Is housing collateral important to the business cycle? Evidence from China*

Yue Gai † Patrick Minford ‡ Zhirong Ou §

Abstract

This paper investigates whether housing collateral is important to the business cycle in China. We develop two models, one without housing collateral as benchmark and one variant allowing for it. Indirect Inference procedure tests these two models' compatibility with the data. We find that the benchmark model passes the test, while the collateral model is strongly rejected. According to the benchmark model, shocks from the housing market have limited impact on the Chinese business cycle. By contrast, the exogenous spending shock from government and net exports, the monetary policy shock and the goods-sector cost/productivity shock, all in turn most likely connected to world business cycle shocks (especially the global financial crisis), are found to be the main drivers.

Keywords: *Housing market; DSGE model; Housing collateral; Indirect Inference; China;*

JEL classification: *E32; E44; E52; R31*

1 Introduction

Since Kiyotaki and Moore (1997), it has been quite usual in macroeconomics to model financial frictions within a structural model by allowing for a borrowing constraint, where loans available to borrowers are limited to be a fraction of the (expected) present value of the collateral supporting such loans. Recent work along these lines is due to Iacoviello (2005) who points out that houses – which are collateralised for a large proportion of borrowing in the US – may have affected the business cycle substantially via a 'collateral effect' of housing value on consumption and investment. The working of such an effect is straightforward: when the value of housing collateral is affected (e.g., by a housing demand shock that changes the market price of houses), the borrowing capacity of households/entrepreneurs who finance their consumption/investment partially with loans is affected in the same manner via the borrowing constraint. The fluctuation in consumption

*We are grateful for helpful comments from an anonymous referee and Prof. Kees Koedijk (the Editor). We remain responsible for all errors and omissions.

†Corresponding author: Cardiff University, UK. Address: Room B48 Aberconway Building, Colum Dr, Cardiff CF10 3EU. Email: GaiY@cardiff.ac.uk

‡Cardiff University and CEPR, UK. Email: MinfordP@cardiff.ac.uk

§Cardiff University, UK. Email: Ouz@cardiff.ac.uk

and investment then causes output to fluctuate, which further affects the value of the housing collateral and so on and so forth. The extent to which the business cycle is affected depends on the responsiveness of the housing collateral to shocks, and the size of the financial friction (as reflected by the loan-to-value ratio).

The Iacoviello model has greatly influenced the way the business cycle is modelled and understood. Indeed, since the original model, many have assumed, as a rule of thumb, that houses are collateralised for borrowing, to allow for 'housing market spillovers' to the macroeconomy – using the terminology of Iacoviello and Neri (2010). Most have found housing collateral to be an important contributor to the business cycle. For example, Benito (2006) finds housing collateral contributes significantly to the volatility of consumption in the UK. Walentin (2014) finds similar results for Sweden while pointing out that the collateral effect is the most obvious when monetary policy and housing demand shocks are hitting the economy.

Such a linking of the housing market and the macroeconomy has also inspired many who study the Chinese economy, where the housing market is widely believed to have been an important pillar of the economy over the past twenty years. Thus, Ng (2015) estimates the Iacoviello model for China and finds that there is a spillover effect, albeit weak, from the housing market to the economy; while He et al. (2017) argue that housing collateral, by amplifying the shocks from the housing market, plays a major role in driving business cycle volatility.

However, to what extent are these models (especially the ones allowing for housing collateral which is usually assumed to be part of the 'true' model *a priori*) compatible with the data? Unfortunately, while focusing on comparing model properties the existing literature has made few efforts to answer this fundamental question about model suitability. Indeed, while Iacoviello suggests houses are important collateral in the US and so could also be in other developed economies, the same may not be necessarily true in China. This is most likely due to two reasons. Firstly, Chinese households do not usually borrow to consume. For example, while it is very common to buy a car, a phone, or even everyday purchases with loans in developed economies, Chinese households usually do these with their savings, as 'living within your means' is deeply rooted in the Chinese culture. This is well reflected by China's high savings rate. The second reason is that houses themselves are important assets of Chinese households. House ownership is usually a symbol of economic success and social status, and is also what often felt to be providing the most sense of security. Thus, even when loans are taken by households, it is very rarely that they would collateralise their houses for such loans.These factors conflict with the housing collateral business cycle hypothesis, which is precisely what we want to *test* in the following.

Thus, in this paper our aim is to test whether housing collateral is important to the business cycle in China. We do so by confronting two competing models, one benchmark version without a borrowing constraint and one variant in which houses are collateralised for household borrowing, with the data observed between 2000Q1 and 2014Q4. We evaluate the models' capacity to mimic the behaviour of the data which we summarise using a VARX(1). The evaluation is based on the Indirect Inference Wald test due to Minford, Theodoridis, and Meenagh (2009) and refined by Le et al. (2011). We find that the benchmark model passes the test at the 5% significance level but that the housing collateral model is strongly rejected. According to the benchmark model, we find that compared to the central bank interest rate policy shock, shocks from the housing market have a limited impact on the Chinese business cycle, besides having none via the collateral channel.

The rest of this paper is organised as follows: section 2 sets up the competing models; section 3 explains the method of Indirect Inference; section 4 reviews our test results and their implications for the behaviour of the Chinese economy. Section 5 concludes.

2 Model

2.1 The benchmark model

Our benchmark model is similar to Smets and Wouters (2003) but is extended to include the housing sector. While as we will see China is strongly affected by world fluctuations, notably during the financial crisis, we have followed the Smets-Wouters strategy for the US of a closed economy model, in order to concentrate on domestic sources of fluctuation, especially housing, which is our key focus in this paper. There are three types of agent: households, firms and the public sector. Households consume, buy houses, and work for firms which produce goods. The public sector pursues monetary policy with an interest rate rule, while fiscal policy sets exogenous spending financed by bonds and lump-sum taxes. Labour and capital are free to flow between sectors so there is no sectoral difference in wage or capital price. The market in differentiated final goods is monopolistically competitive. The market in houses is perfectly competitive.

2.1.1 Households

Representative households have life-time utility:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \varepsilon_t^p \left[\frac{C_t^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^{hd} \frac{H_t^{1-\sigma_h}}{1-\sigma_h} - \varepsilon_t^l \frac{N_t^{1+\eta}}{1+\eta} \right] \tag{1}$$

where C_t is the consumption on commodity goods, H_t is the housing stock, and N_t is the supply of labour. The elasticities of consumption, housing and labour are, respectively, σ_c, σ_h and η. The utility is subject to a preference shock ε_t^p, a housing demand shock ε_t^{hd}, and a labour supply shock ε_t^l; and expected future utilities are discounted by β.

The household's budget constraint (in real terms) is given by:

$$C_t + p_{h,t} \left[H_t - (1-\delta_h) H_{t-1} \right] + B_t = w_t N_t + (1 + r_{t-1}) B_{t-1} + \Pi_t - \tau_t \tag{2}$$

where $p_{h,t}$ is the relative price of houses, B_t is the bonds purchased, w_t is the wage rate, and Π_t is the lump-sum profit transferred from firms; τ_t is the lump-sum tax. Houses are assumed to depreciate at δ_h.

The optimisation problem of households is to maximise Equation (1) by choosing C_t, H_t, B_t and N_t subject to Equation (2). The optimal conditions imply the standard Euler Equation (Eq.3) and trade-off between consumption and leisure (Eq.4), as well as the marginal rate of substitution between consumption and houses (Eq.5):

$$E_t(C_{t+1}^{\sigma_c}) = \beta(1+r_t)C_t^{\sigma_c}E_t(\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p}) \tag{3}$$

$$\varepsilon_t^l N_t^\eta = w_t/C_t^{\sigma_c} \tag{4}$$

$$\varepsilon_t^{hd}H_t^{-\sigma_h} = \frac{p_{h,t}}{C_t^{\sigma_c}} - \beta E_t(\frac{p_{h,t+1}}{C_{t+1}^{\sigma_c}})(1-\delta_h)E_t(\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p}) \tag{5}$$

These are the demand for goods, the supply of labour, and the demand for houses equations determined by the household problem.

