure the statistical significance of the empirical outcomes. We engage structural IRFs to measure the effect of a shock in VIX or EPU on the US economy, using IP, UR, and CC as proxies of macroeconomic variables. The second instrument /tool applied in the SVAR analysis is the structural FEVD. Given that a shock associated with a variable not only has an influence on the variable itself, but also has spillover impact on other modelling variables (Volpicella, 2022), the portion of a variable's forecast error variance that the FEVD indicates for a specific timeframe can be interpreted by the shock in the other variables (Brooks, 2014), i.e., IP, UR, and CC in this study. It is worth remembering that the structural IRFs and FEVD used in our analysis are reliable measures even in the presence of non-stationary variables, as highlighted by Phillips (1998).

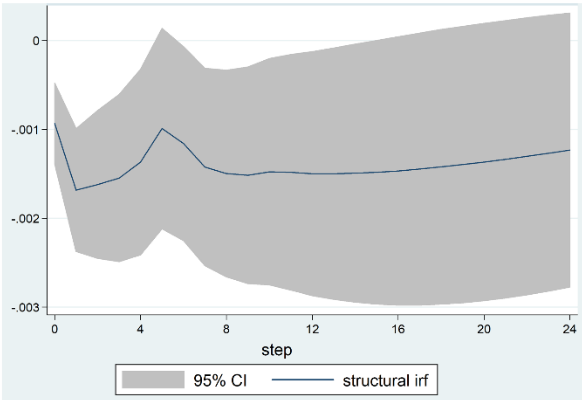
4. Empirical Results

We run our empirical analysis through estimating the SVAR models and investigating the response of our selected macroeconomic indicators to a shock in either VIX or EPU. First, two baseline VARs modelling, including all the macroeconomic variables, are estimated. Each of the baseline VARs corresponded to the VIX as an estimator of risk aversion and to the EPU as an estimator of ambiguity aversion, respectively. Then, a VAR comprising both measures is estimated to assess the dynamic response of the variables. The analysis is sustained by examining two sub-samples: pre- and post- decoupling of the VIX and the EPU that happened in mid-2010. Finally, we carry out some robustness tests in section 5 to check the validity of our empirical results, with specific reference to the most recent Black Swan events, as presented in this section.

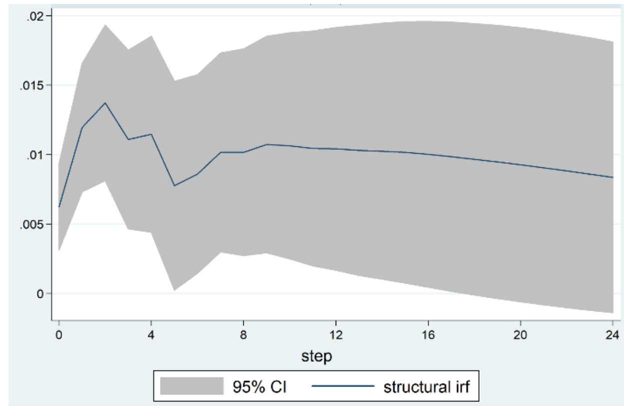
4.1 Results of SVAR modelling considering VIX, IP, UR, CC

Our first estimated SVAR is the following $Y_t = (VIX, IP, UR, CC)$. For this SVAR, the number of lags indicated for the AIC, BIC and HQC criteria ranged between 1 and 6 lags. In this connection, the model and the relative impulse response functions (IRFs) are estimated with 1/6 lags, allowing lag lengths to vary from 1 to 6 for each variable in the SVAR model. This allows for flexibility in determining the appropriate lag order for each variable individually, rather than imposing the same lag length for all variables. The VIX index is ordered first in line with Bloom (2009), hypothesising that it has a concurrent influence on the macroeconomic variables. Figure 2 highlights the structural IRFs of the three macroeconomic variables to a shock in VIX. A SD shock in VIX results in a long-lasting fall in IP of about 0.0012% points, validating the countercyclical nature of the VIX. The reaction of the UR to a one SD shock in VIX is reflected through a long-lasting rise of about 0.01% points, and it is because of the influence of uncertainty that slowed investment and hiring decisions. CC negatively reacts to a shock in VIX because of the rising cost of borrowing as a consequence of excessive level of supply-side uncertainty as well as the rise in precautionary savings and fall in the demand-side borrowing.

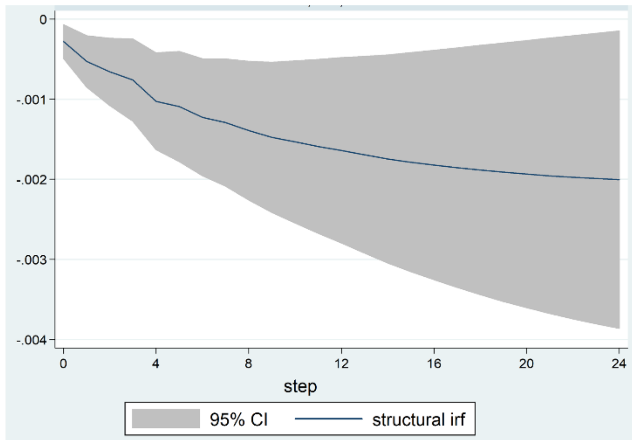
Table 1 highlights the FEVD of the three macroeconomic indicators, providing in particular their variability in percentage, which can be elaborated by a shock in VIX. After 24 months, a SD shock in VIX interprets 14.803% of IP variability, 18.549% of UR variability and 16.923% of CC variability. These results indicate that a shock in VIX corresponds to a consistent share of the variability of the aforementioned macroeconomic variables.



a) response of IP to a shock in VIX



b) response of UR to a shock in VIX



c) response of CC to a shock in VIX

Figure 1. Structural IRFs of the macroeconomic variables to a shock in VIX.

Figure 1 illustrates the IRFs of the log of IP, UR, and CC to a SD shock in VIX. Blue lines indicate the point estimates, and the grey areas indicate the 90% confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock. The study period is between January 1994 and February 2023.

Table 1. Structural FEVD of IP, UR and CC with respect to a shock in VIX.

Horizon in months (*H*)	Industrial Production (*IP*)	Unemployment Rate (*UR*)	Consumer Credit (*CC*)
1	4.645	4.400	1.971
6	9.613	12.745	8.132
12	10.955	14.411	12.194
18	13.092	16.736	14.919
24	14.803	18.549	16.923

Table 1 reveals the percentage of FEVD of IP, UR and CC that can be interpreted by a SD shock in VIX after 1, 6, 12, 18 and 24 month periods.

