SOE and Chinese Real Business Cycle

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Abstract

Chinese real business cycle (henceforth, RBC) exhibited its unique pattern, which is characterized by moderate consumption volatility, substantially low investment volatility, and acyclical trade balance. These features are in contrast with business cycles in other emerging markets and cannot be explained well by existing emerging market RBC theories. Motivated by the facts that China undertook dramatic and persistent reform on State-owned Enterprise (SOE) in the past thirty years, we construct a full-fledged general equilibrium model with SOE sector and show that the model does a fairly good job to account for the above features. The two dominant driving forces are the shock to the share of downstream SOE in manufacturing sector and the shock to upstream SOE's monopolistic position. These two shocks together can explain 85 percent of output volatility, 79 percent of consumption volatility, 72 percent investment volatility, and 57 percent of the volatility of trade balance-to-output ratio. Relatively speaking, 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 real business cycle may be affected substantially by domestic policies on resource reallocation through endogenous TFP fluctuations.

JEL classification: E3, F3, F4

Keywords: State-owned Enterprise, real business cycle, vertical structure, financial friction, permanent shocks, Bayesian Estimation.

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1 Introduction

In the past decades, due to the increased importance of China in the global economy, there have been extensive studies on the macroeconomic aspect of the Chinese economy. However, most of them focus on economic growth. What factors characterize Chinese real business cycle? What drives economic fluctuations in China? The literature has long been mute on these issues. Recently, Shi, Wu and Xu (2013) document Chinese business cycle from 1978 and 2012. They find that Chinese real business cycle exhibits a unique pattern that characterized by moderate consumption volatility, substantially low investment volatility, and acyclical trade balance. They argue that these features are in contrast with business cycles in other emerging markets and cannot be explained well by existing RBC theories. In line of their research, this paper constructs a full-fledged general equilibrium model with State-owned Enterprise (SOE) sector to investigate the Chinese business cycle using Bayesian estimation method.

This paper is motivated the following facts. As shown by Shi, Wu and Xu (2013), the existing theories of emerging market business cycle cannot account for Chinese data very well. This implies that, to explain Chinese business cycle, we need to incorporate some unique elements or institutional features of Chinese economy in the model. During the economic transition, persistent and dramatic SOE reform can be seen as one of the most profound changes in Chinese economy. On the one hand, SOE reform contributes to economic growth (Brandt, Hsieh and Zhu 2008); On the other hand, it also inevitably causes substantial economic fluctuation. The role of SOE in economic growth or transition has been well investigated in the literature recently. For example, Song, Storesletten, and Zilibotti (2011) build a growth model with SOE to explain China's puzzling growth experience. In their model, SOE firms have low productivity but better access to credit markets while private firms have high productivity but limited financial access. Hence, in the economic transition, high-productivity private firms will outgrow low-productivity SOE firms, which lead to sustainable economic growth. As a result, the downsizing of SOE forces domestic savings to be invested abroad, generating a foreign surplus. In this paper, they emphasize the advantage of SOE in the credit market and the productivity differences between SOE and private firms. In contrast to them, Li, Liu, and Wang (2012) argue that SOE has another advantage in industrial structure. That is, SOE monopolize key industries and markets in the upstream, whereas the downstream industries are largely open to private competition. They develop a general equilibrium model and show that this vertical structure, when combined with openness and labor abundance, is critical in explaining why SOE outperformed non-SOE in the past decade. They aruge that the outperformance of SOE after 2000 is simply because the upstream SOE extract rents from the liberalized downstream sectors in the process of industrialization and globalization. In view of the importance of SOE in Chinese economic transitions, it is natural to consider SOE sector when we investigate economic fluctuation in China.

Therefore, in this paper, we develop a small open economy general equilibrium model with a well characterized SOE sector. Our model combine the key features that are emphasized in both Song, Storesletten, and Zilibotti (2011) and Li, Liu, and Wang (2012), namely, the advantage for SOEs to obtain easy credit and its monopolistic power in upstream production.[1] We add the SOE sector into an otherwise standard real business cycle model. The model is estimated using Bayesian methods. The model is driven by eight shocks, including a shock to permanent neutral productivity (Aguiar and Gopinath 2007), a shock to the credit constaint that private owned enterprises (PE hereafter) are subject to (or, for simplicity, credit shock) as in Jermann and Quadrini (2012) and Mendoza (2010) among others; three shocks to SOE sector, including shocks to the markup that upstream SOEs charge (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 other standard shocks used in emerging market business cycle literature—preference shock and country risk premium shock (Garcia-Cicco, Pancrazi and Uribe, 2010). The model is an ideal laboratory for studying the driving forces of fluctuation in China, for two reasons. First, it encompasses within a general equilibrium framework most of views on the source of business cycle fluctuation in the literature[2]. Second, its departure from neoclassical growth prototype gives disturbance other than neutral productivity shock a fair chance to be plausible cyclical forces.

We show that the estimated model can reproduce, to a large extent, the main features of business cycle in China. Specifically, the model predicts the relative volatility of consumption to

[1] 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 impact on SOE firms' total factor productivity and then social welfare. In our model, we do not model the endogenous transition between SOE and private firms, so all the reform policies will be taken as exogenous shocks to some key parameters such as the share of SOEs in the downstream manufacturing sector.

[2] 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, since we consider endogenous TFP fluctuations instead.

output to be 1.06, contrast to 0.98 in the data. The model also predicts the relative volatility of investment to output to be 2.33, which is the same as in the data. The model over predicts the cyclicality of trade balance-to-output ratio, getting 0.29, as opposed to −0.05 in the data. But it predicts a reasonable correlation between trade balance and consumption and the correlation between trade balance and investment (−0.24 and −0.23), respectively, in contrast to −0.23 and −0.48 in the data, respectively. There are two reasons why our benchmark model cannot account for the acyclical trade balance well. Firstly, to match low volatility of consumption and investment in China, SOE shocks dominate permanent technology shocks and credit shocks. The former is transitory and lead to procyclical trade balance while the later two shocks generate countercyclical trade balance. Secondly, we consider a separable preference, which makes it inadequate to generate strong positive correlation between consumption and output, and consequently leaves more room for trade balance to be positively correlated with output.

In summary, in our model, SOE sector shocks are the most important source in explaining China's economic fluctuation. They, as whole, account for 85 percent, 79 percent, 72 percent and 57 percent of the variance of output, consumption, investment and trade balance-to-output ratio, respectively. Among three SOE shocks, share shocks and markup shocks are the two dominant drivers. Dividend shocks, however, virtually has no role. As to shocks emphasizes 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's fluctuation, are basically negligible, indicating there is no failure on intertemporal consumption smoothing.

Why do the share shock and markup shock of SOE sector matter so much for economic fluctuations?[3] The answer is simple. Firstly, due to the productivity difference between SOE and PE firms in the downstream, the share shock will generate endogenous TFP fluctuation, which is transitory. Secondly, the markup itself is also equivalent to a productivity shock for the downstream firms. Therefore, the transmission mechanism of these two SOE shocks is similar to that of transitory productivity shocks.

[3]It should be noted that the contribution of SOE shocks might be exaggerated since we do not consider structure change in the model. In China, some economic fluctuations actually are due to structure changes, but in the model, are also attributed to these SOE shocks.

This paper belongs to the literature on emerging market's business cycle. There are two major hypotheses in this literature. Aguiar and Gopinath (2007) argue that the shock to the trend (or permanent productivity shock) might be the major source of business cycle fluctuation in emerging market economies, while García-Cicco, Pancrazi and Uribe (2010) suggested that international financial friction should be taken into consideration seriously when we investigate business cycle in these small open economies. Our paper differs from their work in two dimensions. One is the specification of preference. We consider the King–Plosser–Rebelo (KPR) preferences (King, Plosser and Rebelo 1988) in our model instead of Greenwood Hercowitz-Huffman (GHH) preference (Greenwood, Hercowitz, and Huffman (1988)) for two reasons. First, KPR preference is compatible with balance growth path. Second, as summarized by Aguiar and Gopinath (2007), GHH preference is helpful to obtain significantly countercyclical trade balance in a standard small open economy model as it generates strong correlation between consumption and output. However, the strong and significant countercyclical trade balance is not found in China.[4] The other difference is that we do not incorporate transitory productivity shocks. Instead, we consider transitory but endogenous productivity changes, which are driven by two SOE shocks. This modelling strategy is consistent with the findings in the resource misallocation literature that argue that there are substantial TFP changes in the transition economy due to the resource reallocation between sectors. For example, Hsieh and Klenow (2009), Song, Storesletten and Zilibotti (2011), and Brandt, Tombe, and Zhu (2013). Overall, our findings echo those in Shi, Wu and Xu (2013), Chinese data provide less support for both "the cycle is the trend" and "financail friction" hypotheses. The former is simply because Chinese economy does not exhibit high consumption volatility and countercyclical trade balance, which are major features of other emerging market economies; the latter is mainly due to the fact that China have not open its capital account yet.

