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The driving forces of China's business cycles: Evidence from an estimated DSGE model with housing and banking[☆]

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ABSTRACT

We study the approximate sources of China's business cycles in an estimated dynamic stochastic general equilibrium (DSGE) model with housing and banking. The model replicates well the volatility and cyclicality of key macroeconomic variables observed in the past two decades in China. A host of shock decomposition exercises demonstrate that, among the shocks being considered, both financial and housing shocks are driving China's business cycles, accounting for a particularly large fraction of the variance in most macroeconomic and financial variables at the business cycle frequencies. In particular, the capital quality, housing demand, and loan-to-value shocks display prominent contributions to the business cycle fluctuations. Moreover, there exists substantial interactions between the banking and housing sectors in China, where the collateral constraint and the financial constraint amplify with each other. The results shed new light in the understanding of China's business cycles, and may serve as a useful benchmark for future quantitative analyses of China's macroeconomic fluctuations using DSGE frameworks.

1. Introduction

China has experienced an unprecedentedly rapid economic growth in forty years since the economic reform was launched in 1978. Yet, the economic growth tended to slow down in the near decade. The annual growth rate rose to 14.23 percent in 2007, and then gradually felt to 6.6 percent in 2018. As shown in the data, the economic growth slows down quickly, accompanied by a rapid growth in house prices and credit expansion. There is a consensus, perhaps among most economists, that the rapid economic growth of China in the previous decades is attributed to technological advances and high capital accumulation. However, the driving forces of China's business cycles, especially in the recent decade, are far from being understood. Using an estimated dynamic stochastic general equilibrium (DSGE) model, we address a number of key issues about China's business cycles: What are the approximate driving forces of China's business cycles? Are there any disturbances other than technology shocks and/or investment shocks serving as the main

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sources of business cycle fluctuations? What is the role of other disturbances, like financial and housing shocks, in affecting business cycle fluctuations in China? Can a standard DSGE model explain the volatility in financial, housing, and other macroeconomic variables being concerned?

To address these issues, we develop and estimate a DSGE model with housing and banking, using Bayesian methods. In particular, we extend a version of the New Keynesian DSGE model developed by Iacoviello and Neri (2010) on housing to encompass financial frictions along the lines of Gertler and Kiyotaki (2010). In doing so, it allows us to study the interactions between banking, housing, and the broader economy. The experience of the Great Recession forcefully demonstrates that business cycle fluctuations can not be understood properly without considering financial disturbances. The objectives of this paper are threefold. First, we want to examine the extent to which a DSGE model with standard setups can reproduce the second moments of key variables observed in the Chinese data. Due to differences in economic structures and institutions between China and the more advanced countries, the off-the-shelf leading business cycle models, such as Smets and Wouters (2007), may not well suited *a priori* to account for business cycle fluctuations in China. In the meanwhile, it is also important to see how far a *standard* DSGE model, i.e., one without many features unique to China, can go to capture the business cycle properties observed in the data for China. Second, we want to investigate the contributions of frictions and disturbances in both the housing and banking sectors to the business cycle fluctuations in China. To this end, we combine key modeling elements from the literature in housing and macro finance in the past decade, so to create a unified quantitative framework for both estimations and simulations. Last, we use the estimated model to identify the main, albeit approximate, driving forces of business cycles in China over the past two decades.[1] The outcome from the quantitative evaluations not only deepens our understanding of China's business cycles, but may also serve as a useful benchmark for future quantitative analyses of China's macroeconomic fluctuations using DSGE models.

We confront the model with quarterly data of China over the period of 2000Q1–2018Q4, including key variables in both financial and housing sectors. Our estimated model explains the business cycle properties of the data well. In particular, it replicates the volatility and cyclicality in consumption, nonresidential investment, house prices, bank net worth, nonresidential loans, deposits, bank leverage, inflation, and hours, as observed in the data over the past two decades. Furthermore, we find that the capital quality, non-housing technology, housing demand and supply, loan-to-value (LTV), and labor supply shocks are the main driving forces of the China's business cycles, accounting for more than 80 percent of the variance in all variables of interest at business cycle frequencies. Of them, the contributions of the financial and housing shocks, such as capital quality shocks, LTV shocks and housing demand shocks, play the most prominent roles in the fluctuations of Chinese macroeconomy at the business cycle frequencies. Moreover, there are substantial interactions between the banking and housing sectors in China. Housing shocks exert a significant influence on the operation of the banking sector via financial frictions.

Our baseline model consists of six main features: (i) two production sectors of consumption goods and housing; (ii) two types of households, savers and borrowers; (iii) nominal rigidities; (iv) collateral constraints in household loans; (v) financial frictions in the banking sector; and (vi) a rich set of shocks. These features are mostly drawn from the two strands of current literature which study the housing and financial cycles. The business cycle models with housing study the behavior of the housing market over the business cycle by dealing with some combination of (i)–(iv).[2] Business cycle models with banking study the role of financial intermediaries in the transmission of financial shocks by dealing with (v).[3] While many papers in the literature focus on housing and banking separately, we stress that a combination of the two is crucial to understand the business cycles in China.

Among the literature considering the interaction between housing and banking over the business cycles, Iacoviello (2015), Ferrante (2019), and Ge et al. (2020) are the closest to this paper. Iacoviello (2015) finds that repayment shocks, housing demand shocks and LTV shocks account for about two-thirds of the decline in output and investment during the Great Recession. In addition to frictions tied to households and banks, Ferrante (2019) introduces endogenous default to a DSGE model in accounting for the comovements in consumption, house prices, business investment and output, and finds that housing risk shocks and MBS collateral shocks are able to explain the pattern of comovements among these variables during the Great Recession. Ge et al. (2020) also develop a DSGE model with housing and banking to explore the transmission of various financial shocks, and find that capital quality shocks, bank liquidity shocks and housing preference shocks play an important role in the housing and financial cycles. None of these studies, however, addresses the issues we raise in this paper about China's business cycles, since all papers focus on the US experience. The novel elements of this paper are goodness-of-fit of a standard model, and the quantification of the approximate sources of the business cycle fluctuations in China.

As in Smets and Wouters (2007), Iacoviello and Neri (2010), and Justiniano et al. (2010), our model considers a rich set of shocks: the technology shocks in both housing and consumption goods sector, the housing demand shock, the intertemporal preference shock, the LTV shock, the capital quality shock, the cost-push shock, the labor supply shock, and the monetary policy shock. Among these

[1] To be very precise, we do not claim that our model captures the *primitive* driving forces and the *genuine* structure of China's macroeconomy. Following Chari et al. (2007) and Buera and Moll (2015), we only interpret our model as approximating the *true* structure of China's economy, and the estimated shocks as representing possibly more primitive driving forces of the actual economy. However, as long as the primitive shocks maps into an observationally equivalent shock in our model, the dynamic properties uncovered from our estimation will also be informative about the behavior of the primitive shocks.

[2] The main references include Greenwood and Hercowitz (1991), Benhabib et al. (1991), Gervais (2002), Davis and Heathcote (2005), Iacoviello (2005), Fisher (2006), Christensen et al. (2016), Iacoviello and Neri (2010), Iacoviello and Pavan (2013), and Kiyotaki et al. (2011).

[3] The main references include Meh and Moran (2010), Gertler and Karadi (2011), Gerali et al. (2010), Angeloni and Faia (2013), Gertler and Kiyotaki (2010), Gertler et al. (2012) and Gertler and Kiyotaki (2015).

shocks, the capital quality shock could be one of the most important driving forces in China's business cycles, given the significant role played by the non-residential investment in China's economy. The estimated model indeed shows that, at the business cycle frequencies, the capital quality shock accounts for more than 15 percent of the variance in consumption, nonresidential investment and output, and a large fraction of the variance in nonresidential loans, net worth, deposits, bank leverage and inflation, between 25 and 70 percent. More broadly, this result is in line with the recent business cycle literature. While the seminal paper of Chari et al. (2007) finds the investment wedge to play a minor role in the US business cycles, the more recent works applying the methodology to emerging countries and Asian economies find that the investment wedge to be a dominant factor in business cycle fluctuations.[4]

There are a few recent papers studying the Chinese housing market using the DSGE framework. Ng (2015) represents an early attempt to understand China's housing market from a macro perspective based on NK DSGE approach, however, due to data limitation, the author relies on annual data to estimate the model. Abstracting from the nominal side, Minetti et al. (2019) focus on the real house price dynamics in China by incorporating an external habits in housing consumption into the preference specification. The recent paper by Gai et al. (2020), which is also based on the NK DSGE framework, focuses on the implications of the housing collateral constraint on China's business cycles. Contrary to the typical findings in the literature, the statistical test of this paper favors the benchmark model without the collateral constraint on house financing. The crucial distinction of our paper from these three papers lies in both the modeling part and the empirical implementation. All the three papers do not incorporate banking and financial frictions into their model frameworks. As showed by our quantitative evaluations, shocks and frictions in the housing sector have significant impacts on the dynamics of the financial sector. Intuitively, Chinese economy features a tight link in the banking sector and housing sector, since housing related loans claim a substantial portion on the bank's balance sheet in China. Moreover, the quarterly data sample we construct for the calibration and estimation spans for nearly two decades and covers all the key variables in both financial and housing sector, the most comprehensive one in the related literature on China's business cycle, as far as we know. This enables us to uncover a more accurate picture of the sources of business cycle fluctuations in China.

The rest of the paper is organized as follows. Section 2 develops the baseline model. Section 3 describes the data, parameter calibration, and Bayesian estimation. Section 4 presents the quantitative results of the baseline model. Section 5 inspects the mechanisms of China's macroeconomic dynamics through the impulse responses to the estimated shocks. Section 6 conducts a series of sensitivity analyses by shutting down key channels of the model economy one by one. Section 7 concludes. Details about the data sources and a complete list of model equations are relegated to the appendix.

2. The model

We consider an infinite discrete-time economy. The economy features households, financial intermediaries, and firms. The household sector includes two types of households, patient and impatient, and each type of households is of unit measure.[5] Households do not hold physical capital directly. They work, consume final goods, buy housing, and either deposit funds into or borrow from banks. In equilibrium, patient households turn out to be net savers and lend funds to impatient households and non-financial firms through financial intermediaries. Impatient households turn out to be net borrowers, and they borrow funds from financial intermediaries against their collateral which is tied to their housing values.

In the economy, there are four types of producers in the production sector, retail and wholesale producers in the consumption good sector, housing producers, and capital goods producers. Each type has a unit mass. In the consumption goods sector, wholesale firms operate under perfect competition, and retail firms operate under monopolistic competition. The retail firms purchase wholesale consumption goods from the wholesale firms and sell them at a markup over the marginal cost. The wholesale firms hire labor from households, purchase physical capital with funds borrowed from financial intermediaries, and produce wholesale consumption goods. The housing producers hire labor from households and rent land as an input from patient households to produce new houses. The capital producers purchase final goods as an input to produce new capital and are subject to an adjustment cost.

Banks operate in an economy-wide market. At the beginning of each period, they obtain deposits from patient households and issue loans to impatient households and non-housing sectors. Banks are subject to an incentive constraint, i.e., each bank with a given portfolio is constrained in its ability to issue deposits to its savers and to make loans to its borrowers. Banks' incentive constraints and households' collateral constraints may interact and reinforce each other in equilibrium, creating the possibility for the effects of shocks on the economy to be amplified and propagated over time.

[4] See, for example, He et al. (2009), Otsu (2010), Lu (2012), Chakraborty and Otsu (2013), Cho and Doblas-Madrid (2013). In contrast, Brinca (2014) reports that for OECD countries, the investment wedge is much less important than the efficiency and labor wedge, confirming the original results by Chari et al. (2007) for the US. For the equivalence of the investment specific shock and the investment wedge, see Brinca et al. (2016) for a formal proof. As pointed out below at the end of the model section, the capital quality shock in our setting is closely related to the investment specific shock as investigated by Fisher (2006) and Justiniano et al. (2010).

[5] In the model, patients can be treated as credit-unconstrained households, and impatients can be treated as credit-constrained households. With the heterogeneity of households, it allows us to investigate the heterogenous behaviors of the two types of households in response to exogenous shocks. As discussed later, the two types of households exhibit different behaviors in consuming, holding houses and supplying labor.

