ANNALS OF ECONOMICS AND FINANCE **21-2**, 415–469 (2020)

SOE and Chinese Real Business Cycle

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Chinese real business cycle (RBC) exhibits a unique pattern, which is characterized by moderate consumption volatility, substantially lower investment volatility, and acyclical trade balance. These features are quite different from business cycles in other emerging markets and cannot be explained by existing emerging market RBC theories. Motivated by the fact that China undertook dramatic and persistent reform on state-owned enterprises (SOE) in the last 30 years, we construct a full-fledged general equilibrium model with SOE sector and show that the model does a fairly good job in accounting for the above features. The two main driving forces are: (1) shock to the share of downstream SOE in manufacturing sectors and (2) shock to upstream SOE's monopolistic position. These two shocks can explain 85 percent of output volatility, 79 percent of consumption volatility, 72 percent of investment volatility, and 57 percent of the volatility of trade balance-to-output ratio. Standard shocks such as permanent productivity shock, credit shocks, country risk premium shocks, and preference shocks are less important in explaining Chinese economic fluctuations. Our results show that Chinese RBC may be affected substantially by domestic policies.

Key Words: State-owned Enterprise; Real business cycle; Vertical structure; Financial friction; Permanent shocks; Bayesian estimation.

JEL Classification Numbers: E3, F3, F4.

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1529-7373/2020

1. INTRODUCTION

With the enhanced importance of China in the global economy, the macroeconomic aspect of the Chinese economy has been extensively investigated recently. However, most studies have mainly focused on economic growth. What factors characterize Chinese real business cycle (RBC)? What drives economic fluctuations in China? The literature has long been mute on these issues.[1] In this paper, we document Chinese business cycle from 1978 to 2010 and reveal that Chinese RBC exhibits a unique pattern characterized by moderate consumption volatility, substantially low investment volatility, and acyclical trade balance.[2] Table 1 shows that Chinese RBC differs from business cycles in other emerging markets. To explain these features, we construct a full-fledged general equilibrium model exhibiting Chinese characteristics and investigate Chinese RBC using the Bayesian estimation method.

Why shall we consider Chinese characteristics? As shown by Shi, Wu and Xu (2014), current theories on emerging market business cycle, such as those proposed in Aguiar and Gopinath (2007) and Garcia-Cicco, Pancrazi and Uribe (2011), cannot explain Chinese data very well. Aguiar and Gopinath (2007) argue that the shock to the trend (or permanent productivity shock) may be a major source of business cycle fluctuations in emerging market economies; conversely, García-Cicco, Pancrazi and Uribe (2010) suggest that international financial friction should be considered when we investigate business cycles of emerging markets. However, excess consumption volatility and strong countercyclical trade balance are not observed in Chinese economy; therefore shock to the trend cannot explain Chinese RBC. Moreover, capital account has not been liberalized in China; as such, international financial frictions cannot be the major source of economic fluctuations either. These findings imply that we need to incorporate institutional features of Chinese economy in the model to explain Chinese business cycle.

What are the most important characteristics of Chinese economy? During Chinese economic transition, the persistent and remarkable reforms on state-owned enterprises (SOEs) are among the most profound changes in Chinese economy. On the one hand, the impact of SOE sector on China's economic growth has been extensively investigated in literature (Brandt, Hsieh and Zhu 2008, Song, Storesletten, and Zilibotti, 2011, Li, Liu, and Wang, 2015 among others). Song, Storesletten, and Zilibotti (2011) build a

[1] Brandit and Zhu (1995) investigate China's growth and inflation cycle from 1978 to 1995. They argue that economic decentralization, government's commit to state sector and credit control are key institutional features to explain the cycle.

[2] Shi, Wu and Xu (2014) also document some stylized facts on Chinese business cycle; however, they do not highlight the three main features.

growth model with SOE sector to explain China's growth experience since 1978. In their model, SOE firms have lower productivity but better access to credit markets; by contrast, private firms have higher productivity but limited financial access. In economic transition, high-productivity credit-constrained private firms will outgrow low-productivity SOE firms. As a result, sustainable economic growth occurs and foreign surplus accumulates. Moreover, Li, Liu, and Wang (2015) argue that SOEs have another advantage in industrial structure. That is, SOE monopolizes key industries and markets in the upstream sectors, whereas downstream industries are largely open to private competition.[3] Li, Liu, and Wang (2015) further show that this vertical structure, when combined with openness and labor abundance, is critical in explaining why SOE outperformed non-SOE after 2000 because upstream SOEs extract rents from liberalized downstream sectors during industrialization and globalization. Their findings suggest that SOE reforms will have important implications for economic fluctuations in China. On the other hand, SOE sector also follows cyclic pattern. For example, SOE's sales share was countercyclical and SOE's profit was procyclical, especially from 1978 to early 2000(Figures 1 and 2). Therefore, in view of the importance of SOE in Chinese economic transitions, it is natural to consider the SOE sector when investigating business cycle in Chinese economy.

We develop a small open economy general equilibrium model with a well-characterized SOE sector in this paper. Key features emphasized in Song, Storesletten, and Zilibotti (2011) and Li, Liu, and Wang (2015) are combined in our model; these key features include the advantage of SOEs in obtaining easy credit and monopolistic power in upstream production.[4] We add the SOE sector into an otherwise standard RBC model and estimate it using Bayesian methods. The model dynamics are driven by eight shocks: a shock to permanent neutral productivity (Aguiar and Gopinath 2007); a shock to credit constraint or a credit shock that private-owned enterprises (PE) are subject to, as in Jermann and Quadrini (2012) and Mendoza (2010) among others; a shock to government spending; three shocks to SOE sector, including shocks to the markup charged by upstream SOEs (markup shock), share of SOE's sales in downstream sector (share shock), and share of SOE's profit distributed to household (dividend shock); and two standard shocks discussed in emerging market business cycle litera-

[3]Song, Storesletten, and Zilibotti (2011) also discuss the asymmetric market power between SOE and PE firms in a two sector model in which SOE is capital intensive

[4]One important policy on SOE reforms in China is "Grasp the Large, Let Go of the Small." Hsieh and Song (2013) find that this policy has substantial impacts on the total factor productivity of SOE firms and social welfare. In our model, we do not model the endogenous transition between SOE and private firms; therefore all of the reform policies are considered as exogenous shocks to some key parameters such as the share of SOE in the downstream manufacturing sector.

ture — preference shock and country risk premium shock (Garcia-Cicco, Pancrazi and Uribe, 2010). The proposed model is an ideal laboratory to investigate the driving forces of fluctuations in China, for two reasons. First, it encompasses most theories on the source of business cycle fluctuation in the literature within a general equilibrium framework.[5] Second, its departure from the neoclassical growth prototype gives disturbance other than neutral productivity shock, such as shocks originated in SOE sector, a fair chance to explain business cycles.

We show that the estimated model can reproduce the main features of business cycle in China to a large extent. In particular, the proposed model predicts that the relative volatility of consumption to output is 1.06, in contrast to 0.98 in the data. The model also predicts that the relative volatility of investment to output is 2.33, which is the same as in the data. The model over-predicts the cyclicality of trade balance-to-output ratio and obtains 0.29, as opposed to −0.05 in the data. Nevertheless, it predicts a reasonable correlation between trade balance and consumption (−0.24) and between trade balance and investment (−0.23); by contrast, the corresponding correlation are −0.23 and −0.48 in the data. The model cannot account for the acyclical trade balance because of two reasons. First, SOE shocks dominate permanent technology shocks and credit shocks in matching low volatility of consumption and investment in China. The former is transitory, leading to a procyclical trade balance; by comparison, the latter two shocks generate a countercyclical trade balance. Second, we consider a separable preference, which is inadequate in generating a strong positive correlation between consumption and output; as a result, the trade balance is positively correlated with output.

In summary, shocks to SOE sector are the most important source in explaining China's economic fluctuation. These shocks generally account for 85 percent, 79 percent, 72 percent and, 57 percent of variance of output, consumption, investment and, trade balance-to-output ratio, respectively. Among the three SOE shocks, share shocks and markup shocks are the two main drivers. Dividend shocks, however, virtually has no role. As to shocks emphasized in the emerging market business cycle literature, the contribution of permanent productivity shock and credit shock are relatively small. Country risk premium shocks, which are the main source of movement of trade balance for Argentina and Mexico in García-Cicco, Pancrazi and Uribe (2010), is also less important. Preference shocks, which are identified as source of consumption fluctuation, are basically negligible, indicating there is no failure on intertemporal consumption smoothing.

[5]We do not analyze the role of transitory neutral productivity shock as in Aguiar and Gopinath (2007) and García-Cicco, Pancrazi and Uribe (2010) and the terms of trade shock (Mendoza, 1991) in this paper, because we consider endogenous TFP fluctuations instead.

Why are the share shock and markup shock of SOE sector so important for economic fluctuations in China? First, because of the productivity difference between SOE and PE firms in the downstream, the share shock will generate endogenous TFP fluctuation which is transitory. The transitory share shock generates moderate consumption volatility; and this is consistent with Chinese data. Second, markup shock is equivalent to a negative supply shock to downstream goods. Therefore, the transmission mechanism of these two SOE shocks is similar to that of transitory productivity shocks.

We compare our SOE model with current emerging market business cycle models, such as those described in Aguiar and Gopinath (2007) and Garcia-Cicco, Pancrazi and Uribe (2011). We find that the SOE model can match Chinese data much better than previous models based on two aspects. First, compared to Aguiar and Gopinath (2007), the SOE model generates substantially lower measurement error and reasonable trade balance volatility of trade balance. Second, the SOE model generates substantially lower volatility of consumption than Garcia-Cicco, Pancrazi, and Uribe (2011). We also evaluate the importance of three key model assumptions or features (vertical structure, credit constraint, and productivity difference) to explain Chinese business cycle. Our estimation results show that vertical structure and credit constraint are crucial to improve overall model fitness, whereas the productivity difference helps generate moderate consumption volatility. This finding implies that the three assumptions are all essential in our model. We also conduct some sensitivity analysis, by considering alternative household preference and by introducing labor market frictions.

This paper belongs to the literature on business cycles in emerging markets. Two major hypotheses are dominant in the literature: "shock to trend" discussed in Aguiar and Gopinath (2007) and "international financial frictions" discussed in García-Cicco, Pancrazi and Uribe (2010). Our paper differs from their work in two dimensions, in addition to the introduction of SOE sector. One involves the preference specification. We consider the King–Plosser–Rebelo (KPR) preferences (King, Plosser, and Rebelo 1988) instead of Greenwood Hercowitz-Huffman (GHH) preference (Greenwood, Hercowitz, and Huffman 1988) for two reasons. First, KPR preference is compatible with the balance growth path. Second, GHH preference helps obtain significantly countercyclical trade balance in a standard small open economy model. As discussed Aguiar and Gopinath (2007), this is because this preference generates a strong correlation between consumption and output. However, a strong and significant countercyclical trade balance is not observed in China. We estimated an alternative model with preference specification used by Jaimovich and Rebelo (2009), which nests GHH and KPR preference. The estimation strongly favors KPR preference. The other difference is that transitory productivity shocks are not incorporated in our model. Instead, we consider transitory but endogenous productivity changes, which are driven by two SOE shocks. This modeling strategy is consistent with findings in the TFP literature. These papers argued that substantial TFP changes occur in the transitional economy because of resource reallocation between sectors. For example, see Hsieh and Klenow (2009), Song, Storesletten, and Zilibotti (2011), and Brandt, Tombe, and Zhu (2013).

Our paper is closely related to Shi, Wu, and Xu (2013), which also documents stylized facts of Chinese business cycle and investigates the extent to which Chinese business cycles can be explained by existing theories. Conversely, our paper focuses on investigating the impact of SOE on Chinese business cycles. Curtis and Mark (2010) show that naively applying the standard business-cycle tools to China is not more ridiculous than applying it to a developed economy, such as Canada, although the dimensions along which the model struggles are different. However, their analysis and results are based on calibration; therefore sources generating business cycles or shocks explaining economic fluctuation cannot be identified. By contrast, our model is a full-fledged general equilibrium model; our Bayesian estimation method helps identify the contribution of different shocks and better understand Chinese business cycle. Brandt and Zhu (1995) investigate growth and inflation cycle in the early period of Chinese economic reform. They argue that the cycle is related to the interaction between government and SOE. In this aspect, our paper shares the same view. However, compared with them, we focus on quantitative assessments. Chang, Chen, Waggoner, and Zha (2016) develops a two-sector model that includes heavy (capital-intensive) sector and light (labor-intensive) sector to study the trend and cycle in Chinese macroeconomy, but facts emphasized and the methods used in their paper differ from ours. For example, we use standard detrending method such as HP-filter to compute the trend and cycle of China macro-data so as to do international comparison, while they use time-variying BVAR model to estimate the trend and cycle. We use Bayesian estimation to estimate the model while they use calibration method to simulate the moments. Moreover, cyclical patterns they emphasize are comovment between consumption and investment, comovement between investment and labor compensation, and comovement between short and long-term loan, which is different from ours. Finally, they argue that preferential credit policy for promoting heavy industries accounts for the unusual cyclical patterns. In contrast, we focus on SOE reforms.

The remaining part of the paper is organized as follows. Section 2 provides background of SOE reform, empirical regularities of Chinese business cycle, and linkage between SOE reform and business cycle. Section 3 presents the model. Section 4 estimates the model by using Bayesian method. Section 5 discusses the mechanism through which SOE sector shocks affect the economy. Section 6 evaluates the sensitivity of the model. Section 7 concludes.

2. SOE AND BUSINESS CYCLE IN CHINA: BACKGROUND

This section briefly describes the history of China's SOE reforms in the past three decades and then provides quantitative facts regarding SOE's relevance at business cycle frequency.

2.1. SOE Reform

China's SOE reforms can be divided into three phases based on SOE's performance. The first phase started in 1978 and ended in 1986. This phase can be characterized by significant changes in share of profit that SOEs submit to the government. Before the reform, SOEs were required to submit the budget any profit they made and received grant funding from the budget to finance all investments and losses (World Bank, 1995). In the early 1980s, the central government began to undergo a series of reforms that aim to give SOE greater autonomy and profit retention (known as system switch from "sharing rice pot" to "contracting responsibility system"). After this reform, the government and SOEs are engaged in one-to-one negotiation on profit division until 1994 when taxation reform began. Managers started to invest more; as a result, the aggregate economy has gained growth momentum.

The second phase started in 1987 and ended in 1998. This phase is characterized by substantial resource reallocation between SOEs and PEs. After 1986, SOEs experienced problems and accumulates huge losses because managers were rewarded for success but not punished for failure; for this reason, managers could exploit effective control over state assets at the expense of the state (Li, Liu, and Wang, 2015). An experimental privatization reform occurred at the beginning of 1987 to allow various types of enterprises, such as foreign, village, and township enterprises to co-exist with SOEs. As a consequence, the share of SOE's fixed investment in total investment decreases. The experiment lasted several years until 1992 when Deng Xiaoping's Southern Tour speech leads to an acceleration of reform. The reform on SOE sector continued and the policy known as "grasping the large and letting the small go" was in effect at the end of 1997. The central government explicitly pursued the strategy of retaining state control in the strategic sectors and granting SOEs in these sectors government monopoly. Meanwhile, the government gives up control over the small and medium-sized SOEs and lets them participate in market competition. The reform immediately reduced the share of SOE's fixed investment in total investment and the return on SOE's asset started to increase soon after the reform.

The third phase started in 1998 and reinforced in 2003, and it remains in effect to some extent. The third phase of SOE reform was designed to strengthen the remaining SOEs by reorganization, such as mergers and grouping. The performance of SOE during this period further improved. SOEs also served as the main carrier of economic stimulus when global financial crises affected China in 2008.

2.2. Empirical Regularity of Business Cycles in China

Table 1 summarizes the empirical moments regarding China's business cycle from 1978 to 2010. We choose this sample period for the following two reasons. First, the third phase of SOE reform was finished around 2005. Secondly and more importantly, the 2008 financial crisis has a large impact on China's business cycle and comovement between macroeconomic variables. Following the emerging market business cycle literature, two methods are used to calculate the moments. The top panel of Table 1 gives the result using the HP filter[6], and the bottom panel presents results using first-order difference.

