



# What determines China's housing price dynamics? New evidence from a DSGE-VAR

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## Abstract

We investigate what determines China's housing price dynamics using a DSGE-VAR estimated with priors allowing for the featured operating of normal and "shadow" banks in China, with data observed between 2001 and 2014. We find that the housing demand shock, which is the essential factor for housing price "bubbles" to happen, accounts for near 90% of the housing price fluctuation. We also find that a prosperous housing market could have led to future economic growth, though quantitatively its marginal impact is small. But this also means that, for policy-makers who wish to stabilize the housing market, the cost on output reduction would be rather limited.

## KEYWORDS

bubbles, China, DSGE-VAR, housing price, market spillovers

## 1 | INTRODUCTION

The past decade has witnessed the first round of China's housing market boom, which started in the early 2000s, and yet, has no sign of ceasing, since its marketization reform in the late 1990s. Over the period between 2002 and 2014, commodity housing price in China had grown by 184% at national level.<sup>1</sup> The average year-on-year growth over this period was about 8.7%, with double digits recorded in 2004 (17%), 2005 (12%), 2007 (16%) and 2009 (22%), albeit the short-lived "downturn" (less than -2%) in 2008. Some cities in the east coast such as Beijing, Fuzhou, Ningbo and Xiamen even experienced a growth of some 15–20% per annum throughout the whole decade (Wang & Zhang, 2014). All in a sudden, the soared housing price in China had become a hot social and economic topic that evoked wide concerns and discussions. Many agree the housing market plays a key role in China's economic growth, and that, to understand what determines its dynamics, boom and bust is of great

importance for understanding the Chinese economy. Especially, given the background that the collapse of U.S. housing market finally led to the "subprime crisis" and that the scene of the Japanese "lost decades" following the burst of its "housing bubbles" remains vivid, many are concerned whether China, now the world's second largest economy, will follow the old road to ruin.

On the other hand, the literature on the determinants of China's housing price is fast growing. Some authors have tested the housing market equilibrium condition derived from a partial equilibrium model and evaluated the significance of the supposed demand and supply factors. Many have come to conclude that the upswing was mainly a reflection of changed market "fundamentals," although as for the specific factors and their respective importance less consensus is made. For example, while most have agreed on the decisive role of disposable income and land price, Wang and Zhang (2014) find population was also important, as opposed to Deng, Ma, and Chiang (2009) and Wang, Yang, and Liu (2011) who

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reject its significance. Similarly, although construction costs and interest rate are shown to have affected little in Deng et al. and Wang et al., respectively, Wang and Zhang—echoing Li and Chand (2013) and Chow and Niu (2015)—find the former mattered in theirs, while Xu and Chen (2012) find evidence for the latter.

Such ambiguities are perhaps not surprising, given the usual difficulties pervading these single-equation studies: first, that most of these work have relied on a casual conceptual framework has determined that “equilibrium conditions” derived from such models are easy victims of omitted variables, such that a factor found significant in one model may simply be so because that model has failed to reflect others that would be embraced by the “true” model. Of course, without an explicit model that details the whole underlying economic structure, there would be no way of telling. Thus, unless one is willing to impose very strong assumptions on how he knows the “true” model, estimating such “equilibrium conditions” could have been a hasty attempt that brings more doubts, if not misconception, than evidence.

In fact, even if one is able to identify the “true” equilibrium condition(s), that macroeconomic variables are widely correlated in practice due to economic interactions would still mean these conditions are hard to estimate, as such interactions endogenize the explanatory variables on them. Thus, econometricians are forced either to assume these variables are pre-determined in other markets (such as Deng et al. and Li and Chand just cited), or to find “instruments” to get approximation of them to avoid inconsistent estimation (Wu, Feng, & Li, 2014). However, none of these could solve the problem to its root, for a) that by imposing exogeneity the economic interactions as reflected by the data would be artificially abandoned in the modelling process, and b) that within a partial equilibrium model where one is much agnostic about the rest of the economy, there is little information about the “true” instruments. Indeed, if endogeneity also arises because the explanatory variables on these equilibrium conditions are correlated, that is, when multi-colinearity happens, it can even overstate the standard error of the coefficients of these variables, causing them to be shown insignificant even when they are not. Thus, while the omitted variable problem just mentioned is one that could be improved by using a more inclusive model, the endogeneity problem here is one that is inherent in any model variant where equilibrium is estimated with single equations.<sup>2</sup>

Both of these technical difficulties are therefore extra challenges to “single-equation studies” which also receive criticisms from theorists. The main issue here is how (little) one could learn about what *determined* the housing

price dynamics from exploiting an estimated equilibrium condition, which is merely a description of the steady-state correlation, rather than *causal relation*, between housing price and other supposed “determinants.” Thus, Wen and Goodman (2013) and Chow and Niu (2015) have gone one step further to use a dynamic econometric model—a VAR in the former and a VECM in the latter—to evaluate what could have “Granger-caused” the housing price. Liang and Cao (2007), Guo and Huang (2010), Chen, Guo, and Zhu (2011), Zhang, An, and Yu (2012), Zhang, Hua, and Zhao (2012) and Chiang (2014) have even waived the partial models and focused only on the empirical responses of housing price to the lags of potential determinants, noting that any equilibrium conditions derived from a partial model would tell little about causal relations. Thus, these authors are able to answer what (Granger-)caused housing price to change as the data dynamics show. That these VAR and VECM being pure econometric models has also allowed them to test the impact of factors which do not usually affect demand and/or supply of houses directly in a partial model (such as money growth and interest rates), and factors that are difficult to model in a structural model (such as gender imbalance and urbanization)—this way, they also circumvent the endogeneity problem now that explanatory variables are all lagged when they enter the model.

However, from the policy viewpoint the usefulness of such VAR/VECM estimates are still rather limited, as these reduced-form models are providing no information about *how* housing price is determined as different economic agents interact. Thus, even if one is able to tell from estimating these models what could have affected housing price and the extent to which they could have affected it, there is little he could exploit with such information (which tells literally nothing about the transmission mechanism which would be key to policy-makers) to guide policies—the well-known problem of the Lucas (1976)’s critique. Although some authors (such as Bian and Gete (2015)) have attempted to fix this hole by imposing theoretical restrictions for their estimations—thus, the structural VAR approach that aims to provide theoretical interpretation for the reduced-form estimates, such a remedying is, however, rather metaphysical, as the implication is usually sensitive to the imposed restrictions, the “identification schemes,” that are often chosen for producing results presumed “reasonable” a priori (Fernández-Villaverde & Rubio-Ramirez, 2008; Uhlig, 2005). Another related difficulty of the SVAR approach is the general disconnect between the true structure of the underlying data-generating process and what is defined as “structural” in the SVAR representation of it; such a “fundamental conceptual weakness”—to quote Benati and Surico (2009)—has determined that SVAR models

are not reliable, either, for understanding how housing price dynamics was fundamentally determined.

All the above thus points the way to using a micro-founded structural model where causal relationships between economic variables are established as different economic agents interact with their optimal choice. Thus in the more recent attempts, a growing number of authors have started to follow Iacoviello (2005) and Iacoviello and Neri (2010) to construct a dynamic stochastic general equilibrium (DSGE) model to identify what could have determined China's housing price dynamics and the transmission mechanism working behind it. Thus, Minetti and Peng (2015) pioneer to use a real business cycle model to study how social psychology—the “keeping up with the Zhangs” behaviour, as they call it, in analogous to Gal (1994)'s “keeping up with the Joneses” hypothesis—could have amplified and prolonged the impact of housing preference shocks on the housing price. Ng (2015) and Wen and He (2015) build a New Keynesian model to study how different monetary policies—a Taylor rule in the former and a McCallum rule in the latter—affect the housing market. Zhou and Jariyapan (2013) consider a policy mix where stabilization is assisted by an affordable housing policy, an ad valorem property tax, and a land policy that aims at stabilizing the land price. Garriga, Tang, and Wang (2016) deviate from these authors by establishing a regional model that replicates the urbanization process caused by structural transformation of the Chinese economy. Thus, almost all these DSGE modellers have found that shocks to housing demand and monetary policy dominated the boom; following this, most have suggested that to stabilize the housing market, measures such as property tax and property-purchasing limitations could be convenient for suppressing demand; for reducing policy mistakes, the implication would be that the People's Bank of China improves its management skills and act more independently in policy-making.

However, one important aspect the existing efforts have not quite explored is the channel through which the banking system could be propagating these shocks. While Gerali, Neri, Sessa, and Signoretti (2010) have offered an early example, many in this area have remained using models where banks work implicitly, with a simple collateral constraint connecting the housing sector and the wider economy. However, since the banking system itself could have also been a source of instability, and that institutional setting of the banking system could have affected the dynamics of the whole economy, as one contribution of this paper, we embed in our DSGE model an explicit banking sector (which resembles, but differs from Gerali et al. (2010)), which has never been attempted for studying the Chinese economy. Our contributions also

come from the novel way in which we model the banking system, where we allow “shadow banks” to operate in a sub-system affiliated to the main system constituted by “normal banks,” to reflect the unique business structure of commercial banks in China, where “shadow” banking business expanded substantially after the Great Stimulus initiative in 2009. Thus, to the literature on the determination of housing price dynamics, we are the first to use a DSGE model where the explicit role of both normal banks and shadow banks is allowed for; to the recent developments in modelling the banking system, our way of modelling shadow banks has allowed them to interact with normal banks, which existing studies (such as Verona, Martins, and Drumond (2013) and Funke, Mihaylovski, and Zhu (2015) as we compare below) are unable to capture.

On the study of house prices itself, we also establish quantitatively robust evidence regarding the nature, frequency and duration of housing booms and “bubbles,” with Monte Carlo experiments for different scenarios, which previous studies have not been able to do. On the interaction between the housing cycle and the business cycle, we also establish to what extent the mean prediction of our DSGE model is supported by the sample data, using a formal statistical test, which is seldom carried out in the literature.

The rest of the paper is organized as the following: Section 2 constructs the DSGE model, with a particular focus on the working of the banking sector. Section 3 explains the DSGE-VAR approach, which we use to estimate the model. We establish the empirical evidence in Section 4. Section 5 concludes the paper.

## 2 | THE DSGE MODEL

We follow the classic Iacoviello (2005) and Iacoviello and Neri (2010) approach to model the Chinese economy with a heterogeneous-agents model consisting of two types of households (“patient” and “impatient”), entrepreneurs, retailers and the public sector. These Iacoviello-type models feature a collateral borrowing constraint in the spirit of Kiyotaki and Moore (1997), which limits the capacity of borrowing to a fraction of the market value of the borrowers' physical assets, such as houses, lands and capitals, where the borrowing constraint also bridges the housing market and the real economy to allow for market spillovers. While most have ignored the role played by financial intermediaries, Gerali et al. (2010) is one of the few pioneers who integrate into the basic model the banking sector to study how banks' optimization problem could have affected the propagation of “macroeconomic” and “monetary”

shocks. By allowing for shocks originated from the banking sector, they also explored how “financial” shocks could have affected the business cycle.

The model we build here extends this progress. It does so by introducing into the basic Iacoviello model a banking sector where a shadow-banking system co-exist with the main system, but it operates effectively as a “shadow-banking department” of normal banks. To keep the paper concise we only outline the key equations of the “standard sectors” here, but elaborate the banking sector which is our innovation in full. The optimization problems of the whole model are outlined in Appendix A. Tables A1 and A2 provide a glossary of the model variables and disturbances.

## 2.1 | Patient households

There is a continuum of measure one of patient households who consume both normal goods and houses ( $c_t^P$  and  $h_t^P$ ), work to produce these products ( $n_{c,t}^P$  and  $n_{h,t}^P$ ),<sup>3</sup> and save with normal time deposits ( $S_t$ ). Their life-time utility is:

$$E_0 \sum_{t=0}^{\infty} (\beta^P G_{c^P})^t j_t \left[ \ln c_t^P + \phi_t \ln h_t^P - \frac{\psi_t}{1 + \eta^P} \left( n_{c,t}^{P1 + \xi^P} + n_{h,t}^{P1 + \xi^P} \right)^{\frac{1 + \eta^P}{1 + \xi^P}} \right] \quad (1)$$

where  $\beta^P$  is the discount factor,  $G_{c^P}$  is the steady-state growth rate of consumption of normal goods,  $\phi_t$  is the relative preference to houses (which can be interpreted as the housing demand shock),  $\psi_t$  is the relative preference to leisure (the labour supply shock),  $\eta^P$  is the inverse of labour elasticity,  $\xi^P$  is the substitutability of labour for goods and for house production, and  $j_t$  is the shock to intertemporal preference.

Patient households have budget constraint:

$$c_t^P + q_{h,t} [h_t^P - (1 - \delta_h) h_{t-1}^P] + S_t = w_{c,t}^P n_{c,t}^P + w_{h,t}^P n_{h,t}^P + (1 + r_{t-1}^S) S_{t-1} + \Pi_t^{Fgds} + (1 - \chi) \Pi_{t-1}^{Nbank} + \Pi_{t-1}^{Sbank} - \tau_t \quad (2)$$

where expenses on the L.H.S. of (2) are financed with resources on the R.H.S., where  $q_{h,t}$  is the price of houses (relative to normal goods' which is normalized to 1),  $\delta_h$  is the depreciation rate of houses,  $w_{c,t}^P$  and  $w_{h,t}^P$  are the real wages for producing goods and houses, respectively,  $r_t^S$  is the real deposit rate,  $\Pi_t^{Fgds}$ ,  $(1 - \chi) \Pi_{t-1}^{Nbank}$  and  $\Pi_{t-1}^{Sbank}$  are lump-sum profit transfers to patient households who are assumed to own both retail firms, normal banks and shadow banks modelled in the later sections,<sup>4</sup> and  $\tau_t$  is a lump-sum tax levied.

Patient households maximize (1) by choosing  $c_t^P$ ,  $h_t^P$ ,  $n_{c,t}^P$ ,  $n_{h,t}^P$  and  $S_t$ , subject to (2). The problem returns a set of optimal conditions which represent the marginal rates of substitution of future consumption, houses and leisure, against current consumption. Intuitively, these set the demand for normal goods and houses, and the supply of labour, of patient households (Equations A.3–A.7 in Appendix A).

## 2.2 | Impatient households

There is a continuum of measure one of impatient households who consume ( $c_t^I$ ), buy houses ( $h_t^I$ ), and work ( $n_{c,t}^I$  and  $n_{h,t}^I$ ), just as patient households. However, impatient households do not save; being impatient, they always spend more than their wage income, and therefore have to finance the excess with loans taken from the banking sector. We assume these loans are provided both by normal banks ( $b_t^I$ ) and by shadow banks ( $b_t^{I''}$ ). However, as we establish later, the cost of normal loans ( $r_t^{NL}$ ) is always lower than that of shadow loans ( $r_t^{IL}$ ). We let the amount one can borrow be restricted to a fraction of the present value of the borrower's physical assets by the time the obligation is due, in the spirit of Kiyotaki and Moore (1997). We also let such a fraction, the loan-to-value ratio (LTV), be affected by credit policy, and that LTV of normal loans ( $\Theta_{H,t}$ ) would shift in an opposite way to that of shadow loans ( $\Xi_{H,t}$ ), should credit policy vary.<sup>5</sup>

Impatient households maximize:

$$E_0 \sum_{t=0}^{\infty} (\beta^I G_{c^I})^t j_t \left[ \ln c_t^I + \phi_t \ln h_t^I - \frac{\psi_t}{1 + \eta^I} \left( n_{c,t}^{I1 + \xi^I} + n_{h,t}^{I1 + \xi^I} \right)^{\frac{1 + \eta^I}{1 + \xi^I}} \right] \quad (3)$$

by choosing  $c_t^I$ ,  $h_t^I$ ,  $n_{c,t}^I$ ,  $n_{h,t}^I$ ,  $b_t^I$  and  $b_t^{I''}$ , subject to budget constraint:

$$c_t^I + q_{h,t} [h_t^I - (1 - \delta_h) h_{t-1}^I] + (1 + r_{t-1}^{NL}) b_{t-1}^I + (1 + r_{t-1}^{IL}) b_{t-1}^{I''} = w_{c,t}^I n_{c,t}^I + w_{h,t}^I n_{h,t}^I + b_t^I + b_t^{I''} \quad (4)$$

and borrowing constraints with normal and shadow banks:

$$b_t^I \leq \Theta_{H,t} \frac{E_t(q_{h,t+1} h_t^I)}{1 + r_t^{NL}} \quad (5)$$

and

$$b_t^{I''} \leq \Xi_{H,t} \frac{E_t(q_{h,t+1} h_t^I)}{1 + r_t^{IL}} \quad (6)$$

where variables have their usual meaning,  $\beta^I < \beta^P$ ,  $\Theta_{H,t} + \Xi_{H,t} < 1$ , and superscript “I” denotes variables for impatient households.

The optimization problem implies the marginal rates of substitution which resemble those in the patient household problem (A.12-A.17 in Appendix A). The borrowing constraints determine the demand for normal and shadow loans for a given level of credit control.

### 2.3 | Entrepreneurs

On the supply side, there is a continuum of measure one of entrepreneurs who produce intermediate goods ( $Y_t$ ) and houses ( $ih_t$ ) with labour ( $n_{c,t}^P$ ,  $n_{h,t}^P$ ,  $n_{c,t}^I$  and  $n_{h,t}^I$ ), capitals ( $k_{c,t}$  and  $k_{h,t}$ ) and lands ( $l_t$ , for houses only), and use profits from these businesses to finance consumption ( $c_t^E$ ), which is the only element that enters their utility function. Like impatient households, entrepreneurs also borrow from normal and shadow banks ( $b_t^{E'}$  and  $b_t^{E''}$ ). Both the intermediate goods market and housing market are perfectly competitive.

Entrepreneurs maximize:

$$E_0 \sum_{t=0}^{\infty} (\gamma G_{c^E})^t j_t \ln c_t^E \quad (7)$$

by choosing  $c_t^E$ , subject to budget constraint:

$$\begin{aligned} c_t^E + i_{c,t} + i_{h,t} + q_{l,t}(l_t - l_{t-1}) + w_{c,t}^P n_{c,t}^P + w_{h,t}^P n_{h,t}^P + w_{c,t}^I n_{c,t}^I + w_{h,t}^I n_{h,t}^I \\ + (1 + r_{t-1}^{NL}) b_{t-1}^{E'} + (1 + r_{t-1}^{IL}) b_{t-1}^{E''} \\ = \frac{Y_t}{X_t} + q_{h,t} i_{h,t} + b_t^{E'} + b_t^{E''} \end{aligned} \quad (8)$$

borrowing constraints with normal and shadow banks:

$$b_t^{E'} \leq \Theta_{E,t} \frac{E_t(q_{l,t+1} l_t + k_{c,t} + k_{h,t})}{1 + r_t^{NL}} \quad (9)$$

and

$$b_t^{E''} \leq \Xi_{E,t} \frac{E_t(q_{l,t+1} l_t + k_{c,t} + k_{h,t})}{1 + r_t^{IL}} \quad (10)$$

and production functions:

$$Y_t = [A_{c,t} (n_{c,t}^P)^\alpha (n_{c,t}^I)^{1-\alpha}]^{1-u_c} k_{c,t-1}^{u_c} \quad (11)$$

and

$$ih_t = [A_{h,t} (n_{h,t}^P)^\alpha (n_{h,t}^I)^{1-\alpha}]^{1-u_h-v_h} k_{h,t-1}^{u_h} l_{t-1}^{v_h} \quad (12)$$

where  $\gamma (< \beta^P)$  and  $G_{c^E}$  are, respectively, the discount factor and the steady-state growth in consumption of entrepreneurs,  $q_{l,t}$  is the relative price of lands,  $\Theta_{E,t}$  and  $\Xi_{E,t}$  are LTVs which ensure  $\Theta_{E,t} + \Xi_{E,t} < 1$  but would shift in opposite ways should credit policy vary,  $\alpha$ ,  $u_c$ ,  $u_h$  and  $v_h$  are input shares of production, and  $A_{c,t}$  and  $A_{h,t}$  are the technologies.<sup>6</sup> Other variables have their usual meaning, and we use superscript “E” to denote “entrepreneurs.”  $\frac{1}{X_t}$  is the relative price of intermediate goods that we define formally in the retailers’ problem in the next section.

