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China's market economy, shadow banking and the frequency of growth slowdown

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Abstract

The activity of the Shadow Banks in China has been the subject of considerable interest in recent years. Total shadow banking lending has reached over 60% of GDP and has grown faster than regular bank lending. It has been argued that unregulated shadow banking has fuelled a credit boom that poses a risk to the stability of the financial system. This paper estimates a model of the Chinese economy using a DSGE framework that accommodates a banking sector that isolates the effects of lending to the private sector including shadow bank lending. A refinement of the model allows for bank lending including lending by the shadow banks to affect the credit premium on private investment. The main finding is that while financial shocks are significant, it is real shocks that dominate. The model is used to simulate the frequency of growth slowdowns in China and concludes that these are more likely to be driven by real sector shocks rather than financial sector, including shadow bank shocks. This paper differs from other applications in its use of indirect inference to test the fitted model against a three-equation VAR of inflation, output gap and interest rate.

KEYWORDS

DSGE model, China, crises, indirect inference, shadow banking

1 | INTRODUCTION

Modelling the Chinese macroeconomy using the DSGE framework has become vogue.[1] But there has been little effort to model the Chinese business cycle with a banking sector that interacts with shadow banking. A notable exception is Funke, Mihaylovski, and Zhu (2015) who develop a detailed calibrated DSGE model with a shadow banking sector that incorporates some Chinese economy features. Our approach in this paper is different in two respects. First, we employ a variant of the Smets and Wouters (2003, 2007, SW) model incorporating the Bernanke et al. (1999, BGG) framework of a banking sector. Second, we take the model to the data and estimate the parameters using the method of *indirect inference* (II). Le, Matthews, Meenagh, Minford, and Xiao (2014) explored such an approach and reported some success. This paper builds on this work by adding a fuller monetary sector, the quantity of money and bank credit, and interaction with a shadow banking sector. The basic idea is that the monetary base acts as collateral for loans because it is entirely liquid and riskless. Hence, it is a powerful agent of credit growth in a way that has hitherto been relatively neglected in DSGE models.

China was not immune to the global financial crisis (GFC). As Le et al. (2014) show, China too experienced a severe growth slowdown and like most Western economies has not caught up with its previous trend growth rate. The purpose of this paper is to see whether the evolution of the Chinese economy during this period can be plausibly explained by such a model and to assess the implication of shadow banking activity on the frequency of severe economic slowdowns. The model is used to evaluate the effect of the GFC in terms of the frequency of severe economic slowdowns and can be used to evaluate whether the Chinese monetary authorities should be engaged in microregulatory policies that constrain shadow banking activity, or rules-based monetary policy in reducing the frequency of financial crisis.

Our empirical procedure is to use the method of *indirect inference* (II) to test the model on some initial parameter values, and then allow the parameters to be moved flexibly to the values that maximize the criterion of replicating the data behaviour—indirect estimation. This allows us to test the model itself rather than a particular set of parameter values that could be at fault. The basic reason for using II over the now popular Bayesian ML is that it tests the overall ability of the model to replicate key aspects of data behaviour—there is no guarantee that Bayesian estimates will pass this test.

The estimated model suggests that the main shocks hitting China in this sample period were a combination of productivity, investment and exogenous (fiscal and trade) shocks but that financial shocks were only a modest contributor. During the GFC period, the state banking system, together with direct government spending, was used to aggressively supplement monetary policy offsetting the potential downturn in GDP growth. The model is used to estimate how often we might expect to see growth slowdowns in China and how often such slowdowns are driven by financial shocks.

The rest of this paper is as follows: in the next section we describe the state of the banking sector in China and review the attempts to incorporate a banking sector in DSGE-type models. In the third

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[1]Most recently Chang et al. (2015), Chen et al. (2012) and Funke and Paetz (2012)

section, we set out the model in outline, incorporating the modified BGG framework to the SW model and extend it to include direct monetary effects. In the fourth section, we explain our testing procedure based on the method of II whereby the model's simulated behaviour is compared statistically with the behaviour found in the data. In the penultimate section, we set out the empirical results for the model and use these to simulate the frequency of growth slowdowns relative to the assumed BGP and to speculate on the causes of future slowdowns. Our final section concludes, with some reflections on the implications for China's banking.

2 | DSGE, (SHADOW) BANKING AND THE CHINESE ECONOMY

It is argued that the Chinese economy does not function like a developed market economy and that the modelling of the economy must include the distortions of a dominant state sector (Song, Storeslatten, & Zilibotti, 2011) that stifles the growth of private enterprise through state capitalism (Huang, 2008) and distortions in the labour market (Dollar & Jones, 2013) and a controlled banking system (Chen, Funke, & Paetz, 2012; Funke et al., 2015). While there is merit in this argument, we argue that it misses the point of using a model as an analytical aid to understand the determinants of the business cycle. No economy can realistically be captured by a DSGE model. The purpose of using a DSGE model of a variant of the SW framework is to use it to isolate the principal factors that drive the business cycle in China even with distorted markets.

DSGE models have been increasingly utilized in modelling the Chinese economy. Zhang (2009) calibrated a DSGE model for China to examine welfare implications of a money supply rule versus an interest rate rule. Mehrotra, Nuutilainen, and Pääkkönen (2013) use a partially estimated (GMM) and calibrated DSGE model based on Christiano, Eichenbaum, and Evans (2005) to evaluate a rebalancing of the Chinese economy from investment-led to consumption-led growth, where the labour market is assumed to be frictionless but rigidities arise from staggered price setting by firms, habit formation in consumption and capital adjustment costs. Technology shocks have a damped effect on output in a re-balanced economy. Li and Meng (2006) discuss quantity-based monetary policy rules, Xi and He (2010) and Ma (2015) discuss price-based rules, Wu and Lian (2016) analyse hybrid rules and Li and Liu (2017) compare the relative performance of alternative quantity and price rules.[2] Wan and Xu (2010) use Bayesian methods to estimate an open-economy DSGE model and find the standard result that technology shocks are the main driver of the business cycle and that they dominate monetary shocks. In contrast, Sun and Sen (2011) estimate a Bayesian-modified SW model to examine the business cycle and find that technology shocks play a subsidiary role. The dominant drivers of output are investment and preference shocks. Most recently Chang, Zheng, and Spiegel (2015) and Cun and Li (2016) evaluate optimal monetary policy with sterilized intervention in the FX market using a calibrated DSGE model.

Several studies using the New-Keynesian DSGE framework have also been published by Chinese scholars (in Chinese). Xu and Chen (2009) incorporate a bank lending channel into a DSGE model with price stickiness. They find that technology shocks explain most of the variations in output, investment and long-term consumption, and the fluctuations of short-term consumption, loans and real money balance are mainly attributed to credit shocks. Xi and He (2010) evaluate the welfare losses of China's monetary policy with a New-Keynesian DSGE model and

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[2]See Chen et al. (2018) for a review of the unique features and history of evolution of China's monetary policy.

TABLE 1   The Chinese banking market 1997–2016

Variable	1997 (%)	2000 (%)	2005 (%)	2016 (%)
Total assets to GDP	125.6	147.1	205.1	290.5
SOCB market share % assets	88.0	71.4	52.5	54.9[1]
Non-performing loans (NPL) ratio	52.7	31.5	10.5	1.7
Return on assets (ROA)	2.32	0.74	1.12	1.21
Average interest rate spread	2.9	3.6	3.3	2.9
Net interest margin (NIM)	1.8	1.5	1.7	2.6%[1]
Cost-income ratio SOCB[1]	40.7	66.3	43.7	31.2

Sources: China Bank Regulatory Corporation Website, Almanac of China's Finance and Banking, Bankscope Data Base, Chinese National Bureau of Statistics. World Bank.

[1]2014 data.

find that the welfare losses are negatively correlated with nominal interest rate-inflation sensitivity, and positively correlated with nominal interest rate-output sensitivity. They recommend using interest rate policy to stabilize the price level but not to adjust economic growth rate. They also find that the welfare losses caused by fluctuations in the money supply are larger than that caused by fluctuations in interest rate and conclude that the appropriate intermediate target of monetary policy should be the interest rate instead of money supply. Yuan, Chen, and Liu (2011) investigate the existence of the financial accelerator within a small open economy. While the financial accelerator amplifies the impacts of shocks to the marginal efficiency of investment and monetary policy, its amplification effect on the technology and preference shocks is subsidiary. Similar results are reported in Liu and Yuan (2012). Overall, the Chinese publications are in line with the results of those in the international arena.[3]

The evolution of the Chinese banking system illustrates the broader evolution of its market economy with Chinese characteristics. Traditionally banking like the rest of the economy has been dominated by the state: state-owned commercial banks (SOCBs) provide credit to state-owned enterprises (SOEs). More recently the non–state-owned banks have grown in parallel with the private sector, but they also are strongly linked to the state through the shareholding of state-owned companies. Because the state banks are closely supported by the government on favourable terms, credit from them also finds its way to the private sector via a roundabout route; to the shadow banking system through lending by state-owned companies that have access to cheap credit and the sale of wealth management products (see Buitelaar, 2014; Lu, Guo, Kao, & Fung, 2015). Thus, emerges the peculiarly Chinese feature of two parallel systems, separate but connected.