From the top panel, the relative volatility of consumption[7] to output is 0.98, which is lower than the average value of 1.23 in emerging market economies. In other words, per-capita consumption has almost the same volatility as per-capita income, which is similar to that in developed economies. Second, the relative volatility of investment to output is 2.33, which is 39 percent lower than the average of emerging markets (3.81) and 34 percent lower than the average of developed economies (3.53). Third, the trade balance is acyclical. The correlation of trade balance-to-output ratio with output is −0.05 and not significantly different from zero. The serial correlation of Chinese output and the cross-correlation of consumption and investment with output is more comparable to emerging market economies than to developed economies. To summarize, three features of Chinese RBCs that differ from those of emerging markets and developed economies can be found; namely, modest consumption volatility, substantially low investment volatility, and acyclical trade balance.

In the bottom panel, we check if these features are still present when the log first-order difference is used for detrending. We can see that although the magnitude of the relative volatility changes, the three features observed in the top panel are still present. The relative volatility of consumption

[6]To be consistent with the emerging market business cycle literature such as Aguiar and Gopinath (2007), we use a smoothing parameter of 100 to detrend Chinese data from 1978-2010 as well as those for the developed and developing countries. For details, please see Table 1 footnote.

[7]Consumption is household consumption, including durable goods and nondurable goods consumption. Investment is defined as gross fixed capital formation, as in many papers in the literature, such as Chang et al. (2016). For detailed definition and source of the data, please refer to the online appendix.

TABLE 1.

Table 1: Moments in China,Emerging and Developed Markets

	China	Emerging Makets	Developed Markets
HP filtered			
$\sigma(y)$	3.16	3.47	2.05
$\rho(y)$	0.74	0.40	0.59
$\sigma(c)/\sigma(y)$	0.98	1.23	0.99
$\sigma(i)/\sigma(y)$	2.33	3.81	3.53
$\sigma(TBy)$	1.675	3.51	1.21
$\rho(TBy, y)$	-0.05(0.80)	-0.61	-0.41
$\rho(c, y)$	0.61(0.00)	0.80	0.81
$\rho(i, y)$	0.80(0.00)	0.85	0.85
	China	Emerging Makets	Developed Markets
Growth rate			
$\sigma(y)$	2.53	3.86	1.82
$\rho(y)$	0.53	0.15	0.40
$\sigma(c)/\sigma(y)$	1.05	1.32	1.00
$\sigma(i)/\sigma(y)$	2.63	3.87	3.49
$\sigma(TBy)$	2.87	3.47	1.29
$\rho(TBy, y)$	0.09(0.61)	-0.32	0.05
$\rho(c, y)$	0.54(0.00)	0.78	0.70
$\rho(i, y)$	0.76(0.00)	0.83	0.78

Note:The top panel gives business cycle moments of China, emerging markets and developed markets detrended using HP filter. The value of emerging markets and developed markets are computed using data from Aguiar and Gopinath (2007) and OECD Database. The time span of countries in emerging market and developed markets are the same as those in the paper. We transform their quarterly data into annual by taking a simple average. We then detrended the transformed annual data using Hodrick-Prescott filter with a smoothing parameter of 100 and compute standard deviation, correlation with output, serial correlation of output for each country. We take means of the computed moments for countries in emerging market group and developed countries group. China's data covers 1978-2010 and are also detrended using HP filter with a smoothing parameter of 100. The standard deviation are in percentages. P-value is in parentheses. The bottom panel lists second-order moments calculated based on first difference (growth rate) for robustness check. The log difference is used to calculate the growth rate and TBy is quadratically detrended, as in Aguiar and Gopinath (2007). Moments comparison based on log-quadratic detrending are also calculated and the results are available upon request.

to output is 1.05, much lower than that of the developed countries and close to that of developed countries. The relative volatility of investment is much lower than that of both developed and emerging market economies. The trade balance is also acyclical, with a correlation of trade balance-to-output ratio with output which is not significant from zero. We also find that these features of Chinese business cycle are robust when using log quadratic detrending methods. [8]

2.3. Is SOE Sector Relevant for Business Cycle: A First Look at Data

This subsection aims to explore whether cyclical linkages exist between SOE's reform and aggregate economic fluctuations in China. Considering the three phases characterized in Section 2.1, we select two most relevant indicators of SOE's reform, namely, share of SOE's sales in total sales and gross return on the net value of asset (ROA), to examine their cyclical behaviors. Figure 1 shows the HP-filterd share of SOE's sales in total sales and HP-filtered per-capita output from 1985 to 2008. We divide the whole sample period into two sample periods, 1985-1997, and 1998-2008. This is because after the second phase SOE reform, many small and medium size SOEs are restructured into SCEs (state-controlled enterprises)[9], so we believe the share of SOE and SCE in total sales is a better measure of state-controlled share in the economy, for the sample period after 1998 when the data on SCE become available in CEIC.[10] Figure 2 compares HP-filtered ROA of SOEs and HP-filtered per-capita output from 1978 to 2010.

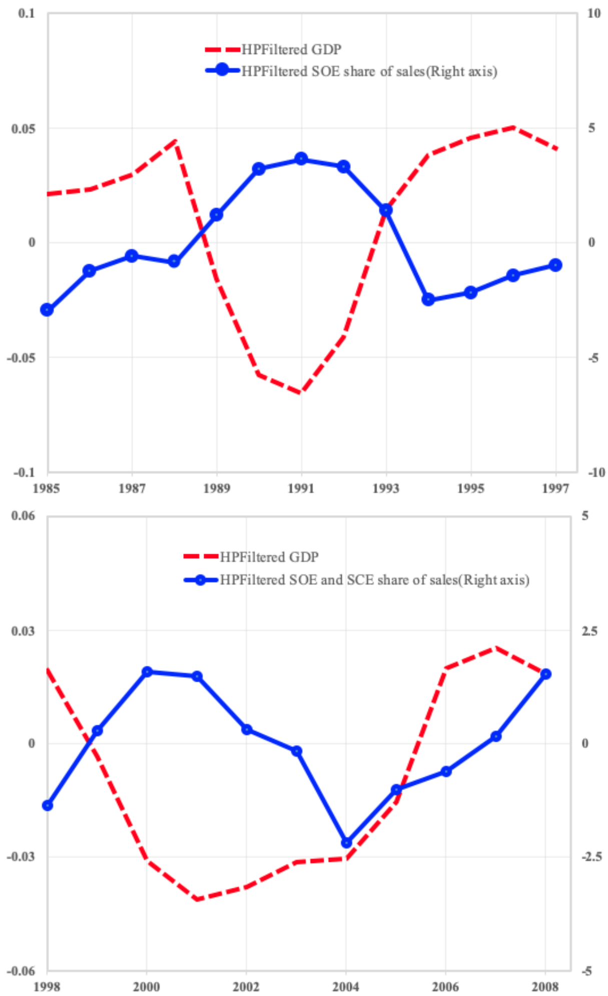
From Figure 1, it can be seen that the share of SOE's sales is roughly countercyclical. The counter-cyclicality was dampened after 2000 when the share of SOE sector gradually reduced after the reform implemented in 1994 and 1998 and was observed again after 2004. The share of SOE's sales seems to be particularly relevant for economic fluctuations before 1997 when the business cycle is much more volatile. In Figure 2, overall speaking, ROA of SOE is procyclical, particularly from 1978 to 1994. The procyclicality almost disappeared from 1994 to 2000 and re-emerged after 2001. This breakdown could be attributed to several reasons, including micro-based domestic factors affecting ROA of SOE, such as the massive layoff of SOE's workers due to policies implemented in 1994, and macro-based factors affecting aggregate output, such as the Asian financial crisis in 1997.

[8]Among the three mostly common-used filtering methods, the first difference helps to highlight the higher frequencies properties of the cycle; HP-filter helps to highlight the conventionally defined business cycle properties, and deviation from a quadratic trend incorporates medium-run variation.

[9]SCEs can also include firms in which the state or SOE owned share is less than 50 percent,as long as the state or SOE has controlling influence over management and operation.

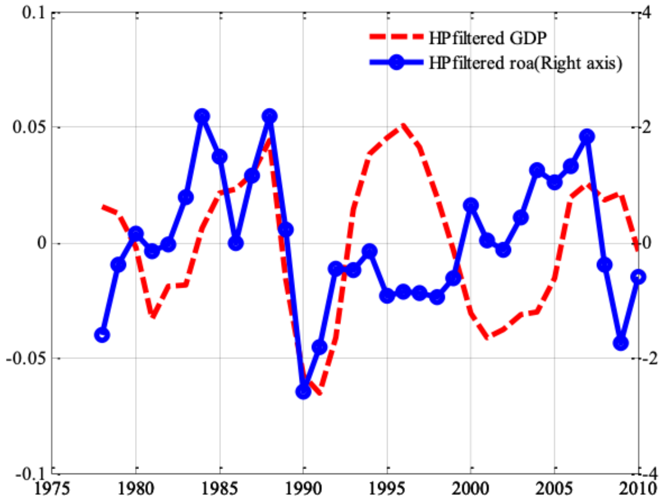
[10]Li, Liu, and Wang (2015) combine the two times series (SOE share from 1985-1997 and SOE and SCE share from 1998-2010) directly to form the share of SOE in total sales. Several other papers in the literature, such as Szamosszegi and Kyle (2015) also use the more general SCE category to estimate the state-controlled share of GDP.

FIG. 1. Output and the share of SOE's sales



Note: All the variables in the figures are detrended using HP filter with a smoothing parameter of 100. As discussed in the paper, we divide the whole sample period into two sub-sample periods, 1978-1997, 1998-2010, since many small and medium size SOEs are restructured into SCEs. The red lines in both figures denote HP-filtered real GDP per capita. The blue line in the top panel denotes HP-filtered share of SOE's (both upstream and downstream SOEs) sales in total sales and the blue line in the bottom panel denotes HP-filtered share of SOE and SCE's (both upstream and downstream) sales. Real GDP is obtained from nominal GDP adjusted for price using GDP deflator. Nominal GDP is obtained from the National Bureau of Statistics. The GDP deflator is from WDI.

FIG. 2. Output and return on asset of SOEs



Note: All the variables in the figures are detrended using HP filter with smoothing parameter 100. The red line denotes HP-filtered real GDP per capita. The blue line denotes HP-filtered ROA of SOEs (both upstream and downstream SOEs). Real GDP is obtained from nominal GDP adjusted for price using GDP deflator. ROA is computed by dividing SOE's gross profit by its asset. Nominal GDP is obtained from the National Bureau of Statistics. The GDP deflator is from WDI. Share of SOE's sale in total sales and ROA are from CEIC database. Li, Liu, and Wang (2015) also use the same source.

In summary, Figure 1 and 2 provide some informative evidence that SOE sector and its reform are indeed relevant for economic fluctuations in China. In the next section, a general equilibrium model with a fully characterized SOE sector is built and its importance at business cycle frequency is quantified.

3. MODEL

We develop an open economy general equilibrium model with two types of firms, namely, SOEs and PEs. Following Li, Liu and, Wang (2015), we incorporate a vertical structure in the model. First, some SOEs monopolize key industries and markets in upstream industries and provide intermediate goods to downstream manufacturing sectors; Second, SOEs compete with PEs in the downstream manufacturing industries. Moreover, we consider asymmetric financial access and productivity difference between SOE and PE in manufacturing sectors, as emphasized in Song, Storesletten, and Zilibotti (2011). We assume that there exist entrepreneurs who borrow from households and invest in PEs; however, they are subject to a borrowing constraint, while SOEs can obtain capital from households directly and without any constraint. Therefore, our model combines the features of SOEs and PEs emphasized in Song, Storesletten, and Zilibotti (2011) and Li, Liu, and Wang (2015).

3.1. Production

3.1.1. Final Goods

The final goods are simple CES aggregation of downstream manufacturing goods produced by SOEs and PEs. The production function is given by

$$Y_t = [\eta_t Y_{dt}^{s\,\frac{\lambda-1}{\lambda}} + (1-\eta_t) Y_{dt}^{p\,\frac{\lambda-1}{\lambda}}]^{\frac{\lambda}{\lambda-1}} \tag{1}$$

where d denotes the downstream industries, and s denotes downstream SOE firms and p denotes downstream PE firms. The elasticity of substitution between downstream SOE goods Y_{dt}^s and downstream PE goods Y_{dt}^p is given by $\lambda > 1$. η_t measures the share of downstream SOE goods in the total manufacturing output. Hence profit maximization gives the following downward-sloping demand functions

$$Y_{dt}^s = \eta_t^\lambda (\frac{P_{dt}^s}{P_t})^{-\lambda} Y_t, \qquad Y_{dt}^p = (1-\eta_t)^\lambda (\frac{P_{dt}^p}{P_t})^{-\lambda} Y_t \tag{2}$$

where P_t is the aggregate price index and given by $P_t = [\eta_t^\lambda (P_{dt}^s)^{1-\lambda} + (1-\eta_t)^\lambda (P_{dt}^p)^{1-\lambda}]^{\frac{1}{1-\lambda}}$. In a small open economy, P_t is assumed to be determined exogenously by the world market. η_t is assumed to be subject to a SOE share shock, $\epsilon_{\eta t}$. Without loss of generality, we assume that the log of η_t follows an $AR(1)$ process

$$\log(\eta_t) = (1-\rho_\eta)\log(\eta_{ss}) + \rho_\eta \log(\eta_{t-1}) + \epsilon_{\eta t} \tag{3}$$

From now on, variable with a subscript ss denotes its steady state value.

3.1.2. Downstream and Upstream Goods

The production technology for downstream SOEs and PEs follows standard Cobb-Douglas production function:

$$Y_{dt}^i = (K_{dt}^i)^\alpha (A_t^i L_{dt}^i)^\beta (Y_{mt}^i)^{1-\alpha-\beta} \tag{4}$$

where K_{dt}^i, L_{dt}^i, and Y_{mt}^i denote capital, labor, and upstream intermediate goods used by different types of firms, $i = \{s, p\}$, and A_t^i is labor productivity. Following Song, Storesletten, and Zilibotti (2011), Brandt, Hsieh, and Zhu (2008), and Hsieh and Klenow (2009), we assume PE firms' labor productivity is higher than that of SOE. That is, $\chi = A_t^p / A_t^s > 1$. Markets for goods produced by both downstream PE and SOE firms are perfect competitive, so we have

$$P_{dt}^i = MC_{dt}^i \tag{5}$$

where $i = \{s, p\}$ and marginal cost MC_{dt}^i is given by $\frac{(r_t)^\alpha (w_t)^\beta (P_{mt})^{1-\alpha-\beta}}{(A_t^s)^\beta \alpha^\alpha \beta^\beta (1-\alpha-\beta)^{1-\alpha-\beta}}$ and $\frac{(r_t^k)^\alpha (w_t)^\beta (P_{mt})^{1-\alpha-\beta}}{(A_t^p)^\beta \alpha^\alpha \beta^\beta (1-\alpha-\beta)^{1-\alpha-\beta}}$ for SOE and PE, respectively. r_t and r_t^k denote capital rental rate for SOE and PE, respectively. P_{mt} is the price of upstream intermediate goods.