2.1. Households

2.1.1. Patient households (savers)

In the economy, a representative patient household chooses consumption $c_{p,t}$, housing $h_{p,t}$, hours supplied to the final goods (wholesale) producers and housing producers, $l_{pc,t}$ and $l_{ph,t}$, to solve the following expected discounted utility:

$$U_p = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta_p^t A_{p,t} \left\{ \Gamma_p ln(c_{p,t} - \tau_p c_{p,t-1}) + j_t ln h_{p,t} - \frac{A_{n,t}}{1+\eta_p} \left(l_{\text{pc},t}^{1+\varepsilon_p} + l_{\text{ph},t}^{1+\varepsilon_p} \right)^{\frac{1+\eta_p}{1+\varepsilon_p}} \right\},$$

where η is the inversed Frisch elasticity of labor supply, and ε captures the degree of sector specificity. Following Horvath (2000), hours are less perfect substitutes if $\varepsilon_p > 0$ while they are perfect substitutes if $\varepsilon_p = 0$. The term τ_p captures the degree of habits in consumption. The parameter β_p denotes the discount factor of patient households. The scaling factor $\Gamma_p = (1 - \tau_p)/(1 - \beta_p \tau_p)$ ensures that the marginal utility of consumption for patient households is $1/c_p$ in the steady state. $A_{p,t}$, $A_{n,t}$ and j_t captures the shocks to intertemporal preference, labor supply and housing demand, respectively, and follow the AR(1) process as follows:[6]

$$\begin{aligned} lnA_{p,t} &= \rho_p lnA_{p,t-1} + u_{p,t}, \\ lnA_{n,t} &= \rho_n lnA_{n,t-1} + u_{n,t}, \\ lnj_t &= (1-\rho_j) lnj + \rho_j lnj_{t-1} + u_{j,t}, \end{aligned}$$

where $u_{p,t}$, $u_{n,t}$ and $u_{j,t}$ are independently and identically distributed with mean 0, and variances σ_p^2, σ_n^2 and σ_j^2, respectively. The term j is the steady-state value of the housing preference weight.

A representative patient household faces the following budget constraint:

$$c_{p,t} + q_t h_{p,t} + p_{x,t} x_t + d_t = w_{\text{pc},t} l_{\text{pc},t} + w_{\text{ph},t} l_{\text{ph},t} + q_t (1-\delta_h) h_{p,t-1} + (p_{x,t} + R_t^x) x_{t-1} + \frac{R_t^d d_{t-1}}{\pi_t} + F_t + T_t,$$

where $w_{\text{pc},t}$ and $w_{\text{ph},t}$ are real wages from supplying labor hours to the wholesale and housing sectors, and q_t and $p_{x,t}$ are house prices and land prices. The term d_t denotes deposits (loans if d_t is negative), which yield a riskless nominal return of R_t^d from period $t-1$ to period t. Land is rented to the housing sector at a real rental rate of R_t^x. The parameter δ_h denotes the depreciation rate of housing. Finally, $\pi_t = p_{c,t}/p_{c,t-1}$ is the inflation rate in the consumption sector, F_t is the net average transfer received by the patient household from banks upon their exit, and T_t is a lump sum profit transfer from the retail firms and capital goods firms.

2.1.2. Impatient households (borrowers)

A representative impatient household chooses consumption $c_{i,t}$, housing $h_{i,t}$, hours $l_{ic,t}$ and $l_{ih,t}$ to maximize the following expected discounted utility:

$$U_i = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta_i^t A_{p,t} \left\{ \Gamma_i ln(c_{i,t} - \tau_i c_{i,t-1}) + j_t ln h_{i,t} - \frac{A_{n,t}}{1+\eta_i} \left(l_{\text{ic},t}^{1+\varepsilon_i} + l_{\text{ih},t}^{1+\varepsilon_i} \right)^{\frac{1+\eta_i}{1+\varepsilon_i}} \right\},$$

subject to the budget constraint

$$c_{i,t} + q_t h_{i,t} + \frac{R_t^b b_{t-1}}{\pi_t} = w_{\text{ic},t} l_{\text{ic},t} + w_{\text{ih},t} l_{\text{ih},t} + q_t (1-\delta_h) h_{i,t-1} + b_t,$$

and the collateral constraint

$$b_t \le m_t \mathbb{E}_t \left(\frac{q_{t+1} h_{i,t} \pi_{t+1}}{R_{t+1}^b} \right),$$

where $w_{\text{ic},t}$ and $w_{\text{ih},t}$ are real wage rates from supplying hours to the wholesale and housing sectors, respectively. The term b_t denotes loans (savings if b_t is negative), which yield a nominal rate of return of R_{t+1}^b from period t to period $t+1$. The term β_i is the discount factor of impatient households. We set $\beta_i < \beta_p$ to ensure that impatient households are credit-constrained in the neighborhood of the steady state, given other parameters calibrated in the model. The term τ_i captures the degree of habits in consumption. The scaling factor $\Gamma_i = (1 - \tau_i)/(1 - \beta_i \tau_i)$ so that the marginal utility of consumption for impatient households is $1/c_i$ in the steady state. The term m_t denotes the loan-to-value (LTV) ratio which measures the effective degree of liquidity of houses, and is assumed to follow the AR(1) process:

$$lnm_t = (1-\rho_m) lnm + \rho_m lnm_{t-1} + u_{m,t},$$

where $u_{m,t}$ is identically and independently distributed with mean 0 and variance σ_m^2, and m is the steady-state value of the LTV ratio.

[6] The housing demand shock refers to the housing preference shock in this paper.

2.2. Banks

We formulate the problem of financial intermediaries with a modified version of the model proposed by Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). In the economy, there are a large number of banks operating in a national financial market. At each period, each bank obtains deposits d_t from patient households, and pays a nominal interest rate of R^d_{t+1} in the next period. After obtaining funds in the retail market, it issues residential loans b_t to impatient households at a nominal rate of R^b_{t+1}, and nonresidential loans to non-financial firms (wholesale producers) in exchange for state-contingent equities at a price of p_t. Each unit of equity is a state-contingent claim to the future returns from one unit of new capital investment.

Let s_t be the quantity of equities held by a representative bank, and n_t be the net worth of the bank in period t. The flow-of-funds constraint for a bank is

$$p_t s_t + b_t = n_t + d_t, \tag{1}$$

with

$$n_t = [Z_t + (1-\delta_k)p_t]\psi_t s_{t-1} + \frac{R^b_t b_{t-1}}{\pi_t} - \frac{R^d_t d_{t-1}}{\pi_t}, \tag{2}$$

where δ_k is the depreciation rate of capital, Z_t are dividends on equities issued in period $t-1$. The term ψ_t captures shocks to capital quality, and follows the AR(1) process:

$$ln\psi_t = \rho_k ln\psi_{t-1} + u_{k,t},$$

where $u_{k,t}$ is identically and independently distributed with mean 0 and variance σ^2_k. In the economy, a capital quality shock will directly reduce bank net worth, inducing a disruption in the bank's balance sheet. If the losses on the balance sheet initiated by the shock cannot be fully absorbed by banks, a credit crunch may arise.

To motivate an endogenous financial constraint on the bank's ability to obtain funds in the retail market, we follow a moral hazard problem along the lines of Gertler and Kiyotaki (2010): at the beginning of each period, a bank may divert a fraction θ of its assets to its owners (patient households) after obtaining funds (deposits) in the retial market. The bank's assets comprise the value of equities held by the bank, $p_t s_t$, and residential loans issued to impatient households, b_t. If the bank diverts its assets to its owners, it defaults on its debts and is then forced to shut down. The creditors may reclaim the remaining fraction $1-\theta$ of funds. Given the risks of banks' default on their debts, creditors restrict the amount they lend to the bank at the beginning of each period. Accordingly, banks are constrained in their ability to obtain funds in the retail financial market, and in this way a financial constraint may arise.

Let $V_t(s_t, b_t, d_t)$ be the value function of a bank at the end of period t, given its portfolio holdings (s_t, b_t, d_t). Banks are subject to the following incentive constraint

$$V_t(s_t, b_t, d_t) \geq \theta(p_t s_t + b_t). \tag{3}$$

An increase in θ will tighten the incentive constraint and, hence banks are less willing to issue loans to their borrowers for any given level of net worth, vice-versa.

In order to limit banks' ability to save to overcome financial constraint, we assume that each bank survives until the next period with a probability of σ, and exits with a probability of $1-\sigma$. If a bank exits, a new bank will enter the market with a "startup" fund transferred from patient households, and takes over the business of the exiting bank with no costs. Recall that in each period patient households receive an average net transfer F_t from banks. The net transfer then must equal the funds transferred from exiting banks minus funds transferred to start-ups.

Let $\Lambda_{t,t+i}$ be the stochastic discount factor for a bank between date t and date $t+i$. Since banks are owned by patient households, we assume $\beta_b = \beta_p > \beta_i$. Then, the stochastic discount factor for a bank is $\Lambda_{t,t+i} = \beta^i_p \frac{u_{c,t+i}}{u_{c,t}}$. In each period, a representative bank maximizes the expected net worth:

$$V_t(s_t, b_t, d_t) = \mathbb{E}_t \sum_{i=1}^{\infty} (1-\sigma)\sigma^{i-1}\Lambda_{t,t+i} n_{t+i}, \tag{4}$$

subject to the flow-of-funds constraint (1) and the incentive constraint (3). See more details regarding the derivation of the bank's optimality conditions in Appendix B.

From the bank's optimality conditions, one may easily derive the following relationship between assets and liabilities in terms of their returns

$$R_{t+1}^{k}=\frac{R_{t+1}^{b}}{\pi_{t+1}}>\frac{R_{t+1}^{d}}{\pi_{t+1}}. \tag{5}$$

Let S_t be total equities held by all banks at date t, B_t be total residential loans, and N_t be total net worth of all banks. Due to the homogeneity of banks, we obtain the flow-of-funds constraint of the banking system given by

$$p_tS_t+B_t=N_t+D_t, \tag{6}$$

and the relation between total assets and total net worth given by

$$p_tS_t+B_t=\varphi_tN_t, \tag{7}$$

Let $N_{o,t}$ be total net worth of ongoing banks at date t, and $N_{y,t}$ be total net worth of new banks. Then total net worth of the banking system is written as

$$N_t=N_{o,t}+N_{y,t}. \tag{8}$$

Since in each period a fraction σ of banks survive until the next period, the total net worth of ongoing banks is given by

$$N_{o,t}=\sigma\left\{[Z_t+(1-\delta_k)p_t]\psi_tS_{t-1}+\frac{R_t^bB_{t-1}}{\pi_t}-\frac{R_t^dD_{t-1}}{\pi_t}\right\}. \tag{9}$$

As we noted earlier, a fraction $1-\sigma$ of banks exit from the banking system at the end of each period, while new banks enter with a "start-up" fund transferred from patient households. We assume that each period patient households transfer a fraction $\xi/(1-\sigma)$ of total assets held by ongoing banks. Accordingly, the total net worth of new banks is given by

$$N_{y,t}=\xi\left\{[Z_t+(1-\delta_k)p_t]\psi_tS_{t-1}+\frac{R_t^bB_{t-1}}{\pi_t}\right\}. \tag{10}$$

2.3. Nonfinancial firms

2.3.1. The wholesale firms

To motivate price rigidity in the consumption sector, we differentiate between the wholesale firms that operate under competitive competition, and the retail firms that operate under monopolistic competition. At date t, each wholesale producer hires labors $l_{pc,t}$ and $l_{ic,t}$ from patient and impatient households, and pays a real wage of $w_{\text{pc},t}$ and $w_{\text{ic},t}$ to them, respectively. As we noted earlier, wholesale producers face no borrowing constraints. Instead, they borrow funds from banks by issuing new state-contingent equities at a price of p_t. In particular, each unit of equity is a state-contingent claim to the future returns from one unit of capital investment. Conditional on funds borrowed from banks, they purchase new capital as inputs from capital producers. In addition, we assume that wholesale producers combine labor and capital to produce wholesale consumption goods under a CRS technology in a Cobb-Douglas fashion. Due to perfect competition, the wholesale producers earn zero economic profits state-by-state.

A representative wholesale producer chooses hours ($l_{pc,t}$, $l_{ic,t}$) and capital k_t to produce wholesale goods Y_t. The producer solves the firm's profit maximization problem as follows:

$$max\frac{Y_t}{\Xi_t}-w_{\text{pc},t}l_{\text{pc},t}-w_{\text{ic},t}l_{\text{ic},t}-Z_tk_t,$$

where Ξ_t is the markup of retail goods over wholesale goods. The production technology is given by

$$Y_t=\left[A_{c,t}\left(l_{\text{pc},t}^{\alpha}l_{\text{ic},t}^{1-\alpha}\right)\right]^{1-\mu_c}k_t^{\mu_c}, \tag{11}$$

where α is the labor income share of patient households, reflecting labor complementarity across different labor skills among households, and μ_c is the income share of capital used in the production of final goods. Note that capital stock k_t is predetermined in period $t-1$. The term $A_{c,t}$ captures shocks to labor productivity in the wholesale sector, and follows the AR(1) process:

$$lnA_{c,t}=\rho_c lnA_{c,t-1}+u_{c,t},$$

where $u_{c,t}$ is identically and independently distributed with mean 0 and variance σ_c^2.

