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# 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 over 80% 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 stabilise the housing market, the cost on output reduction would be rather limited.

*Keywords: Housing price; Bubbles; Market spillovers; DSGE-VAR; China*

*JEL Classification: C11, E32, E44, R31*

## 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 full marketisation reform in July 1998, when the abolishment of the ‘welfare-oriented public housing distribution system’ ultimately exposed Chinese households to an unprecedented venture in a real marketplace for houses. Over the period between 2002 and 2014, commercial residential housing price in China had grown by 184% at national level<sup>1</sup>. The average year-on-year growth of 3.8% was accompanied by double digit (some 10%) recorded in 2009, albeit the only short-lived ‘downturn’ in 2008 (less than -2%). Some cities in the east coast such as Beijing, Fuzhou, Ningbo and Xiamen saw an even more drastic surge, with growth reported to be up to 20% per annum over pretty much the same period (Wang and 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 would agree that 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 US housing market finally led to the ‘subprime crisis’ in 2007 and that the scene of the Japanese ‘lost decades’ that followed after the burst of its ‘housing bubble’ in the early 1990s remains vivid, many are concerned whether China, now the world’s second largest economy, will follow the old road to ruin.

Accompanied with the above there is a fast-growing literature that aims at uncovering what brought about the bullish market and what has been driving its dynamics. Some authors have tested the housing market equilibrium condition derived from a partial equilibrium model and evaluated the significance of the

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<sup>1</sup>Data source: National Bureau of Statistics of China (‘Average sale price of residential houses’).

supposed demand and supply factors, the ‘fundamentals’, in predicting the housing price. Many have come to conclude that the upswing was mainly a reflection of the market fundamentals, although as for the specific factors and their respective importance there is less consensus. For example, while most along the line have agreed on the decisive roles of disposal income and land price, Wang and Zhang (2014) suggest population growth was also an important determinant, as opposed to Deng et al. (2009) and Wang et al. (2011) who reject its role. 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) show evidence for the latter.

Such an ambiguity is 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 the ‘equilibrium conditions’ these authors derived and put forward for estimation are easy victims of the omitted variable problem. Thus when a factor is shown to be significant in one model, it may simply be so because that model has failed to reflect the role of other important factors that would have been reflected by the ‘true’ model. Of course without an explicit model that details the whole underlying economic structure there would be no way to tell. Thus, unless one is willing to impose very strong assumptions on how he knows the ‘true’ model, estimating such ‘equilibrium conditions’ as implied by a partial model could have been a hasty attempt that brings more doubts, if not misconception, than evidence.

Indeed, even if one is able to identify the ‘true’ equilibrium condition(s), the fact that macroeconomic variables are widely correlated due to economic interactions would still mean that these equilibrium conditions are difficult to estimate, as ‘interaction’ endogenises most, if not all, of the explanatory variables on them. Thus, the endogeneity problem forces econometricians to either assume these variables are pre-determined in other markets (such as Deng et al. and Li and Chand just cited), or try to find ‘instruments’ to obtain prediction of these variables to avoid inconsistent estimation (Wu et al., 2014, e.g.). But none of these ‘solutions’ 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, i.e., when multicollinearity occurs, it can even overstate the standard error of the coefficients of these variables, causing them to be shown insignificant even when they are important. Thus, while the omitted variable problem just mentioned is one that might be improved by employing a more inclusive model, the endogeneity problem here is one that is just inherent in any model version where equilibrium is estimated with single equations<sup>2</sup>.

Both of these technical difficulties are therefore extra challenges to ‘single equation studies’ of this type which are also widely criticised on theoretical grounds. 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 the housing price and the supposed ‘determining factors’. Thus, Wen and Goodman (2013) and Chow and Niu (2015) have gone one step further and used 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 et al. (2011), Zhang et al. (2012a, b) and Chiang (2014) have even waived the partial models and focused only on the empirical responses of the housing price to the lags of potential determinants as in these reduced-form models, as any equilibrium conditions derived from the former would tell little about the causal relation. Thus, these authors are able to answer what (Granger-)caused the housing price to change as the data’s dynamics shows. That these VAR and VECM being pure econometric models has also allowed them to test the impact of factors which do not usually affect the demand and/or supply of houses directly in a partial equilibrium model (such as money growth and interest rates), and factors that are difficult to model in a typical structural model (such as gender imbalance and urbanization) - this way, they also circumvent

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<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 e.g. - are usually endogenously determined by something else which may or may not be within the simultaneous equations framework itself. So the 2SLS approach would not bypass the predicament in a real sense.

the endogeneity problem just mentioned now that the explanatory variables all enter the model as lags.

However, from the policy viewpoint the usefulness of these VAR/VECM estimates are still rather limited, as these reduced-form models are providing no information about *how* the housing price is determined by the factors determining it. Thus, even if one is able to tell from estimating these reduced-form models about what could have affected the 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 that policy-makers would be most interested) to conduct any meaningful policy analyses - the well-known story 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 on estimating these - 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 by SVAR modellers themselves for producing results that are presumed 'reasonable' *a priori* (Uhlig, 2005; Fernandez-Villaverde and Rubio-Ramirez, 2008). 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 tools, either, for understanding how the 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 may be established as a result of different agents' interactions 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 (2012) 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 Gali (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), by contrast, have adopted a New Keynesian model to allow for the role of different monetary policies - a Taylor rule in the former and a McCallum rule in the latter - in stabilization of the housing market. Zhou and Jariyapan (2013) consider in a similar vein 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), by contrast, deviate from these authors by establishing a regional model that replicates the urbanization process caused by structural transformation of the contemporary Chinese economy. Thus, almost all these DSGE modellers have found that shocks to housing demand and monetary policy errors (in the form of excess supply of liquidity) 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 tools for direct suppression of demand; for reducing policy mistakes, the implication would be that the People's Bank of China improves its management skills, as well as being more 'independent' in policy-making.

Despite the progress, however, one important aspect that existing efforts have not quite explored yet is the channel through which the banking system could be propagating these shocks. While Gerali, et al. (2010) have offered an early example, many in this area have remained developing on models where banks work only 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 economy (including that of the housing price) in a major way, as one contribution of this paper, we embed in the DSGE model we construct below an explicit banking sector (which resembles, but differs from Gerali, et al. (2010)), which has never been attempted in studies of the Chinese housing market with DSGE models in the literature. Side by side with it, we also evaluate the role that shocks from the banking sector, thus, 'banking shocks', could have played in destabilizing the housing market as well as the rest of the economy within the model framework. Our contributions also come from the novel way in which we model the banking system, whereby we allow for a 'shadow', sub-system, which is affiliated to the 'normal', main system, and complementing it in provision of credits, which mimics the co-existence and operating of normal and 'shadow' banks in the contemporary Chinese economy. Thus, to the literature of modelling the housing price dynamics, we are the first to utilize a DSGE model where the explicit role in resource re-allocation of not just normal banks, but also shadow banks, is allowed for; to the recent developments in modelling the banking sector, our innovative way of

modelling the shadow system as a sub-system of the normal system has allowed for interactions within the banking sector, which existing studies (such as Verona et al. (2013) and Funke et al. (2015) as we compare in what follows) where shadow banks are modelled in parallel with normal banks are unable to capture.

On a separate (but related) matter, we establish our evidence in this paper using a DSGE-VAR in the spirit of Del Negro and Schorfheide (2004, 2006) and Del Negro et al. (2007). Compared to the conventional efforts where empirical evidence is either based on pure econometric models (such as VAR/VECM as reviewed above) which are hard to identify, or based on pure DSGE models which generally have difficulties fitting the data closely, the DSGE-VAR approach we adopt here provides us with an analytical framework where evidence is founded both in theory (due to the DSGE model restrictions) and in fact (as it is a VAR). The DSGE-VAR is also itself an evaluation tool for the DSGE theory, which also provides diagnostics as for how the theory might be refined to fit the data more closely. Thus, our paper also provides evidence of how the Iacoviello-type model could have fitted the data, with the experience of China.

The rest of our paper is organized as below: in section 2 we construct our DSGE theory, with a particular focus on how the banking system of the contemporary Chinese economy may be modelled within it. We then explain, in section 3, the DSGE-VAR approach and estimate ours using the Bayesian method. We establish what determines China’s housing price dynamics based on the estimated model in section 4, where we also examine the nature of housing price ‘bubbles’, as well as the spillover effect of the housing market on the macroeconomy as our model implies. In section 5 we conclude our 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 availability of credits to end borrowers (thus, impatient households and/or entrepreneurs in these models) to a fraction of the market value of the borrowers’ total assets, such as houses, lands and capitals, where the borrowing constraint functions as a bridge that links together the housing market and the real economy, to allow for ‘spillover’ of disturbances from one sector to the other, through private consumption and investment financed with constrained borrowing. While most Iacoviello-type models have assumed direct lending/borrowing between agents, ignoring the role played by financial intermediaries, Gerali et al. (2010) is one of the few studies which pioneered to integrate into the basic framework the banking sector to investigate how optimization problems in the credit creation process 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 determined the business cycle.

The model we build in what follows extends this progress. It does so by introducing into the basic Iacoviello framework with banking sector the existence of a shadow banking system, which appears as a sub-system of the ‘normal’ system, to reflect the unique characteristics of the contemporary Chinese banking system. To keep the paper concise we only outline in the main text the key equations of the ‘standard sectors’ of the Iacoviello framework as we establish each of them below. We place our focal point, however, on the banking sector which is novel to the standard models, and we discuss its optimization problems in detail. The optimization problems of the whole model are outlined in full in Model Appendix.

### 2.1 Patient households

There is a continuum of measure one of patient households who consume on both normal goods and houses ( $c_t^P$  and  $h_t^P$ ), work for production of both these products ( $n_{c,t}^P$  and  $n_{h,t}^P$ )<sup>3</sup>, and save by purchasing time deposits ( $S_t$ ) from normal commercial banks. They maximise life-time utility:

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

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<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.

where  $\beta^P$  is the discount factor,  $G_{c^P}$  is the steady-state growth in normal goods consumption,  $\phi_t$  is the relative preference to houses (whose variation can be interpreted as shocks to housing demand),  $\psi_t$  is the relative preference to leisure (shocks to the labour supply<sup>4</sup>),  $\eta^P$  is the inverse of labour elasticity,  $\xi^{\dot{P}}$  is the substitutability of labour between normal goods and houses production, and  $j_t$  is the shock to intertemporal preference.

In each period patient households are confronted by the budget constraint:

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

where expenses on the L.H.S. of (2) are financed by funds inflow on the R.H.S., where  $q_{h,t}$  is the price of houses (relative to normal goods' which is normalized to unity),  $\delta_h$  is the depreciation rate of houses,  $w_{c,t}^P$  and  $w_{h,t}^P$  are the real wages, respectively, in the normal goods and houses production sectors,  $r_t^S$  is the real interest rate on saving,  $\Pi_t^{Fgds}$ ,  $(\Pi_{t-1}^{Nbank} - \chi \Pi_{t-1}^{Nbank})$  and  $\Pi_{t-1}^{Sbank}$  are lump-sum profit transfers to patient households who are assumed to own both retail firms, normal commercial banks and 'shadow banks' that are modelled in turn in the following sections<sup>5</sup>, and  $\tau_t$  is a lump-sum tax levied.

The patient household problem is to maximize (1), with respect to (2), by choosing  $c_t^P$ ,  $h_t^P$ ,  $n_{c,t}^P$ ,  $n_{h,t}^P$  and  $S_t$ . This implies a set of optimal conditions as the marginal rates of substitution of future consumption, houses and leisure, respectively, as against current consumption, which determines the demand for normal goods and houses, and the supply of labour of patient households (See equations A.3 - A.7 in Model Appendix).