The accumulation of capitals follows:

$$k_{c,t} - k_{c,t-1} = i_{c,t} - \delta_{kc} k_{c,t-1} \quad (13)$$

and

$$k_{h,t} - k_{h,t-1} = i_{h,t} - \delta_{kh} k_{h,t-1} \quad (14)$$

where  $i_{c,t}$  and  $i_{h,t}$  are private investments and  $\delta_{kc}$  and  $\delta_{kh}$  are the depreciation rates.

The entrepreneurs’ problem determines their demand for normal goods and labours (A.28-A.32 in Appendix A), and the optimal trade-offs between normal goods and capitals and lands which are their demand for the last two (A.33-A.35). Their demand for bank loans is determined by the borrowing constraints. The supply of intermediate goods and houses is determined by the production functions.

### 2.4 | Retailers

There is a continuum of measure one of retailers who buy intermediate goods from entrepreneurs, differentiate them at no cost, and sell the final composite of differentiated goods ( $Y_t^{Final}$ ) at  $P_t$ , which is normalized to 1, and is a mark-up ( $X_t$ ) to the price of the intermediate goods. The final goods market is monopolistically competitive.

We follow Calvo (1983) to assume that in each period only a fraction  $(1 - \omega)$  of retailers are able to reset their prices to the optimal level, while the rest adjust theirs according to an indexation rule in the spirit of Smets and Wouters (2003):

$$p_{t+i}(j) = p_t(j) \left( \frac{P_{t+i-1}}{P_{t-1}} \right)^\epsilon \quad (15)$$

where  $0 \leq \epsilon \leq 1$  is the extent to which prices of differentiated goods,  $p_t(j)$ , are indexed to past inflation.

Retailers who are able to reset prices maximize:

$$E_t \sum_{i=0}^{\infty} (\omega \beta^P G_c)^i V_{t,t+i} \left[ \left( \frac{p_{t+i}(j)}{P_{t+i}} \right) Y_{t+i}(j) - \frac{1}{X_{t+i}} Y_{t+i}(j) \right] \quad (16)$$

by choosing  $p_t(j)$ , subject to the Dixit and Stiglitz (1977)'s CES demand for  $Y_t(j)$ <sup>7</sup>:

$$Y_t(j) = \left[ \frac{p_t(j)}{P_t} \right]^{-\theta} Y_t^{Final} \quad (17)$$

and (15), to find the optimal reset price for differentiated goods,  $p_t^*(j)$ <sup>8</sup>:

$$p_t^*(j) = \frac{\theta}{(\theta-1)} \frac{E_t \sum_{i=0}^{\infty} (\omega \beta^P G_c)^i V_{t,t+i} Y_{t+i}^{Final} \frac{1}{X_{t+i}} P_{t+i}^\theta P_{t+i-1}^{-\theta\epsilon} P_{t-1}^{\theta\epsilon}}{E_t \sum_{i=0}^{\infty} (\omega \beta^P G_c)^i V_{t,t+i} Y_{t+i}^{Final} P_{t+i}^{\theta-1} P_{t+i-1}^{\epsilon(1-\theta)} P_{t-1}^{\epsilon(\theta-1)}} \quad (18)$$

Let the general price level be:

$$P_t = \left[ \int_0^1 p_t(j)^{1-\theta} dj \right]^{\frac{1}{1-\theta}} \quad (19)$$

Equation (19) can be linearized around a zero-inflation steady state, using (15) and (18), to find:

$$\begin{aligned} \pi_t = & \frac{\beta^P G_c}{1 + \beta^P G_c \epsilon} E_t \pi_{t+1} + \frac{\epsilon}{1 + \beta^P G_c \epsilon} \pi_{t-1} \\ & + \frac{(1-\omega)(1-\omega \beta^P G_c)}{\omega(1 + \beta^P G_c \epsilon)} (-\hat{X}_t) + \hat{\epsilon}_{\pi,t} \end{aligned} \quad (20)$$

which is the “hybrid” version of the New Keynesian Phillips curve. It finds that inflation ( $\pi_t$ ) is affected not only by past inflation but also expected future inflation. It also varies with the percentage deviation of real marginal cost of final goods production from the steady-state level ( $-\hat{X}_t$ ), subject to “inflation shock” ( $\hat{\epsilon}_{\pi,t}$ ).

## 2.5 | The banking sector

Our approach to the banking sector is an innovation based on the recent development of Verona et al. (2013),

who initiated to model the banking sector within a DSGE model by allowing for a “shadow” banking system that operates in parallel with the “normal” system. The Verona et al. approach categorizes borrowers (firms, in their case) into two types based on their risk of default. They let “safe” borrowers who are able to issue corporate bonds raise funds with the assistance of investment banks, which they define as shadow banks. “Risky” borrowers who are unable to do so take regular loans from commercial banks. The two systems run in parallel, and are disconnected both in size and in their institutional setting.

Such an approach is then applied by Funke et al. (2015) to China, where development of financial markets is much behind, and short-term financing is much different. Allen, Qian, and Gu (2017) provide an overview. Among others, a key feature they highlight is the coexistence of the formal sector dominated by commercial banks, and a growing informal sector constituted by various non-bank financial service providers not (or less) regulated by the People's Bank of China and the Banking Regulatory Commission. The latter embraces both financial intermediaries (such as bank departments designated for off-balance-sheet businesses, investment banks, hedge funds, micro-credit companies, pawnshops and money houses), and direct lending services (such as interpersonal lending, rotating savings, money lenders and loan sharks)—See also Tsai (2004), Allen, Qian, and Xie (2019) and Arora and Zhang (2019). However, not all borrowers share equal opportunities accessing to these sectors. Most notably, because state-owned/state-holding companies are usually “backed” by the country and they share similar ownership structure with most commercial banks (of which many are also state-owned/state-holding), they are generally considered safer, and hence, have much easier access to regular bank loans compared to non-state-owned companies. By contrast, non-state-owned companies face much higher barriers in accessing to these loans. For accessing to funds, they often turn to the informal sector, where they either sell wealth management products or take entrusted loans via commercial banks, or seek for other sources from the various “capital pools” just mentioned, which generally imply a higher cost of borrowing.<sup>9</sup>

Thus, Funke et al. motivate their application of the Verona et al. model by viewing such funds' channelling to non-state-owned companies as services provided by “shadow banks,” while regular bank loans offered to state-owned/state-holding companies as services provided by “normal banks.” Their modelling of the banking sector is essentially identical to Verona et al., although in their application to China they have let risky borrowers who have difficulties accessing to normal bank loans

engage in shadow-banking activities, whereas in Verona et al. shadow banking arises as safe borrowers raise funds by bond issuing to avoid higher cost of borrowing from normal banks.

However, the fact that both Verona et al. and Funke et al. have modelled the normal and shadow-banking systems in parallel has also determined that these systems in their models are institutionally disconnected. This is practically at odds if we allow for the complex correlations pervading these systems in practice. Especially, since shadow banking in China is much a consequence of difficulties accessing to loans from normal banks, it may well happen that, if credit conditions in the normal system tighten which causes commercial banks to contract their balance sheet, such a change could cause the shadow system to expand as borrowers get around tightened conditions with shadow activities. This also suggests that, in practice, the relative size of the normal/shadow systems may change in response to changed economic conditions, which is abandoned in Verona et al. and in Funke et al.

Such a connection is precisely what we aim to establish in our novel way of modelling the banking sector. In particular, instead of letting normal banks and shadow banks work in parallel, we model shadow banks in China as a “shadow-banking department” of normal banks designated for loan business not to be recorded on the normal banks’ balance sheet. Using the words of Ehlers, Kong, and Zhu (2018), they are more like the “shadow of the banks.” Thus, for lending to impatient households and entrepreneurs, shadow banks first take loans from normal banks at the normal rate. They then lend the collected funds to households and entrepreneurs who fail to raise sufficient funds with normal bank loans at a premium rate. We make no distinction between “safe” and “risky” borrowers as in Funke et al. But we let impatient households and entrepreneurs be customers of both normal and shadow banks, while the proportion of normal/shadow-banking activities be governed by the country’s credit policy; and we let credit policy affect the size of the two systems in opposite ways to reflect the substitutability between normal and shadow loans.

Our approach to the banking sector therefore establishes a connection between the normal banking system and the shadow system. Its structure resembles the interaction between “wholesale banks” and “retail banks” of Gerali et al. (2010), though in our setting the shadow system works as a bypass of frictions in the normal system to mimic the unique loan-providing structure of China. As in standard DSGE models, we confine our scope of the “banking sector” to the marketplace where financial intermediaries play a central role in the channelling of

funds—that is, where *indirect* financing takes place. It therefore precludes direct financing, such as borrowing from friends/relatives, which is part of informal financing as defined in Allen, Qian, and Xie (2019). We go on to describe the banking sector optimization problems in what follows.

### 2.5.1 | The “normal” system

The normal banking system is constituted by a continuum of measure one of normal banks, which take deposits ( $S_t$ ) from patient households, convert them to normal bank loans ( $B_t$ ) with costs, and lend them to impatient households, entrepreneurs and shadow banks (such as investment banks) with no preference, except that lending to the latter is exempt from any collateral conditions. At the end of each period, normal banks retain a fraction ( $\chi$ ) of their profit ( $\Pi_t^{Nbank}$ ) as capital reserve, and send the rest  $(1-\chi)\Pi_t^{Nbank}$  as a lump-sum transfer to patient households who are assumed to be the owners.

We let normal banks be price-takers to reflect the People’s Bank of China’s heavy manipulation on commercial bank interest rates. The normal bank problem is to maximize:

$$\begin{aligned} \text{Max}_{B_t} \Pi_t^{Nbank} = & \sum_{t=0}^{\infty} \Lambda_{0,t}^{Nbank} \left\{ [(1+r_t^{NL})B_t - B_{t+1}] \right. \\ & \left. + [S_{t+1} - (1+r_t^S)S_t] - \frac{c}{2} \left( \frac{F_t}{B_t} - \Omega \right)^2 F_t + \Delta F_{t+1} \right\} \end{aligned} \quad (21)$$

by choosing  $B_t$ , subject to the balance sheet constraint:

$$B_t = S_t + F_t \quad (22)$$

where  $F_t$  is the banks’ capital reserve, accumulated out of retained profit from the last period, following:

$$F_t = (1 - \delta^F)F_{t-1} + \chi \Pi_{t-1}^{Nbank} \quad (23)$$

where  $\chi$  is the retention ratio, and  $\delta^F$  is the real resources used for capital management.  $\Lambda_{0,t}^{Nbank}$  in (21) is the discount factor.  $\frac{c}{2} \left( \frac{F_t}{B_t} - \Omega \right)^2 F_t$  (where  $c > 0$ ) is the real resources used for creating loans.<sup>10</sup>  $\Omega$  is the optimal capital-to-assets ratio.

The normal banks’ problem implies:

$$r_t^{NL} - r_t^S = -c \left( \frac{F_t}{B_t} - \Omega \right) \left( \frac{F_t}{B_t} \right)^2 \quad (24)$$

which suggests that, for given interest spread and dividend policy, profit maximization would require normal banks to set their loan supply to a level, such that the marginal revenue of supplying those loans (the L.H.S. of (24)) is equal to the marginal cost of supplying them (the R.H.S.). Another way of interpreting it is that the supply of loan must be kept to an optimal level, which is “backed” by the banks’ reserve level for given interest spread, which is the basis of the “credit cycle” story of Gerali et al. (2010). Of course, such an optimal condition may not always hold in practice due to the occurrence of “banking shocks” ( $\varepsilon_{B,t}$ ). We therefore allow for such imperfection in our application and modify the above to:

$$\varepsilon_{B,t}(r_t^{NL} - r_t^S) = -c \left( \frac{F_t}{B_t} - \Omega \right) \left( \frac{F_t}{B_t} \right)^2 \quad (25)$$

Equation (25) suggests a rise in  $\varepsilon_{B,t}$  causes the loan supply to fall, *ceteris paribus*. Thus, a positive realization of  $\varepsilon_{B,t}$  is a reflection of tightened credit conditions in the normal system. Since normal banks are the only fund provider to shadow banks, this would also tighten the credit conditions of the shadow system. Hence, the entire banking sector is involved.

## 2.5.2 | The “shadow” system

The shadow system is constituted by a continuum of measure one of monopolistic “shadow banks,” which are not confined by the general rules (especially, requirements on reserve ratios) applicable to normal banks. Shadow banks acquire loans from normal banks, acting as demander of normal loans, just as impatient households and entrepreneurs on the one hand; on the other hand, they lend the acquired loans to impatient households and entrepreneurs simultaneously, acting on that occasion as provider of shadow loans.

Shadow banks are also owned by patient households. For simplicity, we assume they do not keep any profit ( $\Pi_t^{Sbank}$ ), but send all of them to patient households at the end of each period.<sup>11</sup> We let shadow loans be produced with no costs. The optimization problem of an individual shadow bank is to maximize:

$$\begin{aligned} \text{Max}_{r_t^{IL}(z)} \Pi_t^{Sbank}(z) = & \sum_{t=0}^{\infty} \Lambda_{0,t}^{Sbank} \{ [1 + r_t^{IL}(z)] IL_t(z) \\ & - (1 + r_t^{NL}) IL_t(z) \} \end{aligned} \quad (26)$$

by choosing the “shadow loan rate,”  $r_t^{IL}(z)$ , taking  $r_t^{NL}$  as given, subject to the demand for loan function:

$$IL_t(z) = \left[ \frac{1 + r_t^{IL}(z)}{1 + r_t^{NL}} \right]^{-\eta^{Sbank}} IL_t \quad (27)$$

which assumes the demand for loan from individual bank  $z$  is determined by the total loan demanded, and the relative rate of interest the individual bank charges compared to the average rate of the industry, where  $-\eta^{Sbank}$  is the interest-rate elasticity of demand for shadow loans, and  $\Lambda_{0,t}^{Sbank}$  in (26) is the discount factor.

The first order condition of the shadow bank problem implies:

$$1 + r_t^{IL}(z) = \left( \frac{\eta^{Sbank}}{\eta^{Sbank} - 1} \right) (1 + r_t^{NL}) \quad (28)$$

which, by imposing a symmetric equilibrium, further implies:

$$1 + r_t^{IL} = \left( \frac{\eta^{Sbank}}{\eta^{Sbank} - 1} \right) (1 + r_t^{NL}) \quad (29)$$

which shows the optimal shadow rate is a constant markup  $\left( \frac{\eta^{Sbank}}{\eta^{Sbank} - 1} \right)$  to the “normal rate.”

## 2.6 | The public sector

### 2.6.1 | Monetary policy

We let monetary policy follow a Taylor rule, where nominal official rate ( $R_t$ ) responds to inflation ( $\varphi_\pi$ ) and economic growth ( $\varphi_x$ ), with policy inertia ( $\rho_R$ ):

$$\begin{aligned} 1 + R_t = & (1 + R_{t-1})^{\rho_R} (1 + \pi_t)^{(1-\rho_R)\varphi_\pi} \left( \frac{GDP_t}{G_c GDP_{t-1}} \right)^{(1-\rho_R)\varphi_x} \\ & (1 + r^{SS})^{(1-\rho_R)} \varepsilon_{MP,t} \end{aligned} \quad (30)$$

where  $r^{SS}$  is the steady-state value of the real interest rate,  $\varepsilon_{MP,t}$  is the monetary policy error, and  $GDP_t$  is defined to be:

$$GDP_t = Y_t + \bar{q}_h i h_t \quad (31)$$

where  $\bar{q}_h$  is the steady-state value of the real housing price.<sup>12</sup>

For simplicity, we let the central bank rate be equal to the deposit rate normal banks offer to patient households. We can establish the following Fisher identity:



$$R_t = r_t^S + E_t \pi_{t+1} \quad (32)$$

The version relating the real lending rate of normal loans to its corresponding nominal rate is as follows:

$$R_t^{NL} = r_t^{NL} + E_t \pi_{t+1} \quad (33)$$

## 2.6.2 | Credit policy

We also follow Peng (2012) to allow for a credit control policy where credit tightness of the financial market ( $\Theta_t$ ) is governed by a counter-cyclical feedback rule, and we let it mimic the Taylor rule in our application:

$$\Theta_t = \Theta_{t-1}^{\rho_\Theta} \left( \frac{GDP_t}{G_c GDP_{t-1}} \right)^{z_x} \bar{\Theta} \varepsilon_{CP,t} \quad (34)$$

where  $\bar{\Theta}$  is the steady-state degree of credit tightness,  $z_x < 0$  is the counter-cyclical policy response, and  $\varepsilon_{CP,t}$  is the credit policy error. Since the People's Bank of China and the China Banking Regulatory Commission have never announced any specific credit control rules, existing studies have mostly specified a credit rule equation like ours, both as a parsimonious reflection of the counter-cyclical nature of macroprudential policies, and to respect the inverse relationships between credits and growth, and between the loan-to-capital ratio and growth, as in Chinese data. In theory  $\Theta_t$  could have responded to other variables, such as the growth of credits or house prices (Rubio, 2019), or both (Wang & Sun, 2013). But we find none of these alternative specifications outperforms (34) in fitting the data—in fact, they are far less ideal according to the models' marginal likelihood.<sup>13</sup> Hence, our specification of the credit control rule here is both consistent with the literature and favoured by the data.

In contrast to the Taylor rule that determines the price of loans, the credit policy moderates their size directly, by setting a limit beyond which loans in the monitored system cannot be further supplied to the borrowers. We assume that both impatient households' and entrepreneurs' borrowing from the normal banking system are governed by such policy, such that:

$$\hat{\Theta}_{H,t} = \hat{\Theta}_{E,t} = \hat{\Theta}_t \quad (35)$$

where “94” denotes the percentage deviation from the steady-state value. We further assume that, when credit

condition in the normal system tightens/loosens, there will be a proportional increase/decrease in the demand for shadow bank loans, as borrowers get around credit control via the shadow system; and we summarize such a quantitative relationship parsimoniously as the following<sup>14</sup>:

$$\hat{\Xi}_{H,t} = \hat{\Xi}_{E,t} = -\hat{\Theta}_t \quad (36)$$

Thus, while the credit policy provides an additional mechanism through which stabilization policy could be implemented, it would be so implemented by deepening the financial frictions caused by the borrowing constraints on normal loans. However as we just pointed out, such a quantitative distortion would be partially corrected as borrowers get around the restriction by taking shadow loans, so from the policy viewpoint the efficacy of credit control would be subsequently neutralized. Nevertheless, since shadow rate is a mark-up to normal rate, the credit policy would still be stabilizing, in analogous to the Taylor rule.