2.1.2 Firms

Representative firms produce both goods and houses ($Y_{c,t}$ and $Y_{h,t}$, respectively) according to:

$$Y_{i,t} = A_{pi,t}K_{i,t-1}^\alpha N_{i,t}^{1-\alpha} \tag{6}$$

where $A_{pi,t}$ is productivity, $K_{i,t}$ is the capital input whose share is α, and $i(=c,h)$ is the subscript for variables of the goods and housing sectors[1].

The accumulation of capital by investment $I_{i,t}$, subject to depreciation δ_{ki}, follows:

$$K_{i,t} = I_{i,t} + (1-\delta_{ki})K_{i,t-1} \tag{7}$$

Firm optimisation in the goods sector We assume that general goods are produced under imperfect competition by producers who set prices as a mark-up on marginal costs. The standard Calvo (1983) price-setting mechanism implies the New Keynesian Phillips curve which relates inflation to the real marginal cost:

$$\widetilde{\pi}_t = \beta E_t\widetilde{\pi}_{t+1} + \frac{(1-\omega)(1-\omega\beta)}{\omega}\widetilde{mc}_t$$

where $\widetilde{mc}_t = (1-\alpha)(\widetilde{w}_t + \widetilde{\varepsilon}_t^{nc}) + \alpha(\widetilde{r}_t + \widetilde{\varepsilon}_t^{kc}) - \widetilde{a}_t$; ω is the fraction of producers who are unable to reoptimise due to 'menu costs'.

These producers then supply demand at their pre-set prices, and minimise the expected real costs of production (note that capital is a general good, with the same price as other goods):

$$w_t(\varepsilon_t^{nc}N_{c,t}) + I_{c,t}\varepsilon_t^{kc} + \frac{\kappa}{2}(\triangle K_{c,t})^2$$

[1]For simplicity we assume input shares are the same across the two sectors. We also take that 'lands' is fixed in the short run and we normalise it to 1, so that the production function of the housing sector is in form the same as that of the goods sector.

by choosing capital and labour, subject to (**6**) and (**7**), where ε_t^{nc} and ε_t^{kc} are the labour demand shock and capital demand shock, $\frac{\kappa}{2}(\triangle K_{c,t})^2$ is the cost of capital adjustment. The problem implies:

$$(1-\alpha)\frac{Y_{c,t}}{N_{c,t}} = w_t \varepsilon_t^{nc}$$

$$(1+r_t)[\varepsilon_t^{kc} + \kappa(K_{c,t} - K_{c,t-1})] = E_0[\frac{\alpha Y_{c,t+1}}{K_{c,t}} + (1-\delta_{kc})\varepsilon_{t+1}^{kc} + \kappa(K_{c,t+1} - K_{c,t})]$$

which determine the demand for labour and the demand for capital.

Optimisation in the housing sector Optimisation in the housing sector is analogous to that in the goods sector, except that houses – unlike commodity goods – are produced under perfect competition; and sold direct to households at market prices. House producers therefore maximise real profits (i.e. deflated by $p_{c,t}$):

$$V_h = E_0 \sum_{t=0}^{\infty} \frac{1}{1+r_t} \left[p_{h,t} Y_{h,t} - I_{h,t}\varepsilon_t^{kh} - w_t(\varepsilon_t^{nh} N_{h,t}) - \frac{\kappa}{2}(\triangle K_{h,t})^2 \right]$$

$$(1-\alpha)\frac{Y_{h,t}}{N_{h,t}} p_{h,t} = w_t \varepsilon_t^{nh}$$

$$(1+r_t)[\varepsilon_t^{kh} + \kappa(K_{h,t} - K_{h,t-1})] = E_0[\frac{\alpha p_{h,t+1} Y_{h,t+1}}{K_{h,t}} + (1-\delta_{kh})\varepsilon_{t+1}^{kh} + \kappa(K_{h,t+1} - K_{h,t})] \quad (8)$$

where ε_t^{nh} and ε_t^{kh} are, respectively, the labour demand shock and the capital demand shock in the housing sector.

2.1.3 The public sector

The public sector is represented by a central bank which adjusts the interest rate following a Taylor rule of the form:

$$R_t = \bar{R} + \rho(R_{t-1} - \bar{R}) + (1-\rho)\left[\theta_\pi(\pi_t - \pi^*) + \theta_{GDP}(\ln GDP_t - \ln GDP_{t-1})\right] + \varepsilon_t^m$$

where $\bar{R}$ is the steady-state interest rate, π^* is the inflation target, ρ is the 'smoothness' of policy, θ_π and θ_{GDP} are policy responses to inflation and GDP growth, respectively, and ε_t^m is the shock to monetary policy.

Government spending, G_t, is exogenous and follows an AR(1) process. The government issues bonds and sets the lump-sum tax rate as it chooses, while satisfying the solvency constraint: $\tau_T = G_T + (1 + r_{T-1})B_{T-1}(T \to \infty)$.

2.1.4 Market clearing

The goods market clears when:

$$Y_{c,t} = C_t + I_t + G_t + \frac{\kappa}{2}(\triangle K_{c,t})^2$$

where $\ln G_t = \rho_G \ln G_{t-1} + v_{G,t}$, and $I_t = I_{c,t} + I_{h,t}$

$$Y_{h,t} = H_t - (1-\delta_h)H_{t-1}$$

and

$$N_t = N_{c,t} + N_{h,t}$$

GDP is defined as sum of outputs produced by the two sectors:

$$GDP_t = Y_{c,t} + p_h Y_{h,t}$$

where p_h is the steady-state real price of houses.

Nominal and real interest rates are linked by the Fisher identity:

$$1 + r_t = \frac{1+R_t}{1+E_t\pi_{t+1}}$$

According to our default model, all the shocks in the model follow an AR(1) process except for housing productivity (which is non-stationary and also follows an AR(1) but in differences); thus:

$$\ln \varepsilon_t^i = \rho_i \ln \varepsilon_{t-1}^i + v_{i,t}$$

where $i = g, p, l, m, hd, pc, ph, nc, nh, kc, kh$. We check this against the data for these errors extracted from the model; we review the empirical results for these below.

2.2 Model variant with housing collateral (The collateral model)

To extend the benchmark model to one allowing for housing collateral, we follow Iacoviello (2005) to introduce into the households a group whose borrowing is constrained by the value of their houses. These 'impatient' households have life-time utility:

$$U' = E_0 \sum_{t=0}^{\infty} \beta'^t \varepsilon_t^p \left[\frac{C_t'^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^{hd} \frac{H_t'^{1-\sigma_h}}{1-\sigma_h} \right] \tag{9}$$

where variables have their usual meanings but '$\prime$' denotes variables for impatient households. Here, we follow Monacelli (2009) in simplifying the model by omitting labour from the utility function. These impatient households thus have housing wealth but no direct labour income, but we assume that they share some of the labour income of ordinary working households via a lump-sum transfer from them, τ_W; this implies that in the long run they do not need to dispose of all their wealth to consume. We think of these impatient households as being relatives (e.g., parents) of ordinary households (their lump-sum transfer appears in their budget constraints implicitly; we do not redo their behavioural equations explicitly for this, as these do not change).

Correspondingly the budget constraint of impatient households is:

$$C'_t + p_{h,t}\left[H'_t - (1-\delta_h)\,H'_{t-1}\right] + (1+r_{t-1})B'_{t-1} - \tau_{W,t} = B'_t \tag{10}$$

where borrowing B'_t is restricted to be a fraction (m) of the present value of the housing collateral by the time the debt is due:

$$B'_t \leq mE_t\left(\frac{p_{h,t+1}H'_t}{1+r_t}\right) \tag{11}$$

The impatient household problem is to maximise (**9**) by choosing C'_t, H'_t and B'_t, subject to (**10**) and (**11**). The optimal conditions can be combined to imply:

$$\varepsilon_t^{hd} H_t^{'-\sigma_h} = \frac{p_{h,t}}{C_t^{'\sigma_c}} - \beta^{'}(1-\delta_h)E_t\frac{p_{h,t+1}}{C_{t+1}^{'\sigma_c}}\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p} - [\frac{1}{C_t^{'\sigma_c}} - \beta^{'}(1+r_t)E_t\frac{1}{C_{t+1}^{'\sigma_c}}\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p}]mE_t\frac{p_{h,t+1}}{1+r_t}$$

which is the demand for houses of impatient households.