## 2.2 Impatient households

There is also a continuum of measure one of impatient households who consume on normal goods ( $c_t^I$ ) and houses ( $h_t^I$ ), and work both for normal goods production ( $n_{c,t}^I$ ) and for houses production ( $n_{h,t}^I$ ), just as patient households. However impatient households do not save; being impatient, they always spend more than their wage income in each period, with the excess being financed by borrowing from patient households, via the banking system constituted by both normal commercial banks and shadow banks. Impatient households would always borrow from normal banks because of the lower cost of borrowing ( $r_t^{NL}$ ); if it turns out that their demand is not fully met by normal bank loans, they finance the rest with shadow bank loans at a premium rate ( $r_t^{IL}$ ). We let the amount one can borrow, either from normal banks ( $b_t^{II}$ ) or from shadow banks ( $b_t^{I''}$ ), be restricted to only a fraction of the present value of the borrower's total physical assets (houses, on this occasion) by the time the obligation is due, following Kiyotaki and Moore (1997). We also let such a fraction, known as the loan-to-value ratio (LTV), be manipulated by the public sector's credit control policy, and that whenever the LTV for normal bank loans ( $\Theta_{H,t}$ ) goes in one way, that for shadow bank loans ( $\Xi_{H,t}$ ) goes in the other<sup>6</sup>.

Impatient households maximize the life-time utility:

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

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

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

the borrowing constraint for normal bank loans:

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

<sup>4</sup>A positive realization represents a fall in supply.

<sup>5</sup>We have let profit from banks be transferred to patient households with one lag (i.e., when the next period opens) to reflect that these profits are only available when loans are due at the end of each period.

<sup>6</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 controlled by the public sector.

and the borrowing constraint for shadow bank loans:

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

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 impatient household problem implies a set of optimal conditions determining the marginal rates of substitution that resemble the patient households’, which set the demand for normal goods and houses, and the supply of labour (A.12-A.17, Model Appendix). The borrowing constraints then determine the demand for normal and shadow bank loans, for a given level of credit control.

### 2.3 Entrepreneurs

On the supply side, there is a continuum of measure one of homogeneous entrepreneurs who produce intermediate goods ( $Y_t$ ) and houses ( $ih_t$ ), using 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 their consumption on normal goods ( $c_t^E$ ), which is the only element that enters their utility function. Like impatient households, entrepreneurs also borrow from patient households via the banking system ( $b_t^{E'}$  and  $b_t^{E''}$ ) to partially finance their spending, although in this case such spending include factor costs of production.

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 the budget constraint:

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

where  $\gamma (< \beta^P)$  and  $G_{c^E}$  in (7) are their discount factor and the steady-state growth of normal goods consumption. Their spending and funds inflow in each period are summarized on the L.H.S. and R.H.S., respectively, of (8). While variables have their usual meaning, those with superscript ‘E’ are ‘entrepreneur variables’<sup>7</sup>.

Intermediate goods and houses are produced using production functions:

$$Y_t = [A_{c,t} (n_{c,t}^P)^\alpha (n_{c,t}^I)^{1-\alpha}]^{1-u_c} k_{c,t-1}^{u_c} \quad (9)$$

and

$$ih_t = [A_{h,t} (n_{h,t}^P)^\alpha (n_{h,t}^I)^{1-\alpha}]^{1-u_h-v_h} k_{h,t-1}^{u_h} l_{t-1}^{v_h} \quad (10)$$

where  $\alpha$ ,  $u_c$ ,  $u_h$  and  $v_h$  are the input shares of production, and  $A_{c,t}$  and  $A_{h,t}$  are the sectoral technologies<sup>8</sup>.

Capitals are accumulated with private investments ( $i_{c,t}$  and  $i_{h,t}$ ) with laws of motion:

$$k_{c,t} - k_{c,t-1} = i_{c,t} - \delta_{kc} k_{c,t-1} \quad (11)$$

and

$$k_{h,t} - k_{h,t-1} = i_{h,t} - \delta_{kh} k_{h,t-1} \quad (12)$$

<sup>7</sup>  $\frac{1}{X_t}$  is the relative price of intermediate goods, compared to final goods in the retailers’ problem as model below.

<sup>8</sup> We assume capitals are fully utilized at no cost.



with depreciation rates of  $\delta_{kc}$  and  $\delta_{kh}$ . The adjustment of capital is assumed costly, and the costs are:

$$adj_{kc,t} = \frac{\zeta_{kc}}{2G_{kc}} \left( \frac{k_{c,t}}{k_{c,t-1}} - G_{kc} \right)^2 k_{c,t-1} \quad (13)$$

and

$$adj_{kh,t} = \frac{\zeta_{kh}}{2G_{kh}} \left( \frac{k_{h,t}}{k_{h,t-1}} - G_{kh} \right)^2 k_{h,t-1} \quad (14)$$

respectively.

Just as impatient households, entrepreneurs also borrow from normal banks should credits are needed, and their borrowing is constrained by a collateral condition similar to (5), though on this occasion they have as collaterals holding of lands and capitals, such that:

$$b_t^{E'} \leq \Theta_{E,t} \frac{E_t(q_{l,t+1}l_t + k_{c,t} + k_{h,t})}{1 + r_t^{NL}} \quad (15)$$

where  $q_{l,t}$  is the relative price of lands, and  $\Theta_{E,t}$  is the LTV of entrepreneurs' normal bank loans. Likewise their borrowing from shadow banks is constrained by:

$$b_t^{E''} \leq \Xi_{E,t} \frac{E_t(q_{l,t+1}l_t + k_{c,t} + k_{h,t})}{1 + r_t^{IL}} \quad (16)$$

where  $\Xi_{E,t}$  is the LTV of shadow bank loans, and  $\Theta_{E,t} + \Xi_{E,t} < 1$ .

The entrepreneur problem implies a set of optimal intertemporal substitutions of normal goods consumption, which could have been financed with productive factors (thus  $k_{c,t}$ ,  $k_{h,t}$  and  $l_t$ ) and/or bank loans, which determine the demand for capitals and lands (A.33-A.35 in Model Appendix) and the entrepreneurs' demand for normal goods (A.28). It also equates the marginal labour productivity to marginal labour cost for both intermediate goods production and houses production to determine the demand for labour in those sectors (A.29-A.32). These optimal demands for productive factors then determine the supply of intermediate goods and houses via the production functions. The borrowing constraints for entrepreneurs determine their demand for loans from normal banks and shadow banks.

## 2.4 Retailers

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

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 are only able to adjust theirs according to an indexation rule in the spirit of Smets and Wouters (2003):

$$p_{t+i}(j) = p_t(j) \left( \frac{P_{t+i-1}}{P_{t-1}} \right)^\epsilon \quad (17)$$

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:

$$E_t \sum_{i=0}^{\infty} (\omega \beta G_c)^i V_{t,t+i} \left[ \left( \frac{p_{t+i}(j)}{P_{t+i}} \right) Y_{t+i}(j) - \frac{1}{X_{t+i}} Y_{t+i}(j) \right] \quad (18)$$

by choosing  $p_t(j)$ , subject to the Dixit-Stiglitz (1977) CES<sup>9</sup> demand for  $Y_t(j)$ :

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

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<sup>9</sup>Constant elasticity of substitution.

and (17), to find the optimal reset price for differentiated goods,  $p_t^*(j)$ <sup>10</sup>:

$$p_t^*(j) = \frac{\theta}{(\theta-1)} \frac{E_t \sum_{i=0}^{\infty} (\omega\beta G_c)^i V_{t,t+i} Y_{t+i}^{Final} \frac{1}{X_{t+i}} P_{t+i}^{\theta} P_{t+i-1}^{-\theta\epsilon} P_{t-1}^{\theta\epsilon}}{E_t \sum_{i=0}^{\infty} (\omega\beta G_c)^i V_{t,t+i} Y_{t+i}^{Final} P_{t+i}^{\theta-1} P_{t+i-1}^{\epsilon(1-\theta)} P_{t-1}^{\epsilon(\theta-1)}} \quad (20)$$

Let the general price level be:

$$P_t = \left[ \int_0^1 p_t(j)^{1-\theta} dj \right]^{\frac{1}{1-\theta}} \quad (21)$$

Equation (21) can be linearized around a zero-inflation steady state, using the implications of (17) and (20), to find the ‘hybrid-version’ New Keynesian Phillips curve, which determines inflation ( $\pi_t$ ) with expected future inflation, past inflation, the percentage change in real marginal cost of final normal goods production compared to the steady state ( $-\hat{X}_t$ ), and ‘inflation shock’ ( $\hat{\epsilon}_{\pi,t}$ ):

$$\pi_t = \frac{\beta G_c}{1 + \beta G_c \epsilon} E_t \pi_{t+1} + \frac{\epsilon}{1 + \beta G_c \epsilon} \pi_{t-1} + \frac{(1-\omega)(1-\omega\beta G_c)}{\omega(1 + \beta G_c \epsilon)} (-\hat{X}_t) + \hat{\epsilon}_{\pi,t} \quad (22)$$

## 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 a ‘normal’ one. The Verona et al. approach categorises borrowers (firms, in their story) into two types based on their risk of default; they then let ‘safe’ borrowers be financed with direct borrowing (such as issuing corporate bonds), with the assistance of investment banks, while commercial bank loans - whose cost reflects a risk-premium - are needed only by ‘risky’ borrowers to whom direct borrowing is infeasible. Verona et al. view the former the shadow banking system of the U.S., while the latter, the normal system. Their model so embraces within the same banking sector both normal banks and shadow banks which operate in parallel, but are independent of each other both in size and in their institutional setting.

Such an approach is then adopted by Funke et al. (2015) in their exploration for the case of China, where a large number of state-owned/state-holding companies are known to co-exist with the common non-state-owned companies. State-owned/state-holding companies in China do not normally raise funds by direct borrowing such as issuing corporate bonds. By contrast they are more reliant on traditional bank loans from normal commercial banks (of which many are also state-owned/state-holding), because they usually have good connections with these banks due to the same (or similar) ownership structure, and that the short-term financing bonds market in China is still very under-developed so there are few other options. These state-owned/state-holding companies are, in most cases, also preferred customers to typical commercial banks compared to non-state-owned companies (SMEs in particular), on the other hand, because they are ‘backed’ by the government and hence have lower risk of default. This causes the now widely seen phenomenon in China that, while state-owned/state-holding companies generally have easy access to credits, non-state-owned companies - being discriminated for their ownership structure and so labelled ‘risky’ - are often victims to which typical commercial banks are reluctant to lend under usual terms and conditions. For accessing to funds, these non-state-owned companies often have to either bear on harsher terms set by the banks, or pay a premium/side-payment to banks/bankers who sneak to ‘lend’ via other off-balance-sheet businesses (thus, the various sorts of wealth management products, ‘WMPs’), or seek for other private funding opportunities of which many are illegal, which all imply a higher-than-normal cost of borrowing in a shadow system. Thus Funke et al. motivate their application of the Verona et al. model by viewing such funds’ channelling to non-state-owned companies services provided by ‘shadow banks’, while traditional bank loans offered to state-owned/state-holding companies services provided by ‘normal banks’. Their modelling of the banking

<sup>10</sup>  $V_{t,t+i} \equiv \frac{U'_{c,t}}{U'_{c,t+i}}$  in (16) defines the stochastic intertemporal substitution of normal goods consumption.  $\theta$  in (17) is the price elasticity.

sector is in essence identical to Verona et al., although in their application to China they have let risky borrowers who have difficulties accessing to normal bank loans be engaged with shadow banking activities, whereas in Verona et al. such activities are brought about as safe borrowers raise funds by direct financing to circumvent the higher cost of normal bank loans.

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, so that any disturbances, should they arise from one system, would have no direct impacts on the other, which may be practically at odds if we allow for the complex correlations pervading different financial markets in the real world. In particular, if we consider China as just reviewed where shadow banking activities were much a consequence of difficulties accessing to credits from normal banks, it could well happen that, if for some reason credit conditions in the normal system tightened, which caused commercial banks to contract their balance sheet, the impact of such a change would quickly disseminate to the shadow system, as more funds had to be raised with shadow activities, causing the shadow system to expand. This also suggests that, in practice, the relative size of the normal/shadow banking systems and the variation of it could be responding to varying economic conditions, which, with their ‘parallel banking systems’ setting, are not reflected either in Verona et al. or in Funke et al.