Our paper is closely related to Shi, Wu, and Xu (2013). Their paper document stylized facts of Chinese business cycle and investigate to what extent the Chinese business cycle can be explained the existing theories. We differ from their work in that we focus on studying the impact of SOE on Chinese business cycle. In addition, Curtis and Mark (2010) showed that naively applying the standard business-cycle tools to China is no more ridiculous than applying it to a developed economy, such as Canada, although the dimensions along which the model

[4] We estimated a alternative model with preference specification used by Jaimovich and Rebelo (2009). This preference specification nests GHH and KPR preference. The estimation strongly favor KPR preference.

struggles are different. However, their analysis and results are based on calibration, so their paper cannot identify the source of the business cycle or answer which shocks explain economic fluctuation. Instead, our model is a full-fledged general equilibrium model, and our Bayesian estimation method allows us to identify the contribution of different shocks and help to better understand more on Chinese business cycle.

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

2 SOE and Business Cycle in China: Background

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

2.1 SOE Reform

To large extent, China's SOE reforms can be divided into three phases based on SOE's performance. The first phase started from 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 to the budget any profit they made and received grant funding from the budget to finance all the investments and losses (World Bank, 1995). From the early 1980s, central government began to undergo a series of reform aiming to give SOE greater autonomy and profit retention (known as system switch from "sharing rice pot" to "contracting responsibility system"). After this reform, government and SOEs are engaged into one-to-one negotiation on profit division until 1994 when taxation reform began. Managers started to invest more and as a result, the economy, at aggregate level, has gained growth momentum.

The second phase started from 1987 and ended in 1998. This phase is characterized by substantial resource reallocation between SOEs and PEs. After 1986, SOEs began to run into problems and stacks huge losses because managers were rewarded for success but not punished for failure and were able to exploit their effective control over state assets at the expense of the state (Li, Liu, and Wang, 2012). An experimental privatization reform took place at the beginning of 1987 to allow various types of enterprises, e.g. foreign, villiage and township enterprises to coexist with SOEs. The share of SOE's fixed investment in total investment decrease as a consquence. The experiment lasted for several years until 1992, when Deng Xiaoping's Southern Tour speach 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 them government monopoly. Meanwhile, the government gives up control over the small and medium-sized SOEs and let them participate in market competition. The reform immediately brought down the share of SOE's fixed investment in total investment and the return on SOE's asset catched up soon after the reform.

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

2.2 Empirical Regularity of Business Cycles in China

Table 1 gives the empirical moments regarding China's business cycle from 1978 to 2010. First, the level of volatility of per-capita output, consumption and investment is lower, compared to the average of emerging market economies. The ratio between volatility of consumption and output is 0.98, compared to average value of 1.23 in emerging market economies. That is, per-capita consumption has almost the same volatility as per-capital income, which is close to that in developed economies. Second, the relative volatility of investment to output is 2.33, 39 percent lower than emerging markets average and 37 percent lower than developed economy average. Third, trade balance is acyclical. The correlation of trade balance-to-output ratio with output is -0.05 and insignificantly different from zero. Compared to the developed economies, the serial correlation of Chinese output and the cross correlation of consumption and investment with output is more comparable with emerging market economies. To summarize, we single out three features of Chinese real business cycles that are difference from both emerging markets and developed economies; namely, modest consumption volatility, substantially low investment volatility, and acyclical trade balance. These features need particular attention when we explain Chinese real business cycles.

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

The goal of this subsection is to explore whether there are some cyclical linkages between SOE's reform and economic fluctuations in China. To this end, guided by the three phases we characterized in Section 2.1, we select the two most relevent indicators on SOE's reform—the share of SOE's sales in total sales and gross return on the net value of asset (ROA hereafter)— to examine their cyclical behaviors. Figure 1 compares the HP-filterd share of SOE's sales in total sales and HP-filtered per-capita output during 1985 to 2008. Figure 2 compares HP-filtered ROA of SOEs and HP-filtered per-capita output during 1978 to 2010. From Figure 1, it can be seen that the share of SOE's sales is roughly countercyclical. The countercyclicality is dampened after 2000 when the share of SOE sector gradually shrink after the reform implemented in 1994 and 1998 and regain its power through IPOs in 2003. The share of SOE's sales seems to be particularly relevant for economic fluctuations before 1997 when the business cycle is much more volatile. When we look at Figure 2, overall speaking, ROA of SOE is procyclicality, which is especially true for the period from 1978 to 1994. The procyclicality breaks down from 1994 to 2000 and emerges again after 2001. The breakdown could be due to multiple reasons, from micro-based domestic factors affecting ROA of SOE, such as the huge layoff of SOE's workers due to 1994's policy, to macro-based factors affecting aggregate output, such as Asian financial crisis in 1997.

In short, Figure 1 and 2 provide some informative evidence that SOE sector and its reform are indeed relevant for economic fluctuations in China. To verify this hypothesis, we build a general equilibrium model with a fully characterized SOE sector and quantify its importance at business cycle frequency.

3 Model

We develop a small open economy general equilibrium model with two types of firms, SOEs and PEs. Following Li, liu and Wang (2012), we incorporate a vertical structure in the model. First, some SOEs monopolize key industries and markets in the upstream industries and provide intermediate goods to the downstream manufacturing sector; Second, in the downstream manufacturing industries, SOEs compete with PEs. In addition, we also consider asymmetric financial access and productivity differenece between SOE and PE in the manufacturing sectors, which are emphasized in Song, Storesletten and Zilibotti (2011). Specifically, households can invest in SOE firms directly. But for PE firms, we assume that there exists an entrepreneur who borrows from households and invests in PEs, and they are subject to a borrowing constraint because of the limited enforcement. Hence, our model is a combination of Song, Storesletten, and Zilibotti (2011) and Li, liu, and Wang (2012).

3.1 Production

3.1.1 Final Goods

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

$$Y_t = [\eta_t Y_{dt}^{s\,\frac{\lambda-1}{\lambda}} + (1-\eta_t) Y_{dt}^{p}]^{\frac{\lambda}{\lambda-1}} \tag{3.1}$$

where 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 meaures the share of downstream SOE goods in the total manufacturing output. Hence profit maxmization gives the following downward-sloping demand functions

$$Y_{dt}^s = \eta_t^\lambda (\frac{P_{dt}^s}{P_t})^{-\lambda} Y_t, \qquad Y_{dt}^p = (1-\eta_t)^\lambda (\frac{P_{dt}^p}{P_t})^{-\lambda} Y_t \tag{3.2}$$

where the aggregate price index P_t is 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 dteremined 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

$$\log(\eta_t) = (1-\rho_\eta)\log(\eta_{ss}) + \rho_\eta \log(\eta_{t-1}) + \epsilon_{\eta t} \tag{3.3}$$

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 funtion:

$$Y^i_{dt} = (K^i_{dt})^{\alpha}(A^i_t L^i_{dt})^{\beta}(Y^i_{mt})^{1-\alpha-\beta} \tag{3.4}$$

where K^i_{dt}, L^i_{dt},and Y^i_{mt} denote capital, labor, and upstream intermediate goods used by different types of firms, $i = \{s, p\}$, and A^i_t is the labor productivity in the two kinds of firms. 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, $\chi = A^p_t/A^s_t > 1$. Markets for goods produced by both downstream PE and SOE firms are perfect competitive, so we have

$$P^i_{dt} = MC^i_{dt} \tag{3.5}$$

where $i = \{s, p\}$ and the marginal cost MC^i_{dt} is given by $\frac{(r_t)^{\alpha}(w_t)^{\beta}(P_{mt})^{1-\alpha-\beta}}{(A^s_t)^{\beta}\alpha^{\alpha}\beta^{\beta}(1-\alpha-\beta)^{1-\alpha-\beta}}$ and $\frac{(r^k_t)^{\alpha}(w_t)^{\beta}(P_{mt})^{1-\alpha-\beta}}{(A^p_t)^{\beta}\alpha^{\alpha}\beta^{\beta}(1-\alpha-\beta)^{1-\alpha-\beta}}$ for sector s and sector p, respectively. r_t and r^k_t denote capital rental rate for sector s and sector p, respectively. P_{mt} is the price of upstream intermediate goods.