The consumption of impatient households is solved by the budget constraint.

Market-clearing in the extended model is reached when:

$$Y_{c,t} = C_t + I_t + GNX_t + \frac{\kappa}{2}(\triangle K_{c,t})^2 + C'_t$$

and

$$Y_{h,t} = H_t - (1-\delta_h)H_{t-1} + H'_t - (1-\delta_h)H'_{t-1}$$

The log-linearised model is listed in Appendix A.

3 The Method of Indirect Inference

In this section we explain the method of Indirect Inference that we use for comparing the 'match' of the above models to the data behaviour as we report below. While the Bayesian method has been popular in the recent literature for model comparison, we use Indirect Inference here as our purpose is to evaluate whether any individual model is compatible with the data in a formal (frequentist) statistical test, independent of the subjective priors, which can strongly influence Bayesian evaluation. In effect it is the widely used prior of the collateral model that we wish to test here. Indirect Inference originated as a systems estimator with Smith Jr (1993), Gregory and Smith (1991) and Gourieroux, Monfort, and Renault (1993) for getting around the difficulties in estimating models with complex likelihood functions. Minford, Theodoridis, and Meenagh (2009) and Le et al. (2011) then developed the method as a testing procedure based on comparing the behaviour of a model with the behaviour of the data; for a survey of the method and its properties see Le et al. (2016) and Minford (2019), which discuss why the method has extremely high power in small samples against model mis-specification and parameter inaccuracy. The basic idea is to first construct an auxiliary (empirical) model which is fitted to the actual data to give 'descriptors' of the data. Such descriptors can be coefficients of the auxiliary model or functions of them (such as moments or IRFs); they are a parsimonious description of 'the facts'. The method then turns to the model to be tested (the macro model), and uses it to generate a large number of simulated data samples on each of which the same auxiliary model is estimated. This establishes an empirical distribution of the data descriptors conditional on the hypothesis that the macro model is true. The method then evaluates the distance between the actual data descriptors and this distribution of them, to decide whether the macro model is rejected at a selected level of significance; in effect it is asking whether the facts in the data sample could have been generated by the model at some minimum probability level. This testing process is ultimately carried out on the model once estimated, also by indirect inference (which chooses model parameters to minimise the above distance).

When as here the data is mostly non-stationary, the auxiliary model should reflect this; we use the coefficients of a VECM as the descriptors, where the cointegrating equation relates the endogenous non-stationary variables to the exogenous non-stationary errors (here the housing TFP shock) and a time trend. This can be transformed into a VARX(1), where the latter are the X. We choose GDP, inflation and the interest rate as the three main endogenous variables for the VARX. The data descriptors chosen are the VARX coefficients and the variances of the residuals, which between them summarise the dynamic/cointegrating relationships and the volatility of the data. The probability density function of the joint distribution of the data descriptor vector β_s generated by the estimated model with parameter vector $\widehat{\theta}$ is $\frac{1}{(2\pi)^k\left|\Omega(\beta_s[\widehat{\theta}])\right|}e^{-0.5[\beta_s-\overline{\beta_S(\widehat{\theta})}]'\{\Omega(\beta_S(\widehat{\theta}))\}^{-1}[\beta_s-\overline{\beta_S(\widehat{\theta})}]}$ where the exponent is the Wald statistic for all potential β_s vectors of the descriptors. We calculate the value of this for the estimated $\hat{\beta}$ in the actual data sample as:

$$W=\left(\hat{\beta}-\overline{\beta_S(\widehat{\theta})}\right)'\Omega(\beta_S(\widehat{\theta}))\}^{-1}\left(\hat{\beta}-\overline{\beta_S(\widehat{\theta})}\right) \tag{12}$$

To decide whether the macro model is rejected we calculate its p-value defined as:

$$p=(1-WP)/100$$

where WP is the percentile of W as on its empirical distribution found with the simulated data. In practice, we bootstrap the sample errors that we back out using the actual data and the macro model for different bootstraps of simulated data to be found; and we generate 1,000 bootstraps. The parameters of the macro model are estimated using the Simulated Annealing (SA) algorithm which searches over the parameter space for the Wald statistic (12) to be minimised, the minimum point being the Indirect Inference estimator.

3.1 Data

Our data sample is between 2000Q1-2014Q4. The unfiltered data are used to do the testing and estimation together with the other model parameters: we fix the discount factor and the depreciation rates at their calibrated values.

The time series we have used are: real GDP, real consumption, real wage, inflation, real house price, real investment, residential investment and interest rates. We provide a detailed description of the data in Appendix B. Figure 1 plots the time series. An absolutely complete data set is only available from 2000 up to the end of 2014, which is why we use this sample period. There is data for all but housing volumes up to 2019, which enables us to extend the test with this minor gap as a robustness check, as also done below.

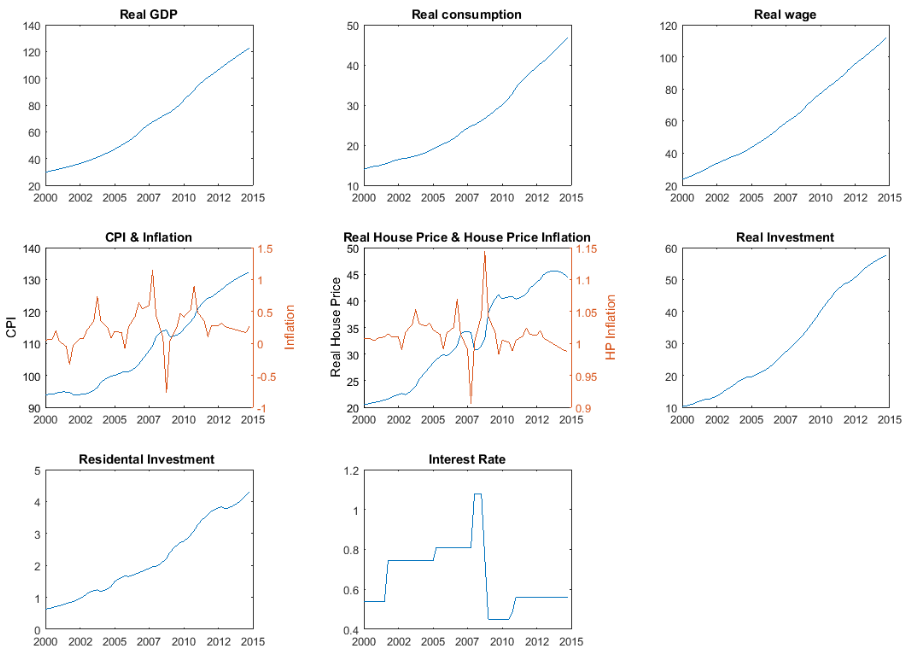


Figure 1: Data

3.2 Calibration

We calibrate the parameter values of the model according to the previous literature, which can be found in Table 1. We test both benchmark and collateral model using these calibrated values in what follows. If both models with calibrated values cannot pass the test, as is normally the case, Indirect Inference estimation is carried out to reestimate these parameters and the models are tested on their estimated parameters.

On the household side, β is set at 0.985, using Chinese quarterly data. This is in line with standard practice in most DSGE models of housing. We set the elasticity of consumption σ_c at 2 in the goods sector according to Walsh (2003) and 1 for the elasticity of housing σ_h in accordance with Iacoviello (2005). In general, a low value of σ_i (high intertemporal elasticity) means that consumption growth is very sensitive to changes in the real interest rate. We set σ_h lower than σ_c since substitution of housing goods is relatively more sensitive compared to the substitution of general consumption goods when the real interest rate changes Xu and Chen (2012). We follow Iacoviello and Neri (2010) in setting the inverse of the elasticity of labour supply η at 0.5. The quarterly depreciation rate of housing δ_h is set at 0.015 following Liu and Ou (2017).

