State Ownership, Asset Prices, and Monetary Policy Transmission: A Tale of Two Sectors

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Abstract

We investigate how firm heterogeneity in state ownership and productivity shapes monetary policy transmission in China. We develop a dynamic model featuring heterogeneous firms—state-owned (SOEs) and private-owned enterprises (POEs)—along with money supply shocks and financial frictions. Our estimation reveals that responses to monetary shocks and risk premia vary significantly both within and across sectors, matching empirical patterns. Counterfactual analysis demonstrates that POEs' severe debt-financing frictions exacerbate capital misallocation during monetary contractions, causing sizable losses in aggregate productivity and output.

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Keywords: State ownership, monetary policy transmission, financial frictions, risk premiums, POE, SOE

1 Introduction

State ownership of corporations is common around the world. It is broadly documented that state-owned enterprises (SOEs) have preferential access to resources compared to private-owned enterprises (POEs) due to the close connections of SOEs to the government, often leading to inefficient resource allocation in the economy.[1] Furthermore, it is also widely documented that changes in government monetary supply policies involving massive credit allocations usually favor SOEs.[2] However, despite the extensive studies on SOEs and POEs which primarily concentrate on the sectoral differences in efficiency and performance, there is a lack of research on how monetary policy transmits in economies where firms differ in both sectoral state ownership and firm-level productivity, and how such heterogeneity affects capital allocation and aggregate output in the broad economy.

To answer these questions, we focus on China, which has undergone a significant economic transformation with rapid growth in SOEs and POEs over the past four decades. During this period, the monetary supply has played a key role in investment and output growth (Chen and Zha, 2018). Using firm-level data, we show both empirically and theoretically that the differential within- and cross-sectoral response of SOEs and POEs, such as firms' decisions and equilibrium risk premium, to monetary supply shocks is important to understanding the monetary policy transmission in China. The novelty of our approach is the utilization of the information in the cross section of the risk premium (expected stock returns) to identify the financial frictions associated with state ownership. We show that the pronounced frictions that hinder POEs' access to the debt market exacerbate capital misallocation, resulting in substantial losses in aggregate productivity and output.

We start by developing a dynamic heterogeneous-firm model with two interconnected blocks: a firm block and a monetary policy block. In the firm block, monetary supply (MS) shocks and aggregate productivity shocks are the key aggregate risks. There are two sources of firm

[1] See the theoretical analysis in Shleifer and Vishny (1994), Shleifer (1998), Song et al. (2011), Xiong (2018), etc., and the empirical analysis in Dewenter and Malatesta (2001), He et al. (2022), etc.

[2] See Chen and Zha (2018), Alok and Ayyagari (2020), etc., for a detailed analysis of the channels through which monetary policies favor SOEs in the world.

heterogeneity. First, firms in the SOE and POE sectors differ in the magnitude of their real investment and financial frictions. Second, within each sector, firms differ in idiosyncratic productivity, which generates within-sector dispersion in risk premia and in firms' responses to MS shocks. The cost of issuing debt is stochastic and depends on the aggregate MS shock, capturing how monetary shocks affect the supply of credit to Chinese firms. This feature is motivated by China's quantity-based monetary policy framework, in which the central bank uses M2 growth as an intermediate target to directly influence banks' credit volumes, so that bank loan supply comoves closely with money growth.

It features aggregate money demand, aggregate supply (a Phillips curve), and aggregate demand equations, together with a monetary policy rule consistent with China's quantity-based framework and a process governing money-supply growth. This block endogenizes inflation and the nominal interest rate in response to both monetary and productivity shocks. Integrating the monetary block with the firm block enables us to examine how monetary policy shocks influence firms' decisions and how these effects propagate differently across SOEs and POEs due to their distinct financing frictions.

Having laid out the model structure, we next discipline the level of real and financial frictions faced by SOEs and POEs by estimating the model using the Simulated Method of Moments. Specifically, we identify the relation between financial frictions and state ownership by matching cross-sectional variation in risk premia within each sector together with several moments of firms' real quantities. The estimation reveals that, relative to SOEs, POEs face significantly more severe debt financing frictions. We then use the estimated model to construct an empirical MS shock proxy for the Chinese economy. This step is crucial because it allows us to link MS shocks to firm outcomes in the data and to test the model's mechanism. Intuitively, the model structure implies that latent (to the econometrician) monetary supply shocks can be inferred from a combination of equilibrium firm-level moments. We map this model-implied relationship to the data to construct a time series of model-implied MS shocks and show that this proxy captures a significant amount of variation in China's monetary supply, validating the interpretation of the time-varying cost of debt in the model as an MS shock.

Using the model implied MS shock proxy, we document three novel patterns regarding the within- and across-sector relationship between monetary supply shocks, asset prices, and corporate policies in the data. First, there is a significant relationship between firms' risk premiums (expected stock returns) and firm's investment within the SOE sector, but this relationship is flat in the POE sector. In the SOE sector, high-investment (high productivity) firms have lower expected stock returns than low-investment (low productivity) ones, and the difference is economically large, about 5% per annum. On the contrary, this investment-return spread is close to zero in the POE sector.

Second, we show that MS shocks are a source of aggregate risk in the economy and carry a positive price of risk. That is, periods in which monetary supply tightens (negative MS shock) are associated with investor's high marginal utility, that is, they are bad economic times. As a result, firms' return exposures to MS shocks ar priced in financial markets and affect firm's equilibrium expected returns.

Third, there is a significant difference in the cyclicality of firms' responses to MS shocks within SOEs. In particular, high-investment SOE firms' responses to MS shocks are countercyclical; that is, even when MS unexpectedly contracts, high-investment SOE firms' stock return, debt issuance, capital investment, and future profit still increase, making these firms good hedges against MS shocks. In contrast, low-investment SOE firms' stock returns are acyclical, while changes in their corporate policies are procyclical. However, in the POE sector, the responses of stock returns to MS shocks are procyclical, whereas the responses of corporate policies do not vary between high- and low-investment firms.

We then show that the model quantitatively replicates the empirical patterns. In the model, the severity of debt market frictions at the sectoral level impacts the risk premium difference between high- and low-productivity (proxied by the level of investment) firms within the sector. Intuitively, high productivity SOE firms are good hedges against monetary policy risks due to the SOE sector's easier access to debt market. In contrast, POEs face tougher constraints in the debt market, resulting in higher risk premia for all firms, regardless of their productivity, thus worsening capital misallocation.

The exact economic mechanism in the model operates as follows. When an adverse MS shock (less credit available) hits the model economy, all firms, including SOEs and POEs, find it more costly to issue debt. However, high-investment (high productivity) SOEs with high capital demand still issue debt to expand their capital as the SOE sector is less constrained, which further relaxes their collateral constraints and raises future dividend payouts and firm values. As a result, the most productive SOEs respond countercyclically to the contractionary MS shock, making these firms good hedges against MS shocks, which explains their relatively lower expected stock return (lower risk) in equilibrium. On the contrary, in response to the adverse MS shock, the low-investment (low productivity) SOEs cut investment and debt issuance, decreasing firm value, resulting in a procyclical response to MS shocks and hence relatively higher expected stock returns (higher risk) in equilibrium.

In contrast to SOEs, firms in the POE sector face more severe financial frictions in the form of higher marginal debt issuance costs for the entire sector. As a result, when an adverse MS shock hits the model economy, the firms in the POE sector find it very difficult to raise debt, regardless of their productivity level. Moreover, firms' capacity to smooth the impact of the MS shock with equity financing is limited since doing so incurs equity financing costs. As a result, the model delivers similar expected stock returns for high- and low-investment POEs, consistent with the data.

Finally, we use the structural model as a laboratory to understand the monetary policy transmission mechanism in China. In particular, we use the model estimation to investigate the impact of MS shocks on sectoral and aggregate variables and perform counterfactual analysis to evaluate how the effects depend on key features of the model. In the baseline estimation, after a negative one-standard-difference MS shock (less credit available), the sectoral output and measured TFP fall substantially more in the POE sector than in the SOE sector, leading to a significant drop in aggregate output and aggregate TFP of -2% and -4%, respectively.

To understand the economic forces driving the previous aggregate level results in the model, we conduct three counterfactual analyses. First, when we set the level of debt financing costs of POEs to be the same (lower) as those of SOEs, the drop in sectoral output and measured

TFP after a contractionary MS shock is smaller than in the baseline, and roughly the same as the drop observed in SOEs. In contrast, when we set the level of capital adjustment costs, collateralizability of capital, and level of equity issuance costs of POEs to be the same as in SOEs, the maximum drop in aggregate output and measured TFP remains roughly the same as in the baseline. These results imply that the key heterogeneity driving the significant differential response of measured TFP and sectoral output to MS shocks in the model are the debt financing frictions. This result has potential policy implications. It implies that leveling the play field for SOEs and POEs in the debt markets can potentially lead to large economic gains. The next table shows that reducing POEs' debt frictions to the same (lower) level as that of SOEs would increase measured TFP by 1.5 percentage points, and aggregate output by 1 percentage point, due to better allocation of capital within firms in the POE sector.

Impact of debt market frictions on aggregate productivity and output

	Drop in productivity	Drop in output
Baseline	−4%	−2%
Levelling up	−2.5%	−1%

Notes: Results from the average of 500 simulations of the calibrated model to a contraction MS shock (see section 4). In the Baseline, the level of real and financial frictions of POE's are different from that of SOE's. In the Levelling up, the level of debt market frictions of POE's are equalized to the level of SOE's.

Second, the level of firm heterogeneity within each sector also matters for the quantitative effect of MS shocks in the economy. When the volatility of firm-level idiosyncratic productivity is reduced to close to zero, the within-sector heterogeneity in risk premium and cashflow is muted. In this case, there is not much capital misallocation within each sector even though there are real and financial frictions. We show that the sectoral output and measured TFP decrease in response to a negative MS shock is substantially smaller than in the baseline model. More importantly, the drop in output and measured TFP is similar across SOEs and POEs despite SOEs having lower debt financing costs. This exercise indicates that capital misallocation within SOEs and POEs resulting from within-sector heterogeneity in productivity is an important driver of the differential sectoral output and measured TFP loss during monetary contractions.

Furthermore, the positive price of risk of MS shocks is quantitatively important as well for the sizeable effect of MS shocks in the economy. Raising the price of risk for the MS shock (investors are more averse to monetary supply risk) increases the average cost of capital, dampening all firms' incentives to invest and produce. In this case, an adverse MS shock is associated with significantly larger drops in output and measured TFP in both sectors.

Lastly, we conduct counterfactual monetary policy experiments to examine whether: 1) a more hawkish policy response to inflation than that estimated by Chen et al. (2018), or 2) favorable nominal rates for POEs, could mitigate the effects of financing frictions on capital misallocation. We find that while a hawkish monetary policy helps mitigate the negative effects of contractionary MS shocks on aggregate output and productivity, the effects are only modest. On the other hand, the experiment in which POEs enjoy more favorable nominal interest rates than SOEs does not resolve the structural financing constraints faced by POEs. Together, these two experiments suggest that the first-order effect of monetary policy transmission in China continues to operate primarily through the heterogeneous financing-frictions channel.

Related literature This paper is closely related to the large and growing literature that studies the links between economic growth, financial markets, and macroeconomic policies in China [3]. Hsieh and Klenow (2009) study the relationship between growth and misallocation in China and demonstrate that if capital and labor are allocated as efficiently as in the US, China's manufacturing TFP can increase by 30% to 50%. Song et al. (2011) study China's economic growth in a neoclassical growth model with SOEs and POEs differing in productivity and access to capital. Chen et al. (2018) study how China's monetary policy affects the shadow banking system. Whited and Zhao (2021) estimate significant losses in real value-added in China due to the cross-sectional misallocation of financial liabilities with the inefficient allocation in the amount of finance being the first-order effect.

[3]Refer to Song and Xiong (2018)and He and Wei (2022) who conduct in-depth reviews of China's financial system and macro-economy, respectively. An incomplete list of papers in this literature includes Bai et al. (2018) who find that SOEs have cheaper bank loans than POEs, Xiong (2018) who studies the China's economic growth using a tournament model, He et al. (2022) who examine the impact of the government-led staggered EVA reform in the performance evaluation policy for Chinese SOEs, Brunnermeier et al. (2022) study China's unique approach to managing the financial system, where government plays an important role, Chen et al. (2023) show how fiscal and monetary interventions affect credit allocation using the loan-level data, etc.

Although we share with these papers the idea that frictions matter for understanding the relation between financial markets and the real economy in China, our work differs in three important ways. First, we focus on both the within- and cross-sectoral heterogeneity of SOEs and POEs in analyzing the monetary transmission in China, while the existing literature mostly explores the cross-sectoral difference. We show that within-sector heterogeneity in firms' productivity plays a key role in understanding the differential impact of monetary supply shocks for SOEs and POEs. Second, we document novel empirical findings that monetary shocks affect firms' risk premium and corporate policies not only across SOE and POE sectors but also within each sector, which sheds new light on the monetary transmission mechanism. Third, we identify the impact of monetary policy shocks by focusing on the cross-sectional risk premium associated with firms' capital investment, whereas the existing literature primarily emphasizes quantities. Lastly, we quantify the effect of capital misallocation within sectors and show that levelling the play field for POEs can lead to significant aggregate productivity gains.

This paper also contributes to the macro-finance literature that investigates the effect of financial frictions on corporate policies, asset prices, and the aggregate economy. Hennessy and Whited (2007) estimate the magnitude of financing costs using a dynamic heterogeneous firms model that incorporates investment, payout, leverage and default decisions. Gomes and Schmid (2010) investigate the relationship between leverage and stock returns in a model with endogenous investment and financing decisions. Croce et al. (2012) investigate the asset pricing implications of fiscal policies in a general equilibrium model with tax uncertainty and financing frictions. Bolton et al. (2013) examine firms' investment, financing, and cash management decisions in a dynamic q-theoretic framework with stochastic external financing conditions. Kung (2015) explores the links between monetary policy shocks and the term structure of interest rates in a stochastic endogenous growth model. Our analysis is complementary to these studies in that we explore both theoretically and empirically the impact of the MS shock (which generates time-varying debt issuance costs) on risk premiums and corporate financing policies across firms with different types of ownership. Furthermore, the use of firm-level cross-sectional data to construct an empirical proxy of the aggregate MS shock follows the empirical approach in Eisfeldt and Muir (2016) and Belo et al. (2022), who infer the aggregate cost of external finance using firms' cross-sectional investment, financing, and saving decisions in a dynamic model.

This paper is also related to the broad literature that studies the monetary policy transmission mechanism, primarily focusing on the US economy. Bernanke and Gertler (1995), Kashyap and Stein (2000), among others, study the bank lending channel through the role of the banks' balance conditions in transmitting monetary shocks. More recently, Drechsler et al. (2017) explore the deposits channel for monetary policy transmission through the bank's market power in deposit markets. Since banks play a major role in facilitating lending in China, our evidence and mechanism are connected to the bank lending channel of monetary policy transmission. Different from this literature, we focus on the impact of monetary supply shocks on firms' risk premium and corporate policies with distinct state ownership levels in China.

In contrast to the bank lending channel emphasized in Bernanke and Gertler (1995) and others, more recently Ottonello and Winberry (2020) and Cloyne et al. (2023) concentrate on the investment channel as a key channel of monetary policy transmission, demonstrating that firms with varying levels of financing risk and age respond differently to monetary shocks. Similarly, our research focuses on the firm's perspective to analyze the effects of monetary policy shocks. However, there are substantial differences in our paper. Different from Ottonello and Winberry (2020), who investigate the impact of default risk in monetary policy transmission, we delve into the role of heterogeneity in state ownership in transmitting monetary supply shocks. Our findings highlight its significant impact on capital misallocation. Unlike Cloyne et al. (2023), who focus on assessing the impact of collateral value fluctuations induced by monetary policy on the debt and investment choices of younger firms, we emphasize that the primary driver of differential responses to monetary policy shocks in China is access to credit markets, rather than the collateral channel. Similar in spirit to Nakamura and Steinsson (2008) and others who use micro moments of price changes to understand the effect of monetary policy, we study the differential sensitivities of firms' risk premium and real and financial decisions to monetary shocks across SOEs and POEs to understand the monetary policy transmission in China.