We now close description of production part by characterizing upstream intermediate goods production. PEs are subject to entry barriers when entering into upsterm intermediate good sector. Therefore upstream intermediate goods sector ends up with only SOEs. Each SOE produces a differentiated variety upstream intermediate goods, Y^j_{mt}. The aggregate output Y_{mt} in the upstream sector is produced by combining these differentiated varities:

$$Y_{mt} = \left[\int_0^1 (Y^j_{mt})^{\varepsilon_t} dj\right]^{\frac{1}{\varepsilon_t}} \tag{3.6}$$

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: $Y^j_m = (K^j_{mt})^{\gamma}(A^s_t L^j_{mt})^{1-\gamma}$. In a symmetric equilibrium, each SOE charges the same price,

$$P_{mt} = \frac{1}{\varepsilon_t} MC_{mt} = \frac{1}{\varepsilon_t}\frac{(r_t)^{\gamma}(w_t)^{1-\gamma}}{(A^s_t)^{1-\gamma}\gamma^{\gamma}(1-\gamma)^{(1-\gamma)}} \tag{3.7}$$

From this intermedaite goods pricing equation, we can observe that both markup and the labor productivity appear in the denominator. However, since the upstream sector is capital intensive[5], the impact of markup on intermediate goods price is larger than that of labor productivity[6]. 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.

$$\log(\varepsilon_t) = (1-\rho_\varepsilon)\log(\varepsilon_{ss}) + \rho_\varepsilon \log(\varepsilon_{t-1}) - \epsilon_{\varepsilon t} \tag{3.8}$$

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 $P_{mt}Y_{mt} = (1-\alpha-\beta)P_tY_t$. Finally, we assume that productivities in both SOE and PE firms are nonstationary and have the same stochastic trend. The log of growth rate of productivity A_t^s and A_t^p also follow $AR(1)$ processes[7]

$$\log g_t = (1-\rho_g)\log(g_{ss}) + \rho_g \log g_{t-1} + \epsilon_{gt} \tag{3.9}$$

3.2 Household

The household is an infinited-lived representative agent. Each period, household supplies his labor L to an economy-wide competitive labor market and optimally saves his income for further consumption. International financial market is incomplete in the sense that household can only hold a risk-free international real bond. In addition, household also have options to invest in SOEs or PEs, but the form is different. Investment in SOEs are directly in terms of physical capital investment, while investment in PEs are indirectly in the form of lending to entrepreneurs, who will then invest in physical capital in the PEs. Nevertheless, for the household, arbitrage between investing in SOEs and PEs yields the same real rate of return.

As discussed earlier, we use the King-Plosser-Rebelo preference to induce a balanced growth path:

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

where C_t^h is household consumption, ρ is the subjective discount factor, v denotes an exogenous

[5] This implies the capital share in the upstream sector production, γ, is greater than that in the downstream sector, α.

[6] ε_t has a one for one effect on P_{mt}, while A_t^s affects P_{mt} through the term $(A_t^s)^{1-\gamma}$.

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

and stochastic preference shock in period t, defined as follows:as following

$$\log(v_t) = \rho_v \log(v_{t-1}) + \epsilon_{vt} \tag{3.10}$$

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).

We assume that the household owns SOEs and receives the profits on the SOE firms. Meanwhile, he/she invests in the SOE firms directly. Regarding the PE firms, the households lends D_t to entrepreneurs who invest in PEs. So the lending of households will not change PE firms' ownership structure. Therefore, the household's revenue flow in any period comes from wage income, capital rental income from SOE sector less capital adjustment costs, repayment from entrepreneurs (PEs), and income from international bond holdings. The household then use its revenue to consume and invest in capital stock in 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 SOEs, his/her capital stock holding in SOEs, lum-sum transfer from the goverand and his/her foreign bond holding, respectively; r_t^d, r_t, and r_t^b denote interest rates between t and $t+1$ on loan to entrepreneurs (PEs), on investment in SOEs, and on international bond holding, respectively. Adjustment in capital is subject to adjustment cost. The budge constaint for the household is given by

$$P_t C_t^h + D_{t+1} + P_t I_t^h + B_{t+1} = w_t L_t + (1 + r_t^d) D_t + r_t K_t^h + \omega_t \Pi_t^s + (1 + r_t^b) B_t - T_t \tag{3.11}$$

and law of motion of capital is

$$K_{t+1}^h = (1-\delta) K_t^h + I_t^h - \frac{\varphi^k}{2} \left(\frac{K_{t+1}^h}{A_t^s} - \overline{K}^h \right)^2 A_t^s \tag{3.12}$$

where Π_t^s denotes all profits earned by upstream SOE firms[8], $\frac{\varphi^k}{2}(\frac{K_{t+1}^h}{A_t^s} - \overline{K}^h)^2 A_t^s$ is adjustment cost. Note that the profits received by the household is subject to a stochastic dividend shock

[8] Note that the downsteam sector is perfectly competitive, so profits of SOE firms in the downstream sector is zero.

$\omega_t \in (0,1)$, which is assumed to follow

$$\log(\omega_t) = (1-\rho_\omega)\log(\omega_{ss}) + \rho_\omega \log(\omega_{t-1}) + \epsilon_{\omega t} \tag{3.13}$$

The retained profits are assumed to be controlled 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)[9].

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

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

$$\log(\mu_t) = \rho_\mu \log(\mu_{t-1}) + \epsilon_{\mu t} \tag{3.14}$$

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

$$\begin{aligned}
p_t\Lambda_t[1+\varphi^k(\frac{K_{t+1}^h}{A_t^s} - \overline{k^h})] &= \rho E_t[p_{t+1}\Lambda_{t+1}\frac{\upsilon_{t+1}}{\upsilon_t}(\frac{r_{t+1}}{p_{t+1}} + 1 - \delta)] \\
\Lambda_t &= \rho E_t[\Lambda_{t+1}\frac{\upsilon_{t+1}}{\upsilon_t}(1 + r_{t+1}^b)] \\
\Lambda_t &= \rho E_t[\Lambda_{t+1}\frac{\upsilon_{t+1}}{\upsilon_t}(1 + r_{t+1}^d)] \\
\frac{w_t}{p_t} &= \nu L_t^\kappa C_t^h
\end{aligned}$$

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

[9] The debt-elastic interest rate premium is used to break down the unit root in the marginal utility of wealth in a small open economy with incomplete financial market.

3.3 Entreprenuers

Now we turn to the discussion of entrepreneurs. It is assumed that there exist a continuum of infinited-lived entrepreneurs with the mass of 1. They own PEs and borrow from households to finance their investment in PEs. Unlike SOEs, we assume that entrepreneurs face financial constaint due to limited enforcement in the spirit of Kiyotaki and Moore(1997). At the beginning of every period, entreprenuers 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 pays the principle 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 positive probability that entrepreneurs will default. In that case, the maximum amount the household can recover is a fration, $\phi_t < 1$, 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 constraint. Hence, in our model ϕ_t represents the degree of financial friction. In addition, 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 dealth, entreprenuers will transfer all their wealth to the newborn entrepreneurs and don't consume.

At each period, entrepreneurs' problem is to maxmize their utility subject to the credit constaint and demand from final goods producer (3.2). Specifically, entrepreneurs' problem can be characterized by the folllowing dynamic problem.

$$
\begin{aligned}
V(D_t, K_{dt}^p) &= \max_{C_t, D_{t+1}, K_{dt+1}^p, L_{dt}^p} v_t \ln C_t^e + \rho(1-\varsigma) E_t V(D_{t+1}, K_{dt+1}^p) \\
P_t C_t^e + P_t I_{dt}^p + (1+r_t^d) D_t &= P_{dt}^p Y_{dt}^p - w_t L_{dt}^p - P_{mt} Y_{mt}^p + D_{t+1} \qquad (3.15) \\
K_{dt+1}^p &= (1-\delta) K_{dt}^p + I_{dt}^p - \frac{\varphi^k}{2} P_t \left(\frac{K_{t+1}^p}{A_t^p} - \overline{k^p}\right)^2 A_t^p \\
D_{t+1} &\leq \phi_t P_t K_{dt+1}^p \qquad (3.16)
\end{aligned}
$$

where C_t^e is entrepreneurs' consumption, L_{dt}^p is labor hired by entrepreneurs. Similar to the household, entrepreneurs pay an adjustment cost when adjusting investment in PE firms, given by $\frac{\varphi^k}{2}P_t(\frac{K^p_{t+1}}{A^p_t}-\overline{k^p})^2A^p_t$. 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 constaint. The first-order conditions for $C^e_t, K^p_{dt+1}, D_{t+1}$,and L^p_{dt} are

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

Under the assumption $\varsigma > 0$, we show in Appendix that the credit constaint is always binding at the steady state and entrepreneurs' consumption and investment are linear in their wealth. The degree of credit contrait, ϕ_t, are assumed to follows an $AR(1)$ process,

$$\log(\phi_t) = (1-\rho_\phi)\log(\phi_{ss}) + \rho_\phi\log(\phi_{t-1}) + \epsilon_{\phi t} \tag{3.17}$$

3.4 Government sector

Government collect lum-sum tax from household and use it as government spending (G_t). Its budget is balanced.

$$T_t = G_t$$

Meanwhile, the government also gets the retained profits, $(1-\omega_t)\Pi^s_t$, 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.

3.5 Market clearing conditions

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

$$Y_t = C^h_t + C^e_t + I^h_t + I^p_{dt} + (1-\omega_t)\Pi^s_t + G_t + TB_t \tag{3.18}$$

Government spending is assumed to be exogenous, following an $AR(1)$ process

$$\log(gc_t) = (1 - \rho_{gc}) \log(gc_{ss}) + \rho_{gc} \log(gc_{t-1}) + \epsilon_{gc,t} \tag{3.19}$$

where $gc_t = G_t / A^s_{t-1}$.