Like many economies that have undeveloped financial and capital markets, the banking sector in China plays a pivotal role in financial intermediation. Table 1 below shows that the ratio of total bank assets to GDP has increased from 125% in 1997 to 290% in 2016. The market is absolutely dominated by the five state-owned banks, although their share of the market has been decreasing steadily through competition from the other nationwide banks (Joint-stock banks and some City Commercial Banks).

Up until 1995, control of the banking system remained firmly under the government and its agencies. Under state control, the banks in China served the socialist plan of directing credits to specific projects dictated by political preference rather than commercial imperative. Traditionally, the PBOC

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[3]Among all existing DSGE modelling of Chinese economy, to our knowledge, only three have incorporated a banking sector: Chen et al. (2012), Funke and Paetz (2012) and Xu and Chen (2009).

set loan quotas for each sector and mainly disbursed these through the branch network in each province. As China evolved towards a market economy, the banks lagged the rest of the economy in improving its efficiency, management and performance.[4] Even with the development of a commercial banking system, the state keeps a strong hold on the banking system by maintaining direct control of the SOCBs.[5] While Table 1 shows a declining share of the market by the SOCBs, state influence remains significant through a complicated process of ownership and governance.

Many of the national joint stock commercial banks (JSCB) are owned by state-owned industries. City commercial banks which have geographical limits to their banking activities are owned mostly by provincial governments. All banks have a governance structure that includes the oversight of the Communist Party and senior officials of the SOCBs are appointed by the government, many who are career officials in the politburo.

One reason for the lag in the full commercialization of the banking sector is that the SOCBs are seen not just as profit maximizing organizations but also organs of the state in promoting social and economic harmony. Profit maximization in the SOCBs is subject to political, social and employment constraints. Another important reason was the high level of inherited non-performing loans (NPLs). Table 1 shows that the NPL ratio of the commercial banks was estimated as 53% in 1997. As a preparation for recapitalization and eventual listing, 1.3 trillion RMB was divested to the Asset Management Companies in 1999, financed by the Ministry of Finance and the PBOC. In 2004, a further 750 billion RMB was divested.

In 2016, NPL ratios had fallen to tolerable levels, although it can be argued that one reason for this was the rapid expansion of bank assets during the period of the global economic crisis. Profitability and net interest margins have reached comparable levels with banks in developed economies on the eve of the global banking crisis. However, the government and the PBOC retain control of the banking system through its levers on quantity and price with the objective of hitting a multiplicity of intermediate targets. Initially, the objective of price stability and economic growth was to be achieved by targets for M1 and M2. By 2007, the PBOC had stopped publishing targets for the money supply. Another, but informal, target is the growth of bank credit which is controlled using its administrative 'window guidance' policy. Up until 2004, the rate of interest on loans was strictly controlled. With strong controls on the lending rates and high levels of NPLs, ROA and NIM were well below what would be expected as appropriate risk pricing by banks in emerging market economies. The recent policy of lifting the ceiling on loan rates has created some potential for risk pricing but there is little evidence yet that banks are independently pricing risk into their loans and taking advantage of this freedom.[6]

The spread between the benchmark loan and deposit rate has remained largely fixed throughout the deregulatory period. However, it is arguable that the average loan–deposit ratio of the SOCBs are around 65% and the current capital–asset ratio (CAR) in excess of 10% provides ample slack for the banks to make credit advances as and when the government decides through its 'window guidance' policy. The PBOC have also used the regulated deposit and loan rate benchmarks as monetary policy tools. While the plan is to move towards market-determined interest rates over time, the reality is that the deposit rate ceiling set by the PBOC remains binding at the time of writing.

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[4]Estimates of average cost inefficiency of Chinese banks have been in the region of 50%, see Fu and Heffernan (2007) and Matthews et al. (2007).

[5]The big 4 banks that constituted the SOCBs in 1997 were, Industrial and Commercial Bank of China, Bank of China, China Construction Bank and Agricultural Bank of China. By 2006 a fifth bank, Bank of Communication was added to the group.

[6]Chen et al. (2011) report that 60% of bank loans remain at the regulated benchmark rate or below it.

The Chinese banking system, particularly the SOCBs, support the SOEs through directed bank credits. The SOEs account for over 50% of the industrial sector, which represents a drop from 70% in 1999 but the number of enterprises has also declined from a share of 40% in 1999 to less than 10% in 2008, indicating a sharp increase in individual size and concentration. The average asset size of an SOE is around RMB 923 million, compared with the average asset base of a non-SOE at RMB 60 million.[7] Nearly 70% of the funding of the SOEs is from bank loans and nearly 70% of the loan portfolio of the SOCBs is to the SOEs. About half of GDP is accounted for by the Small- & Medium-sized Enterprises (SMEs) and their participation in international trade and outward investment is also very significant, representing 69% of the total import and export values and about 80% of outward investment.[8] While it is estimated that 75% of industrial profits are generated by the non-SOE sector, only 3.5% of the SOCBs lending is to the SMEs.[9] With no alternative for funding, China's SMEs[10] have turned to the shadow banking system which according to PBOC estimates has grown to RMB 30 trillion (half of the total assets of the SOCBs).[11]

The consolidation of undercapitalized and failing city commercial banks and urban credit cooperatives in the 2009–2010 period provides an insight into CBRC resolution strategy. Deposit insurance is a very recent innovation in China[12] and the depositors of the small failing city commercial and cooperatives have been quietly compensated by the government. It is therefore inconceivable that any of the SOCBs which together account for more than RMB 60 trillion of assets and 1.6 million employees are allowed to fail, and unlikely that any of the JSCBs which together have RMB 23.5 trillion and 17% of the market by assets be allowed to fail.

The multiple targets and instruments available to the PBOC mean that the methods of monetary control require careful interpretation. The seemingly impossible objective of the PBOC is to control both price and quantity in the money markets. This is possible because of the undeveloped state of the money markets in China which makes interest rate policy less effective, allowing room for quantity adjustment.[13]

The Chinese banking system, state, non-state and shadow, is clearly complex and that its operations are intervened in by the government in many ways. Here, we necessarily abstract from these complexities partly because there is little relevant data and partly because their interactions are hard to model. Instead, we model it as if it behaves like an ordinary banking system, facing idiosyncratic risk and costs of bankruptcy, the result of which is a credit premium that rises with investment needs. Essentially one can think of this as what the marginal investor in the private sector faces as the outcome of the banking system in China.

As set out above, China's banks lend directly to state-owned firms and indirectly to small private firms through secondary lending via the SOEs (Allen, Yiming, Guoqian, & Frank, 2019), and the

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[7]The Second National Economic Census, 2008 and Industrial Enterprises Survey Dataset, China Statistical Bureau.

[8]See Shen et al. (2009)

[9]ICBC 2011 Annual Report.

[10]The term SME is used generically to mean the private sector. While there are some SMEs that are state-owned and some large enterprises (Huawei, Alibaba, Tencent, Baidu etc) that are private, the private sector is dominated by SMEs and MSEs (Medium Sized Enterprises) and most large enterprises are part of the state sector. Many large-scale joint ventures are also with SOEs or their subsidiaries and therefore cannot strictly be called private.

[11]Estimates of the size of the shadow banking system vary from 25%–30% of SOCB bank assets according to recent estimates produced by JP Morgan.

[12]As of 1 May 2015, the deposit insurance scheme covers deposits to maximum of 500,000RMB.

[13]See also Cun and Li (2016), Chen et al. (2012), and Funke and Paetz (2012).

sale of wealth management products. Combined with private equity and trust funds, the latter clients constitute the 'shadow banks' (see also Lin et al. 2015). Our aim is to build into the model the Chinese feature of most of the official lending being targeted to the state-owned enterprises and private investment being largely funded by the shadow banks. The state-owned bank lending to state-owned firms could be regarded as exogenously driven by state plans and might not be affected by banks' charges because of implicit state guarantees. Thus, our model of loans might not apply to these firms; it might only apply to the shadow bank clients and so we would like to separate out these clients' activities from those of the state-owned firms, both their loans and their investments.

It needs to be stressed that this is simply a theoretical possibility. The state-owned sector is ubiquitous in China and is also in practice disciplined by incentives and controls inspired by economic logic. Although this logic and these incentives are not transparent to the outside observer, it may nevertheless be the case that one should treat the state-owned sector as if in practice it behaves like the private sector in a western economy. However, we explore as best we can with the data available how the model will behave if the state-owned sector responds to the risk-free rate of interest, but the private sector only is assumed subject to the incentives created by credit charges.