On the firm side, the depreciation rate of total capital δ_k is set at 0.03 in line with Zhang (2009). And we follow Liu and Ou (2017) in setting the depreciation rate of capital in the goods sector δ_{kc} and the housing sector δ_{kh} at 0.03 and 0.04 respectively, and the capital-output elasticity α in the Cobb-Douglas production function at 0.34. We set the price rigidity parameter ω at 0.84, in line with Zhang (2009) who employs Chinese quarterly data to estimate the New Keynesian Phillips curve. The capital adjustment cost is set at $\kappa = 0.028$, following Rødseth (2000). In terms of monetary policy rule, the standard value of $\theta_\pi = 1.5$ and $\theta_{GDP} = 0.12$ are chosen to be in line with Liu and Ou (2017).

4 Empirical Analyses

4.1 Testing the housing collateral model

Model fit

Table 1 presents the Indirect Inference empirical results, which show the model parameters under both calibration and estimation together with the test results, presented in the form of the Wald statistic as a percentile and p-value. Both benchmark and collateral model are rejected using the calibrated parameters, with a p-value equal to 0, implying no match at all to the data behaviour; however, this is not surprising as these parameters are chosen from other studies which may have little relevance to China. Estimation is therefore necessary.

The last two columns present the estimated coefficients of both benchmark model and collateral model. The bottom two rows show the test results for the two estimated models. We can see that the benchmark model is not rejected by the data, with a p-value of 0.06; the collateral model is strongly rejected by the data, with a p-value of 0. Thus the model without housing collateral is found to be the data generating mechanism.

These results are in line with the findings of Su, Yin, and Tao (2018) that the housing collateral channel is quite weak in China. In their study, they find that households in China consume out of their disposable income, and do not borrow, let alone using housing as collateral. Indeed, they struggle to own houses, highly priced relative to general consumption, for cultural reasons, squeezing their consumption to maintain ownership. This could explain why the housing collateral channel is inoperative in China.

4.1.1 The behaviour of the shocks in the Benchmark model

We can see from Figure 2 that there are significant fluctuations in many of these shocks during the financial crisis that started in 2008. The shock from government and world demand, GNX, the

Table 1: Estimates of Model Coefficients

Definition	Parameter	Calibration	Benchmark	Collateral
Household:				
Elasticity of consumption	σ_c	2	2.83	1.75
Elasticity of housing	σ_h	1	1.36	4.55
Inverse of elasticity of labour	η	0.5	0.53	0.41
Household's discount factor	β	0.985	FIX	FIX
Quarterly depreciation rate of housing	δ_h	0.015	FIX	FIX
Firms:				
quarterly depreciation rate of capital	δ_k	0.03	FIX	FIX
Quarterly depreciation rate of capital-G	δ_{kc}	0.03	FIX	FIX
Quarterly depreciation rate of capital-H	δ_{kh}	0.04	FIX	FIX
Share of capital in production	α	0.34	0.79	0.73
Price rigidity	ω	0.84	0.86	0.84
Capital adjustment	κ	0.028	0.03	0.02
Monetary Policy:				
Interest rate smoothing	ρ	0.75	0.73	0.65
Taylor Rule response to inflation	θ_π	1.5	1.58	2.07
Taylor Rule response to output	θ_{GDP}	0.12	0.10	0.09
Shock Processes:(see also Table 2)				
Government spending+net exports shock	ρ_g		0.93	0.93
Preference shock	ρ_p		0.83	0.94
Labour supply shock	ρ_l		0.97	0.96
Productivity shock-G	ρ_{pc}		0.66	0.58
Productivity shock-H (differenced, I(1))	ρ_{ph}		0.51	0.52
Housing demand shock	ρ_{hd}		0.43	0.32
Monetary policy shock	ρ_m		0.52	0.49
Labour demand shock-G	ρ_{nc}		0.91	0.91
Labour demand shock-H	ρ_{nh}		0.98	0.98
Capital demand shock-G	ρ_{kc}		0.85	0.85
Capital demand shock-H	ρ_{kh}		0.99	0.99
Testing Results:				
WALD(Y, π, i)			94%	100%
P-Value			0.06	0.00

exogenous spending shock, drops precipitously from 2008. The preference shock shows a big drop at the end of 2008 with the collapse of world trade. The labour supply shock also responded, implying a sharp wage cut. The monetary policy shock response was familiarly a big fall in interest rates (though not reaching the zero lower bound). General productivity also fell, with costs (including raw material prices) rising sharply. What we see here is the huge impact on China, via the model shocks, of the world crisis. Thus China's close connection to the rest of the world is the main source of shocks, even in this closed-economy model. In this respect the model behaves similarly to the Smets-Wouters model of the US economy, which similarly treats the US as a self-sufficient continent.

Table 2 shows the stationarity status of the shocks with two statistical tests – the ADF test and KPSS test. In general we expect at least one of the shocks to be non-stationary, on the grounds that Chinese real data is mostly non-stationary, and this must come from the shocks to the model. To decide on the integration order of the shocks, we consider several tests, of which the decisive one is the Wald test of the model inclusive of the chosen error processes: the Wald test acts as the final test of the whole model including these error processes– if they are at fault, the Wald test will reject the model, so checking these error assumptions. As we can see that the ADF test, which tests for non-stationarity as the null, only fails to reject this null at a 0.09 p-value for five shocks: GNX and consumer preferences,housing technology, housing labour demand and capital demand; these we treat as potentially I(1), with the rest as I(0). Notice that for these five the KPSS does not reject trend-stationarity, which it treats as the null; all of them have AR(1) coefficients close to but below 1. So there is some ambivalence surrounding their status. We find that the model is decisively rejected with all five treated as non-stationary but accepted with only housing technology as I(1); accordingly we choose only this error as I(1), with the rest as I(0).

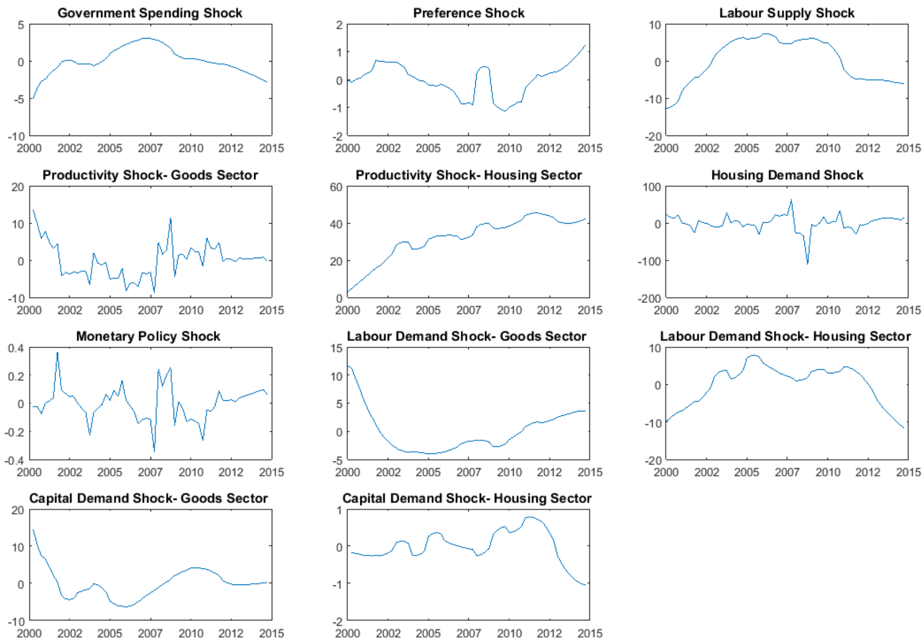


Figure 2: Structural Shocks

Table 2: Stationarity of Shocks

Shocks	ADF p-value	KPSS statistic	Conclusion
Exogenous spending	0.4094	0.2361	Stationary
Preference	0.3498	0.1972	Stationary
Labour supply	0.0658*	0.2360	Trend Stationary
TFP-Goods sector	0.0686*	0.1689	Trend Stationary
TFP- Housing sector	0.0928	0.2199	Non -Stationary
Housing demand	0.0083***	0.0749	Trend Stationary
Monetary policy	0.0000***	0.1017	Stationary
Labour demand - Goods	0.0034***	0.2114	Trend Stationary
Labour demand - Housing	0.1262	0.2137	Stationary
Capital demand - Goods	0.0205**	0.1578	Stationary
Capital demand - Housing	0.4439	0.1409	Stationary