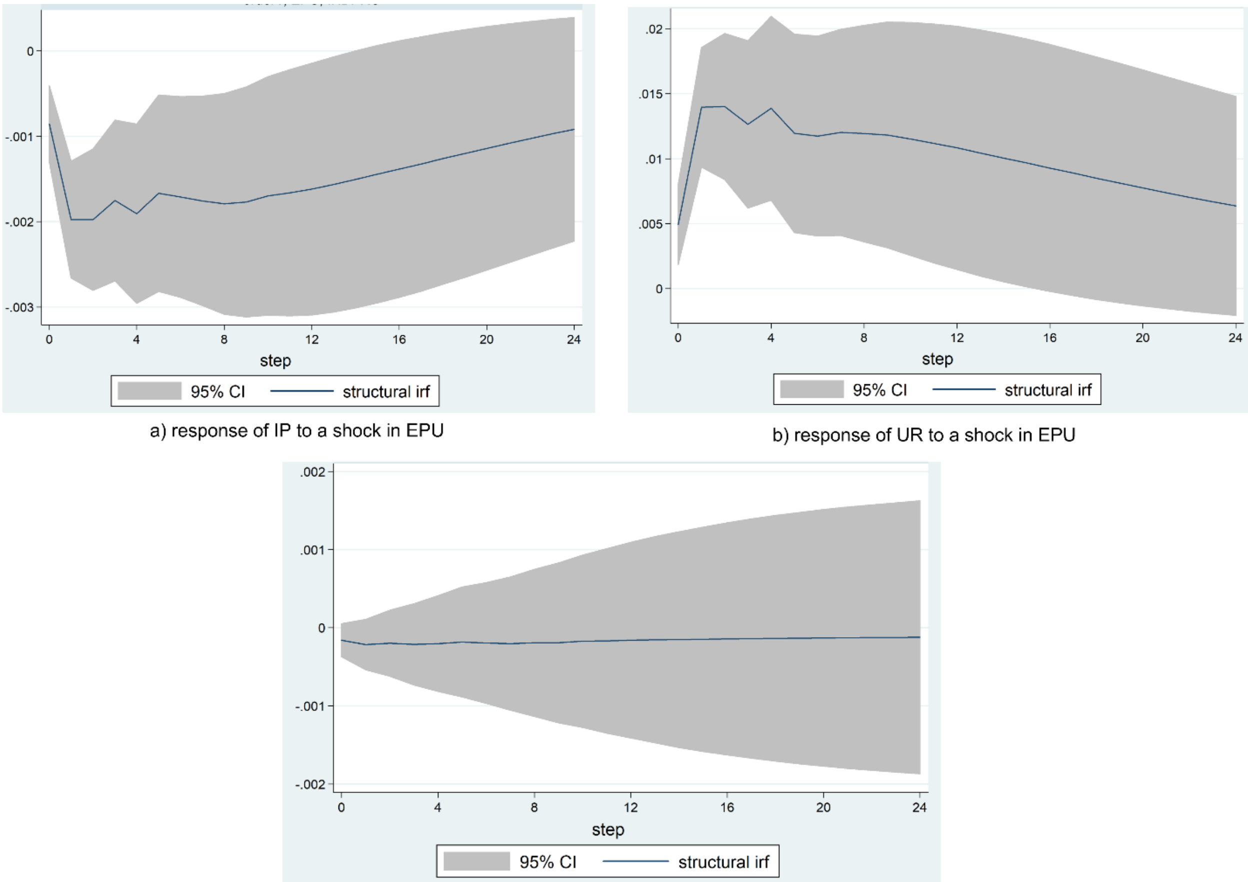
4.2 Results of SVAR modelling considering EPU, IP, UR, CC

The next estimated SVAR is the following $Y_t = (EPU, IP, UR, CC)$. As for the previous estimation, the SVAR modeling and the comparative IRFs are calculated with 1/6 lags, in line with the information criteria. Again, the EPU index is ordered first, hypothesising that it has a concurrent influence on the macroeconomic variables, i.e., IP, UR and CC. Figure 2 illuminates the IRFs of the said variables to a shock in EPU. A standard deviation (SD) shock in EPU has the same impacts to a SD shock in VIX. We observe that IP drops by 0.001% points, the UR reacts with a long-lasting rise of 0.007% points and the effect on CC is negative, although statistically insignificant. The reactions of the IP, UR and CC to a shock in EPU and VIX are approximately the same, hence we can conclude that there is no substantial difference in the explanatory power of the two proxies. Both measures are countervailing, reducing IP and CC and enhancing the UR. Table 2 reveals the FEVD and confirms resemblances between the two measures. After 24 months, a SD shock in EPU describes about 17.727% of IP variability and 20.219% of UR variability. This implies that a shock in EPU interprets the equal amount of the variability of IP and a slightly smaller amount of UR, in comparison to the VIX. The only exception is the CC, i.e., a shock in EPU accounts just for 0.200% of CC variability, compared with 16.923% of the VIX. The distinction between risk and ambiguity could be a possible reason behind the difference in the descriptive power of VIX and EPU with regard to CC. In fact, as an estimator of risk, the VIX is measurable and its inclusion in higher credit spreads can lead to a rising cost of finance, and in turn, depress the credit disposals. On the contrary, as an estimator of ambiguity, the EPU is unmeasurable and it cannot be reflected in credit spreads, therefore not influencing the CC with the similar channels as risk does. At this stage, it is rational to assert with regard to CC that the VIX and the EPU have distinct explanatory power and that it could be associated with the difference between risk aversion and ambiguity aversion, respectively.

Table 2. Structural FEVD of IP, UR and CC with respect to a shock in EPU.

Horizon in Months (*H*)	Industrial Production (*IP*)	Unemployment Rate (*UR*)	Consumer Credit (*CC*)
1	4.010	2.821	0.643
6	14.720	16.838	0.512
12	16.289	18.930	0.335
18	17.340	19.937	0.246
24	17.727	20.219	0.200

This Table reports the percentage of FEVD of IP, UR and CC that can be interpreted by a SD shock in EPU after 1, 6, 12, 18 and 24 month periods.



a) response of IP to a shock in EPU

b) response of UR to a shock in EPU

c) response of CC to a shock in EPU

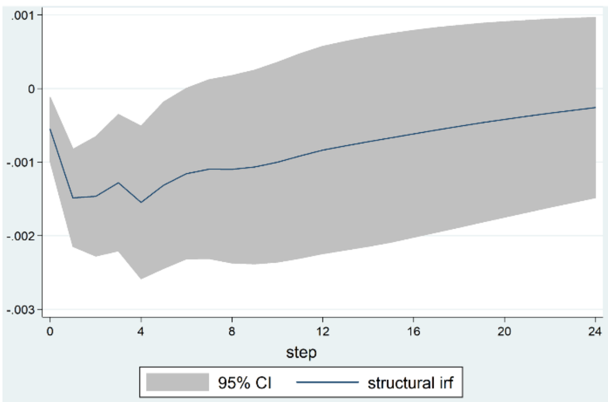
Figure 2. IRFs of the macroeconomic variables to a shock in EPU.

Blue lines indicate the point estimates, and the grey areas reveal the 90% confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock. The study period is between January 1994 and February 2023.