Such a connection is exactly what we aim to establish in our novel way of modelling the banking sector. In particular, instead of viewing it a parallel system, we model the shadow banking system of China as a sub-system, which is affiliated with the main system constituted by normal commercial banks. Thus, besides lending to impatient households and entrepreneurs, commercial banks also lend to ‘shadow banks’ (which may be different in forms, but is the same in nature), which will then re-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 let impatient households and entrepreneurs be customers of both normal banks and shadow banks, while the proportion of normal/shadow banking activities over all banking activities is governed by the country’s credit policy, which affects the relative size of the normal/shadow systems in opposite directions.

Our approach to the banking sector therefore establishes a connection between the normal banking system and the shadow system, such that turbulence from the former can directly intrude the latter, which allows us to investigate the role of the shadow system in transmitting shocks, especially the ‘banking shocks’. Our structure of the banking sector resembles Gerali, et al. (2010), where ‘retail banks’ re-lend to households and entrepreneurs with funds borrowed from ‘wholesale banks’ at a premium rate. But that we let both normal banks and shadow banks be loan providers, and that shadow banks are used here for circumventing frictions in the normal system, make ours not just one for investigating the role of the banking sector in general, but also one where specific loan-providing structure (here, adapted to reflect features of China) is allowed for. The optimization problems of our banking sector are detailed in the following sub-sections.

### 2.5.1 The ‘normal’ system

The normal banking system is constituted by a continuum of measure one of normal banks (such as commercial 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.

We let normal banks be price-takers to reflect the People’s Bank of China’s heavy manipulation on commercial bank interest spreads. In each period normal banks maximize:

$$\Pi_t^{Nbank} = r_t^{NL} B_t - r_t^S S_t - \frac{c}{2} \left( \frac{F_t}{B_t} - \Omega \right)^2 F_t \quad (23)$$

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

$$B_t = S_t + F_t \quad (24)$$

where  $F_t$  is the banks’ capital reserve, accumulated out of retained profit from the last period ( $\Pi_{t-1}^{Nbank}$ ), following:

$$F_t = (1 - \delta^F) F_{t-1} + \chi \Pi_{t-1}^{Nbank} \quad (25)$$

where  $\chi$  is the retention ratio set by the banks' dividend policy, and  $\delta^F$  measures the real resources used for bank capital management.

$\frac{c}{2}(\frac{F_t}{B_t} - \Omega)^2 F_t$  (where  $c > 0$ ) in (23) is the real resources used for creating normal bank loans. This is set to be a quadratic function of the deviation of the capital-to-assets ratio ( $\frac{F_t}{B_t}$ ) from its optimal level ( $\Omega$ ) to imply that there exists an optimal ratio at which such costs would be minimized<sup>11</sup>. This, for the normal banks' problem here, would be the profit-maximizing ratio, too.

The normal banks' problem implies:

$$r_t^{NL} - r_t^S = -c(\frac{F_t}{B_t} - \Omega)(\frac{F_t}{B_t})^2 \quad (26)$$

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 (26)) 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 rates, which founds the basis of Gerali et al. (2010)'s 'credit cycle' story. 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:

$$\varepsilon_{B,t}(r_t^{NL} - r_t^S) = -c(\frac{F_t}{B_t} - \Omega)(\frac{F_t}{B_t})^2 \quad (27)$$

Equation (27) 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 worsened (tightened) credit conditions of the normal system. Since normal banks are the only provider of funds to shadow banks in the sub-system, this would also worsen the credit conditions of the latter, being a shock to the entire banking sector.

### 2.5.2 The 'shadow' system

The shadow system is constituted by a continuum of measure one of monopolistic 'shadow banks' – defined as a variety of non-commercial-bank financial intermediaries (such as investment banks, hedge funds and micro-credit companies), which are not confined by the general rules (especially, requirements on reserve ratios) set for commercial banks in the normal system. More broadly, these would also include commercial banks' shadow lending activities that are not reflected on their balance sheet. Shadow banks acquire loans from normal banks, acting as demanders of normal bank loans, just as impatient households and entrepreneurs on the one hand; they then re-lend the acquired loans to impatient households and entrepreneurs on the other, acting on that occasion as providers of shadow bank loans.

For simplicity we assume shadow banks do not keep profit, and shadow loans are produced with no costs. In each period shadow banks maximize:

$$\Pi_t^{Sbank} = [(1 + r_t^{IL}) - (1 + r_t^{NL})]IL_t \quad (28)$$

by choosing the 'shadow loan rate',  $r_t^{IL}$ , taking  $r_t^{NL}$  and  $IL_t$  as given, of which  $IL_t$  (which equals  $b_t^{I''} + b_t^{E''}$  in equilibrium and is a function of  $r_t^{IL}$  by assumption) is the mediated shadow loans.

Under the usual assumption of constant elasticity (which implies  $\frac{\partial IL_t/IL_t}{\partial r_t^{IL}/r_t^{IL}} = -\eta^{Sbank}$ , where  $-\eta^{Sbank}$  is the interest-rate elasticity of demand for shadow loans), the shadow banks' problem implies:

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

which suggests the optimal shadow rate is a constant mark-up ( $\frac{\eta^{Sbank}}{\eta^{Sbank} - 1}$ ) to the 'normal rate'.

Since shadow bank loans are only needed when impatient households and entrepreneurs run into gaps of financing with cheaper loans due to frictions (as reflected by the borrowing constraints) in the normal system, the relative size of the shadow system ( $IL_t/B_t$ ) will shrink, if such frictions improve, or expand, if they deepen. The role that shadow banks play in this model is therefore to provide a bypass to borrowers,

<sup>11</sup>Carvalho et al. (2014) suggest these in practice could be resources used for agency services and/or the banks' operations.

through which credits constrained in the normal system can still be channeled to them - via the provision of shadow bank loans - such that financing gaps opened by normal banks are mitigated. Such a complementary role of shadow banks is our key difference from the Verona et al. and the Funke et al. models, where shadow banks help little in correcting such frictions, but just operate in parallel with normal banks. In the following section we let the degree of such frictions and the extent to which shadow banks could correct them be governed by a credit control policy, where the LTV ratios are manipulated according to macroeconomic conditions, subject to factitious managerial mistakes.

## 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 ( $\rho_R$ ):

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

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 that normal banks offer to patient households, which, combined with the Fisher identity, implies:

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

and

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

### 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 countercyclical feedback rule, and we let it mimic the Taylor rule in our application:

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

where  $\bar{\Theta}$  is the steady-state degree of credit tightness,  $z_x < 0$  is the countercyclical response, and  $\varepsilon_{\Theta,t}$  is the credit policy error<sup>13</sup>.

In contrast to the Taylor rule that determines the price of loans, the credit policy manipulates 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 credit control, such that:

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

where  $\hat{\cdot}$  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

<sup>12</sup>See Iacoviello and Neri (2010) for example. Such a definition of GDP implies that monetary policy is committed to stabilize not only the commodity market but also the housing market. The same idea is also reflected in the credit policy we assume right below.

<sup>13</sup>Peng (2012) argues that such a credit policy is quite plausible in China given the historical background and institutional setting of the Chinese financial market, and that data seem to support such an assumption - see also Jermann and Quadrini (2012) and Liu, et al. (2013) who treat it as exogenous shocks.

demand for shadow bank loans, as borrowers get around the credit control via the shadow system; and we summarize such a quantitative relationship parsimoniously as the following:

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

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 set for normal banks. However as we just pointed out, such a quantitative distortion would be partially corrected as borrowers opt for shadow bank loans to get around the restriction, so from the policy view point the efficacy of credit control would be subsequently neutralized. Nevertheless, since shadow bank loans are lent at a mark-up rate to the normal rate, the credit policy would still have a stabilizing effect similar to a 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:

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

and

$$g_t = \tau_t \quad (38)$$

where  $\rho_g$  and  $u_{g,t}$  in (37) are the persistence and innovation in government spending, respectively; and we follow Smets and Wouters (2007) to count the impact of innovation in technology ( $u_{c,t}$ ) on net exports in government spending, with the impact being ( $\rho_{gc}$ ).

## 2.7 Market clearing, trends and shocks

Normal (commodity) goods market clearing requires:

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

where  $C_t = c_t^P + c_t^I + c_t^E$  and  $I_t = i_{c,t} + i_{h,t}$ ; thus, aggregate demand is equal to total output net of the resources spent on loan creation, and management of both bank capital and physical capital.

Housing market clearing requires:

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

Financial market clearing requires:

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

Labour market clears because of the Walras's law; and total labour is  $N_t = n_{c,t}^P + n_{h,t}^P + n_{c,t}^I + n_{h,t}^I$ . Land supply is fixed and normalized to unity.

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 ( $\varepsilon_{MP,t}$ ,  $\varepsilon_{\Theta,t}$  and  $g_t$ ), which are all mean-reversing and governed by an  $AR(1)$  process. We specify the evolution process of all these disturbances in Model Appendix (Equations A.68-A.77) 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 et al. (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. As the estimation algorithm searches for the optimal ‘weight’,  $\hat{\lambda}$ , such that:

$$\hat{\lambda} = \arg \max_{\lambda \in \Lambda} p(Y|\lambda)$$

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( $\hat{\lambda}$ ) therefore provides an analytical framework lying between an unrestricted VAR and a pure 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,  $\hat{\lambda}$  can also be viewed as a ‘goodness-of-fit’ indicator of the DSGE model in terms of fitting the observed data dynamics, which is not available in the conventional practice of estimating a pure DSGE model.

While Del Negro et al. (2007) describe the full technical details of estimating a DSGE-VAR, the estimation procedure is based on the familiar Bayesian method, although 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 centered at the DSGE model restrictions. The hyperparameter  $\lambda$  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 with repeated random draws from the prior distributions which are also updated continuously according to the calculated data likelihood conditional on the VAR model and such draws. Draws that are able to increase the conditional likelihood compared to the last update will be included into the existing priors with a probability of unity, and the conditional likelihood is updated; 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 update. This process continues until a desired number of repeated experiments have taken place<sup>14</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 that found from QR-factorizing  $A_0 (= \Sigma_{tr}^* \Omega^*)$ , which determines the contemporaneous response of variables to the structural shocks according to the DSGE model.

#### 3.2 Calibrated parameters and priors

We partition the DSGE model parameters into two groups, where the first of these 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 ( $\Omega, \delta^F, \chi, \eta^{Ibank}$ ), and the relevant steady-state parameters ( $\bar{\phi}, \bar{X}, \bar{\Theta}_H, \bar{\Theta}_E, \bar{\Xi}_H, \bar{\Xi}_E$ ); the second group

<sup>14</sup>We allow for a sample of 5,000,000 draws in our practice, where the first 20% draws are dropped.

of parameters is an assembly of labour share and substitutabilities ( $\alpha$ ,  $\xi^P$  and  $\xi^I$ , respectively), technology advancement ( $\gamma_{ac}$ ,  $\gamma_{ah}$ ), elasticities ( $\eta^P$ ,  $\eta^I$ ), costs ( $c$ ,  $\zeta_{kc}$ ,  $\zeta_{kh}$ ), 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 ( $\sigma_{Ac}$ ,  $\sigma_{Ah}$ ,  $\sigma_j$ ,  $\sigma_\phi$ ,  $\sigma_\psi$ ,  $\sigma_B$ ,  $\sigma_{IB}$ ,  $\sigma_\pi$ ,  $\sigma_{MP}$ ,  $\sigma_{CP}$ ,  $\rho_{Ac}$ ,  $\rho_{Ah}$ ,  $\rho_j$ ,  $\rho_\phi$ ,  $\rho_\psi$ ,  $\rho_B$ ,  $\rho_{IB}$ ,  $\rho_\pi$ ,  $\rho_{MP}$ ,  $\rho_{CP}$ ). 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 and Neri, 2010). We then set up 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

We let impatient households and entrepreneurs always discount more than patient households, as in Iacoviello (2005), thus  $\beta^P=0.985$  and  $\beta^I=\gamma=0.97$ , to ensure the borrowing constraints are always binding in the steady state. The capital shares for normal goods production is set at  $u_c=0.34$ , which, on the one hand, implies a consumption-to-GDP ratio that fits closely to the data (51%), and on the other, remains broadly in line with the literature (OECD, 2013). The capital shares for houses production is set at  $u_h=0.2$ , based on Bai and Qian (2010). The land share for houses production is set at  $v_h=0.1$ , following Davis and Heathcote (2005) and Iacoviello and Neri (2010). The depreciation rates of capital for normal goods production and housing production are set at  $\delta_{kc}=0.03$  and  $\delta_{kh}=0.04$  as in Minetti and Peng (2012), while that of houses is set at  $\delta_h=0.015$  to reflect the long-run relation between housing stock and new supply of houses as the data show.