Notes:

1. p-value with*, **, *** rejects the null hypothesis unit root process at 10%, 5% and 1%

2. None of the KPSS statistics reject the null hypothesis of stationarity at the 5% level (Critical value: 0.463)

4.2 How reliable is the benchmark model?

From the testing results above, we find that the benchmark model can explain the Chinese economy adequately, on the basis of the p-value. However, model users would like to know the model's accuracy for their policy purposes; this can be established by a Monte Carlo experiment assessing the power of the Indirect Inference test. We carry out a Monte Carlo experiment to assess the rejection rate against parameter mis-specification. 10,000 Monte Carlo samples are generated and false models are created by moving the parameters away from their assumed true values (as estimated here) by x% alternately in both directions. We want to find out how many of the 10,000 samples would be rejected for each false model. The idea is that if a model x% false is rejected 100% of the time, then one can be sure that the estimated model lies within x% of the true model, since otherwise it would have been rejected.

Table 3 displays the rejection rates at the 5% significance level, with parameter falseness rising to 7%. We can see clearly from the table that the benchmark model is 100% rejected at 7% falsity, implying that our benchmark model here lies within a 7% perimeter around the true model.

We also check power against mis-specification. We test the frequency with which we would reject the collateral model if the benchmark model was the true one; also vice versa. We assume first that the benchmark model is true (with parameters the same as those we estimated) and generate 1,000 samples of data from it. We then check for how many of these samples the collateral model is rejected at the 5% significance level. We then repeat this experiment the other way round, assuming the collateral model to be the true one. Table 4 shows the results for the test's power against mis-specification- which is clearly virtually absolute. From the results, we can see that if the collateral model was true for China- in contradiction of our results- then we would be certain to reject the benchmark model. We do not, implying that collateral model cannot be true, in line with our rejection of it.

Table 3: Monte Carlo Power Test - 3 variables VARX(1)

Parameter falseness	TRUE	1%	1.5%	3%	3.5%	5%	7%
Rejection rate at the 5% level	5.0	5.9	9.1	34	48.1	88.1	100

Table 4: Mis-specification Power Check: Benchmark Model vs Collateral Model

When the true model is	Rejection rate of the other model at the 5% level
Benchmark model	100%(Collateral)
Collateral model	100%(Benchmark)

4.3 Robustness Test

We conduct a robustness check, by extending the sample to 2019. While we did not use this fuller sample for our main results, for lack of a complete data set,almost all the data is available for this extension, including for the variables used in the VARX with which the simulated model behaviour is matched. There is a gap for housing volume, so that in the bootstrap simulations housing shocks (and a few others whose calculation involves the use of housing volume) are still based on data up to 2014. This is a small deficiency which is unlikely to make much difference to the test. Accordingly we use the extended sample as a robustness check on our results. As can be seen from Table 5, the test findings are robust to this sample extension, with the benchmark model accepted and the housing collateral model rejected.

Table 5: Robustness Test

	Benchmark model	Collateral model
P-value (sample up to 2014)	0.06	0.00
P-value (sample up to 2019)	0.10	0.00

4.4 What does the benchmark model tell us?

4.4.1 Variance Decomposition

Table 6 shows the variance decomposition of GDP, inflation and nominal interest rate at different horizons (short run: 1 year; medium run: 5 years; and long run: 10 years). The exogenous spending shock plays a dominant role at all horizons. It explains 59% of GDP variance in the first year and this decreases to 55.9% after 10 years. This reflects the major role played by exports and government consumption in aggregate demand. By contrast, shocks from the housing market (i.e., housing productivity, housing demand, labour and capital demands in the housing sector) contribute little over all forecast horizons, less than 10% of GDP volatility.

The cyclical fluctuations in inflation are driven mainly by the goods sector cost/technology shock; this accounts for 67.1-74.1% of inflation volatility at different horizons.

Interest rate variance is heavily determined by the monetary policy shock and the goods sector cost/technology shock, which provokes strong Taylor rule responses. The former explains 28.6-36.6% while the latter explains 40-45.3% at different horizons.

4.4.2 Historical Decomposition

We now turn to how these shocks contributed historically over the sample period to GDP, inflation and interest rates (Figure 3).

From the top panel of Figure 3, we see how the exogenous spending shock(GNX) stimulated the economy until 2010. The labour supply error- a large wage cut in response to the crisis- plays a key contractionary role. After 2011, the exogenous spending shock started to fall due to the effect of the crisis, triggering sharply falling output. As we can see clearly from the figure, housing shocks play little part.

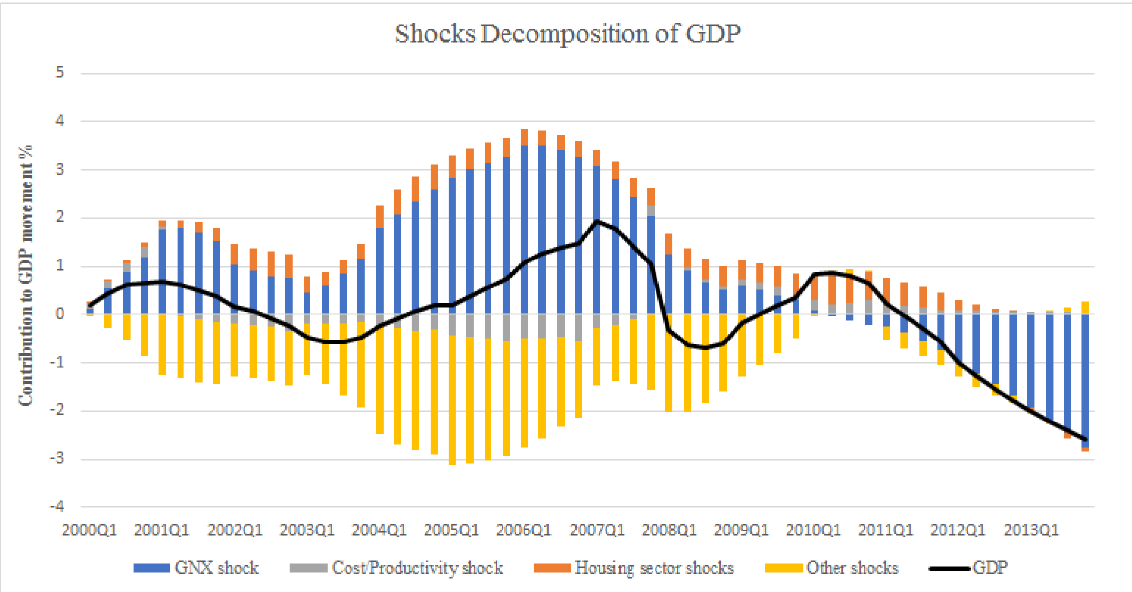
Inflation was heavily affected by the goods sector cost/technology shock, with a price boom in 2007, followed by a collapse after the crisis.