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

$$C_t = C^h_t + C^e_t + (1-\theta)(1-\omega_t)\Pi^s_t \tag{3.20}$$
$$I_t = I^h_t + I^p_{dt} + \theta(1-\omega_t)\Pi^s_t \tag{3.21}$$

Labor market clearing condition is given by

$$L_t = L_{mt} + L^s_{dt} + L^p_{dt} \tag{3.22}$$

where L_{mt} is employment in the upstream sector, and L^s_{dt} and L^p_{dt} 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 [10]and then detrend the real allocation variables (except labor) by productivity A_s or A_p, respectively to get a stationary system. We denote variables with a upper hat, i.e, $\widehat{X}$, as the detrended variables. In the Appendix, we present the detrended equilibrium system and in Appendix, we show that detrended equilibrium has a steady state in which all variables are constant over time. The stationary equibrium is defined as follows: given the stochastic process of all the shocks, an equilibrium in the detrended system is an allocation $\{\widehat{C}^h_t, \widehat{C}^e_t, L_t, L_{mt}, L^s_{dt}, L^p_{dt}, \widehat{Y}_t, \widehat{Y}_{mt}, \widehat{Y}_{dt}, \widehat{Y}_{dp,t}, \widehat{K}_t, \widehat{K}_{mt}, \widehat{K}^s_{dt}, \widehat{K}^p_{dt}, \widehat{I}_t, \widehat{I}_{mt}, \widehat{I}^s_{dt}, \widehat{I}^p_{dt}\}$ and $\{P_{mt}, P^s_{dt}, P^p_{dp,t}, MC_{mt}, MC^s_{dt}, MC^p_{dt}, r, r^k, r^d, r^b, w\}$ that satisfy household's and firms' optimization conditions and the market clearing conditions.

[10] Later in estimation, we set $P_t = 1$ as the numeraire.

4 Calibration and Estimation

To solve the model numerically, we need to get the parameter values of the model. We divided the model parameters into three subsets. The first subset of parameter includes the 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 subset of parameters are estimated by Bayesian method (see Smets and Wouters, 2003, 2007; and Lubik and Schorfheide, 2005). Of particular importance among the estimated parameters are those related to the SOE sector, so we jointly estimate these parameters along with the parameters governing the stochastic processes.

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 fixed 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 $1/\kappa = 1.7$. The value 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 capital share of 0.5, the value estimated by Bai, Hsieh and Qian (2008) and used in Song, Storesletten and Zilibotti (2011), and share of intermediate input in gross output (0.54), 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 $\beta = 1 - \alpha - 0.174$, repectively, where ε_{ss} (the steady state value of inverse of markup of upstream sector goods) and γ (capital share in upstream sector) will be esimated by Bayesian method. Labor productivity difference χ is calibrated to match the average of Brandt, Hsieh and Zhu (2008)'s estimate(1.8 during period 1998-2004) and Brandt and Zhu(2010)'s estimate(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.

4.2 Bayesian Estimation

The Bayesian method is used to characterize the posterior distribution of the structural paramters 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 (TB/y). The five time series are all taken from National Bureau of Statistics (NBS). The sample period covers 1979 through 2010. To out best knowledge, this is the longest conherent sample data we can get. [11]The measurement equations are given by:

$$\begin{bmatrix} g^Y \\ g^C \\ g^I \\ g^G \\ TB/y \end{bmatrix} = \begin{bmatrix} \Delta\widehat{Y}_t \\ \Delta\widehat{C}_t \\ \Delta\widehat{I}_t \\ \Delta\widehat{G}_t \\ \widehat{TB/y} \end{bmatrix} + \begin{bmatrix} g_{t-1} \\ g_{t-1} \\ g_{t-1} \\ g_{t-1} \\ 0 \end{bmatrix}$$

where variables with a hat denotes detrended stationary variable 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 G_t, country risk premium shock μ_t, and preference shock v_t.

Note that in our benchmark model, the number of exogenous shocks are more than that of the observables. So we introduce measurement errors. Naturally, it restricts the ability of

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

observables to identify all the exogenous process. This is because Bayesian estimation procedure has a tendency to pick stochastic processes which are geared towards accounting for movements in their respective observables counterparts. For example, government spending are used to identify government spending shock and thus provide little information to help identifying other stochastic shocks.

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 $i = \{g, \phi, \varepsilon, \eta, \omega, G, \mu, v\}$, 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. In this paper, the prior distribution of parameters are set to be the same for the two regions and over different sample periods. An overview of the prior distribution for the parameters are specified in Table 3.

Specifically, the prior of φ^b is assumed to follow Gamma distribution with mean 3 and standard deviation 1. The 90 percent interval of this prior density covers the range from 1 to 6, which covers 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. 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. Note that we choose a lower mean for ν so that the estimated labor supply is the higher labor supply ratio in China. 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 90 percent interval of prior density of γ is then in the range from 0.2 to 0.8, which is wide enough to cover almost all estimates of capital share in the literature. 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 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 downstreat 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 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 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 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 paramters in group Ψ_2 and Ψ_3. It reports the postior mean and the 5% and 95% confidence interval of the posterior distributions for those parameters obtained by Metropolis-Hasting algorithm with $100,000$ draws.

Some postior estimates of the parameters, especially those related to SOEs, need to be highlighted. First, the steady state value of SOE sector shocks are resonable. 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 aggregate level is 1.05 [12]. 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 the effect of "grasping the

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

large and letting the small go" policy. Second, the estimated markup shock is quite persist 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 e_ϕ, standard deviation of credit constaint shock is just 0.011. The estimated posterior mean of ϕ_{ss}, the steady state value of credit constraint, is only 0.27, much smaller than the value 0.86 used in the calibration by Song, Storesetten and Zilibotti (2011), implying entrepreneurs can only finance 27 percent of their capital stock through external borrowing. Finally, note that share of retained profits used 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 a large percent of retained profits are used in investment, consistent with the fact that govenment plays an important role in physical capital investment in China.

4.3 Model Fitness

To evaluate our model's preformance, Table 4 and 5 presents the simulated second moments of the model using the estimated and calibrated parameters discussed above[13]. Specifically, we look at standard deviations, serial correlation and cross-correlations of output, consumption, investment, government spending and trade balance-to-output ratio. To provide a better understanding of the role of SOE shocks in expalining economic fluctuations in China, we also present the simulated moments of an alternative model. The only deviation of the alternative model from our benchmark model in Section 3 is that we remove all SOE shocks in Equations (3.3), (3.8), (3.13). 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 benchmark model with SOE shocks are thus labeled as "SOE" model. In Tables 4 and 5 predictions of both models are compared to the data. In Table 4 both simulated data and actural data are in logs and HP filtered [14]. Table 5 compares moments of growth rate data and those predicted by both models without HP filter. Before going to detail 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 liklihood of covariance matrix

[13] For esimated parameter values, we use the posterio mean from the Bayesian esitmation.

[14] HP filtered simulated data are obtained by transforming level data to growth rate data first and detrend using HP filter with smoothing parameter 100.

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 the empirical second moments. First, the SOE model captures qualititively and quantitatively well the fact that consumption volatility is moderate in China which, as discussed in Section 2, is likely to be a China-specfic 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, NO-SOE model underepredicts 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 standard deviation of investment to be 7.0 percent, very close to 7.4 in the data. The ratio between investment and 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, SOE model also 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, model underpredicts the correlation of consumption with output by 78 percent (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 the data versus 0.29 in the model). The underestimation of correaltion between consumption and output is partially due to our separable KPR preference specificationtion, which generates 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 absorptions. It is given in Table 4 as well. Specifically, the SOE model's prediction on 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 datal). Finally and more importantly, we also compute log marginal liklihood based on Lapalace approximation to compare the overall fittness of two models. We find that the log marginal liklihood for SOE model and NO-SOE model equal to 378.47 and 300.85 respectively. This suggests data favors the SOE model more.

Table 5 compares predictions of the SOE and NO-SOE model with the second moments in the data based on growth rate data without HP filter. 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 outpu growth rate is underestimated but the magnitute is less severe than that in Table 4 (HP-filtered data). NO-SOE model perform worse in all above dimensions.

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, 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, it is assumed that a higher markup leads to higher profits and returns on assets. Then 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

Before procceding we shall clarify one point about the nature of our exercise and results. First, sinces 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.

Figure 3 and 4 display the comparison. Apparently, SOE share shock tracks SOE's share in total sales reasonablely well. Specifically, the share shock can track the upswing of SOE's sale share from 1985 to 1990, a period during which Chinese government starts the first stage SOE reform and gradually increases 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 the smoothed markup shock and ROA on SOEs in all sectors. As one can be see, in general the model-based markup shock can reasonablly track the cyclical movement of ROA, especially the uptrend of ROA after 1997, which is consistent with the implication of "grasping the large and 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 move 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, Lin and Wang (2010) 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 sectoral or firm data information on SOE sector. The observables we used in estimation are standard macro-level data. Therefore, it is striking that our esimated 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 constibution of each shock, Table 6 presents the variance decomposition of the growth rate of output, consumption, investment and trade balance-to-output ratio. From the 4th to 6th column of the Table, 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 explains 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 rate of output, consumption, investment and trade balance-to-output ratio in the data and in the simulated model, based on the estimated sequence of shocks. The comovement between data and model-predicted macroeconomic aggregates is striking. In Figure 5 we also plot the simulated growth rate of these aggregated 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 flucuation in trade balance-to-output ratio, their explaining power is weaker. But they can still account for major upward and downward movements of this ratio.