We now present upstream intermediate goods production. PEs are subject to entry barriers when entering into upstream intermediate good sector. Therefore, upstream intermediate goods sector ends up with only SOEs. Each SOE produces a differentiated variety upstream intermediate goods, Y_{mt}^j. The aggregate output Y_{mt} in the upstream sector is produced by combining these differentiated varieties:

$$Y_{mt} = \left[\int_0^1 (Y_{mt}^j)^{\varepsilon_t} dj \right]^{\frac{1}{\varepsilon_t}} \tag{6}$$

where $\frac{1}{1-\varepsilon_t}$ is the time-varying elasticity of substitution across differentiated upstream intermediate goods j. Production of each type of upstream intermediate goods is assumed to be Cobbs-Douglas: $Y_m^j = (K_{mt}^j)^\gamma (A_t^s L_{mt}^j)^{1-\gamma}$. In a symmetric equilibrium, each SOE charges the same price,

$$P_{mt} = \frac{1}{\varepsilon_t} MC_{mt} = \frac{1}{\varepsilon_t} \frac{(r_t)^\gamma (w_t)^{1-\gamma}}{(A_t^s)^{1-\gamma} \gamma^\gamma (1-\gamma)^{(1-\gamma)}} \tag{7}$$

where $\frac{1}{\varepsilon_t} > 1$ is the markup over marginal cost. We assume the log of ε_t follows an $AR(1)$ process so as to capture the swing in SOE's market power in setting price of upstream intermediate goods.

$$\log(\varepsilon_t) = (1 - \rho_\varepsilon) \log(\varepsilon_{ss}) + \rho_\varepsilon \log(\varepsilon_{t-1}) - \epsilon_{\varepsilon t} \tag{8}$$

where ϵ_{ε_t} can be interpreted as a markup shock. In face of a positive shock (ϵ_{ε_t}), the elasticity of substitution of $\frac{1}{1-\varepsilon_t}$ decreases, but the markup $\frac{1}{\varepsilon_t}$ goes up. The total demand for upstream intermediate goods is thus given by $P_{mt} Y_{mt} = (1 - \alpha - \beta) P_t Y_t$. Finally, we assume that productivity in both SOE and PE firms are non-stationary and have the same stochastic trend. The log of growth rates of productivity A_t^s and A_t^p also follow $AR(1)$ processes[11]

$$\log g_t = (1-\rho_g)\log(g_{ss}) + \rho_g \log g_{t-1} + \epsilon_{gt} \tag{9}$$

3.2. Household

The household is an infinited lived representative agent, who has the following King-Plosser-Rebelo preference

$$U^h = E_0 \sum_{t=0}^{\infty} v_t \rho^t \big(\ln(C_t^h) - \nu \frac{L_t^{1+\kappa}}{1+\kappa}\big)$$

where C_t^h is household consumption, ρ is the subjective discount factor, v denotes an exogenous and stochastic preference shock in period t, defined as follows:

$$\log(v_t) = \rho_v \log(v_{t-1}) + \epsilon_{vt} \tag{10}$$

The shock to preference has been identified as an important driver of consumption fluctuations in emerging market economies (García-Cicco, Pancrazi,and Uribe, 2010) and developed countries (Smets and Wouters, 2007, Justiniano, Primiceri, and Tambalotti 2011).

Each period, the household consumes, invests, and supplies labor L to an economy-wide competitive labor market. The international financial market is incomplete in the sense that household can only hold a risk-free international real bond. The household has options to invest in SOEs or PEs, but the form is different. Investments in SOEs are directly in terms of physical capital investment, while investments in PEs are indirectly in the form of lending to entrepreneurs, who then invest in physical capital in the PEs.[12] It is assumed that the household owns SOEs and receives part of profits from the SOE firms. Therefore, the household's revenue flow in any period comes from wage income, capital rental income from SOE sector, repayment from entrepreneurs (PEs), and income from international bond holdings. The household then uses the revenue to consume and invest in physical capital for SOE firms, loans to PEs through entrepreneurs, and international bond.Let I_t^h, K_t^h, T_t and B_t denote household's investment in

[11] The assumption that growth rates in the two types of firms are the same is essential in obtaining a balanced growth path, otherwise relative prices of goods will not be constant at the steady state.

[12] For the household, arbitrage between investing in SOEs and PEs yields the same real rate of return.

SOEs, capital stock holding in SOEs, lump-sum transfer from the government and his/her foreign bond holding, respectively; r_t^d, r_t, and r_t^b denote interest rates of loan to entrepreneurs (PEs), of investment in SOEs, and of international bond holding between period t and $t+1$, respectively. Finally, we assume that adjustment in capital is subject to adjustment cost. The budge constraint for the household is given by

$$P_tC_t^h+D_{t+1}+P_tI_t^h+B_{t+1}=w_tL_t+(1+r_t^d)D_t+r_tK_t^h+\omega_t\Pi_t^s+(1+r_t^b)B_t+T_t \tag{11}$$

and law of motion of capital is

$$K_{t+1}^h = (1-\delta)K_t^h + I_t^h - \frac{\varphi^k}{2}(\frac{K_{t+1}^h}{A_t^s} - \overline{K}^h)^2 A_t^s \tag{12}$$

where Π_t^s denotes all profits earned by upstream SOE firms[13], $\frac{\varphi^k}{2}(\frac{K_{t+1}^h}{A_t^s} - \overline{K}^h)^2 A_t^s$ is adjustment cost. Note that the profits received by the household is subject to a stochastic dividend shock $\omega_t \in (0,1)$, which is assumed to follow

$$\log(\omega_t) = (1-\rho_\omega)\log(\omega_{ss}) + \rho_\omega \log(\omega_{t-1}) + \epsilon_{\omega t} \tag{13}$$

The retained profits are assumed to be controlled by the government or SOE managers.

Trade in international bonds is assumed to subject to debt-elastic interest rate premium $\varphi^b(e^{\frac{B_{t+1}}{A_{st}}-\bar{b}}-1)$ as in Schmitt-Grohé and Uribe (2003) and an exogenous stochastic country risk premia shock μ_t (García-Cicco, Pancrazi, and Uribe 2010)[14].

$$r_t^b = r_t^* + \varphi^b(e^{\frac{B_{t+1}}{A_t^s}-\bar{b}} - 1) + e^{\mu_t - 1} - 1$$

where r_t^* is a constant world interest rate and $\log(\mu_t)$ follows and $AR(1)$ process

$$\log(\mu_t) = \rho_\mu \log(\mu_{t-1}) + \epsilon_{\mu t} \tag{14}$$

[13]Note that the downstream sector is perfectly competitive, so profit of SOE firms in the downstream sector is zero.

[14]The debt-elastic interest rate premium is used to solve for the unit root problem in a small open economy with incomplete financial market.

The households' optimal conditions for capital investment, international bond, loan to entrepreneur, and labor supply are given by:

$$\begin{aligned}
P_t\Lambda_t[1+\varphi^k(\frac{K^h_{t+1}}{A^s_t}-\overline{k^h})] &= \rho E_t[P_{t+1}\Lambda_{t+1}\frac{v_{t+1}}{v_t}(\frac{r_{t+1}}{P_{t+1}}+1-\delta)] \\
\Lambda_t &= \rho E_t[\Lambda_{t+1}\frac{v_{t+1}}{v_t}(1+r^b_{t+1})] \\
\Lambda_t &= \rho E_t[\Lambda_{t+1}\frac{v_{t+1}}{v_t}(1+r^d_{t+1})] \\
\frac{w_t}{P_t} &= \nu L^\kappa_t C^h_t
\end{aligned}$$

where $\Lambda_t = \frac{1}{P_t C^h_t}$ is the Lagrange multiplier (or shadow price) associated with the budget constraint, which is also the marginal utility of consumption at period t.

3.3. Entrepreneurs

Now we turn to the discussion of entrepreneurs. It is assumed that there exists a continuum of infinite lived entrepreneurs with a mass of 1. They own PEs and borrow from households to finance their investment in PEs. We assume that entrepreneurs face financial constraints due to limited enforcement in the spirit of Kiyotaki and Moore (1997). At the beginning of every period, entrepreneurs enter with predetermined capital stock. Given the capital stock, entrepreneurs choose the amount of labor they demand and start to produce as described in the production session. After production, at end of every period, entrepreneurs pay the principal and interest of loans, decide how much capital he will purchase for the next period and how much new loan he needs to borrow from the household. When they borrow from the household, there is a positive probability that entrepreneurs will default. In that case, the maximum amount the household can recover is a fraction, $\phi_t < 1$, of the time-t value of capital stock in the next period, $P_t K_{t+1}$. Knowing that, entrepreneur will have no incentive to repay more than $\phi_t P_t K_{t+1}$. So the maximum loan entrepreneurs can borrow from the household is also $\phi_t P_t K_{t+1}$, and thus they face financial constraints. Hence, in our model ϕ_t represents the degree of financial friction. Furthermore, we assume entrepreneurs are subject to an exogenous dying probability ς to assure that entrepreneurs always need external financing in the long run. Upon their death, entrepreneurs will transfer all their wealth to the newborn entrepreneurs and will not consume.

At each period, entrepreneurs' problem is to maximize their utility subject to the credit constraint and demand from the final goods producer (2).

Specifically, entrepreneurs' problem can be characterized by the following dynamic problem.

$$\begin{aligned}
V(D_t, K^p_{dt}) &= \max_{C_t, D_{t+1}, K^p_{dt+1}, L^p_{dt}} v_t \ln C^e_t + \rho(1-\varsigma)E_t V(D_{t+1}, K^p_{dt+1}) \\
P_t C^e_t + P_t I^p_{dt} + (1+r^d_t)D_t &= P^p_{dt}Y^p_{dt} - w_t L^p_{dt} - P_{mt}Y^p_{mt} + D_{t+1} \quad (15) \\
K^p_{dt+1} &= (1-\delta)K^p_{dt} + I^p_{dt} - \frac{\varphi^k}{2}P_t(\frac{K^p_{t+1}}{A^p_t} - \overline{k^p})^2 A^p_t \\
D_{t+1} &\leq \phi_t P_t K^p_{dt+1} \quad (16)
\end{aligned}$$

where C^e_t is entrepreneurs' consumption, L^p_{dt} is labor hired by entrepreneurs. Similar to the household, entrepreneurs pay an adjustment cost when adjusting investment in PE firms, given by $\frac{\varphi^k}{2}P_t(\frac{K^p_{t+1}}{A^p_t} - \overline{k^p})^2 A^p_t$. Logarithmic utility is used so as to be compatible with balance growth path in long run. Let Ω_t be the Lagrange multiplier associated with the credit constraint. The first-order conditions for $C^e_t, K^p_{dt+1}, D_{t+1}$, and L^p_{dt} are

$$\begin{aligned}
\frac{v_t}{C^e_t}\left[1 + \varphi^k(\frac{K^p_{t+1}}{A^p_t} - \overline{k^h})\right] &= \rho(1-\varsigma)E_t\frac{v_{t+1}}{C^e_{t+1}}\left[\frac{r^k_{t+1}}{P_{t+1}} + (1-\delta))\right] + \Omega_t P_t \phi_t \\
\frac{v_t}{C^e_t}\frac{1}{P_t} &= \rho(1-\varsigma)E_t\frac{v_{t+1}}{C^e_{t+1}}\frac{1}{P_{t+1}}\left[1 + r^d_{t+1}\right] + \Omega_t \\
w_t &= \beta\frac{P^p_{dt}Y^p_{dt}}{L^p_{dt}}
\end{aligned}$$

To introduce the credit shock, the degree of credit constraint, ϕ_t, is assumed to follow an $AR(1)$ process,

$$\log(\phi_t) = (1-\rho_\phi)\log(\phi_{ss}) + \rho_\phi \log(\phi_{t-1}) + \epsilon_{\phi t} \quad (17)$$

3.4. Government sector

Government collects lump-sum tax from household and uses it as government spending (G_t). Its budget is balanced.

$$T_t = G_t$$

We assume that the detrended government spending $gc_t = G_t/A^s_{t-1}$ follows an $AR(1)$ process

$$\log(gc_t) = (1-\rho_{gc})\log(gc_{ss}) + \rho_{gc}\log(gc_{t-1}) + \epsilon_{gc,t} \quad (18)$$

Meanwhile, the government also holds the retained profits, $(1-\omega_t)\Pi_t^s$, from SOE firms in the upstream sector. It is assumed that a fraction, θ of the retained profits will be used to buy investment goods while the rest is used to buy consumption goods. However, they are not used for public.[15]

3.5. Market clearing conditions

We close the model by setting market clearing conditions. The goods market clearing condition is given by

$$Y_t = C_t^h + C_t^e + I_t^h + I_{dt}^p + (1-\omega_t)\Pi_t^s + G_t + TB_t \tag{19}$$

Following earlier discussion of the retained profits, aggregate consumption and investment are given by

$$\begin{aligned} C_t &= C_t^h + C_t^e + (1-\theta)(1-\omega_t)\Pi_t^s && (20) \\ I_t &= I_t^h + I_{dt}^p + \theta(1-\omega_t)\Pi_t^s && (21) \end{aligned}$$

Labor market clearing condition is given by

$$L_t = L_{mt} + L_{dt}^s + L_{dt}^p \tag{22}$$

where L_{mt} is employment in the upstream sector, and L_{dt}^s and L_{dt}^p are employment in the downstream SOEs and PEs, respectively.

3.6. Equilibrium and Model Solution

On the balanced growth path, consumption, investment, and output all grow at the rate of g_{ss}, while rental rate of capital, loan rate, and relative prices are constant. Since the model has a unit root, we have to detrend the equilibrium system. Specifically, we normalize the prices by final goods price P_{t-1} and then detrend the real allocation variables (except labor) by productivity A_{dt-1}^s or A_{dt-1}^p, respectively to get a stationary system. We denote lowercase letter, i.e, x , as the detrended real variables. In the Appendix, we present the detrended equilibrium system, we show that detrended equilibrium has a steady state in which all variables are constant over time. The stationary equilibrium is defined as follows: given the

[15]In real life, part of SOE retained profits are distributed to government officer, SOE managers and workers as grey income or benefits. We estimate a model with part of retained SOE profit is indeed used up for government consumption, however, the result does not give good model fitness.

stochastic process of all the shocks, an equilibrium in the detrended system is an allocation $\{c_t^h, c_t^e, L_t, L_{mt}, L_{dt}^s, L_{dt}^p, y_t, y_{mt}, y_{dt}^p, y_{dt}^s, k_t, k_{mt}, k_{dt}^s, k_{dt}^p, i_t, i_{mt}, i_{dt}^s, i_{dt}^p\}$ and $\{P_{mt}, P_{dt}^s, P_{dp,t}^p, MC_{mt}, MC_{dt}^s, MC_{dt}^p, r_t, r_t^k, r_t^d, r_t^b, w_t\}$ that satisfy household's and firms' optimization conditions and market clearing conditions.

4. CALIBRATION AND ESTIMATION

To solve the model numerically, we need to set the parameter values of the model. We divided the model parameters into three subsets. The first subset of parameters includes structural parameters which can be calibrated using steady-state values and ratios, such as depreciation rate, the subjective discount rate, etc. The second subset of parameters is those deep structural parameter values which are related to the SOE sector and the economy structure, such as elasticity of substitution in downstream sector and the capital share in upstream production function. The third subset of parameters includes the persistence parameters and the standard deviation of the eight structural shocks. The second and third subsets of parameters are estimated by Bayesian method (see Smets and Wouters, 2003, 2007; and Lubik and Schorfheide, 2005). In this paper, we jointly estimate the second and third subsets of parameters.