Time-series data on private sector investment are either obtained directly (if available) or constructed based on the decomposition of fixed assets investment (if unavailable) from *China Statistical Yearbooks*. The ownership structure of China's enterprises has changed dramatically since the early 1980's, and the definition of the term 'private' is not a constant. To resolve uncertainties regarding the construction of a private investment data series, China's National Bureau of Statistics published in 2012 an instruction document on its definition for China. For the early years where the private investment data are unavailable, we follow the instruction to construct the data series. Clearly due to the complexity of the ownership change situation, the private investment data might have non-negligible measurement errors hence can at best be viewed as a close proxy to the true investment.

While no official figures are available, several estimates of the size of the shadow banking system in China are available in discrete form. The figures vary from 40% to 69% of GDP,[14] however, even estimates drawn from the PBOC suggest a rapidly growing shadow banking sector that has only begun to decline in recent years. Figure 1 shows the estimated size of shadow bank credit as a per cent of GDP. It reached a peak in 2016 and has then fallen back as a result of the deleveraging policies of the Chinese authorities.

The model is extended so that this credit is mediated via the banks to the private sector. All other credit and investment are treated as exogenous. This addition constitutes the shadow banking variant of the model we consider in this paper.

3 | THE MODEL

We utilize the New-Keynesian framework in our analysis of the Chinese economy including shadow banking. Specifically, we use the model proposed by Le, Meenagh, and Minford (2016), which extends the original SW model in the following ways. First, it allows for final goods and labour being sold and supplied to, respectively, in both perfectly competitive and imperfectly competitive markets. The reason for this is that neither pure DSGE models of the Neo-Classical RBC (NC) type or its New-Keynesian (NK) variant capture the stylized features of the labour market in that the NK model

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[14]For example BBVA (Hong Kong), 'Banking Watch' 8 March 2013, estimate the size of the shadow banking sector as over 50% of GDP in 2012 while JP Morgan (Hong Kong), 'Shadow banking in China' May 3 2013 estimate it as between 28% and 69% of GDP in 2012 depending on definition.
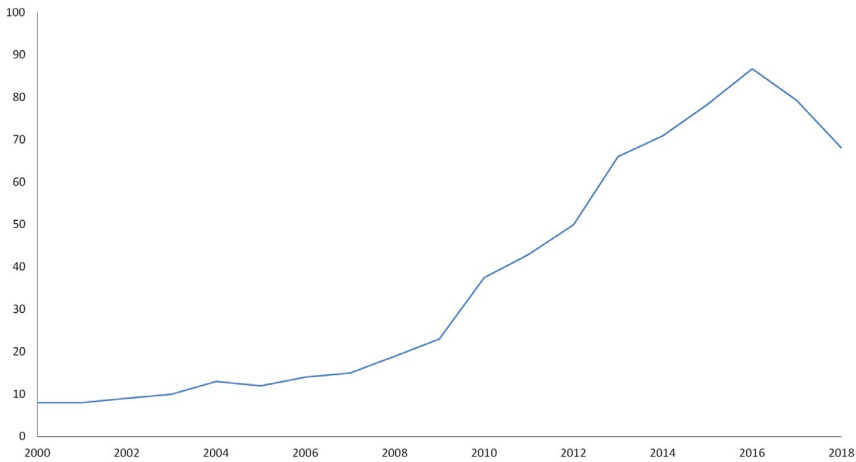
FIGURE 1 Shadow bank credit as a percent of GDP. *Source*: Goldman Sachs, and Moody's, and author calculations

generated too little nominal variation while the NC model delivered too much. Le, Meenagh, Minford, and Wickens (2011) test a hybrid version that captures features of both models based on indirect inference that is a superior representation of the post-war data for the USA. This hybrid is a weighted average of the corresponding NC and NK versions. Secondly, it incorporates the financial accelerator mechanism of Bernanke et al. (1999) to allow for the analysis of a banking/financial sector. Lastly, to make the model more realistic, and in the light of widespread developments in monetary policy, and microprudential policy, it allows for the effects of aggressive open market operations ("Quantitative Easing", henceforth, QE) and an increase in intrusive bank regulation. In our model, the increase in bank regulation raises the cost of lending to firms. In a modelling sense the extra regulation is added as a credit friction in the form of unobserved shocks $(\varsigma_{1t}, \varsigma_{2t})$. To add QE to the model it assumes that firms are required to put up collateral which is a fraction of their net worth. As base money (M0) is issued it is acquired by firms from banks to be held as collateral. Here, we follow the lead of Williamson (2013). The extension we make in this paper is to include two types of intermediate-goods producing firms, SOEs and SMEs. They both must borrow in order to acquire capital from capital producers. SOEs borrow at the risk-free rate because of the implicit state guarantee. Banks lend to these firms at the risk-free rate. However, SMEs are risky. Because of interest rate controls and restrictive regulations, banks lend to SMEs via the off-balance sheet route of supplying wealth management products which effectively place funds in the shadow banking sector.

The demand side of the model consists of intertemporal Euler equations that determine optimal consumption and investment in two production sectors. Let σ_c denote the intertemporal elasticity of substitution, λ the degree of habit formation, β the household's discount factor, γ the trend growth rate of technology, ϕ the cost of adjusting the rate of investment and $\frac{W^*L^*}{C^*}$ the steady-state ratio of labour income to consumption. The equation represents a weighted average of current, past and expected future consumption and labour as a function of the real interest $\left(r_t - E_t\pi_{t+1}\right)$ and the intertemporal shock to preferences ε_t^b.[15]

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[15]Note that consumption and leisure are assumed non-separable in the utility function as in Smets and Wouters (2007). This formulation was also used through other research such as in Le et al. (2011, 2016), where the whole model was estimated and tested against the unfiltered US data. To minimise the changes to the theoretical model, we keep this utility function specification.

$$c_t = \frac{\frac{\lambda}{\gamma}}{1+\frac{\lambda}{\gamma}}c_{t-1} + \frac{1}{1+\frac{\lambda}{\gamma}}E_t c_{t+1} + \frac{(\sigma_c - 1)\frac{W^* L^*}{C^*}}{\left(1+\frac{\lambda}{\gamma}\right)\sigma_c}\left(l_t - E_t l_{t+1}\right) - \left(\frac{1-\frac{\lambda}{\gamma}}{\left(1+\frac{\lambda}{\gamma}\right)\sigma_c}\right)(r_t - E_t \pi_{t+1}) + \varepsilon_t^b \quad (1)$$

In each sector, intermediate-goods firms produce using labour which moves freely across the two sectors so that the labour composite is $l_t = \frac{N^{SOE}}{N}n_t^{SOE} + \frac{N^{SME}}{N}n_t^{SME}$, where each sector labour is a combination of labour hired from imperfectly and perfectly labour markets, and capital is bought from the sector-specific capital producer. These firms produce intermediate goods under perfect competition assumptions, according to the Cobb-Douglas production function and use technology, capital and labour as inputs. Equations (2) and (3) describe the respective outputs of the two sectors.

$$y_t^{SOE} = \phi\left[\alpha^{SOE}k_{t-1}^{SOE} + \left(1-\alpha^{SOE}\right)n_t^{SOE} + \varepsilon_t^{SOE}\right] \quad (2)$$

$$y_t^{SME} = \phi\left[\alpha^{SME}k_{t-1}^{SME} + \left(1-\alpha^{SME}\right)n_t^{SME} + \varepsilon_t^{SME}\right] \quad (3)$$

where α^i with $i = $ SOE, SME denotes the share of capital in production and ϕ equals one plus the share of fixed costs in production. The demand for capital and labour in the two sectors are as follows.

$$\text{mpk}_t^{SOE} = y_t^{SOE} - k_{t-1}^{SOE} + pW_t^{SOE} \quad (4)$$

$$\text{mpk}_t^{SME} = y_t^{SME} - k_{t-1}^{SME} + pW_t^{SME} \quad (5)$$

and

$$n_t^{SOE} = y_t^{SOE} - w_t + pW_t^{SOE} \quad (6)$$

$$n_t^{SME} = y_t^{SME} - w_t + pW_t^{SME} \quad (7)$$

where pW_t^i is the relative price of wholesale output.