An extensive literature studies the relationship between state ownership and efficiency. Atkinson and Stiglitz (1980) and Vernon and Aharoni (2014) suggest that SOEs help address some of the market failures and that the social benefits of SOEs may exceed the costs of inefficiency. Shleifer and Vishny (1994) and Shleifer (1998) show that SOEs are inefficient because the objectives of SOEs are not shareholder-wealth maximizing oriented. Empirically, Dewenter and Malatesta (2001), Alok and Ayyagari (2020), among others, find that SOEs are less efficient than POEs in terms of economic performance. Overall, these papers argue that the costs of inefficiency associated with SOEs outweigh the benefits. Unlike these papers that focus on efficiency, we show that heterogeneity in financial frictions associated with state ownership plays an important role in monetary transmission in China, and is also a key driver of capital misallocation in the economy.

The paper proceeds as follows. Section 2 reviews the evolution and key characteristics of monetary policy in China. Section 3 presents a dynamic model of the firm that we use to understand the empirical evidence. Section 4 solves and estimates the model. Section 5 shows that the model replicates the novel empirical links between MS shocks, asset prices and corporate decisions within and across SOEs and POEs using model data. Section 6 discusses the aggregate implications of MS shocks and provides a detailed analysis of the economic mechanisms driving the results. Section 7 discusses the robustness of the empirical findings and the model results. Finally, Section 8 concludes. A separate appendix with additional results and robustness checks is posted online.

2 Monetary policy in China

This section briefly overviews the evolution of China's monetary policy since the government started the economic reform policy in 1978. We then discuss the objectives, targets, and instruments of monetary policy and the role of the bank lending channel in implementing monetary policies. Lastly, we discuss the relationship between monetary policy and firm's private vs state ownership structure.

2.1 Monetary policy overview

The monetary policy in China has evolved since the start of the economic opening-up and reform in 1978 with two main phases: a period of direct control of money and credit and an indirect control system.[4] Since 1998, to prevent financial risks and maintain financial stability, the People's Bank of China (PBC) abolished the direct control of bank credit and started using M2 growth as the intermediate target, which is often referred to as the new quantity-based approach with indirect control of money and credit supply. The years between 1998 to 2018 also witnessed investment-driven economic growth in which credit and bank loans were used to finance investment in SOEs and POEs. Since 2017, the monetary policy still adheres to the quantity-based approach. However, the PBC has gradually transitioned to a price-based system in which interest rates play an important role.

Since the end of direct credit control in 1998, PBC has used two key intermediate targets to implement the quantity-based monetary policy approach. The first is the M2 growth, and the second is the bank credit. PBC outlines the targets for the M2 growth and the new bank loans at the National Congress each year to support the GDP growth target and price stability. Because M2 growth and bank loan issuance are both intermediate targets to implement the monetary policy, the bank lending channel is also one of the key channels in implementing the monetary policy in China. As is documented in CRZ, M2 growth and bank loan growth comove closely in China from the late 1990s to the late 2010s. The main policy instruments of PBC to implement the monetary policy include required reserve ratio (RRR), central bank lending, rediscounting, open market operations, etc. Change in RRR is among the most well-known instruments. The PBC adjusts the RRR quarterly to meet the M2 growth target. More recently, other policy instruments have been introduced, including short-term liquidity operations (SLO), medium-

[4]Refer to Huang et al. (2019), "Monetary policy framework and transmission mechanisms", chapter 2 of the Handbook of China's Financial System, for a detailed discussion of the transition of the monetary policy in China from 1949, and Chen and Zha (2018), "Macroeconomic effects of China's financial policies", chapter 6 of the Handbook of China's Financial System, for an in-depth discussion of the impact of the monetary, credit and regulatory policies in China.

term lending facilities (MTLF), etc. Since 2018, the PBC has also started to pay close attention to interest rates as a policy instrument, e.g., implementing open market operations. However, because the state-owned banks account for more than half of the total assets and liabilities of the entire banking sector, the role of interest rates in implementing monetary policy in China is still constrained.

2.2 Monetary policy and firm's ownership structure

Since the start of the economic opening-up and reform, SOEs have played an important role in China's economic growth and development. On the one hand, SOEs tend to have lower efficiency than their POE counterparts in productivity, return on capital, etc.; on the other hand, SOEs also take on a variety of non-profit maximizing roles required by the government, e.g., countercyclical employment stabilization, social services provision, etc (Lam et al., 2017).

As is widely documented, China's monetary and credit policies usually favor SOEs. During the SOE-led economic growth period (1978-1998), monetary policy directly allocated credit and bank loans to SOEs, particularly to the SOE-heavy sectors. The monetary policy objective promoted economic growth in SOEs since the SOE sector accounted for a significant fraction of GDP in China's economy. The policy also helped restructure small unprofitable SOEs that suffered losses. The credit from the PBC was also channeled through the local governments which usually order state-owned banks to lend directly to SOEs.

Since implementing the quantity-based framework after 1998, the PBC has focused on M2 growth and credit as the intermediate targets. As a result, PBC's monetary policy stops direct credit allocation to SOEs. However, the bank lending channel is still an important policy mechanism that drives investment-led economic growth during this period. SOEs still enjoy preferential access to credit and bank loans. Banks are more willing to lend to SOEs than POEs because SOEs have implicit government guarantees and support, despite that banks are increasingly able to differentiate between SOEs and POEs in their lending capacity. In addition, SOEs usually have special connections to the central or local government so they can access loans more easily than POEs. Lastly, SOEs can also borrow from the interbank market through their own financing companies. These factors imply that the effective borrowing cost of SOEs differs from POEs because it is easier for SOEs to access debt financing.

3 Model

We develop a dynamic heterogeneous-firm model with real and financial frictions that integrates a monetary block to interpret the cross-sectional evidence and analyze the effects of monetary policy on the economy. The model consists of two interconnected components: a firm (investment) block, which captures heterogeneous firm responses to monetary policy through sector-specific financial frictions, and a monetary block, which incorporates standard New Keynesian features and introduces nominal rigidities into the investment block to characterize the transmission of monetary policy to the real economy.

3.1 Firm block

We allow for two sources of heterogeneity in the firm block: the first is the cross-sectoral differences between SOEs and POEs in the magnitude of the real and financial costs, and the degree of collateralizability of capital; the second is the within sector difference across firms driven by firms' idiosyncratic productivity. To identify and quantify the cross-sectoral differences in real and financial frictions, in the next section we structurally estimate the model for SOEs and POEs using asset pricing and quantity moments.[5]

Firms choose optimal levels of physical capital investment in each period to maximize the market value of equity taken a stochastic discount factor (SDF) to value its cash flows as given. Firms can also issue debt and equity to finance its operations. We do not explicitly model financial intermediation. Instead, we summarize the costs associated with external financing

[5] One additional potential source of heterogeneity across SOEs and POEs that could matter is the interest rate on loans. However, as we discuss in the robustness Section 7 below, empirically we do not find significant differences in the loan rate and the loan rate responses to the monetary supply shocks between SOEs and POEs; in addition, in one of the robustness checks, we add the differential interest channel of SOEs and POEs in the model and find the baseline model result does not change significantly.

with simple functional forms for debt and equity issuances that capture the basic idea that there is a wedge between internal and external funds so that external funds are more costly than internal funds.

We incorporate MS shocks in the model in a simple manner as a time-varying cost of issuing debt. In addition, consistent with the empirical evidence, the MS shocks also affect the SDF that firms use to value their cash-flows. Modeling the MS shocks as a time-varying cost of issuing debt allows us to keep the focus of the analysis on the firms optimal behavior, and is motivated by how the monetary policy transmission mechanism operates in China. As discussed in Section 2, the People Bank of China uses the M2 growth as the intermediate target of monetary policy to support GDP growth and price stability, hence various instruments are used to influence the credit volume in the banking system. As a result, M2 supply growth and bank loans growth are highly correlated, implying that bank lending is the key channel through which the monetary policy affects the economy. Thus, modeling the MS shock a time-varying cost of debt allows us to capture the bank lending channel of the monetary policy transmission mechanism in China in a tractable way.

3.1.1 Technology

There are two types of firms and each type contains a continuum of firms (we interpret the two types of firms as two sectors). We use $\mathcal{O}$ to denote ownership type. The two types of firms differ in the level of real and financial frictions, but they have the same production and capital accumulation technologies. A firm j uses physical capital ($K_{j,t}$) to produce output $Y_{j,t}$. To save on notation, we omit firm index j whenever possible. We specify firm-level level variables in real terms, after adjusting for the price level P_t. The production function is given by

$$Y_t = A_t Z_t K_t, \tag{1}$$

in which A_t is aggregate productivity and Z_t is firm-specific productivity.[6] Aggregate productivity $log(A_t)$ follows an AR(1) process:

$$a_{t+1} = \rho_a a_t + \sigma_a \varepsilon^a_{t+1}, \tag{2}$$

in which $a_{t+1} \equiv log(A_{t+1}), \varepsilon^a_{t+1}$ is an i.i.d standard normal shock and σ_a is the conditional volatility of aggregate productivity. Firm-specific productivity also follows an AR(1) process:

$$z_{t+1} = \bar{z}\left(1 - \rho_z\right) + \rho_z z_t + \sigma_z \varepsilon^z_{t+1}, \tag{3}$$

in which $z_{t+1} \equiv log(Z_{t+1}), \varepsilon^z_{t+1}$ is an i.i.d. standard normal shock that is uncorrelated across all firms in the economy and independent of ε^a_{t+1}. $\bar{z}, \rho_z$ and σ_z are the mean, auto-correlation, and conditional volatility of (log) firm-specific productivity, respectively.

Physical capital accumulation is given by

$$K_{t+1} = (1 - \delta)K_t + I_t, \tag{4}$$

where I_t represents investment and δ_t denotes the capital depreciation rate.

We assume that capital investment entails asymmetric convex adjustment costs denoted as $G_t(\mathcal{O})$:

$$G_t(\mathcal{O}) = \begin{cases} \frac{c^+_k(\mathcal{O})}{2}\left(\frac{I_t}{K_t} - \delta\right)^2 K_t, & I_t \geq \delta K_t \\ \frac{c^-_k(\mathcal{O})}{2}\left(\frac{I_t}{K_t} - \delta\right)^2 K_t, & I_t < \delta K_t \end{cases}, \tag{5}$$

where $c^+_k(\mathcal{O})$ and $c^-_k(\mathcal{O})$ determine the upward and downward adjustment costs. The capital adjustment costs represent costs associated with transforming new investment into productive capital. Such costs include installation costs, transportation costs of machines, or the interruption to ongoing production process. We assume capital adjustment costs to exhibit some degree of asymmetry to capture costly reversibility of capital, that is, downsizing capital stock costs more than expanding it. Note that capital adjustment costs (real frictions) can be different between SOEs and POEs, which captures the fact that SOEs and POEs may face different costs in selling capital in the secondary markets, e.g., informational costs associated

[6] The production function exhibits constant-returns-to-scale, which allows us to reduce the state space in solving and estimating the model. The main quantitative results are robust to using a decreasing returns-to-scale technology.

with lemon problems can be different across SOEs and POEs.

3.1.2 Debt financing and monetary supply shocks

Firms use a mix of debt and equity to finance it operations. At time t, firms optimally choose the amount of borrowing B_t, which must be repaid at $t+1$. The firm's ability to borrow is bounded by the limited enforceability as firms can default on their obligations. Following Jermann and Quadrini (2012), Khan and Thomas (2013), among others, we assume that the only asset available for liquidation is the physical capital K_{t+1}. In particular, we require that the liquidation value of capital is greater than, or equal to, the debt payment. It follows that the collateral constraint is given by:

$$B_{t+1} \leq \varphi(\mathcal{O})K_{t+1}. \tag{6}$$

The parameter $\varphi(\mathcal{O}) \in (0, 1)$, measures the collateralizability of physical capital as well as the borrowing capacity of the firm. Because firms' lending is secured with collateral, the interest rate on the loan coincides with risk-free rate r_f, which is determined by the SDF specified in Section 3.3 below. Note that the collaterilizability is allowed to differ between SOEs and POEs, which captures the fact that SOEs and POEs may face different treatment from banks for valuing of the collateral in pledging for loans.

Firms incur adjustment costs when issuing new debt, denoted as $\Phi_t^B(\mathcal{O})$. The debt adjustment cost depends on a firm's ownership type $\mathcal{O}$, to capture the empirical findings that POEs and SOEs have differential access to debt financing (Maliszewski et al., 2016; Geng and Pan, 2022). The cross-sectoral heterogeneity in debt financing frictions is consistent with several channels documented in the literature: 1) SOEs have implicit government guarrentee and hence banks are more willing to lend to SOEs as opposed to POEs; 2) SOEs have special connections with the government such that they can access loans more easily than POEs, 3) the government credit and monetary policies favor SOEs in certain sectors (Huang et al., 2019). Therefore, even though the risk free rate is the same across the two types of firms, the effective borrowing cost of SOEs is different from POEs.

Specifically, the real debt issuance costs include two components: a linear component ($f_B(\mathcal{O})$) and a quadratic component ($\phi_B(\mathcal{O})$), both of which can vary with the ownership type $\mathcal{O}$. This assumption allows us to capture the differential access of SOEs and POEs to debt financing in a parsimonious way. The debt issuance cost function is given by[7]

$$\Phi_t^B(\mathcal{O}) = \left[f_B(\mathcal{O})\Big(\frac{\Delta B_{t+1}}{B_t}\Big)\mathbf{1}_{\{\Delta B_{t+1}>0\}} + \frac{\phi_B(\mathcal{O})}{2}\Big(\frac{\Delta B_{t+1}}{B_t}\Big)^2\right]\frac{B_t}{1+\pi_t} \times \exp\left(-\eta(\mathcal{O})\xi_t\right), \tag{7}$$

The change in real debt $\frac{\Delta B_{t+1}}{B_t}$ is given by [8]

$$\frac{\Delta B_{t+1}}{B_t} = \frac{B_{t+1}(1+\pi_t) - B_t}{B_t}$$

where inflation rate π_t captures the change in the price level between $t-1$ and t i.e., $1+\pi_t = \frac{P_t}{P_{t-1}}$. The New Keynesian block generates inflation π_t and nominal interest rate $r_{f,t}^{\$}$ as functions of state variables of aggregate productivity and money supply.

ξ_t captures the aggregate time-varying credit market conditions, which follows an AR(1) process,

$$\xi_{t+1} = \rho_\xi \xi_t + \sigma_\xi \varepsilon_{t+1}^{\xi}, \tag{8}$$

in which ρ_ξ and σ_ξ are the first-order autocorrelation coefficient and conditional volatility of ξ_{t+1}. The aggregate shock ε_{t+1}^{ξ} is an i.i.d standard normal shock independent of aggregate and firm-specific productivity shocks. We interpret ε_{t+1}^{ξ} as driven by MS shocks, because, as discussed in Section 2.1 it captures in a simple manner the essence of the monetary policy transmission mechanism in China, that is, the bank lending channel through which the monetary supply shocks directly influence the credit volume that is available to firms through banks. Furthermore, the parameter $\eta(\mathcal{O})$ which determines the sensitivity of the debt issuance costs to the monetary supply shock, are allowed to vary across SOEs and POEs (and hence these parameters will be estimated separately for each sector). This specification is consistent

[7] In the appendix, we show that the asymmetry in debt issuance costs can be micro-founded using a simple model that captures the transmission of quantity-based monetary policy to lenders, when lenders face different levels of financial constraints.

[8] To convert nominal debt $B_{t+1}^{\$}$ as well as nominal debt adjustment cost $\Phi_t^{\$,B}$ into real ones, we have scaled nominal debt by the price level P_t. That is, $B_{t+1} = \frac{B_{t+1}^{\$}}{P_t}$ and $\Phi_t^B = \frac{\Phi_t^{\$,B}}{P_t}$.

with the fact that SOEs and POEs respond to the MS shocks differently in the data.