4.1. Calibration

The first subset of parameters is collected in $\Psi_1 = \{\rho, \varsigma, \chi, g_{ss}, \kappa, by_{ss}, TB/y_{ss}, \alpha, \beta, \delta\}$. Since the data is only available at annual frequency, we assume each period is one year in the model. We first fix the steady state value of growth rate of productivity g_{ss} at 1.083, the average annual growth rate of output from 1979 to 2010. Then we calibrate the value of discount factor, ρ, at 0.98 so as the long run annual interest rate is 0.11, which is risk-free and close to the lower end of range of net of tax return to capital estimated by Bai, Hsieh and Qian (2006). We set the death rate of entrepreneurs, ς, at 0.033 to have an expected working life of 30 years for entrepreneurs. κ is calibrated at 0.6, which implies a labor-supply elasticity of $1/\kappa = 1.7$, which is commonly used in business cycle literature (Schmitt-Grohé and Uribe 2003, García-Cicco, Pancrazi, and Uribe 2010, Mendoza 1991). TB/y_{ss} is calibrated to be 0.019 to match the average trade balance-to-output ratio during $1978 - 2010$. δ is calibrated to be 0.1, which is close to the annual depreciation rate commonly used in business cycle literature and in Song, Storesletten, and Zilibotti (2011). α and β are jointly calibrated to match the aggregate capital share of 0.5 and the share of intermediate input in gross output (0.54). The former value is the one estimated by Bai, Hsieh and Qian (2008) and used in Song, Storesletten and Zilibotti (2011) while the latter is consistent with the literature on growth and intermediate goods (e.g., Jones 2011). As a result, α and β are derived from relationship $\alpha = 0.5 - 0.174(\gamma\varepsilon_{ss} + ((1-\varepsilon_{ss}))$ and $\beta = 1-\alpha-0.174$, respectively, where ε_{ss} (the steady state value of inverse of markup of upstream sector goods) and γ (capital share in upstream sector) will be estimated by Bayesian method. Labor productivity difference χ is calibrated to match the average of the estimates in Brandt, Hsieh and Zhu (2008) (1.8 during period 1998-2004) and Brandt and Zhu (2010) (2.3 in 2004). That is $\chi = 2^{\frac{1}{\beta}}$. Table 2 reports the value assigned to calibrated parameters in the set Ψ_1. Note that values of parameter χ, α, β will vary with values of estimated parameters.

TABLE 2.

Calibrated parameters

Parameter	Name	Value
ρ	Discount factor	0.98
ς	Exiting probability	0.033
δ	Depreciation rate	0.1
κ	labor-supply elasticity	0.6
g_{ss}	Steady state growth rate of productivity	1.083
TBy_{ss}	Steady state value of trade balance-to-output ratio	0.019
by_{ss}	Steady state value of foreign bond-to-output ratio	$\frac{0.019}{g_{ss}-g_{ss}/\rho}$
α	Capital share in downstream sector	$\alpha = 0.5 - 0.174(\gamma\varepsilon_{ss}+1-\varepsilon_{ss})$
β	Labor share in downstream sector	$1-\alpha-0.174$
χ	Labor productivty difference	$2^{\frac{1}{\beta}}$

4.2. Bayesian Estimation

The Bayesian method is used to characterize the posterior distribution of structural parameters in the second and third subsets. Since our model has stochastic trend, we do not detrend the data. Rather, we fit the model to five annual Chinese time series data: growth rate of real output per capita (g^Y) , growth rate of real consumption per capita (g^C), growth rate of real investment per capita (g^I), growth rate of real government spending (g^G), and trade balance-to-output ratio (TBY). The five time-series are all taken from the National Bureau of Statistics of China (NBS). The sample period covers 1979 through 2010. To our best knowledge, this is the longest coherent sample data we can get.[16] The measurement equations are given by:

$$\begin{bmatrix} g_t^Y \\ g_t^C \\ g_t^I \\ g_t^G \\ TBY_t \end{bmatrix} = \begin{bmatrix} \Delta \ln y_t \\ \Delta \ln c_t \\ \Delta \ln i_t \\ \Delta \ln gc_t \\ TB_t/Y_t \end{bmatrix} + \begin{bmatrix} g_{t-1} \\ g_{t-1} \\ g_{t-1} \\ g_{t-1} \\ 0 \end{bmatrix}$$

where lowercase letter denotes detrended stationary variables and Δ stands for first order difference. The model features eight orthogonal shocks: permanent productivity shock g_t, the markup shock ε_t, credit shock ϕ_t, the dividend shock ω_t, the share shock η_t, government spending shock gc_t, country risk premium shock μ_t, and preference shock v_t.

The second subset of parameters is given by $\Psi_2 = \{\varphi^b, \varphi^k, \lambda, \nu, \gamma, \theta, \varepsilon_{ss}, \phi_{ss}, \omega_{ss}, \eta_{ss}\}$, which includes elasticity of interest rate to foreign debt (φ^b), capital adjustment cost (φ^k), elasticity of substitution in downstream sector (λ), scaling factor in labor supply (ν), capital share in upstream production function (γ), the fraction of retained SOE profit that eventually invested (θ) and the steady state value of exogenous shocks regarding to markup, credit constraint, dividend and downstream SOE share ($\varepsilon_{ss}, \phi_{ss}, \omega_{ss}, \eta_{ss}$), respectively. The third subset of parameters is summarized by $\Psi_3 = \{\rho_i, \sigma_i\}$ with $i = \{g, \phi, \varepsilon, \eta, \omega, gc, \mu, v\}$, including the persistence parameters and the standard deviation of the eight structural shocks.

4.2.1. Prior Distribution

Generally, for prior densities, Beta distributions are chosen for parameters that are constrained in the unit interval; Gamma distributions are chosen for parameters defined to be non-negative and inverse Gamma distribution are selected for standard deviation of shocks. The prior distribution for the parameters are reported in Table 3. Specifically, the prior of φ^b is assumed to follow Gamma distribution with mean 3 and standard deviation 1. It is wide enough to cover the most commonly calibrated or estimated value in the literature(e.g., García-Cicco, Pancrazi, and Uribe 2010, Aguiar and Gopinath 2007). The prior distribution of φ^k is also assumed to follow Gamma distribution with mean 2 and standard deviation 1. The prior distribution of elasticity of substitution in downstream sector λ follows gamma distribution with mean 5 and standard deviation 1. It is

[16]Recent data on consumption, output, investment and government spending published by NBS are usually seasonally unadjusted or based on current price levels.

based on the finding in Chang et al. (2015). They estimated the elasticity of substitution between SOE and POE output is about 4.53 when annual output data were used. The scaling factor in labor supply, ν, is also assumed to have a Gamma prior distribution with mean 0.6 and standard deviation 0.2. The mean of prior gives labor supply to be 0.49, consistent with high labor supply in China.[17] The share of capital in upstream sector γ, is assumed to follow Beta distribution with mean 0.5 and standard deviation 0.1, consistent with the fact that upstream SOE are capital intensive (Bai, Hsieh and Qian, 2006). The share of retained SOE profit that eventually invested, θ, is assumed to follow Beta distribution with mean 0.7 and standard deviation 0.1. The mean of θ is get through trial and error process. The prior distribution of ε_{ss}, is assumed to follow Beta distribution with mean 0.6 and standard deviation 0.2. This prior distribution implies the elasticity of substitution in the upstream sector centers around 2.5. The prior distribution of ϕ_{ss} (steady state credit constraint) and η_{ss} (steady state SOE share in downstream sector) are assumed to follow Beta distribution with mean 0.4 and standard deviation 0.1, which gives 90 percent interval ranging from 0.2 to 0.6. Finally, the prior distribution of ω_{ss}, steady state dividend share, is assumed to follow a Beta distribution with mean 0.3 and standard deviation 0.1, capturing the very low dividend payment after $1990'$s.

Regarding the parameters related to shock processes, the priors of persistence parameters are assumed to follow a Beta distribution with mean 0.5 and standard deviation 0.2, which is commonly used in the Bayesian estimation business cycle literature. The priors of standard deviation are assumed to follow a inverse Gamma distribution with mean 0.03 and standard deviation ∞, which corresponds to a rather loose prior. The assumption of prior information gives each shock an equally significant role to account for variations of all observables.

4.2.2. Posterior Estimates

Table 3 presents the prior distribution of the parameters in group Ψ_2 and Ψ_3. It reports the posterior mean and the 95% confidence interval of the posterior distributions for those parameters obtained by Metropolis-Hasting algorithm with $100,000$ draws. To provide a better understanding of the role of SOE shocks in explaining economic fluctuations in China, we also present the estimation result of an alternative model. The only

[17] We don't have data on the working hour. But there is a survey conducted, showing that the average weekly working hour is above 50 hours.

TABLE 3.

Prior and Posterior distribution of the parameters in SOE and NO-SOE model

				SOE			NO-SOE		
Param	Prior Mean	Prior std	Prior density	Post. Mean	5%	95%	Post. Mean	5%	95%
φ^b	3	1	G	2.94	1.48	4.37	2.62	1.17	3.92
γ	0.5	0.1	B	0.51	0.36	0.66	0.57	0.41	0.71
λ	5	1	G	5.15	3.66	6.58	4.58	2.83	6.17
ν	0.6	0.2	G	0.63	0.32	0.95	0.58	0.27	0.87
ε_{ss}	0.6	0.2	B	0.73	0.55	0.92	0.71	0.50	0.95
ϕ_{ss}	0.4	0.1	B	0.27	0.17	0.37	0.34	0.20	0.47
ω_{ss}	0.3	0.1	B	0.26	0.11	0.38	0.30	0.14	0.47
η_{ss}	0.4	0.1	B	0.39	0.30	0.48	0.59	0.43	0.73
φ^k	2	1	G	1.74	0.56	2.78	2.83	1.13	4.35
θ	0.7	0.1	B	0.74	0.64	0.85	0.68	0.52	0.85
ρ_g	0.5	0.2	B	0.38	0.10	0.63	0.53	0.33	0.75
ρ_ϕ	0.5	0.2	B	0.52	0.19	0.84	0.53	0.19	0.85
ρ_ε	0.5	0.2	B	0.87	0.80	0.95			
ρ_η	0.5	0.2	B	0.67	0.50	0.84			
ρ_ω	0.5	0.2	B	0.51	0.21	0.85			
ρ_{gc}	0.5	0.2	B	0.66	0.45	0.89	0.68	0.49	0.89
ρ_μ	0.5	0.2	B	0.61	0.33	0.89	0.57	0.25	0.88
ρ_v	0.5	0.2	B	0.61	0.33	0.92	0.63	0.44	0.82
ϵ_g	0.03	∞	$invg$	0.011	0.007	0.015	0.016	0.011	0.020
ϵ_ϕ	0.03	∞	$invg$	0.013	0.007	0.018	0.013	0.006	0.021
ϵ_ϵ	0.03	∞	$invg$	0.316	0.215	0.426			
ϵ_η	0.03	∞	$invg$	0.028	0.017	0.040			
ϵ_ω	0.03	∞	$invg$	0.027	0.007	0.052			
ϵ_{gc}	0.03	∞	$invg$	0.041	0.032	0.050	0.045	0.035	0.055
ϵ_μ	0.03	∞	$invg$	0.013	0.007	0.019	0.018	0.007	0.029
ϵ_v	0.03	∞	$invg$	0.025	0.007	0.043	0.070	0.041	0.100
Measurement Error									
$g^{Y,ME}$	0.002	∞	$invg$	0.001	0.001	0.002	0.016	0.011	0.020
$g^{C,ME}$	0.003	∞	$invg$	0.002	0.001	0.004	0.032	0.024	0.041
$g^{I,ME}$	0.007	∞	$invg$	0.004	0.002	0.005	0.023	0.009	0.037
$g^{G,ME}$	0.005	∞	$invg$	0.005	0.001	0.008	0.006	0.001	0.013
$g^{TBy,ME}$	0.002	∞	$invg$	0.001	0.001	0.001	0.002	0.001	0.003
Log Data Density				378.47			300.85		

Note:$G, B, invg$ denote gamma, beta and inverse gamma distribution respectively. Posterior distribution are computed by using Metropolis-Hasting algorithm with 100,000 draws. Variable with subscript ME denotes measurement error. The prior of measurement error is assumed to absorb 10 percent of standard deviation of corresponding observables.

deviation of the alternative model from our benchmark model in Section 3 is that we remove all SOE shocks in Equations (3), (8), (13). That is, we set $\varepsilon_t = \overline{\varepsilon}$, $\eta_t = \overline{\eta}$ and $\omega_t = \overline{\omega}$. We call it the "NO-SOE" model and the model with SOE shocks are thus labeled as "SOE" model.

In SOE model, some posterior estimates of the parameters, especially those related to SOEs, need to be highlighted. First, the steady state values of SOE sector shocks are reasonable. In particular, the posterior mean of steady state value of dividend payment of SOEs is 0.26, implying a low dividend payment share consistent with data. Posterior mean of ε_{ss} is 0.73, which gives a markup of 1.37 charged by upstream SOEs. This implies that the markup at aggregated level is 1.05.[18] The posterior mean of η_{ss} in downstream sector is 0.39, implying only less than 40% of firms in the downstream sector are SOEs and capturing the effect of "grasping the large and letting the small go" policy. Second, the estimated markup shock is quite persistent and volatile. The posterior mean of ρ_ε, $AR(1)$ coefficient, and e_ε, standard deviation of the markup shocks, equal 0.87 and 0.316, respectively. This implies the markup shock is around 10 times volatile than other seven shocks. Third, the volatility of credit shock to which PEs are subject in downstream sector is very small. The posterior mean of ϵ_ϕ, standard deviation of credit constraint shock is just 0.011. The estimated posterior mean of ϕ_{ss}, the steady state value of credit constraint, is only 0.27, which implies that entrepreneurs can only finance 27 percent of their capital stock through external borrowing. Fourth, the share of retained profits burned in investment, θ, is also estimated to be high (0.74) and its confidence interval [0.64, 0.85] shows that the estimate is quite accurate. This implies that a large percentage of retained profits are used in investment. Lastly, measurement error of observable in SOE model is estimated to be very low. It only absorbs 0.2 percent variance of output, 0.5 percent variance of consumption, 0.4 percent variance of investment, 1 percent variance of government spending, and 0.1 percent variance of trade balance. This suggests model mechanisms account for almost all of the economic fluctuation.

Compared with SOE model, NO-SOE model delivers similar estimates of structural parameters except for parameter regarding to steady state SOE share and adjustment cost. For instance, the parameter η_{ss} that measures steady state SOE share is estimated to be 0.59, much higher than 0.39 in SOE model. Meanwhile capital adjustment cost φ^k is estimated

[18] The value is derived from formula for monopolisctic rent $m = \frac{1}{1-\frac{\pi_t}{PY}} = \frac{1}{1-(1-\alpha-\beta)(1-\varepsilon_t)}$.

to be 2.83, also larger than 1.74 in benchmark SOE model. In addition, measurement error is substantially larger in NO-SOE model. It explains almost all the fluctuation of consumption, above one fourth of output and above 10 percent of investment. Put in another way, measurement error is way too large that NO-SOE model itself cannot explain much for the economic fluctuation.

4.3. Model Fitness

To evaluate our model's performance, Table 4 and 5 present simulated second moments of the model using estimated and calibrated parameters discussed above.[19]

Specifically, we look at standard deviations, serial correlation, and cross-correlations of output, consumption, investment, government spending, and trade balance-to-output ratio. In Table 4 both simulated data and actual data are in logs and HP filtered[20]. Table 5 compares moments of original growth rate data and those of observable time series predicted by both models. Before going to detailed discussion of model fitness, it should be acknowledged that it is natural that model does not precisely predict empirical moments as the method is designed to maximize the log likelihood of covariance matrix of observables. As a consequence, it involves a trade-off to match the standard deviation and other second moments.

From Table 4, we observe that, overall, the estimated model does a good job in matching empirical second moments. First, the SOE model captures qualitatively and quantitatively well the fact that consumption volatility is moderate in China which, as discussed in Section 2, is likely to be a China specific feature and is in contrast with other developing countries. In accordance with data, the SOE model predicts that the standard deviation of output is 3.0 percent and that of consumption is 3.2 percent. The predicted relative volatility of consumption to output is 1.06, in contrast with 0.98 in data. By contrast, the NO-SOE model underpredicts the standard deviation of consumption and output (2.4 and 2.1 percent, respectively) and overestimates relative volatility of consumption by around 20 percent. Second, the SOE model also captures well the low standard deviation of investment. It predicts the standard deviation of investment to be 7.0 percent, very close to 7.4 in the data. The ratio between investment and

[19]For estimated parameter values, we use the posterior mean of 100,000 draws from the Bayesian estimation.

[20]HP filtered simulated data are obtained by simulating 3000 periods of observable growth rate data first and transforming it to level data. We then detrended level data using HP filter with smoothing parameter 100.

TABLE 4.