## 2.6.3 | Fiscal policy

We assume fiscal policy is Ricardian, and for simplicity, government spending ( $g_t$ ) is financed with the lump-sum tax revenue levied from patient households, such that:

$$g_t = g_{t-1}^{\rho_g} u_{g,t} u_{Ac,t}^{\rho_{gc}} \quad (37)$$

and

$$\bar{g}_t = \tau_t \quad (38)$$

where  $\rho_g$  and  $u_{g,t}$  in (37) are the persistence and innovation in government spending, respectively; and  $\rho_{gc}$  is the impact of innovation in technology ( $u_{Ac,t}$ ) on net exports, counted in government spending as in Smets and Wouters (2007).

## 2.7 | Market clearing, trends and shocks

Normal goods market clearing requires:

$$C_t + I_t + g_t = Y_t - \frac{c}{2} \left( \frac{F_{t-1}}{B_{t-1}} - \Omega \right)^2 F_{t-1} - \delta^F F_{t-1} \quad (39)$$

where  $C_t = c_t^P + c_t^I + c_t^E$  and  $I_t = i_{c,t} + i_{h,t}$ .

Housing market clearing requires:

$$h_t^P - (1 - \delta_h)h_{t-1}^P + h_t^I - (1 - \delta_h)h_{t-1}^I = ih_t \quad (40)$$

Financial market clearing requires:

$$b_t^I + b_t^{I''} + b_t^{E'} + b_t^{E''} = B_t \quad (41)$$

Labour market clears automatically because of Walras's law, where total labour  $N_t = (n_{c,t}^P)^\alpha (n_{c,t}^I)^{1-\alpha} + (n_{h,t}^P)^\alpha (n_{h,t}^I)^{1-\alpha}$ .

Land supply is fixed at its steady-state value, following the standard “perfect inelasticity” assumption in the literature:

$$l_t = \bar{l} \quad (42)$$

This is to reflect the fact that, although land supply elasticity varies across regions in China, the aggregate supply grows slowly and, taking into account population growth, the per capita supply is close to a constant. Liu, Wang, and Zha (2013) provide a similar discussion and show that even if a deterministic trend is allowed for the land process it would not materially change the result. Hsu, Li, Tang, and Wu (2017) find evidence from data of 286 Chinese cities which echoes this assumption.

We let the steady-state equilibrium be driven by technologies advancing with deterministic trends ( $\gamma_{Ac}$  and  $\gamma_{Ah}$ ) over the long run along the “balanced growth path,” and that cyclical movements around it in the short run be caused by stochastic shocks not only to technologies ( $Z_{c,t}$  and  $Z_{h,t}$ ), but also to preferences ( $j_t$ ,  $\phi_t$  and  $\psi_t$ ), loan provision ( $\varepsilon_{B,t}$ ) and policies ( $\varepsilon_{MP,t}$ ,  $\varepsilon_{CP,t}$  and  $g_t$ ), which are all mean-reversing and governed by an AR(1) process. We specify these shock processes in Appendix A (Equations A.69–A.78) to save space. Now, we proceed to estimate the model.

### 3 | MODEL ESTIMATION

#### 3.1 | The DSGE-VAR approach

Unlike the mainstream literature where a DSGE model is mostly estimated on its own, we follow Del Negro and Schorfheide (2004, 2006) and Del Negro, Schorfheide, Smets, and Wouters (2007) to estimate ours as a DSGE-VAR, which can be seen as a weighted combination of a DSGE model and an unrestricted VAR—hence, a VAR embedded with cross-equation restrictions imposed by the DSGE model.

The main advantage of adopting a DSGE-VAR in substitution of a pure DSGE model lies in that, by allowing for discrepancy between the data and a DSGE model, the DSGE-VAR approach calibrates a “hyper-parameter,”  $\lambda = [0, \infty]$ , which measures the extent to which cross-equation restrictions of a DSGE model have to be released for the resulted VAR to best mimic the data. When  $\lambda = 0$ , the DSGE restrictions are fully released, and the DSGE-VAR reduces to an unrestricted VAR; when  $\lambda = \infty$ , the DSGE restrictions are strictly imposed, and the DSGE-VAR is an equivalent transformation of the DSGE model. The estimation algorithm searches for the optimal “weight,”  $\hat{\lambda}$ , such that:

$$\hat{\lambda} = \underset{\lambda \in \Lambda}{\operatorname{argmax}} p(Y|\lambda)$$

where  $p(Y|\lambda) = \int p(Y|\theta, \Sigma, \Phi) \cdot p(\theta, \Sigma, \Phi|\lambda) \cdot d(\theta, \Sigma, \Phi)$  is the marginal data likelihood,  $\theta$  is the vector of DSGE model parameters,  $\Sigma$  is the variance–covariance matrix of the VAR innovations,  $\Phi$  is the vector of VAR parameters, and  $\Lambda$  is the vector of all possible  $\lambda$ 's. The resulted DSGE-VAR( $\hat{\lambda}$ ) is an analytical framework lying between the unrestricted VAR and the DSGE model, which, on the one hand, reflects the working of the DSGE model, and on the other, is “calibrated” to fit the data as closely as possible—thus, a model founded both in theory and in facts. Since  $\lambda$  measures how much DSGE model restrictions are used for the best-fitting model to be found, it can also be viewed as a “goodness-of-fit” indicator of the DSGE model, which is not available in the conventional practice of estimating a pure DSGE model.

While Del Negro and Schorfheide (2004) describe the full technical details of estimating a DSGE-VAR, the estimation procedure is based on the familiar Bayesian method, though in this application the Markov Chain Monte Carlo (MCMC) method is used, not for updating the prior distributions of the DSGE model parameters directly, but for updating the priors of the VAR coefficients which are centred at the DSGE model restrictions. The hyper-parameter  $\lambda$  then scales the covariance matrix of the priors of the VAR coefficients that determines how diffuse such priors are, as the random-walk Metropolis algorithm searches over the parameter space. Draws that are able to increase the conditional likelihood compared to the last attempt will be included into the existing priors with a probability of 1; draws that fail to do so will still be included, but with a probability only equal to the proportion of the calculated likelihood (which is lower) compared to the last calculation. The process continues until a desired number of repeated experiments have taken place,<sup>15</sup> and the last update of the distribution of the VAR coefficients reveals the posterior distributions of

them,  $p(\Phi|Y)$ , whose means, or modes, or medians may be seen as descriptors of the “average model,” the DSGE-VAR( $\hat{\lambda}$ ). The posterior distributions of the DSGE model parameters,  $p(\theta|Y)$ , are then “solved” subsequently with the DSGE cross-equations restrictions imposed on the VAR coefficients. The structural shocks of the DSGE model ( $\varepsilon_t$ ) are identified from the VAR innovations ( $u_t$ ), using the fact that  $u_t = \Sigma_{tr}\Omega\varepsilon_t$  in any exactly identified VAR, by replacing the rotation matrix  $\Omega$  with  $\Omega^*$  found from QR-factorizing  $A_0 (= \Sigma_{tr}^*\Omega^*)$  which determines the contemporaneous response of variables to the structural shocks of the DSGE model.

### 3.2 | Calibrated parameters and priors

We partition the DSGE model parameters into two groups, where the first includes the discount factors ( $\beta^P, \beta^I, \gamma$ ), the technology parameters ( $u_c, u_h, v_h, \delta_{kc}, \delta_{kh}, \delta_h$ ), the banking sector parameters ( $\Omega, \delta^F, \chi, \eta^{bank}$ ), and the relevant steady-state parameters ( $\bar{\phi}, \bar{X}, \bar{\Theta}_H, \bar{\Theta}_E, \bar{\Xi}_H, \bar{\Xi}_E$ ); the second is an assembly of labour share and substitutabilities ( $\alpha, \xi^P$  and  $\xi^I$ , respectively), technology advancement ( $\gamma_{Ac}, \gamma_{Ah}$ ), elasticities ( $\eta^P, \eta^I$ ), cost ( $c$ ), determinants of nominal rigidity ( $\epsilon, \omega$ ), policy parameters ( $\rho_R, \varphi_\pi, \varphi_x, \rho_\Theta, z_x$ ) and parameters governing the shocks' size and evolution ( $\sigma_{Ac}, \sigma_{Ah}, \sigma_j, \sigma_\phi, \sigma_\psi, \sigma_\pi, \sigma_B, \sigma_{MP}, \sigma_{CP}, \sigma_g, \rho_{Ac}, \rho_{Ah}, \rho_j, \rho_\phi, \rho_\psi, \rho_\pi, \rho_B, \rho_{MP}, \rho_{CP}, \rho_g, \rho_{gc}$ ). We follow the general practice to calibrate the first group for that they are either hard to identify or better pinned down with non-sample information (e.g., Iacoviello & Neri, 2010). We then set priors for the second group and have them updated using the data information with the MCMC procedure, conditional on the model. Our calibration and choice of priors are as the following.

#### 3.2.1 | Calibration

Within the theoretical boundaries, we set numerical values for the calibrated parameters such that these parameters or the implication of them is in line with the Chinese data or established empirical literature on the Chinese economy.

Specifically, we follow Liu (2008), Zhang (2009) and Ma (2011) to set the discount factor for patient households to  $\beta^P = 0.985$ , which implies a steady-state value of annual real interest rate of 6%. The discount factors for impatient households and entrepreneurs are set to  $\beta^I = \gamma = 0.97$ , which is somewhat lower, to ensure that these agents have sufficient motive for borrowing and that all borrowing constraints in the steady state are binding. The capital share for normal goods production is set to  $u_c = 0.34$ , which implies a labour share under the

constant return-to-scale (CRS) assumption of 66%, which resembles Bai and Qian (2010)'s calculation for the non-construction sector of China of about 61%. The capital share for house production is set to  $u_h = 0.2$ , again, based on the CRS assumption and Bai and Qian's calculation that finds labour share in the construction sector to be about 70%, while assuming the land share for house production to be 10% (i.e.,  $v_h = 0.1$ ) as in Davis and Heathcote (2005).<sup>16</sup> The depreciation rates of productive capital are set to  $\delta_{kc} = 0.03$  and  $\delta_{kh} = 0.04$ , such that they work with  $u_c$  to imply a steady-state non-residential investment-to-GDP ratio ( $\frac{I}{GDP}$ ) of 21.2%, which resembles the long-run Chinese data of 32%. The depreciation rate of houses is set to  $\delta_h = 0.015$ , and the steady-state preference to houses is set to  $\bar{\phi} = 0.1$ , such that our model generates a steady-state (commercial) residential investment-to-GDP ratio ( $\frac{q_{hh}}{GDP}$ ) of 3.4%, which, again, mimics the data (2.7%).

As for the banking sector parameters, the optimal capital-to-loan ratio is set to  $\Omega = 0.09$ , which is just above the minimum requirement of capital adequacy of 8% set by the Basel Accord. While existing literature fails to provide much information about capital management cost of commercial banks in China, we refer to the Euro Area experience, thus, Gerali et al. (2010), and set  $\delta^F = 0.1049$ . It turns out that these calibrations, together with the banks' profit retention ratio that we set to  $\chi = 0.96$ , imply a steady-state interest-rate spread of the normal banking system of 3.24% per annum, which is literally what the Chinese data implies. The interest-rate elasticity of demand for shadow bank loans is set to  $\eta^{Sbank} = 50.5$ , to match the observation by Jiang (2015) that shadow loans in China are about twice as expensive as normal loans.

Finally, we set the steady-state price mark-up to intermediate goods to  $\bar{X} = 1.1$ , following Liu and Ma (2015). The steady-state LTV ratios are set to  $\bar{\Theta}_H = 0.3$ ,  $\bar{\Xi}_H = 0.1$ ,  $\bar{\Theta}_E = 0.156$  and  $\bar{\Xi}_E = 0.052$ , respectively, according to the debt-to-GDP ratios of households and firms in China (about 23% and 107%, respectively) found by Edwards (2016), and the relative size of the Chinese shadow-banking system compared to the normal system (about 1:3) as Jiang (2015) gauges.

These calibrations are summarized in Table 1. In Table 2, we compare the key steady-state ratios implied by these calibrations and the long-run Chinese data; it turns out that the implied steady-state ratios are fairly similar to what are observed in practice. Thus, these calibrations are highly plausible.

#### 3.2.2 | Priors

We choose priors that are commonly accepted in the literature of empirical studies with DSGE models. Thus, we

**TABLE 1** Calibration

Parameter	Definition	Calibrated value
$\beta^P$	Discount factor (patient households)	0.985
$\beta^I$	Discount factor (impatient households)	0.97
$\gamma$	Discount factor (entrepreneurs)	0.97
$u_c$	Capital share (normal goods production)	0.34
$u_h$	Capital share (house production)	0.2
$v_h$	Land share (house production)	0.1
$\delta_{kc}$	Depreciation of capital (normal goods production)	0.03
$\delta_{kh}$	Depreciation of capital (house production)	0.04
$\delta_h$	Depreciation of houses	0.015
$\Omega$	Optimal capital-to-loan ratio	0.09
$\delta^F$	Bank capital management cost	0.1049
$\chi$	Bank profit retention ratio	0.96
$\eta^{Sbank}$	Interest-rate elasticity of shadow bank loans	50.5
$\bar{\phi}$	preference to houses	0.1
$\bar{X}$	price mark-up to intermediate goods	1.1
$\bar{\Theta}_H$	loan-to-value ratio (households; normal)	0.3
$\bar{\Theta}_E$	loan-to-value ratio (entrepreneurs; normal)	0.156
$\bar{\Xi}_H$	loan-to-value ratio (households; shadow)	0.1
$\bar{\Xi}_E$	loan-to-value ratio (entrepreneurs; shadow)	0.052

follow Iacoviello and Neri (2010) to let the share of patient households ( $\alpha$ ) follow a beta distribution, with mean equal to 0.65; labour substitutabilities ( $\xi^P$  and  $\xi^I$ ) are normally distributed around 0.5, while labour elasticities ( $\eta^P$  and  $\eta^I$ ) have the same mean values but follow a gamma distribution. Growth of technologies ( $\gamma_{Ac}$ ,  $\gamma_{Ah}$ ) is let follow a normal distribution around 1.2% to reflect the Chinese data. The cost parameter ( $c$ ) follows a gamma distribution as in Gerali et al. (2010), with mean in our case equalling to 80. The degree of price indexation ( $\epsilon$ ) and the Calvo contract non-resetting probability ( $\omega$ ) both have a beta distribution, and their means are 0.5 and 0.667, as in Iacoviello and Neri (2010). Monetary policy parameters follow Smets and Wouters (2007), where

inflation response ( $\varphi_\pi$ ) and output response ( $\varphi_x$ ) are normally distributed around 1.5 and 0.12, respectively, while policy inertia ( $\rho_R$ ) follows a beta distribution with mean equalling 0.75. At this stage we are agnostic about the credit policy parameters ( $\rho_\Theta$ ,  $z_x$ ); but since the credit policy resembles the Taylor rule in a major way, we assume as the starting point that these parameters mimic the Taylor rule counterparts. Finally, for using the method of DSGE-VAR, we assume a uniform distribution for the DSGE weight parameter ( $\lambda$ ), with lower bound set to 0.3704 (which is the minimum value required for a valid prior in our case), and upper bound set to 10, in analogous to Adjemian, Paries, and Moyen (2008).

These priors (as well as the posteriors of them that we estimate below) are summarized in Table 3. The distributions of shock parameters are standard, and Table 4 summarizes the details.

### 3.3 | Data

Estimation of a DSGE-VAR requires the number of observable variables to be equal to the number of structural shocks in the DSGE model for such shocks to be identifiable. Since our DSGE model involves 10 structural shocks, we choose 10 observable variables here, which are real GDP, real total consumption, real total non-residential investment, real house production, inflation, real housing price, real land price, total labour hours, nominal central bank rate, and nominal normal bank (lending) rate. The data observed between 2001Q1 and 2014Q4 are plotted in Figure 1. All variables, except inflation and the two interest rates, are measured in natural logarithm, of which all, except total labour hours, are measured in first difference for deterministic trends to be removed. The data are all demeaned. The measurement equations linking the data to the (log-linearized) model are the following:

$$\begin{bmatrix} d\ln(GDP_t^{Obs}) \\ d\ln(C_t^{Obs}) \\ d\ln(I_t^{Obs}) \\ d\ln(ih_t^{Obs}) \\ \pi_t^{Obs} \\ d\ln(q_{h,t}^{Obs}) \\ d\ln(q_{l,t}^{Obs}) \\ \ln(N_t^{Obs}) \\ R_t^{Obs} \\ R_t^{NL,Obs} \end{bmatrix} = \begin{bmatrix} \widehat{GDP}_t - \widehat{GDP}_{t-1} \\ \hat{C}_t - \hat{C}_{t-1} \\ \hat{I}_t - \hat{I}_{t-1} \\ \hat{i}h_t - \hat{i}h_{t-1} \\ \pi_t \\ \hat{q}_{h,t} - \hat{q}_{h,t-1} \\ \hat{q}_{l,t} - \hat{q}_{l,t-1} \\ \hat{N}_t \\ \hat{R}_t \\ \hat{R}_t^{NL} \end{bmatrix}$$

**TABLE 2** Steady-state ratios

Steady-state ratios	Definition	Calibrated value	Data <sup>c</sup>
$C/GDP$	Consumption ratio	56.8%	50.1%
$I/GDP$	Non-residential investment ratio	21.2%	32%
$q_{ih}/GDP$	Residential investment ratio <sup>a</sup>	3.4%	2.7%
$G/GDP$	Government spending ratio <sup>b</sup>	18.4%	14.6%

<sup>a</sup>Commodity houses only.

<sup>b</sup>Inclusive of net export which counts for about 3.7%.

<sup>c</sup>Period between 1952–2014.