2.3.2. The retail firms

As in Bernanke et al. (1999), retail firms operate under monopolistic competition at the retail market. There are a continuum of retail firms of mass 1 in the market. Retail firms buy wholesale goods Y_t from wholesale firms at the competitive nominal price $p_{c,t}/\Xi_t$, differentiate the goods at no costs, and sell them at a price $p_{c,t}(i)$. Following Smets and Wouters (2003), the aggregate output index is given by the CES aggregator with *time-varying* desired markup $1+\zeta_t$:

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{1}{1+\zeta_t}} \mathrm{d}i\right]^{1+\zeta_t},$$

where $Y_t(i)$ is the quantity of good i supplied by the retail firm in period t, and $\zeta_t = \zeta + u_{cp,t}$, where $u_{cp,t}$ is the cost-push shock in equilibrium. Also note that, in equilibrium, the steady state markup Ξ equals to $1+\zeta$.

Retail firms choose price according to Calvo pricing, so that a fraction $1-\lambda$ of retial firms reset their prices optimally in any given period, while a fraction λ of retail firms index their prices automatically. As in Smets and Wouters (2003), we allow for partial indexation. Consequently, a representative retail firm sets its optimal price $p_{c,t}(i)$ to maximize the discount profits as follows:

$$\sum_{\tau=0}^{\infty} \lambda^\tau \mathbb{E}_t \left\{ \Lambda_{t,t+\tau} \left(\frac{p_{c,t}(i)\Delta_{t,t+\tau}}{p_{c,t+\tau}} - \frac{1}{\Xi_{t+\tau}} \right) Y_{t+\tau}(i) \right\}, \tag{12}$$

where $Y_{t+\tau}(i)$ is the demand function for good i in period $t+\tau$, given reset price $p_{c,t}(i)$:

$$Y_{t+\tau}(i) = \left[\frac{p_{c,t}(i)\Delta_{t,t+\tau}}{p_{c,t+\tau}}\right]^{-\frac{1+\zeta_{t+\tau}}{\zeta_{t+\tau}}} Y_{t+\tau},$$

and $\Delta_{t,t+\tau}$ stands for inflation indexation which is defined as:

$$\Delta_{t,t+\tau} = \begin{cases} \prod_{k=0}^{\tau-1} (\pi_{t+k})^{\iota}, & \tau \geq 1, \\ 1, & \tau = 0, \end{cases}$$

with $\iota > 0$ determining the degree of indexation. The resulting Phillips curve is given by:

$$ln\pi_t - \iota ln\pi_{t-1} = \beta_p(\mathbb{E}_t ln\pi_{t+1} - \iota ln\pi_t) - \frac{(1-\lambda)(1-\beta_p\lambda)}{\lambda} ln\frac{\Xi_t}{\Xi} + u_{cp,t}, \tag{13}$$

where $u_{cp,t}$ denotes the cost-push shock, which is independently and identically distributed with mean 0 and variance σ_{cp}^2. For simplicity, we assume that profits from retail firms will be redistributed to patient households.

2.3.3. The housing firms

Housing producers hire labor ($l_{ph,t}$, $l_{ih,t}$) from the two groups of households, and rent land x_{t-1} from patient households to produce new houses $I_{h,t}$ under the CRS technology in a perfectly competitive market. Accordingly, a representative housing producer solves

$$max q_t I_{h,t} - w_{ph,t} l_{ph,t} - w_{ih,t} l_{ih,t} - R_t^x x_{t-1}.$$

The production technology is given by

$$I_{h,t} = [A_{h,t}(l_{ph,t}^{\alpha} l_{ih,t}^{1-\alpha})]^{1-\mu_h} x_{t-1}^{\mu_h}, \tag{14}$$

where μ_h is the income share of land used to produce new houses. The term $A_{h,t}$ captures shocks to labor productivity in the housing sector, and follows the AR(1) process:

$$lnA_{h,t} = \rho_h lnA_{h,t-1} + u_{h,t},$$

where $u_{h,t}$ is identically and independently distributed with mean 0 and variance σ_h^2.

2.3.4. The capital goods firms

Capital goods producers produce new capital using consumption goods as inputs, and are subject to an adjustment cost. A capital producer chooses capital investment $I_{k,t}$ to solve

$$max\mathbb{E}_t\sum_{i=t}^{\infty}\Lambda_{t,i}\{p_iI_{k,i}-[1+\frac{\chi_k}{2}(\frac{I_{k,i}}{I_{k,i-1}}-1)^2]I_{k,i}\},$$

where p_t is the price of new capital, χ_k is the parameter of the adjustment cost, and $\Lambda_{t,i}$ is the patient household's stochastic discount factor from date i to date t.

The optimality condition then yields the price function for capital:

$$p_t=1+\frac{\chi_k}{2}(\frac{I_{k,t}}{I_{k,t-1}}-1)^2+\chi_k(\frac{I_{k,t}}{I_{k,t-1}}-1)\frac{I_{k,t}}{I_{k,t-1}}-\chi_k\Lambda_{t,t+1}(\frac{I_{k,t+1}}{I_{k,t}}-1)(\frac{I_{k,t+1}}{I_{k,t}})^2. \tag{15}$$

Note that profits will arise only outside of the steady state, and will be redistributed to patient households by a lump sum transfer.

2.4. The central bank

To close the model, the central bank sets the nominal interest rate R_t^d, based on a Taylor rule that responds to inflation and GDP growth:[7]

$$\frac{R_t^d}{R^d}=(\frac{R_{t-1}^d}{R^d})^{\alpha_r}[\pi_t^{\alpha_\pi}(\frac{\mathrm{GDP}_t}{\mathrm{GDP}_{t-1}})^{\alpha_y}]^{1-\alpha_r}exp(u_{\mathrm{mp},t}), \tag{16}$$

where R^d is the steady-state value of nominal interest rate. The monetary policy shock $u_{mp,t}$ is independently and identically distributed with mean 0 and variance σ_{mp}^2.

2.5. Equilibrium

In equilibrium, the market clearing conditions for goods, housing, and equities/capital are as follows,

$$Y_t=C_t+[1+\frac{\chi_k}{2}(\frac{I_{k,t}}{I_{k,t-1}}-1)^2]I_{k,t}, \tag{17}$$

$$I_{h,t}=H_t-(1-\delta_h)H_{t-1}, \tag{18}$$

$$S_t=I_{k,t}+(1-\delta_k)K_t, \tag{19}$$

$$K_{t+1}=\psi_{t+1}[I_{k,t}+(1-\delta_k)K_t]. \tag{20}$$

Note that $C_t=c_{p,t}+c_{i,t}$ is aggregate consumption, $H_t=h_{p,t}+h_{i,t}$ is aggregate housing stock. The equation (20) is the law of motion for capital in the presence of an exogenous capital quality shock. Land per capita is fixed and normalized to one. The model GDP_t is defined as the sum of consumption output and the housing investment evaluated at house prices:

$$\mathrm{GDP}_t=Y_t+q_tI_{h,t}. \tag{21}$$

The dynamic system of the baseline model is described in details in Appendix C.

A final remark before discussing the quantitative results is about the capital quality shock. Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) make the capital quality shock ψ_t a standard modeling device for studying financial friction. Yet viewing through the lens of capital accumulation process (20), it is evident that the capital quality shock is closely related to the so called investment specific shock, which is identified as the major source of business cycle fluctuations for the US by Justiniano et al. (2010). More precisely, we can write the law of motion for capital as $K_{t+1}=\psi_{t+1}I_{k,t}+\psi_{t+1}(1-\delta)K_t$, where the capital quality shock ψ_{t+1} associated with investment $I_{k,t}$ is equivalent to the marginal efficiency of investment shock named by Justiniano et al. (2011). In the quantitative evaluation of Justiniano et al. (2011), this shock is shown to be the most important driving force for the US business cycles, and its "news" shock version is also confirmed by Schmitt-Grohé and Uribe (2012) to play the major role in investment fluctuations. Given that the investment shock plays such an important role in an advanced country such as the US, it is intuitive to expect that the closely related capital quality shock can play an even more significant role in an emerging economy such as China, where investment and capital accumulation at large claim a much bigger share of the economy compared to advanced countries.

[7] Although the Taylor rule specification is standard in the DSGE literature, there are still a lot of debates on how to characterize China's monetary policy rule in DSGE frameworks. Recent studies on China offer a variety of modeling choices and wide-range variations in terms of quantitative implications; a partial list of references inludes: Li and Liu (2017), Chen et al. (2018), Minetti and Peng (2018), Gai et al. (2020), and Le et al. (2021). Indeed, during the past two decades, the monetary policy operation framework has undergone important transformations from a quantity based to an interest rate based system in China, which poses a difficult modeling obstacle. We do not take a strong stand on this issue, but simply use a Taylor-type rule to close the model.

Table 1
Calibrated parameters.

Parameters	Description	Value
β_p	Discount factor for savers	0.9975
β_i	Discount factor for borrowers	0.965
δ_k	Depreciation rate of capital	0.03
δ_h	Depreciation rate of houses	0.0097
μ_c	Share of capital	0.30
μ_h	Share of land	0.3097
θ	Fraction of assets diverted by banks	0.5961
ξ	Fraction of funds transferred to new banks	0.0089
j	Housing preference weight	0.2502
m	Steady state loan-to-value ratio	0.70
σ	Survival rate of banks	0.95
α	Labor income share of patient households	0.64
Ξ	Steady state gross markup	1.15

3. Model calibration and estimation

We proceed to parameterize the model by dividing parameters into two sets. For the first set, we calibrate the parameters so that the model steady state replicates the key features of China's macroeconomy. For the second set, mostly related to shock processes, we use the standard Bayesian method to estimate the parameters. Taken together, the model is able to capture both the steady state structure and the dynamics of China's macroeconomy.

3.1. Data and calibration

We first calibrate a subset of parameters to match a range of targeted ratios of key economic quantities consistent with the Chinese data from 2000Q1 to 2018Q4. Table 1 summarizes our calibrations. The discount factor of patient households β_p is set equal to 0.9975, implying that a steady-state annual real interest rate of 1%. Following Iacoviello and Neri (2010), the discount factor of impatient households β_i is arbitrarily set equal to 0.965, which is less than the value of β_p, ensuring that the borrowing constraint of impatient households is binding around the neighborhood of the steady state. In general, the lower is the value of β_i, the more likely will the borrowing constraint bind away from the steady state. The survival rate of banks σ is arbitrarily set equal to 0.95, implying that the expected survival horizon of banks are five years on average.[8] The fraction of funds transferred from patient households ξ, and the fraction of assets that can be diverted from banks to patient households θ are set equal to 0.0089 and 0.5961, respectively, in order to match two targets: an average leverage ratio of 2.96 from all commercial banks in China and an average annual interest spread of 3%. We set the target for the annual interest spread to 3%, based on a rough average of the following two spreads: AA-corporate bond rates versus government bond rates, and mortgage rates versus government bond rates.

Due to the availability of the data, we choose the depreciation rate of capital $\delta_k = 0.03$, and the capital share in the wholesale sector $\mu_c = 0.3$ in line with the existing literature.[9] The depreciation rate of housing δ_h is set equal to 0.0097, and the land share in the housing production μ_h is set equal to 0.3097, implying a steady-state residential investment to GDP ratio of 12% and a steady-state land value to annual GDP ratio of 3.7. Land share in the housing production in China is greater than that in the United States, since land prices relative to wages on average are higher in the former than that in the latter.[10] The housing preference weight j is set equal to 0.25. Given the value of input shares in the housing production function and other parameters calibrated, the choice of housing preference weight implies a steady-state housing wealth to annual GDP ratio of 3.1. The value of housing preference weight calibrated is greater than that for the United State.[11] Due to the differences in culture and saving behaviors, households in China exhibit more preference towards housing than households in the United States. This partially explains why the ownership rate of housing in China is much higher than that in the United States.[12] According to the recent housing policies in China, home buyers are allowed to borrow up to a limit equal to 70 percent of the housing value when they buy their first home with mortgages. In this regard, we set the LTV ratio equal to 0.70.

The labor income share α, obtained by unconstrained households from wholesale good production, is not available in China's data. As a result, we follow Iacoviello (2005) and set $\alpha = 0.64$, which is within the range of the estimates reported by the existing literature

[8] Although the expected survival time of banks might be longer, we only require that the expected time horizon is finite in order to prevent the banks from accumulating assets to overcome the incentive constraints. An alternative choice of the survival rate has little effect on the business cycle properties reproduced by the model.

[9] The data for capital stock in China is not available. For simplicity, we set the values of the capital depreciation rate and capital share equal to that used commonly in the literature.

[10] Land share is only 0.1 in the U.S., as calibrated by Iacoviello and Neri (2010).

[11] The housing preference weight for the U.S. calibrated by Iacoviello and Neri (2010) is only 0.12.

[12] According to the Current Population Survey conducted by the U.S. Census Bureau, the ownership rate of housing is roughly 65 percent in 2018. The ownership rate of housing in China is about 90 percent in recent years, based on the report by the National Bureau of Statistics of China.