Moments predicted by SOE, NO-SOE, AG and GPU model (HP filtered)

Statistic	Y	C	I	G	TBy
Standard deviation					
SOE Model	3.0	3.2	7.0	4.0	1.8
NO-SOE Model	2.1	2.4	5.1	4.9	1.8
AG Model	2.9	2.4	5.9	4.7	1.8
GPU Model	2.6	4.2	5.9	3.8	1.8
Data	3.2	3.1	7.4	3.9	1.7
Correlation with output					
SOE Model		0.18	0.73	0.29	0.29
NO-SOE Model		0.04	0.51	0.58	0.30
AG Model		0.97	0.63	0.26	0.13
GPU Model		0.67	0.58	0.05	−0.06
Data		0.61	0.80	0.14	−0.05
		(0.00)	(0.00)	(0.44)	(0.80)
Correlation with trade balance					
SOE Model		−0.23	−0.24	0.06	
NO-SOE Model		−0.27	−0.49	0.20	
AG Model		−0.01	−0.66	−0.13	
GPU Model		−0.33	−0.59	−0.03	
Data		−0.24	−0.48	−0.26	
		(0.18)	(0.01)	(0.15)	
Serial correlation					
SOE Model	0.57	0.54	0.56	0.37	0.35
NO-SOE Model	0.75	0.52	0.37	0.45	0.36
AG Model	0.51	0.47	0.43	0.47	0.45
GPU Model	0.52	0.51	0.44	0.39	0.32
Data	0.74	0.68	0.63	0.35	0.42

Note: Empirical moments are computed using annual real per-capita output, consumption, investment, government spending and trade balance-to-output ratio from 1979-2010. The model moments are computed using the simulated data (3,000 periods) from the estimated model at the mean of posterior distribution of parameters with 100,000 draws. All series are logged and detrended with the HP filter using a smoothing parameter 100 . The columns labeled Y, C, I, G, TBy refer, respectively, to output, consumption, investment, government spending and trade balance-to-output ratio. P-value is in parentheses.

output volatility is predicted to be 2.33 by the SOE model, compared to 2.33 in the data. The NO-SOE model, however, underpredicts the volatility of investment (with a 5.1 percent standard deviation) and slightly overpredicts the relative volatility of investment (2.42). Third, the SOE model also

TABLE 5.

Moments predicted by SOE, NO-SOE, AG and GPU model (Growth rate)

Statistic	g^Y	g^C	g^I	g^G	TBy
Standard deviation					
SOE Model	3.0	3.3	6.9	4.7	2.7
NO-SOE Model	1.9	2.6	6.0	5.3	2.7
AG Model	3.4	2.7	6.8	5.3	21.5
GPU Model	3.0	4.7	6.8	4.3	3.0
Data	2.5	2.7	6.7	4.5	2.9
Correlation with output					
SOE Model		0.31	0.66	0.26	−0.13
NO-SOE Model		−0.10	0.43	0.50	−0.21
AG Model		0.97	0.65	0.25	−0.06
GPU Model		0.69	0.58	0.03	−0.15
Data		0.54	0.76	0.14	0.09
		(0.00)	(0.00)	(0.44)	(0.61)
Correlation with trade balance					
SOE Model		0.04	−0.44	−0.11	
NO-SOE Model		−0.29	−0.33	−0.09	
AG Model		−0.03	−0.09	−0.07	
GPU Model		−0.24	−0.27	−0.08	
Data		−0.22	−0.08	0.07	
		(0.24)	(0.68)	(0.72)	
Serial correlation					
SOE Model	0.11	0.04	0.13	−0.14	0.70
NO-SOE Model	0.50	0.07	−0.15	−0.06	0.71
AG Model	0.19	0.08	−0.04	0.04	1.00
GPU Model	0.17	0.09	−0.03	−0.12	0.73
Data	0.53	0.31	0.37	−0.03	0.79

Note: Empirical moments are computed using growth rate of real per-capita output,consumption,investment,government spending and also trade balance-to-output ratio data from 1979-2010. The model moments are computed from simulated series (3000 periods) from estimated model at the mean of parameters of posterior distribution. P-value is in parentheses.

predicts reasonable cross-correlation between investment and output and government spending and output, while NO-SOE model performs worse in this dimension. Although both models underpredicts the correlation between consumption and output, the NO-SOE model performs worse than the SOE model.

From Table 4, the most notable discrepancies between the SOE model's prediction and data lie in the cross-correlation of output with consumption and trade balance-to-output ratio. In particular, the model underpredicts the correlation of consumption with output (0.61 in the data versus 0.18 in the model). SOE model also overestimates the correlation between trade balance-to-output ratio and output (-0.05 in the data versus 0.29 in the model). The underestimation of the correlation between consumption and output is partially due to our separable KPR preference specifications, which generates a low correlation between consumption and labor supply. As a consequence, the correlation between consumption and output is also underestimated, which leaves more room for trade balance to be positively correlated with output. Later in the sensitivity analysis, we consider an alternative preference specification which gives a better prediction on the correlation between consumption and output. Since the correlation between trade balance-to-output ratio and output is insignificantly different from zero, we also check our model's fitness by looking at its prediction on the correlation between trade balance and other domestic adsorptions. It is reported in Table 4 as well. Specifically, the SOE model's prediction on the correlation between trade balance and consumption is very close to data (-0.24 in the data versus -0.23 in the model). It overpredicts correlation between trade balance and investment (-0.24 in the model versus -0.48 in the data) and that between trade balance and government spending (0.06 in the mode versus -0.26 in the data). Finally and more importantly, we also compute log marginal likelihood based on Laplace approximation to compare the overall fitness of two models. We find that the log marginal likelihood for SOE model and NO-SOE model equal to 378.47 and 300.85, respectively. This suggests that data favors the SOE model more.

Table 5 compares predictions of the SOE and NO-SOE model with second moments in the data based on growth rate data (unfiltered data). SOE model predicts reasonable consumption growth rate volatility and investment growth rate volatility relative to output. The correlation between consumption growth rate and output growth rate is also reasonable. The correlation between trade balance and output growth rate is underestimated but the magnitude is less severe than that in Table 4 (HP-filtered data). The NO-SOE model perform worse in all above dimensions.

We also compare the SOE model with the existing emerging market real business cycle model in the literature, namely AG model developed by Aguiar and Gopinath (2007) and GPU model developed by García-Cicco, Pancrazi and Uribe (2010)[21]. Table 6 displays the posterior distribution of parameter under both AG and GPU models.

TABLE 6.

Posterior distribution of parameter in AG and GPU model

				AG Model			GPU Model		
Param	Prior Mean	Prior std	Prior density	Post. Mean	5%	95%	Post. Mean	5%	95%
g_{ss}	0.083	0.02	G	0.071	0.063	0.080	0.084	0.077	0.092
α	0.5	0.1	B	0.447	0.356	0.530	0.371	0.348	0.394
τ	1.174	0.5	G	1.248	0.473	1.952	1.818	0.931	2.683
ψ^k	2	1.0	G	0.900	0.476	1.347	2.182	1.131	3.302
ψ^b	1.5	1	G				0.400	0.032	0.774
ρ_g	0.5	0.2	B	0.833	0.705	0.965	0.415	0.150	0.685
ρ_z	0.5	0.2	B	0.675	0.569	0.790	0.774	0.647	0.902
ρ_{gc}	0.5	0.2	B	0.714	0.527	0.923	0.575	0.330	0.823
ρ_v	0.5	0.2	B				0.918	0.873	0.968
ρ_μ	0.5	0.2	B				0.923	0.852	0.992
ϵ_g	0.03	∞	$invg$	0.012	0.008	0.016	0.014	0.007	0.020
ϵ_z	0.03	∞	$invg$	0.016	0.013	0.020	0.015	0.012	0.019
ϵ_{gc}	0.03	∞	$invg$	0.043	0.033	0.055	0.036	0.027	0.045
ϵ_v	0.03	∞	$invg$				0.393	0.226	0.555
ϵ_μ	0.03	∞	$invg$				0.020	0.010	0.031
Measurement Error									
$g^{Y,ME}$	0.002	∞	$invg$	0.001	0.001	0.003	0.001	0.001	0.002
$g^{C,ME}$	0.003	∞	$invg$	0.022	0.017	0.026	0.003	0.001	0.005
$g^{I,ME}$	0.007	∞	$invg$	0.025	0.020	0.031	0.004	0.002	0.006
$g^{G,ME}$	0.005	∞	$invg$	0.007	0.001	0.016	0.005	0.001	0.009
$g^{TBy,ME}$	0.002	∞	$invg$	0.001	0.001	0.004	0.001	0.001	0.001
	Log Data Density			324.43			359.55		

Note:$G, B, invg$ denote gamma, beta and inverse gamma distribution respectively. Posterior distribution are computed by using Metropolis-Hasting algorithm with 100,000 draws. Variable with subscript ME denotes measurement error. The prior of measurement error is assumed to absorb 10 percent of standard deviation of corresponding observables. $g_{ss}, \alpha, \tau, \psi^k, \psi^b$ represent steady state growth rate of productivity, labor share, scaling factor to labor supply in GHH utility function, adjustment cost to capital and elasticity to foreign bond adjustment. ψ^b is calibrated to be 0.001 as consistent with AG model. $g, z, gc, v, \mu$are permanent productivity shock, transitory productivity shock, government spending shock, preference shock and risk premium shock. AG refers to Aguir and Gopinath (2007) and GPU refers to Gacia-Cicco, Pancrazi and Uribe (2010).

Table 4 and 5 also report simulated moments of model under these two models. The major findings are summarized below. First, as shown in Table 6, the estimated measurement error of consumption and investment in AG model is substantially large. It absorbs 50 percent and 12 percent

[21]The detailed AG and GPU model in this paper is present in appendix.

of variance of growth rate of consumption and investment in data respectively, leaves only the other half of consumption and less than 90 percent explained by model. Consequently, even though AG model quantitatively predict moderate consumption volatility, it does not precisely replicate the movement of consumption. In addition, in Table 6, AG model predicts enormous trade balance volatility, which is about 10 times larger than data. It also predicts a nearly random walk process of trade balance, contrast with 0.79 in data. All of evidences suggest AG model cannot fit in China's data well. Second, as for GPU model, the measurement error is small. It only absorbs less than 1 percent of variance of each observable time series. It also predicts reasonable correlation between trade balance and output for each time series in data. However, the main drawback for GPU is that it predicts excessive consumption volatility, which is more than 60 percent larger than data shown. Its predictions on volatility of investment and output are also fall below the level data shown. Lastly, due to GHH preference setting, AG model and GPU model can predict better correlation between consumption and output. However, Table 6 shows that the improvement in predicted correlation between trade balance and output in AG model and GPU model is not substantial.[22]

4.4. Shocks and Business Cycle

To check if the identified/estimated SOE shocks, especially the markup shock and the share shock, are reasonable in signs and magnitudes for economic fluctuation in China. In this section, we first compare the estimated smoothed shocks to its empirical counterparts. Specifically, we compare SOE share shock with HP-filtered share of SOE's sales in total sales. For the markup shocks, since we do not have data on the markup charged by upstream sector's markup, we plot the markup shock with average ROA in all SOEs. We then present model-based evidence on the importance of SOE sector shocks as sources of business-cycle fluctuations in China by looking at variance decomposition of main macroeconomic variables.

4.4.1. Estimated Shocks

[22]The result displays some extent of discrepancy in Table 4 and 5 in term of correlation between trade balance and output. In Table 5, there is only a very slightly difference regarding the correlation of trade balance and output in SOE model and GPU model. While in Table 4, when we simulated observable time series using each model and detrend them by HP filter, the moments computed from detrended cycle component of observable time series give different picture about the prediction of correlation of trade balance with output. SOE model overpredicts it but GPU model predicts the same with data. As we use growth rate data to estimate model, we rely more on comparison based on the original growth rate. HP filtered data is present to be comparable with literature.

Before proceeding we shall clarify one point about the nature of our exercise and results. First, since we only have the data on the share of SOE's sales and average ROA in SOEs in all sectors, the purpose of this exercise is to check if estimated shocks are *reasonable*, based on *ad hoc* assumption that markup shock in upstream sector and share shock in downstream sector may be tightly associated with the movement of their relative empirical counterparts of SOEs in all the sectors.

FIG. 3. Smoothed Share Shock and HP-filtered SOE share of sales

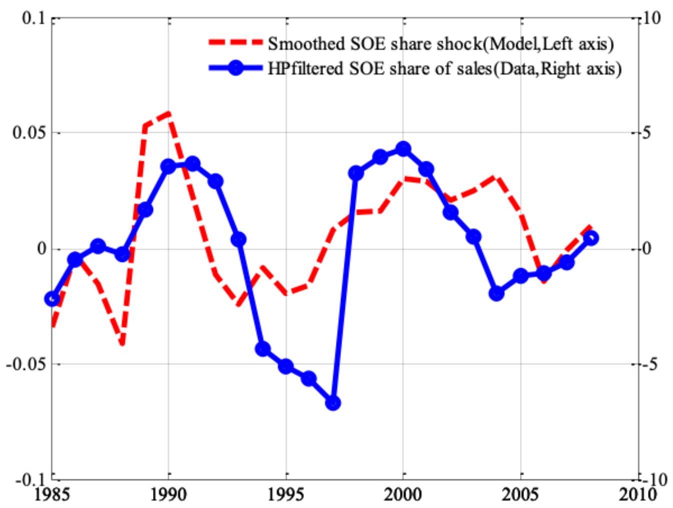
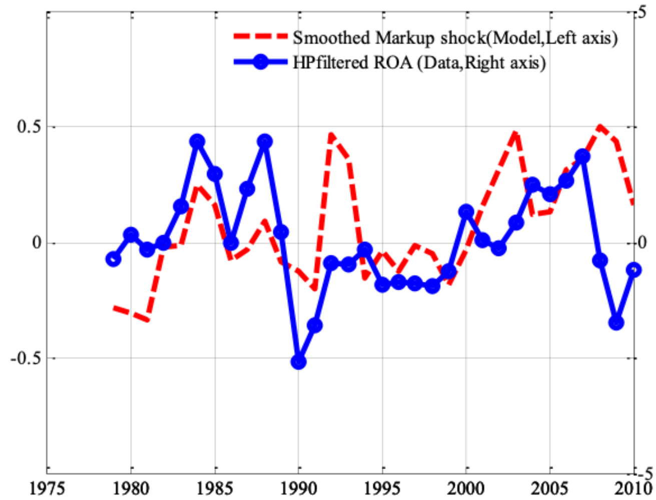


Figure 3 and 4 display the comparison. Apparently, SOE share shock tracks SOE's share in total sales reasonably well. Specifically, the share shock can track the upswing of SOE's sale share from 1985 to 1990, a period during which Chinese government started the first stage SOE reform and gradually increased SOE's managerial autonomy and profit retention. It also captures the downswing of SOE's sale share during 1990-1997, when SOE firms massively ran into problems and the large-scale layoff of SOE's workers since 1994. It also tracks well the boom-bust cycle from 1998 to 2010. This comparison indicates that downstream SOE share shock can largely explain the overall cyclical movements of SOE's share in total sales.

Figure 4 plots smoothed markup shock and ROA on SOEs in all sectors. As one can see, in general the model-based markup shock can reasonably track the cyclical movement of ROA, especially the uptrend of ROA after 1997, which is consistent with the implication of "grasping the large and

FIG. 4. Smoothed Markup Shock and HP-filtered ROA



Note: All the variables in the figures are detrended using HP filter with smoothing parameter 100. The red lines in both figures denote estimated shocks by SOE model. The blue line in the upper figure denotes HP-filtered share of SOE's (Both upstream and downstream SOEs) sales in total sales and the blue line in the lower figure denotes HP-filtered ROA of SOEs (both upstream and downstream SOEs). Share of SOE's sale in total sales and ROA of SOEs are taken from Li, Liu and Wang (2015).

letting the small go" policy introduced at the end of 1997. Although it does not capture the big decrease in smoothed ROA in 2007 − 2008, this is not surprising since the decrease of ROA might come from the global market. It also moves closely with ROA in the data before 1994, although the magnitude of downward trend of the markup shock is less pronounced in 1989 than that in data. Moreover, the comparison gives some further information. First, the ROA on SOEs is very volatile, while estimated markup shock displays a similar degree of high volatility. Second, estimated markup shock rises above zero after 2000 and it increases together with ROA after 2005, which means SOEs charge a higher markup above trend since then. This is consistent with the argument made by Li, Liu, and Wang (2015) about state capitalism and the third stage SOE reform discussed in Section 2.