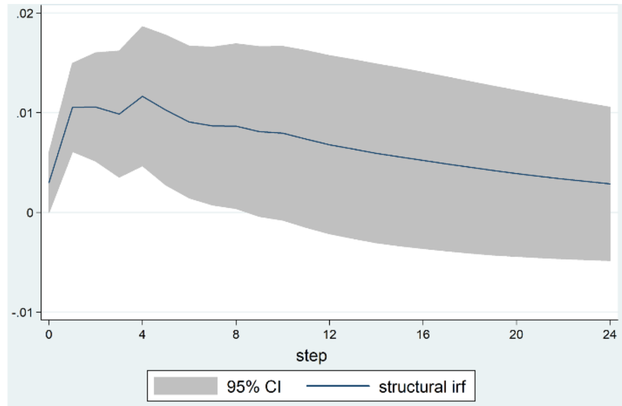
4.3 Results of SVAR modelling considering VIX, EPU, IP, UR, and CC

Now, the SVAR is estimated as follows $Y_t = (VIX, EPU, IP, UR, CC)$. The VIX index is included in the SVAR together with the EPU index in order to see if the responses to a shock in EPU change controlling for the impact of VIX. The VIX is ordered first, hypothesising that it has a concurrent influence on the EPU and variables IP, UR and CC. Figure 3 highlights the IRFs of the above economic variables to a shock in EPU in a system where the VIX is also incorporated. The reactions of IP and UR to a SD shock in EPU, although statistically insignificant, do not vary so much from the one demonstrated by the baseline VAR with EPU and the macroeconomic indicators. However, we note that the reaction of CC to a shock in EPU, although statistically insignificant, is now positive, in contrary to the negative reaction as demonstrated by the baseline

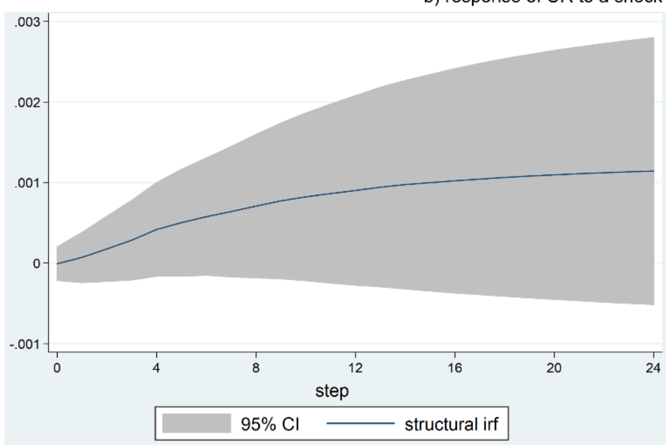
VAR in Figure 2. When integrating VIX and EPU in the same model, the reaction of CC to a shock in EPU varies from the one estimated in the baseline VAR and this could confirm the different channel through which VIX and EPU influence consumer credit, hence confirming their different explanatory ability with respect to this macroeconomic indicator.



a) response of IP to a shock in EPU controlling for VIX



b) response of UR to a shock in EPU controlling for VIX



c) response of CC to a shock in EPU controlling for VIX

Figure 3. Structural IRFs of the macroeconomic variables to a shock in EPU controlling for VIX.

In Figure 3, red lines indicate the point estimates, and the grey areas indicate the 90% confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock. The study period is between January 1994 and February 2023.

The structural FEVD in Table 3 reveals that when VIX is incorporated in the model and it is ordered first, it captures all the variations of the macroeconomic indicators. In fact, after 24 months, a SD shock in VIX corresponds to 13.633% of the change in the IP against 6.544% of EPU, 16.663% of the variations in UR against 9.710% of EPU and 16.522% of the variations in

CC against 4.989% of EPU. A shock in VIX is responsible for all the variability of the macroeconomic indicators when it is in a system with EPU, leading to the conclusion that the explanatory power of EPU does not differ from the one of VIX. However, when looking at the FEVD of the VAR in which EPU is ordered first, the proportion of variability related to a shock in EPU increases to 12.446% for IP against 7.731% of VIX, and to 17.670% for the UR against 8.700% of VIX. When EPU is ordered first, it appears that VIX still corresponds to all the variations in CC, but it is now the EPU that captures a sizeable portion of UR variations and a stable portion of IP variations. These results endorse that the nexus between EPU and CC is not as resilient as the one with VIX, as seen in the case of baseline VARs above. Further, when VIX is incorporated and ordered second, the EPU sustains the illustrative power during the variabilities of IP and UR, keeping open the likelihood of diverse descriptive power of these two measures.

Table 3: Structural FEVD of IP, UR and CC with respect to a shock in VIX and EPU.

VIX ordered first						
Horizon in months (*H*)	Industrial Production (*IP*)		Unemployment Rate (*UR*)		Consumer Credit (*CC*)	
	VIX	*EPU*	*VIX*	*EPU*	*VIX*	*EPU*
1	3.809	1.743	3.577	1.072	1.974	0.006
6	8.386	8.651	11.212	10.600	8.570	1.130
12	9.773	7.883	12.663	10.818	11.460	3.084
18	11.900	7.138	14.861	10.279	14.440	4.251
24	13.633	6.544	16.663	9.710	16.522	4.989
EPU ordered first						
Horizon in months (*H*)	Industrial Production (*IP*)		Unemployment Rate (*UR*)		Consumer Credit (*CC*)	
	VIX	*EPU*	*VIX*	*EPU*	*VIX*	*EPU*
1	2.051	3.500	2.147	2.502	1.749	0.225
6	3.377	13.661	4.725	17.087	9.775	0.106
12	4.427	13.228	5.556	17.923	14.612	0.386
18	6.160	12.875	7.194	17.946	18.088	0.603
24	7.731	12.446	8.700	17.670	20.796	0.715

This Table reports the percentage of structural forecast error variance of industrial production, unemployment rate and consumer credit that can be explained by a standard deviation shock in VIX or EPU after 1, 6, 12, 18 and 24 month periods. The model is estimated using 2 lags.

4.4 Results of VAR modelling considering Pre- and Post- decoupling of VIX and EPU

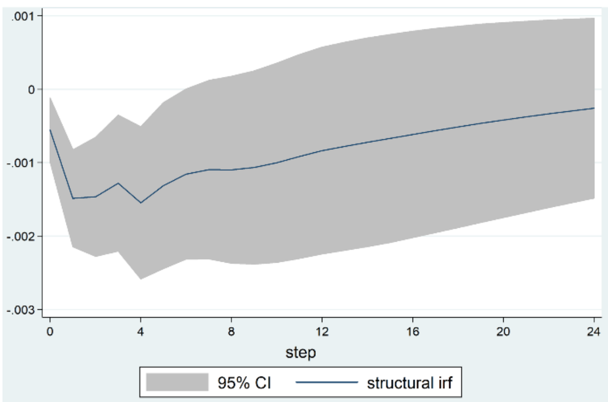
In this section, we explore evidence of the mid-2010 decoupling phenomenon in the impact that the VIX and EPU indexes have on the real economy and analyse the IRFs to a shock in these indexes in the pre- and post- decoupling periods. We divide our sample into two subperiods: the first goes from January 1994 to June 2010, i.e., the pre-decoupling, and the second goes from July 2010 to February 2023, i.e., the post-decoupling. Figures 4 and 5 compare the structural IRFs of three macroeconomic variables to a shock in VIX and EPU in the pre- and post- decoupling periods, respectively. In the pre-decoupling, the IRFs of the macroeconomic indicators to a shock in VIX or EPU are really the same with the ones observed in the baseline SVARs, as illustrated in Figures 1 and 2. On the other hand, in the post-decoupling, the structural IRFs lose nearly all the statistical significance. The key distinction that is worth indicating is the behaviour of UR. In fact, in the pre-decoupling, the UR negatively reacts to a shock in VIX, but positively responds to a shock in EPU. Although this finding is not statistically significant, it could represent another sign of the different explanatory ability of the VIX and the EPU.

Table 4: Structural FEVD of IP, UR and CC with respect to a shock in VIX and EPU in the pre- and post-decoupling periods.