**TABLE 3** Prior and posterior (structural parameters)

Parameter	Definition	Prior distribution			Posterior Mean
		Distribution	Mean	SD	
$\alpha$	Share of patient households	Beta	0.65	0.05	0.65
$\xi^P$	Labour substitutability (patient households)	Normal	0.5	0.1	0.60
$\xi^I$	Labour substitutability (impatient households)	Normal	0.5	0.1	0.51
$\eta^P$	Inverse of labour elasticity (patient households)	Gamma	0.5	0.1	0.48
$\eta^I$	Inverse of labour elasticity (impatient households)	Gamma	0.5	0.1	0.47
$100\gamma_{Ac}$	Technology advancement (normal goods production)	Normal	1.2	1	1.03
$100\gamma_{Ah}$	Technology advancement (house production)	Normal	1.2	1	1.16
$c$	Loan creation cost (normal banks)	Gamma	80	10	80
$\epsilon$	Degree of price indexation (normal goods)	Beta	0.5	0.2	0.06
$\omega$	Calvo contract non-resetting probability	Beta	0.67	0.05	0.39
$\varphi_\pi$	Interest-rate response to inflation	Normal	1.5	0.1	1.56
$\varphi_x$	Interest-rate response to output growth	Normal	0.12	0.1	0.14
$\rho_R$	Monetary policy inertia	Beta	0.75	0.2	0.79
$\rho_\Theta$	Credit policy inertia	Beta	0.75	0.2	0.99
$z_x$	Credit policy response to output growth	Normal	-0.1	0.1	-0.44
$\lambda$	Weight of DSGE theory	Uniform	N.A.	N.A.	0.5

where “ $d$ ” is the difference operator, “ $\ln(\cdot)$ ” denotes the natural logarithm of a variable, “ $Obs$ ” denotes the observed data, and “94” and “126” are the deviation of a variable from its steady-state value in percentage terms and in level terms, respectively.<sup>17</sup>

### 3.4 | Posteriors

We may now compare the posteriors of the DSGE model parameters to their priors in Tables 3 and 4. Most of these parameters are found to have a posterior mean that is very similar to their prior mean, suggesting that the priors chosen are quite compatible with the data. However, the data do suggest a much lower degree of price indexation ( $\epsilon$ ) and a somewhat shorter contract life ( $\omega$ ). This means the Chinese economy may not be as “sticky” as some might have expected. The data also suggest a stronger credit policy response to

output ( $z_x$ ), and that credit policy is rather “smoothed” ( $\rho_\Theta$ ). All the shocks—except for those to preference ( $\rho_j$ ), government spending ( $\rho_g$ ), inflation ( $\rho_\pi$ ), loan provision ( $\rho_B$ ) and monetary policy ( $\rho_{MP}$ )—are quite persistent, but their sizes are quite different (the  $\sigma$ 's). The estimation also suggests the optimal weight of the DSGE theory ( $\hat{\lambda}$ ) to be 0.5. While this means our DSGE theory has good potential to be further improved, it does show that our current specification is providing useful theoretical restrictions for the VAR structure to best mimic the data; and, since this value is within the theoretical boundaries, it is perfectly valid.

Such an optimal theory-data combination, a DSGE-VAR(0.50) (with one lag), is the structural model upon which our empirical analyses in the rest of this paper are built. As we show in Table 5, this model clearly outperforms its pure DSGE variant and the popular Bayesian VAR specification with the Sims and Zha (1998) prior in that it yields the highest marginal data likelihood. As for

**TABLE 4** Prior and posterior (shock processes)

Parameter	Prior distribution			Posterior Mean
	Distribution	Mean	SD	
$\rho_{Ac}$	Beta	0.5	0.2	0.82
$\rho_{Ah}$	Beta	0.5	0.2	0.78
$\rho_j$	Beta	0.5	0.2	0.46
$\rho_\phi$	Beta	0.5	0.2	0.93
$\rho_\psi$	Beta	0.5	0.2	0.89
$\rho_\pi$	Beta	0.5	0.2	0.65
$\rho_B$	Beta	0.5	0.2	0.62
$\rho_g$	Beta	0.5	0.2	0.5
$\rho_{MP}$	Beta	0.5	0.2	0.13
$\rho_{CP}$	Beta	0.5	0.2	0.99
$\rho_{gc}$	Beta	0.5	0.25	0.49
$100\sigma_{Ac}$	Inv. gamma	0.1	2	0.3
$100\sigma_{Ah}$	Inv. gamma	0.1	2	1.33
$100\sigma_j$	Inv. gamma	0.1	2	0.21
$100\sigma_\phi$	Inv. gamma	0.1	2	3.24
$100\sigma_\psi$	Inv. gamma	0.1	2	0.41
$100\sigma_\pi$	Inv. gamma	0.1	2	0.13
$100\sigma_B$	Inv. gamma	0.1	2	0.04
$100\sigma_{MP}$	Inv. gamma	0.1	2	0.05
$100\sigma_{CP}$	Inv. gamma	0.1	2	0.09
$100\sigma_g$	Inv. gamma	0.1	2	0.63

the model's absolute fit to the data, we also find in Table 6 that it mimics the volatility and the correlation of most of the observable variables fairly precisely (except for GDP and consumption which are however not the focus of this paper), though future improvement of the model would require higher variable persistence. Overall, these comparisons suggest our DSGE-VAR (0.5) is a valid and empirically superior model for analysing the housing price in China, as we implement below. The impulse responses of this model (of which we present those of the main variables in Figure A1, Appendix A, to save space) are standard. Our empirical findings with this model are presented in the next section.

## 4 | EMPIRICAL ANALYSES

### 4.1 | What determines the housing dynamics?

#### 4.1.1 | Variance decomposition

Figure 2 decomposes the forecast error variance of real housing price and house production over various forecast

horizons. The decomposition suggests that housing price is mostly a matter of the housing demand shock, which accounts for up to 90% of its variation, both in the short run (within a year's time), in the medium run (10 quarters ahead), and in the long run (10 years ahead), although as the impact of the credit policy shock looms large (which accounts for some 12%) in the long run, it dominates less overwhelmingly. The labour supply shock and the goods-producing technology shock each contributes to a small proportion over all forecast horizons, both accounting for some 4%. Government spending and preference both play a role in the short run, but empirically they hardly affect anything. Interestingly, although many existing efforts based on pure DSGE models (including those cited at the beginning of this paper) have suggested monetary policy could have been an important source, our DSGE-VAR-based decomposition (which has better account for the fit to the data) reveals that monetary policy shock actually affects little—just like the remaining others.

On the production of houses, the house-producing technology shock dominates the other two key factors—in this case, the housing demand shock and the labour supply shock—by a substantial margin, where the former accounts for up to 83% in the short run, while as it moves towards the longer runs it reduces to about 45% ultimately (though it is still dominating). The credit policy shock contributes to a similar proportion as in the case for house prices. Other shocks are either not affecting at all, or their impacts are hardly noticeable.

The above suggests that, although house production is a more balanced mix of consequences of demand and supply, house prices are hardly determined by supply factors. As one of our referees pointed, these supply factors would include the “land factor” which, given the background of “land financing” of local Chinese governments, is often thought to be significant a priori. In our model, this is implicitly embraced by the house production technology shock, which hardly matters for house prices as just shown. In more recent work, Liu and Ou (2019) relax the perfect inelastic land supply assumption by introducing an explicit “land supply shock” partially driven by innovations to government investment, to allow for the land financing behaviour. They confirm that the land supply shock does not affect housing price. In fact, they find that the housing demand shock remains the most important and dominating factor, as found here, and widely in the literature.

#### 4.1.2 | Historical decomposition

If we now decompose the historical data (measured as deviation from the steady-state values) over the shocks



FIGURE 1 Data [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Marginal likelihood of models

Model	Log marginal data likelihood
DSGE-VAR(0.5)	1947
Pure DSGE	1,402
BVAR with Sims and Zha (1998) prior	789

Note: results reported for the DSGE-VAR and the pure DSGE model are calculated with the modified harmonic mean estimator.

we identify for the sample period (Figures 3 and 4), we find that the upswing of housing price since the early 2000s was mainly caused by excess demand for houses, which, before 2007, was aided by a rise in labour supply, and thereafter, strong improvement in productivity in the

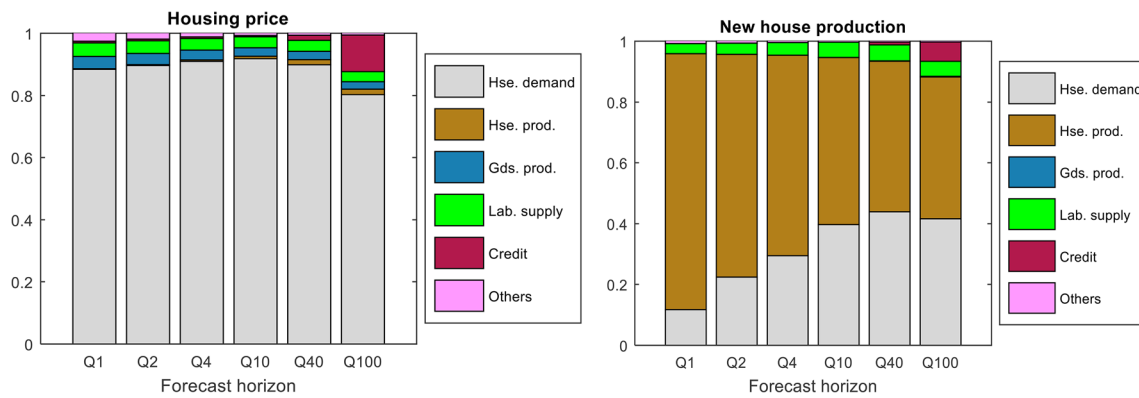
normal goods sector. A sudden fall in demand in 2008, which could have reflected the market's reaction to the global crisis, explains the temporary slowdown at the time, while the rapid rebound that followed could be a direct result of recovered confidence (which could have been accompanied by some overshooting) after the crisis. A series of property purchase restrictions adopted by major first- and second-tier cities since 2010 could have explained the lower demand that followed, which, nevertheless, failed to stabilize the market on its own. However, as demand and productivity *both* continued to fall from 2013, it triggered another major slowdown, where the housing price was corrected towards its equilibrium level.

House production was a close follower of productivity in the housing sector, which was quite volatile except

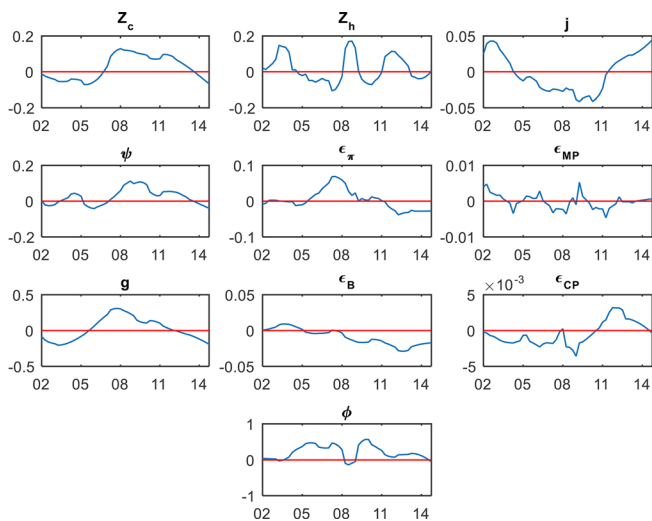
**TABLE 6** Comparison of moments

	$\Delta \widehat{GDP}$	$\Delta \widehat{C}$	$\Delta \widehat{I}$	$\Delta \widehat{ih}$	$\pi$	$\Delta \widehat{q}_h$	$\Delta \widehat{q}_l$	$\widehat{N}$	$\widetilde{R}$	$\widetilde{R}^{NL}$
<i>SD (%)</i>										
Data	0.44	0.52	1.07	3.08	0.58	2.65	1.43	1.72	0.11	0.13
Model	1.46	1.30	3.30	3.68	0.66	2.71	1.32	1.50	0.16	0.18
<i>Cross-correlation with <math>\Delta \widehat{q}_h</math></i>										
Data	-0.05	0.21	0.048	-0.72	-0.63	1	0.72	-0.20	-0.43	-0.39
Model	0.10	-0.23	0.13	-0.45	-0.70	1	0.67	-0.17	-0.55	-0.33
<i>Autocorrelation (Order = 1)</i>										
Data	0.62	0.49	0.55	0.40	0.50	0.37	0.44	0.91	0.76	0.85
Model	-0.06	-0.23	0.05	0.01	-0.03	-0.12	-0.08	0.61	0.36	0.43

*Note:* model moments are calculated with 10,000 simulations of the same length as the data, generated by bootstrapping the shocks identified over the sample period, using the posterior mean of the model parameters. Both the simulated data and actual data are HP-filtered before moments are calculated.



**FIGURE 2** Forecast error variance decompositions [Colour figure can be viewed at wileyonlinelibrary.com]



**FIGURE 3** Structural shocks [Colour figure can be viewed at wileyonlinelibrary.com]

between 2004 and 2007. The robust demand for houses had been supporting production since 2004, especially when reduced supply of labour caused substantial

downward pressure in the post-crisis period. Shocks to productivity of normal goods, intertemporal preference, inflation and government spending also affected occasionally; but compared to the previous factors their impacts were trivial.

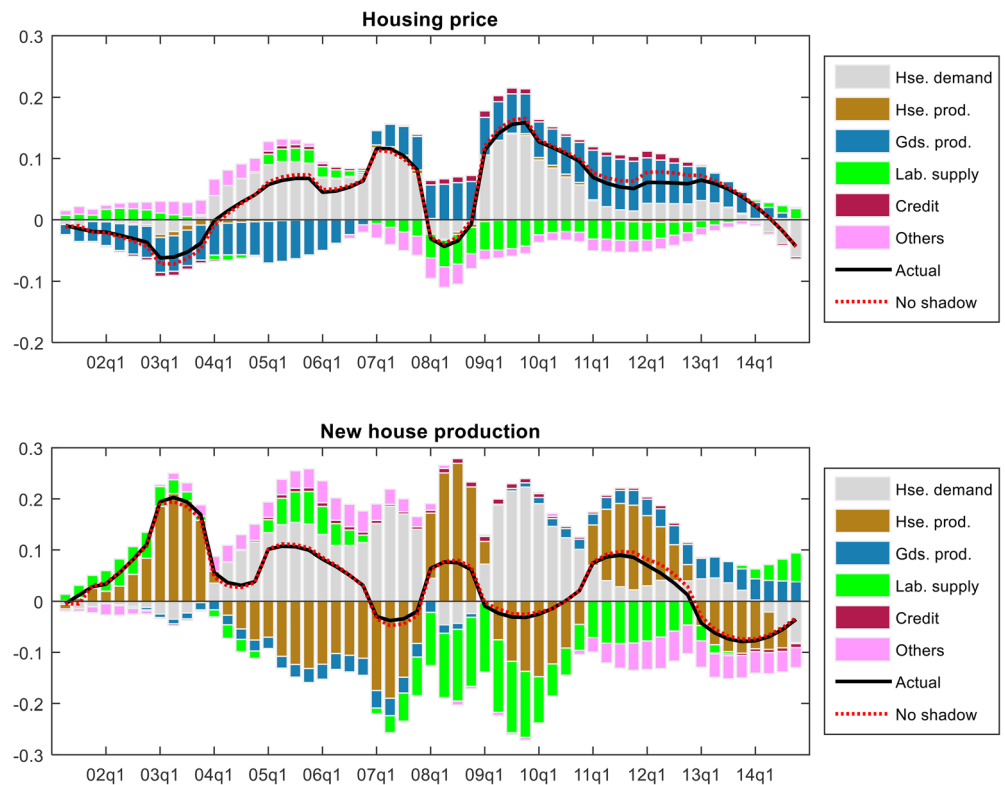
### 4.1.3 | The role of shadow banking

It is interesting to know how shadow banking—the most important innovation in our model—affects the previous findings. Here we consider two aspects, one on the model's fit, and the other on the timelines of the historical data.

Table 7 compares the marginal data likelihood of a model variant where the shadow-banking channel is turned down, to that of the benchmark model. It shows the model without shadow banking has a clearly worse fit. Thus from the modelling point of view omitting shadow banking would bias our calculations due to specification errors. Qualitatively this is caused by the failure of reflecting shadow banks' capacity in mitigating the



**FIGURE 4** Historical decompositions [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



**TABLE 7** Marginal likelihood of models with and without shadow banks

	Model with shadow banks	Model without shadow banks
Log marginal data likelihood	1947	1760

Note: Based on the modified harmonic mean estimator.

credit shock, which is fully absorbed in the mis-specified model by normal banks. Quantitatively this misspecification biases the estimates of the model's parameters including the standard errors of the structural shocks which, in relation to what we analysed above, would bias the variance decomposition of all the model variables.<sup>18</sup>

To see how shadow banks have helped mitigate the credit shock in the history, we simulate its effect on the housing variables using, respectively, the benchmark model with shadow banking and the counter-factual model variant without, using the same parameter values, in Figure 5. We find house prices and house production would have both been heavily destabilized by the credit shock, especially in the post-crisis episode, had there not been shadow banking. However, we also find this difference would not have substantially changed the timelines of these variables—as we reproduce them in Figure 4 shutting down shadow banking—as the credit shock

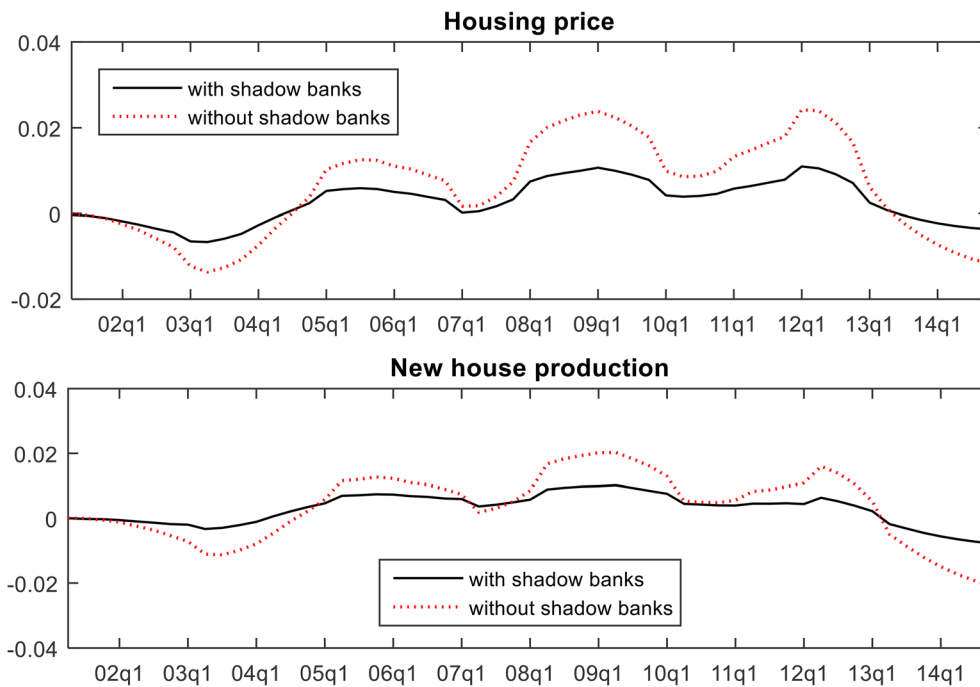
itself is small compared to other shocks in the model and hence, has never been a dominating factor in determining the housing cycle. In fact, we find what is more affected is the PBoC interest rate, as we show the timelines of the key business cycle variables in Figure C1, Appendix C, along with a detailed account of how the importance of each shock is affected without shadow banking in Tables C1 and C2.

Unfortunately, we are unable to study how shocks from the shadow-banking system itself could have affected in this case, as without reliable shadow-banking data at the macro level we are unable to identify these shocks. Nevertheless, it is worth pointing that these shocks reflect risks within the shadow-banking system, which could have spread over the whole economy playing an important role in determining the data's dynamics, via shadow-banking. This promises to be a fruitful research area which we leave for future studies.

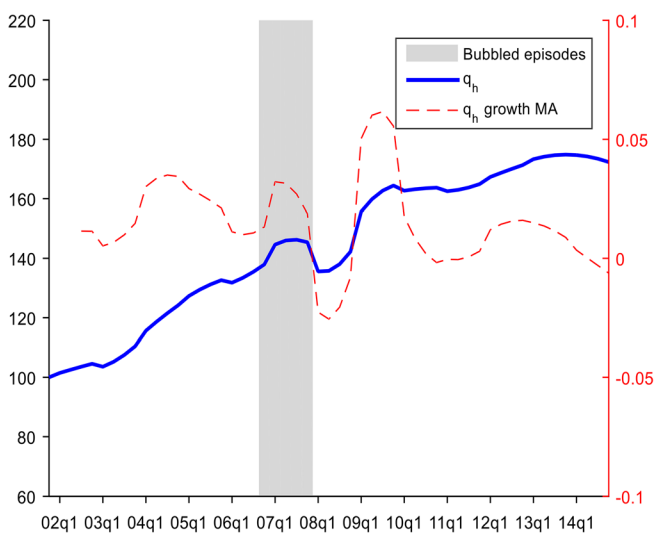
## 4.2 | The housing price “bubbles”: Were there any, and what is the nature of them?