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. Compared to other emerging market business cycle literature(e.g., Aguitar and Gopinath 2007), the contribution of permanent productivity shocks in our model is substantially limited. But this seems to be consistent with the fact that in China excess volatility of consumption and countercyclical trade balance are not observed, since this shock is important in explaining these features in emerging market business cycles. This result is also in line with the findings in García-Cicco, Pancrazi and Uribe (2012). They introduce an international financial constaint (which is similar to the one in our model) in a standard Neoclassical model and find permanent productivity shocks are not a major driving force for business cycles using Argetina and Mexican data.

Another result need to be highlighted is related the contribution of credit shocks. Song, Storesletten and Zilibotti (2011) empahsize the rold 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 constrast 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. Neverthelss, our result is similar to that in Mendoza (2010), who finds that business cycle moments in emerging market are largely unaffected by the collateral constaint. 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 exsits in our model. It is optimal for entrepreneurs to save more to overcome collateral constraint. Nevertheless, in our model it should be noted that the finite life assumption of entrepreneurs may reduce the explaning power of precaustionary saving motive on low contribution of credit shocks.

Another plausible explanation is that in China credit constaint 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 constaint may have moderate effects on fluctuations in macroeconomic aggregates if the decline took place gradually, but not dramatically and agent has time to adjust to the new lower level of credit constaint. In our estimation result in Table 3, it is evident that the estimated standard deviation of credit constaint shock is quite small, compared to SOE sector shocks.

Since the credit contraint 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 downsteam sector. However, our Bayesian estimation gives an estimated share of PE's sale in downstream sector of 0.61. So low size seems not a reason for this result. Furthermore, credit constraint works through standard intertemporal mechanism. It leads to fluctuations in entreprenuer's investment and aggregate investment immediately at the time the shock hits the economy, and later the shock will be propogated through capital stock change. Therefore, to induce sizeable fluctuations as seen in the data, the volatility of credit constaint shock must be equally sizeable. This will in turn lead to much more volatile investment, which is not evident in China's data.

It seems that when SOE sector shocks is present, they took over the role of credit shocks and become the driving force of economic fluctuations. This is because they do a better job in matching the moderate consumption volatility and substantial low volatility of investment observed in the data, which credit shock fails to capture. Nevertheless, without strong intertemporal smoothing mechanism, SOE sector shocks generate procyclical trade balance, since production varies with SOE sector shocks while consumption and investment are less respondent.

Regarding the role of other shocks, in contrast to findings in García-Cicco, Pancrazi, and Uribe (2012), the contribution of country risk premia 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 Uribe (2012) and Justianiao, Primiceri and Tambalotti (2009) among other researchers, we find preference shock can only explain 3.6 percent of movements in consumption. The ability of preference shocks in accounting for movement of consumption comes from failure of consumption's Eulur equation (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 6 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 upexpectedly large and frequent change in SOE's monopolistic power in upstream sector and final goods producers' demand for SOE's products in the more competitive downstream sector. Second, pernament productivity shock, credit constraint and country risk premia shock are less relevant for Chinese business cycle.

5 Inspecting the Mechanism: Why SOE Sector Shocks are so Important?

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 shock, specifically share shock and markup shock, affect business cycle in China? To address these questions, in this section, we investigate model's dynamic mechanism more closely by looking 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. Since the world price for final goods is exgenously given, the domestic factor prices fall down in response to the markup shock. Meanwhile, when P_m increases, demand for upstream goods also decreases. So employment and investment in the upstream sector decreases, which further reduces the factor prices. From the impulse response functions, the decrease in wage and capital rental rate dominate the increase in intermediate goods prices. So the downstream firms' competitiveness in the world market increases. As a result, for both SOE and PE downstream firms, their output increase.

Moreover, the downstream SOE and PE firms are affected asymmetrically. For PE firms, the wedge between marginal product of capital and borrowing cost increases, which leads to more investment in PE firms. But for downstream SOE firms, since capital rental rate decreases, investment falls. 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 increase slightly. The expansion of downstream sector and the decline of wage push up the employment for both SOE and PE firms. For the household, they will consume less and work more since the wage income and capital income fall down. But entrepreneurs' consumption increases because the increas in marginal product of captial on PE firms in downstream sector.

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 increase and thus tends to reallocate resource to SOE firms. As PEs is more productive than SOEs, the measured productivity in the aggregate level thus decrease. So the share shock is like a negative aggregate TFP shock for the whole economy. As a result, the aggregate output falls down, so does 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 decline of factor prices increases the competitiveness of downstream sector in the world market and encourage 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 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 increases of employment. For the intermediate goods sector, the price goes down since factor prices fall, which increases the demand for intermediate goods slightly. So 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, the simple idea is that the share shock and markup shock play similar roles as transitory productivity shocks in standard RBC literatures. So unlike permanent productivity shocks, they will generate moderate instead of excess consumption volatility. Regarding investment volatility, from the variance decomposition, volatility of investment can be largely attributed to markup shocks. The less volatile investment comes from divergent responses of firms in response of markup shocks. For example, to respond a positive markup shock, investment 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 procyclical trade balance while a positive share shock generates countercyclical trade balance. Since markup shock is the most important driver of investment volatility, it also contributes a lot to the movement of trade balance. Meanwhile, recall that markup shock is also much more volatile than other shocks. So it plays dominant role, making trade balance procyclical.

6 Sensitivity Analysis

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 or some missing frcitions in our model. To check these conjectures, we consider an alternative perference setting and introduce labor market friction in this section for robustness check.

6.1 Alternative Preference Setting

In this section we explore the sensitivity of our result to an alternative preference specification. This preference setting combines features of both KPR and GHH preference. As shown in Section 4.3, the KPR preference is used to be compatible with balance growth path but it gives poor prediction on correlation of consumption and trade balance with output. In KPR preference setting, consumption and labor supply respond to external shock in separate ways. Meanwhile, as argued by Aguiar and Gopinath (2007), GHH preference is often used in emerging market business cycle literatures 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 perserving compatibility with balance growth in the long run. The alternative preference takes the following form as in Jaimovich and Rebelo (2009, JR preference hereafter)

$$U = E_0 \sum_{t=0}^{\infty} \rho^t \frac{(C_t - \nu L^{\kappa} X_t)^{1-\sigma} - 1}{1-\sigma} \tag{6.23}$$

where $X_t = C_t^h X_{t-1}^{1-h}$. This preference introduces paramter h to govern the strength of wealth elasticity of labor supply. When $h = 1$, the period utlity 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 elascticity 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.

Table 7 gives prior and posterior mean of each parameter estimated. Tables 8 and 9 display the model fittness and variance decomposition. Three observations are noteworthy. First, from table 7, 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 sufficient large for us to get that conclusion. Meanwhile, for the estimates of other parameter values, there seem no big changes. The volatility of markup shocks is still high relative to other shocks. Second, from Tables 8, 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 of 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 9 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. Preference shock can also explain more consumption volatility. Comparing Table 7 and Table 9 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 preferece shocks increases (3.6% in benchmark model vs 21.7% in JR model). But one problem of the JR model is that this specification gives excessive consumption volatility which is not observed in the Chinese data.

This exercise confirm that KPR preference helps to generate first 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 display 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 in the data.

6.2 Labor Wedge

Another important friction in Chinese economy lies in the labor market, as shown in Brandt, Tombe, and Zhu (2013). Chong, He and Shi (2009) measure the contribution of different frictions in accounting for Chinese business cycle movement and conclude that labor wedge is important. So in this subsection we consider labor market friction and check if the effect of SOE sector shocks in the Chinese economy has been exaggerated in the benchmark model because of 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 subsitution between household consumption and labor supply. So the first-order condition with respective 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

$$\log(\tau_{l,t}) = \rho_{\tau_l} \log(\tau_{l,t-1}) + e_{\tau_l,t} \tag{6.24}$$

Tables $10 - 12$ present estimation results of parameters, model fittness and variance decomposition for the model with labor wedge. From these tables, we can get three points. First, from Table 10, the estimated posterior means of parameters is 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 model. Second, from Table 11, we can also see that overall speaking, model fitness in terms of second moments is close to the benchmark SOE model. But it overpredicts the consumption volatility and underpredicts the investment volatility compared to the benchmark model. Third, variance decomposition of model suggest 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 busines cycle. The two shocks, overall, 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 result as those in the benchmark SOE model.

7 Conclusion

This paper examines the role of SOE sector in explaining China's real business cycle fluctuations. Compared to the developed economies and emerging market countries, China's business cycle exhibits some unique features; namely, moderate volatility of consumption, substantial lower investment volatility and acylical trade balance, which cannot be explained by shocks or mechanisms emphasized in the emerging market business cycle literatures. So we link these features to the SOE reforms which perhaps represents the most important and dramatic reforms in China during the last few decades. Meanwhile, in the China growth literature, the role of SOEs and PEs are also widely discussed.