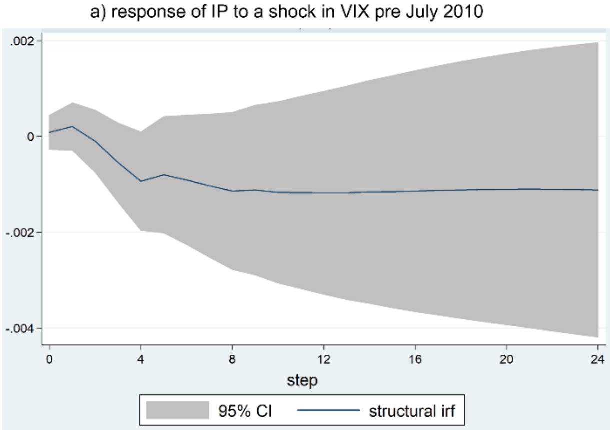
Pre-decoupling						
Horizon in months (*H*)	Industrial Production (*IP*)		Unemployment Rate (*UR*)		Consumer Credit (*CC*)	
	VIX	*EPU*	*VIX*	*EPU*	*VIX*	*EPU*
1	0.110	3.097	0.017	0.510	0.682	1.023
6	2.557	12.986	9.120	24.086	9.975	0.303
12	3.730	15.486	13.039	27.900	24.965	2.019
18	4.313	15.885	13.355	26.706	34.844	5.401
24	5.041	16.199	13.632	26.009	38.843	8.757
Post-decoupling						
Horizon in months (*H*)	Industrial Production (*IP*)		Unemployment Rate (*UR*)		Consumer Credit (*CC*)	
	VIX	*EPU*	*VIX*	*EPU*	*VIX*	*EPU*
1	11.917	5.524	10.670	7.154	3.872	0.945
6	23.824	23.797	28.682	34.990	15.309	9.240
12	24.896	21.191	33.060	40.087	15.002	8.394
18	24.095	20.384	34.375	40.495	12.034	5.988
24	23.326	21.124	34.202	39.869	9.428	5.064

Table 4 reveals the percentage of structural FEVD of IP, UR and CC that can be interpreted by a SD shock in VIX or EPU after 1, 6, 12, 18 and 24 month periods, distinguishing between the time period of the pre- and post-decoupling happened in 2010.

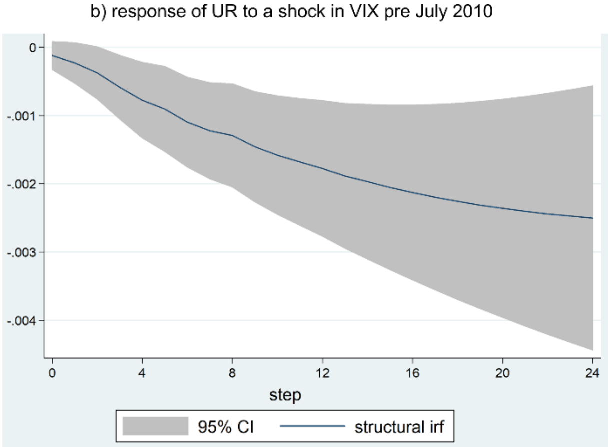
Table 4 reports the structural FEVD in the pre- and post-decoupling periods. In the pre-decoupling, a shock in EPU elaborates much more variations in the macroeconomic indicators in contrast to the VIX. In the post-decoupling, the descriptive ability of both indexes is very much increased, except for CC.



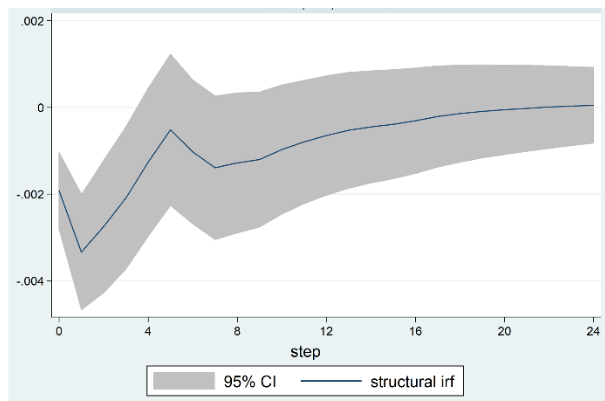
a) response of IP to a shock in VIX pre July 2010



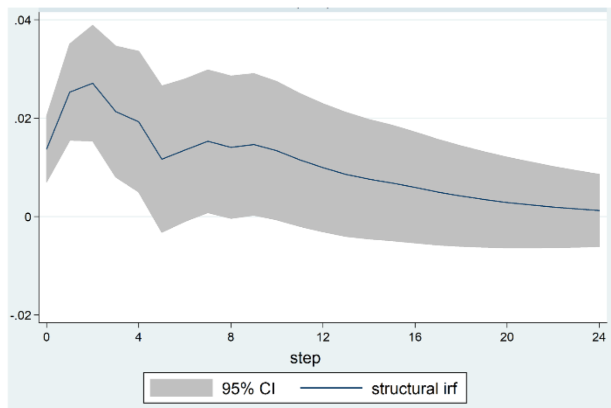
b) response of UR to a shock in VIX pre July 2010



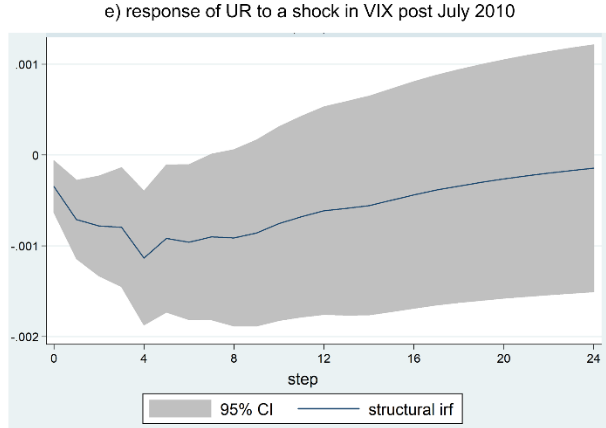
c) response of CC to a shock in VIX pre July 2010