For the banking sector parameters, we follow Gerali et al. (2010) to set the optimal capital-to-loan ratio at  $\Omega=0.09$ , and the cost of bank capital management at  $\delta^F=0.1049$ . These, together with the banks' profit retention ratio that we set at  $\chi=0.96$ , imply a steady-state interest rate spread of normal banks that is hardly different from the data (about 3.2% per annum). The interest rate elasticity of demand for shadow bank loans is set at  $\eta^{Sbank}=50.5$ , to match the observation by Jiang (2015) that shadow bank loans are about twice as expensive as normal bank loans.

The steady-state preference to houses is set at  $\bar{\phi}=0.1$  to reflect the (commercial) residential investment-to-GDP ratio as the data show (3%). The steady-state price markup to intermediate goods is set at  $\bar{X}=1.1$ , following Liu and Ma (2015). The steady-state loan-to-value ratios are set at  $\bar{\Theta}_H=0.3$ ,  $\bar{\Theta}_E=0.156$ ,  $\bar{\Xi}_H=0.1$  and  $\bar{\Xi}_E=0.052$ , respectively, according to the observed debt-to-GDP ratios of households and firms (23% and 107%, respectively) (Edwards, 2016), as well as the relative size of the Chinese shadow banking system (about 1:3, compared to the normal system) as Jiang (2015) gauges.

These calibrations are summarized in table 1; the comparison between the key steady-state ratios implied and the long-run Chinese data in table 2 suggests that these calibrations are highly plausible.

### 3.2.2 Priors

We choose priors that are commonly accepted in the literature for empirical studies of DSGE models, most of which are based on the experience of US.

Thus, we 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 parameters ( $c$ ,  $\zeta_{kc}$  and  $\zeta_{kh}$ ) all follow a gamma distribution following the literature (e.g., Gerali, et al., 2010), with means in our case equal, respectively, to 80, 10 and 10. 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 ( $\rho_R$ ) has a mean of 0.75, following a beta distribution. 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 ( $\lambda$ ),



Table 1: Calibration

Parameter	Definition	Calibrated value
$\beta^I$	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 (houses production)	0.2
$v_h$	Land share (houses production)	0.1
$\delta_{kc}$	Depreciation of capital (normal goods production)	0.03
$\delta_{kh}$	Depreciation of capital (houses 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 markup 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

Table 2: Steady state ratios

Steady-state ratios	Definition	Calibrated value	Data <sup>c</sup>
$I/GDP$	Investment ratio (non residential)	0.21	0.28
$q_h i_h / GDP$	Residential investment ratio <sup>a</sup>	0.0340	0.03
$G/GDP$	Government spending ratio <sup>b</sup>	0.1835	0.18

a: Commercial houses only.

b: Inclusive of net export which counts for about 3.7%.

c: Period between 1952-2014.

with lower bound set to 0.3774 (which is the minimum value required for a valid prior in our case), and upper bound set to 10, in analogous to Adjemian, et al. (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.

Table 3: Prior and posterior (structural parameters)

Parameter	Definition	Prior distribution			Posterior
		Distribution	Mean	SD	Mean
$\alpha$	Share of patient households	Beta	0.65	0.05	0.64
$\xi^P$	Labour substitutability (patient households)	Normal	0.5	0.1	0.60
$\xi^I$	Labour substitutability (impatient households)	Normal	0.5	0.1	0.50
$100\gamma_{ac}$	Technology advancement (normal goods production)	Normal	1.2	1	1.20
$100\gamma_{ah}$	Technology advancement (houses production)	Normal	1.2	1	1.21
$\eta^P$	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	0.48
$c$	Loan creation cost (normal banks)	Gamma	80	10	80.0
$\zeta_{kc}$	Capital adjustment cost (normal goods production)	Gamma	10	2.5	9.47
$\zeta_{kh}$	Capital adjustment cost (houses production)	Gamma	10	2.5	10.03
$\epsilon$	Degree of price indexation (normal goods)	Beta	0.5	0.2	0.06
$\omega$	Calvo contract non-resetting probability	Beta	0.67	0.05	0.41
$\rho_R$	Monetary policy inertia	Beta	0.75	0.2	0.76
$\varphi_\pi$	Interest rate response to inflation	Normal	1.5	0.1	1.57
$\varphi_x$	Interest rate response to output growth	Normal	0.12	0.1	0.17
$\rho_\Theta$	Credit policy inertia	Beta	0.75	0.2	0.99
$z_x$	Credit policy response to output growth	Normal	-0.1	0.1	-0.45
$\lambda$	Weight of DSGE theory	Uniform	N.A.	N.A.	0.44

### 3.3 Data

Estimation of a DSGE-VAR requires that the number of observable variables is equal to the number of the structural shocks in the DSGE model for these shocks to be identifiable. The observable variables in this case are chosen to be real GDP, total real consumption, total real non-residential investment, houses production, inflation, real prices of houses and lands, total labour hours, and nominal lending rates of central bank and normal banks; hence:

$$[GDP; C; I; ih; \pi; q_h; q_l; N; R; R^{NL}]$$

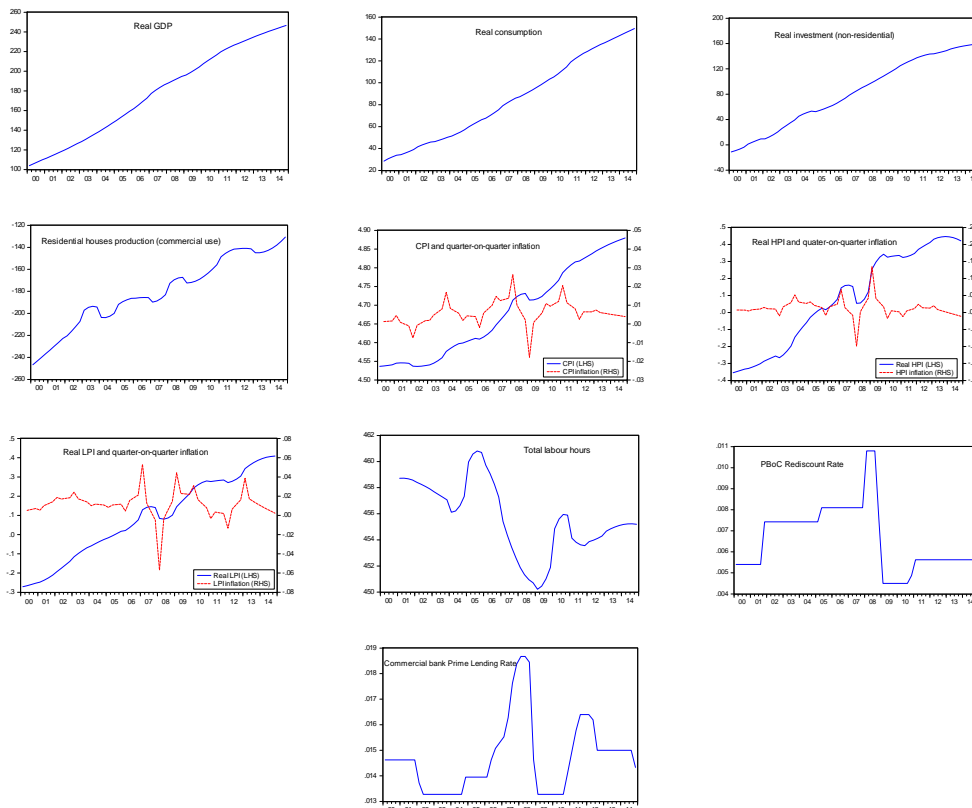
The data are observed between 2001Q1 and 2014Q4, and are plotted in figure 1<sup>15</sup>.

<sup>15</sup>Details about data sources and manipulation are outlined in Data Appendix.

Table 4: Prior and posterior (shock processes)

Parameter	Prior distribution			Posterior
	Distribution	Mean	SD	Mean
$\rho_{Ac}$	Beta	0.5	0.2	0.82
$\rho_{Ah}$	Beta	0.5	0.2	0.71
$\rho_j$	Beta	0.5	0.2	0.45
$\rho_\phi$	Beta	0.5	0.2	0.93
$\rho_\psi$	Beta	0.5	0.2	0.92
$\rho_G$	Beta	0.5	0.2	0.51
$\rho_{Gc}$	Beta	0.5	0.25	0.52
$\rho_{CP}$	Beta	0.5	0.2	0.99
$\rho_\pi$	Beta	0.5	0.2	0.55
$\rho_{MP}$	Beta	0.5	0.2	0.16
$\rho_B$	Beta	0.5	0.2	0.61
$100\sigma_{Ac}$	Inv. gamma	0.1	2	0.27
$100\sigma_{Ah}$	Inv. gamma	0.1	2	1.24
$100\sigma_j$	Inv. gamma	0.1	2	0.19
$100\sigma_\phi$	Inv. gamma	0.1	2	3.06
$100\sigma_\psi$	Inv. gamma	0.1	2	0.42
$100\sigma_G$	Inv. gamma	0.1	2	0.60
$100\sigma_{CP}$	Inv. gamma	0.1	2	0.083
$100\sigma_\pi$	Inv. gamma	0.1	2	0.11
$100\sigma_{MP}$	Inv. gamma	0.1	2	0.051
$100\sigma_B$	Inv. gamma	0.1	2	0.036

Figure 1: Data



We can see that the real price of houses in China has been rising significantly since the end of 2002, when the ‘Bid Invitation, Auction and Listing’ system of land market reform was introduced by the Ministry of Land and Resources, which first triggered off the upswing of land price as real estate developers competed to hoard lands, with expectations of long-lasting excess demand for houses due to urbanization, and the reliability on land sales of local governments (the so-called ‘land financing’ policy) which hijacked them to be defenders for a prosperous housing market. Although the surging housing price was once refrained in 2007, as the People’s Bank of China attempted to suppress expanding credits by raising both the Rediscount Rate and the reserve ratio, such contractional measures were soon abandoned in the late 2008, as the Central government prioritized to maintain growth and employment in facing the global crisis. An immediate rebound of the housing price then followed, as consumer prices recovered, despite the steady growth of housing supply. The real housing price then reached its peak growth rate in 2009 before it continued to develop. Yet, with a series of property purchase restrictions subsequently imposed by local governments in most first and second-tier cities since 2010, the growth in this round had become less immoderate.

### 3.4 Posteriors

We may now compare the posteriors of the DSGE model parameters to their priors as outlined earlier. Most of these parameters are found to have a posterior mean that is very similar to their prior mean, which suggests the priors we have chosen are quite compatible with the data, so that when sample information is adopted the parameters’ distributions are not much affected. However the data do suggest a much lower degree of price indexation ( $\epsilon$ ) and somewhat shorter contract life ( $\omega$ ), which means the Chinese economy may not be as ‘sticky’ as some might have thought. The data also suggest a higher 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 ( $\rho_\pi$ ) and monetary policy ( $\rho_{MP}$ ) – are generally quite persistent, and they are quite varied in size (the  $\sigma$ ’s). The estimation also returns the optimal ‘weight’ of the DSGE theory,  $\hat{\lambda}$ , which equals 0.44. While this suggests our DSGE theory has good potential to be further improved, it does mean that the current model version is providing useful theoretical restrictions for the VAR specification to best mimic the data; and, since such a weight is within the allowed theoretical boundary, it is perfectly valid.