Having known what determined China's housing price dynamics, we now ask: “were there any “bubbles,” and what is the nature of them?”

While the theoretical literature has established quite different mechanisms through which “bubbles” could



**FIGURE 5** The effect of historical credit shocks [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



**FIGURE 6** Bubbled episode (actual data) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

have arisen, it is beyond the scope of our paper to debate on which of them are more sensible when they are applied to the housing market in China. Instead, our purpose in this section is to evaluate what structural disturbances in a standard New Keynesian DSGE model like ours could have accounted for what may be perceived as housing price “bubbles” in the data, *irrespective of how they could have been triggered*—whether by herding behaviour (DeMarzo, Kaniel, & Kremer, 2008; Scharfstein & Stein, 1990) or self-fulfilling expectations (Miao, Wang, & Xu, 2015, 2016), as in “rational bubbles”

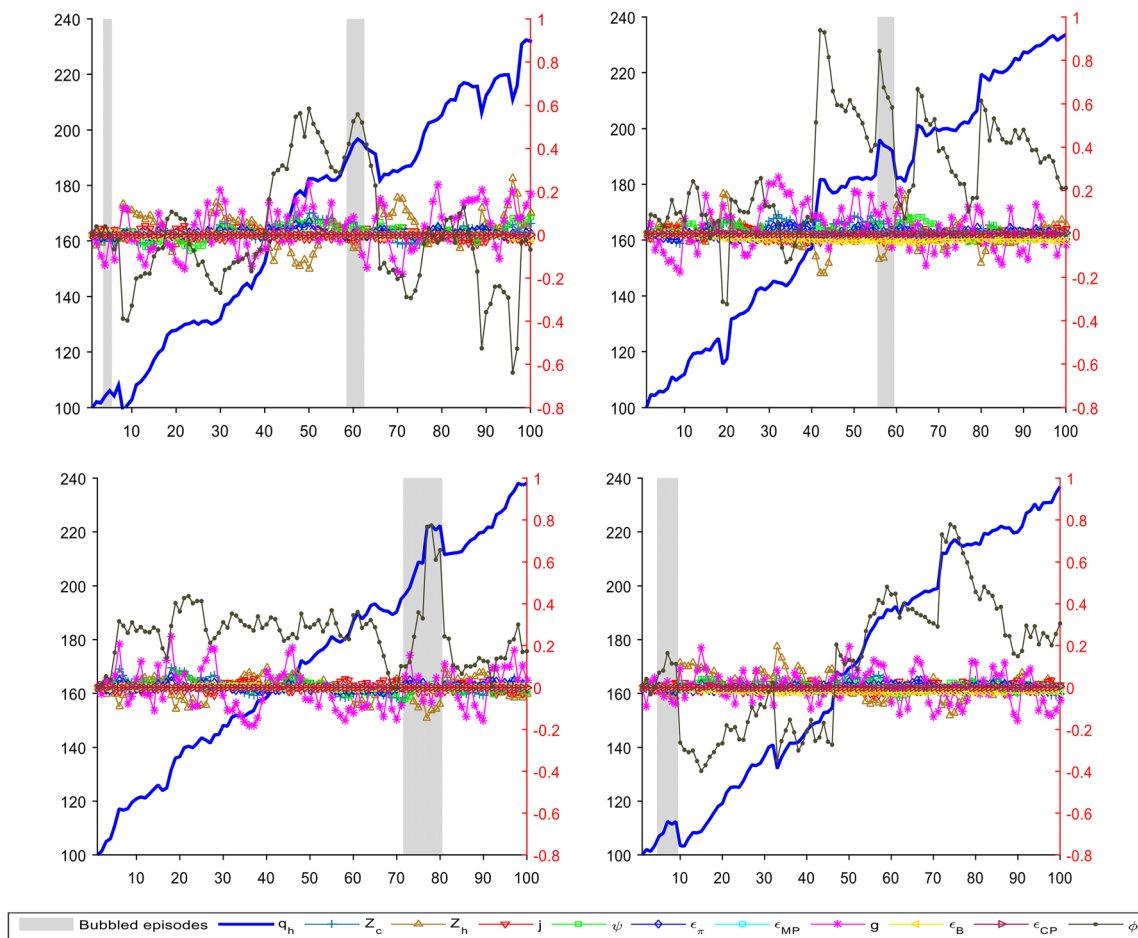
models, or by money illusion (Brunnermeier & Julliard, 2008) or “agree to disagree” (Scheinkman & Xiong, 2003), as in bounded-rational expectations models.

Since bubbles are not directly observable, and that competing theories of bubble formation (like the ones just cited) “extract” bubbles from the data in completely different ways, any bubbles gauged by a particular theory may only be viewed as “bubbles” within that theory but not in the others, as without that theory such bubbles would not have been defined. For this reason, we choose to follow the empirical literature to define “bubbles” with indicators directly measurable with the data. Typical examples of these include Meese and Wallace (1994) who measure overpricing of houses based on the price-to-rent ratio, and Glaeser and Gyourko (2005), based on price-construction-costs differentials, and Joebges, Dullien, and Márquez-Velázquez (2015), based on the deviation of short-run house prices from long-run moving-average values and the rapidity of boom-bust alterations. It is Joebges et al. that we follow here, as what we are interested is not the extent to which housing price in China deviates from the “fundamentals,” but what causes it to boom and bust in some episodes, of which some can be viewed as “bubbled.”

Specifically, we define bubble as a rapid increase in real housing price (a “boom”), followed by an equally severe decrease in it (a “bust”) within a short period of time. We follow the IMF (2009) to define boom/bust as a period during which the four-quarter moving average of the annual growth of real housing price is above/below

**TABLE 8** Frequency and duration of housing price booms/bubbles

Shocks to the economy	Boom frequency	Bubble frequency	Bubble duration
All shocks	Per 3.23 y	Per 32.8 y	16.2 mo
All, but no housing demand shock	Never	Never	N.A.
Only housing demand shock	Per 4.8 y	Per 80 y	17.8 mo

**FIGURE 7** Simulations of housing price (all shocks) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

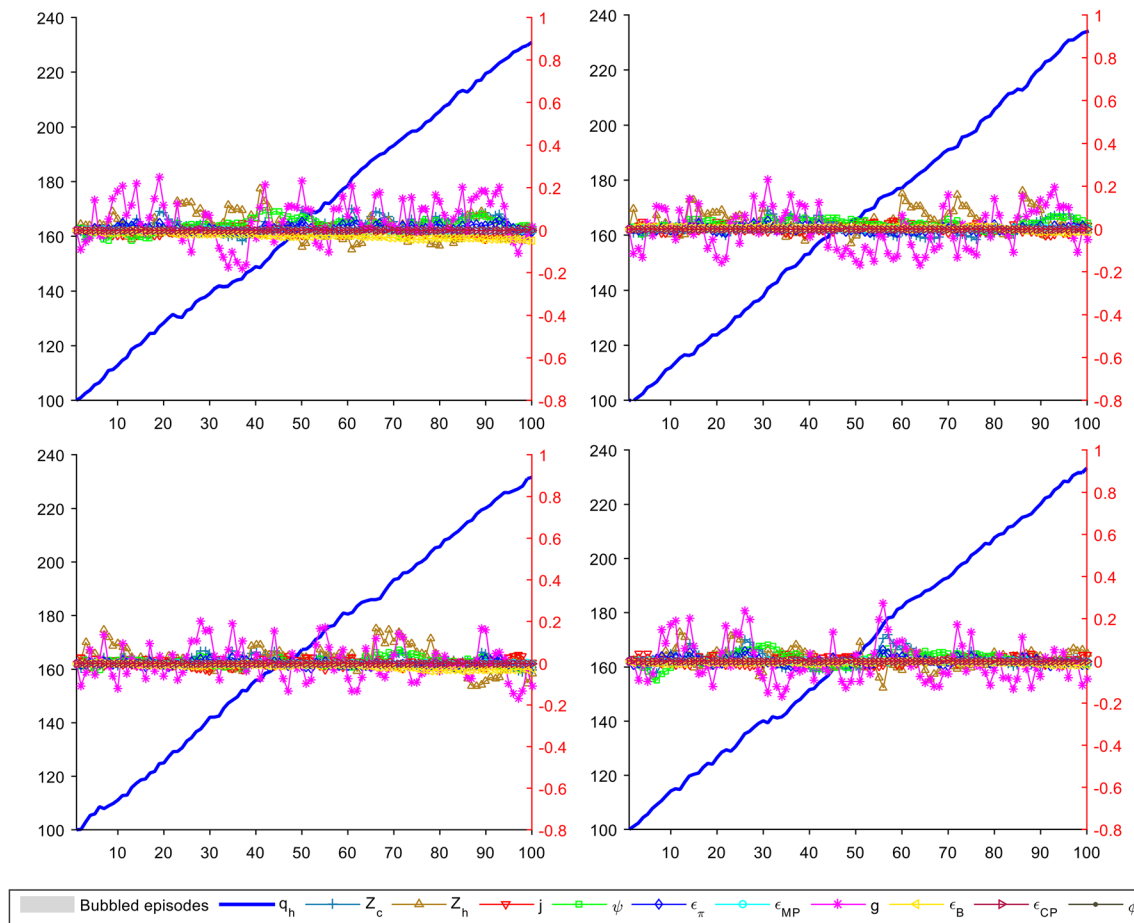
$\pm 5\%$  (or in terms of quarterly growth,  $\pm 1.25\%$ ). We also stipulate that a bust must happen within six months after the end of a boom for such a boom to be viewed as a bubble. With this definition, we identify one bubbled episode between 2006Q4 and 2007Q4 over the data sample, as illustrated in Figure 6. According to the previous historical decomposition, we know this was mainly due to shocks to housing demand and productivity in the normal goods sector happened in that period.

But what is the nature of such bubbles (i.e., what cause(s) them in general) according to the model? In order to answer this question, we bootstrap the historical shocks identified in Figure 3, for potential housing price dynamics to be simulated under randomly different simulations where the same shocks come in different time

orders.<sup>19</sup> We repeat such an experiment for 80 times, with simulation in each experiment lasting for 25 years; thus, a total simulation of 2,000 years.

Table 8 summarizes the main findings of our simulation exercise under three different scenarios: first, with all the shocks hitting the economy; second, with all, but not the housing demand shock; and third, with the housing demand shock only. Each of Figures 7–9 plots four sample simulations of the housing price (left axis) against the shocks hitting (right axis) in these experiments. We find that:

a) While housing price booms happen quite regularly in the medium run perspective (about every 3.2 years), only 10% of them are followed by a bust within 6 months for them to be regarded as “bubbles.” Thus, with all



**FIGURE 8** Simulations of housing price (all, but no housing demand shock). Monetary policy shock, credit policy shock and banking shock are rescaled up by ten times in this figure for illustration purposes [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

shocks hitting the economy, they happen about every 33 years, with bubbled episodes lasting for about 16 months.

b) Housing demand shocks are necessary for a housing price boom/bubble to happen; without them, a boom/bubble would never occur, even when shocks to the other factors are relatively sizeable (compare Figures 7 and 8 for how the simulated housing price is different with/without the housing demand shock).

c) The housing demand shock is the only factor that is capable to generate booms/bubbles on its own, therefore, causing “pure bubbles” which do not reflect any changes in the “fundamentals,” although without the assistance of other shocks they happen far less frequently—about every 80 years (Sample simulations in Figure 9). Any other shocks, either on their own, or grouped as a bundle as just attempted, are incompetent to generate bubbles.

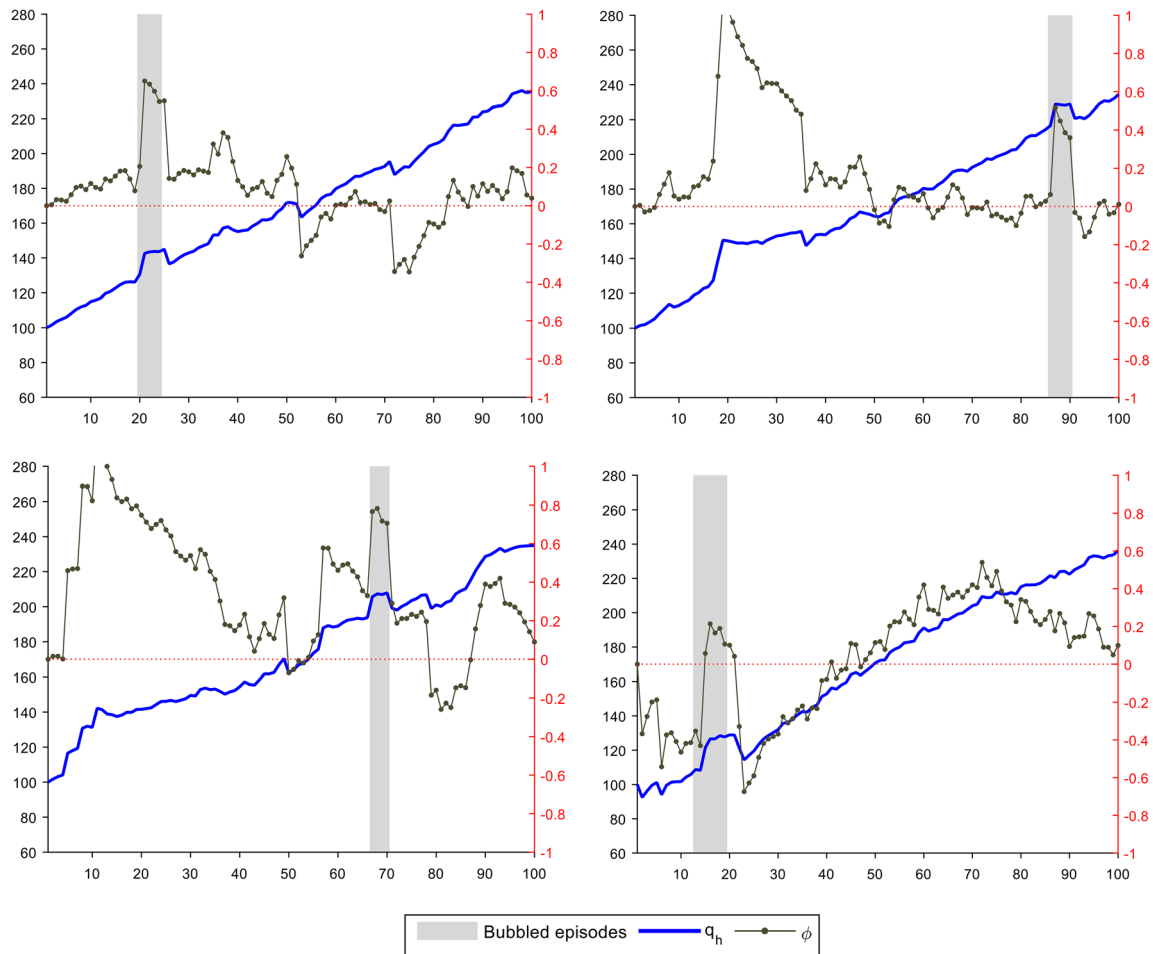
Thus, our simulation exercise suggests that housing price bubbles in China—as they are defined—are most likely a joint outcome of non-fundamental factors (which could have been changes of preference and/or

expectations) which cause demand for houses to be “unreasonably” high, and fundamental factors (such as changes in labour supply and/or productivities<sup>20</sup>) which require housing price to rise for restoring equilibrium—just as we saw from the historical decomposition. Of these, the non-fundamental factors, as abstracted to be the housing demand shock, play the decisive role, while the fundamental factors deepen its effect. In other words, such bubbles are mostly “demand-driven,” though in most cases they are not only “pure bubbles,” but also a reflection of changed fundamentals.

### 4.3 | Housing market spillovers: How important is housing market prosperity to economic growth?

We now come to the last question we aim to address in this paper; that is, how could housing market prosperity have meant to the growth of the Chinese economy?

As we motivated at the beginning of this paper, one important reason why development of the housing price,



**FIGURE 9** Simulations of housing price (only housing demand shock) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**TABLE 9** Estimates of the unrestricted VAR

Coeff.	Sim. mean	95% LB	95% UB	Actual
$\beta_{12}$	0.1275	-0.0693	0.3123	0.0463
$\beta_{13}$	0.0632	-0.0634	0.1958	0.0261
$\beta_{21}$	-0.1243	-0.6785	0.4136	-0.0369
$\beta_{23}$	-0.0336	-0.2617	0.2078	0.0248
$\beta_{31}$	-0.6685	-1.3209	0.0365	0.0780
$\beta_{32}$	0.5262	0.0948	0.9585	0.0279
Joint Wald percentile	92			
<i>p</i> -value	.08			

or more broadly, that of the housing market, has received wide concerns is that it is often shown to have an implication to the growth of an economy according to world experience—Japan in the 1990s, the United States in the late 2007, Australia between the late 1990s and the early 2000s and Colombia in the early 1990s, and so on. Existing studies in this area have mostly built on a reduced-form model such as a VAR/VECM to test the

“spillover” effects from the housing market to the wider economy. Most have found the former affects the latter positively; for example, Iacoviello and Neri (2010) find U.S. consumption is positively affected by the value of housing stock; Liu, Park, and Zheng (2002) and Chen et al. (2011) find GDP growth in China is positively affected by residential investment. While these reduced-form models do not establish evidence of “why”/“how” one variable affects another (for the reasons we explained at the beginning of this paper), one could still use them as a parsimonious description of the data dynamics generated by the “true,” structural model (like our DSGE-VAR or other DSGE models). The focus in this case is on the so-called “Granger causality,” which predicts how changes in one variable affect those of another in statistical terms.

Thus, to investigate how housing market prosperity could have affected growth following this convention, we set up an unrestricted VAR for the growths of real output, real housing price and house production. However, instead of estimating it on the actual data as most previous authors, we first use our structural model (our DSGE-

VAR) to generate 1,000 sets of simulated data with the same length as the sample data.<sup>21</sup> We then estimate a VAR (1) on the simulated data to generate 1,000 sets of VAR coefficients, and we calculate their mean values.<sup>22</sup> The coefficients on the lagged terms of the VAR therefore suggest how one variable is Granger-caused by the others, according to our structural model. If we specify the unrestricted VAR as:

$$\begin{bmatrix} \Delta Y_t \\ \Delta q_{h,t} \\ \Delta ih_t \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} \Delta Y_{t-1} \\ \Delta q_{h,t-1} \\ \Delta ih_{t-1} \end{bmatrix} + Errors_t \quad (43)$$

These will be  $\beta_{12}$ ,  $\beta_{13}$ ,  $\beta_{21}$ ,  $\beta_{23}$ ,  $\beta_{31}$  and  $\beta_{32}$ .