d) response of IP to a shock in VIX post July 2010



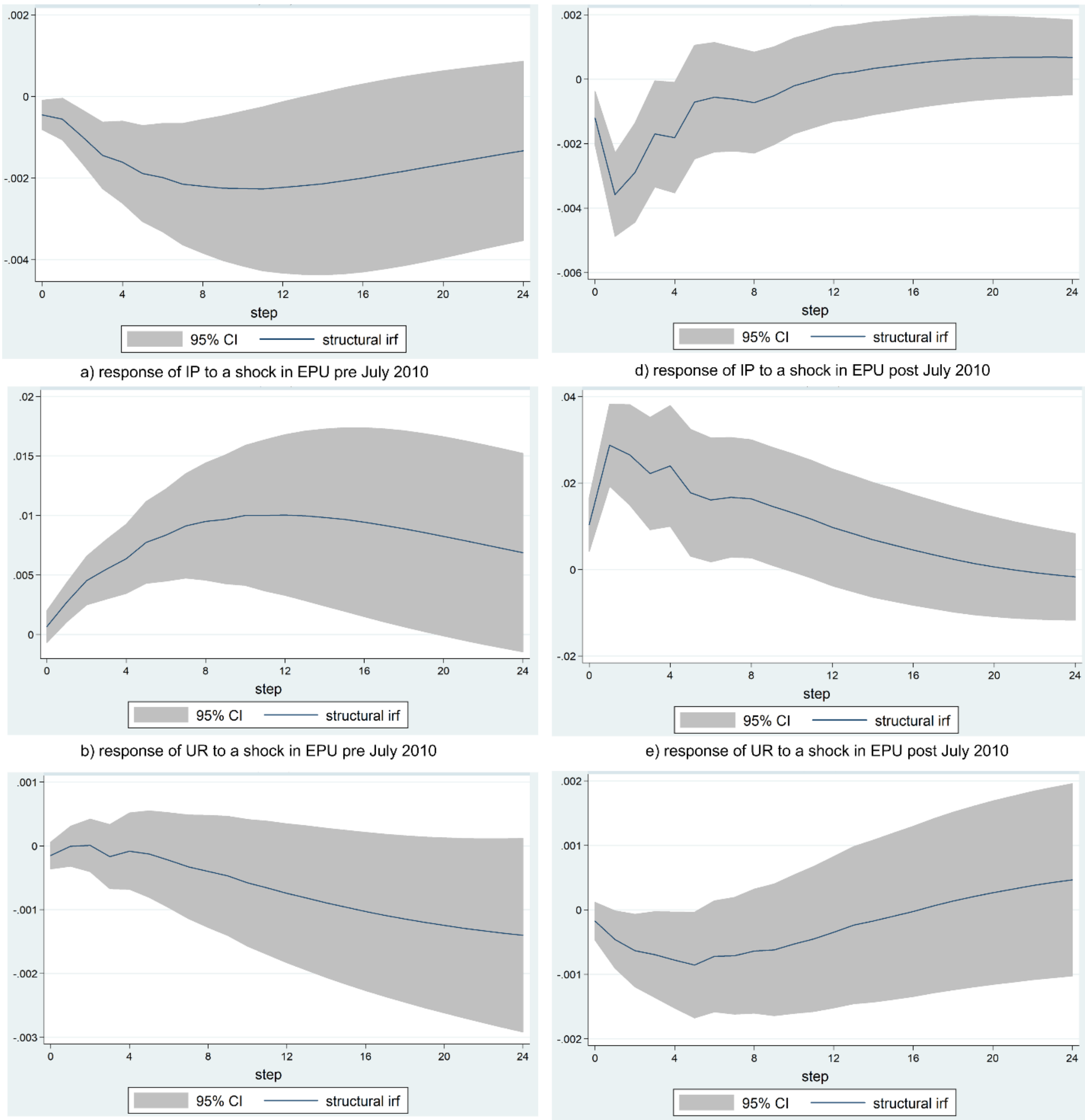
e) response of UR to a shock in VIX post July 2010



f) response of CC to a shock in VIX post July 2010

Figure 4. Structural IRFs of the macroeconomic variables to a shock in VIX in the pre- and post-decoupling periods.

Structural IRFs of the log of IP, UR, and CC to a SD shock in VIX, distinguishing between the time period of the pre- and post-decoupling happened in 2010. Blue lines show the point estimates, and the grey areas correspond to the 90% confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock. The study subperiods are between January 1994 and June 2010, and between July 2010 and February 2023.



a) response of IP to a shock in EPU pre July 2010

d) response of IP to a shock in EPU post July 2010

b) response of UR to a shock in EPU pre July 2010

e) response of UR to a shock in EPU post July 2010

c) response of CC to a shock in EPU pre July 2010

f) response of CC to a shock in EPU post July 2010

Figure 5. Structural IRFs of the macroeconomic variables to a shock in EPU in the pre- and post-decoupling periods.

Structural IRFs of the log of IP, UR, and CC to a SD shock in EPU, distinguishing between the time period of the pre- and post-decoupling happened in 2010. Blue lines show the point estimates, and the grey areas correspond to the 90% confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock. The study subperiods are between January 1994 and June 2010, and between July 2010 and February 2023.

5. Robustness Tests

We run in this section some robustness tests to check our results.

5.1 Results of test for SVAR modelling considering Pre- and Post- stressful periods including the COVID-19 pandemic and the Russia-Ukraine war

In this section, we analyse the structural IRFs to a shock in both the VIX and the EPU in the pre- and post- crisis periods, such as the COVID-19 pandemic that started in January 2020 and the Russia-Ukraine war that started in February 2022. We divide the sample period into two subperiods: before and after 19 January 2020, the day the World Health Organization (WHO) declared the COVID-19 as a pandemic, following detection of the first confirmed case of the COVID-19 reported in the US (Holshue et al., 2020) as well as the ongoing Russia-Ukraine war period, which officially started on 24 February 2022, following the entry of the Russia troops to Ukraine (Yousaf et al., 2022).