3.1.3 Equity financing

Firms can also issue equity which is subject to financing costs. We summarize these costs in a reduced form way as in Hennessy and Whited (2007) and Bolton et al. (2011). Specifically, when the sum of investment in capital, investment adjustment cost and change in debt financing exceeds the output, firms can take external sources of equity as a last resource.

Because external financing costs will be paid only if payouts are negative in real terms, we define the real firm's payout before financing cost ($E_t(\mathcal{O})$) as output minus investment in capital and change in debt, less investment adjustment costs and debt issuance costss,

$$E_t(\mathcal{O}) = (1-\tau)Y_t + \tau\delta K_t + \tau r^{\$}_{f,t}\frac{B_t}{1+\pi_t} - I_t - G_t(\mathcal{O}) + B_{t+1} - \left(1 + r^{\$}_{f,t}\right)\frac{B_t}{1+\pi_t} - \Phi^B_t(\mathcal{O}), \quad (9)$$

in which τ is the corporate tax rate, $\tau\delta K_t$ is the depreciation tax shield, $r^{\$}_{f,t}$ is nominal interest rate and $\tau r_{f,t}\frac{B_t}{1+\pi_t}$ is the interest tax shield in real term. The equity financing costs $\Psi_t(\mathcal{O})$ are proportional to the proceeds raised:

$$\Psi_t(\mathcal{O}) = \psi(\mathcal{O})\left|E_t(\mathcal{O})\right|\mathbf{1}_{\{E_t(\mathcal{O})<0\}}, \quad (10)$$

in which parameter $\psi(\mathcal{O})$ determines the per unit cost of issuing equity. The equity issuance costs can also vary with state ownership, which captures the fact that the informational or agency costs may be different between SOEs and POEs when firms do seasoned equity offerings. Firms do not incur costs when paying dividends or repurchasing shares. The effective cash flow $D_t(\mathcal{O})$ distributed to shareholders is given by:

$$D_t(\mathcal{O}) = E_t(\mathcal{O}) - \Psi_t(\mathcal{O}). \quad (11)$$

3.2 Monetary block

We augment the investment model with a parsimonious monetary block that captures the standard transmission mechanism of monetary policy under nominal rigidities. This block endogenizes inflation and the nominal interest rate in response to both monetary and productivity shocks, which subsequently influence firms' decisions through the real interest rate and financing channel as in Gomes et al. (2016) and Corhay and Tong (2025).

The monetary block follows a canonical New Keynesian framework in the spirit of Woodford (2003) and Galí (2015). Its key components are summarized as follows.

Money in the Utility Function. A representative household derives utility from real money balances, with the inverse intertemporal elasticity of substitution and the inverse Frisch elasticity of labor governed by parameters σ and χ, respectively. The subjective discount factor is denoted by β.

Nominal Rigidity. A final-goods sector aggregates differentiated intermediate goods into aggregate output $\mathbf{Y}_t$. Each intermediate-goods producer employs labor and faces aggregate productivity a_t, as specified in (2). These producers possess monopolistic pricing power and are subject to Calvo-style price rigidity, with ϕ denoting the probability of price adjustment. Firms in the investment block are assumed to be atomistic price takers: they take the aggregate price level set by the two sectors as given when making optimal investment and financing decisions, and their individual output has a negligible impact on aggregate production.

Monetary Policy. The monetary authority adjusts the nominal money supply in response to deviations of inflation and output from their steady-state levels, according to policy coefficients ϕ_π and $\phi_{\mathbf{x}}$, as defined in (16).

For brevity, we focus on these three core components, while the remaining equilibrium conditions that complete the monetary block are detailed in Appendix B.6. Log-linearization allows us to express the monetary block as a compact system of equations:

IS Curve. The IS curve links the real interest rate to the output gap and is derived from the household's intertemporal Euler equation:

$$x_t = \mathbb{E}_t x_{t+1} - \frac{1}{\sigma}\left(r^{\$}_{f,t} - \mathbb{E}_t \pi_{t+1} - r^f_t\right), \tag{12}$$

where $x_t \equiv \mathbf{y}_t - \mathbf{y}^f_t$ denotes the output gap. Lowercase $\mathbf{y}_t$ represents the log deviation of aggregate output $\mathbf{Y}_t$ from its steady state in the monetary block. $r^{\$}_{f,t}$ is the nominal interest rate, while $\mathbf{y}^f_t$ and r^f_t denote, respectively, the natural level of output and the natural real interest rate under flexible prices.

New Keynesian Phillips Curve. The Phillips curve relates current inflation to the output gap (or real marginal cost) and expected future inflation:

$$\pi_t = \gamma x_t + \beta \mathbb{E}_t \pi_{t+1}, \tag{13}$$

with

$$\gamma = \frac{(1-\phi)(1-\beta\phi)}{\phi}(\sigma + \chi).$$

A higher Calvo price stickiness parameter ϕ flattens the Phillips curve by reducing the slope γ, making inflation less responsive to the output gap and thus increasing inflation persistence.

Money Demand. Real money balances are derived from money-in-utility preferences and depend negatively on the nominal rate and positively on economic activity:

$$m_t = \sigma \mathbf{y}_t + \frac{r^{\$} - 1}{r^{\$}} r^{\$}_{f,t}, \tag{14}$$

where m_t denotes (log) real money balances and $r^{\$}$ is the steady-state nominal rate.

Real Money Growth. Money growth equals the sum of real money growth and inflation:

$$g_t = m_t - m_{t-1} + \pi_t. \tag{15}$$

Policy Rule for Money Growth. The monetary authority adjusts money growth in response to deviations of inflation and the output gap from their targets, subject to a persistent policy shock:

$$g_t = \phi_\pi \pi_t + \phi_x x_t + \xi_t, \tag{16}$$

where ϕ_π and ϕ_x are policy response coefficients (calibrated following Chen et al. (2018)), and ξ_t follows the process in (8).

Together, equations (12)–(16) and the exogenous processes (2) and (8) define a two-state system in aggregate productivity a_t and the monetary policy shock ξ_t. The monetary block endogenously determines inflation π_t and the nominal interest rate $r^{\$}_t$ as functions of the state variables (a_t, ξ_t), which in turn affect firms' decisions through the real interest rate $r_{f,t}$ and the real debt channel, as in Gomes et al. (2016) and Corhay and Tong (2025). Specifically,

$$\pi_t = \theta^a_\pi a_t + \theta^\xi_\pi \xi_t, \tag{17}$$

$$r^{\$}_t = \theta^a_{r^{\$}} a_t + \theta^\xi_{r^{\$}} \xi_t, \tag{18}$$

where the coefficients $\theta_{\pi}^{a}, \theta_{\pi}^{\xi}, \theta_{r^{\$}}^{a}$, and $\theta_{r^{\$}}^{\xi}$ depend on the structural parameters of the monetary block. Full derivations of the endogenous inflation and nominal rate processes, using the method of undetermined coefficients, are provided in Section B.6 of the Online Appendix.

3.3 Firm's maximization problem and equilibrium risk and return

Firms take the SDF as given and choose investment, debt/equity issuance to maximize the present value of future dividends. For tractability, we directly specify the SDF as a function of the two aggregate shocks:

$$\Lambda_{t,t+1} = \frac{1}{1 + r_{f,t}} \frac{e^{-\gamma_A \Delta A_{t+1} - \gamma_\xi \Delta \xi_{t+1}}}{\mathbb{E}_t \left[e^{-\gamma_A \Delta A_{t+1} - \gamma_\xi \Delta \xi_{t+1}} \right]}, \tag{19}$$

where $r_{f,t}$ is the real interest rate and equals the difference between nominal rate and expected inflation.

$$r_{f,t} = r_{f,t}^{\$} - \mathbb{E}_t \left[\pi_{t+1} \right]$$

The prices of risk (γ_A, γ_ξ) for both types of shocks are positive. A positive price of risk for the MS shock is consistent with the empirical evidence reported here. A positive price of risk for the aggregate productivity shock is consistent with Song et al. (2011) that positive TFP shocks are associated with higher consumption and output growth in China. This specification of the SDF is broadly consistent with the SDF in Equation (23) used in the empirical analysis.

The firm's maximization problem is then:

$$V_t(K_t, B_t, A_t, \xi_t, Z_t; \mathcal{O}) = \max_{I_t, B_{t+1}, K_{t+1}} D_t(\mathcal{O}) + (1 - \kappa_D) \mathbb{E}_t [\Lambda_{t,t+1} V_{t+1}(K_{t+1}, B_{t+1}, A_{t+1}, \xi_{t+1}, Z_{t+1}; \mathcal{O})], \tag{20}$$

subject to capital accumulation equation (Eq. 4), collateral constraint (Eq. 6), the definition of payout (Eq. 9) and the definition of cash flow (Eq. 11). The parameter κ_D is the probability of a firm to receive a death shock. Given that the production technology (Eq. 1) has constant returns to scale in the capital input (a 'AK' technology) we introduce this shock to ensure the stationarity of the endogenous firm distribution through exogenous entry and exit dynamics. In particular, at time t, if a firm is hit by a random death shock, it immediately disappears from the economy and investors lose the stream of cash flow from it. New entrants enter the economy and the number of new entrants is identical to that of exiting firms. New entrants start with median level of firm level state variables and start to produce immediately upon entry.

In the model, risk and return relations are determined endogenously in line with firm's optimal decisions. Our model features a two factor structure, and a firm's exposures to aggregate productivity and MS shocks determine its risk, and hence the expected stock return. In particular,

$$E_t\left[r^e_{t+1}\right] = \gamma_A \times \mathrm{Cov}\left(r^e_{t+1}, \Delta A_{t+1}\right) + \gamma_\xi \times \mathrm{Cov}\left(r^e_{t+1}, \Delta \xi_{t+1}\right), \tag{21}$$

in which r^e_{t+1} is the excess return for stock. The positive price of risk of both shocks implies that assets with returns that have a high positive covariance with the aggregate productivity, and or with the aggregate MS shocks, are considered risky, and hence have high average returns in equilibrium.

4 Model estimation and model implied monetary shocks

This section presents the model solution and estimation results. In addition, we show how to use the model to recover the (unobserved) MS shocks in the real data.

4.1 Structural estimation

To solve the model, we need to specify the full set of parameters, which we denote by the vector θ. The econometric problem consists of estimating this parameter vector θ. Since the model has no analytical closed form solution, we estimate this vector of parameters by the simulated method of moments (SMM), which minimizes a distance criterion between key moments from actual data of SOEs and POEs and simulated data $\Gamma(\theta) = \left[\Psi^A - \Psi^S(\theta)\right]' W \left[\Psi^A - \Psi^A(\theta)\right]$,

$$\hat{\theta} = \underset{\theta \in \Theta}{\arg\min} \; \left[\Psi^A - \Psi^S(\theta)\right]' W \left[\Psi^A - \Psi^S(\theta)\right], \tag{22}$$

where W is a weighting matrix. We solve the model at the quarterly frequency (we describe the solution algorithm and the numerical implementation of the model in detail in Sections B.1 and B.2 of the Online Appendix). To make the selected aggregate moments in the model comparable to those in the data, we aggregate the simulated firm-level data from the model across firms and over time in the same way as in the real data. To search for the parameters over the parameter space, we use an annealing algorithm (see Section B.3 of the Online Appendix). Different initial values of θ are selected to ensure that the solution converges to the global minimum. Since the target moments (discussed below) are in various categories, their standard errors vary significantly. To avoid that certain moments dominate the estimation, we use an identity matrix as the weighting matrix W in the SMM estimation. This approach also allows us to directly focus on economically interesting moments.

In principle, every parameter could be estimated, but in practice the size of the estimated parameter space is limited by computational constraints. We therefore focus the estimation on the main parameters of interest in terms of the economic mechanism in the model —the 6 sector-specific parameters of the real and financial adjustment frictions of SOEs and POEs. This way we let the data quantify the importance of these frictions for the model fit. The remaining 16 parameters, common to both SOEs and POEs, are calibrated based on values in the data and the prior literature.

Pre-determined parameters Table 1 presents the pre-determined parameters that are common to the two sectors. The capital depreciation rate δ is set to 0.023 following the literature that examines the Chinese economy in DSGE models such as Song et al. (2011) and Whited and Zhao (2021). Corporate tax rate τ is set to 0.17. Since we do not observe significant difference between SOEs and POEs in terms of the persistence in investment, we set $c_k^+(\mathcal{O})$ to 0 for both sectors so that the model implied investment rate persistence is close to that of SOEs and POEs.

The persistence ρ_a is set at 0.91 consistent with the data estimate and the conditional volatility of the aggregate productivity shock σ_a is set to be $\sigma_a = 0.035$ to match the volatility of aggregate profits as in the model the aggregate productivity shock is essentially a profitability shock. Matching profit volatility is important to match the aggregate stock market volatility. The persistence of the MS shock ρ_ξ is set the same as the persistence the M2 growth in the data and the volatility σ_ξ is pinned down by matching the volatility of the aggregate debt growth rate, which is around 5% per annum in the data. As for the idiosyncratic productivity process, we set the persistence ρ_z and the conditional volatility σ_z the same as the data moments which are 0.6 and 0.13, respectively. Because of the 'AK' specification, the long-run average level of firm-level productivity, $\bar{z}$ determines the average investment rate in the model. We set $\bar{z}$ at 0.052 and 0.055 for SOEs and POEs respectively so that the implied annual average investment rate is 14.1% and 16.8% for the two sectors.

To calibrate the stochastic discount factor, we set the real risk-free rate to be 2.25% per annum consistent with the data. The price of risks for productivity and MS shocks (γ_A, γ_ξ) are set to be 5.5 and 25, respectively, which imply that the market excess return and Sharpe ratio are 13.40% and 0.36, consistent with the data counterparts of 12.70% and 0.36 in the Chinese equity market.

The monetary block endogenizes inflation and the nominal policy rate, which then feed into firms' decisions in the investment block. As shown in Appendix B.6, the loadings of inflation and the nominal rate on aggregate productivity and MS shocks are functions of the NK block's structural parameters. We calibrate these parameters to estimates for China. The money-growth rule follows Chen et al. (2018), with coefficients $\phi_\pi = -0.397$ and $\phi_x = 0.183$; while Chen et al. (2018) document regime dependence in the output coefficient, our results are robust to alternative values. We set Calvo price stickiness to imply an average price duration of about three quarters, the inverse Frisch elasticity of labor to 2, and relative risk aversion (the inverse intertemporal elasticity) to 1. Steady-state inflation is normalized to zero, so nominal and real rates coincide in steady state. Subjective discount rate β is chosen to match a 2.25% real rate at the steady state. These choices are broadly consistent with studies of NK transmission in China (e.g., Chen et al. (2018)). Under this calibration, Equations (17) and (18) yield intuitive comovements: a contractionary MS shock reduces money growth and inflation ($\theta_\pi^\xi > 0$) and raises the nominal rate ($\theta_{r^\$}^\xi < 0$), a classic liquidity effect arising from nominal rigidities (Galí, 2015).

Estimated parameters We estimate the capital adjustment cost, the collateralizabilty of physical capital, the fixed and quadratic debt issuance costs, the sensitivity parameter of debt issuance cost to the MS shock, and the equity issuance cost parameters for SOEs and POEs, respectively. We define this set as $\Theta(\mathcal{O}) = \left(c_k^-(\mathcal{O}), \varphi(\mathcal{O}), f_B(\mathcal{O}), \phi_B(\mathcal{O}), \psi(\mathcal{O}), \eta(\mathcal{O})\right)$.[9]

Panel A in Table 2, columns 1 and 3, present the targeted moments in the estimation. We select these moments as follows. In general, the variations of the estimated parameter values affect all moments but, to a first order, we find that the cross-sectional investment rate volatility help mainly for identifying the real adjustment cost $c_k^-(\mathcal{O})$; the spikes in debt issuance and the cross-sectional debt issuance volatility help mainly for identifying the fixed and quadratic debt issuance cost parameters $f_B(\mathcal{O})$ and $\phi_B(\mathcal{O})$; the equity issuance fraction mainly helps identifying the equity issuance cost parameter $\psi(\mathcal{O})$; the leverage ratio helps mainly identifying the collateralizibility parameter $\varphi(\mathcal{O})$, and investment-portfolios return spreads help identifying the debt issuance cost sensitivity parameter to the MS shocks $\eta_B(\mathcal{O})$.