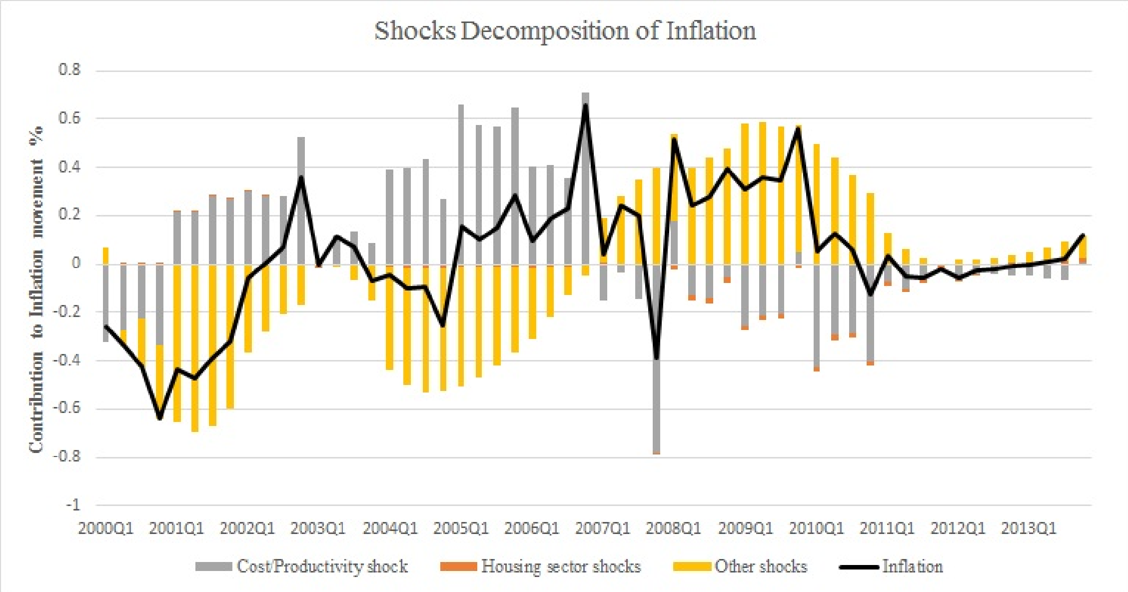
Table 6: Variance Decomposition

	Shocks										
	ε_t^g	ε_t^p	ε_t^l	ε_t^{pc}	ε_t^{ph}	ε_t^{hd}	ε_t^m	ε_t^{nc}	ε_t^{nh}	ε_t^{kc}	ε_t^{kh}
1 Year											
GDP	59	13.5	4.3	6.3	0.3	0.01	6.6	0.2	0.04	8.9	0.6
Inflation	0.06	1.4	1.6	74.1	0.02	0.00	0.01	0.6	0.02	22.2	0.01
Interest rate	0.2	1.1	0.9	45.3	0.01	0.00	36.6	0.4	0.01	15.5	0.01
5 Years											
GDP	62.6	8.6	8.4	4.4	0.5	0.01	4.3	0.2	0.09	7.8	3
Inflation	0.1	1.5	4.1	67.9	0.04	0.00	0.01	0.9	0.06	25.3	0.04
Interest rate	0.2	1.4	4.5	40.9	0.02	0.00	29.2	0.9	0.06	23	0.04
10 Years											
GDP	55.9	7.3	9.7	3.8	1.3	0.01	3.6	0.2	0.1	8.7	9.4
Inflation	0.1	1.5	5.3	67.1	0.08	0.00	0.01	0.9	0.1	25	0.05
Interest rate	0.2	1.3	6.2	40	0.07	0.00	28.6	0.9	0.1	22.6	0.06

We can see that the interest rate was driven by the monetary policy shock and goods sector cost/productivity shock. The cost/productivity shock dominates inflation fluctuations which in turn affect the interest rate, responding via the Taylor rule. But after 2008, the monetary policy shock moves into strong easing, reducing interest rates sharply.

In summary, we can see from the shock decomposition that the housing sector shocks have little influence on China's business cycle. By contrast, the exogenous spending shock(GNX), cost/technology shock and monetary policy shock, all play influential roles.





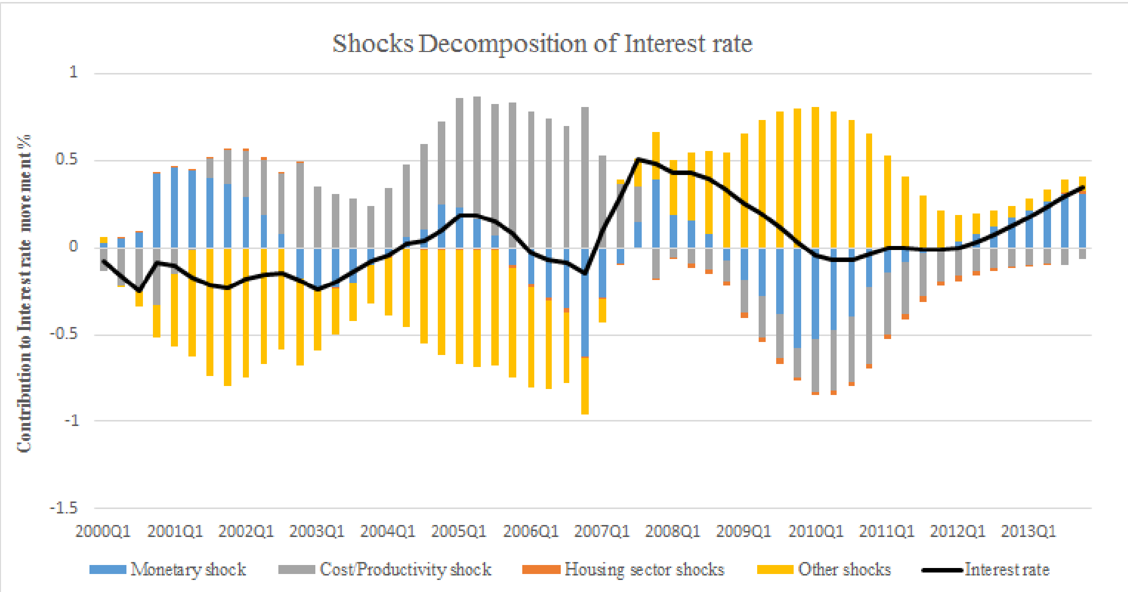


Figure 3: Shocks Decomposition of GDP, Inflation and Interest rate

Note: Housing sector shocks include productivity shock, housing demand shock, labour demand shock and capital demand shock in the housing sector.

4.4.3 Impulse Response Functions

Figure 4 plots the impulse responses of a monetary policy shock to the economy. A contractionary monetary policy shock reduces activity quite generally. Consumption and housing demand fall via the standard interest rate channel, lowering GDP. This lowers house prices. Interest rates react via the Taylor Rule, falling back gradually and restoring demand. These results are quite standard in the previous literature.

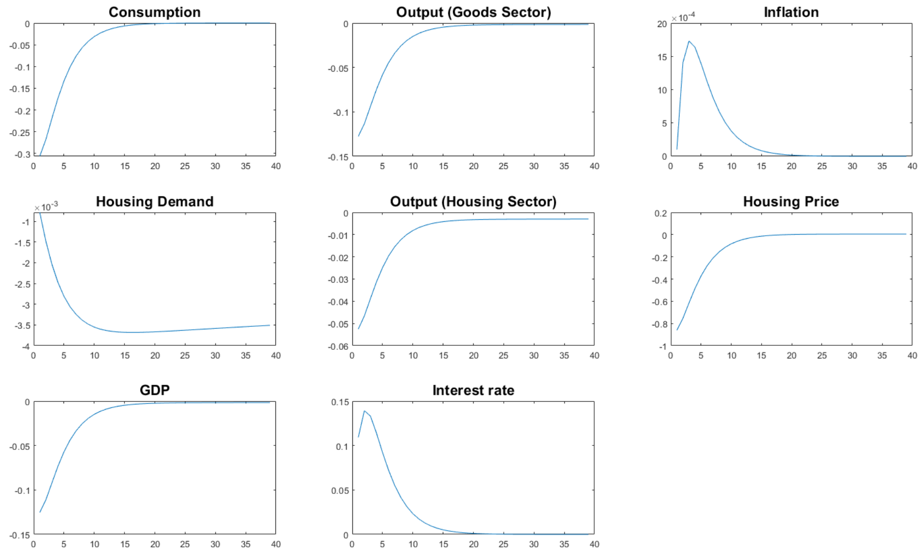


Figure 4: Monetary Policy Shock (standard error=0.11)

Figure 5 shows the impulse responses to a positive government spending shock. This pushes up GDP and inflation, so raising interest rates. This in turn dampens consumption and housing demand, which lowers house prices and housing supply.