Based on above discussion, we conclude that estimated shocks are reasonable. It should be noted that the estimated share shock and markup shock are obtained without any sector or firm level data information on SOE sector. The observables we used in estimation are standard macro-level data. Therefore, it is striking that our estimated SOE sector shocks match so well with data regarding SOE share and return on SOE, which can be considered as a strong evidence that the cyclical movements of macroeconomic aggregates contain non-negligible information about SOE sector shocks.

4.4.2. Variance Decomposition

Now we are ready to gauge the relative importance of each shocks in explaining economic fluctuations at business cycle frequency. To evaluate the contribution of each shock, Table 7 presents the variance decomposition of the growth rates of output, consumption, investment and trade balance-to-output ratio.

TABLE 7.

Variance decomposition by SOE model

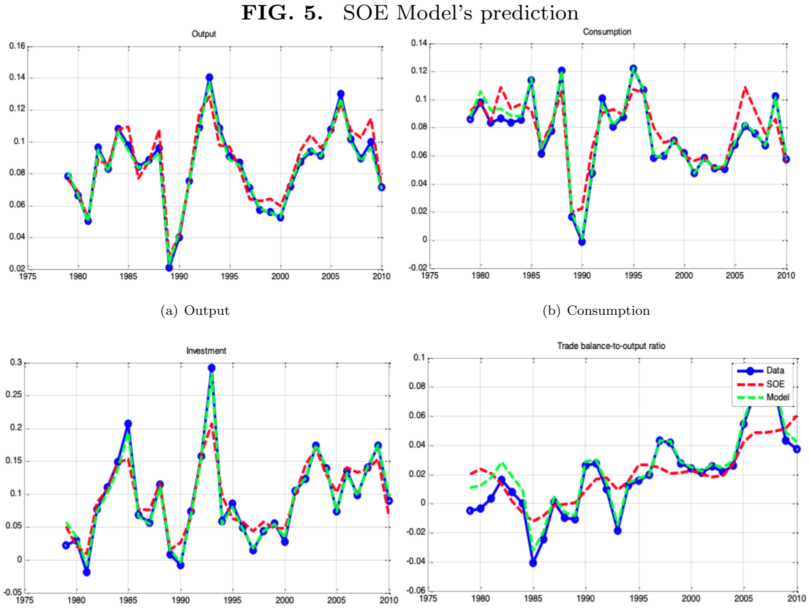
Shocks	Perm. prod. shock	Cred. shock	Markup shock	Share shock	Divid. shock	Gov.sped. shock	Risk prem. shock	Prefer. shock
Observ.	g	ϕ	ϵ	η	ω	gc	μ	v
g^Y	5.6	4.5	17.5	67.9	0.0	1.6	2.4	0.5
g^C	3.0	7.8	10.6	68.4	0.0	2.5	4.0	3.6
g^I	8.0	16.2	46.6	25.2	0.0	0.0	1.6	2.4
g^G	5.3	0.0	0.0	0.0	0.0	94.7	0.0	0.0
TBy	15.6	10.2	45.9	11.1	0.0	1.1	11.6	4.6

Note: The column denotes stochastic shocks considered, the rows are the five observables. Variance decomposition is the mean of posterior moments computed from 100,000 draws of parameters from posterior distribution. It represents the fraction of the unconditional variance of estimated observables that each structural shock would explain. Absence of measurement error is assumed. Therefore, it is based on structural model solely.

From the 4th to 6th column of the Table 7, it is clear that SOE sector shocks, as a whole, are the most important driving force for China's business cycle. Among them, the two dominant drivers are markup shock and share shock. In particular, markup shock can explain 17.5 percent of output volatility, 10 percent of consumption volatility, 46.6 percent of investment volatility, and 45.9 percent volatility of trade balance-to-output ratio. Share shock can account for 67.9 percent output volatility, 68.4 percent consumption volatility, and 25 percent of investment volatility. Meanwhile, the contribution of dividend shock in explaining the variance of each aggregate is virtually zero. Overall, SOE sector shocks explain 85 percent output volatility, 79 percent consumption volatility, 72 percent investment volatility and 57 percent volatility of trade balance-to-output ratio.

Figure 5 also provides a historical time series decomposition of the contribution of SOE sector shocks to the variance of macroeconomic aggregates by plotting the growth rates of output, consumption, investment, and trade balance-to-output ratio in the data and in the simulated model, based on the estimated sequence of all shocks. The comovement between data and model-predicted macroeconomic aggregates is striking. In Figure 5 we also plot the simulated growth rate of these aggregate variables based on the SOE shocks only. That is, only markup shock, share shock, and dividend shock are considered. We can see that SOE sector shocks, by themselves, can explain most movements in growth rate of output, consumption and investment. For the fluctuation in the trade balance-to-output ratio, their explaining power is weak. But they can still account for major upward and downward movements of this ratio.

FIG. 5. SOE Model's prediction



(a) Output (b) Consumption

(c) Investment (d) Trade balance-to-output ratio

Note: This figure plots actual and predicted year-on-year growth rate of output, consumption and investment, and trade balance-to-output ratio. Data: actual data. SOE: Model with only SOE-sector shocks. Model: All shocks are turned on.

Permanent productivity shock seems to be less important. It explains less than 10 percent of fluctuations in growth rate of output, consumption, and investment. For TB/y, it does better, but still can only explain less than 20 percent of its volatility. This seems to be consistent with the fact that in China excess volatility of consumption and countercyclical trade balance are not observed. This result is also in line with the findings in García-Cicco, Pancrazi and Uribe (2012). They introduce an international financial constraint (which is similar to the one in our model) in a standard Neoclassical model and find that permanent productivity shocks are not a major driving force for business cycles using Argentina and Mexican data.

Another result needs to be highlighted is related to the contribution of credit shocks. Song, Storesletten, and Zilibotti (2011) emphasize the role of financial friction in explaining China's growth experience. But in our model, the credit shock does not play a very important role in explaining China's business cycle. Our result is in sharp contrast with the finding of Jermann and Quadrini (2012), who find that credit shock can explain a substantial variation of output and hours in US's business cycle. Nevertheless, our result is similar to that in Mendoza (2010), who finds that business cycle moments in emerging markets are largely unaffected by the collateral constraint. He argues that the key intuition behind the result is the precautionary saving motive. Agents who are collateral constrained accumulate precautionary savings to self-insure against the risk of large consumption collapses, which leads to unchanged business cycle moments. The precautionary save motive also exists in our model. It is optimal for entrepreneurs to save more to overcome collateral constraint.

Another plausible explanation is that in China credit constraint itself is not variable enough to induce significant economic fluctuations. As argued by Jermann and Quadrini (2012), it is the unexpected "change", not the "level", in credit shock that matters. A lower value of credit constraint may have moderate effects on fluctuations in macroeconomic aggregates if the credit tightening takes place gradually, therefore the agent has time to adjust to the new lower level of credit constraint. In our estimation result in Table 3, it is evident that the estimated standard deviation of credit constraint shock is quite small, compared to that of SOE sector shocks.

Since the credit constraint only applied to entrepreneurs who invest in PEs, people may question that this result might come from a low size of private economy in our model setting, measured as the share of PEs' sales in downstream sector. However, our Bayesian estimation gives an estimated share of PE's sales in downstream sector of 0.61. So the low size seems not a reason for this result. Furthermore, credit constraint works through the standard intertemporal mechanism. It leads to fluctuations in entrepreneur's investment and aggregate investment immediately at the time the shock hits the economy, and later the shock will be propagated through capital stock change. Therefore, to induce sizable fluctuations as seen in the data, the volatility of credit constraint shock must be equally sizable. This will in turn lead to much more volatile investment, which is not evident in China's data.

Regarding the role of other shocks, in contrast to findings in García-Cicco, Pancrazi, and Uribe (2012), the contribution of country risk premia shock to the movement of consumption and investment in our benchmark model is predicted to be nearly zero. This result, however, is not surprising in China, since the capital account of China is not open. So the fraction of China's external borrowing is limited and leaves little room for international financing condition to play an important role. Meanwhile, unlike García-Cicco, Pancrazi, and Uribe (2012) and Justianiao, Primiceri and Tambalotti (2009) among other research, we find preference shock can only explain 3.6 percent of movements in consumption. The ability of preference shocks in accounting for the movement of consumption comes from failure of intertemporal consumption smoothing (see Justianiao, Primiceri and Tambalotti, 2009). This failure, however, is not present when SOE sector shocks are added in.

Based on the evidence in Table 7 and discussions above, we come to our conclusions. First, SOE sector shocks are the main source of economic fluctuations in China. The importance of SOE sector shocks mostly comes from the unexpected large and frequent changes in SOE's monopolistic power in upstream sector and the demand for SOE's products in the more competitive downstream sector. Second, permanent productivity shock, credit constraint, and country risk premia shock are less relevant for Chinese business cycle.

5. MECHANISM AND KEY ASSUMPTIONS

5.1. Transmission Mechanism of SOE Sector Shock

The prominent role of SOE sector shocks in our variance decomposition gives us a new perspective to look at business cycle in China. The next follow-up question is that what's the mechanism through which SOE sector shocks, specifically share shock and markup shock, affect business cycle in China. To address these questions, in this section, we investigate the model's dynamic mechanism more closely by looking at the impulse response of variables of interest to SOE sector shocks.

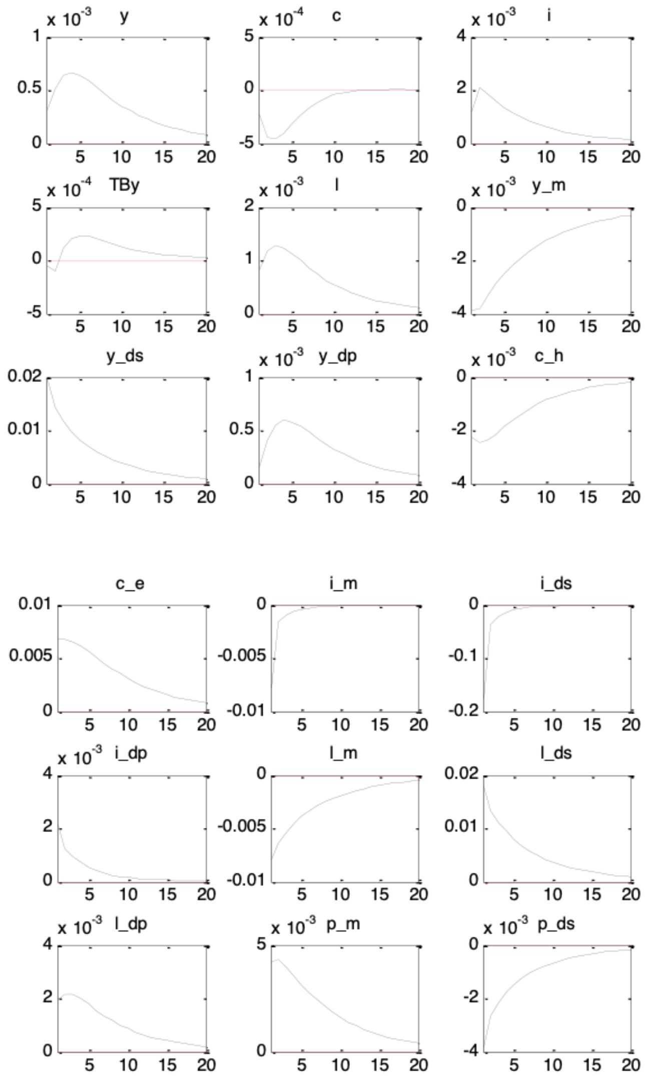
We first discuss the dynamic effect of markup shocks on the economy as shown in Figure 6. In the presence of a positive markup shock, the upstream SOE firms will set a higher intermediate goods price. For downstream firms, this is equivalent to a negative supply shock, they will cut the demand for upstream intermediate goods and increase demand for capital and labor. Due to less demand for upstream goods, employment and investment demand in the upstream sector decreases as well. The overall effect on labor and capital demand will depends on which sector dominates. As for supply side of labor and capital, given the KPR preference setting, household will supply more labor and invest more if his consumption decrease (labor supply curve shift to right). Entrepreneur also investment more if he consumes less. The equilibrium factor price (wage and capital rental rate) depend on the relative strength of supply and demand of labor and capital. Impulse response in figure 6 show that labor supply side dominates, since equilibrium wage decrease and labor increase in effect. While the demand side of capital dominates, we can see the return to capital and investment move in same direction.

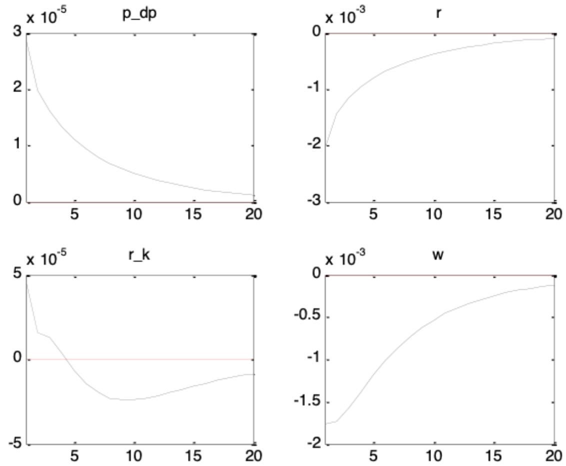
Moreover, SOE and PE firms are affected asymmetrically. For PE firm, as there is larger demand for capital, its return on capital r^k increases. This leads to more investment in PE firms. But for SOE firms, the upstream SOE firms dominate downstream ones so as there is less demand for capital, capital rental rate r decreases, investment falls. The wedge between the marginal product of capital in PE firm and borrowing cost increases, indicating PE firm suffers from more severe borrowing constraint. Because of the difference in marginal product of capital across downstream SOE and PE firms, the price of their products also moves in opposite direction. Price of the downstream SOE goods falls, while that of the PE goods increases slightly, so as that price of final goods does not change and is still fixed at exogenous world price.

It is also worth noting that positive markup shock leads to expansion of both sectoral and aggregate output. That is mainly due to expansion in employment in these sectors. For the household, they will consume less and work more since the wage income and capital income fall down. However, entrepreneurs' consumption increases because the increases in the marginal product of capital on PE firms in downstream industry.

In Figure 7, we report the impulse response of the economy to the share shock. Due to the productivity difference between SOE and PE firms in the downstream sector, the share shock will generate endogenous TFP fluctuation, which is transitory. A positive share shock implies that demand for downstream SOE's products increases and thus tends to reallocate resource to SOE firms. As PEs are more productive than SOEs, the measured productivity in the aggregate level thus decrease. So the share shock is like

FIG. 6. Impulse response to one percent increase in markup shock





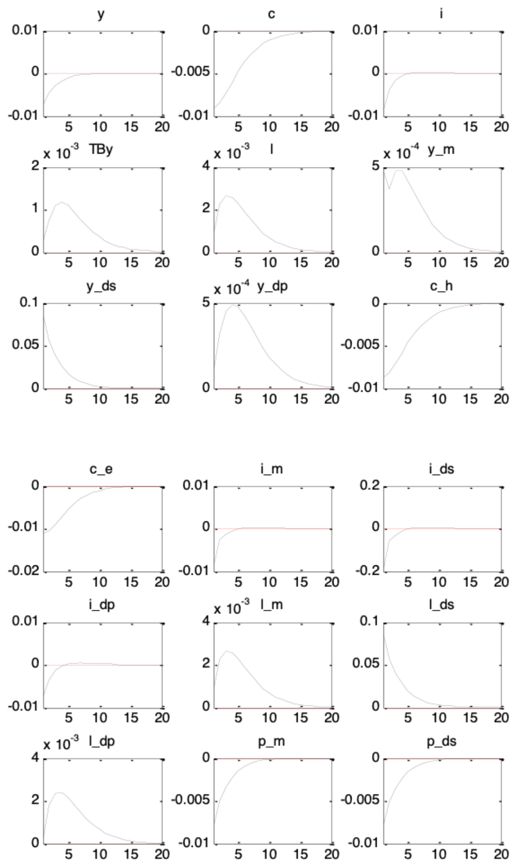
Note: This figure plots impulse response of key macro aggregates to 1% increase in markup shock, which will lead to markup increase from 1.373 to 1.392 in upstream sector. The vertical axis is the percentage deviation from steady state of each variable in face with the shock. The vertical $y, c, i, TBy, l, y_m, y_ds, y_dp$ stands for total output, total consumption, total investment,trade-balance-to-output ratio, employment, output in downstream SOE sector, output in downstream private sector respectively. $c_h, c_e, i_m, i_ds, i_dp, l_m, l_ds, l_dp, p_m, p_ds, p_dp, r, r_k, w$ denote household consumption, entrepreneur consumption, investment in upstream intermediate sector, investment in downstream SOE sector, investment in downstream private sector, employment in upstream intermediate goods sector, employment in downstream SOE sector, employment in downstream private sector, price of upstream intermediate goods, price of downstream SOE goods, price of downstream private goods, rate of return of total capital, rate of return of entrepreneur capital respectively.