Table 2
Prior and posterior distribution of the parameters.

Parameter	Prior distribution			Posterior distribution		
	Dist. type	Mean	Std. Dev.	Mean	5%	95%
χ_k	Gamma	1	0.50	2.6554	1.8223	3.4940
ι	Beta	0.50	0.20	0.1969	0.0362	0.3577
λ	Beta	0.667	0.05	0.6659	0.6164	0.7172
α_r	Beta	0.75	0.10	0.7899	0.7158	0.8609
α_π	Normal	1.50	0.10	1.5323	1.4014	1.6770
α_y	Normal	0	0.10	0.0779	0.0033	0.1555
τ_p	Beta	0.50	0.075	0.3621	0.2882	0.4299
τ_i	Beta	0.50	0.075	0.4372	0.2954	0.5413
η_p	Gamma	0.50	0.10	0.6408	0.4814	0.7976
η_i	Gamma	0.50	0.10	0.5492	0.3815	0.6819
ε_p	Normal	1.00	0.10	1.0519	0.9345	1.1916
ε_i	Normal	1.00	0.10	1.0210	0.8370	1.1906
ρ_c	Beta	0.80	0.10	0.9176	0.8791	0.9698
ρ_h	Beta	0.80	0.10	0.8939	0.8350	0.9495
ρ_k	Beta	0.80	0.10	0.9648	0.9391	0.9903
ρ_j	Beta	0.80	0.10	0.9928	0.9879	0.9974
ρ_p	Beta	0.80	0.10	0.8979	0.8227	0.9596
ρ_m	Beta	0.80	0.10	0.7050	0.6077	0.8181
ρ_n	Beta	0.80	0.10	0.7818	0.6870	0.8785
σ_c	Inv. Gamma	0.001	0.01	0.0164	0.0138	0.0181
σ_h	Inv. Gamma	0.001	0.01	0.0474	0.0423	0.0543
σ_k	Inv. Gamma	0.001	0.01	0.0018	0.0012	0.0023
σ_j	Inv. Gamma	0.001	0.01	0.0728	0.0573	0.0864
σ_p	Inv. Gamma	0.001	0.01	0.0159	0.0110	0.0202
σ_m	Inv. Gamma	0.001	0.01	0.0384	0.0320	0.0431
σ_n	Inv. Gamma	0.001	0.01	0.0237	0.0194	0.0282
σ_{mp}	Inv. Gamma	0.001	0.01	0.0005	0.0003	0.0007
σ_{cp}	Inv. Gamma	0.001	0.01	0.0008	0.0002	0.0012

such as Jappelli (1990) and Kiyotaki et al. (2011). We choose $\Xi = 1.15$ in line with Iacoviello and Neri (2010), implying a markup of 15% in the consumption good market.

3.2. Bayesian estimation

We estimate the remaining structural parameters and shock processes using the standard Bayesian method (An & Schorfheide, 2007). The prior distribution of the parameters used are along the lines of Iacoviello and Neri (2010) and Iacoviello (2015). Table 2 reports the prior distribution of the parameters. The observables we used in the estimation include (i) real private consumption, (ii) real residential investment, (iii) real house prices, (iv) real residential loans, (v) bank leverage ratio, (vi) inflation, and (vii) total working hours.[13,14] We choose the set of observables with the aim of describing the dynamics of the housing and financial sector in aggregate as accurately as possible.[15] Except for inflation, all data are log-transformed and detrended using the HP-filter with the smoothing parameter equal to 1, 600. The detrended data are plotted in Fig. 1. We combine different data sources to construct the set of observables. In particular, we overcome a host of typical data limitations to construct the sectoral bank loan series dating back to 2000, and to construct a total labor series measured in working hours rather than persons. See Appendix A for data description and construction in details.

Table 2 also reports the posterior mean and 90% confidence interval for the parameters being estimated. Most shocks are quite

[13] Within the model, consumption refers to consumption of non-durable goods and services net of housing services, if a housing sector is explicitly modelled. Since the data on consumption of durables and consumption of non-durables for China is not available, the use of consumption expenditure (including both durables and non-durables) is a compromise. An important caveat is that consumption of durables should be included into nonresidential investment so long as the data is available. Failure to do so always reproduces a much higher volatility in nonresidential investment, relative to its data counterpart. This is crucial since different treatments over consumption of durables could affect the results on the drivers of business cycles within the DSGE framework. We conjecture that the contribution of capital quality shocks to nonresidential investment, output and hours would be increased if nonresidential investment including consumption of durables is used as observables in the estimated model. See more discussions on this issue in Justiniano et al. (2010).

[14] To deal with the concerns regarding the credibility of the estimation, which is based on the data of mis-specified consumption and noisy hours, we alternatively estimate the model using the observables without consumption and hours, and find that the estimated values of most parameters are quite similar to that of the baseline model, and data statistics are still within the 95% simulated confidence interval using alternative estimated parameters.

[15] Consistent with the previous discussion on our choice of monetary policy specification, we do not use the policy rule as an observation equation in the estimation.

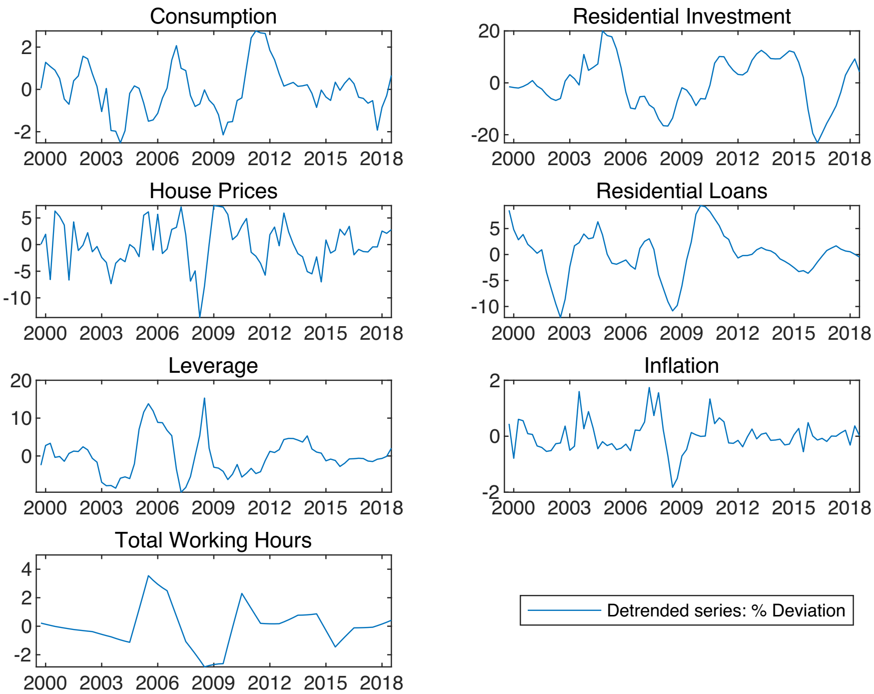

Fig. 1. Data used in estimation. Notes: All time series are detrended using the HP filter with the smoothing parameter equal to 1600, except for inflation.

persistent, with autocorrelation coefficients ranging from 0.70 to 0.99. The volatility of housing demand shocks is found to be much higher than that of the other shocks, with a standard deviation of 0.0728, implying that the housing demand shocks play an important role in China's business cycles. The volatilities of the monetary and cost-push shocks are quite small, and are only 0.0005 and 0.0008, respectively. The labor supply elasticities of the two types of households are approximately close to 0.5 (i.e. $\eta_p = 0.6408$ and $\eta_i = 0.5492$), and the values of the parameters that measure the degree of labor mobility across the production sectors are approximately close to 1 (i.e. $\varepsilon_p = 1.0519$ and $\varepsilon_i = 1.0210$), both of which are consistent with the literature. Moreover, the degree of habits in consumption for impatient households is larger than that for patient households ($\tau_p = 0.3621$ and $\tau_i = 0.4372$), along the lines of Iacoviello and Neri (2010). Last, our estimation gives a reasonable value of the cost adjustment parameter (i.e. $\chi_k = 2.6554$). According to Born and Pfeifer (2014) and Christiano et al. (2015), the value of the parameter in general is within the range between 1 and 6.

4. Quantitative results

4.1. The fitting of the baseline model

In this section, we investigate whether our estimated model fits the business cycle properties observed in the Chinese data, focusing in particular on the volatility and cyclicality of the observed variables, and then determine the main driving forces of business cycle fluctuations in the housing and financial markets and the macroeconomy in China. Table 3 reports the model implied volatility and cyclicality of the variables of interest. We find that most of the data statistics are within the 95% probability interval simulated from the baseline model, and it replicates well the volatility and cyclicality of these observed variables. In particular, the estimated model approximately reproduces the volatilities of consumption, nonresidential investment, house prices, net worth, nonresidential loans, deposits, bank leverage, inflation and hours relative to GDP. However, it underestimates the volatility in residential investment, and overestimates the volatility in residential loans. In addition, the model replicates well the comovement of output with consumption, investment, net worth, loans, deposits, leverage and inflation, but it overstates the comovement with house prices and hours. Though the baseline model has its own shortcomings in replicating few data statistics, it is successful in its ability in accounting for the volatility and cyclicality of most variables being concerned.

4.2. Further validation of the baseline model

One of the main critiques on DSGE models is that they can do a good job at fitting the data in sample, but might have poor performance otherwise (Iacoviello, 2015). To address this problem, we conduct an external validation test to assess the reliability of the model in fitting time series that were not used as observables in the estimation. Fig. 2 plots the time series for net worth, nonresidential loans and deposits simulated by the estimated model against their data counterparts. In particular, net worth simulated by the model

Table 3
Business cycle properties of the baseline model.

Variables	Data	Model	2.5%	97.5%
Panel A: *SD of GDP and relative SD w.r.p.t GDP* (%)				
GDP	1.48	1.86	1.28	2.61
Consumption	0.78	0.75	0.52	1.06
Invest., capital	2.12	2.92	1.68	4.60
Invest., housing	6.49	3.66	2.42	5.30
House prices	2.83	2.78	1.80	4.10
Net worth	4.95	4.34	2.80	6.46
Loans, non-res.	2.46	1.80	1.17	2.67
Loans, res.	3.03	8.79	5.81	12.78
Deposits	1.96	2.12	1.45	3.01
Bank leverage	3.48	3.78	2.41	5.63
Inflation	0.39	0.38	0.23	0.58
Labor, total	0.91	1.22	0.84	1.72
Panel B: *Correlations with GDP*				
Consumption	0.38	0.66	0.32	0.87
Invest., capital	0.49	0.41	−0.07	0.76
Invest., housing	0.57	0.58	0.23	0.82
House prices	0.13	0.54	0.15	0.80
Net worth	0.24	0.13	−0.23	0.46
Loans, non-res.	0.25	0.17	−0.18	0.49
Loans, res.	0.38	0.39	0.03	0.67
Deposits	0.29	0.48	0.16	0.72
Bank leverage	−0.12	0.08	−0.27	0.41
Inflation	0.01	−0.03	−0.34	0.27
Labor, total	0.20	0.55	0.21	0.79

Notes: The table reports the mean value of simulated statistics and its 95% confidence interval. The statistics are computed with a random selection of 500 draws from the posterior distribution and, for each of them, 100 artificial time series of the variables of length equal to that of the data. Each simulated time series has been detrended using the HP filter with the smoothing parameter equal to 1600.

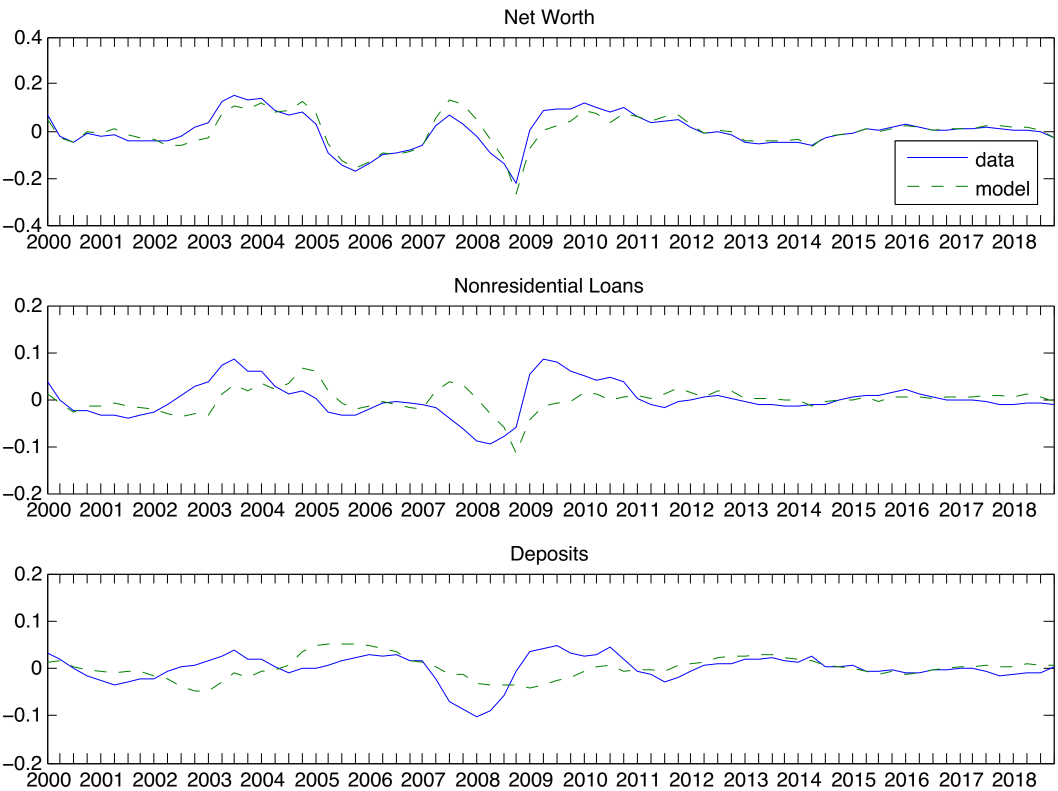

Fig. 2. External validation test. Notes: The solid line plots actual data over the period of 2000–2018, and the dash line plots time series simulated by the model. The y-axis measures deviation from the trend. All time series are detrended using the HP filter with smoothing parameter equal to 1600.