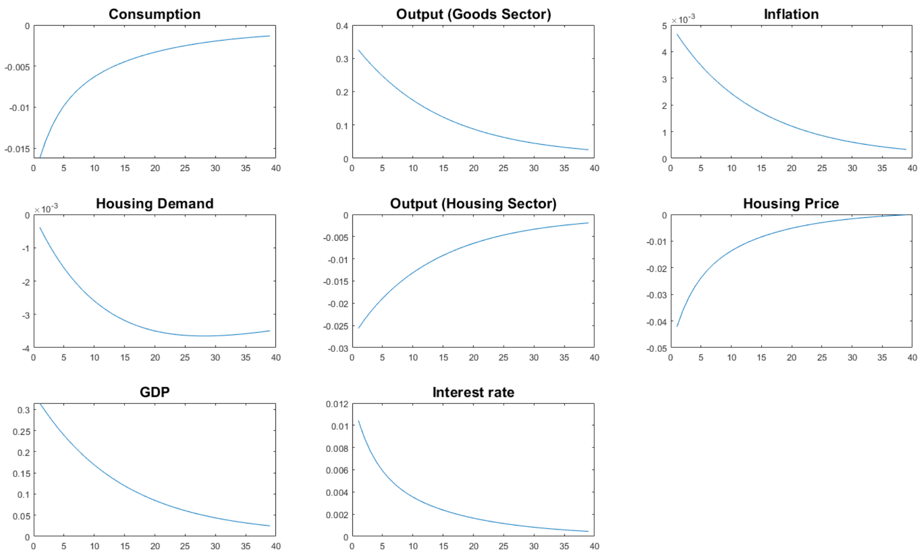


Figure 5: Government Spending Shock (standard error=0.32)

Figure 6 plots the impulse responses of model variables to a positive productivity shock in the goods sector. This raises output and lowers inflation, reducing interest rates. This pushes up consumption, housing demand and house prices, raising housing supply.

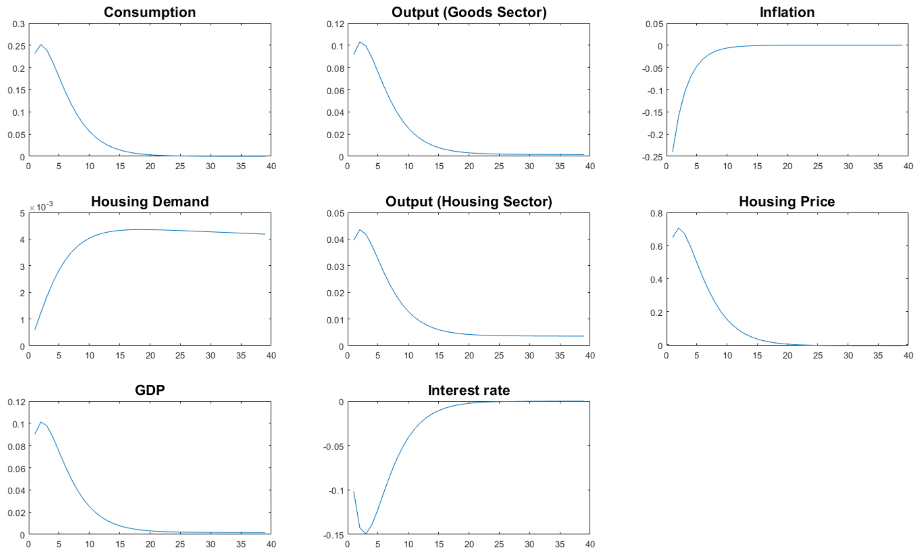


Figure 6: Productivity Shock in the Goods Sector (standard error=3.56)

5 Conclusion

This paper aims to test whether housing collateral helps to explain the business cycle in China. We set up two competing models, one with housing collateral and one without, to investigate this question. The empirical results of our powerful indirect inference test show that the housing collateral model cannot explain the business cycle well compared to the model without housing collateral: the model is strongly rejected, while the benchmark model without housing collateral is accepted. The benchmark model implies that the main drivers of the Chinese business cycle are the exogenous spending shock from government and net exports, the monetary policy shock and the goods-sector cost/productivity shock, all in turn most likely connected to world business cycle shocks, especially the global financial crisis. By contrast, shocks from the housing sector affect the business cycle little, nor is there evidence that they affect it via the collateral channel.

Our finding highlights the importance of *testing* widely accepted theoretical model assumptions - here, the housing collateral borrowing condition - in empirical studies. This is a brand-new research agenda which has never been explored systematically before; and we establish, for the first time, evidence against it with Chinese data which seem to reflect people's reluctance to collateralise houses for borrowing. This may be simply due to Chinese culture and clearly, our findings should not be taken as a general rejection of the housing collateral condition. However it does suggest the need for more research on whether the collateral model can fit the data in other countries. We leave this for future work.

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Appendices

A Model Appendix

A.1 Benchmark Model

Households:

Consumption Function:

$\widetilde{c}_t = E_t\widetilde{c}_{t+1} - \frac{1}{\sigma_c}\widetilde{r}_t + \frac{1}{\sigma_c}(\widetilde{\varepsilon}^p_t - \widetilde{\varepsilon}^p_{t+1})$

Housing Demand Equation:

$A\sigma_h\widetilde{h}_t = (\sigma_c\widetilde{c}_t - \widetilde{p}_{h,t}) - \beta(1-\delta_h)E_t[\sigma_c\widetilde{c}_{t+1} - \widetilde{p}_{h,t+1} + (\widetilde{\varepsilon}^p_t - \widetilde{\varepsilon}^p_{t+1})] + A\widetilde{\varepsilon}^{hd}_t \qquad where\ A = 1-\beta(1-\delta_h)$

Total Labour Supply Equation:

$\widetilde{w}_t = \eta\widetilde{n}_t + \sigma_c\widetilde{c}_t + \widetilde{\varepsilon}^l_t$

Goods Sector:

Labour Demand Equation:

$\widetilde{n}_{c,t} = \widetilde{y}_{c,t} - \widetilde{w}_t - \widetilde{\varepsilon}^{nc}_t$

Capital Demand Equation:

$\kappa(K_c + \beta + \frac{\alpha\beta}{\kappa}\frac{Y_c}{K_c})\widetilde{k}_{c,t} = \kappa K_c\widetilde{k}_{c,t-1} + \kappa\beta E_t\widetilde{k}_{c,t+1} + \alpha\beta\frac{Y_c}{K_c}E_t(\widetilde{y}_{c,t+1} - \widetilde{r}_t) + \beta(1-\delta_{kc})E_t\widetilde{\varepsilon}^{kc}_{t+1} + \widetilde{\varepsilon}^{kc}_t$

Price Setting:

$\widetilde{\pi}_t = \beta E_t\widetilde{\pi}_{t+1} + \frac{(1-\omega)(1-\omega\beta)}{\omega}\widetilde{mc}_t$

Marginal Cost:

$\widetilde{mc}_t = (1-\alpha)(\widetilde{w}_t + \widetilde{\varepsilon}^{nc}_t) + \alpha(\widetilde{r}_t + \widetilde{\varepsilon}^{kc}_t) - \widetilde{\varepsilon}^{pc}_t$

Housing Sector:

Labour Demand Equation:

$\widetilde{n}_{h,t} = \widetilde{y}_{h,t} + \widetilde{p}_{h,t} - \widetilde{w}_t - \widetilde{\varepsilon}^{nh}_t$

Capital Demand Equation:

$\kappa(K_h + \beta + \frac{\alpha\beta}{\kappa}\frac{Y_h}{K_h}p_h)\widetilde{k}_{h,t} = \kappa K_h\widetilde{k}_{h,t-1} + \kappa\beta E_t\widetilde{k}_{h,t+1} + \alpha\beta\frac{Y_h}{K_h}p_h E_t(\widetilde{y}_{h,t+1} - \widetilde{r}_t + \widetilde{p}_{h,t+1}) + \beta(1-\delta_{kh})E_t\widetilde{\varepsilon}^{kh}_{t+1} + \widetilde{\varepsilon}^{kh}_t$