The first column of Table 9 reports the mean of the Least Squares estimates of these coefficients. It shows that a 1% rise in real housing price would “cause” real output to grow by 0.13% ( $\beta_{12}$ ), while the same rise in house production would raise output by just less than 0.06% ( $\beta_{13}$ ). While these numbers are broadly consistent with those found with actual data in the literature (such as the ones just cited), they suggest that:

- a. A prosperous housing market would benefit growth of the macroeconomy, mostly via the rise in housing price, though its marginal impact is small.
- b. A corollary that follows is that, unless in extreme cases when housing price collapses substantially, “modest” falls in them are not likely to lead to recessions—just as we observed in 2008 (Figure 6) when the burst of housing price bubbles did not cause any real damages to China's output.

On the other way around, a rise in output leads to a fall both in housing price ( $\beta_{21}$ ) and in house production ( $\beta_{31}$ ), so real residential investment falls. Regarding the interaction between housing price and house production, there is a small, negative impact of the latter on the former ( $\beta_{23}$ ); but the feedback from the former to the latter is positive and much bigger ( $\beta_{32}$ ).

Such theoretical implications can be tested formally by comparing the distribution of  $\beta$ 's to their corresponding values estimated with the actual data. Specifically, we set the null hypothesis ( $H_0$ ) that “ $\beta_{12}$ ,  $\beta_{13}$ ,  $\beta_{21}$ ,  $\beta_{23}$ ,  $\beta_{31}$  and  $\beta_{32}$  are all equal to their simulated mean values, and test it against the alternative ( $H_1$ ) that “not all these  $\beta$ 's equal their simulated means.” We then find the joint distribution of  $\beta$ 's with the 1,000 sets of simulated data by calculating the Wald statistic ( $WS$ ):

$$WS = (\Phi - \bar{\Phi})' \sum^{-1} (\Phi - \bar{\Phi}) \quad (44)$$

which measures the “Mahalanobis distance” between each set of  $\beta$ 's estimated with the simulated data ( $\Phi$ ) and

their mean values ( $\bar{\Phi}$ ), normalized by their variance-covariance matrix ( $\Sigma$ ). The 1,000 sets of simulated data therefore generate an empirical distribution of  $WS$ ,  $\{WS_i^{Sim}\}_{i=1}^{1000}$ , which can be evaluated against the  $WS$  value calculated with the actual data,  $WS^{Act}$ . Since  $WS = 0$  when  $H_0$  is true, the bigger  $WS^{Act}$  is, the more  $H_0$  is rejected by the actual data. In practice, one can use the percentile of  $\{WS_i^{Sim}\}_{i=1}^{1000}$  where  $WS^{Act}$  lies—call it the “Joint Wald percentile”—to decide whether  $H_0$  is rejected or not. The  $p$ -value, by definition, is  $p = (100 - \text{Joint Wald percentile})/100$ .<sup>23</sup>

It turns out that  $H_0$  passes the Joint Wald test easily, as the  $p$ -value reported (0.08) is well above the usual 5% threshold (though as for individual parameters the model slightly under-predicted  $\beta_{31}$  and over-predicted  $\beta_{32}$ ). Thus, our final assessment of the structural model using the method of Indirect Inference testifies to the following implications: although the macroeconomy could benefit from a prosperous housing market, it would be quite costly to maintain growth by just boosting the latter, for its efficacy is low. On the contrary, if policies are to stabilize the housing market, such small spillovers would also mean that the cost on output reduction would be rather limited, especially when the key determinant of housing price is correctly identified; and, according to our decomposition exercise above, this would be the housing demand shock, which determines most of the housing price, but affects output just a little.

## 5 | CONCLUSION

In this paper, we have studied what determines China's housing price dynamics by establishing a DSGE model, allowing for the unique feature of the Chinese banking system where “shadow banks” operate as a shadow-banking department of “normal” commercial banks, which has never been attempted before. We estimate the model using the DSGE-VAR method in the spirit of Del Negro and Schorfheide (2004, 2006) and Del Negro et al. (2007), for a best theory-data combination to be found, and we build our investigation on such a combination.

We find that the housing demand shock, which may be interpreted as shocks to preference for houses (or other factors not modelled within the model's structure), explains near 90% of the housing price fluctuation, with the rest assisted by shocks to labour supply, productivity and credit policy. Although Iacoviello and Neri (2010) point out that whether such housing demand shocks are spontaneous, primitive and interpretable remains an open question for further research, the preliminary investigation by Ng (2015) suggests these could

have been variations in gender imbalance, stock market performance, the number of potential buyers, and urban unemployment in China. Monetary policy shocks, which are often claimed to play a role by authors using pure DSGE models (which generally fit the data less well compared to a DSGE-VAR), are muted on this occasion; and so are the main others, including the fiscal policy shock, the inflation shock, and the banking shock. The housing demand shock is also found to be the essential cause of the housing price “bubbles,” deepened, and made happen more often than otherwise by the others. Hence, housing price bubbles in China are mostly a joint outcome of “pure bubbles,” and changed fundamentals that require housing price to rise for an equilibrium to be restored. Finally, our model also implies a weak spillover effect from the housing market to the macroeconomy, which is not rejected by the sample data. This means that, if policy-makers attempt to maintain growth of the Chinese economy by simply boosting the housing market, they would find the efficacy is very low. However, if policies are made for stabilizing the housing market, on the contrary, they should not be threatened that such stabilization would weigh on the real economy any seriously.

#### DATA AVAILABILITY STATEMENT

The data support the findings of this study are openly available in: 1: Oxford Economics at <https://www.oxfordeconomics.com>; 2: The Ministry of Labour and Social Security, P.R.C. (via the China Labour Statistical Yearbook for 2004, 2006 and 2015); 3: The Ministry of Land and Resources, P.R.C. (via China Urban Land Price Dynamic Monitor) at <http://www.landvalue.com.cn>; 4: The National Bureau of Statistics of China at <http://www.stats.gov.cn>; 5: The People's Bank of China at <http://www.pbc.gov.cn>.

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#### ENDNOTES

- <sup>1</sup> Data source: National Bureau of Statistics of China (“Average sale price of residential houses”).
- <sup>2</sup> Some authors—such as Chow and Niu (2014)—do not estimate the equilibrium equation(s) directly; instead, they try to imply the equilibrium indirectly by estimating the partial model as a simultaneous equations framework using the 2SLS approach. However, the endogeneity problem does not go away even if the equilibrium is found in this way. This is because to apply the 2SLS approach one has to force at least some variables in the simultaneous equations framework to be exogenous, for the “endogenous explanatory variables” to be predicted with the reduced-form model in “the first stage.” However, from a practical viewpoint these variables that are forced to be exogenous—“real disposal income” and “real construction cost” as in Chow and Niu, for example, are

usually endogenously determined by something else which may or may not be within the simultaneous equations framework itself. Thus, the 2SLS approach would not bypass the predicament in a real sense.

- <sup>3</sup> We assume patient households supply homogeneous labour services to the union, who will then differentiate them for them to be used in different producing sectors, as in Smets and Wouters (2007). This assumption is also made to impatient households as we model below.
- <sup>4</sup> We have let profit from banks be transferred to patient households with one lag to reflect that these profits are only available when loans are due at the end of each period.  $\chi$  is the retention ratio that normal banks set for accumulating bank capitals as we define in the banking sector below.
- <sup>5</sup> For example, a tightened credit policy can lower the amount of loans borrowed from normal banks; this causes more loans (in terms of fraction) to be borrowed from shadow banks which are much less manipulated by the public sector.
- <sup>6</sup> We follow the standard practice to treat patient household labour and impatient household labour to be imperfect substitutes for each other to reflect heterogeneity of labour skills carried by the two kinds of households (Gerali et al., 2010; Iacoviello & Neri, 2010; Ng, 2015). The assumption highlights the complementarity of different labour skills. Iacoviello and Neri find that this has the advantage of keeping the model dynamics tractable while the empirical implication is not much affected compared to the alternative specification where perfect substitution is allowed for.
- <sup>7</sup> CES stands for “constant elasticity of substitution.”
- <sup>8</sup>  $V_{t,t+i} \equiv \frac{U'_{ct}}{U'_{ct+i}}$  in (16) defines the stochastic inter-temporal substitution of normal goods consumption.  $\theta$  in (17) is the price elasticity.
- <sup>9</sup> Allen, Qian, and Xie (2019) study how informal financing has supported the growth of different firms and the economy. Allen, Qian, Tu, and Yu (2019) study the properties, lenders and borrowers, and pricing of entrusted loans.
- <sup>10</sup> Carvalho, Pasca, Souza, and Zilberman (2014) suggest these could be resources used for agency services and/or the banks' operations.
- <sup>11</sup>  $\Pi_t^{Sbank} = [(1 + r_t^{LL}) - (1 + r_t^{NL})]IL_t$ , where  $IL_t = b_t^{L''} + b_t^{E''}$ .
- <sup>12</sup> We have chosen to use a Taylor rule, rather than a money supply rule, as a parsimonious description of the complex policy-making process of the People's Bank of China. While the use of a money supply rule would not have altered the underlying mechanism through which other main variables of our model could have been affected by a “monetary policy shock,” the use of a Taylor rule has the advantage of circumventing the well-known difficulties in measuring monetary aggregates due to the increasing degrees of financial deregulation and innovation. Essentially, the Taylor rule here can be interpreted as an implicit interest rate target the PBoC aims to achieve—by whatever means, whether using money supply, guidance, or other policy instruments.
- <sup>13</sup> Four model variants including the benchmark model are compared. The benchmark specification embedded (34) has a log marginal likelihood of 1947. The other model variants assuming  $\Theta_t$  responds a) only to credit growth, b) only to house price

growth and c) to both credit and house price growths have likelihood of 1,689, 1,698 and 1,657, respectively.

<sup>14</sup> As one of our referees has pointed out, interactions between the normal banking system and the shadow banking system are so complex in practice. Thus, our assumption that, when monetary authority attempts to manipulate the size of the credit market using macro-prudential policy, tightened credit controls reduce the size of the normal banking system but (unintendedly) lead to an expansion of the shadow system as borrowers get around credit controls by substituting more shadow loans for normal loans, is one of many possible ways normal banks and shadow banks in China interact. This assumption highlights the substitutability of the two systems when one is imposed with restrictions that do not apply to the other. Thus, although the shadow system is not regulated, its size can still vary in an opposite direction to that of the normal system when changes in credit condition in the latter are caused, not by systematic shifts of risk of the whole financial market (which would affect both the systems in the same way), but by non-systematic shifts of regulatory policies, *ceteris paribus*.

<sup>15</sup> We allow for a sample of 10,000,000 draws in our practice, where the first 20% draws are dropped.

<sup>16</sup>  $v_h$  is the only parameter that we are unable to find direct evidence from China but have to assign a value with reference to the US literature. Nevertheless, as we go on to elaborate, this value—combined with others chosen according to the Chinese data—implies a steady-state residential investment ratio ( $\frac{q_h^{ih}}{GDP}$ ) that mimics the data very well. Thus, this calibration is highly plausible.

<sup>17</sup> Details about data sources and how raw data are manipulated before they are used here are outlined in Appendix B.

<sup>18</sup> We find the bias is substantial, mainly because the mis-specified model implies very different standard errors of the shocks. Since this is purely a numerical issue and there is no way to know how the mis-specification would affect the final decomposition *ex-ante*, we do not present the spurious result here in detail. However the result is available on request.

<sup>19</sup> In particular, we bootstrap our sample innovation matrix

$$\begin{bmatrix} u_{i,t} & \cdots & u_{z,t} \\ \vdots & \ddots & \vdots \\ u_{i,T} & \cdots & u_{z,T} \end{bmatrix}, \text{ where } i \dots z \text{ represent different shocks and } t \dots T$$

are time subscripts, by time vectors in each random draw. This is to preserve any potential correlations between the different shocks as reflected by the sample data.

<sup>20</sup> Recall that Figure 2 suggests other factors do not contribute much to the housing price variation.

<sup>21</sup> This is done by bootstrapping the historical shocks identified for the sample period, just as how we did in the simulation exercise above.

<sup>22</sup> We choose a VAR (1) here because for each simulation the sample size is small.

<sup>23</sup> This is essentially the *Indirect Inference Wald test* recently developed by Le, Meenagh, Minford, and Wickens (2011) for testing DSGE models with the frequentist method. While  $\Phi$  can in principle embrace any parameters of a chosen reduced-form model (or functions of them), we only include those as listed in Table 9

here, as our purpose is just to test whether the Granger causal relations among the variables chosen, as predicted by our DSGE-VAR, are rejected by the actual data.

<sup>24</sup> We assume that shifts of credit policy affect household and entrepreneur borrowing from normal banks in the same manner, so that  $\hat{\Theta}_t = \hat{\Theta}_{H,t} = \hat{\Theta}_{E,t} = -\hat{\Xi}_{H,t} = -\hat{\Xi}_{E,t}$ .

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## DATA CITATION:

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- 3: The Ministry of Land and Resources, P.R.C. (via China Urban Land Price Dynamic Monitor) at <http://www.landvalue.com.cn>;
- 4: The National Bureau of Statistics of China at <http://www.stats.gov.cn>;
- 5: The People’s Bank of China at <http://www.pbc.gov.cn>.

## APPENDIX A: MODEL, IMPULSE RESPONSES, AND GLOSSARY OF VARIABLES AND DISTURBANCES

### Optimisations, policies and identities

#### The patient household problem:

Patient households maximize:

$$L^P = E_0 \sum_{t=0}^{\infty} (\beta^P G_{c^P})^t j_t \left( \ln c_t^P + \phi_t \ln h_t^P - \frac{\psi_t}{1 + \eta^P} \left( n_{c,t}^{P1 + \xi^P} + n_{h,t}^{P1 + \xi^P} \right)^{\frac{1 + \eta^P}{1 + \xi^P}} \right) \quad (\text{A.1})$$

by choosing  $c_t^P$ ,  $h_t^P$ ,  $n_{c,t}^P$ ,  $n_{h,t}^P$  and  $S_t$ , subject to budget constraint:

$$c_t^P + q_{h,t} [h_t^P - (1 - \delta_h) h_{t-1}^P] + S_t = w_{c,t}^P n_{c,t}^P + w_{h,t}^P n_{h,t}^P + (1 + r_{t-1}^S) S_{t-1} + \Pi_t^{\text{Fgds}} + (\Pi_{t-1}^{\text{Nbank}} - \chi \Pi_{t-1}^{\text{Nbank}}) + \Pi_{t-1}^{\text{Sbank}} - \tau_t \quad (\text{A.2})$$

The first order conditions are:

$$\frac{\partial L^P}{\partial c_t^P} : j_t \frac{1}{c_t^P} = \lambda_t^P \quad (\text{A.3})$$

$$\frac{\partial L^P}{\partial h_t^P} : j_t \frac{\phi_t}{h_t^P} + \beta^P G_{c^P} E_t \lambda_{t+1}^P q_{h,t+1} (1 - \delta_h) = \lambda_t^P q_{h,t} \quad (\text{A.4})$$

$$\frac{\partial L^P}{\partial n_{c,t}^P} : j_t \psi_t \left( n_{c,t}^{P1 + \xi^P} + n_{h,t}^{P1 + \xi^P} \right)^{\frac{\eta^P - \xi^P}{1 + \xi^P}} n_{c,t}^{P \xi^P} = \lambda_t^P w_{c,t}^P \quad (\text{A.5})$$

$$\frac{\partial L^P}{\partial n_{h,t}^P} : j_t \psi_t \left( n_{c,t}^{P1 + \xi^P} + n_{h,t}^{P1 + \xi^P} \right)^{\frac{\eta^P - \xi^P}{1 + \xi^P}} n_{h,t}^{P \xi^P} = \lambda_t^P w_{h,t}^P \quad (\text{A.6})$$

$$\frac{\partial L^P}{\partial S_t} : \beta^P G_{c^P} E_t \lambda_{t+1}^P (1 + r_t^S) = \lambda_t^P \quad (\text{A.7})$$

$$\frac{\partial L^I}{\partial b_t^{I''}} : \lambda_t^I - \beta^I G_{c^I} E_t \lambda_{t+1}^I (1 + r_t^{IL}) = \lambda_t^{I''} \quad (\text{A.17})$$

### The impatient household problem:

Impatient households maximize:

$$L^I = E_0 \sum_{t=0}^{\infty} (\beta^I G_{c^I})^t j_t \left[ \ln c_t^I + \phi_t \ln h_t^I - \frac{\psi_t}{1 + \eta^I} \left( n_{c,t}^{I1+\xi^I} + n_{h,t}^{I1+\xi^I} \right)^{\frac{1+\eta^I}{1+\xi^I}} \right] \quad (\text{A.8})$$

by choosing  $c_t^I$ ,  $h_t^I$ ,  $n_{c,t}^I$ ,  $n_{h,t}^I$ ,  $b_t^{I'}$  and  $b_t^{I''}$ , subject to budget constraint:

$$c_t^I + q_{h,t} [h_t^I - (1 - \delta_h) h_{t-1}^I] + (1 + r_{t-1}^{NL}) b_{t-1}^{I'} + (1 + r_{t-1}^{IL}) b_{t-1}^{I''} = w_{c,t}^I n_{c,t}^I + w_{h,t}^I n_{h,t}^I + b_t^{I'} + b_t^{I''} \quad (\text{A.9})$$

borrowing constraint for normal bank loans:

$$b_t^{I'} \leq \Theta_{H,t} \frac{E_t(q_{h,t+1} h_t^I)}{1 + r_t^{NL}} \quad (\text{A.10})$$

and borrowing constraint for shadow bank loans:

$$b_t^{I''} \leq \Xi_{H,t} \frac{E_t(q_{h,t+1} h_t^I)}{1 + r_t^{IL}} \quad (\text{A.11})$$

The first order conditions are:

$$\frac{\partial L^I}{\partial c_t^I} : j_t \frac{1}{c_t^I} = \lambda_t^I \quad (\text{A.12})$$

$$\begin{aligned} \frac{\partial L^I}{\partial h_t^I} : j_t \frac{\phi_t}{h_t^I} + \beta^I G_{c^I} E_t \lambda_{t+1}^I q_{h,t+1} (1 - \delta_h) + \lambda_t^{I'} \Theta_{H,t} \frac{E_t q_{h,t+1}}{1 + r_t^{NL}} \\ + \lambda_t^{I''} \Xi_{H,t} \frac{E_t q_{h,t+1}}{1 + r_t^{IL}} = \lambda_t^I q_{h,t} \end{aligned} \quad (\text{A.13})$$

$$\frac{\partial L^I}{\partial n_{c,t}^I} : j_t \psi_t \left( n_{c,t}^{I1+\xi^I} + n_{h,t}^{I1+\xi^I} \right)^{\frac{\eta^I - \xi^I}{1+\xi^I}} n_{c,t}^{I\xi^I} = \lambda_t^I w_{c,t}^I \quad (\text{A.14})$$

$$\frac{\partial L^I}{\partial n_{h,t}^I} : j_t \psi_t \left( n_{c,t}^{I1+\xi^I} + n_{h,t}^{I1+\xi^I} \right)^{\frac{\eta^I - \xi^I}{1+\xi^I}} n_{h,t}^{I\xi^I} = \lambda_t^I w_{h,t}^I \quad (\text{A.15})$$

$$\frac{\partial L^I}{\partial b_t^{I'}} : \lambda_t^I - \beta^I G_{c^I} E_t \lambda_{t+1}^I (1 + r_t^{NL}) = \lambda_t^{I'} \quad (\text{A.16})$$