4.2 Baseline estimation results

Panel B in Table 2, columns 2 and 4, reports the estimated parameters for the baseline model of SOEs and POEs. The estimation shows that SOEs have lower (marginal) debt financing costs than POEs, consistent with the literature that SOEs have preferential access to bank loans. SOEs also have lower marginal investment adjustment cost and higher collateralizability. Interestingly, SOEs' debt issuance costs have higher sensitivity to MS shocks than POEs.

These estimated adjustment cost parameters reported in Table 2 may appear large, but the implied capital adjustment cost to firm output ratio is 0.62% when we take the average between SOEs and POEs, close to the low end of the estimated adjustment cost reported in Bloom (2009). The estimated debt and equity financing costs are 1.24% and 1.58%, respectively, close to those reported in Altınkılıç and Hansen (2000) for the US estimates.

[9]The average firm-specific productivity $\bar{z}$ is set to make the average investment rate close to the data for both SOEs and POEs.

Panel A in Table 2, columns 1 to 4, shows that the baseline model fits the data well. The model-implied cross-sectional investment volatility is 0.20 and 0.28, respectively for SOEs and POEs, which exactly match the data. The model implied debt issuance spikes and cross-sectional volatility are 0.15 and 0.14 for SOEs, and 0.20 and 0.18 for POEs, close to the data moments. The model implied fraction of firms issuing equity is 0.16 for SOEs and 0.13 POEs, also matching the data moments well. Finally, the model implied investment portfolio spreads are 5.37 and -0.15 for SOEs and POEs, close to the data moments at 5.58 and 0.00.

Taken together, the estimation results show that the model matches the target moments well and with economically reasonable parameter values.

4.3 Model implied monetary supply shock proxy

We construct a model-based MS shock proxy to identify monetary supply shocks in the real data in China, which we label as model-implied MS shock proxy. This step is important because it allows us to characterize the links between MS shocks and firm variables in the data, and to test the model's economic mechanism. Intuitively, the model structure implies that the latent (unobserved to the econometrician) monetary supply shocks can be inferred in the data from a combination of equilibrium firm-level moments. We then map the model implied relationship between these variables in the model, to the real data to construct a time series of model-implied MS shocks.

Specifically, following the literature (e.g., Eisfeldt and Muir (2016)), we look for a set of moments in the model that are most informative about the MS shocks that drive the aggregate debt issuing cost state variable ξ. Variations in the aggregate debt issuance cost will impact the entire distributions of debt issuance and leverage. Therefore, moments that reflect the distributions of new debt issuance and leverage should be particularly informative about ξ. We find that *the first principal component* from the following four moments, the cross-sectional median of firms' leverage ratios, the median in new debt issuance, and the fraction of firms that experience (abnormal) large leverage change and debt growth, capture 85% of the variation of the debt issuance cost state variable ξ. The first two moments capture the average debt financing changes when aggregate debt financing cost varies. The last two moments contain information about the tails of the debt issuance and leverage distributions in our model.

To establish the exact relationship between the aggregate debt issuance cost state (unobserved in the real data) and the four moments in the model, we normalize all four moments to have mean zero and unit standard deviation. We identify the MS shock proxy by extracting the *first principal component* on the four moments mentioned above computed across SOEs because these firms react more to MS shocks in the model (less constrained by financial frictions) which allows for a better identification of the shock. [10].

We then apply the same methodology and extract the first principal component on measures of the four moments in the real data, to construct an empirical time series of the debt issuance cost state. These four variables include median changes in leverage, median debt growth rate, the fraction of firms with abnormal leverage ratio, and the fraction of firms with abnormal debt growth rate. All variables are standardized when extracting the first principal component. A firm's leverage ratio is defined as its total debt to fixed assets ratio at time t. A firm's debt growth equals the change in its total debt from $t-1$ to t, divided by the average of total fixed assets during the same periods. The fraction of (abnormal) large leverage ratios at time t is the proportion of firms with leverage ratios above 2/3 of the firms in the entire firm pooled distribution. The abnormal fraction of debt growth rate at time t is the proportion of firms with absolute value of debt growth rate above 2/3 of the firms in the entire firm pooled distribution. We then take the first difference in the fitted state to extract the empirical proxy for the MS shock ε^{ξ}.

[10]Using POEs to identify the MS shock generates an MS shock that is highly correlated with the one estimated using SOEs.

4.4 Interpretation and validation of model implied monetary supply shock proxy

The model implied MS shock proxy captures the sources of aggregate fluctuations that affect credit available to firms. We interpret the MS shock proxy as a monetary supply shock because, as discussed in Section 2, China has a unique quantity-based monetary system and always use M2 growth as the intermediate target to support growth of gross domestic product (GDP). M2 is the most important monetary policy tool used by the central bank. Money supply affects the lending capacity of Chinese financial institutions, which significantly affects the cost of loans for firms. Given that the monetary policy in China operates through the bank lending channel, the MS shock captures the change in the availability of credit to firms caused by the monetary supply changes. In particular, a negative MS shock proxy captures a contractionary monetary policy shock, that is, there is less money circulating in the system (and the converse is true for a positive MS shock), implying that there is less credit available to (at least some) firms, as it is more costly to access. Therefore, it is natural to expect that some firms are more affected than others depending on their financing needs and ability to get credit.

To validate the interpretation of the model-implied MS shock proxy as a monetary supply shock, we show that the MS shock proxy indeed captures variations in China's monetary supply because it highly correlates with measures of monetary supply in China including M2 growth, monetary supply shock identified in earlier works, and the aggregate financing to the real economy. For example, Chen et al. (2018) develops and estimates an endogenously switching monetary policy rule in the spirit of Taylor (1993). Then they use the M2 growth as the intermediate tool of the People' Bank of China and obtain a time series of monetary supply shocks, which we denote as M2 shock. As reported in Figure 1, the correlation of the estimated model-implied MS shock proxy and the M2 shock estimated by Chen et al. (2018) is quite high, about 83.4%. This shows that our proposed proxy captures significant variation in China's monetary supply shocks, as is evident in Figure 1 which reports the model implied MS shock. Our MS shock also closely follows variation in the M2 growth itself, with a correlation above

63 %.

Aggregate financing to the real economy (AFRE) is another important intermediate targets that the People's Bank of China regulates in order to achieve its monetary policy objectives. AFRE covers a broader set of financing channels that firms can access which includes corporate bonds, equity financing, and loans denominated in foreign currencies, etc. Indeed, our constructed MS shock proxy captures significant variation in the component of AFRE that is related to bank-loans (aggregate financing through RMB loan, entrusted loan and trust loans). The correlation between MS shock proxy and the bank-loan component of AFRE is above 50 %.

Relationship with other macroeconomics shocks. One possible concern with the interpretation that the MS shock proxy in the empirical analysis captures time-variation in the aggregate monetary supply shock, is that this proxy relies on a model that is a simplified version of the real economy, and hence it might be contaminated by other aggregate shocks in the data. For example, the MS shock measure in the real data might be contaminated by time-varying investment opportunities, if investment opportunities vary more in the real data than in the model, or by time-varying credit risk, which is absent from the model. Indeed, in the real economy, it is natural to expect that variation in investment opportunities and cost of debt also drive the cross section of debt issuance and leverage decisions, the variables used to construct the MS shock.

For example, when investment opportunities are good, the demand for capital is high. To address this concern, we report the correlation between the MS shock proxy and other aggregate macroeconomic variables related to time-varying investment opportunities in Table A.3. For example, the correlation of the MS shock proxy with the aggregate TFP shock stands at -8%, the correlation with investor sentiment shocks is 11%, the correlation with the change in earnings-to-price ratio and book-to-market ratio are -13% and -15%, respectively, while the correlation with the change in credit spread is close to zero. This implies that the MS shock proxy is unlikely to be driven by time-varying investment opportunities or credit risk shocks within the aggregate economy.

In the empirical analysis below, we focus on the model-based MS shock proxy because this approach provides a tight link between the model analysis and the data analysis, that is, we can replicate the empirical procedures inside the model. As a result, we can analyze the role of SOEs and POEs in monetary policy transmission in a consistent manner in the data and in the model. In Section A.5 of the Online Appendix, we show that the empirical results using the MS shock proxy and the M2 shock constructed by Chen et al. (2018) are very similar.

5 Main findings

In this section, we investigate the link between MS shocks, asset prices and corporate policies in firms across SOE and POE sectors, both in the real data and in the model. To quantitatively evaluate the model fit, we replicate the empirical analyses using data simulated from the estimated model and the MS shock proxy.

5.1 Data

We describe the data in detail here. China's domestic stock exchanges, known as the A-share market, were founded in 1990 and are based in Shanghai and Shenzhen. In 2014, China's A-share market became the second largest stock exchanges in the world in market capitalization. By 2019, China's A-share market has 3,760 listed companies with the total market value at 59.2 trillion RMB, or 60% of China's GDP. The stock return data we use are from China Stock Market & Accounting Research Database (CSMAR), one of the major financial data providers in China. Our sample period is from July 2004 to June 2019. The sample includes publicly traded firms listed in both Shanghai and Shenzhen stock exchanges. Following the literature, we exclude three types of firms from our sample: i) financial firms; ii) firms that are publicly listed for less than 6 months; and, iii) the so-called "shell" firms.[11]

Following Liao et al. (2014), we classify a firm to be a SOE or POE based on the ultimate

[11]As is shown in Liu et al. (2019), shell companies are attractive merge and acquisition targets for private firms to go public since the IPO process is costly and time-consuming in China. We remove shell companies to avoid the effect of shell values on our empirical analysis.

controlling shareholders, which is disclosed in firms' annual financial report. According to the "Administration of the Takeover of Listed Companies Procedures" issued by the China Securities Regulatory Commission (CSRC), the state is the ultimate controlling party of a firm if: (i) the state is the majority shareholder holding more than 50% of the company's shares; (ii) the state holds and controls over 30% of the voting rights; (iii) the state's voting rights grant it the authority to elect over 50% of the board of directors; (iv) the state can exert significant influence on decisions made in shareholder meetings; and (v) the state falls under other circumstances as determined by the CSRC. Based on the nature of the property rights of ultimate controlling shareholders, firms can be split into SOEs, POEs, foreign-funded, and other firms, with SOEs and POEs accounting for more than 90% of all public firms. Section A.1 of the Online Appendix provides more details of the data construction.

We also keep track of several accounting variables for our analysis. The firm's investment rate is given by $IK_t = \frac{I_t}{0.5(K_{t-1}+K_t)}$, where the physical capital stock K_t is given by net fixed assets, and physical capital investment I_t is defined as the change in gross fixed assets plus the decrease in accumulated depreciation. The firm-level debt flow ΔD_t is the first difference of the change in a firm's total debt, divided by the average capital of the current and previous fiscal years. Firm-level profit measure ΔCF_t is the change in a firm's EBIT, divided by the average capital of the current and previous fiscal years. Table A.5 (columns Data) in the Online Appendix presents selected firm characteristics of SOEs and POEs. Overall, SOEs use more financial leverage, and issue more debt. On the other hand, POEs invest more, and have higher TFP.

5.2 Monetary supply shocks and asset prices

To study the empirical links between monetary supply shocks and asset prices we investigate the relationship between state ownership and expected stock returns. In addition, to characterize within sector heterogeneity, we also investigate the relationship between firms' capital investment and expected stock returns within SOEs and POEs. We focus here on firms' capital investment because of its crucial role in driving economic growth in China during the last few decades, and also because of the well-established link between firms' investment and expected stock returns (i.e. the investment return spread) in the U.S. economy (Titman et al., 2004). Because a firm's capital investment is naturally positively correlated with firms' productivity (which is more difficult to measure), this analysis also allows us to investigate the link between firm-level productivity and expected stock returns within SOEs and POEs.

Stock returns, state ownership, and capital investment. To facilitate the analysis, we present the results here using a portfolio approach. To characterize the average difference in excess returns (in excess of the risk-free rate) across the two sectors, we first form two broad SOE and POE portfolios. In each portfolio, we include all SOEs and POEs, respectively (All), and we then compute the post-formation average excess stock returns of each portfolio. To investigate heterogeneity within each sector, we then form three one-way-sorted investment rate (IK) portfolios (L:low IK, M: medium IK, and H:high IK) separately within SOEs and POEs.[12] In Section A.3 of the Online Appendix, we show that the main results reported here also hold in a regression approach –which allow us to control for the effect of several firm-characteristics known to be correlated with future returns–, and when we form five, instead of three, investment rate portfolios in each sector.

Panel A in Table 3 (columns Data) reports the average excess stock returns (r^e) and Sharpe ratios (SR), of the investment portfolios in the SOE sector (left columns under SOE) and POE sector (right columns under POE), and of the portfolio of all firms in the each sector (column All). The average annual excess returns of the POEs is significantly higher than in POEs, 18.6% and 11.7%, respectively, a difference of 6.9% per annum. Thus, overall, POEs seem to be riskier than SOEs.

Panel A in Table 3 also shows that the average stock return of a long low investment

[12] Specifically, following Fama and French (1992), at the end of June of year t, we sort all firms in a given sector into three portfolios based on the firm's investment rate at the end of year $t-1$. The investment rate breakpoints used to allocate firms into portfolios are the terciles of the investment rate cross-sectional distribution of all firms in the sector. Once the portfolios are formed, their value-weighted returns (using time-varying net fixed asset (PPENT) as weight) are tracked from July of year t to June of year $t+1$. The procedure is repeated at the end of June of year $t+1$.

rate–short high investment rate firms portfolio (L-H), which we refer to the investment-return spread, is positive and sizable in the SOE sector at 5.6% per annum, and this value is more than 2 standard errors from zero. Thus, in the SOE sector, the relationship between firms' current investment rate and future stock returns is negative, consistent with the investment return spread documented in the U.S. economy. Across POEs, however, the investment return spread is only 0.5% per annum, and this value is less than 0.2 standard errors from zero. The difference (in absolute terms) of the investment return spread in the SOE and POE sectors is economically large, about 5.1% per annum. The Sharpe ratio of the investment spread portfolio is also significantly higher in the SOE sector than in the POE sector, 0.45 vs 0.04 respectively. Thus, although POEs seem to be riskier than SOEs, there is no investment-return spread in the POE sector.

MS shocks and firm's risk. To investigate the impact of MS shocks on firm's risk across SOEs and POEs, we consider a two-factor asset pricing model with the aggregate stock market (MKT) excess return (the market factor in the standard capital asset pricing model, CAPM, which captures broad market conditions), and the MS shock proxy as the two factors. We then investigate the price of risk of MS shocks, and the firms' return exposure (covariance) with this shock.

Specifically, we specify the following stochastic discount factor (SDF):

$$M_t = 1 - b_{MKT} \times \mathrm{MKT}_t - b_{MS} \times \mathrm{MS}_t, \tag{23}$$

which states that investors' marginal utility is potentially driven by market and MS aggregate shocks. We then estimate the price of risk of these shocks ((b_{MKT} and b_{MS}) by the generalized method of moments (GMM) using the standard asset pricing moment condition $E\left[r^e_{it} M_t\right] = 0$, in which r^e_{it} is the excess return of test asset i, in year t. To help in the interpretation of the results, we can write this moment condition as:

$$E\left[r^e_{it}\right] = \alpha_i + b_{MKT}\mathrm{Cov}(\mathrm{MKT}_t, r^e_{it}) + b_{MS}\mathrm{Cov}(\mathrm{MS}_t, r^e_{it}), \tag{24}$$

where we added the term α_i (alpha), the pricing error associated with asset i. For comparison, we also estimate the one-factor CAPM (which corresponds to the restricted case in which

$b_{MS} = 0$ in Equation (24)), to establish the marginal importance of the MS shock for capturing systematic risk in the economy.

Table 4 reports the GMM estimates of the prices of risk, and the implied mean absolute pricing errors (MAE) across portfolios, obtained from the estimation of the asset pricing model in Equation (24).[13] The table shows that the estimated price of risk of the MS shock is positive, and this value is more than 1.9 standard errors from zero. In addition, Table 4 shows that the two-factor model performs better than the CAPM in explaining the returns of these portfolios (MAE of the two-factor model is 2.5% per annum versus 3.1% in the CAPM).