The starting point of our investigation is that there are frequent reforms on SOEs implemented by different leadership, which cause frequent changes in SOE's share and profitability. So we construct a full-fledged general equilirium model with detailed characterization of SOE sector. 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 literatures. By comparing the prediction of this SOE model and an alternative model without SOE setor shocks, we concludes 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 source of economic fluctuations in China. The two dominant driving force 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 friciton, the esimation results show that these conclusions regarding SOE sector shocks are robust.

References

[1] Aguiar, Mark, and Gita Gopinath, 2007. "Emerging Market Business Cycles: The Cycle Is the Trend," Journal of Political Economy, 115:69-102.

[2] An, Sungbae, and Frank Schorfheide, 2007, "Bayesian Analysis of DSGE Models", Econometric Reviews, 26(2-4):113-172.

[3] Brandt, Loren, Trevor Tombe, and Xiadong Zhu, 2013. "Factor Market Distortions Across Time, Space, and Sectors in China", Review of Economic Dynamics, 16(1):39-58.

[4] Brandt, Loren, Chang-Tai Hsieh, and Xiadong Zhu, 2008. "Growth and Structural Transformation in China ", China's Great Economic Transformation, 569-632, Cambridge University Press.

[5] Brandt, Loren, Chang-Tai Hsieh, and Yingyi Qian, 2006, " The Return to Capital in China", Brooking Papers on Economic Activity, 37(2):61-102.

[6] Brandt, Loren, and Xiaodong Zhu, 2000, "Redistribution in a Decentralized Economy: Growth and Inflation in China under Reform", Journal of Political Economy, 108(2): 422-439.

[7] García-Cicco, Javier, Roberto Pancrazi, and Martin Uribe. 2010. "Real Business Cycles in Emerging Countries?" , American Economic Review, 100(5):2510-31.

[8] Greenwood, Jeremy, Zvi Hercowitz and Gregory W. Huffman, 1988, "Investment, Capacity Utilization, and the Real Business Cycle", American Economic Review, 78(3): 402-417.

[9] Hsieh, Chang-Tai, and Peter J. Klenow, 2009, "Misallocation and Manufacturing TFP in China and India", Quarterly Journal of Economics, 124(4):1403-1448.

[10] V.V. Chari, Patrick J. Kehoe, and Ellen R. Mcgrattan, 2007, "Business Cycle Accounting", Econometrica, 75 (3): 781–836

[11] He, Qing, Tai-Leung Chong, and Shi, Kang, 2009, "What accounts for Chinese Business Cycle?," China Economic Review, 20(4): 650-661.

[12] King, Robert G., Charles I. Plosser, and Sergio T. Rebelo, 1988, "Production, Growth and Business Cycles I: the Basic Neoclassical Model", Journal of Monetary Economics, 21:195-232.

[13] Kiyotaki, Nobuhiro, and John Moore, 1997,"Credit Cycles", Journal of Political Economy, 105(2):211-248.

[14] Jaimovich, Nir, and Sergio Rebelo, 2009, "Can News about the Future Drive the Business Cycle?", American Economic Review, 99(4):1097-1118.

[15] Jaimovich, Nir, and Max Floetotto, 2008, "Firm Dynamics, Markup Variations, and the Business Cycle", Journal of Monetary Economics 55:1238–1252.

[16] Jermann, Urban, and Vincenzo Quadrini. 2012. "Macroeconomic Effects of Financial Shocks." American Economic Review, 102(1):238-271.

[17] Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti, 2010, "Investment Shocks and Business Cycles", Journal of Monetary Economics, 57(2):132-145.

[18] Li, Xi, Xuewen Liu, and Yong Wang, 2012, "A Model of China's State Capitalism ", Working Paper.

[19] Loecker,Jan De, and Frederic Warzynski, 2012, "Markups and Firm-Level Export Status", American Economic Review, 102(6):2437-2471.

[20] Mendoza, Enrique G., 2010, "Sudden Stops, Financial Crises, and Leverage", American Economic Review, 100(5):1941-66.

[21] Mendoza, Enrique G., 1991, " Real Business Cycle in Small Open Economy",American Economic Review, 81(4):797-818.

[22] Neumeyer, Pablo A and Fabrizio Perri, 2005, "Business Cycles in Emerging Economies: the Role of Interest Rates", Journal of Monetary Economics, 52(2):345-80.

[23] Quadrini,Vincenzo, 2011, "Financial Frictions in Macroeconomic Fluctuations", Economic Quarterly, 97(3):209-254.

[24] Ravn, Morten, Stephanie Schmitt-Grohé, and Martin Uribe, 2006, "Deep Habits", The Review of Economic Studies, 73:195-218.

[25] Rotemberg, Julio J. and Michael Woodford, 1991, "Markups and the Business Cycle", NBER Macroeconomics Annual, Volume 6, MIT Press.

[26] Schmitt-Grohé, Stephanie and Martin Uribe, 2003, "Closing small open economy models," Journal of International Economics, 61(1):163-185.

[27] Smets, Frank, and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." American Economic Review, 97(3):586-606.

[28] Word Bank, 1995,"SOE Dividends: How Much and to Whom?", No.56651.

[29] Song, Zheng, Kjetil Storesetten, and Fabrizio Zilibotti, 2011, "Growing Like China", American Economic Review, 101(1):196-233.

Table 1: Moments in China,Emerging and Developed Markets

	China	Emerging Makets	Developed Markets
$\sigma(y)$	3.16	3.47	1.94
$\rho(y)$	0.74	0.40	0.59
$\sigma(c)/\sigma(y)$	0.98	1.23	0.96
$\sigma(i)/\sigma(y)$	2.33	3.81	3.71
$\sigma(TBy)$	1.675	3.51	1.22
$\rho(TBy, y)$	$-0.05(0.80)$	-0.61	-0.44
$\rho(c, y)$	0.61(0.00)	0.80	0.84
$\rho(i, y)$	0.80(0.00)	0.85	0.86

Note:This table list values of moments of China, emerging markets and developed markets. The value of emerging markets and developed markets are computed using data from Aguiar and Gopinath (2007). We transform their quarterly data into annual by taking simple average. We then detrend the tranformed 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 countries. We take means of the computed moments for countries in emerging market group and developed countries group. The classfication of emerging and develop countries are same with Aguiar and Gopinath (2007). To be comparable with moments computed from Aguiar and Gopinath (2007), we also detrend China's data using Hodrick-Prescott filter with smoothing parameter 100. The time of China's data span $1978 - 2010$. The time from countries in emerging market and developed markets are the same with Aguiar and Gopinath (2007). The standard deviation are in percentages. P-value is in parentheses.

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	$2^{\frac{1}{\beta}}$

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 repsectively. 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.

Table 4: Moments predicted by SOE and NO-SOE 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
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
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	
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
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.

Table 5: Moments predicted by SOE and NO-SOE 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
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
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	
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
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 using mean of posterior distribution of parameters. P-value is in parentheses.

Table 6: 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 computed from 100,000 draws of parameters from posterior mean with the first 45 percent discarded.

Table 7: 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 repsectively. 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 8: Moments predicted by JR model

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. 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 9: 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 mean with the first 45 percent discard.

Table 10: 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 repsectively. 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 11: Moments predicted by model with labor wedge

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 12: 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	0.0	1.8	1.3	4.9
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 mean with the first 45 percent discard.

Figure 1: Output and the share of SOE's sales

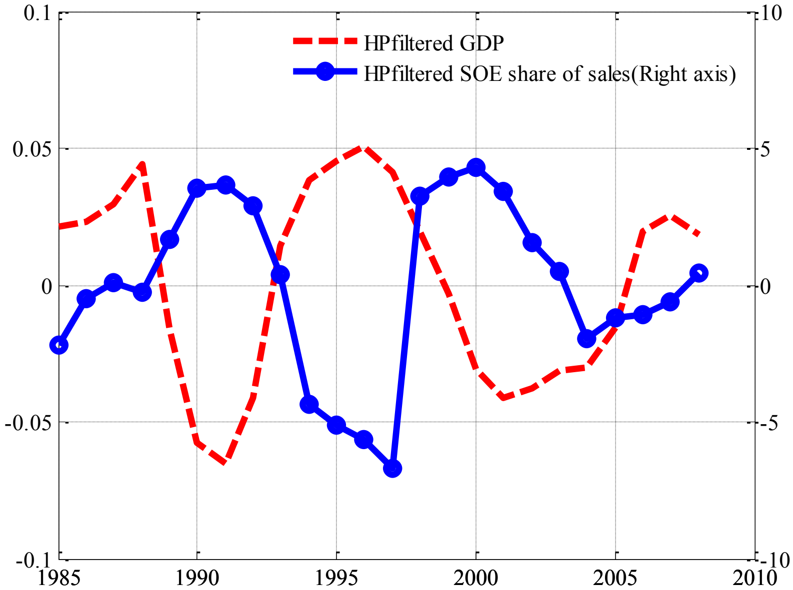
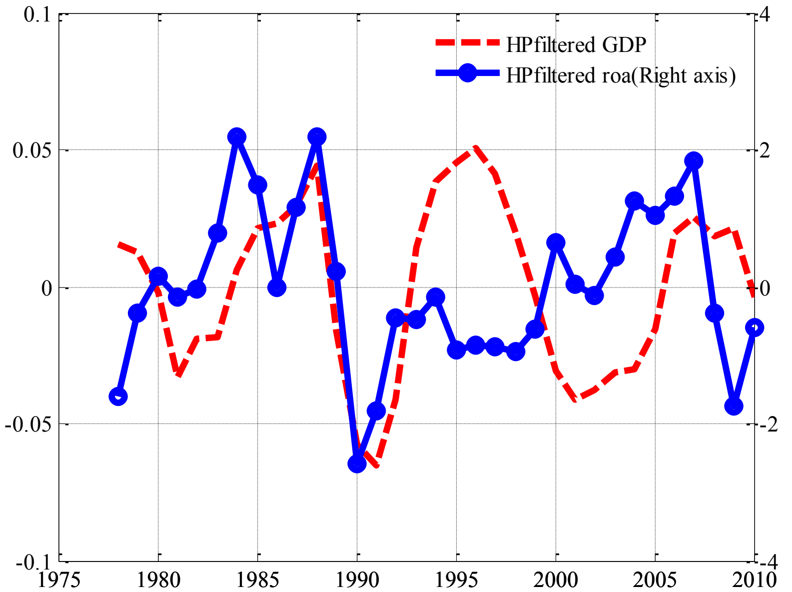