Such an optimal theory-data combination, a DSGE-VAR(0.44) (with one lag), is the structural model upon which our empirical analyses in the following sections are built. Just for the purpose of illustration, we show in table 5 that this model has the highest marginal data likelihood, compared to the pure DSGE model and the popular Bayesian VAR with the Sims and Zha (1998) prior. The impulse responses of the model are standard; and we present those of the main variables in the Model Appendix.

Table 5: Marginal likelihood of models

Model	Laplace log marginal likelihood
DSGE-VAR(0.44)	1896
Pure DSGE	1736
BVAR with Sims and Zha (1998) prior	789

## 4 Empirical Analyses

### 4.1 What determines the housing price and the other main variables, and how were they determined over the sample period?

#### 4.1.1 Forecast error variance decomposition

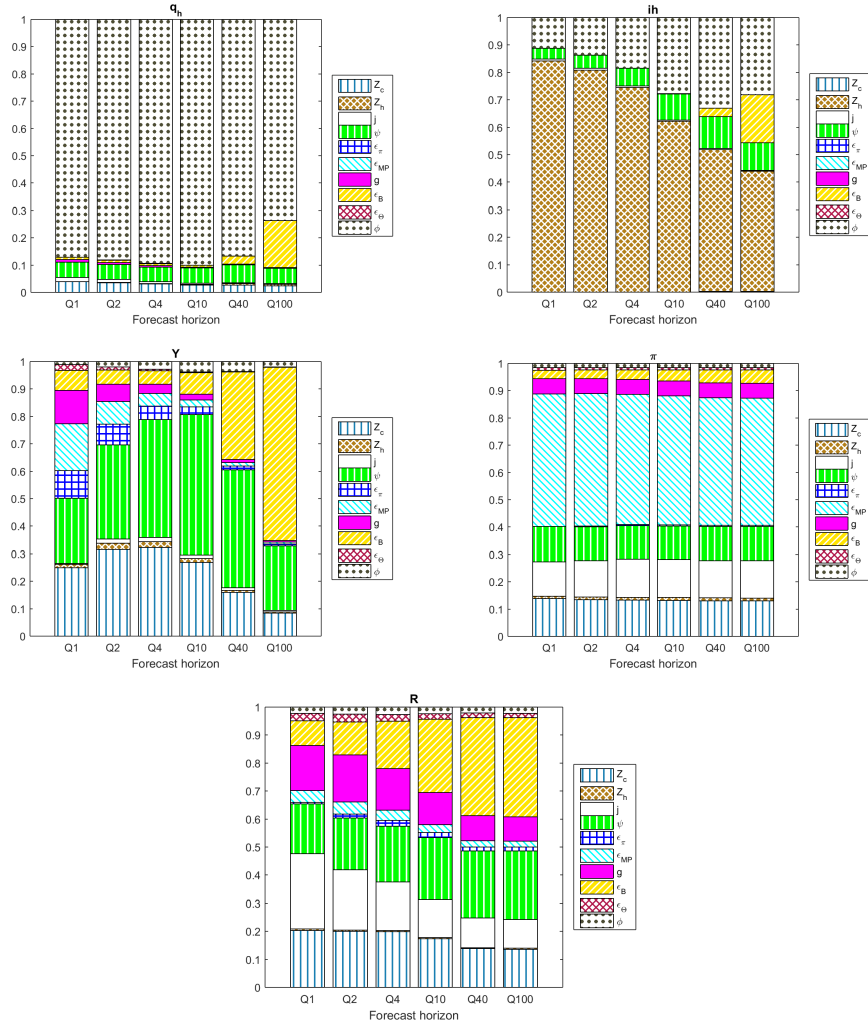
Figure 2 decomposes the forecast error variance of real housing price, houses production, real output, inflation and (central bank) interest rate using the DSGE-VAR over various forecast horizons. The decomposition

suggests that housing price is mostly a matter of the housing demand shock, which accounts for more than 85% 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 banking shock looms large (which accounts for some 17%) in the longer 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, accounting, respectively, for about 7% and 3%. 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.

Turning to 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 toward the longer runs it reduces to just below 45% ultimately (which, however, still dominates any others). The banking shock contributes to a similar proportion as in the previous case for the housing price. Other shocks are either not affecting at all, or their impacts are so trivial that they are not even noticeable as in the figure.

On the other key macroeconomic variables, output is mainly a mixture of the labour supply shock, the goods-producing technology, monetary and fiscal policies, the inflation shock, and the banking shock, assisted by the others in the short run, while the labour supply shock becomes dominating in the medium run (over 40%), and the banking shock overtakes it (accounting for more than 60%) at the end, as the other main contributors weaken. Inflation is always mostly due to monetary policy (close to 50%), amplified by the labour supply shock, the preference shock, and the goods-producing technology (which are equally important, each contributing to some 10%), with fiscal policy and the banking shock both play a small role. Interest rate is determined by pretty much the same factors because of the Taylor rule, but fiscal policy and the banking shock are no longer trivial (Of these, the latter turns to be the most important in the long run, which contributes to more than 30%). The preference shock is twice as important in the short run, compared to the case of inflation (about 20% on average), while the labour supply shock and the goods-producing technology remain to play a stable, but a slightly bigger role throughout (also about 20%). Monetary policy, however, ceases to affect much on this occasion.

Figure 2: Forecast error variance decompositions



#### 4.1.2 Historical decomposition

If we now decompose the historical data (measured as deviation from the steady-state values) over the shocks we identify for the sample period (figures 3 & 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 mostly by higher employment, and thereafter, strong improvement in productivity in the normal goods sector (There had always been a small contribution from higher supply of bank credits, too). 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 onwards, it triggered another major slowdown, where the housing price was corrected toward its equilibrium level.

On the other hand, houses production was a close follower of productivity in the housing sector, which was quite volatile except 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, government spending and bank credits also affected occasionally; but compared to the previous factors their impacts were rather small.

As for the macroeconomy, the output dynamics was mainly driven by that of productivity in the normal goods sector, though the recession in the early 2000s was partly caused by lower government spending, whose later rebound clearly helped the recovery in the following years. Shocks to labour supply and inflation caused pressure during the global crisis, but as productivity and government spending remained strong a recession did not happen. However, as productivity started to fall from 2012, and government spending had tightened, output became falling, which generated a sign of recession in the end.

Both inflation and interest rate were joint effects of shocks to productivity (in the normal goods sector), preference, inflation, government spending and bank credits, which largely offset each other; but inflation was also heavily affected by monetary policy, whose misconduct had led to the major hassles in 2004, 2008 and 2011. Nominal interest rate, by contrast, had been operating fairly smoothly, except in the late 2007 and 2008 when it responded to the high inflation.

Figure 3: Structural shocks

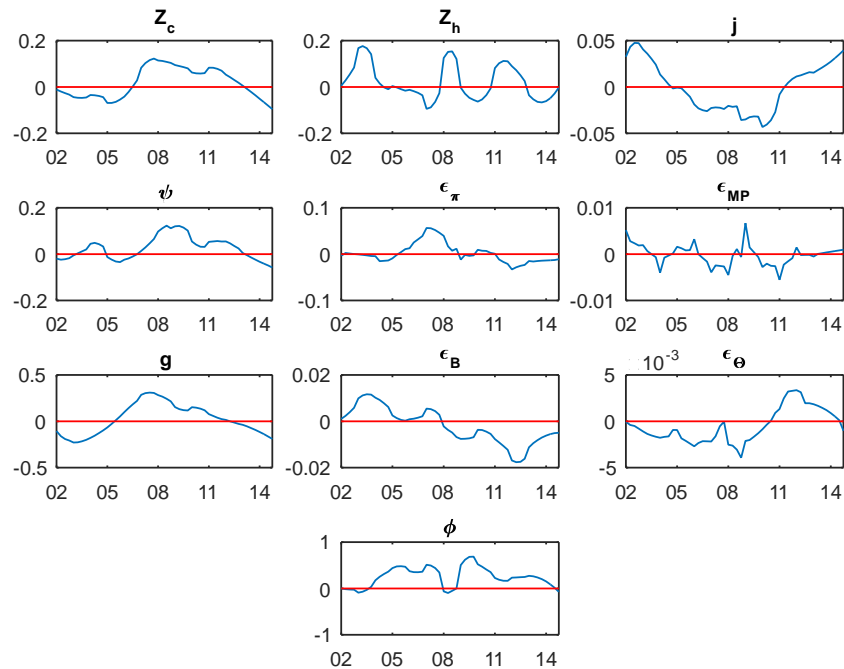
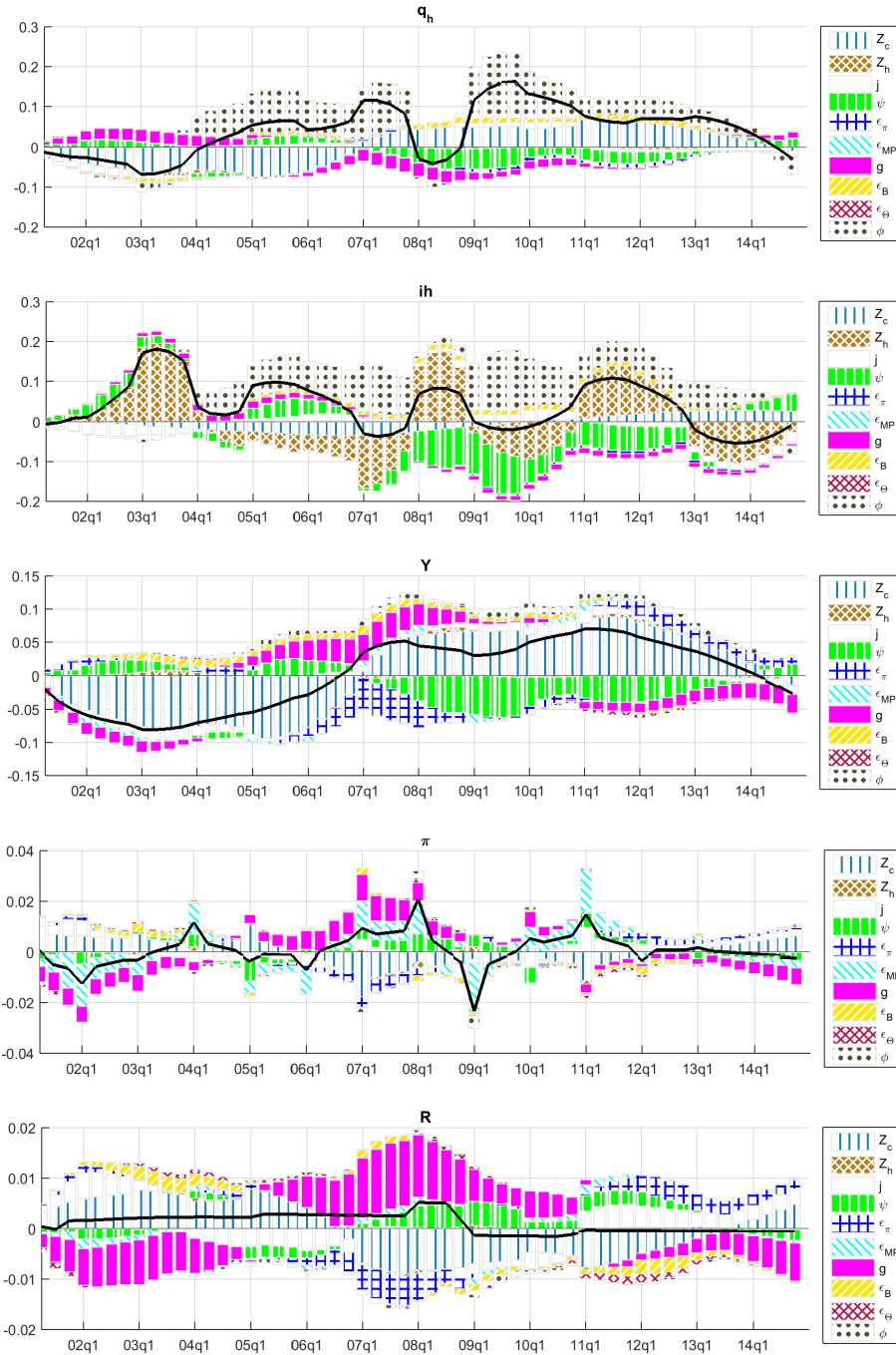