The capital producers are sector specific. The capital accumulation functions are as in (8) and (9).

$$k_t^{SOE} = \left(\frac{1-\delta}{\gamma}\right)k_{t-1}^{SOE} + \left(1-\frac{1-\delta}{\gamma}\right)inv_t^{SOE} + \left(1-\frac{1-\delta}{\gamma}\right)\left(1+\beta\gamma^{1-\sigma_c}\right)\gamma^2\varphi\varepsilon_t^{SOEinv} \quad (8)$$

$$k_t^{SME} = \left(\frac{1-\delta}{\gamma}\right)k_{t-1}^{SME} + \left(1-\frac{1-\delta}{\gamma}\right)inv_t^{SME} + \left(1-\frac{1-\delta}{\gamma}\right)\left(1+\beta\gamma^{1-\sigma_c}\right)\gamma^2\varphi\varepsilon_t^{SMEinv} \quad (9)$$

where δ is the depreciation rate and assumed to be the same between the two sectors. It is assumed that there are increasing marginal investment adjustment costs and the productive capital is a fraction $\left(1-\varphi\left(\frac{I_t^i}{I_{t-1}^i}\right)\right)$ of output. Following this assumption, in each sector the price of new capital depends positively on the expected future marginal product of capital and the expected future value of capital and negatively on the real cost of borrowing as shown in (10) and (11) below:

$$qq_t^{SOE} = \frac{1-\delta}{1-\delta+R_*^{KSOE}}E_t qq_t^{SOE} + \frac{R_*^{KSOE}}{1-\delta+R_*^{KSOE}}\left(y_t^{SOE} - k_t^{SOE} + pW_t^{SOE}\right) - \left(r_t - E_t \pi_{t+1}\right) \quad (10)$$

$$qq_t^{\text{SME}} = \frac{1-\delta}{1-\delta+R_*^{\text{KSME}}} E_t qq_t^{\text{SME}} + \frac{R_*^{\text{KSME}}}{1-\delta+R_*^{\text{KSME}}} \left(y_t^{\text{SME}} - k_t^{\text{SME}} + pW_t^{\text{SME}} \right) - \left(r_t - E_t \pi_{t+1} + s_t \right) \quad (11)$$

where R_*^i with $i =$ SOE, SME are the steady-state values of the return on capital and δ is the rate of capital depreciation. The Euler equations for investment in SOE and SME sectors specify the optimal investment plan. The weighted average of past, current and future investment in each sector depends on the price of new capital, qq_t^i, where $i =$ SOE, SME,

$$inv_t^{\text{SOE}} = \frac{1}{1+\beta\gamma^{(1-\sigma_c)}} inv_{t-1}^{\text{SOE}} + \frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}} E_t inv_{t+1}^{\text{SOE}} + \frac{1}{\left(1+\beta\gamma^{(1-\sigma_c)}\right)\gamma^2\varphi} qq_t^{\text{SOE}} + \varepsilon_t^{\text{SOEinv}} \quad (12)$$

$$inv_t^{\text{SME}} = \frac{1}{1+\beta\gamma^{(1-\sigma_c)}} inv_{t-1}^{\text{SME}} + \frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}} E_t inv_{t+1}^{\text{SME}} + \frac{1}{\left(1+\beta\gamma^{(1-\sigma_c)}\right)\gamma^2\varphi} qq_t^{\text{SME}} + \varepsilon_t^{\text{SMEinv}} \quad (13)$$

Aggregate investment is a combination of two sectors investment

$$\text{inv}_t = \frac{\text{INV}^{\text{SOE}}}{\text{INV}} \text{inv}_t^{\text{SOE}} + \frac{INV^{\text{SME}}}{\text{INV}} \text{inv}_t^{\text{SME}} \quad (14)$$

Firms producing intermediate goods in each sector hire labour from the organized labour sector and capital bought from the sector-specific capital producer. Since the SOE firms are assumed to be able to borrow at the risk-free rate, the price of capital will therefore depend negatively on this real risk-free rate interest. However, the firms in the SME sector are assumed to be risky and obtain loans at a risk premium from banks. There are many ways that banks can perform this lending channel to risky firms. One way is to lend at the risk-free rate plus a mark-up to high-value individuals or intermediary firms, who then pass it on, together with a slice of their own capital to risky SMEs. These intermediaries share the risks with SME firms to whom they are lending. The banks pay a risk-free rate on their deposits and make risky loans to SMEs. We can think of this as banks charging SMEs a higher premium than the rate at which they lend to SOEs. SMEs use the borrowing and their net worth together in purchasing the capital needed for future production. SMEs could reduce the premium by pledging a high net worth and/or pledging some of their cash collateral. Besides the cash collateral element taken from Le et al. (2016), the dynamics of the risk premium is as described in Bernanke et al. (1999). The SMEs risk premium is given by (15);

$$s_t = E_t cy_{t+1} - \left(r_t - E_t \pi_{t+1} \right) = \chi \left(qq_t^{\text{SME}} + k_t^{\text{SME}} - nw_t^{\text{SME}} \right) - \psi_1 m_t + \varsigma_{1t} + \varepsilon_t^{pr} \quad (15)$$

The risk premium is reduced with a higher cash collateral (m_t) and a higher net worth relative to the gross value of capital ($-(qq_t^{\text{SME}} + k_t^{\text{SME}} - nw_t^{\text{SME}})$),[16] and rises with more regulations (ς_{1t})[17] and ex-

---

[16]The balance sheet of the firm is fixed capital and cash as assets and loans and equity (net worth) as liabilities. The loans and equity are used to purchase capital goods. The higher the equity the lower the dependence on bank debt and the lower the riskiness of the firm and consequently the lower the risk premium. See Le et al. (2016a) for a theoretical underpinning.

[17]Regulations here are interventions that raise the cost of capital to the firm such as increased bank capitalisation, but in the China context these will include shocks to the bank's reserve ratio, loan-deposit caps, window guidance, and quantitative controls on lending.

ogenous shocks (ε_t^{pr}). There is also an assumption that in every period a fixed death rate $1 - \theta$ happens so that the stock of SME firms is kept constant by an equal birth rate of new firms, and the net worth remains below the demand for capital. This means that the SMEs net worth is the past net worth of surviving firms plus their total return on capital minus the expected return (which is paid out in borrowing costs to the bank) on the externally financed part of their capital stock.

$$\text{nw}_t^{\text{SME}} = \theta \text{nw}_{t-1}^{\text{SME}} + \frac{K^{\text{SME}}}{\text{NW}^{\text{SME}}} \left(cy_t - E_{t-1} cy_t \right) + E_{t-1} cy_t + \varsigma_{2t} + \varepsilon_t^{\text{NW}} \tag{16}$$

where $\frac{K^{\text{SME}}}{\text{NW}^{\text{SME}}}$ is the steady-state ratio of SMEs' capital expenditures to SMEs net worth, cy_t is the real external financing rate, ς_{2t} is a regulatory-specific shock to net worth and $\varepsilon_t^{\text{NW}}$ represents all other net worth shocks. The regulations are the instruments that the central bank can also use to influence the credit premium and indirectly the net worth of the firms. However, since data on microprudential measures are very poor, for simplicity we include these in the errors ε_t^{pr} and $\varepsilon_t^{\text{NW}}$.

While the BGG net worth channel has been used extensively in the literature and is well known, the cash collateral variant requires greater elaboration. The idea of costly state verification is that net worth is all invested in plant, machinery and other capital and thus cannot be recovered at original value and has less value when the firm goes bankrupt because it has become specialized to the firm's activities. It is normal for banks also to request an amount of collateral (e.g., Kiyotaki and Moore, 1997). If this collateral was in terms of cash, that is, a firm holds some cash on its balance sheet, this can be recovered directly without loss of value and no verification cost. The elimination of the collateral cost helps to bring down the credit premium for given net worth and it allows firms to increase leverage and so raise their expected returns. It assumes that banks and SME firms have a mutual interest in firms holding as much cash as can be acquired for collateral. The process of cash being used as collateral is as follows. As the central bank issues cash through open market operations to households in exchange for government bonds they hold, households deposit cash with banks, firms want to acquire as much of this cash as possible for their collateral needs (they invest their net worth in cash to the maximum available with the rest going into other collateral and capital). In practice, the firms' profits are continuously paid out as dividends to the banks which lend to them, so they have nothing with which to acquire these assets if they do not collaborate with banks. They achieve this balance sheet outcome by agreeing with the banks that, as a minimum counterpart to the credit advanced, they will hold the maximum cash collateral available, which is M0. Thus, all M0 at once finds its way to firm's balance sheet, where it is securely pledged to the banks in the event of bankruptcy.[18]

The resource constraint states that aggregate output y_t depends on consumption, investment and an exogenous (government spending and net trade) shock, ε_t^G and it ignores the contribution from the entrepreneurs' consumption as it is negligible.

$$y_t = \frac{C}{Y} c_t + \frac{I}{Y} \text{inv}_t + \varepsilon_t^G \tag{17}$$

The final goods producer would gather these intermediate goods with a CES production function into final goods and pay intermediate firms pW_t^i with $i = \text{SOE, SME}$. The final output together is.