Table 4
Variance decomposition of the forecast errors.

Variables	Capital q.	Tech., n-h	Tech., h	Dem., h	Int. pref.	LTV	Labor	Money	Cost push
GDP	2.22	39.76	12.92	12.72	2.01	2.54	27.75	0.07	0.02
Consumption	9.15	44.79	0.23	6.54	10.62	5.33	23.18	0.11	0.04
Invest., capital	26.73	21.09	0.14	15.48	10.95	17.70	7.87	0.04	0.00
Invest., housing	0.12	0.06	80.00	11.95	1.13	0.99	5.74	0.00	0.00
House prices	1.58	3.91	0.25	87.79	3.87	0.25	2.32	0.02	0.01
Net worth	30.67	2.35	0.13	32.28	0.54	32.53	1.09	0.40	0.01
Loans, non-res.	20.26	6.80	0.11	34.81	3.57	28.09	6.20	0.14	0.02
Loans, res.	3.31	2.20	0.10	60.81	1.92	30.91	0.59	0.16	0.01
Deposits	7.16	8.49	0.12	42.50	10.22	25.22	6.21	0.06	0.02
Bank leverage	20.45	0.43	0.17	40.08	1.38	36.91	0.35	0.23	0.00
Inflation	24.80	13.57	0.17	13.64	17.92	6.34	21.85	1.56	0.15
Labor, total	2.70	6.53	13.28	15.02	1.14	15.06	46.22	0.03	0.02

Notes: The table reports the variance decomposition of the forecast errors at business cycle frequencies correspond to periodic components with cycles between 6 and 32 quarters (extracted using the bandpass filter). All values are measured in percentage.

mimics its data counterpart over the sample period. Both nonresidential loans and deposits simulated by the model mimic their data counterparts in most of the sample period, especially during the post-crisis period. Accordingly, the estimated model is reliable in accounting for the China's business cycles, since it replicates well the business cycle statistics of most variables being concerned.

4.3. Shock decomposition

Since the estimated model fits the data reasonably well, we use it to determine the sources of China's business cycles. Table 4 reports the variance decomposition of the forecast errors at business cycle frequencies. As shown in Table 4, capital quality shocks explain more than 25 percent of the variance in nonresidential investment, and explain a large fraction of the variance in net worth, nonresidential loans, bank leverage and inflation at business cycle frequencies, between 20 and 31 percent. But, the contribution of capital quality shocks to the variance in housing and labor quantities is small. Housing demand and supply shocks together explain a significant portion of the variance in most variables, indicating that the housing market is at the center in driving the China's business cycles in our sample period. LTV shocks and labor supply shocks also play an important role in the China's business cycles. In particular, LTV shocks explain more than 25 percent of the variance in financial variables such as net worth, loans, deposits and bank leverage, and relatively less of the variance in other macroeconomic variables. Labor supply shocks explains more than 20 percent of the variance in consumption, output, inflation and hours, but the effects on the variance of other quantities are relatively small. Non-housing technology shocks explains a large portion of the variance in consumption, nonresidential investment, output and inflation, between 13 and 45 percent, implying that the non-housing technology shocks are critical to the business cycle fluctuations along the lines of the literature such as Kydland and Prescott (1982), King and Rebelo (1999), Smets and Wouters (2007).

The model identified monetary policy and cost-push shock both play a limited role in the business cycle fluctuations in China. For the cost-push shock, the result is consistent to the recent findings of Le et al. (2021). For the monetary policy shock, the recent literature seems to suggest substantial uncertainty of its quantitative significance in China and stress the sensitivity on policy rule specifications.[16] Given the continual debate on modeling China's monetary policy rule in DSGE frameworks, we tend to be conservative in drawing out any conclusion on the role of monetary policy shock identified in our model and estimation.

Taken together, capital quality, non-housing technology, housing demand and supply, LTV and labor supply shocks are the main driving forces of the China's business cycles, accounting for more than 80 percent of the variance in all variables being concerned. A related question that one might ask is how these shocks contribute to cyclical movements of business cycles, or perhaps, how important were the shocks in shaping the recent business cycles in China. To answer these questions, we provide a visual representation of historical decompositions for several key variables being concerned. Fig. 3 illustrates the historical contribution of these driving forces under our estimated parameters. The solid line plots actual data, which is expressed in deviation from its trend. The bars show the historical contribution of the six factors under our estimated parameters. As shown in Fig. 3, capital quality shocks play an important role in accounting for the variations in inflation and leverage, especially during the Great Recession. Notice that they also explain a relatively large fraction of the variations in consumption over the sample period. It suggests that capital quality shocks are critical to the China's business cycles, and thus cannot be neglected. The contribution of housing demand shocks to the fluctuations in house prices appears relatively more important than the contribution of other shocks, accounting for the variations in house prices at a significantly large degree. In addition, housing demand shocks are important to the fluctuations in financial variables, such as leverage

[16] The recent literature suggests that the importance of monetary policy shock to China's business cycles really hinges on the policy rule specifications. For instance, according to the estimation results reported by Li and Liu (2017), the contribution of monetary policy shock to GDP may range from 90% under the interest rate rule to 2–4% under the money growth rule, while the contribution to inflation is trivial. In contrast, Le et al. (2021) reports that shocks to the interest rate rule of monetary policy accounts for 11% of output fluctuation while money growth shock accounts for 0.7% only. Moreover, Minetti and Peng (2018) specifies a money growth rule and find that the monetary policy shock contributes around 6% to output fluctuation, while Gai et al. (2020) reaches a similar number around 4–5% using an interest rate rule.

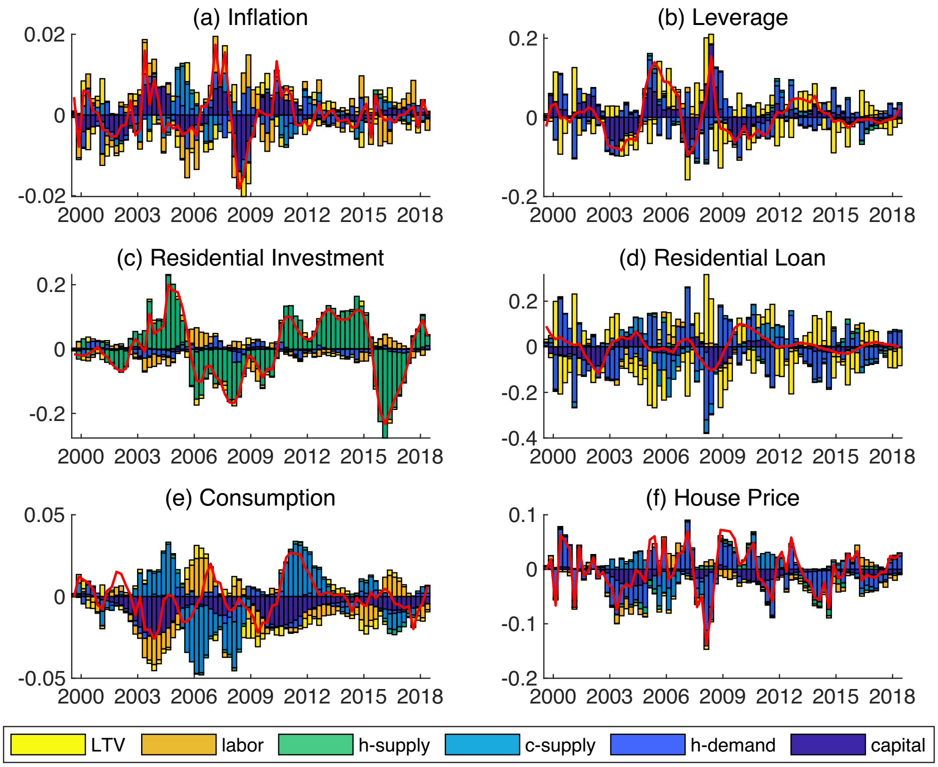

Fig. 3. Historical decomposition of the estimated model. Notes: The solid lines plot actual data series over the period of 2000–2018, and the bars show the contributions of the estimated shocks. The y-axis measures deviation from the trend. All time series are detrended using the HP filter with smoothing parameter equal to 1600.

and residential loans, which supports the prevalent view that financial cycles are also driven by housing disturbances. Housing demand and supply shocks together account for almost the entire variations in residential investment, but the latter dominates the former over the sample period. Not surprisingly, the contributions of the LTV shocks to the fluctuations in financial variables are larger than that to the fluctuations in non-financial variables, since the LTV shocks have a direct impact on the bank's balance sheet. The contribution of non-housing technology shocks to the fluctuations in consumption is large, whereas it is modest to the fluctuations in other macroeconomic variables.

5. Inspecting the mechanisms of China's macroeconomic dynamics

5.1. Capital quality shocks

Fig. 4 plots the impulse responses of the key variables of interest to a negative capital quality shock. The solid line represents the dynamic paths for the baseline model, and the dash line represents the dynamic paths for the model without incentive constraints (financial frictions).

With financial frictions, a decline in capital quality immediately leads to a decrease in bank net worth. The decline in net worth is fundamentally a product of a high bank leverage ratio and a large loss in asset values. In particular, an exogenous shock affects bank net worth in two ways. First, an initial capital quality shock directly reduces the value of equities held by banks, and hence their net worth. Because the bank is highly leveraged, the effect on its net worth would be magnified by a factor equal to the bank's leverage ratio. Second, the decline in bank net worth then tightens the bank's incentive constraint, causing a decrease in assets (equities) demanded. Eventually, the price of equities falls. This second round effect further depresses the value of equities, and thereby induces a large loss in bank net worth and a significant rise in the spread.