Figure 4: Historical decompositions



## 4.2 The housing price ‘bubbles’: were there any, and what is the nature of them?

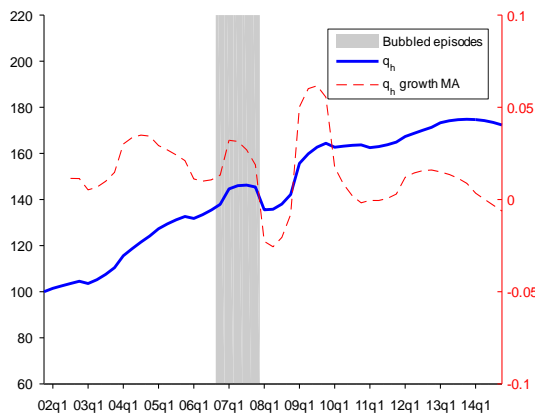
Having known what determined China’s housing price dynamics, we now ask: ‘were there any ‘bubbles’ over the sample period, and what is the nature of them?’

While existing literature – based on different theories – has proposed various ways in which ‘housing



price bubbles’ may be defined<sup>16</sup>, it is not our purpose to discuss which may be providing the best definition here. Instead, for our purpose of studying the nature of housing price bubbles *once they are well-defined*, we follow Joebges et al. (2015) by adopting the ‘pragmatic’ approach to define them *ex post*, as a rapid increase in real housing price (identified as a ‘boom’) that is followed by an equally-severe decrease in it (a ‘bust’) within a certain time (half a year in this case), where a ‘boom’/‘bust’ – being consistent with the IMF (2009)’s definition – is a period during which the four-quarter moving average of the annual growth of real housing price is above/below  $\pm 5\%$  (or in terms of quarterly growth,  $\pm 1.25\%$ ). With such a definition we identify one bubbled episode between 2006Q4 and 2007Q4 over the sample, as figure 5 illustrates; and, according to the historical decomposition exercise above, we know this was mainly due to shocks to housing demand and productivity in the normal goods sector then happened.

**Figure 5: Bubbled episode (actual data)**



But what is the nature of housing price bubbles (i.e., what generally cause(s) them) according to our model? In order to answer this question, we bootstrap the historical shocks identified earlier as in figure 5, for potential housing price dynamics to be simulated under randomly-different scenarios where the same shocks come in different time orders<sup>17</sup>. We repeat such an experiment for 80 times, with simulation in each scenario lasting for 25 years; thus, a total simulation of 2,000 years.

We find that:

a) While housing price booms happen quite regularly in the medium run perspective (about every 3.3 years), only 10% of them are followed by a bust within a short time for them to be regarded as ‘bubbles’. Thus, with all shocks hitting the economy, they happen about every 35 years on average, with bubbled episodes lasting on average for about 16 months.

b) Housing price bubbles are *always* accompanied by strong housing demand shocks, which are necessary for the bubbles to happen; without them, bubbles never occur, even when shocks to the other factors are notably big – see as we illustrate in figures 6 and 7 with selected scenarios simulated with/without the housing demand shock.

<sup>16</sup>Case and Shiller (2004) and Brunnermeier and Julliard (2008), for example.

<sup>17</sup>In particular, we bootstrap the sample shock matrix  $\begin{bmatrix} u_{i,t} & \cdots & u_{z,t} \\ \vdots & \ddots & \vdots \\ u_{i,T} & \cdots & u_{z,T} \end{bmatrix}$  with time vector in each random draw, for any potential correlations between different shocks to be preserved.

Figure 6: Simulations of housing price (all shocks)

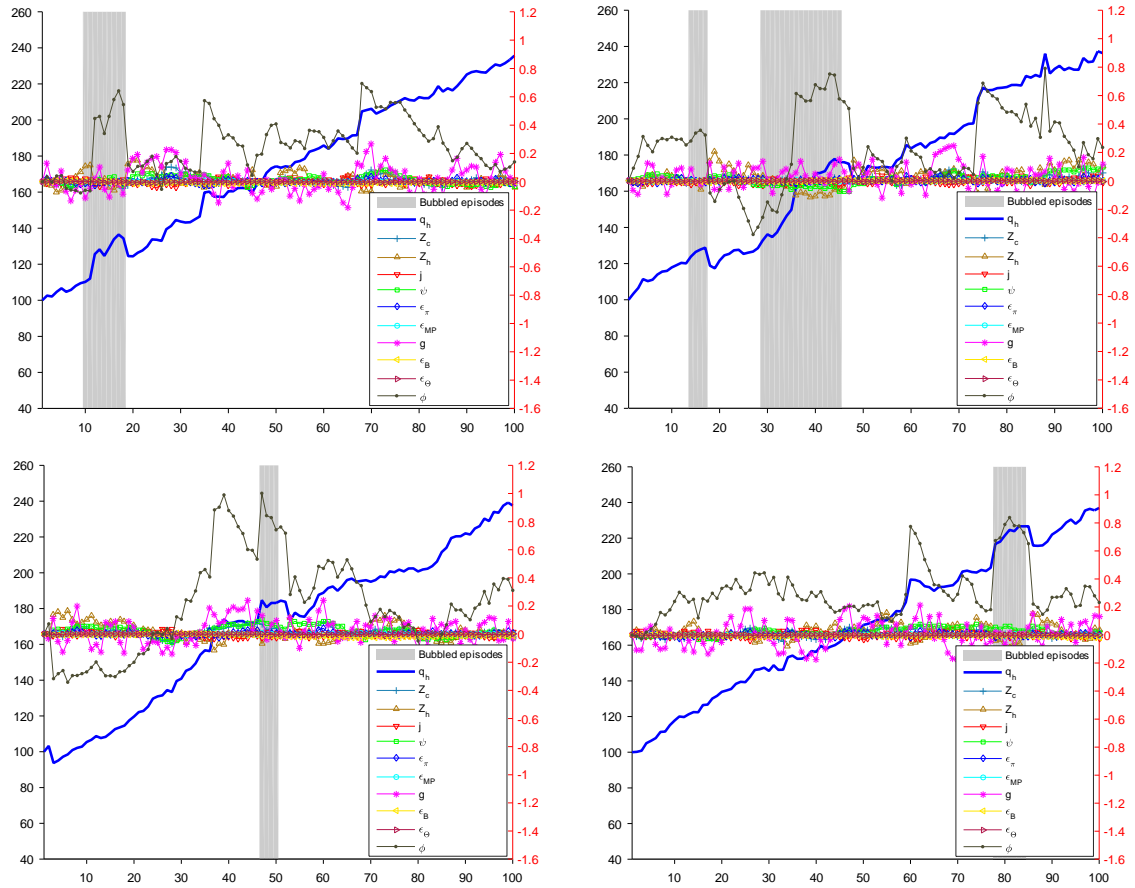
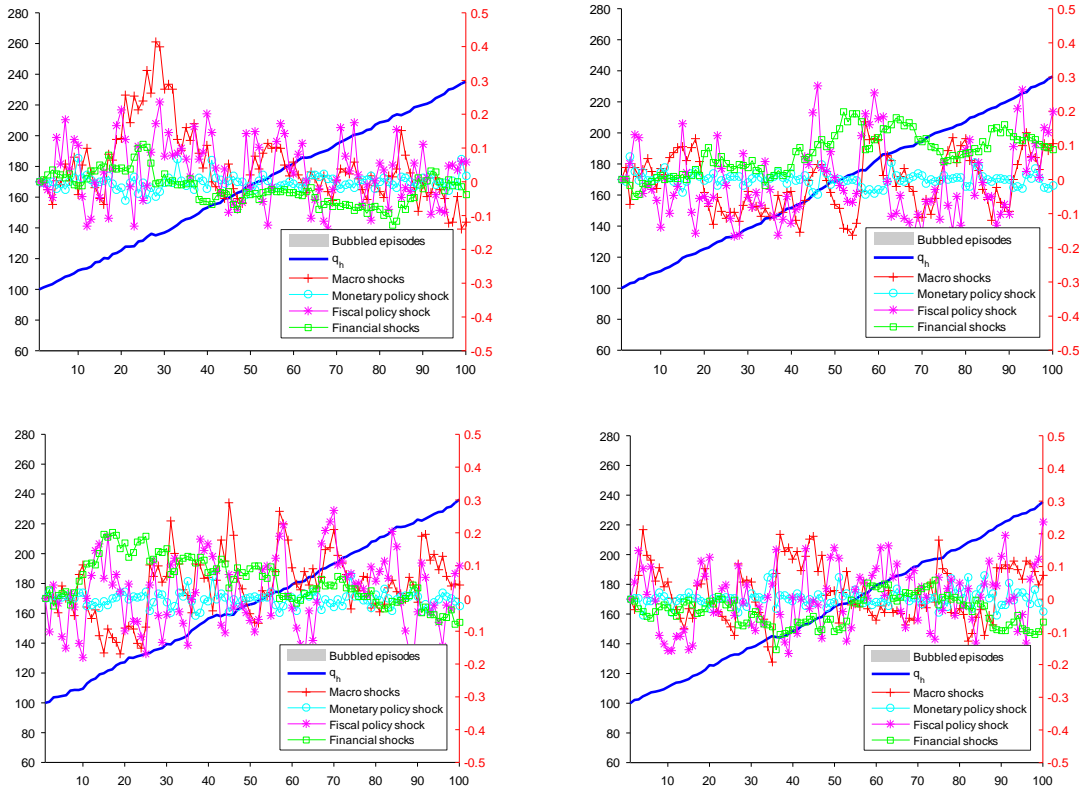


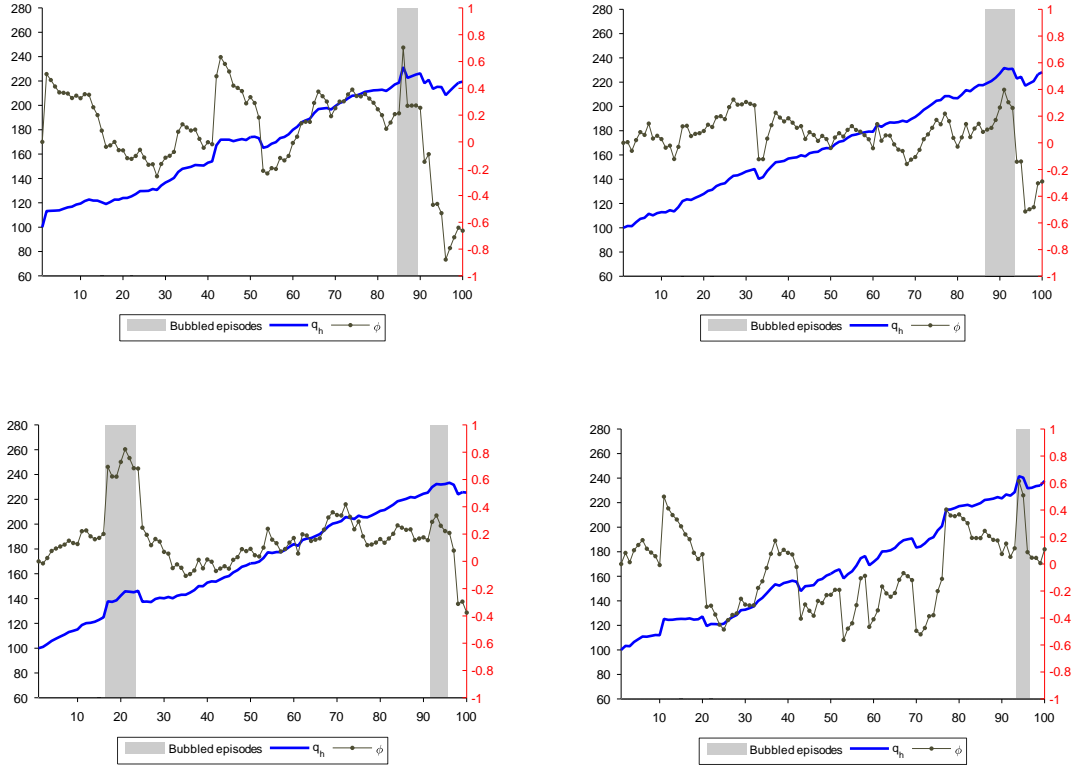
Figure 7: Simulations of housing price (all except housing demand shock)<sup>18</sup>



c) The housing demand shock is the only factor that is capable to generate 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 77 years, which doubles the time needed when all shocks were affecting as point a) just summarised – see sample scenarios in figure 8. Any other shocks, either on their own, or grouped as a bundle as attempted in point b), are incompetent to generate bubbles; but according to the finding in point a) they do facilitate the occurrence of them, making them happen much more often than otherwise with the housing demand shock alone.