Figure 2: Output and return on asset of SOEs



Note: All the variables in the figures are detrended using HP filter with smoothing parameter 100. The red lines in both figures denote HP-filtered real GDP per capita. 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).Real GDP is obtained from nominal GDP adjusted for price using GDP deflator. Nominal GDP is obtained from National Bureau of Statistics. GDP deflator is from WDI. Share of SOE's sale in total sales is from Li, Lin and Wang (2012). SOE's ROA before 1999 is also from Li, Lin and Wang (2012) and ROA after 1999(include 1999) is from CEIC. ROA is computed by dividing SOE's gross profit by its asset. Therefore, SOE's ROA in figure 2 is before-tax return on asset.

Figure 3: Smoothed Share Shock and HP-filtered SOE share of sales

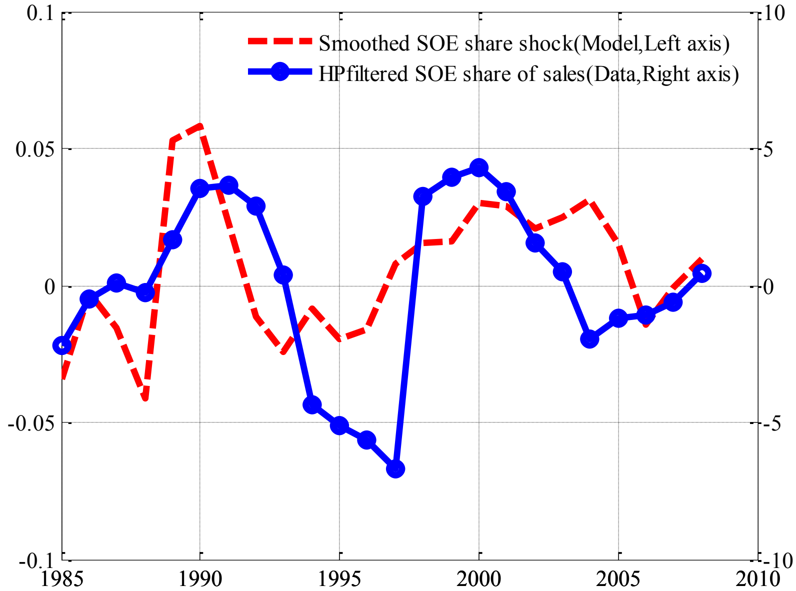
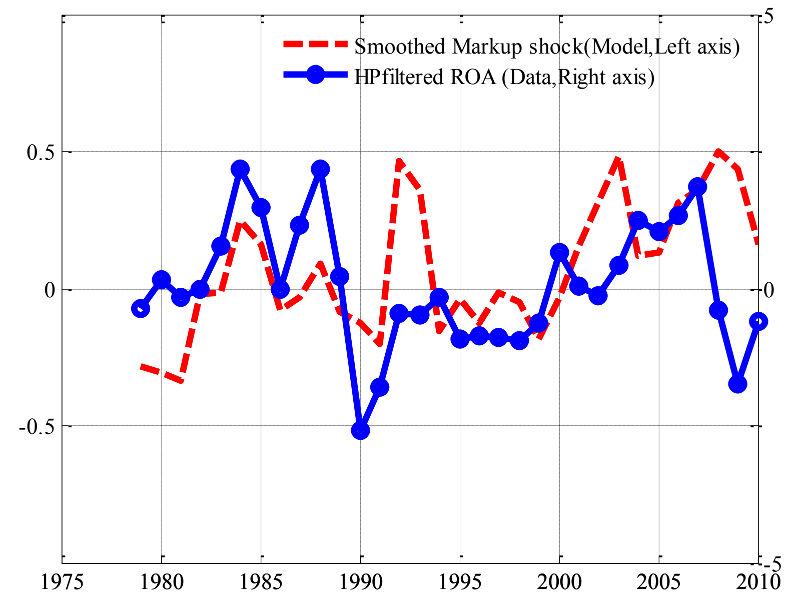
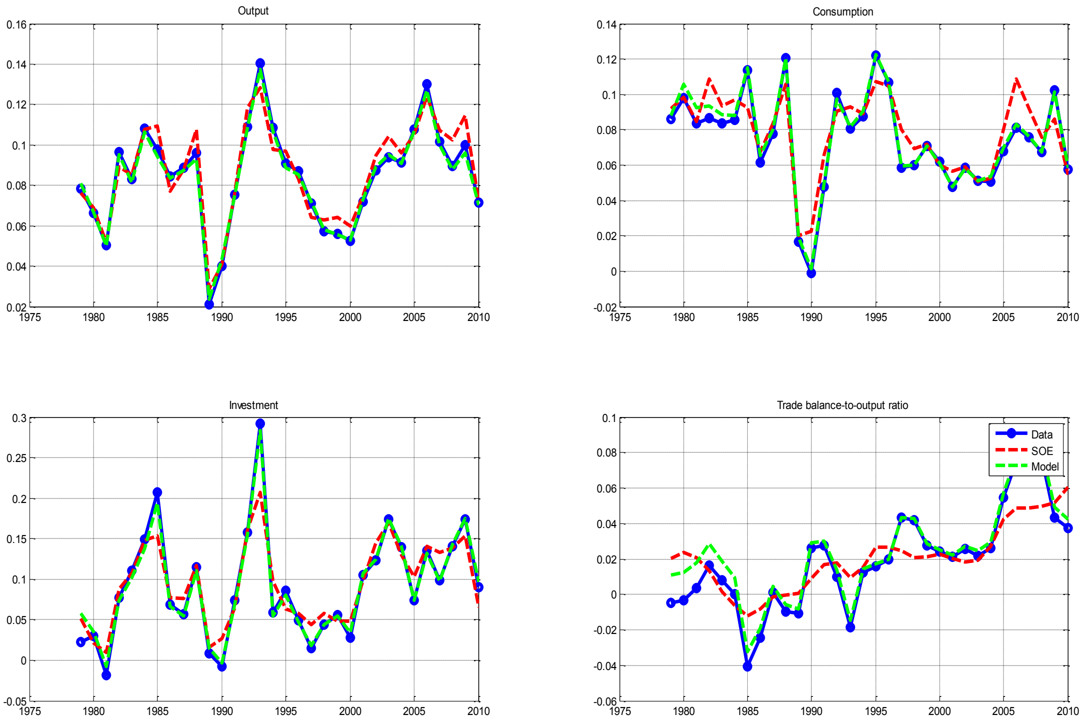