In order to respond to the decline in net worth, the bank must reduce the amount of funds lent to impatient households and wholesale firms. This leads to a significant decline in residential loans and nonresidential loans. Since nonresidential investment is financed by nonresidential loans, the former declines as the latter falls. As a result, both capital stock and output decrease. Because the decline in bank net worth exceeds that in loans, the bank leverage ratio rises. Banks can restore their leverage ratio either by deleveraging or accumulating more net worth. In the process of deleveraging, banks have to increase their net worth. As shown in Fig. 4, an increase in net worth is accompanied by a decline in the spread. So long as the spread is above its trend, net worth cannot immediately revert to it's steady-state level. Throughout the transition path to the long-run trend, the convergence process is slow and it takes a long

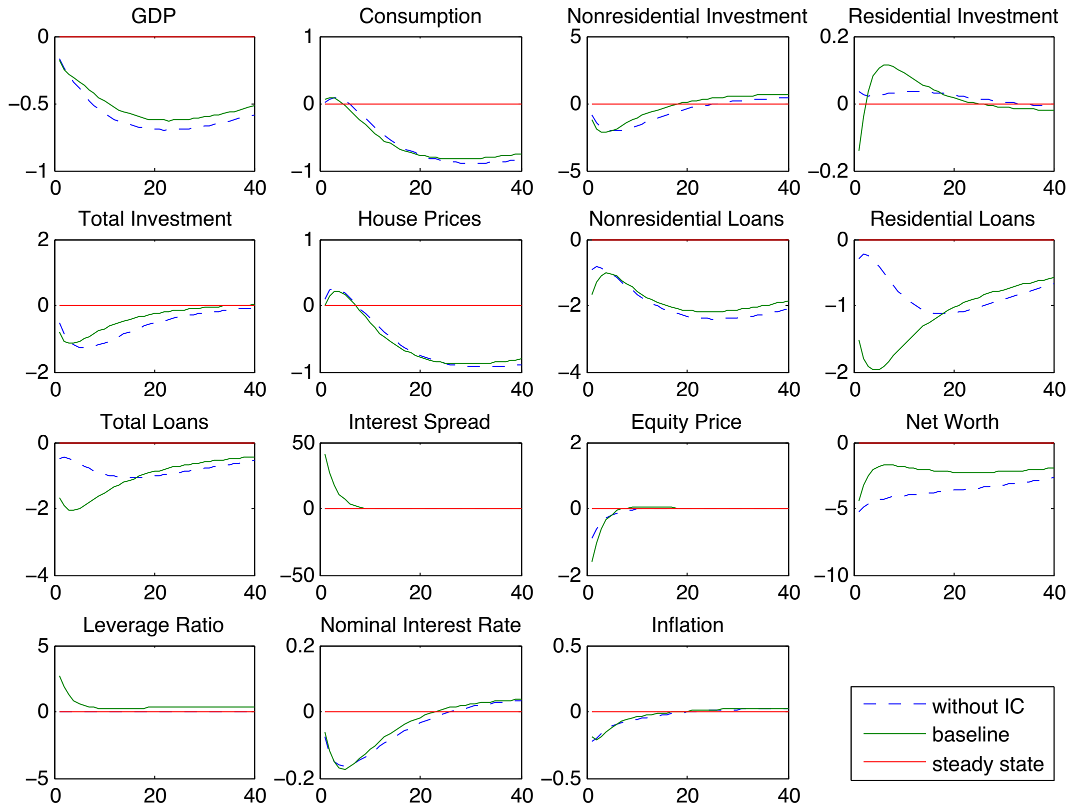

Fig. 4. Impulse responses to a negative capital quality shock. Notes: The vertical axis measures percent deviation from the steady state.

time for a bank to restore its leverage ratio. Strictly speaking, the change in the spread between expected returns on assets and costs on liabilities induced by the financial frictions slows down the pace of economic recovery. In this way, our baseline model is able to capture the mechanism through which the deleveraging process slows down the recovery of the economy during the recession in line with Gertler and Kiyotaki (2010).

Next, we consider the responses of residential investment and consumption. The dynamics of these variables are affected by the behaviors of households. For impatient households, both housing investment and consumption fall since the shock mitigates their collateral capacities. For patient households, residential investment rises but consumption declines over time. This can be attributed to a dominant substitution effect by which patient households substitute towards housing and away from consumption goods, since the expected gains from housing exceeds the temporary losses induced by a decline in house prices. Due to the offsetting mechanism between the two types of households, both house prices and residential investment fall. Note that house prices rise initially due to the fact that the increase in residential investment of patient households outweighs the decline in residential investment of impatient households. But, house prices eventually fall as the negative effects on residential investment of impatient households dominate.

Fig. 4 also displays the impulse responses for the model without financial frictions, while holding the parameters at the benchmark values. Absent financial frictions, interest spread and bank leverage ratio remain constant over time. Accordingly, a frictionless model is unable to capture the dynamics of these variables.

Last, we consider the responses of nominal interest rate (policy rate) and inflation. When GDP decreases in response to a negative capital quality shock, inflation falls, causing a decline in policy rate.

5.2. *Housing demand shocks*

Fig. 5 plots impulse responses to an estimated housing demand shock. In the baseline model, a positive housing demand shock drives up housing demand and house prices, and in turn, relaxes the collateral constraints of borrowers. Consequently, residential loans increase. Aggregate consumption rises on impact as a consequence of the increase in consumption of credit-constrained households, even if consumption of unconstrained households falls. Since an increase in residential loans crowds out nonresidential loans, both nonresidential investment and equity prices fall over time. In particular, when the demand for capital decreases, equity prices must fall, and thus a drop in net worth. So long as net worth is below the trend, the spread must rise. Similar to the case with capital quality shocks, bank leverage rises on impact as an outcome of the decline in net worth. When both consumption and residential investment increase, GDP rises over time, even if nonresidential investment falls.

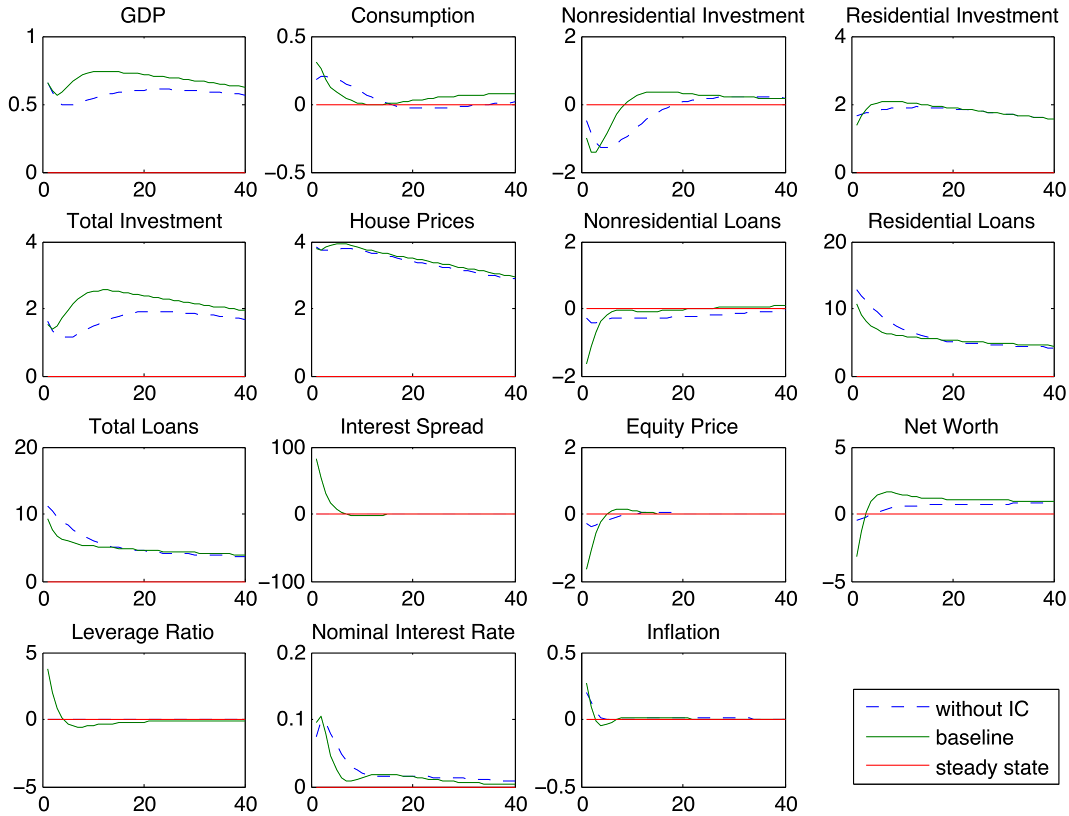

Fig. 5. Impulse responses to a housing demand shock. Notes: The vertical axis measures percent deviation from the steady state.

5.3. Other shocks

Next, we summarize the responses of aggregate variables to the other shocks (not reported).[17] A contractionary monetary shock reduces loans and house prices. The negative response of nonresidential investment to the shock is primarily due to a decline in nonresidential loans. When the demand for capital decreases, equity prices fall over time, and bank net worth is then reduced. Consequently, both the spread and leverage rise. The responses of consumption and residential investment to the shock are affected by the behaviors of households. In particular, a decrease in residential loans tightens the budget constraints of credit-constrained households, leading to a decline in consumption and housing demand. However, consumption and the housing demand of unconstrained households vary in a different way. Due to the substitution effects induced by the decline in house prices, consumption falls but housing demand rises. When the substitution effects dominate, aggregate consumption falls, and aggregate residential investment rises. Residential investment is sensitive to the interest rate only when wage rigidity is present, following Iacoviello and Neri (2010). Absent this friction, residential investment may rise in response to a contractionary monetary shock.

Positive technology shocks in the consumption goods sector drive up consumption, nonresidential investment, GDP and house prices, but crowd out residential investment, implying that the model with supply-side shocks alone is unable to account for the positive comovement between residential investment and house prices observed in the data. Positive technology shocks in the housing sector lead to an increase in consumption, residential investment and GDP, and a decrease in nonresidential investment and house prices. The negative comovement between residential investment and house prices reproduced by the model is a general outcome of the supply-side shocks. Positive LTV shocks would eventually drive up consumption, investment, GDP and house prices, thanks to a relaxation of collateral constraints.

6. Sensitivity analysis

Our baseline model introduces various frictions and shocks to account for the business cycle properties observed in the data. One

[17] Impulse responses to the other shocks are provided upon requests.

Table 5
Business cycle properties of the alternative models.

Variables	Data (a)	Baseline model (b)	No capital quality shocks (c)	No incentive constraints (d)	$LTV = 0.5$ (e)	Full labor mobility (f)	Homogenous labor preference (g)
Panel A: *SD of GDP and relative SD w.r.p.t GDP* (%)							
GDP	1.48	1.86	1.92	1.72	2.10	1.75	1.86
Consumption	0.78	0.75	0.76	1.02	0.67	0.92	0.75
Invest., capital	2.12	2.92	3.15	5.93	2.47	3.64	2.82
Invest., housing	6.49	3.66	3.54	3.79	3.24	6.77	3.73
House prices	2.83	2.78	3.00	3.53	2.67	2.59	2.91
Net worth	4.95	4.34	4.06	6.55	3.07	4.24	4.40
Loans, non-res.	2.46	1.80	1.69	1.61	1.16	1.69	1.81
Loans, res.	3.03	8.79	9.49	11.64	7.23	9.34	8.95
Deposits	1.96	2.12	2.37	3.35	1.28	2.33	2.19
Bank leverage	3.48	3.78	3.62	0	2.41	3.82	3.85
Inflation	0.39	0.38	0.36	0.40	0.28	0.29	0.36
Labor, total	0.91	1.22	1.19	1.11	1.07	0.99	1.19
Panel B: *Correlations with GDP*							
Consumption	0.38	0.66	0.52	−0.07	0.74	0.37	0.67
Invest., capital	0.49	0.41	0.47	0.55	0.58	0.35	0.37
Invest., housing	0.57	0.58	0.58	0.54	0.59	0.47	0.59
House prices	0.13	0.54	0.59	0.24	0.56	0.48	0.56
Net worth	0.24	0.13	0.20	0.49	0.19	0.13	0.11
Loans, non-res.	0.25	0.17	0.25	0.57	0.38	0.18	0.15
Loans, res.	0.38	0.39	0.44	0.27	0.43	0.30	0.42
Deposits	0.29	0.48	0.52	0.29	0.61	0.37	0.51
Bank leverage	−0.12	0.08	0.08	−0.04	0.05	0.05	0.11
Inflation	0.01	−0.03	−0.03	0.34	−0.09	−0.05	−0.08
Labor, total	0.20	0.55	0.62	0.76	0.74	0.36	0.56

Notes: The table reports the mean value of simulated statistics in alternative models. The statistics are computed with a random selection of 500 draws from the posterior distribution and, for each of them, 100 artificial time series of the variables of length equal to that of the data. Each simulated time series has been detrended using the HP filter with the smoothing parameter equal to 1, 600.

may raise the concerns as to which role each of them plays. Table 5 reports the simulated volatilities and correlations of the alternative models shutting off certain frictions or shocks.[18]

Column (c) in Table 5 reports the business cycle statistics of the model without capital quality shocks. A model without capital quality shocks underestimates the volatility in net worth and nonresidential loans. Because the capital quality shock is one of the main driving forces in China's financial cycles, a removal of the shock inevitably reduces the volatility in these variables. In the baseline model, a negative capital quality shock directly lowers bank net worth and tightens the banks' incentive constraints, causing an amplified effect on equity prices. Consequently, the volatility in net worth and nonresidential loans would be larger. To better account for the volatility in financial variables, capital quality shocks need to be incorporated in the model.

Column (d) in Table 5 reports the business cycle statistics of the model without incentive constraints. A version without incentive constraints is unable to account for the volatility of the leverage ratio as in this case banks earn zero excess returns on their assets over liabilities so that the leverage remains constant over time. Moreover, it generates excessive volatility in financial variables (e.g. residential loans, deposits and net worth) and macroeconomic variables (e.g. consumption, investment and house prices). In the absence of the incentive constraints, banks are allowed to accept more deposits from savers and issue more loans to their borrowers. Since borrowers can now borrow more funds from banks, their debt burdens will be driven up over time. As a result, the volatility in residential loans increases, and subsequently, generating excessive volatility in consumption, residential investment and house prices. Last, it overstates the procyclicality in net worth, nonresidential loans, inflation and total labor, and understates the procyclicality in consumption.