### The entrepreneur problem:

Entrepreneurs maximize:

$$L^E = E_0 \sum_{t=0}^{\infty} (\gamma G_{c^E})^t j_t \ln c_t^E \quad (\text{A.18})$$

by choosing  $c_t^E$ ,  $n_{c,t}^P$ ,  $n_{h,t}^P$ ,  $n_{c,t}^I$ ,  $n_{h,t}^I$ ,  $k_{c,t}$ ,  $k_{h,t}$ ,  $l_t$ ,  $b_t^{E'}$  and  $b_t^{E''}$ , subject to budget constraint:

$$\begin{aligned} c_t^E + i_{c,t} + i_{h,t} + q_{l,t} (l_t - l_{t-1}) + w_{c,t}^P n_{c,t}^P + w_{h,t}^P n_{h,t}^P + w_{c,t}^I n_{c,t}^I + w_{h,t}^I n_{h,t}^I \\ + (1 + r_{t-1}^{NL}) b_{t-1}^{E'} + (1 + r_{t-1}^{IL}) b_{t-1}^{E''} \\ = \frac{Y_t}{X_t} + q_{h,t} i h_t + b_t^{E'} + b_t^{E''} \end{aligned} \quad (\text{A.19})$$

borrowing constraint for normal bank loans:

$$b_t^{E'} \leq \Theta_{E,t} \frac{E_t (q_{l,t+1} l_t + k_{c,t} + k_{h,t})}{1 + r_t^{NL}} \quad (\text{A.20})$$

borrowing constraint for shadow bank loans:

$$b_t^{E''} \leq \Xi_{E,t} \frac{E_t (q_{l,t+1} l_t + k_{c,t} + k_{h,t})}{1 + r_t^{IL}} \quad (\text{A.21})$$

production function for normal goods:

$$Y_t = [A_{c,t} (n_{c,t}^P)^\alpha (n_{c,t}^I)^{1-\alpha}]^{1-u_c} k_{c,t-1}^{u_c} \quad (\text{A.22})$$

production function for houses:

$$i h_t = [A_{h,t} (n_{h,t}^P)^\alpha (n_{h,t}^I)^{1-\alpha}]^{1-u_h-v_h} k_{h,t-1}^{u_h} l_{t-1}^{v_h} \quad (\text{A.23})$$

evolution of capital for normal goods production:

$$k_{c,t} - k_{c,t-1} = i_{c,t} - \delta_{kc} k_{c,t-1} \quad (\text{A.24})$$

evolution of capital for house production:

$$k_{h,t} - k_{h,t-1} = i_{h,t} - \delta_{kh} k_{h,t-1} \quad (\text{A.25})$$

The first order conditions are:

$$\frac{\partial L^E}{\partial c_t^E} : j_t \frac{1}{c_t^E} = \lambda_t^E \quad (\text{A.28})$$

$$\frac{\partial L^E}{\partial n_{c,t}^P} : \alpha(1-u_c) \frac{Y_t}{X_t} = w_{c,t}^P n_{c,t}^P \quad (\text{A.29})$$

$$\frac{\partial L^E}{\partial n_{c,t}^I} : (1-\alpha)(1-u_c) \frac{Y_t}{X_t} = w_{c,t}^I n_{c,t}^I \quad (\text{A.30})$$

$$\frac{\partial L^E}{\partial n_{h,t}^P} : \alpha(1-u_h-v_h) q_{h,t} i h_t = w_{h,t}^P n_{h,t}^P \quad (\text{A.31})$$

$$\frac{\partial L^E}{\partial n_{h,t}^I} : (1-\alpha)(1-u_h-v_h) q_{h,t} i h_t = w_{h,t}^I n_{h,t}^I \quad (\text{A.32})$$

$$\begin{aligned} \frac{\partial L^E}{\partial k_{c,t}} : \gamma G_{c^E} E_t \lambda_{t+1}^E \left[ 1 - \delta_{kc} + u_c \frac{Y_{t+1}}{X_{t+1} k_{c,t}} \right] \\ + \lambda_t^{E'} \frac{\Theta_{E,t}}{1+r_t^{NL}} + \lambda_t^{E''} \frac{\Xi_{E,t}}{1+r_t^{IL}} = \lambda_t^E \end{aligned} \quad (\text{A.33})$$

$$\begin{aligned} \frac{\partial L^E}{\partial k_{h,t}} : \gamma G_{c^E} E_t \lambda_{t+1}^E \left[ 1 - \delta_{kh} + u_h \frac{q_{h,t+1} i h_{t+1}}{k_{h,t}} \right] \\ + \lambda_t^{E'} \frac{\Theta_{E,t}}{1+r_t^{NL}} + \lambda_t^{E''} \frac{\Xi_{E,t}}{1+r_t^{IL}} = \lambda_t^E \end{aligned} \quad (\text{A.34})$$

$$\begin{aligned} \frac{\partial L^E}{\partial l_t} : \gamma G_{c^E} E_t \lambda_{t+1}^E \left[ 1 + v_h \frac{q_{h,t+1} i h_{t+1}}{E_t q_{l,t+1} l_t} \right] + \lambda_t^{E'} \frac{\Theta_{E,t}}{1+r_t^{NL}} \\ + \lambda_t^{E''} \frac{\Xi_{E,t}}{1+r_t^{IL}} = \lambda_t^E \left[ \frac{q_{l,t}}{E_t q_{l,t+1}} \right] \end{aligned} \quad (\text{A.35})$$

$$\frac{\partial L^E}{\partial b_t^{E'}} : \lambda_t^E - \gamma G_{c^E} E_t \lambda_{t+1}^E (1+r_t^{NL}) = \lambda_t^{E'} \quad (\text{A.36})$$

$$\frac{\partial L^E}{\partial b_t^{E''}} : \lambda_t^E - \gamma G_{c^E} E_t \lambda_{t+1}^E (1+r_t^{IL}) = \lambda_t^{E''} \quad (\text{A.37})$$

### The retailer problem:

In each period retailers maximize:

$$L_t^R = E_t \sum_{i=0}^{\infty} (\omega \beta^P G_c)^i V_{t,t+i} \left[ \left( \frac{p_{t+i}(j)}{P_{t+i}} \right) Y_{t+i}(j) - \frac{1}{X_{t+i}} Y_{t+i}(j) \right] \quad (\text{A.38})$$

by choosing  $p_t(j)$ , subject to the Dixit-Stiglitz (1977) CES demand function:

$$Y_t(j) = \left( \frac{p_t(j)}{P_t} \right)^{-\theta} Y_t^{Final} \quad (\text{A.39})$$

and the price indexation rule:

$$p_{t+i}(j) = p_t(j) \left( \frac{P_{t+i-1}}{P_{t-1}} \right)^\epsilon \quad (\text{A.40})$$

The first order condition implies the optimal reset price to be:

$$p_t^*(j) = \frac{\theta}{(\theta-1)} \frac{E_t \sum_{i=0}^{\infty} (\omega \beta^P G_c)^i V_{t,t+i} Y_{t+i}^{Final} \frac{1}{X_{t+i}} P_{t+i}^\theta P_{t+i-1}^{-\theta \epsilon} P_{t-1}^{\theta \epsilon}}{E_t \sum_{i=0}^{\infty} (\omega \beta^P G_c)^i V_{t,t+i} Y_{t+i}^{Final} P_{t+i}^{\theta-1} P_{t+i-1}^{\epsilon(1-\theta)} P_{t-1}^{\epsilon(\theta-1)}} \quad (\text{A.41})$$

Let the general price level be:

$$P_t = \left[ \int_0^1 p_t(j)^{1-\theta} dj \right]^{\frac{1}{1-\theta}} \quad (\text{A.42})$$

Equations A.40, A.41 and A.42 then imply the “hybrid-version” New Keynesian Phillips curve, where inflation shock ( $\hat{\epsilon}_{\pi,t}$ ) is also allowed for:

$$\begin{aligned} \pi_t = \frac{\beta^P G_c}{1 + \beta^P G_c \epsilon} E_t \pi_{t+1} + \frac{\epsilon}{1 + \beta^P G_c \epsilon} \pi_{t-1} \\ + \frac{(1-\omega)(1-\omega \beta^P G_c)}{\omega(1 + \beta^P G_c \epsilon)} (-\hat{X}_t) + \hat{\epsilon}_{\pi,t} \end{aligned} \quad (\text{A.43})$$

Retailers' profit in each period is:

$$\Pi_t^{Fgds} = \left( 1 - \frac{1}{X_t} \right) Y_t \quad (\text{A.44})$$

### The normal bank problem:

In each period, normal banks maximize:

$$\begin{aligned} \text{Max}_{B_t} \Pi_t^{Nbank} = \sum_{t=0}^{\infty} \Lambda_{0,t}^{Nbank} \left\{ [(1+r_t^{NL})B_t - B_{t+1}] \right. \\ \left. + [S_{t+1} - (1+r_t^S)S_t] - \frac{c}{2} \left( \frac{F_t}{B_t} - \Omega \right)^2 F_t + \Delta F_{t+1} \right\} \end{aligned} \quad (\text{A.45})$$

by choosing  $B_t$ , subject to balance sheet constraint:

$$B_t = S_t + F_t \quad (\text{A.46})$$

and the accumulation process of bank capital:

$$F_t = (1 - \delta^F) F_{t-1} + \chi \Pi_{t-1}^{Nbank} \quad (\text{A.47})$$

The first order condition is:

$$(r_t^{NL} - r_t^S) = -c \left( \frac{F_t}{B_t} - \Omega \right) \left( \frac{F_t}{B_t} \right)^2 \quad (\text{A.48})$$

Here, we assume that the above optimal condition may not always hold in practice, so that implementation of it is subject to “banking shock” ( $\varepsilon_{B,t}$ ), as the following:

$$\varepsilon_{B,t} (r_t^{NL} - r_t^S) = -c \left( \frac{F_t}{B_t} - \Omega \right) \left( \frac{F_t}{B_t} \right)^2 \quad (\text{A.49})$$

### The shadow bank problem:

In each period, individual shadow bank  $z$  maximizes:

$$\text{Max}_{r_t^{LL}(z)} \Pi_t^{Sbank}(z) = \sum_{t=0}^{\infty} \Lambda_{0,t}^{Sbank} \{ [1 + r_t^{LL}(z)] IL_t(z) - (1 + r_t^{NL}) IL_t(z) \} \quad (\text{A.50})$$

by choosing  $r_t^{LL}$ , subject to the demand for loan equation:

$$IL_t(z) = \left[ \frac{1 + r_t^{LL}(z)}{1 + r_t^{NL}} \right]^{-\eta^{Sbank}} IL_t \quad (\text{A.51})$$

The first order condition is:

$$1 + r_t^{LL}(z) = \left( \frac{\eta^{Sbank}}{\eta^{Sbank} - 1} \right) (1 + r_t^{NL}) \quad (\text{A.52})$$

which, by imposing a symmetric equilibrium to the economy, further implies:

$$1 + r_t^{LL} = \left( \frac{\eta^{Sbank}}{\eta^{Sbank} - 1} \right) (1 + r_t^{NL}) \quad (\text{A.53})$$

### Public sector policies:

Taylor rule:

$$1 + R_t = (1 + R_{t-1})^{\rho_R} (1 + \pi_t)^{(1 - \rho_R) \varphi_\pi} \left( \frac{GDP_t}{G_c GDP_{t-1}} \right)^{(1 - \rho_R) \varphi_x} (1 + r^{SS})^{(1 - \rho_R)} \varepsilon_{MP,t} \quad (\text{A.54})$$

Credit policy<sup>24</sup>:

$$\Theta_t = \Theta_{t-1}^{\rho_\Theta} \left( \frac{GDP_t}{G_c GDP_{t-1}} \right)^{\alpha_\Theta} \bar{\Theta}^{1 - \rho_\Theta} \varepsilon_{CP,t} \quad (\text{A.55})$$

Government spending:

$$g_t = \tau_t \quad (\text{A.56})$$

### Market clearing

Normal goods market clearing:

$$C_t + I_t + g_t = Y_t - \frac{c}{2} \left( \frac{F_{t-1}}{B_{t-1}} - \Omega \right)^2 F_{t-1} - \delta^F F_{t-1} \quad (\text{A.57})$$

Housing market clearing:

$$h_t^P - (1 - \delta_h) h_{t-1}^P + h_t^I - (1 - \delta_h) h_{t-1}^I = i h_t \quad (\text{A.58})$$

Land market clearing:

$$l_t = \bar{l} \quad (\text{A.59})$$

Financial market clearing:

$$b_t^I + b_t^{I''} + b_t^{E'} + b_t^{E''} = B_t \quad (\text{A.60})$$

Labour market clears automatically due to the Walras's law.

### Identities

Total consumption:

$$c_t^P + c_t^I + c_t^E = C_t \quad (\text{A.61})$$

Total investment:

$$i_{c,t} + i_{h,t} = I_t \quad (\text{A.62})$$

Total labour:

$$\ln Z_{h,t} = \rho_{Ah} \ln Z_{h,t-1} + \ln u_{Ah,t} \quad (\text{A.70})$$

$$(n_{c,t}^P)^\alpha (n_{c,t}^I)^{1-\alpha} + (n_{h,t}^P)^\alpha (n_{h,t}^I)^{1-\alpha} = N_t \quad (\text{A.63})$$

Definition of GDP:

$$GDP_t = Y_t + \bar{q}_h i h_t \quad (\text{A.64})$$

Fisher identity a:

$$r_t^S = R_t - E_t \pi_{t+1} \quad (\text{A.65})$$

Fisher identity b:

$$r_t^{NL} = R_t^{NL} - E_t \pi_{t+1} \quad (\text{A.66})$$

### Trends and shock evolution

Technology growth (normal goods production):

$$A_{c,t} = (1 + \gamma_{Ac})^t Z_{c,t} \quad (\text{A.67})$$

Technology growth (house production):

$$A_{h,t} = (1 + \gamma_{Ah})^t Z_{h,t} \quad (\text{A.68})$$

Technology shock (normal goods production):

$$\ln Z_{c,t} = \rho_{Ac} \ln Z_{c,t-1} + \ln u_{Ac,t} \quad (\text{A.69})$$

Technology shock (house production):

Intertemporal preference shock:

$$\ln j_t = \rho_j \ln j_{t-1} + \ln u_{j,t} \quad (\text{A.71})$$

Housing preference shock:

$$\ln \phi_t = (1 - \rho_\phi) \ln \bar{\phi} + \rho_\phi \ln \phi_{t-1} + \ln u_{\phi,t} \quad (\text{A.72})$$

Labour supply shock:

$$\ln \psi_t = \rho_\psi \ln \psi_{t-1} + \ln u_{\psi,t} \quad (\text{A.73})$$

Inflation shock:

$$\ln \varepsilon_{\pi,t} = \rho_\pi \ln \varepsilon_{\pi,t-1} + \ln u_{\pi,t} \quad (\text{A.74})$$

Banking shock:

$$\ln \varepsilon_{B,t} = \rho_B \ln \varepsilon_{B,t-1} + \ln u_{B,t} \quad (\text{A.75})$$

Monetary policy shock:

$$\ln \varepsilon_{MP,t} = \rho_{MP} \ln \varepsilon_{MP,t-1} + \ln u_{MP,t} \quad (\text{A.76})$$

Credit policy shock:

$$\ln \varepsilon_{CP,t} = \rho_{CP} \ln \varepsilon_{CP,t-1} + \ln u_{CP,t} \quad (\text{A.77})$$

Government spending shock:

$$\ln g_t = \rho_g \ln g_{t-1} + \ln u_{g,t} + \rho_{gc} \ln u_{Ac,t} \quad (\text{A.78})$$

where  $u_{Ac,t}$ ,  $u_{Ah,t}$ ,  $u_j$ ,  $u_\phi$ ,  $u_\psi$ ,  $u_\pi$ ,  $u_B$ ,  $u_{MP}$ ,  $u_{CP,t}$  and  $u_{g,t}$  are all *i. i. d.* innovations.

Impulse responses of main model variables

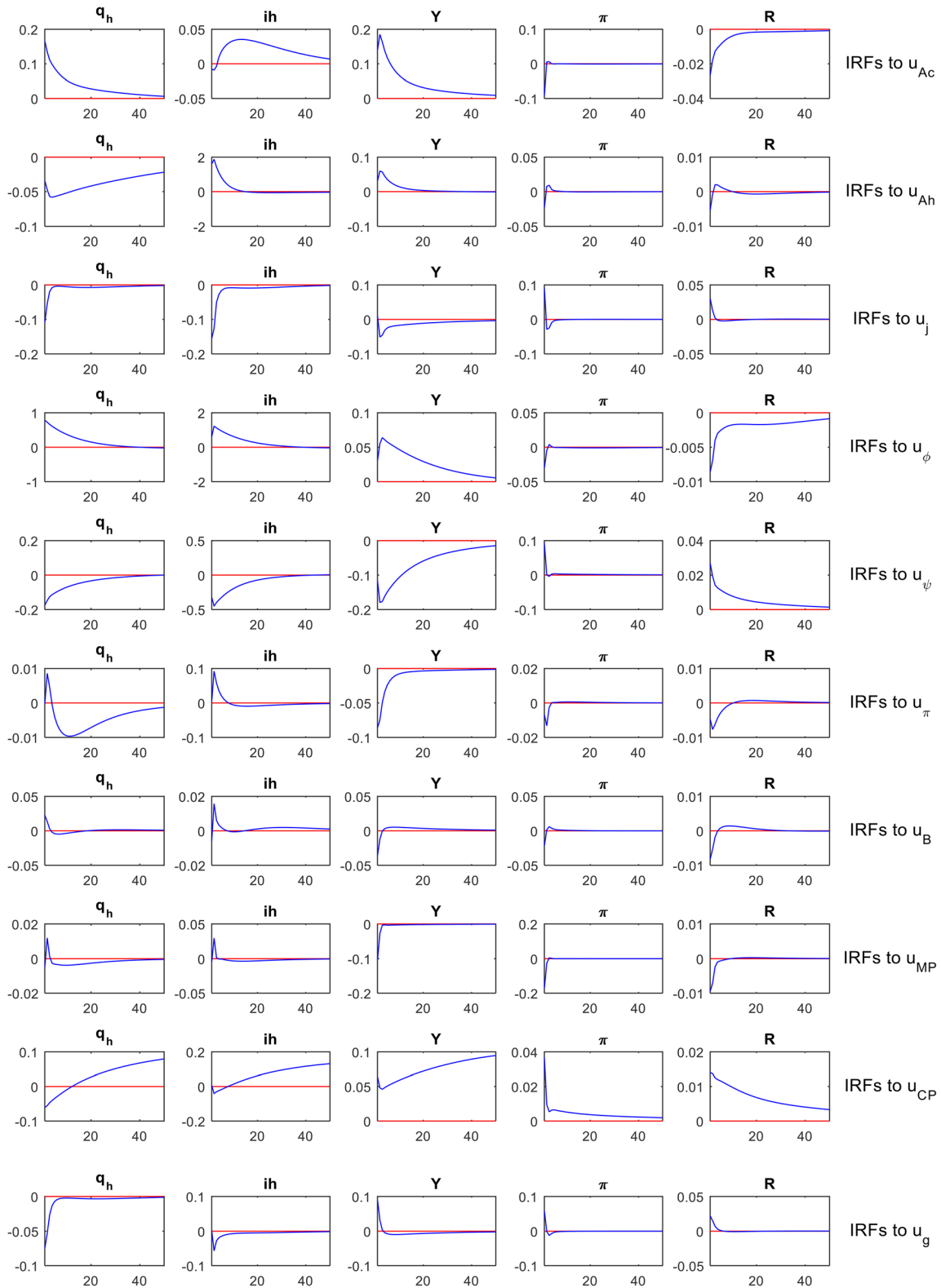


FIGURE A1 Impulse responses of main model variables [Colour figure can be viewed at wileyonlinelibrary.com]