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[18]There are many ways that money can be brought into a model such as this. The way we have done it is in the spirit of the credit channel where cash is pledged as collateral and serves to reduce the risk premium. A real-world feature is the availability of liquidity to the financial system which reduces interest rates and spreads.

$$y_t = \eta y_t^{\text{SOE}} + (1-\eta) y_t^{\text{SME}} \tag{18}$$

where η is the share of SOE output in total output.

Cost minimization implies the following demand for intermediate goods

$$y_t^{\text{SOE}} = -\epsilon p W_t^{\text{SOE}} + y_t \tag{19}$$

$$y_t^{\text{SME}} = -\epsilon p W_t^{\text{SME}} + y_t \tag{20}$$

where ϵ is the elasticity of substitution between the two intermediate goods.

Following Le et al. (2011), we assume that the final goods producers then sell a part of final goods in the competitive market at the marginal cost and it differentiates the rest and then marks up for sale in the market characterized by the nominal rigidities. Therefore, the model introduces the monopolistic power and nominal price rigidities at the retail level. For simplicity, we solve for prices under the competitive market assumption and then under the imperfect competition assumption and take the weighted average between the two as the solution for the price in our model. Labour supply also works in the same way.[19] Households supply labour to a regulated labour market and to competitive labour markets, so that the aggregate wage index is a weighted average of the perfectly competitive and imperfectly competitive wage levels. The imperfectly competitive market set-up gives the New-Keynesian Phillip curve where a weighted average of current, past and expected future inflation depends on the price mark-up and an exogenous cost-push shock to prices, ϵ_t^p:

$$
\begin{aligned}
\pi_t &= \frac{\beta \gamma^{(1-\sigma_c)}}{1 + \beta \gamma^{(1-\sigma_c)} \iota_p} E_t \pi_{t+1} + \frac{\iota_p}{1 + \beta \gamma^{(1-\sigma_c)} \iota_p} \pi_{t-1} \\
&+ \left(\frac{1}{1 + \beta \gamma^{(1-\sigma_c)} \iota_p} \right) \left(\frac{\left(1 - \beta \gamma^{1-\sigma_c} \xi_p\right)\left(1 - \xi_p\right)}{\xi_p \left(\left(\phi_p - 1\right) \varepsilon_p + 1\right)} \right) \left(\eta p W_t^{\text{SOE}} + (1-\eta) p W_t^{\text{SME}} \right) + \epsilon_t^p
\end{aligned}
\tag{21}
$$

and the weighted average of current, past and expected future wages depends on the wage mark-up, inflation and a cost-push shock to wages, ϵ_t^W:

$$
\begin{aligned}
w_t &= \frac{\beta \gamma^{(1-\sigma_c)}}{1 + \beta \gamma^{(1-\sigma_c)}} \left(E_t w_{t+1} + E_t \pi_{t+1} \right) + \frac{1}{1 + \beta \gamma^{(1-\sigma_c)}} w_{t-1} - \frac{1 + \beta \gamma^{(1-\sigma_c)} \iota_w}{1 + \beta \gamma^{(1-\sigma_c)}} \pi_t + \frac{\iota_w}{1 + \beta \gamma^{(1-\sigma_c)}} \pi_{t-1} \\
&- \left(\frac{1}{1 + \beta \gamma^{(1-\sigma_c)}} \right) \left(\frac{\left(1 - \beta \gamma^{1-\sigma_c} \xi_w\right)\left(1 - \xi_w\right)}{\xi_w \left(\left(\phi_p - 1\right) \varepsilon_w + 1\right)} \right) \left(w_t - \sigma_l l_t - \left(\frac{1}{1 - \frac{\lambda}{\gamma}} \right) \left(c_t - \frac{\lambda}{\gamma} c_{t-1} \right) \right) + \epsilon_t^w
\end{aligned}
\tag{22}
$$

The perfectly competitive market set-up produces the labour supply that reacts to expected inflation

$$w_t = \sigma_L l_t + \left(\frac{1}{1 - \frac{\lambda}{\gamma}} \right) \left(c_t - \frac{\lambda}{\gamma} c_{t-1} \right) - \left(\pi_t - E_{t-1} \pi_t \right) \tag{23}$$

---

[19]As we are unaware of a long time series of wage for SOEs and SMEs, this modelling convenience enables us to work with a single wage series.

and the natural log of real marginal costs for the final goods producer must be equal to zero

$$\varepsilon p W_t^{\text{SOE}} + (1-\varepsilon) p W_t^{\text{SME}} = 0 \tag{24}$$

To close the model, we allow the short-term rate on official lending to the banks to be set by the PBOC in accordance with a Taylor Rule. We assume that the PBOC enforces this rule via open market operations. That is, households hold part of their savings in government bonds and the rest in bank deposits, which pay the short-term interest rate also obtainable on short-term government bonds. In order to control the short-term rate, the PBOC would sell/buy the long-term government bond to buy/sell the short-term government bonds to influence the prices of these assets and thus their rates. Cash is issued in this model, but is only held by firms, as households have no use for it and deposit it in banks where it is lent to firms to hold as collateral and affect the credit premium. Beside the regulations, the monetary authorities therefore have two instruments, M0 and r:

$$r_t = \rho r_{t-1} + (1-\rho)\left(\rho_\pi \pi_t + \rho_y y_t + \rho_{\Delta y}\left(y_t - y_{t-1}\right)\right) + em_t \tag{25}$$

$$\Delta m_t = \psi_2 \Delta M_t + errm_{2t} \tag{26}$$

where ψ_2 is positive and M_t is the supply of money, which is defined as the sum of deposits and base money. Using the firms' balance sheet, the money supply is expressed as a function of base money, capital and net worth, υ, μ and c are, respectively, the ratios of net worth, M0 and collateral to money,

$$M_t = (1 + v - \mu) k_t + \mu m_t - v n_t \tag{27}$$

This now gives our monetary authorities three instruments: base money, the interest rate and microprudential policy.

4 | THE METHOD OF INDIRECT INFERENCE

We evaluate the model's capacity in fitting the data using the method of II originally proposed in Minford, Theodoridis, and Meenagh (2009). The approach employs an auxiliary model that is completely independent of the theoretical one to produce a description of the data against which the performance of the theory is evaluated indirectly. Such a description can be summarized either by the estimated parameters of the auxiliary model or by functions of these; we will call these the descriptors of the data. While these are treated as the 'reality', the theoretical model being evaluated is simulated to find its implied values for them.

Indirect inference has been widely used in the estimation of structural models (e.g., Canova, 2005; Gregory & Smith, 1991, 1993, Gourieroux, Monfort, & Renault, 1993; Gourieroux & Monfort, 1995; Smith, 1993). Here, we make a further use of indirect inference to evaluate an already estimated or calibrated structural model. The common element is the use of an auxiliary time-series model.[20] In estimation, the parameters of the structural model are chosen such that when this model is simulated it generates estimates of the auxiliary model similar to those obtained from the actual data. The

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[20]This is not the first model of the Chinese economy to take this approach. Le et al. (2014) use II to estimate a more aggregative structure than that proposed in this paper, and Dai et al. (2015) test the method of II on a DSGE model.

optimal choices of parameters for the structural model are those that minimize the distance between a given function of the two sets of estimated coefficients of the auxiliary model. Common choices of this function are the actual coefficients, the scores or the impulse response functions. In model evaluation, the parameters of the structural model are taken as given. The aim is to compare the performance of the auxiliary model estimated on simulated data derived from the given estimates of a structural model—which is taken as a true model of the economy, the null hypothesis—with the performance of the auxiliary model when estimated from the actual data. If the structural model is correct then its predictions about the impulse responses, moments and time-series properties of the data should statistically match those based on the actual data. The comparison is based on the distributions of the two sets of parameter estimates of the auxiliary model, or of functions of these estimates.

The testing procedure thus involves first constructing the errors implied by the previously estimated/calibrated structural model and the data. These are called the structural errors and are backed out directly from the equations and the data.[21] These errors are then bootstrapped and used to generate for each bootstrap new data based on the structural model. An auxiliary time-series model is then fitted to each set of data and the sampling distribution of the coefficients of the auxiliary time-series model is obtained from these estimates of the auxiliary model. A Wald statistic is computed to determine whether functions of the parameters of the time-series model estimated on the actual data lie in some confidence interval implied by this sampling distribution.

Following Le, Meenagh, Minford, Wickens, and Xu (2016) we use as the auxiliary model a VECM which we re-express as a VAR(1) for the three macrovariables (interest rate, output gap and inflation) with a time trend and with the productivity residual entered as an exogenous non-stationary process (these two elements having the effect of achieving co-integration—Le, Meenagh, Minford, & Ou, 2013). Thus, our auxiliary model in practice is given by: $y_t = Ay_{t-1} + \gamma \bar{x}_{t-1} + gt + v_t$, where $\bar{x}_{t-1}$ is the stochastic trend in productivity, gt are the deterministic trends and v_t are the VECM innovations. We treat as the descriptors of the data the VAR coefficients (on the endogenous variables only, (A)). The Wald statistic is computed from these.[22] Thus, effectively we are testing whether the observed dynamics and volatility of the chosen variables are explained by the simulated joint distribution of these at a given confidence level.