Figure 4: Smoothed Markup Shock and HP-filtered ROA



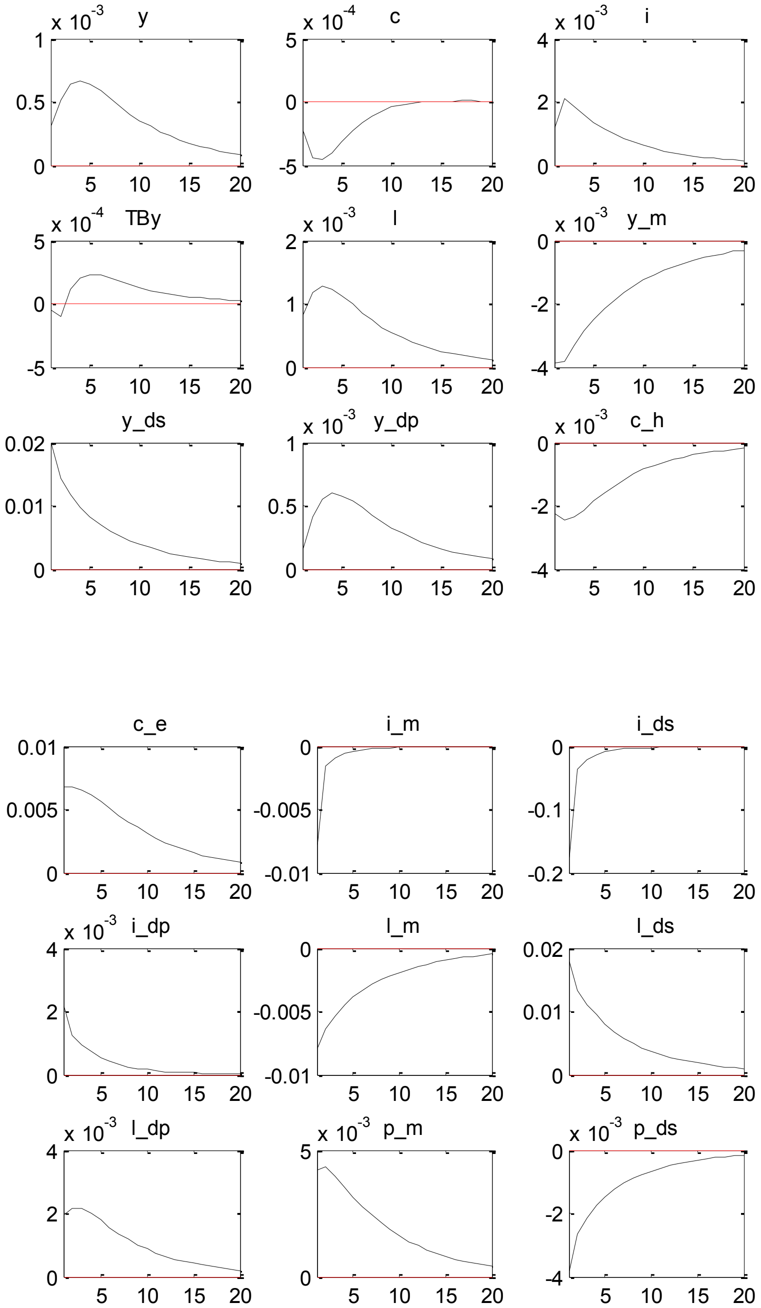
Note: All the variables in the figures are detrended using HP filter with smoothing parameter 100. The red lines in both figures denote estimated shocks by SOE model. The blue line in the upper figure denotes HP-filtered share of SOE's (Both upstream and downstream SOEs) sales in total sales and the 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, Lin and Wang (2012).

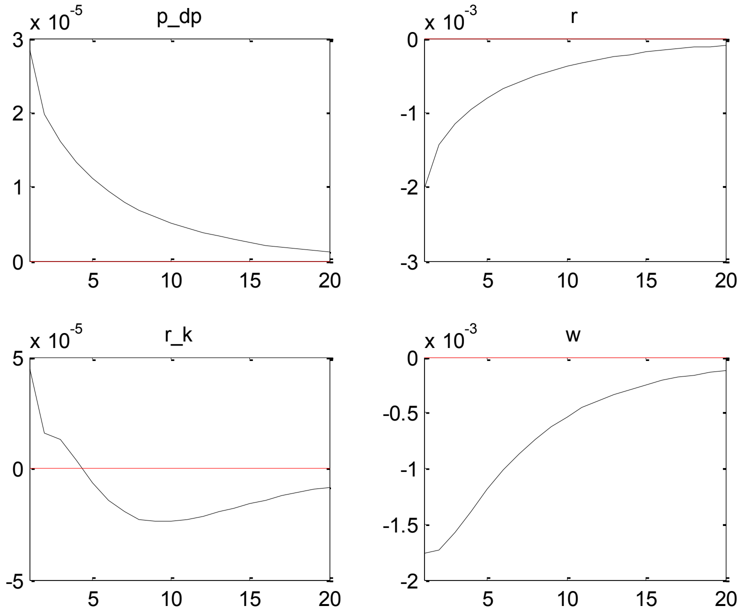
Figure 5: SOE Model's prediction



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.

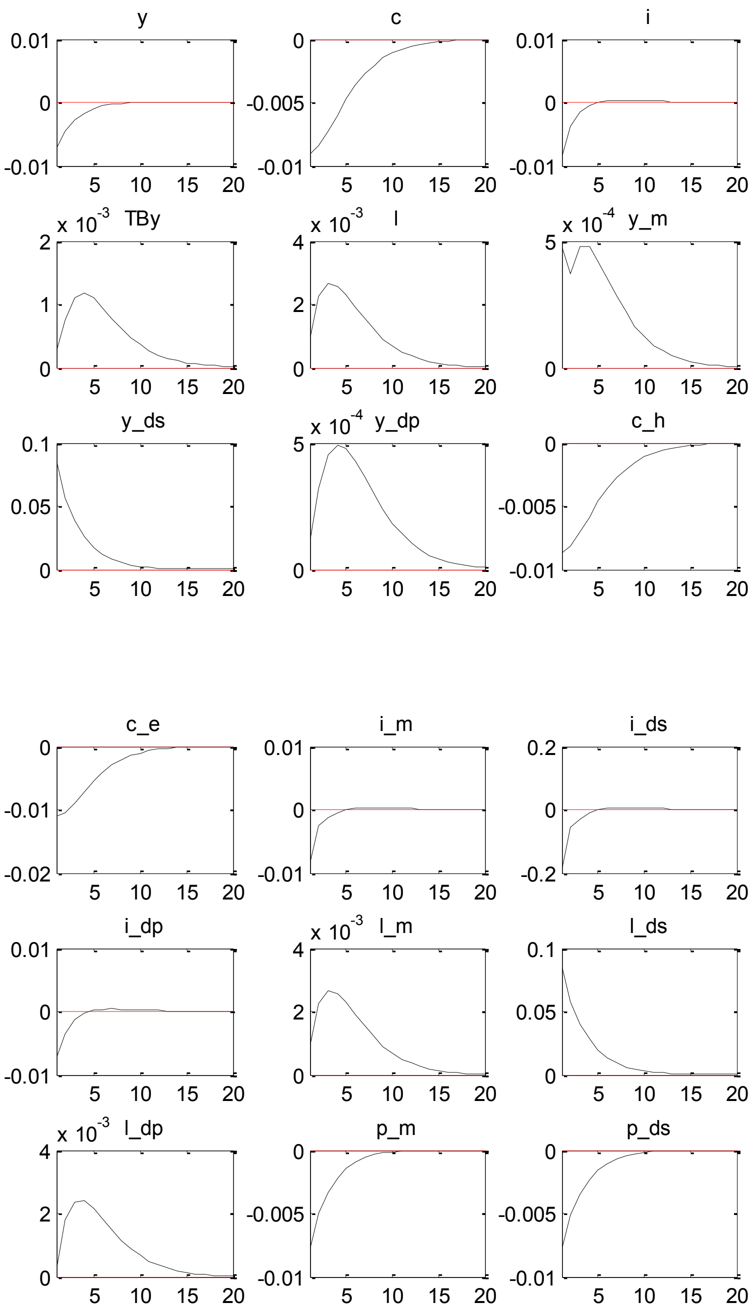
Figure 6: Impulse response to one percent increase in markup shock

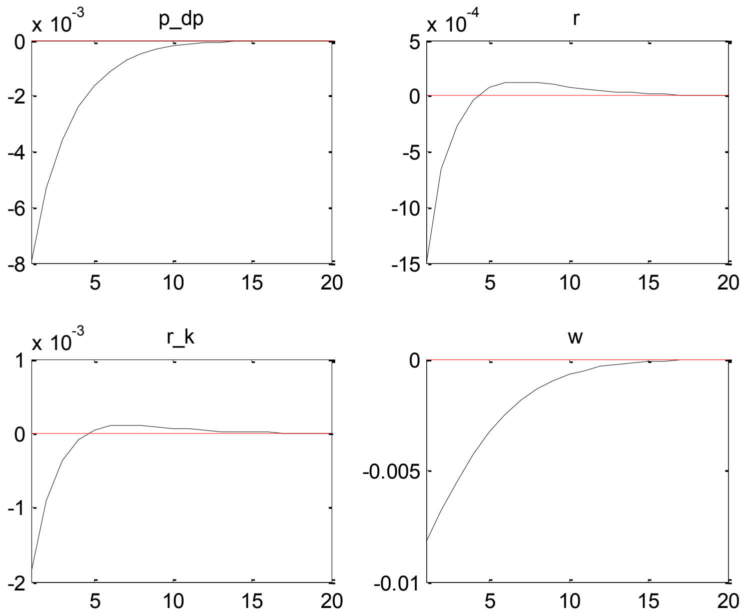




Note: This figure plots impulse response of key macro aggregates to 1% increase in markup shock, which will lead to markup increase from 1.373 to 1.392 in upstream sector. The vertical axis is the percentage deviation from steady state of each variable in face with the shock. The vertical y, c,i,TBy,l,y_m,y_ds,y_dp 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.

Figure 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. The same notation in Figure 7 denote the same variable with figure 6.