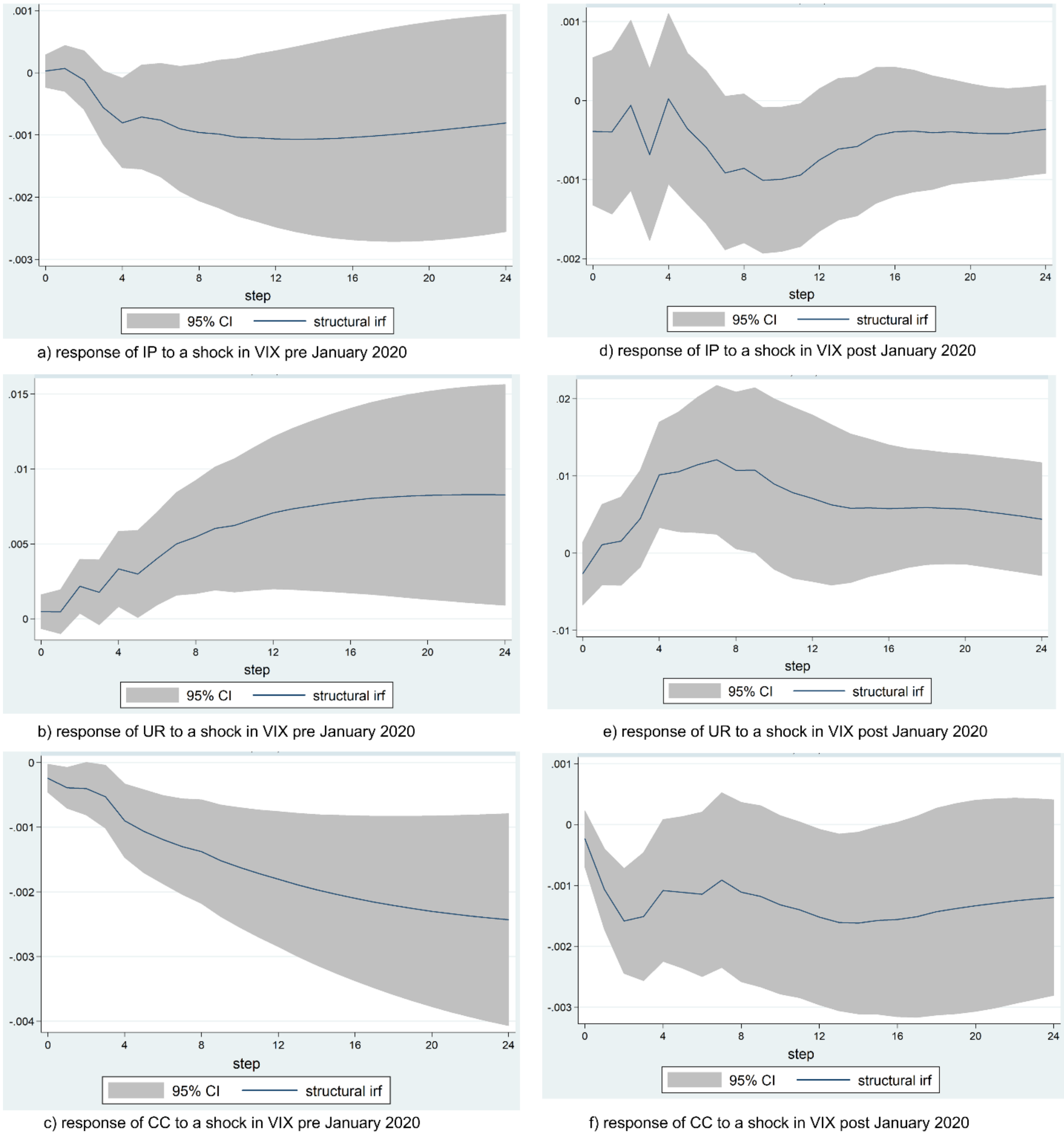


Figure 6. Structural IRFs of the macroeconomic variables to a shock in the VIX in the pre- and post-stressful periods of the Covid-19 pandemic and the Russia-Ukraine war.

Figure 6 highlights structural IRFs of the log of IP, UR, and CC to a SD shock in the VIX differentiating between the pre- and post- crisis periods in 2020. Blue lines indicate the point estimates and the grey areas indicate the 90% confidence interval. The *y*-axis represents percentage points and the *x*-axis gives the months after the shock. The study subperiods are between January 1994 and 19 January 2020; and between 20 January 2020 and February 2023.

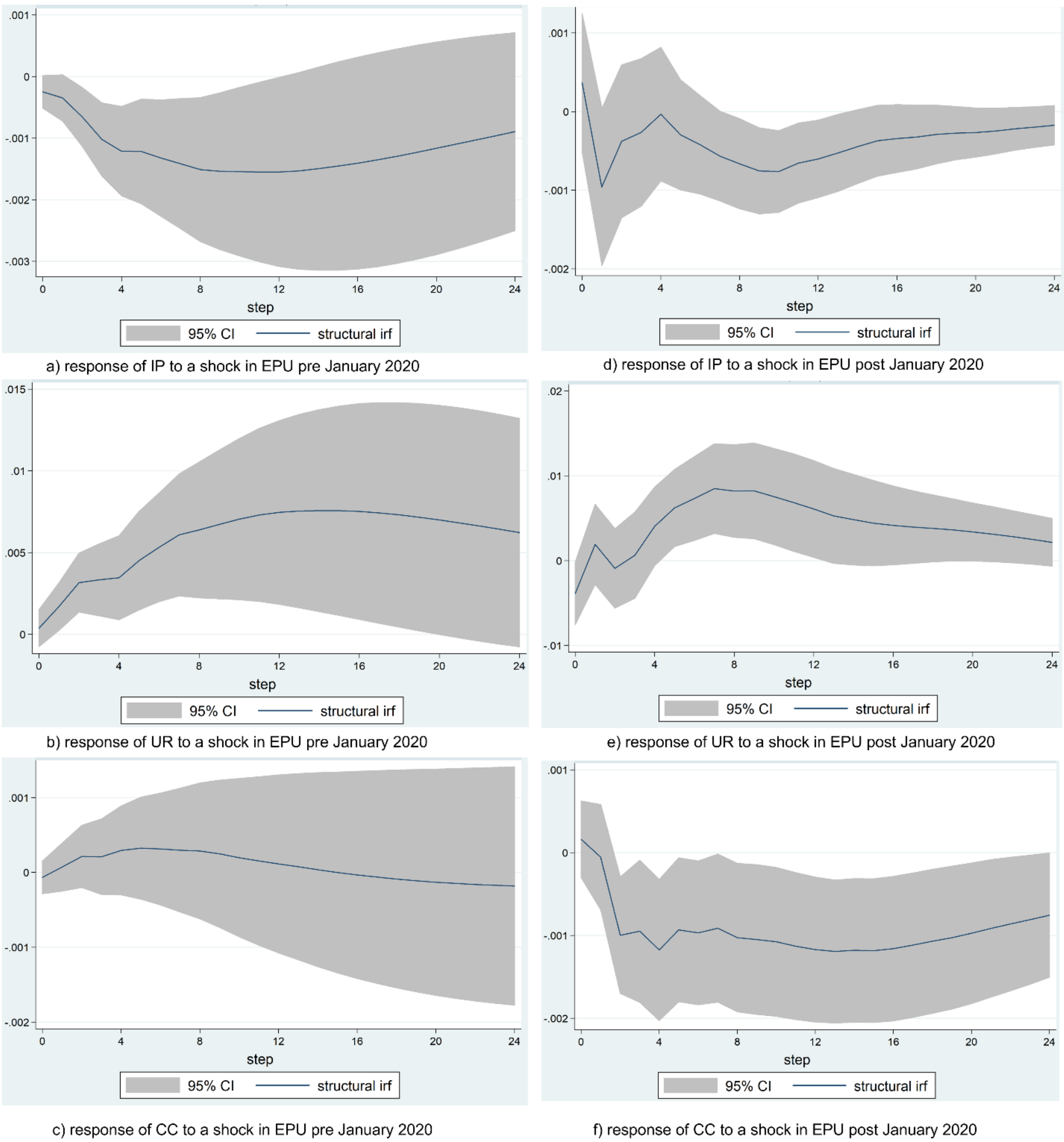
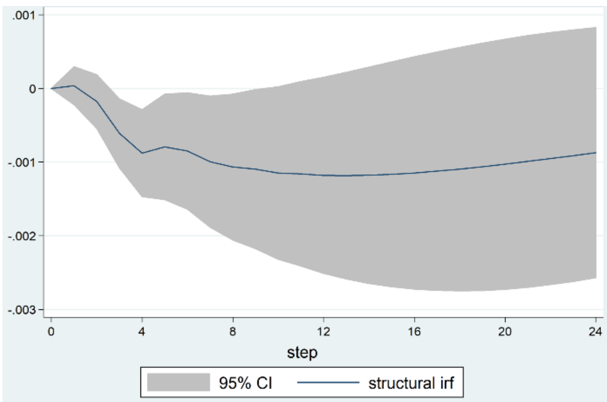


Figure 7. Structural IRFs of the macroeconomic variables to a shock in the EPU in the pre- and post-stressful periods of the Covid-19 pandemic and the Russia-Ukraine war.

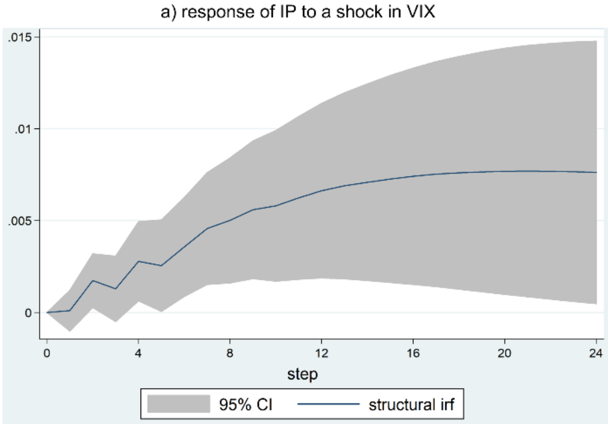
Figure 7 highlights structural IRFs of the log of IP, UR, and CC to a SD shock in the EPU differentiating between the pre- and post- crisis periods in 2020. Blue lines indicate the point estimates and the grey areas indicate the 90% confidence interval. The *y*-axis represents percentage points and the *x*-axis gives the months after the shock. The study subperiods are between January 1994 and 19 January 2020; and between 20 January 2020 and February 2023.