The joint distribution of the Φ (the vector of VAR estimates) is obtained by bootstrapping the innovations implied by the data and the theoretical model; it is therefore an estimate of the small sample distribution.[23] Such a distribution is generally more accurate for small samples than the asymptotic distribution; it is also shown to be consistent by Le et al. (2011) given that the Wald statistic is

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[21]Some equations may involve calculation of expectations. The method we use here is the robust instrumental variables estimation suggested by McCallum (1976) and Wickens (1982): we set the lagged endogenous data as instruments and calculate the fitted values from a VAR(1) — this also being the auxiliary model chosen in what follows.

[22]We do not attempt to match the time trends and the coefficients on non-stationary trend productivity; we assume that the model coefficients yielding these balanced growth paths and effects of trend productivity on the steady state are chosen accurately. However, for our exercise, we are not interested here in any effects on the balanced growth path, as this is fixed. As for the effects of productivity shocks on the steady state we assume that any inaccuracy in this will not importantly affect the business cycle analysis we are doing here- any inaccuracy would be important in assessing the effect on the steady state which is not our focus. Thus, our assessment of the model is as if we were filtering the data into stationary form by regressing it on the time trends and trend productivity. The Wald statistic is given by: $(\Phi - \overline{\Phi})' \sum_{(\Phi\Phi)}^{-1} (\Phi - \overline{\Phi})$, where Φ is the vector of VAR estimates of the chosen descriptors yielded in each simulation, with $\overline{\Phi}$ and $\sum_{(\Phi\Phi)}$ representing the corresponding sample means and variance-covariance matrix of these calculated across simulations, respectively.

[23]The bootstraps in our tests are all drawn as time vectors so contemporaneous correlations between the innovations are preserved.

'asymptotically pivotal'; they also showed it had quite good accuracy in small sample Monte Carlo experiments.[24]

This testing procedure is applied to a set of (structural) parameters put forward as the true ones (H_0, the null hypothesis); they can be derived from calibration, estimation or both. However derived, the test then asks: could these coefficients within this model structure be the true (numerical) model generating the data? Of course, only one true model with one set of coefficients is possible. Nevertheless, we may have chosen coefficients that are not exactly right numerically, so that the same model with other coefficient values could be correct. Only when we have examined the model with all coefficient values that are feasible within the model theory will we have properly tested it. For this reason, we later extend our procedure by a further search algorithm, in which we seek alternative coefficient sets that could do better in the test.

Thus, we calculate the minimum-value full Wald statistic using an algorithm in which search takes place over a wide range around the initial values. In effect this is Indirect Inference estimation of the model; however, here this estimation is being done to find whether the model can be rejected *in itself* and not for the sake of finding the most satisfactory estimates of the model parameters. Nevertheless, of course the method does this latter task as a by-product so that we can use the resulting unrejected model as representing the best available estimated version. The merit of this extended procedure is that we are comparing the best possible versions of each model type when finally conducting our comparison of model compatibility with the data.

5 | ESTIMATION AND MODEL FIT

A description and the source of the data used can be found in Table 2 and the descriptive statistics are in Table 3.

The model is estimated using the method of II for the 1992–2016 period. It is tested against the data using the main macroeconomic variables, output, inflation and the interest rate. We use a test of whether the model can match the time-series properties of the data jointly.

The reason for the choice of these particular variables is that we want the model to be able to explain the variables that macroeconomists and policymakers are most interested in. The focus of the paper is not about modelling shadow banking in reality, but whether a model that includes shadow banking, as here, can match the general macroeconomic environment. If the model can match these variables, then we can use the model to explore policies that may improve these variables' behaviour. The reason we have chosen only three variables is because of the power of the Indirect Inference test. As the number of variables in the auxiliary model increases, so does the power of the test because the model will be required to replicate more detailed features of the data. Including too many variables will result in no model being able to pass the test. Using three variables in the auxiliary model has been shown to be a good balance of high power and model tractability (Meenagh, Minford, Wickens, & Xu, 2019).

The model is not rejected by the data according to the Wald statistic and p-values representing conventional levels of significance. The estimated parameters can be found in Table 4. We show three impulse response functions to key variables when the model is applied to non-stationary data in Figure 2. Note that the second set of IRFs in the figure is due to a non-stationary productivity shock.

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[24]Specifically, they found on stationary data that the bias due to bootstrapping was just over 2% at the 95% confidence level and 0.6% at the 99% level. Meenagh et al. (2019) found even greater accuracy in Monte Carlo experiments on non-stationary data.

TABLE 2 Description and source of the data

Variable	Description	Source
Consumption	Real household final consumption expenditure	National Bureau of Statistics of China
GDP	Real gross domestic product	OECD Quarterly National Accounts
Labour	Employment	Oxford Economics
CPI	Consumer price index	OECD Economic Outlook
Wages	Average overall wages for staff and workers in Urban units	Ministry of Human Resources and Social Security, China
Interest rate	Discount rate	IMF—International Financial Statistics
Lending rate	Lending rate	IMF—International Financial Statistics
Net worth	Shanghai stock exchange stock market capitalization	Shanghai Stock Exchange
M0	Money supply M0	The People's Bank of China
Total credit	Credit to private non-financial sector	Bank for International Settlements
Shadow credit	Shadow banking credit	Goldman Sachs and Moody's and author calculations
M2	Total credit+shadow credit	The People's Bank of China and author calculations
Total investment	Total investment	National Bureau of Statistics China
Private investment	Private fixed investment	National Bureau of Statistics China & I-Find Financial Database
Population	Population	World Bank

TABLE 3 Descriptive statistics of the data (1992Q1–2016Q4)

	Mean	*SD*	Min	Max
Consumption (% GDP)	41.550	4.139	35.485	47.395
Investment (% GDP)	49.566	17.950	27.815	83.113
Annual Output (Growth)%	9.235	3.060	3.724	16.294
Labour (millions)	730.301	36.333	656.562	776.030
Annual Inflation%	0.971	1.528	−1.043	6.552
Annual real Wage (Growth)%	9.643	3.595	−0.528	17.304
Interest Rate%	4.694	2.643	2.700	10.440
Net Worth (billions)	8,316.014	9,142.408	6.534	34,669.084
Premium%	2.198	0.791	0.090	4.140
Lending Rate%	6.891	2.103	4.350	12.060
Real M0 (Growth)%	7.607	5.654	−3.912	28.514
Real M2 (Growth)%	18.196	5.548	2.622	30.340
Private Investment (% GDP)	24.718	14.542	9.108	51.806
Other Investment (% GDP)	24.848	3.717	18.707	32.805
Shadow Banking Credit (% GDP)	79.322	90.686	8.953	324.072

TABLE 4 Coefficient estimates (1992–2016)

Elasticity of consumption	σ_c	2.8544
Steady-state elasticity of capital adjustment	φ	9.1094
External habit formation	λ	0.0001
Elasticity of labour supply	σ_l	1.1497
Probability of not changing prices (SME)	ξ_p	0.9008
Price indexation (SME)	ι_p	0.0281
Probability of not changing wages	ξ_w	0.8122
Wage indexation	ι_w	0.1264
Substitution between demand for SOE and SME intermediate goods	ε	2.1414
Elasticity of the premium with respect to leverage	χ	0.0098
Elasticity of the premium to M0	ψ_1	0.0265
Monetary response	ψ_2	0.0052
Interest rate smoothing	ρ	0.8647
Taylor Rule response to inflation	ρ_π	2.5126
Taylor Rule response to output	ρ_y	0.2998
Taylor Rule response to change in output	$\rho_{\Delta y}$	0.0487
NK weight on inflation	ω_π	0.0899
NK weight on wage	ω_w	0.9979
Cobb Douglas weight on SOE output	α^{SOE}	0.5502
Cobb Douglas weight on SME output	α^{SME}	0.1364
	Wald	17.4968
	Trans. wald	1.5250
	p value	0.0600

Broadly the parameters reveal that in China the structure of the product market is strongly competitive while the labour market operates in an imperfectly competitive market. In the imperfectly competitive labour market wages are rigid, and there is little wage indexation. In the small proportion of the goods market that is imperfectly competitive prices are very sticky. Output in the SOE sector is more capital intensive than the SME sector.

From the IRFs we can also see that the SMEs react more to a monetary policy shock than the SOEs due to the financial accelerator mechanism. This result contrasts with the consensus view that the effect of monetary policy on output is dampened as firms switch from conventional bank credit to shadow bank credit (e.g., Chen, Ren, & Zha, 2018). We find here that a tightening of monetary policy has a stronger effect on the SME sector than the financially protected SOE sector.