<sup>18</sup>The monetary policy shock and financial shocks (i.e., the credit policy shock and the banking shock) are rescaled up by ten times in this figure for illustration purposes.

Figure 8: Simulations of housing price (only housing demand shock)



Thus, our simulation exercise in this section suggests that housing price bubbles in China 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>19</sup>) which require housing price to rise for reaching a new 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, housing price bubbles in China have a ‘self-fulfilling’ nature; but in most cases they are not just ‘pure bubbles’, but also a reflection of changed fundamentals where equilibrium has to be restored with a higher housing price.

### 4.3 Housing market spillovers: how important is housing market prosperity to growth?

We now come to the last question we aim to address in this paper; i.e., how housing market prosperity could 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, 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 past experience – Japan in the 1990s, US in the late 2007, Australia between the late 1990s and early 2000s, Colombia in early 1990s, and to name a few. Existing studies in this area have mostly built on a reduced-form model such as a VAR/VECM (or similar) for the ‘spillover’ effects from the housing market to the wider macroeconomy to be modelled, and (Granger) causal relationships between housing market variables and macroeconomic variables to be identified with the coefficients on the lagged terms of the reduced-form models. Most, using the sample data, have found that development of the housing market affects that of the macroeconomy positively. For example, Iacoviello and

<sup>19</sup>Recall that figure 2 suggests other factors do not contribute much to the housing price variation.

Neri (2010) find that US consumption is Granger-caused by the real value of housing stock, hence, ‘housing wealth’, as they call it; Liu, et al. (2002) and Chen et al. (2011) both show that GDP growth in China is Granger-caused by residential investment.

While, as we commented at the beginning of the paper, empirical findings produced with reduced-form models like these do not by themselves establish any evidence regarding ‘why’/‘how’ one variable affects another because reduced-form models are not a description of how the economy works, one could still use these models as a parsimonious description of the dynamic relationships among the data 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 reveals how changes in one variable ‘predict’ those of another in a future time.

Thus, to investigate how housing market prosperity could have affected growth, following the convention, we set up an unrestricted VAR for the growths of real output, real housing price and houses production. However, instead of estimating it on the actual data directly as most previous authors did, we first use our structural model (our DSGE-VAR) to generate 1,000 sets of simulated data with the same sample size as the actual data, by bootstrapping the historical shocks (just as we did in the simulation exercise above); we then estimate a VAR(1) on these simulated data for 1,000 sets of VAR coefficients to be estimated, and we calculate the means of these estimates<sup>20</sup>. The coefficients on the lagged terms of the VAR will therefore suggest how one variable is Granger-caused by the others, *according to our structural model*. If we specify the unrestricted VAR as:

$$\begin{bmatrix} \Delta Y_t \\ \Delta q_{h,t} \\ \Delta ih_t \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} \Delta Y_{t-1} \\ \Delta q_{h,t-1} \\ \Delta ih_{t-1} \end{bmatrix} + Errors_t \quad (42)$$

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

The first column of table 6 reports the means 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 0.11% ( $\beta_{12}$ ), while the same rise in houses production would raise output by just less than 0.04% ( $\beta_{13}$ ). 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, whose marginal impact is nevertheless quite small.

b) A corollary that follows is that, unless in extreme cases when housing price falls abnormally substantially, ‘regular’ shocks to them are not likely to lead to serious falls in output, so recessions are not likely to happen simply because the housing market is running into troubles – just as we observed in 2008 (figure 5) 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 houses production ( $\beta_{31}$ ), so real residential investment falls. On the interaction between housing price and houses production, the model suggests a small, negative impact of the latter on the former ( $\beta_{23}$ ); but growths in the former could have stimulated the latter quite clearly ( $\beta_{32}$ ).

We can of course compare these estimates to what are observed in practice to evaluate ‘how such theoretical implications fit the facts’. One typical example of this would be Iacoviello and Neri (2010) who compare these means of the simulation-based estimates to those estimated with the actual data directly with the informal ‘eyeballing’ method. While this is cheap and easy, it is nevertheless not a formal hypothesis test based on the distributions of these estimates when the structural model is assumed to be true. Thus, in order to *test* these mean estimates (which represent the theory) with the actual data (which represent the facts) formally, we set up the null hypothesis ( $H_0$ ) that ‘ $\beta_{12}$ ,  $\beta_{13}$ ,  $\beta_{21}$ ,  $\beta_{23}$ ,  $\beta_{31}$  and  $\beta_{32}$  all equal their simulated mean values’, and test it against the alternative ( $H_1$ ) that ‘not all these  $\beta$ ’s equal their mean values’.

Specifically, we first establish the joint distribution of these parameters with the 1,000 sets of simulated data by calculating the Wald test statistic ( $WS$ ):

$$WS = (\Phi - \bar{\Phi})' \sum (\Phi - \bar{\Phi}) \quad (43)$$

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<sup>20</sup>We choose a VAR(1) here because for each simulation the sample size is small.

which measures the ‘Mahalanobis distance’ between each set of the simulation-based estimates ( $\Phi$ ) and their mean values ( $\bar{\Phi}$ ); and  $\Sigma$  is the inverse of the variance-covariance matrix of  $\Phi$  calculated with all simulations. With 1,000 sets of simulated data, we can therefore find 1,000 possible values of  $WS$ ,  $\{WS_i^{Sim}\}_{i=1}^{1000}$ , for an empirical distribution of  $WS$  (which represents the theory) to be found, which can then be evaluated against the  $WS$  value calculated with the actual data,  $WS^{Act}$  (which represents the facts), to decide whether the actual-data-based estimate of  $\Phi$  ( $\Phi^{Act}$ ) can be viewed as a random realization of it under the null hypothesis, for a given confidence level. Since  $\Phi = \bar{\Phi}$  when the null hypothesis is true and this implies  $WS = 0$ , the further  $WS^{Act}$  is away from zero, the more likely that the null hypothesis will be rejected by the actual data. In practice, one can indicate such a distance with the percentile of the distribution of Wald statistic where  $WS^{Act}$  lies – call it the ‘Joint Wald percentile’ – for deciding whether the null hypothesis is rejected or not; and the p-value, by definition, is equal to  $(100 - \text{Joint Wald percentile})/100$ .

This is essentially the *Indirect Inference Wald test* recently developed by Le, et al. (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) as ‘descriptors’ of the actual data against which a structural model can be tested, we only include those as listed in table 6 here, as our purpose is just to test whether the Granger causal relations about growth and housing market prosperity we just identified are rejected by the Chinese data.

It turns out that the null hypothesis passed the joint Wald test very easily, as the p-value reported (0.89) is well above the usual 5% threshold (and all the  $\beta$ 's calculated with the actual data are within the simulated 95% bounds). Thus, our final assessment of the structural model using the method of Indirect Inference testifies to its theoretical implications: that, although the macroeconomy could have benefited from a prosperous housing market, it would be quite costly to maintain a decent growth by just boosting the latter, for that its efficacy is poor. However, if policies are for stabilizing 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 well 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.

Table 6: Estimates of the unrestricted VAR

Coeff.	Sim. mean	95% LB	95% UB	Actual
$\beta_{12}$	0.1097	-0.0696	0.2766	0.0463
$\beta_{13}$	0.0421	-0.0739	0.1540	0.0261
$\beta_{21}$	-0.1311	-0.6790	0.4480	-0.0369
$\beta_{23}$	-0.0326	-0.2754	0.1833	0.0248
$\beta_{31}$	-0.2096	-0.9451	0.5464	0.0780
$\beta_{32}$	0.2296	-0.2329	0.6956	0.0279
Joint Wald percentile			11.0	
P-value			0.89	

## 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 in a sub-system affiliated to the main system constituted by 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 more than 80% of the housing price

fluctuation, with the rest assisted by shocks to labour supply, productivity and bank credits. 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, such as shocks to fiscal policy and inflation. 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 other shocks; so housing price bubbles in China are mostly a joint outcome of ‘pure bubbles’, and changes in the fundamentals that require housing price to rise for restoring equilibrium. Finally, our model also implies a weak spillover effect from the housing market to the macroeconomy, which is not rejected by the data, which further implies a), that it would be quite inefficient (and potentially costly) if policy-makers attempt to maintain economic growth by just boosting the housing market, and b), that if policies are for stabilizing the housing market, on the other way around, they should not be threatened that such stabilization would weigh on the real economy any seriously.

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## A Model Appendix

### A.1 Optimization problems, policies, identities and market clearing

#### A.1.1 The patient household problem:

Patient households maximize:

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

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

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

The first order conditions are:

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

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

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

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

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

#### A.1.2 The impatient household problem:

Impatient households maximize:

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

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:

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

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

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

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

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

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

### A.1.3 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:

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

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 houses production:

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

adjustment cost of capital for normal goods production:

$$adj_{kc,t} = \frac{\zeta_{kc}}{2G_{k_c}} \left( \frac{k_{c,t}}{k_{c,t-1}} - G_{k_c} \right)^2 k_{c,t-1} \quad (\text{A.26})$$

adjustment cost of capital for houses production:

$$adj_{kh,t} = \frac{\zeta_{kh}}{2G_{k_h}} \left( \frac{k_{h,t}}{k_{h,t-1}} - G_{k_h} \right)^2 k_{h,t-1} \quad (\text{A.27})$$

The first order conditions are:

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

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

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

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

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

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

21

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

22

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

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

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

---


$$\begin{aligned} 21 \frac{\partial adj_{kc,t+1}}{\partial k_{c,t}} &= -\frac{\zeta_{kc}}{2G_{k_c}} \left( \frac{k_{c,t+1}}{k_{c,t}} - G_{k_c} \right) \left( \frac{k_{c,t+1}}{k_{c,t}} + G_{k_c} \right), \quad \frac{\partial adj_{kc,t}}{\partial k_{c,t}} = \frac{\zeta_{kc}}{G_{k_c}} \left( \frac{k_{c,t}}{k_{c,t-1}} - G_{k_c} \right). \\ 22 \frac{\partial adj_{kh,t+1}}{\partial k_{h,t}} &= -\frac{\zeta_{kh}}{2G_{k_h}} \left( \frac{k_{h,t+1}}{k_{h,t}} - G_{k_h} \right) \left( \frac{k_{h,t+1}}{k_{h,t}} + G_{k_h} \right), \quad \frac{\partial adj_{kh,t}}{\partial k_{h,t}} = \frac{\zeta_{kh}}{G_{k_h}} \left( \frac{k_{h,t}}{k_{h,t-1}} - G_{k_h} \right). \end{aligned}$$