The previous results show that the MS shock is correlated with systematic risk in the economy, and has a positive price of risk. That is, periods with negative MS shocks (monetary contractions) tend to occur at times when investor's marginal utility is high, that is, are bad economic times.

According to Equation (24), the effect of the positive price of risk of MS shocks on the firm's level of risk (expected stock return) depends on a firm's return covariance (exposure) with the MS factor. The positive price of risk of MS shocks implies that firms with a negative return covariance with the MS factor have lower risk because these firms provide a hedge against negative MS shocks (this hedge is stronger the more negative this covariance is). Similarly, firms with a positive return covariance with the MS factor have higher risk because these firms tend to underperform during bad economic times, that is, periods of negative MS shocks. Thus, understanding the return covariances with the MS factor is potentially useful to understand the differences in the overall risk of SOEs and POEs, as well as different investment-return relationship in the two sectors.

Panel C in Table 3 reports the (multivariate) covariances of each portfolio return with the MS factor, and the market factor. In the SOE sector, the covariance of the portfolio returns with the MS factor is overall negative, and *decreasing* across the investment portfolios. The more

[13] As test assets, we consider the benchmark 3 SOE-investment rate, and 3 POE-investment rate portfolios. To enhance the precision in the measurement of the price of risk of the MS shock (especially given the relatively small number of test assets in the benchmark portfolios), we also consider a larger set of test assets in the real data by including 5 SOE-size, and 5 SOE-book-to-market(BM) portfolios.

negative MS covariance makes the high investment (high productivity) SOEs better hedges against MS shocks, which explains the strong negative relationship between investment and average returns (that is, a large investment return spread) in the SOE sector (the exposure to the market factor is essentially flat across these portfolios).

The pattern of MS return covariances is significantly different in the POE sector. As reported in panel C of Table 3, the exposure of POEs to the MS shock is overall positive, and *increasing* across the investment portfolios. At the same time, the low investment firms are somewhat more sensitive to the market risk factor. These two forces together lead to similar returns for high and low investment POEs in the data, and hence to an insignificant investment-return spread in the POE sector.

The overall exposures to the MS factor in the two sectors (negative across SOEs and positive across POEs) also helps understand the higher average returns in the POE sector relative to the SOE sector. Essentially, SOEs, as a whole, provide an hedge against MS shocks, while POEs do not.

The differential MS shock covariances within and across SOEs and POEs also has implications for the asset pricing errors. Panel B in Table 3 shows that the CAPM alpha of the investment spread portfolio (L-H) is 5.3% per annum in the SOE sector, and this pricing error nearly drops to zero in the two-factor model (Panel C) when the MS shock is included ($\alpha^{2F} = 2.5\%$ which is only 0.7 standard errors from zero).

Model implied result Panel A in Table 3 (columns Model) show that the baseline model replicates the negative relationship between investment and excess return in the SOE sector, as well as the insignificant investment-return patterns in the POE sector. In the SOE sector, the investment return spread is 5.4% per annum in the model versus 5.6% in the data. In the POE sector, similar to the data, the investment return spread is statistically indistinguishable from 0. More interestingly, the model is also able to capture the overall level of average returns in each sector, and the difference across the two sectors with SOEs of 11% in the model versus 11.7% in the data, and POEs of 18.5% in the model versus 18.6% in the data.

The model replicates the large dispersion in the covariance of stock returns with the MS shocks across high and low investment firms within the SOEs, and the overall negative exposure to MS shocks of the firms in the SOE sector. Panel C in Table 3 (columns Model) shows that this covariance is decreasing in investment with high investment-SOE firms' covariance being significantly negative, as in the data and that the difference between MS covariances for high-low investment firms is sizable which indicate that the negative investment return relation in the SOE sector is mainly driven by exposure to the MS shocks. Consistent with the data, the model also matches the relationship between POEs and firm's stock return sensitivity to MS shocks. Panel C in Table 3 shows high investment firms are somewhat more exposed to MS shocks and less exposed to the market factor in the POE sector, but these differences are small, hence the investment return spread in the POE sector is very small in the model, as in the data.

For completeness, Table 4 compares the pricing of MS shock in the model and in the data. Our model captures the empirical fact that a two risk factor structure with both the market and MS shock prices the cross-section of equity returns reasonably well while the CAPM fails with a large mean absolute error and a low regression R^2.

5.3 Monetary supply shocks and corporate policies

We also investigate the responses of firms' corporate decisions to MS shocks within SOEs and POEs. Specifically, we study the responses of firms' investment, debt issuance, and profits to monetary supply shocks in the data by estimating the following panel OLS regression:

$$\Pi_{i,t+h} = a + b \times \Pi_{i,t-1} + c \times MS_t + \sum_{j=2}^{3} (d_j \times Pj_t + e_j \times Pj_t \times MS_t) + \epsilon_{i,t}, \tag{25}$$

where $h = 0, 1$, and $\Pi_{i,t+h}$ is the change in the dependent variable (debt-flow, investment, profits) of listed firm i at time $t + h$. MS_t is the MS shock. Pj_t is the investment portfolios for $j = 2, 3$ quintile dummy, respectively.

The relevant regression coefficients for our analysis are the slope coefficients c and e_j. In particular, the coefficient e_j measures the differential exposure of the firms in the investment-rate portfolio $j = 2$ *or* 3 relative to the exposure of the firms in the low ($j = 1$) investment-rate portfolio. When $h = 0$, the previous coefficients give the contemporaneous responses of the dependent variable to the MS shock, and when $h = 1$, the previous coefficients give the one year ahead responses. We estimate the equation separately for SOEs and POEs. To save space, for the response of the debt and investment variables, we focus our discussion here on the contemporaneous responses only because these variables can change immediately in response to shock. For the profit measure we look at both the contemporaneous and the one-year ahead responses because it might take some time for some variables affected by the shock (such as investment) to affect profits. The results are robust after adding commonly-used control variables. In Figures A.2 to A.3 of the Online Appendix, we also show that the responses are similar when use the Jordà (2005)-style local projection method instead of panel OLS regressions.

Debt issuance. Table 5 reports the estimates of the relevant slope coefficients of Equation (25) for the change in debt issuance. We see that the contemporaneous debt issuance's response to the MS shock decreases in investment portfolios, with the high investment SOEs responding negatively (countercyclical) to the MS shock, while low investment SOEs responding positively to the MS shock. Specifically, the coefficient c is 0.59 while the coefficient e_3 is -0.80, and these coefficient are statistically significant. This implies that the high investment (high productivity) SOEs can still increase debt issuance despite a negative MS shock (which are bad economic times). However, for POEs, the coefficient c is 0.34 and the coefficient e_3 is 0.33, and these estimates are statistically insignificant. Thus, the high and low investment POEs have similar debt issuance responses upon the impact of a change in aggregate credit market conditions.

Investment. Similar to the response of debt issuance, Table 5 shows that the contemporaneous response of the change in investment to the MS shock decreases in the investment portfolios, with the high investment SOEs responding negatively to the MS shock while low investment SOEs responding positively. The corresponding coefficient c is 0.60 while the coefficient e_3 is -1.19, and they are statistically significant. This implies that high investment (high productivity) SOEs can still increase their investment rate despite a negative MS shock (bad economic times). For POEs, the response across high and low investment firms' is not monotonic and the relevant coefficients are all statistically insignificant.

Profits Table 5 shows that one-year ahead change in profits (EBIT) of low investment SOEs respond to the MS shock positively while high investment SOEs respond negatively (coefficient c is 0.06 while the coefficient e_3 is -0.17, respectively for time $t+1$ response). This implies that the high investment (high productivity) SOEs produce more cash flows going forward despite a current negative MS shock. However, the profit change of POEs respond to the MS shock uniformly because the relevant e_2 and e_3 slopes are statistically insignificant.

Taken together, the empirical results show that MS shocks have a strong effect on firm's asset prices (risk and expected returns) and corporate policies, and these effects vary within and across SOEs and POEs in a systematic manner.

Model implied result We also replicate the panel regressions of the responses of firm's corporate policies to the MS shock in the simulated data. Table 5 (columns Model) show that, consistent with the data, high investment (more productive) SOEs increase current investment, debt issuance, and one year ahead profits in response to an adverse MS shock (which is associated with an increase in debt issuance costs and is the high marginal utility state for investors). Across POEs, the responses do not vary much across the portfolios, which is also consistent with the data.

6 Monetary policy transmission

We use the model as a laboratory to understand the monetary policy transmission mechanism in China. In particular, we first examine the impulse response functions of key variables in the model to a negative MS shock (credit contraction), then we investigate the impact of MS shocks on aggregate variables, such as aggregate and sectoral output and productivity, and perform counter-factual analysis to evaluate how these effects depend on key features of the model.

6.1 Impulse responses to MS shocks

To understand how firms adjust to monetary supply (MS) shocks in the model, Figure 2 reports the impulse responses of debt issuance, investment, profits, and continuation values to a negative MS shock (i.e., a credit contraction) for SOEs and POEs, respectively. For each sector, we display responses relative to a benchmark firm, a firm that receives the same adverse MS shock and is endowed with median productivity. To introduce cross-firm heterogeneity within each sector, we compare two additional firms whose productivity levels are set one standard deviation above and below the median, labelled "high-productivity" and "low-productivity" firms. These productivity differences map naturally into differences in corporate policies including investment and debt issuance etc.

For SOEs, the responses exhibit strong countercyclicality for high-productivity firms and significant procyclicality for low-productivity firms. Following a negative MS shock, high-productivity SOEs increase investment, financing the associated investment costs through sizable debt issuance. Their profits and continuation values rise above peer levels despite the tightening shock, implying that their equity provides a good hedge against MS shocks (i.e., their return covariance with MS shocks is negative). By contrast, low-productivity SOEs reduce investment, cut back on debt issuance, and experience declines in profits and firm values, making them poor hedges and therefore riskier.

A key distinction between SOEs and POEs lies in the magnitudes of these countercyclical corporate policies. Although high-productivity POEs also display countercyclical investment dynamics, the responses are substantially weakened compared with SOEs. High-productivity POEs raise investment only modestly because their debt issuance responds almost acyclically, generating much weaker movements in profits and continuation value. Consequently, they provide only limited hedging value against MS shocks. Low-productivity POEs, in turn, show less pronounced procyclical behavior such as reducing investment, scaling back debt issuance, and suffering declines in profits and continuation values after the tightening shock.

These model-implied patterns are consistent with the empirical findings in Section 2: high-productivity SOEs exhibit strongly countercyclical debt issuance and investment following negative MS shocks, whereas high-productivity POEs display much weaker countercyclicality. When we implement the same panel-regression specifications used in the data (see Table 5), the model successfully replicates this differential sensitivity across ownership types.

6.2 Aggregate implications of MS shocks

We evaluate how MS shocks affect aggregate and sectoral output and measured total factor productivity (TFP). Aggregate output equals the sum of firm outputs; sectoral output sums outputs over firms within a sector. Measured TFP at the aggregate or sectoral level is computed as Y/K, where Y denotes output (aggregate or sectoral) and K denotes the corresponding capital stock (sum of firm capital). Given the model's constant-returns-to-scale technology, Y/K is a natural measure of TFP at either level. Following Khan and Thomas (2014), we examine measured TFP in addition to output because it is informative about capital misallocation within a sector. Intuitively, real and financial frictions prevent some high productivity firms from reaching their frictionless optimal capital, causing capital shares to be misaligned with productivity. This misallocation depresses endogenous measured TFP.

Figure 3 plots the responses of aggregate and sectoral measured TFP and output to a negative MS shock (one standard deviation drop, that is, a credit contraction). The figure shows that an adverse MS shock generates a large and persistent drop in measured TFP and output in both sectors, with the negative impact lasting for more than 8 quarters. But the size of the impact varies across sectors. The drop in TFP and output in the POE sector are significantly larger than in the SOE sector. In particular, the initial drops in TFP and output in the SOE sector are -2.9% and -3.6%, respectively, while the initial drops in productivity and output in the POE sector are -6.5% and -5.7%, respectively.

Turning to aggregate effects of the MS shocks, Figure 3 shows that measured TFP and aggregate output decrease by -5.1% and -4.9%, respectively, after a negative MS shock.[14]

[14] To compute the aggregate output and productivity of the economy, we follow the 2018 press conference by China's National Development and Reform Commission which reports the shares of POEs and SOEs in China's GDP to be 60% and 40%, respectively .

6.3 Tests of capital misallocation and MS Shocks

This section tests the model predictions on capital misallocation and monetary supply shocks across SOE and POE sectors in the data. We first investigate the relationship between industry-level TFP growth and MS shocks and then the relationship between the dispersion between MPK with SOE and POE sectors and MS shocks.

Specifically, we compute the mean change in aggregate TFP growth at the industry level within each sector and year, using net property, plant, and equipment (PPENT) as weights. We then regress the change in TFP growth on the negative of the M2 shock (so that higher values correspond to contractionary monetary policy shocks) constructed by CRZ, focusing on the interaction between the POE dummy and the M2 shock.

Columns (1)–(3) of panel A in Table 6 show that a contractionary M2 shock is associated with a significant decline in the change in TFP growth for the POE sector, but not for the SOE sector. More importantly, the interaction coefficient between the POE dummy and the negative M2 shock is significantly negative, indicating that a contractionary monetary policy shock leads to a larger reduction in the change in TFP growth in the POE sector, consistent with our model's prediction. Furthermore, when we include additional control variables and re-estimate the panel regression, the results (reported in Columns (4)–(6) of panel A) remain virtually unchanged, confirming the robustness of our findings.

In addition to the industry-level analysis using TFP growth, we also examine how monetary supply shocks affect sectoral misallocation in SOEs and POEs by analyzing the dispersion in marginal revenue products of capital (MRPK). Following Hsieh and Klenow (2009), we measure sectoral capital misallocation using the dispersion in the MRPK across firms within each sector. Specifically, MRPK is defined as the ratio of firms' revenue to their net property, plant, and equipment (PPENT). To compute the dispersion of MRPK within SOEs and POEs, we first demean each firm's MRPK by its corresponding industry mean to remove industry fixed effects. We then calculate the standard deviation of MRPK within each sector and year. Finally, we regress the dispersion of MRPK on the negative of the M2 shock constructed by CRZ, focusing on the interaction between the POE dummy and the M2 shock. We also replicate this analysis at the industry level to confirm robustness.

Columns (1)–(3) of panel B in Table 6 show that a contractionary M2 shock is associated with an increase in the dispersion of MRPK for both SOE and POE sectors. More importantly, the interaction coefficient between the POE dummy and the negative M2 shock is significantly positive, indicating that a contractionary monetary policy shock leads to a more pronounced increase in capital misallocation in the POE sector, consistent with the model's prediction. Furthermore, when we repeat the panel regression using industry-level data, the results (reported in Columns (4)–(6) of Table 1) remain unchanged, confirming the robustness of our findings.

6.4 Inspecting the mechanism

To understand the model mechanism in generating the aggregate effects of MS shocks, we investigate three key channels in the model: i) cross-sectoral heterogeneity in financial and real frictions; ii) monetary policy stance in fighting inflation; iii) the price of risk of MS shocks; and iv) within-sector heterogeneity in productivity.

6.4.1 The role of cross-sectoral heterogeneity

The estimation results show that SOEs and POEs differ in the levels of both real and financial frictions. To understand the economic implications of these differences, we conduct several counterfactual analyses in which we give POEs the same levels of real and financial frictions as SOEs, one at a time, i.e., we level the playing field.

Figure 3 reports the impulse responses of sectoral measured TFP and output to a one-standard-deviation negative MS shock.[15] The figure shows that when POEs have the same (lower than in the baseline) capital adjustment costs $c_k(\mathcal{O})$ as SOEs, the drop in sectoral measured TFP and output for POEs is only slightly lower than in the baseline model; when

[15]For completeness, we report the target moments and the investment portfolio spreads of these counterfactual analyses in Table A.15 of the Online Appendix.