When there is a permanent productivity shock to the SME sector it pulls resources from the SOEs to permanently increase SME output at the cost of SOE output. Overall output still expands as the SME sector is dominant. A positive premium shock increases the cost of borrowing for SMEs, decreasing investment and output. Consequently, resources move to the SOEs boosting investment and output. The overall effect on the economy is a decrease in output. A money supply shock causes the SMEs to have cheaper collateral, thus reducing their premium having an opposite macroeconomic effect to that of a positive premium shock.

5.1 | The errors driving the episode of the GFC

What does the model say about the period of the GFC? We begin by showing the behaviour of the main model errors from 2006. We can see from Figure 3 that there was turbulence over the GFC period in many of these shocks. We can single out ones where this was greatest. Exogenous demand shows the collapse of world trade at the end of 2008. There are parallel falls in consumption and
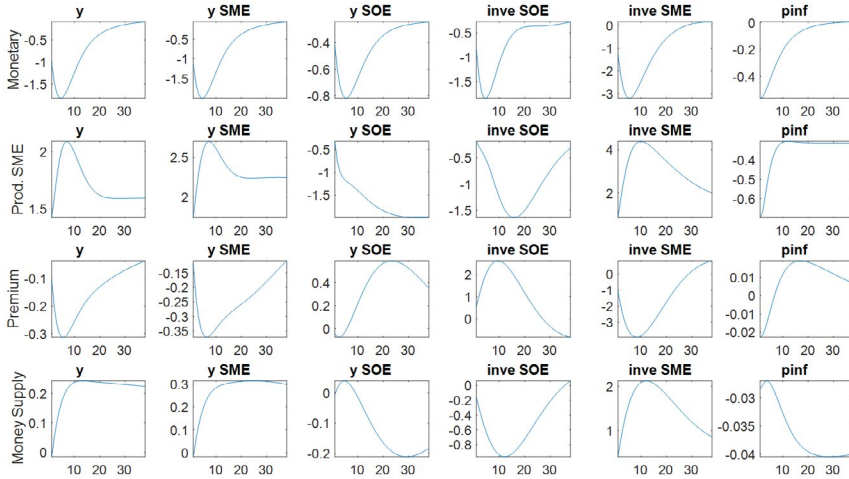

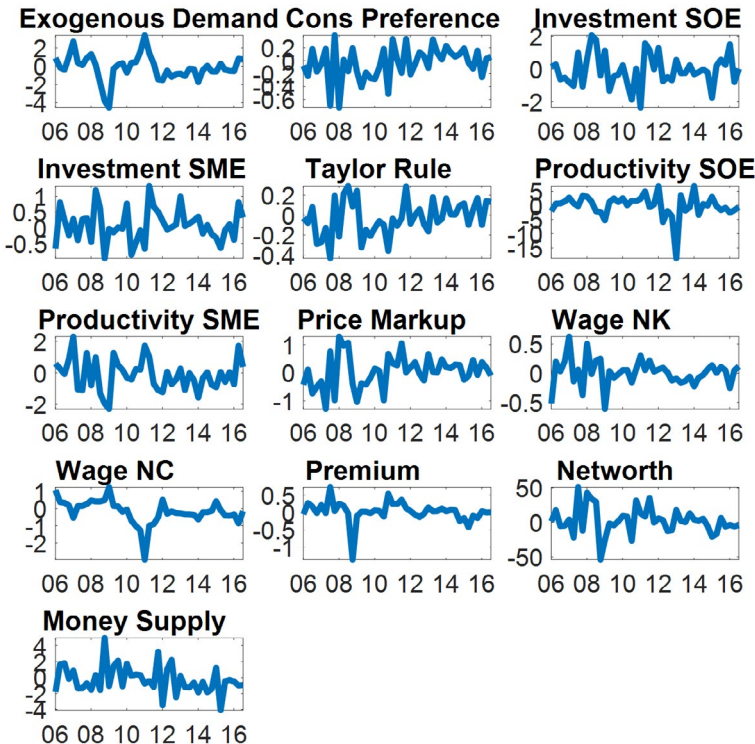**FIGURE 2**   IRFs for productivity shock, premium shock and M0 shock

FIGURE 3   Shocks from 2006 to 2016

investment by SMEs, along with productivity. The price mark-up fluctuated with world commodity price movements.[25] The Taylor Rule error appears to be associated with these and with world trade movements. There is a strong shock coming via M0, which rose sharply during 2009 by Bank policy, which also saw a reduction in the premium as banks were encouraged to lend.

Clearly, the GFC had international ramifications, but we cannot identify the causality of these in a China-only model. The shocks that show up in the model are partly coming from these international effects. Thus, commodity price shocks that enter through the 'price mark-up' here are themselves responding to the crisis. Also, the exogenous demand shock, which consists of government spending and net exports, contains the international downturn in world trade.

A further limitation of our account is our inability to analyse connections between the shocks to the model. No doubt the financial shocks we identify had simultaneous and lagged effects on the non-financial shocks; but also vice versa. The model assumes that each shock is separate from the others and only related to its own past. The model then disentangles how each shock works through the economy to affect final outcomes. Anyone that wished to take matters further would have to model the interactions of the shocks themselves through a wider model, such as one of political economy.

Overall, we can see that there was a wide set of shocks hitting the Chinese economy during the GFC period, the major ones being external but in turn triggering domestic counterpart shocks. The Chinese authorities' response was, as we know, to compel the SOCBs to lend for investment projects, mainly infrastructure. We can see this response in the SOE investment error, which turns sharply positive from the end of 2011. We can also see a strong reaction to the crisis in government spending in the years following the crisis.

We next look at the variance decomposition of the model. Again, we are using unfiltered data when performing this analysis which treats the episode stochastically—that is, we take the shocks in the episode and replay them by redrawing them randomly and repeatedly. For the variance decomposition we consider the financial shocks to be the premium, net worth, money supply and monetary policy.[26] What we see from Table 5 is that financial shocks account for only 15% of total output variance, with a much larger per cent of SME output variance (22%) due to financial shocks than SOE output (2%). This is mainly due to the monetary policy and net worth shocks. The rest is due to the usual non-financial shocks. This is also the case for investment, but the difference is not as stark. The monetary policy shock is not so important, with the other financial shocks increasing in importance.

Of the non-financial shocks, the non-stationary productivity shocks dominate, especially in the SOE sector. The investment shocks also play a prominent role. In sum, there is a distinct role for financial shocks, but the bulk of the variation comes from the other shocks: notably productivity and investment.

Figure 4 shows the historical decomposition for output. At the start of the GFC period there was an initial slowdown in GDP. From the decomposition we find that this is mainly driven by exogenous demand, which had a positive effect on output before the GFC struck, then shifts to a negative effect quite rapidly. There is also a reduction in the positive effect of SME productivity. The slowdown in GDP after 2012 is due to a large drop in SME productivity as well as a reduction in SOE productivity.

We can now examine the question whether a reasonable attempt to allow explicitly for the role of the shadow banks makes any material difference to the model's conclusions. We can get a feel for the answer by looking at the sum of net worth and premium shocks. The answer is that it makes a huge

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[25]Jian et al. (2010) use a standard sticky-price DSGE, to identify the effects of oil price shocks on productivity. They confirm that oil price shocks have permanent negative effects on output.

[26]It may seem strange to include the M0 error among financial shocks when its rise at the end of the period reflects a strong policy response. However, in this it parallels the behaviour of the credit premium shock in the US which was clearly a financial shock but also later embodied a strong policy response in the form of bank bailout.