## Glossary of model variables and disturbances

TABLE A1 Model variables

$GDP_t$	Gross domestic product	$\Pi_t^{Sbank}$	Shadow banks' profit
$Y_t$	Total normal goods production	$F_t$	Normal banks' capital
$ih_t$	Total house production	$\pi_t$	Inflation in the normal goods sector
$c_t^P$	Patient household consumption	$q_{h,t}$	Real price of houses
$c_t^I$	Impatient household consumption	$q_{l,t}$	Real price of lands
$c_t^E$	Entrepreneur consumption	$R_t$	Central bank nominal interest rate
$C_t$	Total private consumption	$R_t^{NL}$	Normal bank nominal loan rate
$h_t^P$	Patient household demand for houses	$r_t^{NL}$	Normal bank real loan rate
$h_t^I$	Impatient household demand for houses	$r_t^{IL}$	Shadow bank real loan rate
$i_{c,t}$	Investment for normal goods production	$r_t^S$	Normal bank real saving rate
$i_{h,t}$	Investment for houses production	$\Theta_t$	Credit tightness
$I_t$	Total (non-residential) private investment	$\Theta_{H,t}$	Loan-to-value ratio (households; normal bank loans)
$g_t$	Government spending	$\Theta_{E,t}$	Loan-to-value ratio (entrepreneurs; normal bank loans)
$\tau_t$	Tax revenue	$\Xi_{H,t}$	Loan-to-value ratio (households; shadow bank loans)
$n_{c,t}^P$	Patient household labour for normal goods production	$\Xi_{E,t}$	Loan-to-value ratio (entrepreneurs; shadow bank loans)
$n_{h,t}^P$	Patient household labour for houses production	$X_t$	Mark-up to price of intermediate goods
$n_{c,t}^I$	Impatient household labour for normal goods production	$w_{c,t}^P$	Real wage for patient households for normal goods production
$n_{h,t}^I$	Impatient household labour for houses production	$w_{h,t}^P$	Real wage for patient households for houses production
$N_t$	Total labour hours	$w_{c,t}^I$	Real wage for impatient households for normal goods production
$k_{c,t}$	Physical capital for normal goods production	$w_{h,t}^I$	Real wage for impatient households for houses production
$k_{h,t}$	Physical capital for houses production	$b_t^I$	Impatient household borrowing from normal banks
$l_t$	Lands	$b_t^{II}$	Impatient household borrowing from investment banks
$A_{c,t}$	Technology for normal goods production	$b_t^{EI}$	Entrepreneur borrowing from normal banks
$A_{h,t}$	Technology for houses production	$b_t^{EII}$	Entrepreneur borrowing from investment banks
$\Pi_t^{Fgds}$	Retailers' profit	$B_t$	Total borrowing
$\Pi_t^{Nbank}$	Normal banks' profit	$S_t$	Total saving

TABLE A2 Model disturbance

$Z_{c,t}$	Technology shock (normal goods production)	$\varepsilon_{\pi,t}$	Inflation shock
$Z_{h,t}$	Technology shock (house production)	$\varepsilon_{B,t}$	Banking shock
$j_t$	Inter-temporal preference shock	$\varepsilon_{MP,t}$	Monetary policy shock
$\phi_t$	Housing preference shock	$\varepsilon_{CP,t}$	Credit policy shock
$\psi_t$	Labour supply shock	$g_t$	Government spending shock



## APPENDIX B: MEASUREMENT, SOURCES AND ADJUSTMENTS OF DATA

We use as observable variables of the model the time series of  $GDP_t$ ,  $C_t$ ,  $I_t$ ,  $ih_t$ ,  $\pi_t$ ,  $q_{h,t}$ ,  $q_{l,t}$ ,  $N_t$ ,  $R_t$  and  $R_t^{NL}$ . All real-sector variables (where applicable) are normalized by the Consumer Price Index (*CPI*) and the working-age population index (*pop*), and are measured in natural logarithm.  $\pi_t$  measures the quarter-on-quarter growth of *CPI*.  $q_{h,t}$  and  $q_{l,t}$  are both log relative prices to *CPI*.  $R_t$  and  $R_t^{NL}$  are both quarterly interest rate. All the data are demeaned, detrended when they are used for estimation.

The observation sample spans from 2001Q1 to 2014Q4, and are sourced from the National Bureau of Statistics of China, the Ministry of Land and Resources, P.R.C., the Ministry of Labour and Social Security, P.R.C., the People's Bank of China and Oxford Economics. In cases where the source data are only available on annual basis, we convert them to quarterly data by using either the “quadratic-match sum” or the “quadratic-match average” algorithms with *Eviews*<sup>®</sup>. Wherever applicable, the data are seasonally adjusted using the U.S. Census Bureau's “X-13ARIMA-SEATS” method.

The measurement and sources of the data and the adjustments to them are summarized in Table B1.

**TABLE B1** Measurement, sources and adjustments of data

Time series	Measurement	Source <sup>f</sup>	Normalized by <i>CPI</i> ?	Normalized by <i>pop</i> ?	Natural logarithm?	Seasonally adjusted?
$GDP_t$	Gross domestic product	NBSC	√	√	√	√
$C_t$	Total private consumption	NBSC	√	√	√	√
$I_t$	Total private investment, net of residential investment	NBSC	√	√	√	√
$ih_t$	House production (newly built commodity houses) <sup>a</sup>	NBSC	√	√	√	√
$\pi_t$	Quarter-on-quarter <i>CPI</i> inflation <sup>b</sup>	NBSC	N.A.	N.A.	N.A.	√
$q_{h,t}$	House Price Index (HPI) <sup>c</sup>	NBSC	√	N.A.	√	√
$q_{l,t}$	Land Price Index (LPI)	MLR	√	N.A.	√	√
$N_t$	Total labour hours <sup>d</sup>	MLSS	N.A.	√	√	√
$R_t$	PBoC Rediscount Rate	PBoC	N.A.	N.A.	N.A.	N.A.
$R_t^{NL}$	Commercial bank Prime Lending Rate	PBoC	N.A.	N.A.	N.A.	N.A.
$pop_t$	Working-age population index <sup>e</sup>	OE	N.A.	N.A.	N.A.	√

Note: MLR—Ministry of Land and Resources, P.R.C. (via China Urban Land Price Dynamic Monitor; <http://www.landvalue.com.cn/>); MLSS—Ministry of Labour and Social Security, P.R.C. (via the *China Labour Statistical Yearbook* [2004, 2006 and 2015]); PBoC—People's Bank of China (via Datastream<sup>®</sup>); OE—Oxford Economics (via Datastream<sup>®</sup>).

<sup>a</sup>Based on the “Value of Completed Commodity Houses” from NBSC and the House Price Index (for commodity houses).

<sup>b</sup>Based on the Consumer Price Index from NBSC.

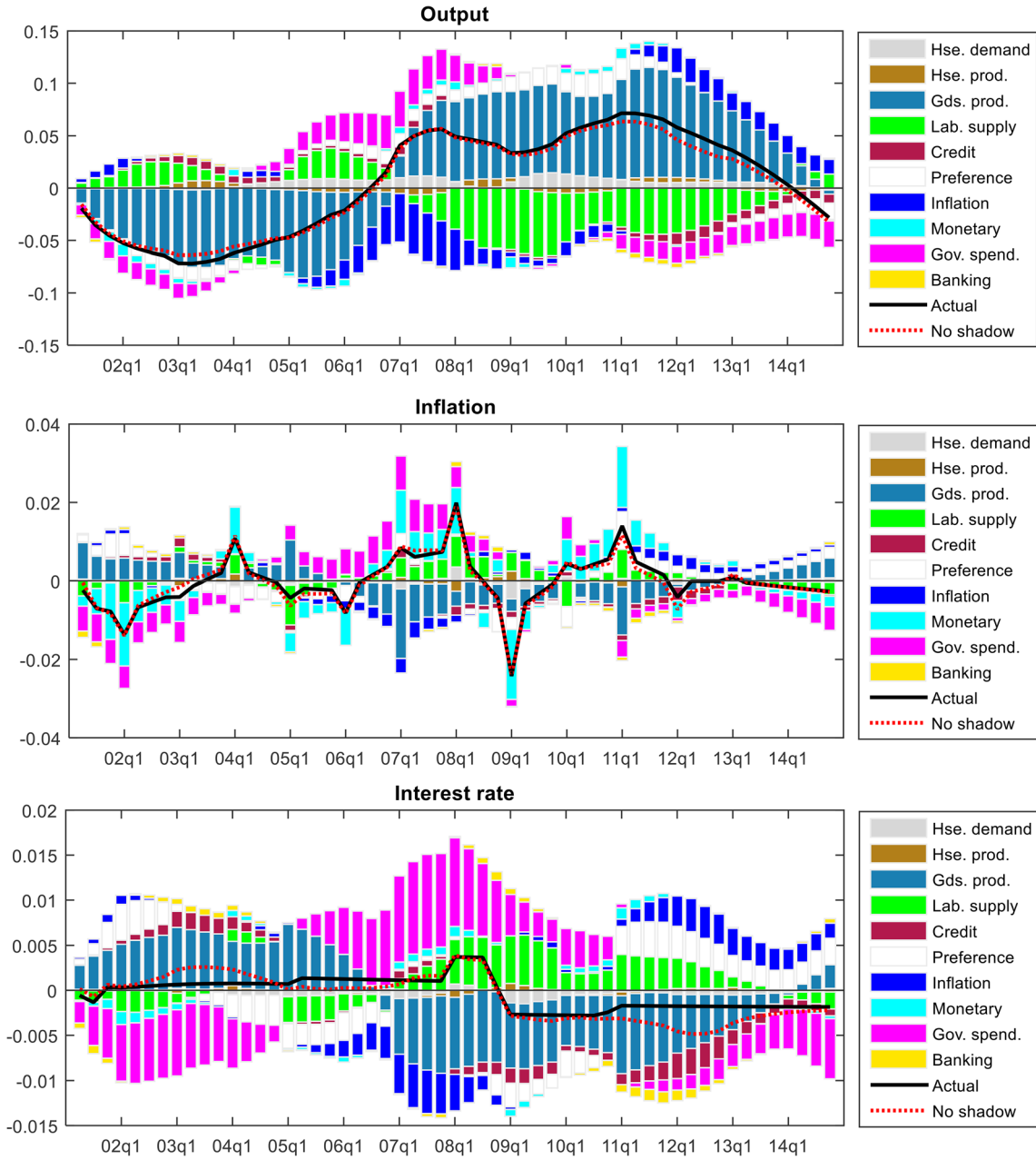
<sup>c</sup>Based on the “Average Sales Price of Commodity Houses” from NBSC.

<sup>d</sup>Based on the “Weekly working hours in urban area” from MLSS.

<sup>e</sup>Based on the “Working-age Population” from OE.

<sup>f</sup>NBSC—National Bureau of Statistics of China;

**APPENDIX C: TIMELINES FOR BUSINESS CYCLE VARIABLES AND IMPORTANCE OF SHOCKS WITHOUT SHADOW BANKING**



**FIGURE C1** Historical decomposition of business cycle variables [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**TABLE C1** Variance decomposition of housing variables (and changes without shadow banking)

Variable	Forecast horizon	Hse. demand	Hse. prod.	Gds. prod.	Lab. supply	Credit	Others
Housing price	1	88.36	0.17	3.98	4.38	0.53	2.58
		(−3.25)	(−0.08)	(+0.72)	(+0.57)	(+2.2)	(−0.16)
	2	89.59	0.27	3.60	4.11	0.53	1.89
		(−3.45)	(−0.08)	(+0.51)	(+0.44)	(+2.56)	(+0.03)
	4	90.92	0.47	3.16	3.77	0.49	1.19
		(−3.19)	(+0.00)	(+0.20)	(+0.15)	(+2.78)	(+0.07)
	10	91.79	0.79	2.72	3.57	0.39	0.74
		(−2.85)	(+0.04)	(+0.05)	(−0.05)	(+2.77)	(+0.05)
	40	89.83	1.66	2.66	3.57	1.63	0.66
		(−2.58)	(+0.02)	(+0.00)	(−0.12)	(+2.65)	(+0.03)
	100	80.29	1.77	2.38	3.18	11.79	0.59
		(−6.72)	(−0.08)	(−0.14)	(−0.28)	(+7.24)	(−0.01)
New house production	1	11.67	84.20	0.00	3.34	0.00	0.79
		(−0.24)	(+0.33)	(+0.00)	(−0.07)	(+0.00)	(−0.02)
	2	22.40	73.26	0.00	3.68	0.02	0.64
		(−0.33)	(+0.04)	(+0.00)	(+0.04)	(+0.22)	(+0.03)
	4	29.45	65.90	0.00	4.18	0.02	0.44
		(−0.42)	(+0.16)	(+0.00)	(−0.07)	(+0.30)	(+0.03)
	10	39.72	54.88	0.02	5.04	0.02	0.32
		(−0.48)	(+0.26)	(−0.01)	(−0.15)	(+0.36)	(+0.02)
	40	43.93	49.44	0.12	5.27	0.93	0.31
		(−0.47)	(+0.33)	(−0.02)	(−0.2)	(+0.35)	(+0.01)
	100	41.64	46.65	0.12	4.97	6.34	0.29
		(−0.97)	(−0.3)	(−0.03)	(−0.24)	(+1.54)	(+0.01)

TABLE C2 Variance decomposition of business cycle variables (and changes without shadow banking)

Variable	Forecast horizon	Hse. demand	Hse. prod.	Gds. prod.	Lab. supply	Credit	Prof.	Inflation	Monetary	Gov. spend	Banking
Output	1	1.36	1.43	28.99	20.18	6.18	0.16	11.13	16.38	12.26	1.94
		(-0.52)	(-0.96)	(-6.22)	(-4.19)	(+14.46)	(+0.02)	(-1.04)	(-0.93)	(-0.73)	(+0.1)
	2	2.6	2.98	35.2	30.03	4.22	1.79	8.53	7.66	6.05	0.94
		(-0.69)	(-0.72)	(-4.55)	(-3.71)	(+11.15)	(-0.57)	(-0.28)	(-0.61)	(-0.22)	(+0.2)
	4	4.21	3.51	35.49	36.87	3.9	2.08	5.94	4.18	3.31	0.52
		(-0.62)	(-0.22)	(-3.81)	(-3.51)	(+10.08)	(-0.58)	(-0.29)	(-0.72)	(-0.4)	(+0.07)
10	5.99	2.86	31.71	42.76	6.18	1.76	3.83	2.5	2.07	0.34	
		(-1)	(-0.26)	(-5.12)	(-6.15)	(+14.67)	(-0.68)	(-0.39)	(-0.6)	(-0.47)	(-0.01)
	40	6.14	1.76	22.31	36.65	26.32	1.43	2.31	1.49	1.36	0.24
		(-2.2)	(-0.52)	(-8.18)	(-13)	(+26.64)	(-0.8)	(-0.69)	(-0.61)	(-0.6)	(-0.06)
	100	3.54	1	12.81	21.2	57.54	0.83	1.31	0.84	0.78	0.14
		(-1.16)	(-0.26)	(-4.31)	(-6.89)	(+14.07)	(-0.45)	(-0.34)	(-0.32)	(-0.32)	(-0.03)
Inflation	1	1.49	0.9	13.93	13.83	2.19	13.55	0.07	47.77	5.5	0.77
		(+0.16)	(+0.77)	(+3.86)	(+3.2)	(+3.47)	(-1.39)	(-0.07)	(-8.29)	(-1.61)	(-0.11)
	2	1.47	0.96	13.57	13.42	2.26	14.45	0.35	47.43	5.34	0.75
		(+0.13)	(+0.74)	(+3.49)	(+2.82)	(+4.37)	(-2.09)	(+0.14)	(-8)	(-1.52)	(-0.08)
	4	1.47	1.09	13.37	13.2	2.33	15.25	0.35	46.58	5.54	0.81
		(+0.17)	(+0.94)	(+3.51)	(+2.73)	(+4.66)	(-2.19)	(+0.18)	(-8.23)	(-1.65)	(-0.14)
10	1.47	1.09	13.3	13.23	2.63	15.21	0.35	46.34	5.54	0.83	
		(+0.15)	(+0.91)	(+3.32)	(+2.54)	(+5.63)	(-2.33)	(+0.17)	(-8.58)	(-1.69)	(-0.14)
	40	1.49	1.09	13.22	13.28	3.15	15.1	0.35	45.99	5.5	0.83
		(+0.12)	(+0.87)	(+3.01)	(+2.24)	(+7.2)	(-2.54)	(+0.16)	(-9.17)	(-1.74)	(-0.15)
	100	1.49	1.08	13.2	13.28	3.33	15.07	0.35	45.89	5.49	0.82
		(+0.11)	(+0.86)	(+2.95)	(+2.18)	(+7.5)	(-2.58)	(+0.16)	(-9.28)	(-1.75)	(-0.15)
Interest rate	1	2.23	0.88	21.44	21.83	5.92	27.84	0.67	2.72	14.42	2.05
		(+0.06)	(+1.1)	(+4.29)	(+2.99)	(+6.85)	(-6.67)	(-0.61)	(-1.58)	(-5.85)	(-0.59)
	2	2.55	0.62	21.58	22.96	8.02	22.73	1.7	2.94	14.88	2.01
		(-0.15)	(+0.75)	(+1.31)	(+0.52)	(+11.38)	(-6.37)	(-0.86)	(-1.01)	(-5.34)	(-0.23)
	4	2.5	0.64	22.28	24.76	11.62	18.54	2.36	2.5	13.12	1.69
		(-0.48)	(+0.58)	(-2.4)	(-3.28)	(+18.05)	(-6.14)	(-0.76)	(-0.84)	(-4.69)	(-0.04)

TABLE C2 (Continued)

Variable	Forecast horizon	Hse. demand	Hse. prod.	Gds. prod.	Lab. supply	Credit	Pref.	Inflation	Monetary	Gov. spend	Banking
	10	2.33	0.56	20.94	26.97	18.45	14.87	2.1	1.97	10.36	1.45
		(-0.83)	(+0.39)	(-5.54)	(-8.3)	(+26.84)	(-6.27)	(-0.74)	(-0.82)	(-4.46)	(-0.28)
	40	2.66	0.54	17.64	26.95	27.39	11.93	1.75	1.59	8.28	1.27
		(-1.32)	(+0.14)	(-6.74)	(-11.7)	(+32.12)	(-6.15)	(-0.82)	(-0.81)	(-4.32)	(-0.41)
	100	2.73	0.52	16.98	26.21	29.87	11.4	1.68	1.51	7.9	1.21
		(-1.38)	(+0.12)	(-6.69)	(-11.67)	(+31.73)	(-5.96)	(-0.8)	(-0.78)	(-4.18)	(-0.4)