Housing Supply Equation:

$\widetilde{y}_{h,t} = \alpha\widetilde{k}_{h,t} + (1-\alpha)\widetilde{n}_{h,t} + \widetilde{\varepsilon}^{ph}_t$

Identities:

GDP definition:

$\widetilde{GDP}_t = \frac{Y_c}{GDP}\widetilde{y}_{c,t} + \frac{Y_h}{GDP}\widetilde{y}_{h,t}$

Total Labour Demand:

$\widetilde{n}_t = \frac{N_c}{N}\widetilde{n}_{c,t} + \frac{N_h}{N}\widetilde{n}_{h,t}$

Total Capital Demand:

$\widetilde{k}_t = \frac{K_c}{K}\widetilde{k}_{c,t} + \frac{K_h}{K}\widetilde{k}_{h,t}$

Fisher Equation:

$\widetilde{r}_t = \widetilde{R}_t - E_t\widetilde{\pi}_{t+1}$

Market Clearing:

Goods Market Clearing:

$\widetilde{y}_{c,t} = \frac{C}{Y_c}\widetilde{c}_t + \frac{K}{Y_c}\widetilde{k}_t - \frac{K}{Y_c}(1-\delta_k)\widetilde{k}_{t-1} + \widetilde{\varepsilon}^g_t$

Housing Market Clearing:

$\widetilde{y}_{h,t} = \frac{H}{Y_h}\widetilde{h}_t - (1-\delta_h)\frac{H}{Y_h}\widetilde{h}_{t-1}$

Taylor Rule:

$\widetilde{R}_t = \rho\widetilde{R}_{t-1} + (1-\rho)[\theta_\pi\pi_t + \theta_{GDP}(\widetilde{GDP}_t - \widetilde{GDP}_{t-1})] + \widetilde{\varepsilon}^m_t$

Shock Process:

Government Spending Shock:

$\widetilde{\varepsilon}^g_t = \rho_g\widetilde{\varepsilon}^g_{t-1} + \widetilde{v}_{g,t}$

Preference Shock:

$\widetilde{\varepsilon}^p_t = \rho_p\widetilde{\varepsilon}^p_{t-1} + \widetilde{v}_{p,t}$

Labour Supply Shock:

$\widetilde{\varepsilon}^l_t = \rho_l\widetilde{\varepsilon}^l_{t-1} + \widetilde{v}_{l,t}$

Productivity Shock(Goods Sector):

$\widetilde{\varepsilon}^{pc}_t = \rho_{pc}\widetilde{\varepsilon}^{pc}_{t-1} + \widetilde{v}_{pc,t}$

Productivity Shock(Housing Sector):

$\widetilde{\varepsilon}^{ph}_t - \widetilde{\varepsilon}^{ph}_{t-1} = \rho_{ph}(\widetilde{\varepsilon}^{ph}_{t-1} - \widetilde{\varepsilon}^{ph}_{t-2}) + \widetilde{v}_{ph,t}$

Housing Demand Shock:

$\widetilde{\varepsilon}^{hd}_t = \rho_{hd}\widetilde{\varepsilon}^{hd}_{t-1} + \widetilde{v}_{hd,t}$

Monetary Policy Shock:

$\widetilde{\varepsilon}^m_t = \rho_m\widetilde{\varepsilon}^m_{t-1} + \widetilde{v}_{m,t}$

Labour Demand Shock(Goods Sector):

$\widetilde{\varepsilon}^{nc}_t = \rho_{nc}\widetilde{\varepsilon}^{nc}_{t-1} + \widetilde{v}_{nc,t}$

Labour Demand Shock(Housing Sector):

$\widetilde{\varepsilon}^{nh}_t = \rho_{nh}\widetilde{\varepsilon}^{nh}_{t-1} + \widetilde{v}_{nh,t}$

Capital Demand Shock(Goods Sector):

$\widetilde{\varepsilon}^{kc}_t = \rho_{kc}\widetilde{\varepsilon}^{kc}_{t-1} + \widetilde{v}_{kc,t}$

Capital Demand Shock(Housing Sector):

$\widetilde{\varepsilon}^{kh}_t = \rho_{kh}\widetilde{\varepsilon}^{kh}_{t-1} + \widetilde{v}_{kh,t}$

A.2 Collateral Model

Impatient households:

Consumption Function:

$$\frac{C^{'}}{Yc}\widetilde{c}^{'} + \frac{P_h H}{Y_c}[\widetilde{h}_t^{'} - (1-\delta_h)\widetilde{h}_{t-1}^{'}] + \frac{(1+r)B^{'}}{Y_c}(\widetilde{r}_{t-1} + \widetilde{b}_t^{'}) = \frac{B^{'}}{Y_c}\widetilde{b}_t^{'}$$

Housing Demand Equation:

$$A\sigma_h\widetilde{h}_t^{'} = (1-m\beta)(\sigma_c\widetilde{c}_t - \widetilde{p}_{h,t}) - \beta^{'}[(1-\delta_h)-m]E_t[\sigma_c\widetilde{c}_{t+1}^{'} - \widetilde{p}_{h,t+1} + (\widetilde{\varepsilon}_t^{p} - \widetilde{\varepsilon}_{t+1}^{p})] + m\beta(E_t\,\widetilde{p}_{h,t+1} - \widetilde{p}_{h,t} - \widetilde{r}_t) + A\widetilde{\varepsilon}_t^{hd} \qquad where \;\; A = 1 - m\beta - \beta^{'}[(1-\delta_h) - m]$$

Borrowing Constraint:

$$\widetilde{b}_t^{'} = \widetilde{p}_{h,t+1} + \widetilde{h}_t^{'} - \widetilde{r}_t$$

Market Clearing:

Goods Market Clearing:

$$\widetilde{y}_{c,t} = \frac{C}{Y_c}\widetilde{c}_t + \frac{C^{'}}{Y_c}\widetilde{c}_t^{'} + \frac{K}{Y_c}\widetilde{k}_t - \frac{K}{Y_c}(1-\delta_k)\widetilde{k}_{t-1} + \widetilde{\varepsilon}_t^{g}$$

Housing Market Clearing:

$$\widetilde{y}_{h,t} = \frac{H}{Y_h}\widetilde{h}_t - (1-\delta_h)\frac{H}{Y_h}\widetilde{h}_{t-1} + \frac{H^{'}}{Y_h}\widetilde{h}_t^{'} - (1-\delta_h)\frac{H^{'}}{Y_h}\widetilde{h}_{t-1}^{'}$$

B Data Appendix

The sources of these observable from 2000Q1 to 2014Q4 are from the National Bureau of Statistics of China (NBSC), Ministry of Human Resources and Social Security, P.R.C(MHRSS), the People's Bank of China (PBOC) and the Oxford Economics (OE). We convert annual data into the quarterly data using either the 'quadratic-match sum' or 'quadratic-match average' algorithms with Eviews, which quarterly data are not available. All variables are converted into the real term per capita basis by dividing by working age population and CPI index.

The Table B below summarises the definition, sources of data used in this paper.

Table B: Data Description

Symbol	Variable	Source
GDP	Total Output	NBSC
Y_c, Y_h	Output in two sectors	Model implied
C	Private consumption	NBSC
$C^{'}$	Impatient households consumption	Model implied
H	Housing consumption	Model implied
$H^{'}$	Impatient households housing consumption	Model implied
B	Total borrowing of impatient households	Model implied
W	Average Wage per person	MHRSS
π	Quarter-on-quarter CPI inflation	NBSC
N	Employment	OE
N_c, N_h	Employment in two sectors	Model implied
p_h	Real housing price	NBSC
I, I_c, I_h	Investment	NBSC
K, K_c,K_h	Capital stock	Model implied
R	Nominal interest rate	PBOC