5.2 Results of test for SVAR modelling with ordering of the variables VIX and EPU

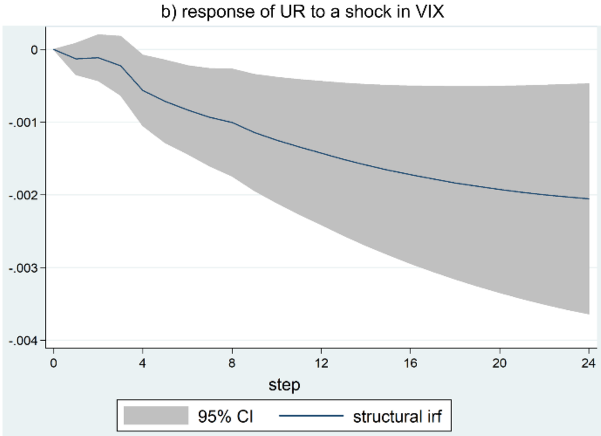
What matters most in an SVAR modelling is that there is sensitivity to ordering the variables. For this reason, we test the robustness of our findings through ordering the VIX and EPU indexes last in their VARs, respectively. Figure 8 depicts these findings for the VIX and the EPU, respectively. It can be seen that in both cases the structural IRFs seem to be similar to the one estimated by the baseline VARs, as illustrated in Figures 1 and 2.



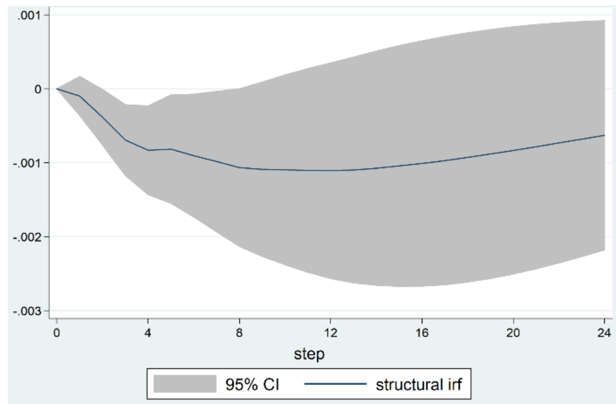
a) response of IP to a shock in VIX



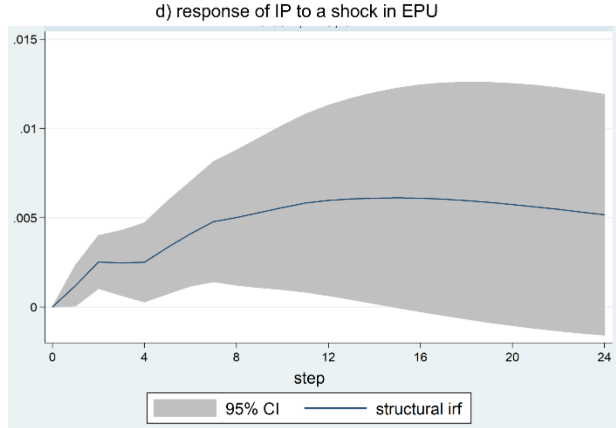
b) response of UR to a shock in VIX



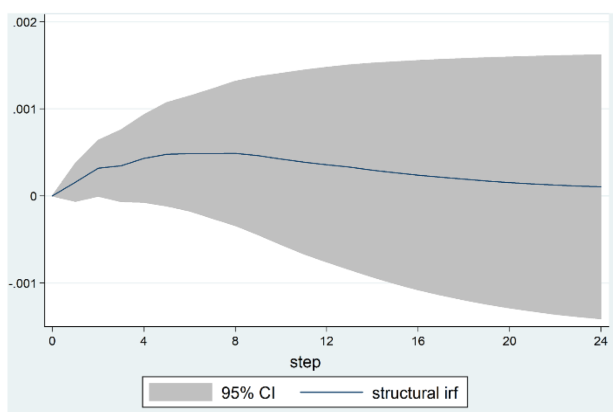
c) response of CC to a shock in VIX



d) response of IP to a shock in EPU



e) response of UR to a shock in EPU



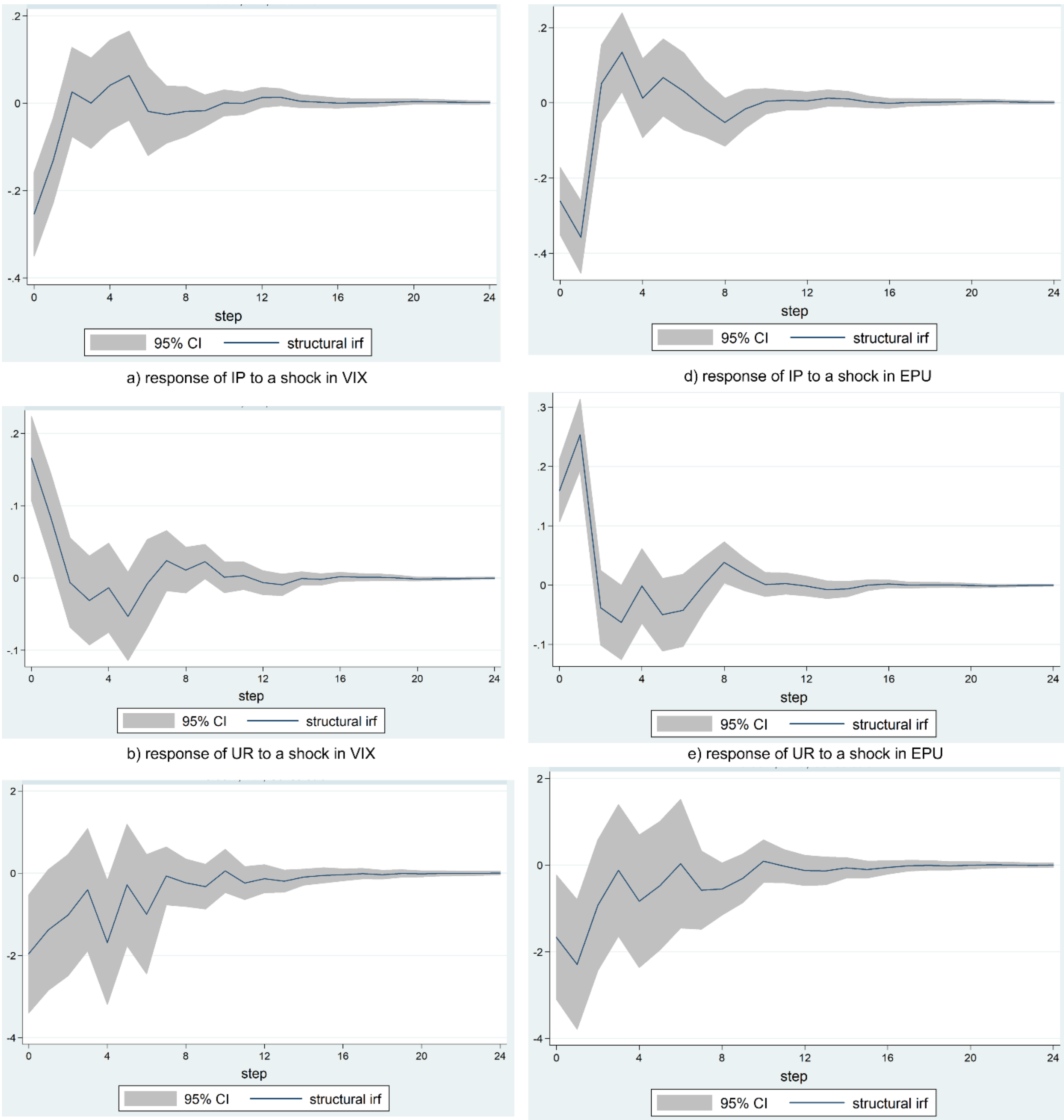
f) response of CC to a shock in EPU

Figure 8. IRFs of the macroeconomic variables to a shock in VIX and EPU ordering them as last.