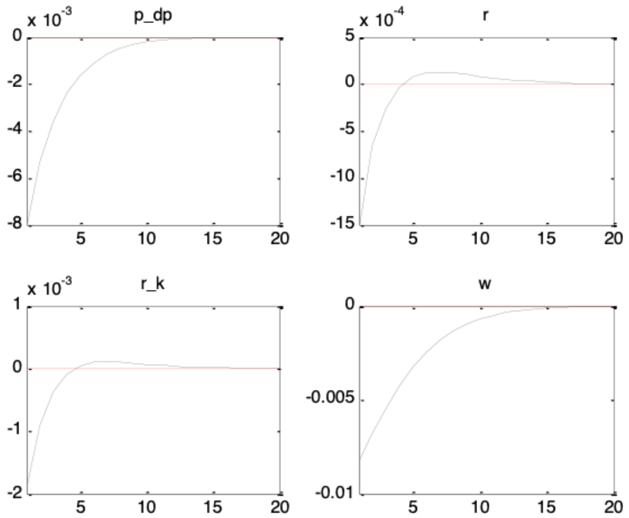
a negative aggregate TFP shock for the whole economy. As a result, the aggregate output falls down, so do the consumption and investment.

However, at the sector level, we find that both SOE and PE firms in the downstream sector expand. This is because the decrease of factor prices induces more demand and encourages them to produce more. As shown in Figure 7, prices of both downstream SOE and PE goods decrease. It should be noted that, since the share of SOE goods is subject to a shock, the increase of output in both SOE and PE goods does not necessarily lead to an increase in aggregate output. Moreover, the decline of capital return also causes capital outflow (trade balance increases) and decrease in domestic investment, so that the expansion of downstream firms has to rely on the increase of employment. For the intermediate goods sector, the price goes down since factor prices fall, which increases the demand for intermediate goods slightly, thus, Y_m increases. Finally, consumption of households decreases because of the decrease in wage income and capital return. So is the consumption of entrepreneurs since marginal product of capital in downstream PE firms falls as well.

We now explain why the share shock and markup shock can help to explain the three features of China's business cycle. For the consumption volatility, variance decomposition shows that volatility of output and consumption can be largely attributed to share shock. As discussed above, share shock in essence plays similar roles as transitory productivity shocks in standard RBC literature. So unlike permanent productivity shocks, they

FIG. 7. Impulse response to one percent increase in SOE's share





Note: This figure plots impulse response of key macro aggregates to 1% increase in share of SOE. The vertical axis is the percentage deviation from steady state of each variable in face with the shock. Notation of variable is the same in Figure 6 and 7.

will generate moderate instead of excess consumption volatility. Regarding investment volatility, as it is mostly influenced by the return to capital, shocks that have direct effect on rate of return could be potential drivers. In our model, markup shock, risk premia shock, and permanent productivity shock have the same nature of effect. But markup shock dominates and dampen the effect of the rest two shocks[23], making markup shock is the most important driver for investment. The less volatile investment comes from divergent responses of firms to markup shocks. For example, to respond to a positive markup shock, investments in both upstream and downstream SOE firms decrease while investment in the downstream PE rises. Hence, the aggregate investment will be less volatile.

Finally, our model does not do a very good job in explaining the acyclical trade balance-to-output ratio. This can be seen from the impulse response of trade balance to markup shock and share shock. A positive markup shock generates countercyclical consumption and procyclical trade balance,

[23]Markup shock can deliver procyclical trade balance while the other two shocks generate countercyclical trade balance. So markup shock can match the profound procyclical trade balance in the last decade.

while a positive share shock generates countercyclical trade balance[24]. As markup shock is the most important driver for fluctuation in trade balance, it plays a dominant role, making trade balance procyclical.

5.2. Evaluation of Key Model Assumption

We also investigate specifically the role of model assumptions in replicating the key moments in data. As discussed above, the specific model structures we assumed are vertical production structure, credit constraint, and productivity difference. We shut down the model structure one by one and re-estimate it. Therefore we can clearly see the difference with the SOE model. Table 8 and 9 display estimation results. The key message is that overall vertical structure and credit constraint are crucial to explain China's business cycle, and labor productivity difference helps in generating moderate consumption volatility. From Table 8, we observe that when shutting down vertical structure or credit constraint in the benchmark SOE model, the models generate lower log marginal likelihood (357 when we shut down vertical structure, 364 when we shut down credit constraint), suggesting overall SOE model outperforms the two models. Second, as for prediction of moments listed in Table 9, when there is no vertical structure or credit constraint, models predict excess consumption volatility. The relative consumption volatility are 1.43 and 1.41 respectively, much higher than the level in data. They also predict much lower relative investment volatility, the relative investment volatility are 1.80 and 1.91 respectively, far below 2.33 in data. Third, when we shut down labor productivity difference, the magnitude of excess consumption volatility is less severe, but still shows more consumption volatility (1.23) than the SOE model (1.06).

6. SENSITIVITY ANALYSIS

6.1. Alternative Preference Setting

As discussed before, our benchmark model fails in accounting for the correlation of consumption and trade balance with output. And this failure may come from our specific preference setting in our model. To check these conjectures, we explore the sensitivity of our result to an alternative preference specification. This preference setting combines features of both KPR and GHH preferences. As shown in Section 4.3, the KPR prefer-

[24]The countercyclical consumption in response to a positive markup shock is a desired result when markup shock shift labor supply to increase employment and output, because it can only happen when marginal utility of consumption increase. The countercyclical consumption is most likely lead to procyclical trade balance.

TABLE 8.

Posterior distribution of parameter in alternative models

Param	Prior Mean	Prior std	Prior density	NoVer Post. Mean	NoVer 5%	NoVer 95%	NoCredit Post. Mean	NoCredit 5%	NoCredit 95%	NoProddiff Post. Mean	NoProddiff 5%	NoProddiff 95%
φ^b	3	1	G	2.77	1.15	4.24	2.60	1.17	3.92	3.22	1.90	4.41
γ	0.5	0.1	G				0.49	0.32	0.66	0.40	0.26	0.52
α	0.3	0.1	B	0.47	0.45	0.50						
λ	5	1	G	4.60	3.03	6.15	5.03	3.45	6.54	5.39	3.86	7.13
ν	0.6	0.2	G	0.57	0.28	0.87	0.54	0.22	0.82	0.57	0.26	0.84
ε_{ss}	0.6	0.2	B				0.38	0.19	0.56	0.85	0.73	0.98
ϕ_{ss}	0.4	0.1	B	0.28	0.16	0.40	0.41	0.24	0.56	0.32	0.22	0.43
ω_{ss}	0.3	0.1	B				0.38	0.21	0.54	0.18	0.08	0.29
η_{ss}	0.4	0.1	B				0.40	0.26	0.52	0.26	0.19	0.34
φ^k	2	1	G	2.82	1.37	4.42	3.28	1.09	5.38	2.08	0.73	3.19
θ	0.7	0.1	B				0.62	0.45	0.78	0.83	0.75	0.92
ρ_g	0.5	0.2	B	0.73	0.57	0.91	0.71	0.55	0.88	0.43	0.18	0.72
ρ_ϕ	0.5	0.2	B	0.57	0.26	0.90	0.48	0.15	0.81	0.51	0.21	0.86
ρ_ε	0.5	0.2	B				0.56	0.25	0.98	0.84	0.77	0.91
ρ_η	0.5	0.2	B	0.90	0.81	0.99	0.87	0.78	0.98	0.58	0.35	0.75
ρ_ω	0.5	0.2	B				0.51	0.21	0.86	0.52	0.20	0.85
ρ_{gc}	0.5	0.2	B	0.77	0.60	0.95	0.74	0.54	0.93	0.63	0.41	0.85
ρ_μ	0.5	0.2	B	0.58	0.27	0.90	0.61	0.33	0.90	0.57	0.26	0.85
ρ_v	0.5	0.2	B	0.69	0.52	0.87	0.65	0.46	0.84	0.64	0.38	0.94
ϵ_g	0.03	∞	*invg*	0.014	0.011	0.018	0.014	0.011	0.017	0.011	0.008	0.015
ϵ_ϕ	0.03	∞	*invg*	0.012	0.006	0.018	0.025	0.007	0.045	0.012	0.007	0.017
ϵ_ϵ	0.03	∞	*invg*				0.030	0.007	0.061	0.222	0.175	0.280
ϵ_η	0.03	∞	*invg*	0.026	0.015	0.036	0.034	0.016	0.052	0.048	0.029	0.069
ϵ_ω	0.03	∞	*invg*				0.028	0.007	0.049	0.034	0.008	0.070
ϵ_{gc}	0.03	∞	*invg*	0.047	0.036	0.056	0.048	0.037	0.058	0.040	0.032	0.049
ϵ_μ	0.03	∞	*invg*	0.011	0.007	0.014	0.015	0.007	0.024	0.014	0.007	0.021
ϵ_v	0.03	∞	*invg*	0.071	0.036	0.105	0.061	0.027	0.095	0.023	0.007	0.042
Measurement Error												
$g^{Y,ME}$	0.002	∞	*invg*	0.001	0.001	0.002	0.001	0.010	0.002	0.001	0.001	0.002
$g^{C,ME}$	0.003	∞	*invg*	0.002	0.001	0.004	0.002	0.001	0.003	0.002	0.001	0.003
$g^{I,ME}$	0.007	∞	*invg*	0.004	0.002	0.005	0.004	0.002	0.006	0.004	0.002	0.006
$g^{G,ME}$	0.005	∞	*invg*	0.008	0.001	0.015	0.008	0.001	0.014	0.004	0.001	0.008
$g^{TBy,ME}$	0.002	∞	*invg*	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Log Data Density				357.33			364.46			371.24		

Note: $G, B, invg$ denote gamma, beta and inverse gamma distribution respectively. Posterior distribution are computed by using Metropolis-Hasting algorithm with 100,000 draws. Variable with subscript ME denotes measurement error. The prior of measurement error is assumed to absorb 10 percent of standard deviation of corresponding observables. NoVer refers to SOE model without upstream production sector, NoCredit refers to SOE model without credit constraint, NoProddiff refers to SOE model without productivity difference.

TABLE 9.

Moments predicted by alternative models (HP filtered)

Statistic		Y	C	I	G	TBy
Standard deviation						
	SOE Model	3.0	3.2	7.0	4.0	1.8
	NoVer	3.5	5.0	6.3	5.0	1.9
	NoCredit	3.2	4.5	6.1	5.0	1.6
	NoProddiff	2.6	3.2	5.6	4.0	1.7
	Data	3.2	3.1	7.4	3.9	1.7
Correlation with output						
	SOE Model		0.18	0.73	0.29	0.29
	NoVer		0.63	0.49	0.39	0.29
	NoCredit		0.64	0.54	0.36	0.15
	NoProddiff		0.35	0.66	0.29	0.23
	Data		0.61	0.80	0.14	−0.05
			(0.00)	(0.00)	(0.44)	(0.80)
Correlation with trade balance						
	SOE Model		−0.23	−0.24	0.06	
	NoVer		−0.01	−0.41	0.17	
	NoCredit		−0.06	−0.49	0.21	
	NoProddiff		−0.26	−0.35	0.14	
	Data		−0.24	−0.48	−0.26	
			(0.18)	(0.01)	(0.15)	
Serial correlation						
	SOE Model	0.57	0.54	0.56	0.37	0.35
	NoVer	0.63	0.54	0.48	0.51	0.43
	NoCredit	0.64	0.57	0.40	0.45	0.22
	NoProddiff	0.50	0.52	0.48	0.37	0.35
	Data	0.74	0.68	0.63	0.35	0.42

Note: Empirical moments are computed using annual real per-capita output, consumption, investment, government spending and trade balance-to-output ratio from 1979-2010. The model moments are computed using the simulated data (3,000 periods) from the estimated model at the mean of poseterior distribution of parameters with 100,000 draws. All series are logged and detrended with the HP filter using a smoothing parameter 100 . The columns labeled Y, C, I, G, TBy refer, respectively, to output, consumption, investment, government spending and trade balance-to-output ratio. P-value is in parentheses. NoVer refers to model without vertical structure, NoCredit refers to model without credit constraint. NoProddiff refers to model without labor productivity difference.

ence is used to be compatible with balance growth path but it gives poor prediction on correlation of consumption and trade balance with output. GHH preference, as argued by Aguiar and Gopinath (2007), is often used in emerging market business cycle literature so as to reproduce strong countercyclical trade balance. So a preference setting nesting both features of GHH and KPR preference will help on the cyclicality of trade balance while preserving compatibility with balance growth in the long run. The alternative preference takes the following form as in Jaimovich and Rebelo (2009, JR preference hereafter)

$$U = E_0 \sum_{t=0}^{\infty} \rho^t \frac{(C_t - \nu L^{\kappa} X_t)^{1-\sigma} - 1}{1-\sigma} \tag{23}$$

where $X_t = C_t^h X_{t-1}^{1-h}$. This preference introduces parameter h to govern the strength of wealth elasticity of labor supply. When $h = 1$, the period utility function becomes the KPR preference. When $h = 0$, it becomes GHH preference and this special case implies the labor supply is independent of marginal utility of income. In other words, the wealth elasticity increases with h. σ is assumed to be 1 to be compatible with balance growth. We estimate h by Bayesian estimation using the same data sample as in Section 3. Prior of h is assumed to follow Beta distribution with mean 0.2 and standard deviation 0.2, so as it posterior favors GHH preference.

Table 10 gives the prior and posterior mean of each parameter estimated. Tables 11 and 12 display the model fitness and variance decomposition. Three observations are noteworthy.

First, from Table 10, the Bayesian estimation of the JR model shows that data favor KPR preference over GHH preference given the sample we used. The posterior mean of h is 0.66, which is sufficiently large for us to get that conclusion. Meanwhile, for the estimates of other parameter values, there are no big changes. The volatility of markup shocks is still high relative to other shocks. Second, from Tables 11, compared to the benchmark model, log data density of the model with JR preference is similar, indicating a similar model fitness. In the JR model, the correlation between consumption and output is closer to the data (0.30 vs 0.62 in the data), but the consumption displays higher volatility relative to the data (4.2% in JR model vs 3.2% in SOE model). Third, variance decomposition in Table 11 suggests that the share shock and the markup shock remain to be important drivers for China's economic fluctuations. However, permanent productivity shock, and country risk premium shock gain more important roles in explaining investment and trade balance behavior.

TABLE 10.