POEs have the same (higher than in the baseline) debt collateralizability $\phi(\mathcal{O})$ or the same (lower than in the baseline) equity issuance costs $\varphi(\mathcal{O})$ as SOEs, the responses of sectoral measured TFP and output remain largely unchanged relative to the baseline. However, when we level the playing field (lower than in the baseline) in debt issuance costs $(f_B(\mathcal{O}), \phi_B(\mathcal{O}), \eta(\mathcal{O}))$, the drop in POEs' measured TFP and output is significantly smaller than in the baseline case, and is almost the same as the drop observed in the SOEs. This is an important result. It implies that the heterogeneity in debt market frictions between SOEs and POEs is the key driver of the difference in output and measured TFP responses to MS shocks between the two sectors.

Intuitively, the adverse impact of negative MS shocks on output is larger in the POE sector because debt market frictions naturally lead to capital misallocation, as captured by the drop in sectoral measured TFP. This misallocation arises because debt market frictions prevent firms from reaching the frictionless capital level. A negative MS shock in the model increases misallocation of capital as a growing fraction of firms find it increasingly difficult to finance investment to reach their optimal frictionless target. Because POEs face tougher debt market conditions, this capital misallocation is more severe in POEs.

This result has potential policy implications. It implies that leveling the playing field for SOEs and POEs in the debt markets can lead to large economic gains. Figure 3 shows that giving POEs the same access to debt markets significantly improves aggregate measured TFP by 1.8 percentage points, and increases aggregate output by 1 percentage point.

6.4.2 The role of monetary policy stance

Incorporating the monetary block enriches the model, enabling us to analyze conventional monetary transmission mechanisms and the differential impact of monetary policy on SOEs and POEs arising from heterogeneous financing frictions. We consider two policy experiments. First, we assess whether alternative policy stances can mitigate the effects of financing frictions. Second, we examine the impact of a policy reducing the nominal interest rate specifically for POEs.

In the first experiment, we implement a more hawkish policy scenario than that estimated by Chen et al. (2018). We model the central bank as responding more aggressively to inflation by doubling the policy response coefficient from Chen et al. (2018) and doubling the sticky price parameter to make the transmission mechanism more pronounced. The results are reported in the upper-left panel of Figure 4. We find that a hawkish central bank that is more committed to fighting inflation mitigates capital misallocation only marginally. The initial drop in measured TFP for SOEs is slightly smaller (-2.6%) than in the baseline (-2.9%), while the initial drop in measured TFP for POEs is also slightly smaller (-6.3%) than in the baseline (-6.5%). As pointed out by Gomes et al. (2016) and Corhay and Tong (2025), inflation (deflation) reduces (amplifies) firms' real debt burdens through the sticky leverage channel. Thus, a hawkish monetary policy that responds quickly to inflation helps to stabilize firms' real debt burdens and mitigates capital misallocation, but the quantitative effect is modest.

In the second experiment, we hold inflation identical to the benchmark but reduce the nominal interest rate for POEs by 100 basis points. The results are reported in the upper-right panel of Figure 4. Surprisingly, the results show that reducing the nominal interest rate for POEs modestly exacerbates capital misallocation compared to the baseline. The initial drop in measured TFP worsens, declining further to -6.8% from -6.5% in the baseline. A lower nominal interest rate incentivizes POEs to borrow more, which increases their leverage and amplifies financial frictions when a negative MS shock hits the economy. As a result, capital misallocation worsens slightly.

In principle, both the sticky leverage channel and the nominal rate channel could influence the differential impact of monetary policy shocks on SOEs and POEs. After estimating the nominal model separately for the two sectors, however, we find that these two channels have only modest quantitative effects in explaining the differences in asset-price and quantity outcomes across SOEs and POEs. The first-order effect of monetary policy transmission in China continues to operate primarily through the heterogeneous financing-frictions channel, and the model's main quantitative results on asset prices, corporate quantities, and misallocation remain robust. It is worth noting that our policy experiments are illustrative, and a comprehensive analysis of optimal policy design requires a General Equilibrium framework in which firms' real decisions feed back into nominal variables and policy considerations. We leave this for future research.

6.4.3 The role of the price of risk of MS shocks

To understand the role of the price of risk of the MS shock for the model results, we increase γ_ε from the baseline value of 25 to 35, which implies that investors are more risk averse to monetary contractions. The results are reported in the lower-left panel of Figure 4.

Figure 4 reports the impulse responses of sectoral measured TFP and output to a negative MS shock. We observe larger drops in output and measured TFP for both sectors. Moreover, we also see significant increases in the investment-return spreads and the sector-average returns for both SOEs and POEs in Table A.15 of the Online Appendix. Two competing effects drive these exacerbated responses. First, a higher price of risk of MS shocks increases the average risk premium, leading to higher discount rates and dampening firms' incentives to invest. Second, the cross-sectional return difference between high- and low-productivity SOEs is larger when the price of risk of MS shocks is higher, which implies that more capital flows to high-investment SOEs and mitigates the first effect by improving capital-allocation efficiency. Overall, the effect of a higher average risk premium dominates, and we see larger declines in output and TFP. Thus, the effect of MS shocks on the economy depends on the price of risk of MS shocks.

6.4.4 The role of within-sector heterogeneity in productivity

The model estimation also hinges on the within-sector investment-return spread, which depends on within-sector heterogeneity in productivity. To understand the role of this heterogeneity, we lower the volatility of idiosyncratic productivity Z in both sectors from 0.23 to 0.023. The results are displayed in the lower-right panel of Figure 4.

Figure 4 reports the impulse responses of sectoral output and measured TFP to a negative MS shock. The figure shows that the losses of sectoral output and TFP are significantly smaller in both sectors than in the baseline. More importantly, the difference in the output and measured TFP responses between SOEs and POEs is also much smaller than in the baseline calibration. In addition, Table A.15 in the Online Appendix shows that both the investment-return spreads and the sector-average returns drop substantially in both SOEs and POEs. This result is intuitive. Lower dispersion of idiosyncratic productivity within SOEs and POEs leads to smaller dispersion in expected returns (risk premia) and cash flow, and hence to less capital misallocation. In turn, this leads to smaller output losses and a smaller difference in the output and measured TFP responses of SOEs and POEs after a contractionary MS shock.

7 Robustness checks

To check the robustness of our main findings, we conducted a series of robustness checks (in addition to the robustness checks already discussed in the previous sections). To save space, we report the full set of results in the online appendix, and we briefly summarize the main conclusions from these analyses here.

When we use the China's monetary supply shock (M2 shock) constructed by Chen et al. (2018), the empirical results are very similar to those reported using the model-implied MS shock. This result is not surprising given that the two variables are, as noted, highly correlated. We also investigate the role of two potential alternative explanations for the differential exposures of high- and low-investment SOEs and POEs to MS shocks.

The first channel is the interest rate channel, in which the different exposures of high- and low-investment SOEs and POEs to MS shocks arise due to different interest rate responses of these firms to the shocks. To test this channel, we collect firm-level interest rate data, and compute the interest rate as the firm's loan interest rate minus the benchmark interest rate of the banks.[16] We find that most of the responses of SOEs and POEs' interest rates to MS shocks are insignificant, and do not vary systematically across high- and low-investment SOE firms. This result is perhaps also not surprising because, as noted in Section 2, the monetary

[16]The sample size for this analysis is significantly smaller: only 4.6% of the firms in our data report the interest rates on their loans. However, the key firmlevel characteristics including investment rate, debt growth, profitability, etc., are similar to those of the full sample.

policy in China uses the M2 growth as the intermediate target, and interest rates do not play an important role in implementing monetary policies.

The second channel is the shadow banking channel. As is documented in the literature (e.g., Chen et al. (2018)), shadow banking activities started to increase significantly since 2009 in China as the monetary growth slows down. Thus, a possible channel for our findings is that POEs are constrained in borrowing bank loans but are still able to access loans from shadow banks. In turn, this could explain why the responses of high- and low-investment POEs to MS shocks do not differ. To test this hypothesis, we construct an aggregate shock to the aggregate shadow bank loan growth rate[17] and redo the empirical analyses. We find that this shock is not priced in asset pricing tests. In addition, the responses of investment, debt issuance and profit growth to the shadow banking growth shocks do not exhibit any systematic difference across high and low-investment POE firms, and most of these response are statistically insignificant. Interestingly, SOEs' responses are largely insignificant as well. These results imply that shadow banking activities do not drive our main findings.

The details of these robustness analyses are reported in Sections A.5 to A.8 in the Online Appendix.

8 Conclusion

This paper investigates how firm heterogeneity in state ownership and productivity affects the monetary policy transmission in China. Empirically we document that firms' risk premium and the impact of MS shocks on firms' risk premium and real and financial decisions vary both within and across SOEs and POEs. In the SOE sector, high investment (high productivity) firms are associated with lower expected stock returns, whereas there is no significant relationship between investment and expected stock returns in POE firms. Furthermore, there is a large difference in the cycality of firms' responses to the MS shock within SOEs. In the SOE sector, high investment firms increase the new debt issuance despite contractionary monetary supply.

[17] The shock is estimated by taking the first difference of the real aggregate shadow bank loan growth rate.

This in turn implies that high investment firms are more able to use debt to finance investment and raise profitability in bad times, and hence are less exposed to negative monetary supply shocks than low investment firms. However, in the POE sector neither high investment firms nor low investment firms are able to raise new debt when the monetary supply shrinks, and hence they do not significantly respond to monetary supply shocks. As a result, high and low investment firms in the POE sector are not differentially exposed to the MS shock.

We develop a dynamic heterogeneous-firm model with two interconnected blocks: a firm block and a monetary policy block. The monetary block builds on a canonical New Keynesian framework with nominal rigidities. The firm block has two features: First the SOE and POE sectors differ in real and financial frictions and firms differ in idiosyncratic productivity within the sector. Second, the cost of debt issuance is stochastic and varies with an aggregate shock that captures the impact of MS shocks on debt supply for firms in China. We quantify the capital misallocation effect due to the preferential access to debt markets by SOEs and show that it leads to sizable losses in aggregate productivity and output. If we level up the play field for POEs with the same debt market access as SOEs, aggregate productivity and output would increase by 1 to 2 percentage points.

The results reported here have implications for asset pricing, corporate finance, and macroeconomics literature. Going forward, incorporating an explicit modeling of state ownership and MS shocks that affect the cost of debt financing in current dynamic stochastic general equilibrium (DSGE) models may be important for an accurate understanding of aggregate quantity dynamics, time-varying risk premiums, and financial flows over the business cycle for countries with heterogeneous state ownership structure across firms. Finally, in our analysis, we treat the aggregate monetary supply shock as exogenous, as a first step towards understanding the joint behavior of financing frictions, asset prices, and financial flows in the cross-section. To help us better understand the links between the financial sector and the real economy, future research should endogenize the source of the monetary supply shock in a DSGE model.

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Table 1: Calibration–Pre-determined parameters

parameter	Symbol	Value
Technology		
Corporate tax rate	τ	0.17
Capital depreciation rate	δ	0.023
Fix operating Cost	F	0.0007
Upward capital adjustment cost	$c_k^+(\mathcal{O})$	0
Stochastic processes		
Conditional volatility of aggregate productivity	σ_a	0.035
Persistence of aggregate productivity	ρ_a	0.91
Mean of firm-specific productivity: SOE	μ_z	0.052
Mean of firm-specific productivity: POE	μ_z	0.055
Persistence of firm-specific productivity	ρ_z	0.6
Conditional volatility of firm-specific productivity for SOE	σ_z	0.13
Persistence coefficient of debt issuance cost	ρ_ξ	0.95
Conditional volatility of debt issuance cost	σ_ξ	0.055
Price of risk: aggregate productivity shock	γ_a	5.5
Price of risk: aggregate MS shock	γ_ξ	25
Monetary block		
Subjective discount factor	β	0.978
Inverse intertemporal elasticity of substitution	σ	1
Inverse Frisch elasticity of labor	χ	2
Calvo price stickiness	ϕ	0.67
Policy response to inflation	ϕ_π	-0.397
Policy response to output gap	ϕ_x	0.183

This table presents the pre-determined parameter values of the baseline model

Table 2: Structural estimation: target moments and parameter estimates

		SOE		POE	
		Data	Model	Data	Model
		(1)	(2)	(3)	(4)
		Panel A: Target moments			
Cross-sectional investment volatility		0.20	0.20	0.28	0.28
Spikes in debt issuance		0.15	0.16	0.20	0.19
Cross-sectional debt issuance volatility		0.14	0.14	0.18	0.13
Equity issuance fraction		0.16	0.14	0.13	0.14
Leverage ratio		0.53	0.54	0.45	0.44
Investment return spread (in %)		5.58	5.37	0.00	−0.15
		Panel B: Estimated parameters			
$c_k^-(\mathcal{O})$:	Downward capital adjustment cost		5.35		10.5
			(0.01)		(0.01)
$f_B(\mathcal{O})$:	Fixed debt issuance cost		0.001		0.003
			(0.000)		(0.000)
$\phi_B(\mathcal{O})$:	Quadratic debt issuance cost		5.21		6.75
			(0.11)		(0.16)
$\eta(\mathcal{O})$:	Sensitivity to monetary shock		20.52		10.05
			(0.21)		(0.17)
$\psi(\mathcal{O})$:	Equity issuance cost		0.11		0.15
			(0.01)		(0.01)
$\varphi(\mathcal{O})$:	Tightness of collateral constraint		0.65		0.52
			(0.01)		(0.01)

Panel A presents the target moments for the estimation of the baseline model. We compare the moments in the data with moments of simulated data. The model-implied moments are the mean value of the corresponding moments across simulations. The cross-sectional firm-level moments are computed by first computing the cross sectional moments and then taking the average of these moments across years. The results for the model part (columns "Model") are obtained from 500 samples of simulated data, each with 3,000 firms for both types and 100 quarterly observations for both POE and SOE firms. Panel B presents the estimated parameter values using the Simulated Method of Moments (SMM). We estimate 6 parameters, c_k^-, f_B, ϕ_B,η, ψ,φ, for SOEs and POEs respectively with the point estimates and their standard errors in parenthesis.