Figure 8 depicts the structural IRFs of the log of IP, UR, and CC to a SD shock in the VIX and the EPU both ordered at the end of the model, for the January 1994 – February 2023 period. Blue lines indicate the point estimates, and the grey areas highlight the 90% confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock.

5.3 Results of test for VAR modelling with first difference responses for macroeconomic variables

The macroeconomic variables are entered into the model using their logarithm in our baseline analysis, which implies that the stationary assumption is not respected. For this reason, we test our findings by including the first difference of those variables and so respecting stationarity condition. Figure 8 depicts the findings of this test. We find that a standard deviation shock in VIX and EPU results in a drop in industrial production and consumer credit and an increase in unemployment rate, approving thus the robustness of our base findings.



a) response of IP to a shock in VIX

d) response of IP to a shock in EPU

b) response of UR to a shock in VIX

e) response of UR to a shock in EPU

c) response of CC to a shock in VIX

f) response of CC to a shock in EPU

Figure 9: IRFs of the first difference macroeconomic variables to a shock in VIX and EPU.

Structural IRFs of the first difference of log of IP, UR, and CC to a SD shock in the VIX and the EPU. Red lines indicate the point estimates, and the grey areas depict the 90 percent confidence interval. The *y*-axis represents percentage points, and the *x*-axis gives the months after the shock. The study period runs from January 1994 to February 2023.

5. Concluding Remarks

We presented in this paper a fairly general SVAR-test based methodology to determine the impact of the VIX and the EPU on the real economy, examining the distinctions between these two measures and inspecting their possible links to the demarcation between risk aversion and ambiguity aversion. Overall, the empirical outcomes of this study reveal the countervailing nature of the VIX index and the EPU index, which can induce recessions. It implies that a shock in these measures is associated to a fall in industrial production (IP) and consumer credit (CC), and an increase in unemployment rate (UR), thus evidencing the influence of both measures on the US business cycle. Also, the SVAR-test approach compares the impact on IP, UR and CC of a shock in the VIX and the EPU in the post-decoupling period and in the post-COVID-19 pandemic period as well as the period of the ongoing Russia-Ukraine conflict. The only sign of the presumably different explanatory ability of the VIX and the EPU is the impulse response function (IRF) of the IP that negatively reacts to a shock in the VIX, but positively reacts to a shock in the EPU. This, combined with the low proportion of the CC variations illuminated by the EPU in respect to the VIX and the dissimilar reaction of CC to a shock in the EPU when controlling for the VIX index, provides evidence of the distinct captures that the EPU index and the VIX index make. However, the divergences found in this study are difficult to relate to the difference among risk aversion and ambiguity aversion.

Although there is weak evidence that the VIX and the EPU capture different dimensions of uncertainty, there is not adequate empirical indications to formally endorse the VIX as an estimator measure of risk aversion and the EPU as an estimator of ambiguity aversion. But, in some sense, it is worthy to recall the fundamental differences among these two measures and all other uncertainty measures and, hence reminding the importance of checking always the robustness of findings by using different uncertainty proxies. The current paper contributed to highlight the use of uncertainty proxies that is done in the structural models in previous literature and empirically studied the disparities in the descriptive power of the two indexes. More elaborately, this study empirically demonstrated that the EPU index captures a slightly different dimension of uncertainty than just risk, and this finding could be extended to all news-based measure. Further, given that the measures using google searches concentrate on the individual perceptions, it is intuitive that among the news-based measures, the google search measures capture the widest dimension of uncertainty.

One of the unavoidable limitations of this study has been associated with the ongoing Russia-Ukraine conflict. Although we claim to have compared the impact on IP, UR and CC of a shock in VIX and EPU in the post- Russia-Ukraine conflict, besides post-decoupling and post-COVID-19 periods, the Russian aggression in Ukraine is still ongoing and the situation is turning more uncertain due to the variably shifting global economic dynamics, influenced by the NATO-led geo-political order and encountered by the enlarging BRICS bloc. A further study on the same subject matter will be required once the ongoing conflict comes to a peaceful end. The outcome can then be compared to the findings of this study and an earlier unpublished work of Melany (2019), and hence generalised for implementing trading decision strategies by investors and portfolio managers.

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Appendix 1.

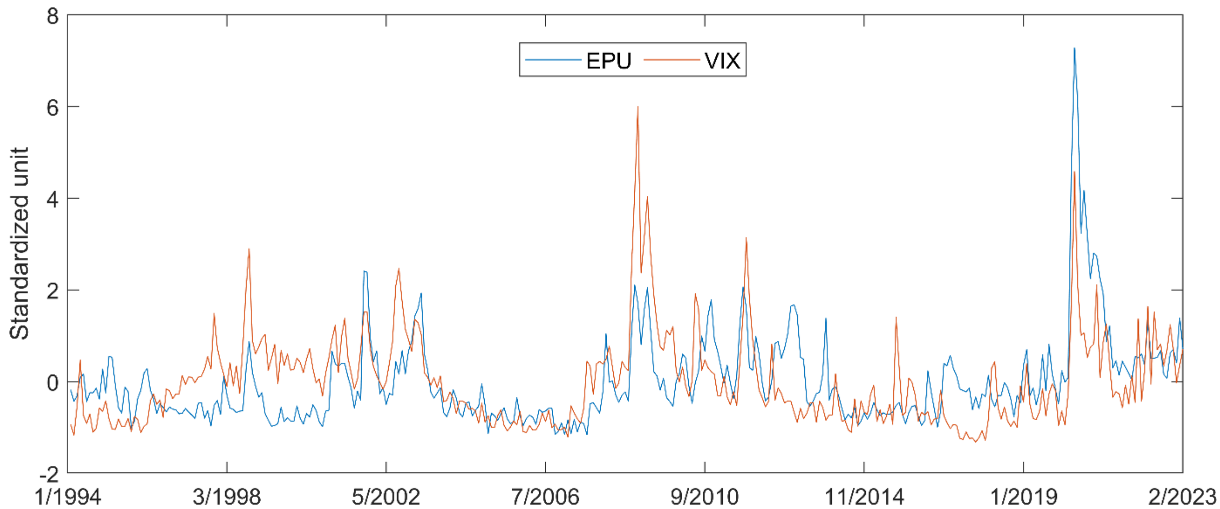

Figure A: Monthly observations of EPU and VIX in standardized terms between January 1994 and February 2023.