Column (e) in Table 5 reports the business cycle statistics of the model with higher downpayment requirements. In the baseline model, the steady-state LTV ratio is fixed at 0.70. We now decrease the ratio to 0.50, reflecting that borrowers make more downpayment than before while borrowing funds from banks with their houses as collateral. Higher downpayment requirements lead to a significant decrease in the relative volatility of financial and macroeconomic variables. That a tightening of the LTV ratio depresses the volatility of financial variables is primarily attributed to the effects on the behaviors of impatient households. As the LTV ratio falls, impatient households would borrow less from the banks, and thus their debt burdens are mitigated. As a result, the volatility of residential loans falls, and thus the volatility in other financial variables.

[18] The statistics are simulated using the parameters at their estimated value. The mode of the posterior distribution of the parameters in alternative models is reported in Table D.1

Column (f) in Table 5 reports the business cycle statistics of the model with full labor mobility across the production sectors. In this version of the model, we assume that labor hours are perfect substitutes by setting the labor supply parameters ε_p and ε_i to zero. A version with full labor mobility generates excessive volatility in residential loans, consumption and investment, and attenuates the volatility of total hours. The underlying reason is quite straightforward. With perfect labor mobility, households are more likely to substitute hours between the non-construction and construction sectors, exacerbating the fluctuations of hours in these sectors. Consequently, the volatility in nonresidential investment and residential investment rises, and so does the volatility in consumption and residential loans. In addition, a decrease in the volatility of total hours is primarily attributed to the perfect substitution between the two types of labor. A larger part of the increase in hours in a sector arises from a decrease in hours in another sector, vice-versa, and thus, the fluctuations in total hours would be smaller, relative to that in the baseline model.

Column (g) in Table 5 reports the business cycle statistics of the model with homogenous labor preferences. Recall that in the baseline model we assume that the two types of households differ in their labor supply parameters, reflecting the heterogenous labor supplied to a particular non-financial sector across households. We now constrain η and ε to be the same across the two types of households in order to investigate the role of the homogenous labor preferences in accounting for several key properties of the business cycles. The business cycle statistics reproduced by the version with homogenous labor preferences are virtually similar to that in the baseline model. Accordingly, the restriction of homogenous labor preferences does not matter for the simulated statistics of the business cycles.

7. Conclusion

In this paper, we develop and estimate a DSGE model with housing and banking to address several important questions related to the China's business cycles: Do the business cycle models with housing and banking better account for the volatility and cyclicality of macroeconomic variables in the China's business cylces? What are the main driving forces of the China's business cycles? We show that the estimated model fits the data very well, when it allows for an interaction between housing and banking. Capital quality, non-housing technology, housing demand and supply, LTV and labor supply shocks are the main driving forces of the China's business cycles, accounting for more than 80 percent of the variations in all variables being concerned at business cycle frequencies. Of them, the contributions of financial and housing shocks (capital quality shocks, housing demand shocks and LTV shocks) to the fluctuations in the China's business cycles are particularly large, suggesting that these shocks are at the core of the China's business cycles in the past two decades.

The model presented in this paper could be extended in various directions to address a number of other issues associated with housing and financial cycles in China. For instance, what are the joint behaviors between land prices and financial factors in a general equilibrium framework? and how are the dynamics of the firm's leverage associated with financial factors over the business cycle? Since our baseline model rules out financial frictions tied to the firms, and does not pay more attentions to the land-price dynamics and its joint behaviors with financial fluctuations, these issues remain to be answered. To address these issues, one could extend our baseline model to introduce financial frictions (collateral constraints) tied to the firms along the lines of Liu et al. (2013). Moreover, identifying and quantifying the source of business cycles are challenging but critical to the authorities while designing policies. This paper, however, provides a deeper understanding of the driving forces of the China's business cycles, and would increase the confidence in using this type of model for policy and welfare analysis. Perhaps, one could extend the model to investigate how monetary authority in China coordinates with macroprudential and fiscal authorities in an efficient way to tackle with financial risks sustained by a rapid growth of house prices and credit expansions. From our point of views, addressing these issues is challenging but important task in future research.

Appendix A. Data and sources

The following list includes all variables with sources we use in the Bayesian estimation and calculation of the business cycle moments reported in Table 3.

Real private consumption: Nominal Household Consumption Expenditure divided by Consumer Price Index (2005Q3 = 100), and divided by the Population. Source: China's Macroeconomic Time Series (CMTS) from Federal Reserve Bank of Atlanta (FRBA), https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=1.

Real residential investment: Nominal Residential Investment divided by Consumer Price Index (2005Q3 = 100), and divided by the Population. Source: CMTS from FRBA, https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=1.

Real nonresidential investment: Nominal Gross Fixed Capital Formation excluding government and residential investment divided by Consumer Price Index (2005Q3 = 100), and divided by the Population. Source: CMTS from FRBA, https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=1.

Real gross domestic product: The sum of Real Private Consumption, Real Nonresidential Investment and Real Residential Investment. Source: CMTS from FRBA, https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=1.

Real house prices: We first calculate the nominal housing price using the housing sales value and housing sales volume reported by the National Bureau of Statistics of China (NBSC). The nominal house price is normalized by setting 2005Q3 = 100. Then, we divide the nominal housing price by Consumer Price Index (2005Q3 = 100) to obtain the real housing price. Source: NBSC.

Real nonresidential loans: Loans to Non-financial Corporations and Others divided by Consumer Price Index (2005Q3 = 100), and divided by the Population. Source: Sources & Uses of Credit Funds of Financial Institutions (by Sectors), the People's Bank of China (PBC). Since the data on loans to non-financial firms is not available prior to 2007, we estimate it by multiplying aggregate loans (source: Sources & Uses of Credit Funds of Financial Institutions, PBC) by the loan ratio for the non-financial firms (source: China Banking Database (CBD)). We choose not to use the corresponding data series from CMTS (NonFinBusinessLoans), since the total bank loans from CMTS (BankLoansTotal) can be smaller in magnitude than the non-financial business loans for the early 2000, resulting in negative residential loans.

Real residential loans: Loans to Resident Sector divided by Consumer Price Index (2005Q3 = 100), and divided by the Population. Source: Sources & Uses of Credit Funds of Financial Institutions (by Sectors), PBC. Since the data on household loans is not available prior to 2007, we estimate it by multiplying aggregate loans (source: Sources & Uses of Credit Funds of Financial Institutions, PBC) by the loan ratio for the household sector (source: CBD).

Real household deposits: Deposits of Resident Sector divided by Consumer Price Index (2005Q3 = 100), and divided by the Population. Source: Sources & Uses of Credit Funds of Financial Institutions, PBC.

Real net worth: The sum of Real Nonresidential Loans and Real Residential Loans minus Real Household Deposits. Source: PBC.

Bank leverage ratio: The sum of Real Nonresidential Loans and Real Residential Loans divided by Real Net Worth. Source: PBC.

Inflation: Quarter on quarter log differences in Consumption Price Index (2005Q3 = 100). Source: FRBA, https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=1.

Total working hours: Total labor input measured in working hours are not available directly from the NBSC. Typical choice of labor series is the total employment in persons. However, this ignores the variations in working hours across time, hence potentially underestimates the fluctuations in labor input in aggregate. To overcome this shortcoming, we utilize the data of average weekly working hours per employed worker for the urban sector reported in China Labour Statistical Yearbook (CLSY) for each year in our sample periods, and then adjust this measure by considering the average weekly working hours per person for the rural area, which is based on data from the 2005 1% population survey and 2010 population census, both reported in CLSY as well. We construct the aggregate total working hours series by first interpolating the weekly working hours series in annual frequency to arrive at a measure in quarterly frequency, second multiplying the weekly working hours in quarterly frequency by the quarterly employment (interpolated from annual data from the NBSC), and lastly multiplying again by 13 to convert the weekly working hours into quarterly working hours. As for other observables, we divide the total quarterly working hours by the population to obtain the final total working hours series. Fig. A.1 plots the aggregate working hours and weekly working hours over the sample periods considered in this paper. Evidently, there is considerable variation in average weekly working hours over time.

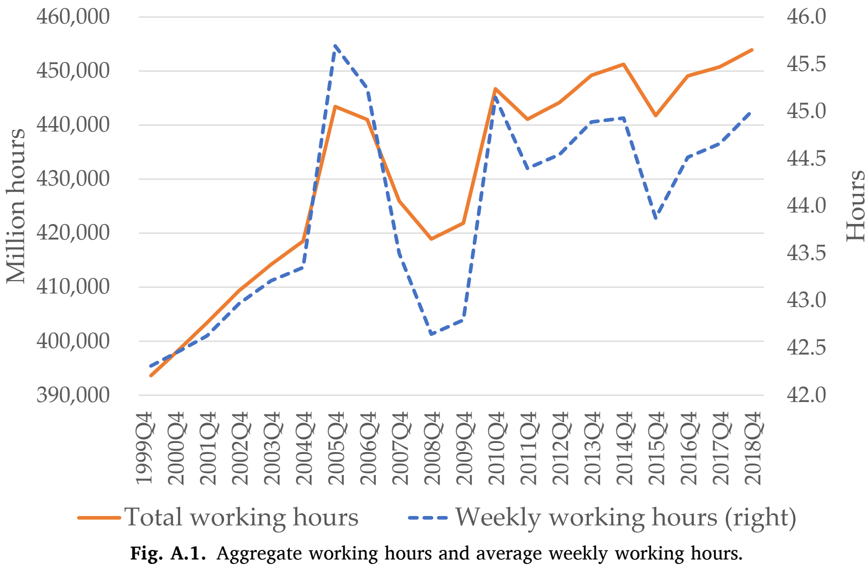

Fig. A.1. Aggregate working hours and average weekly working hours.

Appendix B. Derivation of the bank's problem

To solve the bank's problem, one may write the bank's sequential problem as the Bellman equation

$$V_{t-1}(s_{t-1}, b_{t-1}, d_{t-1}) = \mathbb{E}_{t-1}\Lambda_{t-1,t}\{(1-\sigma)n_t + \sigma max_{s_t,b_t,d_t} V_t(s_t, b_t, d_t)\}. \tag{B.1}$$

We guess that the value function V_t is linear in (s_t, b_t, d_t),

$$V_t(s_t, b_t, d_t) = \nu_{s,t}s_t + \nu_{b,t}b_t - \nu_{d,t}d_t, \tag{B.2}$$

where $\nu_{s,t}$ is the marginal value of equities at the end of period t, $\nu_{b,t}$ is the marginal value of residential loans, and $\nu_{d,t}$ is the marginal cost of deposits.

Given the Bellman equation and the conjectured value function, the bank's optimality conditions are:

$$\frac{\nu_{s,t}}{p_t} - \nu_{b,t} = 0, \tag{B.3}$$
$$(1 + \lambda_t^b)(\nu_{b,t} - \nu_{d,t}) = \theta\lambda_t^b, \tag{B.4}$$
$$[\theta - (\nu_{b,t} - \nu_{d,t})]b_t + [\theta - (\frac{\nu_{s,t}}{p_t} - \nu_{d,t})]p_t s_t \leq \nu_{d,t} n_t. \tag{B.5}$$

Moreover, the value function $V(s_t, b_t, d_t)$ is linear in (s_t, b_t, d_t) if and only if the following conditions are satisfied:

$$\nu_{b,t} = \mathbb{E}_t \Lambda_{t,t+1} \Omega_{t+1} \frac{R_{t+1}^b}{\pi_{t+1}}, \tag{B.6}$$
$$\nu_{d,t} = \mathbb{E}_t \Lambda_{t,t+1} \Omega_{t+1} \frac{R_{t+1}^d}{\pi_{t+1}}, \tag{B.7}$$
$$\nu_{s,t} = \mathbb{E}_t \Lambda_{t,t+1} \Omega_{t+1} \psi_{t+1} [Z_{t+1} + (1 - \delta_k) p_{t+1}], \tag{B.8}$$

with

$$\Omega_{t+1} = 1 - \sigma + \sigma(\nu_{d,t+1} + \varphi_{t+1}\mu_{t+1}), \tag{B.9}$$
$$\mu_t = \mathbb{E}_t \Lambda_{t,t+1} \Omega_{t+1} \left(R_{t+1}^k - \frac{R_{t+1}^d}{\pi_{t+1}}\right), \tag{B.10}$$
$$R_{t+1}^k = \psi_{t+1} \frac{Z_{t+1} + (1 - \delta_k) p_{t+1}}{p_t}, \tag{B.11}$$

where Ω_{t+1} is the marginal value of net worth at period $t + 1$, and μ_t is the excess value of returns on assets over liabilities. Note that if $0 < \mu_t < \theta$, the incentive constraint implies that the leverage is