#### A.1.4 The retailer problem:

In each period retailers maximize:

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

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:

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

Let the general price level be:

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

Equation A.40, A.41 and A.42 then imply the ‘hybrid-version’ New Keynesian Phillips curve, where inflation shock ( $\hat{\pi}_{\pi,t}$ ) is also allowed for:

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

Retailers’ profit in each period is:

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

#### A.1.5 The normal bank problem:

In each period normal banks maximize:

$$\Pi_t^{Nbank} = r_t^{NL} B_t - r_t^S S_t - \frac{c}{2} \left( \frac{F_t}{B_t} - \Omega \right)^2 F_t \quad (\text{A.45})$$

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:

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

### A.1.6 The Shadow bank problem:

In each period shadow banks maximize:

$$\Pi_t^{Sbank} = [(1 + r_t^{IL}) - (1 + r_t^{NL})]IL_t \quad (\text{A.50})$$

by choosing  $r_t^{IL}$ , subject to the constant interest-rate elasticity assumption:

$$\frac{\partial IL_t / IL_t}{\partial r_t^{IL} / r_t^{IL}} = -\eta^{Sbank} \quad (\text{A.51})$$

The first order condition is:

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

### A.1.7 Public sector policies:

Taylor rule:

$$1 + R_t = (1 + R_{t-1})^{\rho_R}(1 + \pi_t)^{(1-\rho_R)\varphi_\pi} \left(\frac{GDP_t}{G_c GDP_{t-1}}\right)^{(1-\rho_R)\varphi_x} (1 + r^{ss})^{(1-\rho_R)} \varepsilon_{MP,t} \quad (\text{A.53})$$

Credit policy<sup>23</sup>:

$$\Theta_t = \Theta_{t-1}^{\rho_\Theta} \left(\frac{GDP_t}{G_c GDP_{t-1}}\right)^{z_\Theta} \bar{\Theta}^{1-\rho_\Theta} \varepsilon_{\Theta,t} \quad (\text{A.54})$$

Government spending:

$$g_t = \tau_t \quad (\text{A.55})$$

### A.1.8 Market clearing

Normal goods market clearing:

$$C_t + I_t + g_t = Y_t - \frac{c}{2} \left(\frac{F_{t-1}}{B_{t-1}} - \Omega\right)^2 F_{t-1} - \delta^F F_{t-1} - adj_{kc,t} - adj_{kh,t} \quad (\text{A.56})$$

Housing market clearing:

$$h_t^P - (1 - \delta_h)h_{t-1}^P + h_t^I - (1 - \delta_h)h_{t-1}^I = ih_t \quad (\text{A.57})$$

Lands market clearing:

$$l_t = 1 \quad (\text{A.58})$$

Financial market clearing:

$$b_t^{I'} + b_t^{I''} + b_t^{E'} + b_t^{E''} = B_t \quad (\text{A.59})$$

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

<sup>23</sup>We assume that shifts of credit policy affect household and entrepreneur borrowing from normal banks in the same manner, so that  $\hat{\Theta}_t = \hat{\Theta}_{H,t} = \hat{\Theta}_{E,t} = -\hat{\Xi}_{H,t} = -\hat{\Xi}_{E,t}$ .

### A.1.9 Identities

Total consumption:

$$c_t^P + c_t^I + c_t^E = C_t \quad (\text{A.60})$$

Total investment:

$$i_{c,t} + i_{h,t} = I_t \quad (\text{A.61})$$

Total labour:

$$n_{c,t}^P + n_{h,t}^P + n_{c,t}^I + n_{h,t}^I = N_t \quad (\text{A.62})$$

Definition of GDP:

$$GDP_t = Y_t + \bar{q}_h i_{h,t} \quad (\text{A.63})$$

Fisher identity a:

$$r_t^S = R_t - E_t \pi_{t+1} \quad (\text{A.64})$$

Fisher identity b:

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

### A.1.10 Trends and shock evolution

Technology growth (normal goods production):

$$A_{c,t} = (1 + \gamma_{ac})^t Z_{c,t} \quad (\text{A.66})$$

Technology growth (houses production):

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

Technology shock (normal goods production):

$$\ln Z_{c,t} = \rho_{Ac} \ln Z_{c,t-1} + \ln u_{c,t} \quad (\text{A.68})$$

Technology shock (houses production):

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

Intertemporal preference shock:

$$\ln j_t = \rho_j \ln j_{t-1} + \ln u_{j,t} \quad (\text{A.70})$$

Housing preference shock:

$$\ln \phi_t = (1 - \rho_\phi) \ln \bar{\phi} + \rho_\phi \ln \phi_{t-1} + \ln u_{\phi,t} \quad (\text{A.71})$$

Labour supply shock:

$$\ln \psi_t = \rho_\psi \ln \psi_{t-1} + \ln u_{\psi,t} \quad (\text{A.72})$$

Banking shock:

$$\ln \varepsilon_{B,t} = \rho_B \ln \varepsilon_{B,t-1} + \ln u_{B,t} \quad (\text{A.73})$$

Inflation shock:



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

Monetary policy shock:

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

Credit policy shock:

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

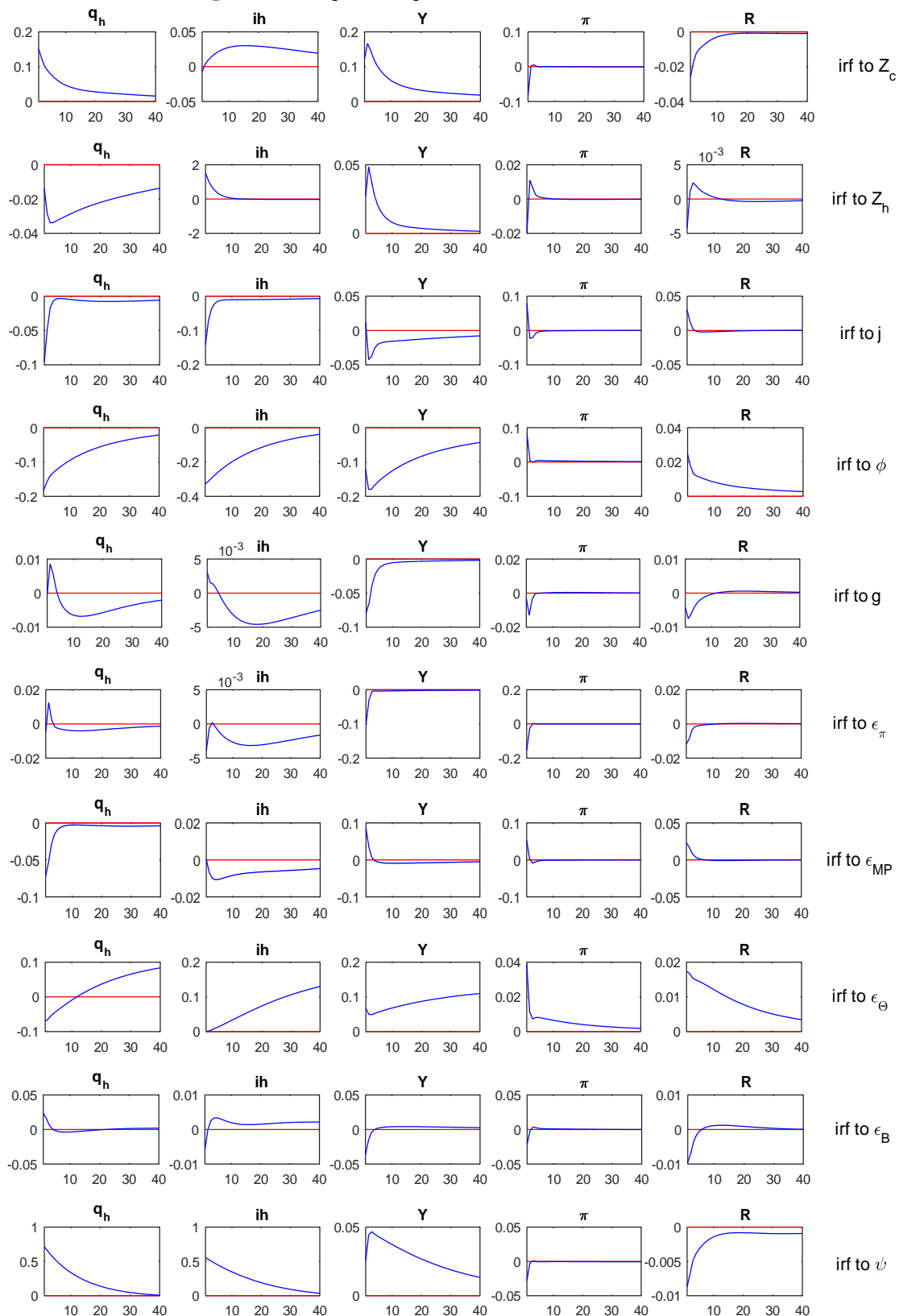
Government spending shock:

$$\ln g_t = \rho_g \ln g_{t-1} + \ln u_{g,t} + \rho_{gc} \ln u_{c,t} \quad (\text{A.77})$$

where  $u_{c,t}$ ,  $u_{h,t}$ ,  $u_{j,t}$ ,  $u_{\phi,t}$ ,  $u_{\psi,t}$ ,  $u_{B,t}$ ,  $u_{\pi,t}$ ,  $u_{MP,t}$ ,  $u_{\Theta,t}$  and  $u_{g,t}$  are all *i.i.d.* innovations.

## A.2 Impulse responses of main variables

Figure A.1: Impulse responses of main model variables



### A.3 Glossary of model variables and disturbances

Table A.1: Model variables

$GDP_t$		$\Pi_t^{Sbank}$	
$Y_t$	Gross domestic product	$F_t$	Shadow banks' profit
$ih_t$	Total normal goods production		Normal banks' capital
$c_t^P$	Total houses production	$\pi_t$	Inflation in the normal goods sector
$c_t^I$	Patient household consumption	$q_{h,t}$	Real price of houses
$c_t^E$	Impatient household consumption	$q_{l,t}$	Real price of lands
$C_t$	Entrepreneur consumption	$R_t$	Central bank nominal interest rate
$h_t^P$	Total private consumption	$R_t^{NL}$	Normal bank nominal loan rate
$h_t^I$	Patient household demand for houses	$r_t^{NL}$	Normal bank real loan rate
$h_t^J$	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	$b_t^{I''}$	Impatient household borrowing from investment banks
$A_{c,t}$	Technology for normal goods production	$b_t^{E'}$	Entrepreneur borrowing from normal banks
$A_{h,t}$	Technology for houses production	$b_t^{E''}$	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 A.2: Model disturbance

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

## B Data Appendix

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 (i.e.,  $GDP_t$ ,  $C_t$ ,  $I_t$ ,  $ih_t$  and  $N_t$ ) 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  $CPI$ .  $q_h$  and  $q_l$  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 manipulations to them are summarized in table A.3.

Table A.3: Measurement, sources & manipulations 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	✓	✓	✓	✓
$ih_t$	Houses production (newly-built commercial residential houses) <sup>a</sup>	NBSC	✓	✓	✓	✓
$\pi_t$	Quarter-on-quarter CPI 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 Rediscout 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.	✓

a: Based on the 'Value of Completed Commercial Residential Houses' from NBSC and the House Price Index (for commercial residential houses).  
b: Based on the Consumer Price Index from NBSC.  
c: Based on the 'Average Sales Price of Commercial Residential Houses' from NBSC.  
d: Based on the 'Weekly working hours in urban area' from MLSS.  
e: Based on the 'Working-age Population' from OE.  
f: NBSC - National Bureau of Statistics of China;  
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>).