Table 3: Investment portfolios across SOEs and POEs

	SOE										POE									
	Data					Model					Data					Model				
	L	M	H	L-H	All	L	M	H	L-H	All	L	M	H	L-H	All	L	M	H	L-H	All
Panel A. Excess Returns																				
r^e	15.08	12.43	9.50	5.58	11.71	14.43	9.80	8.82	5.61	11.01	18.58	18.40	18.12	0.46	18.62	18.93	18.20	18.46	0.47	18.46
[t]	1.36	1.13	0.88	2.19	1.04	11.16	9.06	8.63	7.96	8.63	1.43	1.63	1.64	0.11	1.55	43.18	42.65	38.24	2.44	25.81
SR	0.47	0.38	0.30	0.45	0.37	0.35	0.29	0.31	0.32	0.32	0.49	0.52	0.51	0.04	0.52	0.71	0.74	0.71	0.06	0.71
Panel B. CAPM																				
α	4.24	1.99	-1.08	5.32	1.22	1.57	-1.04	-0.69	2.26	-0.05	5.76	6.17	5.87	-0.11	6.24	5.17	4.91	4.89	0.28	4.99
[t]	1.65	0.66	-0.42	2.10	0.49	5.60	-5.98	-3.20	4.66	-1.19	1.71	2.10	1.90	-0.03	2.45	44.53	21.75	36.09	1.11	34.12
b	0.97	0.93	0.95	0.02	0.94	1.23	0.96	0.80	0.43	1.00	1.15	1.09	1.09	0.05	1.11	1.03	0.97	1.00	0.03	1.00
[t]	27.49	20.47	24.49	0.64	24.21	71.88	77.43	45.18	12.53	64.83	29.78	35.59	30.56	1.15	41.43	66.11	32.96	55.02	0.75	51.36
R^2	0.87	0.80	0.83	0.00	0.85	0.97	0.99	0.96	0.61	0.97	0.86	0.90	0.90	0.02	0.91	0.98	1.00	0.97	0.01	0.98
Panel C. Asset pricing tests																				
α^{2F}	2.01	4.48	-0.49	2.49	0.16	0.10	-1.01	-0.23	0.33	-0.38	2.93	2.87	1.18	1.75	0.58	2.37	2.61	2.35	0.02	2.44
[t]	0.74	1.44	-0.47	0.74	0.41	0.06	-1.20	-0.41	0.30	-0.52	1.47	1.48	0.77	0.75	1.09	4.54	5.75	3.29	0.03	4.54
Cov^{MKT}	24.27	25.55	25.86	-1.60	24.63	13.92	11.25	9.51	4.41	11.56	29.09	25.79	25.44	3.65	25.94	6.69	6.29	6.52	0.17	6.50
[t]	1.93	1.76	1.81	-0.86	1.78	3.30	3.35	3.45	2.81	3.37	1.96	2.01	1.95	1.94	1.97	7.52	7.61	7.53	0.73	7.55
Cov^{MS}	-0.18	-7.40	-5.68	5.50	-5.78	3.96	-2.11	-2.37	6.33	-0.17	2.16	5.30	9.07	-6.91	5.23	-0.25	-0.77	0.91	-1.16	-0.04
[t]	-0.10	-1.79	-1.65	1.92	-0.77	2.27	-2.99	-1.57	1.96	-0.76	0.56	1.28	2.86	-3.50	0.65	-0.42	-4.13	1.52	-0.99	-1.01

Panels A and B report the average excess stock returns and the CAPM alphas (abnormal returns) of three one-way sorted on investment rate portfolios of the SOE sector (left panel) and the POE sector (right panel). r^e is the average annualized ($\times$1200) portfolio excess stock return; [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). SR is the portfolio Sharpe ratio; α and b are the portfolio average CAPM alpha (reported in annual percentage($\times$1200)) and market beta, obtained as the intercept and slope coefficient from monthly CAPM regressions. L, M, and H stand for the low, median, and high investment portfolios, respectively. L-H stands for the low-minus-high investment portfolio. ALL stands for the investment portfolio of all firms in the each sector. Panel C reports the asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}Cov(MKT_t, r^e_{i,t}) + b_{MS}Cov(MS_t, r^e_{i,t})$, in which MKT is the market factor, and MS is the monetary supply shocks (the CAPM model is the restricted case in which b_{MS} =0). b_{MKT} denotes the risk factor loading of the market factor. b_{MS} denotes the risk factor loading of the monetary supply shocks. Estimation is by GMM, and the test assets are the six 2-sectors $\times$ 3-IK portfolios. α^{2F} is the two-factor model alpha, Cov^{MKT} is the multivariate covariance between the portfolio returns and the market factor, and Cov^{MS} is the covariance between the portfolio returns and the monetary supply shocks. The data sample is monthly from July 2004 to June 2019 in panel A and B and is annual from 2004 to 2018 in panel C. The results for the model part (column "Model") are obtained from 500 samples of simulated data, each with 3,000 firms for both types and 100 quarterly observations.

Table 4: The price of risk of MS shocks

	Data		Model	
	CAPM	2-Factor	CAPM	2-Factor
MKT	0.27	0.20	1.21	0.84
[t]	1.04	0.77	31.81	4.87
MS		0.73		0.17
[t]		1.91		4.48
R^2	0.80	34.31	19.24	96.03
MAE	3.06	2.52	2.56	0.56

This table reports the GMM asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}Cov(MKT_t, r^e_{i,t}) + b_{MS}Cov(MS_t, r^e_{i,t})$, in which MKT is the market factor, and MS is the monetary supply shocks(the CAPM model is the restricted case in which b_s =0). b_{MKT} denotes the risk factor loading of the market factor. b_{MS} denotes the risk factor loading of the monetary supply shocks. The test assets are SOE 3-IK portfolios, five SOE size, and five SOE BM portfolios. MAE denotes the mean absolute error of the pricing errors. All the portfolio returns are annual returns. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). R^2 is the regression R-squares adjusted for the degree of freedom. The sample is from 2004 o 2018. The results for the model part (column "Model") are obtained from 500 samples of simulated data, each with 3,000 firms for both types and 100 quarterly observations.

Table 5: Debt growth, investment and profits responses to MS shocks

	Data				Model			
	Panel A. SOE							
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
MS	0.59	0.60	0.25	0.06	0.03	0.04	−0.00	−0.05
$[t]$	3.22	1.96	4.18	0.95	3.13	1.58	−0.06	−7.43
$P2 \times MS$	−0.46	−0.41	−0.06	−0.12	−0.03	−0.03	0.00	−0.01
$[t]$	−1.89	−1.08	−0.80	−1.39	−3.46	−1.17	0.49	−0.98
$P3 \times MS$	−0.80	−1.19	0.03	−0.17	−0.14	−0.23	0.04	−0.06
$[t]$	−3.03	−2.62	0.43	−2.02	−22.56	−18.70	4.03	−6.49
N	11,413	11,406	11,163	10,016	14,075	14,075	14,075	13,782
R^2	0.21	0.29	0.08	0.02	0.71	0.79	0.76	0.65
	Panel B. POE							
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
MS	0.34	0.21	0.73	0.43	0.01	0.01	0.00	−0.00
$[t]$	1.47	0.48	6.37	3.47	1.29	0.91	0.41	−0.24
$P2 \times MS$	−0.07	0.61	−0.23	−0.09	−0.01	−0.00	−0.00	0.00
$[t]$	−0.22	1.11	−1.75	−0.57	−2.15	−1.65	−0.28	0.03
$P3 \times MS$	0.33	−0.38	0.02	0.01	−0.02	−0.01	−0.01	0.01
$[t]$	0.96	−0.57	0.16	0.08	−6.59	−1.35	−1.12	0.94
N	9,387	9,385	9,260	7,662	14,095	14,095	14,095	13,809
R^2	0.09	0.31	0.05	0.02	0.73	0.77	0.03	0.03

This table reports the relevant slope coefficients from a panel OLS regressions of the form:

$$\Pi_{i,t+h} = a + b \times \Pi_{i,t-1} + c \times MS_t + \sum_{j=2}^{3} (d_j \times Pj_t + e_j \times Pj_t \times MS_t) + \varepsilon_{i,t},\ h = 0, 1,$$

$\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (ΔD_t), the first difference of firm's i investment rate at time t (ΔIK_t), or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$) (ΔCF_t and ΔCF_{t+1}). MS is the monetary supply shock series. $Pj_t$is the investment rate portfolios $j = 2,\ 3$ quintile dummy, respectively. The control variables include firms' physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. $[t]$ is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). N is the total number of firm-year observations. R^2 is the regression R-squares adjusted for degree of freedom. All dependent variables are winsorized at the top and bottom 1 percent in each year to decrease the influence of outliers. The sample period in the real data is 2004 to 2018. The results for the model part (column "Model") are obtained from 500 samples of simulated data, each with 3,000 firms for both types and 100 quarterly observations for both POE and SOE firms.

Table 6: Tests of capital misallocation and M2 shocks

Panel A: Industry TFP growth and MS shocks

	Without Controls			With Controls		
	SOE	POE	Both	SOE	POE	Both
M2	0.0748	-0.1241**	0.0748	0.0422	-0.1069*	0.0797
	(0.840)	(-2.601)	(0.839)	(0.528)	(-1.732)	(0.947)
M2 × POE dummy			-0.1989**			-0.1823*
			(-1.968)			(-1.721)
Controls	No	No	No	Yes	Yes	Yes
N	189	162	351	189	162	351
Adj. R^2	0.001	0.039	0.007	-0.053	0.108	0.004

Panel B: MPK dispersion and M2 shocks

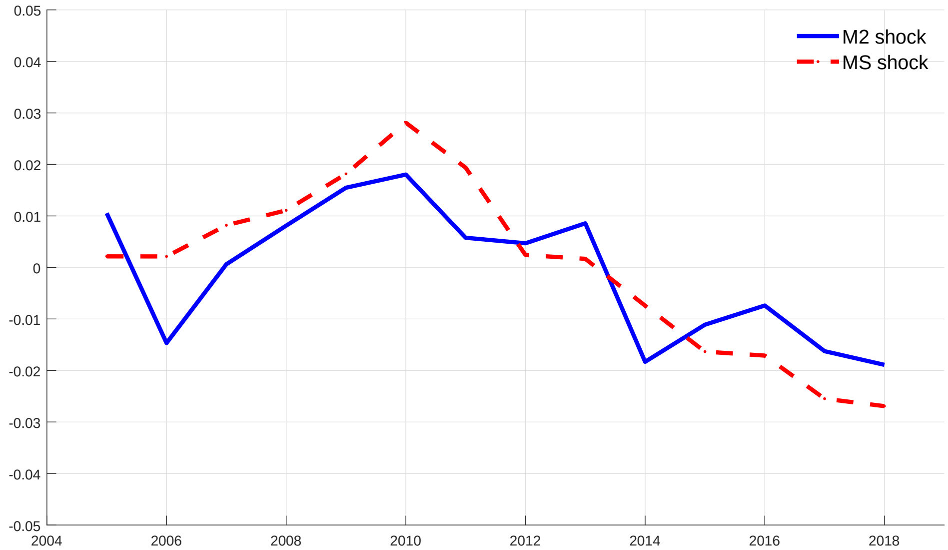
	Sector Level			Industry Level		
	SOE	POE	Both	SOE	POE	Both
M2	0.1401***	0.4648**	0.0067	0.2158**	0.7167***	0.2214*
	(3.423)	(2.686)	(0.061)	(2.191)	(3.295)	(1.873)
M2 × POE dummy			0.6302***			0.6029**
			(2.933)			(2.096)
N	15	15	30	815	716	1531
Adj. R^2	0.93	0.76	0.73	0.61	0.45	0.41

Panel A reports firm-level regressions of the dispersion of the marginal product of capital (MRPK) on M2 monetary policy shocks, estimated separately for SOEs, POEs, and the pooled sample, with and without firm-level controls. Panel B reports analogous regressions using sector-level and industry-level measures of MRPK dispersion. In both panels, the specifications are of the form

$$\text{Disp(MRPK)}_{k,t} = \alpha + b\,\text{M2Shock}_t + c\big(\text{POE}_k \times \text{M2Shock}_t\big) + \beta X_{k,t-1} + \varepsilon_{k,t},$$

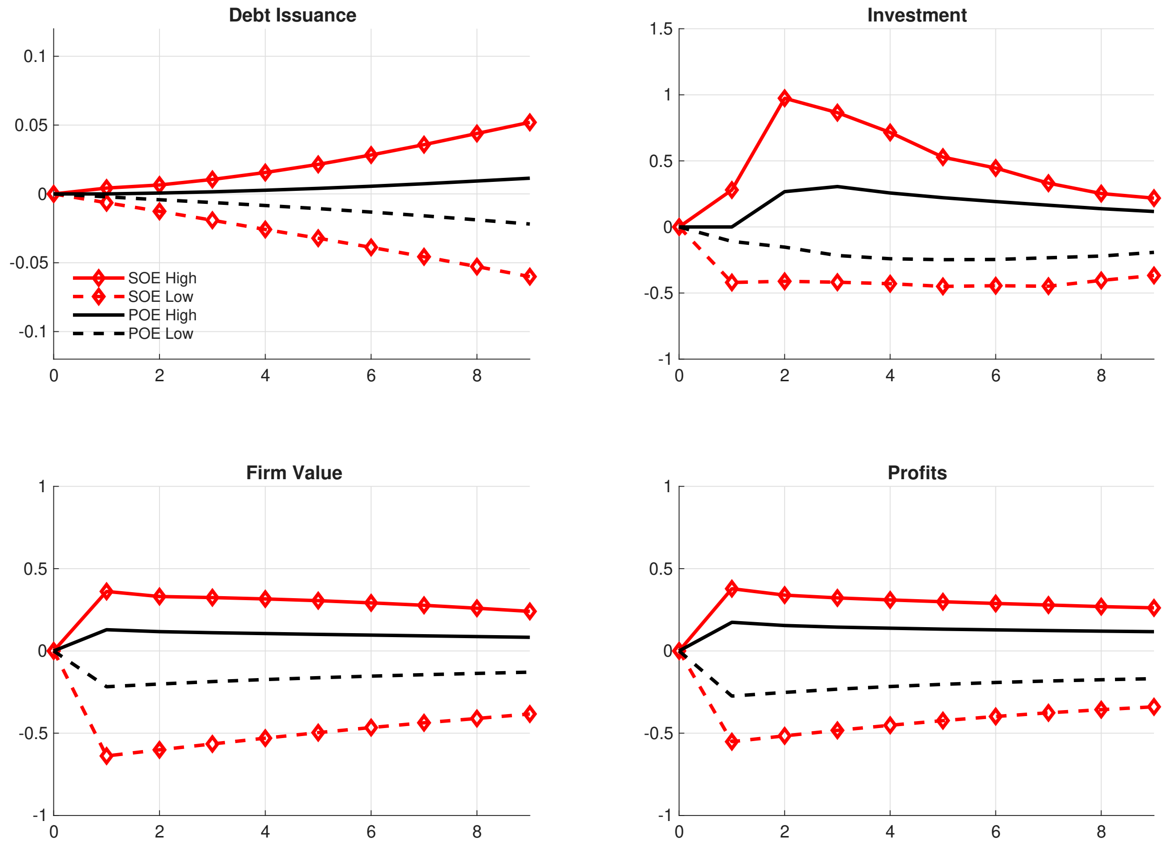
where $\text{Disp(MRPK)}_{k,t}$ denotes the dispersion of MRPK for unit k (firm, sector, or industry) in year t, M2Shock_t is the negative of the M2 shock constructed by CRZ, and POE_k is a dummy variable equal to one if unit k is privately owned and zero otherwise. The table reports the coefficients b (row "M2") and c (row "M2 × POE dummy"). The vector $X_{k,t-1}$ includes the physical capital-to-market equity ratio (KM), book capital-to-market equity ratio (BM), Tobin's Q, size, and leverage; for industry-level regressions, industry fixed effects are also included. t-statistics, reported in parentheses, are heteroskedasticity- and autocorrelation-consistent (Newey–West). R^2 is the coefficient of determination adjusted for degrees of freedom. The sample covers the period from 2004 to 2018.

Figure 1: Time series of the M2 and MS shocks



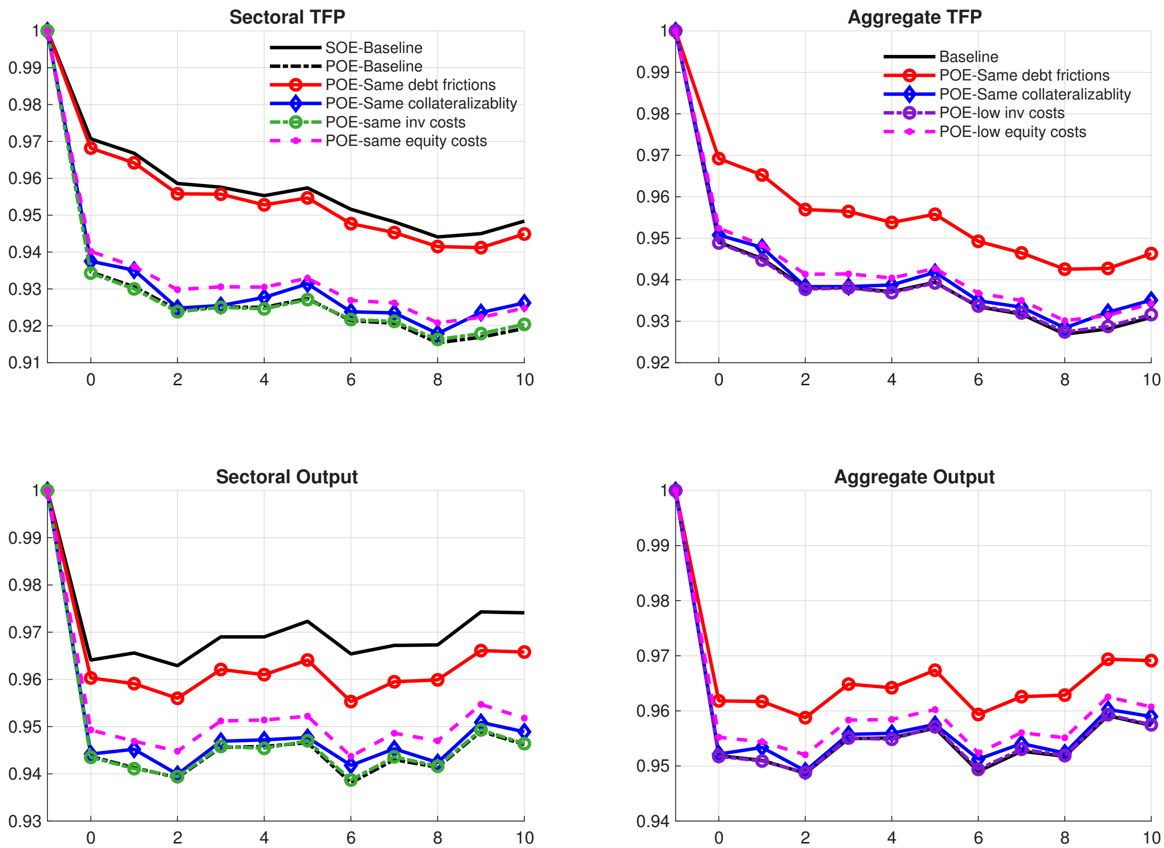
This figure reports the time series of two monetary supply shocks: 1) the M2 shock (solid line) that we construct following CRZ and extend to a longer sample which ranges from 2005 to 2018, and 2) the MS shock (dashed line) that we estimate in the data with the identification guided by our structural model.