TABLE 5 Variance decomposition

	Output	SME output	SOE output	Interest rate	Investment	SME investment	SOE investment	Inflation
Govt spending	1.25	1.94	0.33	0.60	4.38	0.09	2.71	0.12
Cons preference	0.09	0.11	0.01	0.21	0.11	0.02	0.03	0.07
Investment SOE	7.81	8.01	8.11	22.34	10.15	10.12	29.69	1.20
Investment SME	6.71	12.58	2.72	8.22	7.68	57.04	25.22	1.75
Taylor rule	11.73	14.26	0.52	3.11	7.91	2.63	0.89	18.92
Productivity SOE	48.59	18.39	83.89	42.06	63.83	2.40	30.89	46.07
Productivity SME	19.60	36.60	2.97	21.08	2.60	5.14	0.77	25.31
Price mark-up	0.02	0.03	0.00	0.54	0.01	0.02	0.01	3.77
Wage NK	0.26	0.31	0.01	0.64	0.17	0.03	0.04	0.86
Wage NC	0.21	0.25	0.01	0.21	0.13	0.04	0.02	0.22
Premium	0.46	1.03	0.41	0.60	0.50	5.62	2.77	0.08
Net worth	2.53	5.26	0.96	0.15	1.44	14.23	6.49	1.10
Money supply	0.72	1.23	0.05	0.24	1.08	2.62	0.45	0.53
Financial shocks	15.44	21.77	1.94	4.10	10.93	25.10	10.61	20.63
Non-financial shocks	84.56	78.23	98.06	95.90	89.07	74.90	89.39	79.37
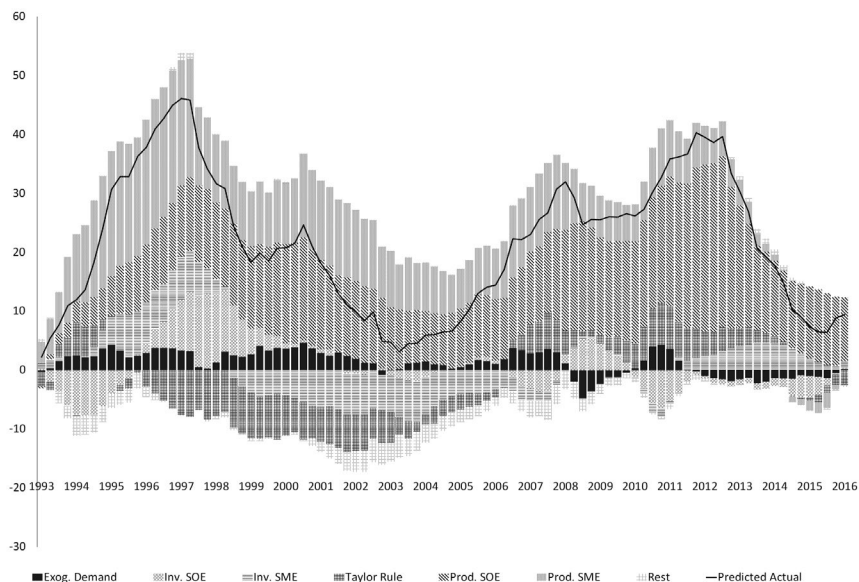
FIGURE 4 Historical decomposition for output

TABLE 6 Frequency of economic growth slowdown generated by the model for the whole sample and the post-GFC sample

1992–2016		Length (quarters)			2006–2016		Length (quarters)		
		4	**8**	**12**			**4**	**8**	**12**
Growth %	5	148	60	20	Growth %	5	162	77	33
	3	111	35	9		3	130	49	17
	0	62	12	2		0	76	20	4

difference to private (SME) investment, but not to total output. This clearly makes sense as private investment is more responsive to the premium being less exposed to the cheap credit available to SOEs. However, the SME sector is less capital intensive than the SOE sector which explains the dampened effect on total output. The basic result is that shadow banking shocks make up about one fifth of the variance of private sector investment but only 3% of the variance of total output.

What lessons can we draw for China from the above analysis? China has maintained robust economic growth throughout the GFC relative to its western counterpart. So, a crisis such as negative growth has never occurred. To project into future, we thus need an appropriate definition of extremely undesirable growth outcomes, which will be termed as severe economic slowdowns (SES) hereafter. Given the recent experience in China, we define a SES as a growth slowdown below that of the assumed balanced growth path (BGP) of 6% per year for a sustained period.

What does this model have to say in general about the causes of these slowdowns? We examine this question by inspecting the bootstrap experience (potential scenarios over the period) from the model and its normal shocks. Again, this analysis is done on unfiltered data. Table 6 shows the frequency of economic growth slowdown generated from repeated simulation of 1,000 bootstraps using the shocks generated for the full period and compare this with the same for the period of the GFC.

The way to interpret Table 6 is that each column shows the number of times per 1,000 years of simulation that growth will fall below a specific rate for a given length of time. So, in the first column

of the left side of Table 6, the number 148 is the number of times in 1,000 years of simulations that growth falls below 5% for a period of four quarters. Another way of thinking about it is that China could experience a growth slowdown of 5% every 7 years (1000/148). The next element in the same column is 111 which says that the frequency of growth slowdown of 4% is 111 times per 1,000 years, or every 9 years. Given the history of shocks over this sample period, the model states that the frequency of growth slowdown diminishes with the severity and length.

The right side of Table 6 shows the same analysis using the shocks of the crisis period to 2016. Here, we can see that the frequency of growth slowdowns is a little higher. A growth slowdown of 5% for four quarters occurs 162 times per 1,000 years, or every 6 years. Zero growth for four quarters occurs every 13 years. The GFC did make a difference to the Chinese economy, but principally through the exogenous shocks to trade. This result confirms the insulation of the Chinese banking sector from the GFC and that its impact was indirect through trade.

Clearly the simulations reveal normal economic fluctuations of the Chinese market economy: this economy will generate growth slowdowns regularly from 'standard' shock sequences. The model predicts that without additional reforms and innovations, a growth slowdown of 3% lasting 2 years would occur every 29 years, and a zero-growth prospect (which for a China accustomed to regular 6% plus is a severe interruption) every 83 years. This reflects the fact that shocks in this sample period were not as large as for some earlier periods in China.

Clearly these figures are affected by the nature of the sample shocks; here, we have used the experience of the last two decades, which apart from the crisis itself was the period of the Great Moderation in the world economy. As we know that the variance of shocks in this period was markedly lower than in earlier post-war history, extending our sample backwards in time would no doubt change our estimates in detail.

So, what does this all say about the Chinese financial sector and its economy? Some of the extreme scenarios we have just considered such as 3% or zero growth are surely unacceptable for China, and means have to be found to respond to slowing growth quickly so as to prevent it getting to such a scale—much as was done during the GFC. The means the Chinese state has found are in the existence of one economy two systems: the publicly owned alongside the private sector. The state still directly owns half the banking system and it still controls more than half of the economy. The state-owned banks (SOCBs) and firms (SOEs) act as twin channels through which the government can rapidly respond to events where necessary. Thus, in the GFC, the SOCBs were required to lend to SOEs: the response is visible in the SOE investment residual which picks up sharply from the start of 2011 onwards. Additionally, central and local government directly spent on infrastructure and consumption, this time funded directly by the Central Bank. This response too is visible in the behaviour of the exogenous demand residual from 2011 onwards.

6 | CONCLUSIONS

The method of indirect inference was used to estimate the model which was then used to carry out an accounting exercise in the shocks causing the growth slowdown in the GFC episode. The estimation was done on unfiltered data, allowing for non-stationary shocks. The model was not rejected by the data and a variance decomposition was conducted to establish what a typical crisis generated by these shocks if redrawn randomly would be caused by. Two simulations exercises were conducted using two different sets of the shocks in the sample to shed light on the causes of growth slowdown and the growth slowdown associated with the GFC in particular. The conclusion of the exercise is perhaps not very surprising. China experienced a growth slowdown rather than a precipitous drop in output as in

the rest of the world. The cause was mainly the result of external shocks from world trade and commodity prices, which in turn triggered responses from the Chinese authorities in the form of monetary policy shocks and shocks to investment (via targeted loans from state banks). Financial shocks as identified by the model played only a minor role, although they added to fluctuations over the whole period to date.

The model also tells us that growth slowdowns, even recessions, are regular occurrences in market economies, as in China, and that they frequently will have as their by-product financial roots in the sense that the premium rises sharply. These slowdowns will occur despite there being no extreme financial shocks such as that occurred in the GFC; so serious financial shocks are not required for severe growth slowdowns to happen. Furthermore, extreme financial shocks on their own of the type identified in this sample can cause temporary recessions. Thus, both severe economic downturns and financial crises result from non-financial shocks, and naturally financial shocks if extreme enough will add an extra layer to the already undesirable outcomes.

However, it must be stressed that the financial shocks identified in this sample all occurred in a political environment where the Chinese government acted aggressively with counter-cyclical loans for investment by SOEs and infrastructure spending by central and provincial governments; absent this, the scale of these shocks would have been very different. So what this work tells us about the current Chinese banking system is that, firstly, the use of directed credit to the state firms in times of crisis served the Chinese economy well in the short term, helping it to avoid the worst of the global downturn. However, this policy if became systematic could create instability as shown in Le et al. (2014) and the longer-term implications of focussing lending on state firms and starving the high growth private sector could return to haunt the banks with bad debts in the future.

While it can be argued that private firms are able to finance investment through the unregulated shadow banking system, the concentration of the country's main regular banking system on the low productive state sector represents a colossal misallocation of resources. Further study on the relationship between investment by private enterprises and shadow bank financing is called for. Until better information on the relationship of private investment to state-sponsored investment is available so that the effects of the shadow banking sector can properly understood, any conclusion on the stability of the economy with a shadow banking sector must be tentative. The attempts by the Chinese regulators to use the banking system for aggressive stabilization of the economy in the face of imported crisis may be breeding instability for the future.

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