Prior and Posterior distribution of the parameters in JR model

Param	Prior Mean	Prior std	Prior density	Post. Mean	5%	95%
φ^b	3	1	G	3.40	2.00	4.72
γ	0.5	0.1	B	0.53	0.37	0.69
λ	5	1	G	4.91	3.35	6.40
ν	0.6	0.2	G	0.58	0.29	0.89
ε_{ss}	0.6	0.2	B	0.76	0.61	0.92
ϕ_{ss}	0.4	0.1	B	0.36	0.24	0.46
ω_{ss}	0.3	0.1	B	0.26	0.12	0.39
η_{ss}	0.4	0.1	B	0.41	0.32	0.51
φ^k	2	1	G	1.84	0.63	2.83
θ	0.75	0.1	B	0.71	0.60	0.82
h	0.2	0.2	B	0.66	0.48	0.84
ρ_g	0.5	0.2	B	0.41	0.12	0.65
ρ_ϕ	0.5	0.2	B	0.45	0.17	0.77
ρ_ε	0.5	0.2	B	0.87	0.77	0.95
ρ_η	0.5	0.2	B	0.66	0.50	0.83
ρ_ω	0.5	0.2	B	0.49	0.17	0.82
ρ_{gc}	0.5	0.2	B	0.61	0.41	0.82
ρ_μ	0.5	0.2	B	0.58	0.27	0.87
ρ_v	0.5	0.2	B	0.58	0.28	0.88
ϵ_g	0.03	∞	*invg*	0.010	0.006	0.013
ϵ_ϕ	0.03	∞	*invg*	0.014	0.008	0.021
ϵ_ϵ	0.03	∞	*invg*	0.283	0.175	0.384
ϵ_η	0.03	∞	*invg*	0.026	0.016	0.035
ϵ_ω	0.03	∞	*invg*	0.031	0.008	0.057
ϵ_{gc}	0.03	∞	*invg*	0.040	0.031	0.047
ϵ_μ	0.03	∞	*invg*	0.013	0.007	0.019
ϵ_v	0.03	∞	*invg*	0.018	0.007	0.030
Measurement Error						
$g^{Y,ME}$	0.002	∞	*invg*	0.001	0.001	0.002
$g^{C,ME}$	0.003	∞	*invg*	0.002	0.001	0.004
$g^{I,ME}$	0.007	∞	*invg*	0.004	0.002	0.006
$g^{G,ME}$	0.005	∞	*invg*	0.004	0.001	0.009
$g^{TBy,ME}$	0.002	∞	*invg*	0.001	0.001	0.001
Log Data Density				379.07		

Note: $G, B, invg$ denote gamma, beta and inverse gamma distribution respectively. Posterior distribution are computed by using Metropolis-Hasting algorithm with 100,000 draws. Variables with subscript ME denote measurement error. The prior of measurement error is assumed to absorb 10 percent of standard deviation of corresponding observables. The differences between JR model and SOE model are two aspects. One is the preference setting, introducing parameter h. The other is prior distribution of ω_{ss} and θ. The prior distribution of rest parameters are the same with SOE model. JR model stands for model with JR preference.

TABLE 11.

Moments predicted by JR model(HP filtered)

Statistic		Y	C	I	G	TBy
Standard deviation						
	JR Model	2.9	4.2	6.5	3.8	1.9
	Data	3.2	3.1	7.4	3.9	1.7
Correlation with output						
	JR Model		0.30	0.66	0.13	0.27
	Data		0.62	0.80	0.14	−0.05
			(0.00)	(0.00)	(0.44)	(0.80)
Correlation with trade balance						
	JR Model		−0.33	−0.24	0.13	
	Data		−0.24	−0.48	−0.26	
			(0.18)	(0.01)	(0.15)	
Serial correlation						
	JR Model	0.52	0.62	0.49	0.34	0.45
	Data	0.74	0.68	0.63	0.35	0.42

Note: Empirical moments are computed using using annual real per-capita output, consumption, investment, government spending and trade balance-to-output ratio from 1979-2010. The model moments are computed using the simulated data (3,000 periods) from the estimated model. All series are logged and detrended with the HP filter with smoothing parameter 100. The columns labeled Y, C, I, G, TBy refer, respectively, to output, consumption, investment, government spending and trade balance-to-output ratio. P-value is in parentheses.

Preference shock can also explain more consumption volatility. Comparing Table 10 and Table 12, we can see that the share shock now plays a smaller role in explaining consumption volatility (68.4% in benchmark model vs 27.6% in JR model) while the explanation power of preference shocks increases (3.6% in benchmark model vs 21.7% in JR model). But one problem of the JR model is that this specification delivers excessive consumption volatility, which is not observed in Chinese data.

This exercise confirms that KPR preference helps to generate the moderate volatility of consumption. When the feature of GHH preference is present, preference shock and permanent productivity shock gain more credence. As a result, consumption displays excess volatility as in Aguiar and Gopinath (2007) and García-Cicco, Pancrazi and Uribe (2010). Meanwhile, KPR preference dominates GHH preference in the estimation, and is perhaps the source of a higher correlation between consumption and output than that in SOE model.

TABLE 12.

Variance decomposition predicted by JR model

Shocks	Perm. prod. shock	Cred. shock	Markup shock	Share shock	Divid. shock	Gov.sped. shock	Risk prem. shock	Prefer. shock
Observ.	g	ϕ	ϵ	η	ω	gc	μ	v
g^Y	10.4	1.5	23.6	62.1	0.0	0.6	1.4	0.4
g^C	6.1	4.8	27.6	27.0	0.0	6.1	6.7	21.7
g^I	22.0	2.8	34.8	17.8	0.0	0.6	14.4	7.7
g^G	5.8	0.0	0.0	0.0	0.0	94.2	0.0	0.0
TBy	18.7	6.9	42.1	2.7	0.0	2.2	17.0	10.5

Note: The column denotes stochastic shocks considered, the rows are the five observables. Variance decomposition is computed from 100,000 draws of parameters from posterior distribution. It represents the fraction of the unconditional variance of estimated observables that each structural shock would explain. Absence of measurement error is assumed. Therefore it is based on structural model solely.

6.2. Labor Wedge

It is well documented that there are substantial labor market frictions in Chinese economy. For example, see Chong, He and, Shi (2009) and Brandt, Tombe, and Zhu (2013). In this section we consider labor market friction following and check if the effect of SOE sector shocks in the Chinese economy has been exaggerated in the benchmark model because of the absence of labor market distortion.

For simplicity, we model the labor market friction as a labor wedge, following the business cycle account literature. As interpreted by Chari, Kehoe and Macgrattan (2007), labor wedge is a reduced form friction of three types of friction commonly used in general equilibrium: tax, monopoly power, and sticky price. Specifically, as in Chong, He and, Shi (2009), we introduce a reduced form labor wedge which breaks down the intratemporal substitution between household consumption and labor supply. So the first-order condition with respect to labor supply becomes

$$\frac{w_t}{p_t} = v\tau_l L_t^{\kappa} C_t^h$$

where τ_l represents the labor market friction. Log of τ_l is assumed following an $AR(1)$ process

$$\log(\tau_{l,t}) = \rho_{\tau_l} \log(\tau_{l,t-1}) + \epsilon_{\tau_l,t} \tag{24}$$

Tables 13 − 15 present estimation results of parameters, model fitness and variance decomposition for the model with labor wedge.

First, from Table 13, the estimated posterior means of parameters are close to those estimated in the benchmark model. Nevertheless, log data density suggests estimation results of model with labor wedge are worse than those of the benchmark (SOE) model. Second, from Table 14, we can also see that model fitness in terms of second moments is close to the benchmark (SOE) model. However, it overpredicts consumption volatility and underpredicts investment volatility compared to the benchmark (SOE) model. Third, variance decomposition of model suggests that labor wedge shock is not important in explaining variations of all five macroeconomic aggregates. The markup shock and share shock are still the most important drivers of China's business cycle. Overall, they can explain 90.5 percent, 83.7 percent, 76.4 percent, and 61.7 percent of fluctuation of output, consumption, investment, and trade balance-to-output ratio, respectively. These observations suggest that adding labor wedge does not provide further improvement in model fitness. It generates similar results as those in the benchmark SOE model.

6.3. Other sensitivity check

In this subsection, we consider another two cases for sensitivity analysis, but to save spaces, we put all the modification of model and tables in appendix. In the first case, we enrich the model by incorporating habit formation, intending to smooth consumption, and reduce consumption volatility. In the second case, we consider world price shock, as it represents global demand shock, in order to see how is the importance of exogenous shock coming from outside of the country.

Consistent with conjecturing, habit formation form of utility function does help reduce volatility of consumption, it also significantly increases serial correlation of consumption, in terms of growth rate and level as well. As a consequence, habit formation of utility function improves model fitness. Those effects come from the non-separable feature of utility function. In short, the main conclusion in our benchmark SOE model does not change, that is, the share shock and markup shock still are the main sources of economic fluctuation in China.

As for world price shock, it contributes to explain about one third fluctuation of trade balance and about one fourth fluctuation of consumption. But still share shock and markup shock together are the most significant source. More importantly, the model prediction gets worse after the world price shock is introduced. Consumption volatility increases substantially.

TABLE 13.

Prior and Posterior distribution of the parameters in model with labor wedge

Param	Prior Mean	Prior std	Prior density	Post. Mean	5%	95%
φ^b	3	1	G	2.96	1.42	4.40
γ	0.5	0.1	B	0.52	0.37	0.67
λ	5	1	G	5.23	3.41	6.61
ν	0.6	0.2	G	0.64	0.33	0.97
ε_{ss}	0.6	0.2	B	0.76	0.58	0.96
ϕ_{ss}	0.4	0.1	B	0.27	0.17	0.36
ω_{ss}	0.3	0.1	B	0.25	0.12	0.38
η_{ss}	0.4	0.1	B	0.39	0.28	0.49
φ^k	2	1	G	1.64	0.57	2.72
θ	0.7	0.1	B	0.75	0.64	0.87
ρ_g	0.5	0.2	B	0.37	0.11	0.63
ρ_ϕ	0.5	0.2	B	0.51	0.20	0.85
ρ_ε	0.5	0.2	B	0.86	0.79	0.94
ρ_η	0.5	0.2	B	0.68	0.51	0.85
ρ_ω	0.5	0.2	B	0.50	0.18	0.82
ρ_{gc}	0.5	0.2	B	0.65	0.41	0.87
ρ_μ	0.5	0.2	B	0.61	0.32	0.91
ρ_v	0.5	0.2	B	0.59	0.32	0.87
ρ_{τ_l}	0.5	0.2	B	0.74	0.53	0.98
ϵ_g	0.03	∞	$invg$	0.011	0.007	0.015
ϵ_ϕ	0.03	∞	$invg$	0.013	0.007	0.018
ϵ_ϵ	0.03	∞	$invg$	0.296	0.193	0.400
ϵ_η	0.03	∞	$invg$	0.029	0.017	0.043
ϵ_ω	0.03	∞	$invg$	0.024	0.008	0.044
ϵ_{gc}	0.03	∞	$invg$	0.041	0.031	0.050
ϵ_μ	0.03	∞	$invg$	0.013	0.007	0.018
ϵ_v	0.03	∞	$invg$	0.020	0.008	0.033
ϵ_{τ_l}	0.03	∞	$invg$	0.007	0.005	0.008
Measurement Error						
$g^{Y,ME}$	0.002	∞	$invg$	0.001	0.001	0.002
$g^{C,ME}$	0.003	∞	$invg$	0.002	0.001	0.003
$g^{I,ME}$	0.007	∞	$invg$	0.003	0.002	0.005
$g^{G,ME}$	0.005	∞	$invg$	0.003	0.001	0.005
$g^{TBy,ME}$	0.002	∞	$invg$	0.001	0.001	0.002
Log Data Density				366.06		

Note:$G, B, invg$ denote gamma, beta and inverse gamma distribution respectively. Posterior distribution are computed by using Metropolis-Hasting algorithm with 1,000,000 draws. Variable with subscript ME denotes measurement error. The prior of measurement error is assumed to absorb 10 percent of standard deviation of corresponding observables.

TABLE 14.

Moments predicted by model with labor wedge(HP filtered)

Statistic	Y	C	I	G	TBy
Standard deviation					
Labor wedge Model	2.8	3.4	6.4	4.1	1.7
Data	3.2	3.1	7.4	3.9	1.7
Correlation with output					
Labor wedge Model		0.23	0.68	0.21	0.29
Data		0.62	0.80	0.14	−0.05
		(0.00)	(0.00)	(0.44)	(0.80)
Correlation with trade balance					
Labor wedge Model		−0.19	−0.26	0.04	
Data		−0.24	−0.48	−0.26	
		(0.18)	(0.01)	(0.15)	
Serial correlation					
Labor wedge Model	0.54	0.53	0.52	0.37	0.32
Data	0.74	0.68	0.63	0.35	0.42

Note: Empirical moments are computed using using annual real per-capita output, consumption, investment, government spending and trade balance-to-output ratio from 1979-2010. The model moments are computed using the simulated data (3,000 periods) from the estimated model. All series are logged and detrended with the HP filter. The columns labeled Y, C, I, G, TBy refer, respectively, to output, consumption, investment, government spending and trade balance-to-output ratio. P-value is in parentheses.

TABLE 15.

Variance decomposition predicted by model with labor wedge

Shocks	Perm. prod. shock	Cred. shock	Markup shock	Share shock	Divid. shock	Gov.sped. shock	Risk prem. shock	Prefer. shock	Lab. shock
Observ.	g	ϕ	ϵ	η	ω	gc	μ	v	τ_l
g^Y	4.2	2.7	14.5	76.0	0.0	1.2	0.8	0.7	0.0
g^C	2.1	4.6	8.5	75.2	0.0	1.8	1.3	4.9	1.6
g^I	7.3	11.6	43.2	33.2	0.0	0.0	0.7	4.0	0.0
g^G	5.2	0.0	0.0	0.0	0.0	94.8	0.0	0.0	0.0
TBy	15.2	8.1	44.7	17.0	0.0	1.1	5.1	8.4	0.5

Note: The column denotes stochastic shocks considered, the rows are the five observables. Variance decomposition is computed from 100,000 draws of parameters from posterior distribution. It represents the fraction of the unconditional variance of estimated observables that each structural shock would explain. Absence of measurement error is assumed. Therefore it is based on structural model solely.

This evidence suggests that domestic factors are the main sources of economic fluctuation, world condition may also contribute to the fluctuation, but its power is mainly confined to the external sector of the economy.[25]

7. CONCLUSION

This paper examines the role of SOE sector in explaining China's real business cycle. Compared to developed economies and emerging market countries, China's business cycle exhibits some unique features; namely, moderate volatility of consumption, substantial low investment volatility, and acyclical trade balance, which cannot be explained by shocks or mechanisms emphasized in the emerging market business cycle literature. So we connected these features to SOE reforms that represent the most important and dramatic reforms in China during the last few decades.

We construct a full-fledged general equilibrium model with SOE sector. The key features in the model are: asymmetric financial access and productivity between SOE and PE firms, and SOE monopolizes key industries and markets in the upstream. These two features are emphasized by Song, Storesletten, and Zilibotti (2011) and Li, Liu, and Wang (2015), respectively. We consider three SOE sector shocks; the dividend shock, the markup shock, and the share shock. Meanwhile, we also incorporate most shocks emphasized in business cycle literature. By comparing the prediction of this SOE model and an alternative model without SOE sector shocks, we conclude that the SOE model does a better goods job in replicating business cycle moments in Chinese economy. We then evaluate the importance of each shock and find that SOE sector shocks, as a whole, are the main sources of economic fluctuations in China. The two dominant driving forces are share shock and markup shock. Other shocks emphasized as the main source in the literature, such as permanent productivity shock, credit shock, and country risk premia shock, are not important to explain economic fluctuations at business cycle frequency in China. Finally, we also consider an alternative preference specification and labor market friction for sensitivity analysis.

In spite of model and data limitations, we believe our results here help to understand Chinese real business cycle and also have important policy implication. The next research question for us is to explore what is the

[25]In this paper, we do not model the trade sector in detail, so it is possible that the importance of world price shock in explaining Chinese economic fluctuations is understated.

institutional foundation for those SOE shocks. This remains to be done in future work.

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