$$\varphi_t = \frac{\nu_{d,t}}{\theta - \mu_t}. \tag{B.12}$$

Appendix C. Dynamic system of the baseline model

$$u_{\mathrm{cp},t} = \Gamma_p \left(\frac{A_{p,t}}{c_{p,t} - \tau_p c_{p,t-1}} - \frac{\beta_p \tau_p A_{p,t+1}}{c_{p,t+1} - \tau_p c_{p,t}} \right) \tag{C.1}$$
$$1 = \beta_p \mathbb{E}_t \left(\frac{u_{\mathrm{cp},t+1}}{u_{\mathrm{cp},t}} \frac{R_{t+1}^d}{\pi_{t+1}} \right) \tag{C.2}$$
$$q_t = \frac{A_{p,t} j_t}{u_{\mathrm{cp},t} h_{p,t}} + \beta_p \mathbb{E}_t \left[\frac{u_{\mathrm{cp},t+1}}{u_{\mathrm{cp},t}} (1 - \delta_h) q_{t+1} \right] \tag{C.3}$$
$$p_{x,t} = \beta_p \mathbb{E}_t \left[\frac{u_{\mathrm{cp},t+1}}{u_{\mathrm{cp},t}} (p_{x,t+1} + R_{t+1}^x) \right] \tag{C.4}$$
$$w_{\mathrm{pc},t} = \frac{A_{p,t} A_{n,t}}{u_{\mathrm{cp},t}} \left(l_{\mathrm{pc},t}^{1+\varepsilon_p} + l_{\mathrm{ph},t}^{1+\varepsilon_p}\right)^{\frac{\eta_p - \varepsilon_p}{1+\varepsilon_p}} l_{\mathrm{pc},t}^{\varepsilon_p} \tag{C.5}$$
$$w_{\mathrm{ph},t} = \frac{A_{p,t} A_{n,t}}{u_{\mathrm{cp},t}} \left(l_{\mathrm{pc},t}^{1+\varepsilon_p} + l_{\mathrm{ph},t}^{1+\varepsilon_p}\right)^{\frac{\eta_p - \varepsilon_p}{1+\varepsilon_p}} l_{\mathrm{ph},t}^{\varepsilon_p} \tag{C.6}$$
$$u_{\mathrm{ci},t} = \Gamma_i \left(\frac{A_{p,t}}{c_{i,t} - \tau_i c_{i,t-1}} - \frac{\beta_i \tau_i A_{p,t+1}}{c_{i,t+1} - \tau_i c_{i,t}} \right) \tag{C.7}$$
$$\frac{A_{p,t} j_t}{u_{\mathrm{ci},t} h_{i,t}} + \beta_i \mathbb{E}_t \left[\frac{u_{\mathrm{ci},t+1}}{u_{\mathrm{ci},t}} (1 - \delta_h) q_{t+1} \right] = q_t - \lambda_{i,t} m_t \mathbb{E}_t \left(\frac{q_{t+1} \pi_{t+1}}{u_{\mathrm{ci},t} R_{t+1}^b} \right) \tag{C.8}$$
$$1 = \beta_i \mathbb{E}_t \left(\frac{u_{\mathrm{ci},t+1}}{u_{\mathrm{ci},t} \pi_{t+1}} R_{t+1}^b \right) + \frac{\lambda_{i,t}}{u_{\mathrm{ci},t}} \tag{C.9}$$
$$w_{\mathrm{ic},t} = \frac{A_{p,t} A_{n,t}}{u_{\mathrm{ci},t}} \left(l_{\mathrm{ic},t}^{1+\varepsilon_i} + l_{\mathrm{ih},t}^{1+\varepsilon_i}\right)^{\frac{\eta_i - \varepsilon_i}{1+\varepsilon_i}} l_{\mathrm{ic},t}^{\varepsilon_i}, \tag{C.10}$$
$$w_{\mathrm{ih},t} = \frac{A_{p,t} A_{n,t}}{u_{\mathrm{ci},t}} \left(l_{\mathrm{ic},t}^{1+\varepsilon_i} + l_{\mathrm{ih},t}^{1+\varepsilon_i}\right)^{\frac{\eta_i - \varepsilon_i}{1+\varepsilon_i}} l_{\mathrm{ih},t}^{\varepsilon_i} \tag{C.11}$$
$$b_t = m_t \mathbb{E}_t \left(\frac{q_{t+1} h_{i,t} \pi_{t+1}}{R_{t+1}^b} \right) \tag{C.12}$$
$$c_{i,t} + q_t h_{i,t} + \frac{R_t^b b_{t-1}}{\pi_t} = w_{\mathrm{ic},t} l_{\mathrm{ic},t} + w_{\mathrm{ih},t} l_{\mathrm{ih},t} + q_t (1 - \delta_h) h_{i,t-1} + b_t \tag{C.13}$$
$$w_{\mathrm{pc},t} = \alpha(1 - \mu_c) \frac{Y_t}{\Xi_t l_{\mathrm{pc},t}} \tag{C.14}$$

$$w_{\mathrm{ic},t} = (1-\alpha)(1-\mu_c)\frac{Y_t}{\Xi_t l_{\mathrm{ic},t}} \tag{C.15}$$

$$Z_t = \mu_c \frac{Y_t}{\Xi_t k_t} \tag{C.16}$$

$$ln\pi_t - \iota ln\pi_{t-1} = \beta_p[\mathbb{E}_t ln(\pi_{t+1}) - \iota ln\pi_t] - \frac{(1-\lambda)(1-\beta_p\lambda)}{\lambda} ln\frac{\Xi_t}{\Xi} + u_{\mathrm{cp},t} \tag{C.17}$$

$$Y_t = [A_{c,t}(l_{\mathrm{pc},t}^{\alpha} l_{\mathrm{ic},t}^{1-\alpha})]^{1-\mu_c} k_t^{\mu_c} \tag{C.18}$$

$$w_{\mathrm{ph},t} = \alpha(1-\mu_h)\frac{q_t I_{h,t}}{l_{\mathrm{ph},t}} \tag{C.19}$$

$$w_{\mathrm{ih},t} = (1-\alpha)(1-\mu_h)\frac{q_t I_{h,t}}{l_{\mathrm{ih},t}} \tag{C.20}$$

$$R_t^x = \mu_h \frac{q_t I_{h,t}}{x_{t-1}} \tag{C.21}$$

$$I_{h,t} = [A_{h,t}(l_{\mathrm{ph},t}^{\alpha} l_{\mathrm{ih},t}^{1-\alpha})]^{1-\mu_h} x_{t-1}^{\mu_h} \tag{C.22}$$

$$\Lambda_{t,t+1} = \beta_p \frac{u_{\mathrm{cp},t+1}}{u_{\mathrm{cp},t}} \tag{C.23}$$

$$\begin{aligned} p_t &= 1 + \frac{\chi_k}{2}(\frac{I_{k,t}}{I_{k,t-1}} - 1)^2 + \chi_k(\frac{I_{k,t}}{I_{k,t-1}} - 1)\frac{I_{k,t}}{I_{k,t-1}} \\ &= -\chi_k \Lambda_{t,t+1}(\frac{I_{k,t+1}}{I_{k,t}} - 1)(\frac{I_{k,t+1}}{I_{k,t}})^2 \end{aligned} \tag{C.24}$$

$$\nu_{b,t} = \mathbb{E}_t \Lambda_{t,t+1}\Omega_{t+1}\frac{R_{t+1}^b}{\pi_{t+1}} \tag{C.25}$$

$$\nu_{d,t} = \mathbb{E}_t \Lambda_{t,t+1}\Omega_{t+1}\frac{R_{t+1}^d}{\pi_{t+1}} \tag{C.26}$$

$$\nu_{s,t} = \mathbb{E}_t \Lambda_{t,t+1}\Omega_{t+1}\psi_{t+1}[Z_{t+1} + (1-\delta_k)p_{t+1}] \tag{C.27}$$

$$\Omega_{t+1} = 1 - \sigma + \sigma(\nu_{d,t+1} + \varphi_{t+1}\mu_{t+1}) \tag{C.28}$$

$$\mu_t = \mathbb{E}_t \Lambda_{t,t+1}\Omega_{t+1}(R_{t+1}^k - \frac{R_{t+1}^d}{\pi_{t+1}}) \tag{C.29}$$

$$p_t S_t + B_t = \varphi_t N_t \tag{C.33}$$

$$\varphi_t = \frac{\nu_{d,t}}{\theta - \mu_t} \tag{C.34}$$

$$N_t = (\sigma + \xi)\{[Z_t + (1-\delta_k)p_t]\psi_t S_{t-1} + \frac{R_t^b B_{t-1}}{\pi_t}\} - \sigma\frac{R_t^d D_{t-1}}{\pi_t} \tag{C.35}$$

$$Y_t = C_t + [1 + \frac{\chi_k}{2}(\frac{I_{k,t}}{I_{k,t-1}} - 1)^2]I_{k,t} \tag{C.36}$$

$$I_{h,t} = H_t - (1-\delta_h)H_{t-1} \tag{C.37}$$

$$S_t = I_{k,t} + (1-\delta_k)K_t \tag{C.38}$$

$$C_t = c_{p,t} + c_{i,t} \tag{C.39}$$

$$H_t = h_{p,t} + h_{i,t} \tag{C.40}$$

$$\mathrm{GDP}_t = Y_t + \mathrm{qI}_{h,t} \tag{C.42}$$

$$\frac{R_t^d}{R^d} = (\frac{R_{t-1}^d}{R^d})^{\alpha_r}[\pi_t^{\alpha_\pi}(\frac{\mathrm{GDP}_t}{\mathrm{GDP}_{t-1}})^{\alpha_y}]^{1-\alpha_r} exp(u_{\mathrm{mp},t}) \tag{C.43}$$

$$ln\psi_t = \rho_k ln\psi_{t-1} + u_{k,t} \tag{C.44}$$

$$lnA_{c,t} = \rho_c lnA_{c,t-1} + u_{c,t} \tag{C.45}$$

$$lnA_{h,t} = \rho_h lnA_{h,t-1} + u_{h,t} \tag{C.46}$$

$$lnA_{p,t} = \rho_p lnA_{p,t-1} + u_{p,t} \tag{C.47}$$

$$lnA_{n,t} = \rho_n lnA_{n,t-1} + u_{n,t} \tag{C.48}$$

$$lnm_t = (1-\rho_m)lnm + \rho_m lnm_{t-1} + u_{m,t} \tag{C.49}$$

$$lnj_t = (1-\rho_j)lnj + \rho_j lnj_{t-1} + u_{j,t} \tag{C.50}$$

Appendix D. Posterior mean of parameters in alternative models

Table D.1
Posterior mean of parameters in alternative models.

Parameter	Baseline model (a)	No capital quality shocks (b)	No incentive constraints (c)	$LTV = 0.5$ (d)	Full labor mobility (e)	Homogenous labor preference (f)
χ_k	2.6554	2.3656	0.8575	2.6464	2.1574	2.8050
ι	0.1969	0.5920	0.5230	0.3130	0.1993	0.1962
λ	0.6659	0.7335	0.7126	0.6397	0.8317	0.6763
α_r	0.7899	0.6586	0.6486	0.7852	0.6451	0.7208
α_π	1.5323	1.6890	1.5762	1.5263	1.5139	1.5198
α_y	0.0779	0.0875	0.1480	0.0675	0.1262	0.0848
τ_p	0.3621	0.4728	0.3985	0.4104	0.3762	0.3574
τ_i	0.4372	0.4769	0.6051	0.4661	0.4345	0.4406
η_p	0.6408	0.5688	0.5449	0.6256	0.5138	0.7034
η_i	0.5492	0.5928	0.5961	0.6313	0.6034	0.7034
ε_p	1.0519	1.0332	1.0086	1.0368	–	1.0580
ε_i	1.0210	1.0291	1.0321	0.9326	–	1.0580
ρ_c	0.9176	0.8314	0.7999	0.9481	0.9472	0.8804
ρ_h	0.8939	0.8906	0.9226	0.9157	0.9963	0.8903
ρ_k	0.9648	–	0.9660	0.9399	0.9736	0.9331
ρ_j	0.9928	0.9919	0.9941	0.9959	0.9921	0.9929
ρ_p	0.8979	0.9372	0.7873	0.9455	0.8888	0.8798
ρ_m	0.7050	0.7407	0.6456	0.7884	0.8607	0.6901
ρ_n	0.7818	0.8487	0.9852	0.8786	0.9258	0.7834
σ_c	0.0164	0.0148	0.0006	0.0170	0.0176	0.0162
σ_h	0.0474	0.0474	0.0437	0.0459	0.0390	0.0477
σ_k	0.0018	–	0.0039	0.0019	0.0017	0.0023
σ_j	0.0728	0.0791	0.0748	0.0652	0.0754	0.0756
σ_p	0.0159	0.0347	0.0142	0.0234	0.0165	0.0140
σ_m	0.0384	0.0408	0.0350	0.0402	0.0387	0.0394
σ_n	0.0237	0.0188	0.0091	0.0250	0.0007	0.0242
σ_{mp}	0.0005	0.0062	0.0005	0.0005	0.0008	0.0008
σ_{cp}	0.0008	0.0070	0.0064	0.0014	0.0050	0.0009

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