Figure 2: Firms' responses to the monetary supply (MS) shock SOE vs POE



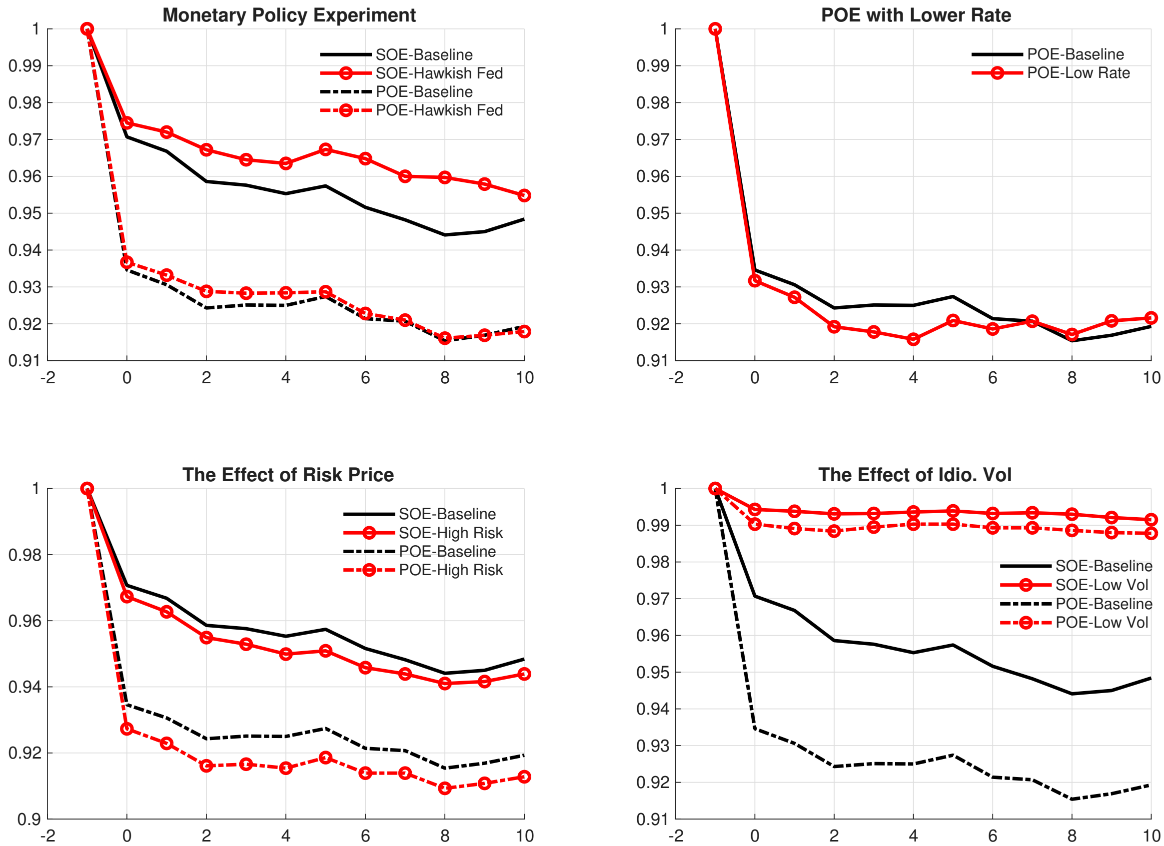
This figure plots impulse responses of key endogenous variables under the baseline calibration to a one-standard-deviation contractionary monetary-supply shock, which raises the marginal cost of debt issuance and corresponds to a high–marginal-utility state. Responses are reported as percent deviations relative to a benchmark firm that faces the same aggregate shock and has median idiosyncratic productivity. High (low)-productivity firms's current productivity is one standard deviation above (below) the median. Investment denotes the investment rate, debt issuance the stock of debt, firm value the ex-dividend equity value, and profit equals revenue net of costs.

Figure 3: Sectoral and aggregate TFP and output responses to MS shocks



This figure plots impulse responses of measured TFP and output to a one-standard-deviation contractionary monetary supply shock in the baseline SOE and POE models. The counterfactuals equalize, one at a time, POE frictions to SOE levels: (i) debt-issuance costs (both fixed and variable in the debt adjustment cost), (ii) collateralizability of capital, (iii) investment adjustment costs, and (iv) equity-issuance costs. Responses are reported as percent deviations from long-run averages (time-detrended where applicable). Sector-level series are obtained by simulating a large panel of firms in each sector and aggregating their optimal policies at each horizon. Measured productivity is the log of the sectoral aggregate output-to-capital ratio.

Figure 4: Measured TFP-the role of Monetary Policy, risk and firm heterogeneity



This figure plots impulse responses of sectoral output and measured TFP to a one-standard-deviation contractionary MS shock under four alternative specifications: (i) a more hawkish policy rule with a stronger response to inflation, (ii) a lower nominal rate for POEs, (iii) a lower market price of MS risk, and (iv) lower firm-level productivity volatility for both SOE and POE firms. Responses are reported as percent deviations from long-run averages (time-detrended where applicable). Sector-level series are obtained by simulating a large panel of firms in each sector and aggregating their optimal policies at each horizon. Measured productivity is the log of the sectoral aggregate sales-to-capital ratio.

Appendix For Online Publication

A Data

We describe additional details of the data construction and robustness checks in the data.

A.1 Sample details

The stock trading data and firm financial data are from CSMAR (China Stock Market & Accounting Research Database). In China, each stock in exchange market has a unique six-digit ticker. Based on the first two digits of stock tickers , we can broadly identify different stock types. Our sample includes all A-share stocks from the main boards of the Shanghai and Shenzhen exchanges as well as the board of the GEM (Growth Enterprises Market), and their first two digits of ticker are 60, 00, and 30, respectively. The gross fixed assets and accumulated depreciation of fixed assets come from the notes to firm financial statements , which starts from 2003. The stock return data is monthly from July 2004 to June 2019, and firm financial data is annual from 2003 to 2018.

We impose two filters. First, we omit the financial firms in accordance with the industry classification guidelines for listed firms issued by CSRC. Their codes are J-66, J-67, J-68, and J-69. Second, we exclude observations within the first six months since stocks become public since the stock prices of Chinese listed firms tend to rise significantly in the first few months of listing. Third, we omit the "shell" firms since the value of "shell" firms may be affected by acquisition activities.

CSMAR reports state ownership identifier that is available in annual frequency since 2003. CSMAR uses the information disclosed in the firm financial annual report to identify the actual controlling shareholder. If the information is not disclosed, CSMAR identifies the actual controlling shareholder based on the shareholding chain. Following Liu et al. (2019), we use the one-year deposit rate as the risk-free rate, which is obtained from the CEIC database. The China's monetary supply shocks data is from the website of Tao Zha.

A.2 Measuring invetment and portfolio returns

According to accounting standards, gross fixed assets at time t - gross fixed assets at time $t-1$ = the changes in gross fixed assets = the purchase of gross fixed assets at time t - the gross value of the sales of gross fixed assets at time t = the purchase of gross fixed assets at time t - (the net value of the sales of gross fixed assets at time t + the decrease in accumulated depreciation at time t) = physical capital investment at time t - the decrease in accumulated depreciation at time t.

To compute the portfolio-level stock return in each period, we weight each firm in the portfolio by net fixed asset(PPENT). Specifically, at the time of portfolio formation in July of year t, we compute the weight of each firm in the portfolio using the last year's PPENT last year (K_{t-1}), and compute the weighted return. Then, in the following month, we compute the value adjusted new weight as $K_{t-1} \times Return_{July,t}$. And then, in September, it would be, $K_{t-1} \times Return_{July,t} \times Return_{August,t}$, etc, until June of next year. This procedure ensures that the portfolio returns correspond to an investment strategy with annual (not monthly as it would be the case if the weight was kept constant throughout the year) re-balancing. The use of PPENT weights helps to avoid some extreme outliers in the firms' market equity cross sectional distribution, especially in the SOE sector.

A.3 Regression analysis of investment-return relationship

We also examine the link between firm's investment rate and future stock returns using firm-level regressions, thus allowing us to control for the effect of other firm characteristics. Specifically, we run standard firm-level cross-sectional regressions (Fama and MacBeth,1973) of the form:

$$r_{i,t} = a + b \times IK_{i,t-1} + c \times IK_{i,t-1} \times SOE_{i,t-1} + d \times SOE_{i,t-1} + Controls_{i,t-1} + \epsilon_{i,t}, \quad (26)$$

in which $r_{i,t}$ is the firm i monthly stock return, $IK_{i,t-1}$ is the lagged value of firm i investment, $SOE_{i,t-1}$ is a dummy variable that is equal to one if firm i is state-owned firm at year $t-1$, and $Controls_{i,t-1}$ are firm-level control variables (market equity, ROA, leverage ratio, wage-to-profit ratio, and industry dummy $\times$ time).

Table A.4 reports the results from cross-sectional predictability regressions performed at a monthly frequency. The regression's main coefficient of interest is the coefficient c, which captures the effect of the interaction between investment rate and the SOE dummy. This slope coefficient c is estimated to be negative, and is statistically significant. The difference in the investment rate slope coefficient in SOE and in POE sector is economically large. In column 3, the slope coefficient on the interaction of investment rate and the SOE dummy is -0.39. This difference is large in economic terms: A 10% increase in the firm's investment rate, is associated with a decrease of 0.039% in firms' expected monthly stock return in the SOE sector than in the POE sector. The results are robust to the inclusion of control variables. Thus, consistent with the portfolio-level analysis, the negative investment-return relation is significantly steeper across SOEs than across POEs. The coefficient d of SOE dummy is significantly negative when including control variables, indicating SOE sector has lower return than POE sector.

A.4 Characteristics across portfolios

This subsection presents selected firm characteristics of SOEs and POEs. Table A.5 reports the characteristics of the firms in the low investment (L), high investment (H), and spread (L-H) portfolios in both the real data (column "Data") and in the model (column "Model"). Overall, SOEs are bigger (market capitalization), use more financial leverage, and issue more debt. On the other hand, POEs invest more, and have higher TFP and cash flows. The differential exposures to the monetary supply shock across investment sorted portfolios naturally reflects differences in the characteristics of the firms in these portfolios. To understand these differences and evaluate if the model is consistent with them. Panel A exhibits characteristics for SOEs and the lower panel B shows results for POEs. Table A.5 shows that the model matches basic firm characteristics of chinese SOEs and POEs. low investment (high investment) poes as well as soes are associated with low (high) productivity, low (high) investment rate, low (high) debt issuance, and high book leverage ratio, both in the data and in our model.

A.5 Alternative measure of monetary supply shocks

We also provide empirical findings using the M2 shock estimated in CRZ as alternative measure. Specifically, CRZ develop and estimate an endogenously switching monetary policy rule that is tractable in the spirit of Taylor (1993). Then they use the M2 growth as the intermediate tool of China's central bank instead of interest rates and obtain a time series of monetary supply shocks, which we denote by M2 shocks. Figures A.4 to A.5 and Tables A.6 to A.8 report the results using the M2 shock.

Overall, our main findings remain robust. We find the estimated price of risk for the M2 shocks, and the estimated responses to the M2 shocks within- and cross-sectors remain largely consistent with those using the model implied monetary supply shock (M2 shock). Specifically, first the market price of risk of the M2 shock is positive and significant, and is close to the price of risk of the MS shock in economic magnitude. In addition, the two factor model with the market factor and the M2 shock factor prices the investment portfolios well. These result implying that the M2 shock and the MS shock capture a common comoponent that drives the monetary growth in the China. Furthermore, in the SOE sector, we see that the changes of investment, debt issuance and profit growth of the high-investment firms' responses to M2 shock is countercyclical while low investment firms are procyclical. In the POE sector, there is no significant difference between high- and low-investment firms' responses to M2 shocks, and most of these responses are insignficant. All these responses to the M2 shock are consistent with those to the MS shock.

A.6 Interest rates across SOEs and POEs

A possible channel driving the result of differential exposures to the monetary shocks is that SOEs firms' interest respond to monetary shocks differently while POEs do not. We examine this possible channel in Table A.9. We measure firms' interest rate as the firm's loan interest rate minus the the benchmark interest rate of the banks. However due to the data limitation, there are only less than 10% of firms report the interest rates on their loans. Even though we can not completely ruled out that interest rates might play a role, but the result shows that most of the responses of SOEs and POEs' interst rates to monetary shocks are insignificant and that high- and low-investment SOE firms' do not respond to the MS or M2 shocks differently. This is perhaps not surprising because the monetary policy in China uses the M2 growth as the intermediate target, as noted in Section 2, interest rates do not play an important role in implementing monetary policies.

A.7 Shadow banking

As is documented in the literature (e.g., CRZ), shadown banking activities started to increase significantly since 2009 in China as the monetary growth slows down. A possible channel for our findings is that POEs are constrained in bank loans but still access loans from shadow banks, and hence the responses of high- or low-investment POE firms to monetary shocks do not differ. To test this channel, we construct the shocks to the aggregate shadow bank loan growth rate and redo the panel regressions as in Equation (25) by replacing the MS shock by the shadow banking growth rate shocks. Table A.10 reports the result. We find the responses of investment, debt issuance and profit growth to the shadow banking growth shocks do not exhit any differences across high and low-investment POE firms, and most of these response are statistically insignificant. Interestingly, SOEs' responses are largely insignificant as well. These results imply that shadow banking activities are not driving our main findings.

A.8 Five one-way-sorted investment rate portfolios

To check the robustness of the empirical results based on three portfolios, we also form five one-way-sorted investment rate portfolios separately in the SOE and POE sectors, and then compute the portfolio-level results using MS shock and M2 shock. Table A.11 to A.14 report the results. Overall the main findings remain robust.

B Model

This appendix describes some of the key steps in the numerical techniques used to solve the firm's maximization problem.

B.1 Detrending the model

Before solving the model numerically, we exploit the homogeneity property of firm optimization problem 20 and reduce the number of state variable by 1. Note that all variables can be scaled by physical capital K_t,

$$v_t = \frac{V_t}{K_t}, \quad b_t = \frac{B_t}{K_t}, \quad i_t = \frac{I_t}{K_t}, \quad h_t = \frac{H_t}{K_t}, \quad d_t = \frac{D_t}{K_t}, \quad y_t = \frac{Y_t}{K_t}, \quad e_t = \frac{E_t}{K_t}, \quad g_t = \frac{G_t}{K_t}$$

The scaled Bellman equation now reads as

$$v_t(b_t, A_t, \xi_t, Z_t) = \max d_t + (1 - \kappa_D)(1 - \delta + i_t)\mathbb{E}[\Lambda_{t,t+1} v_{t+1}(b_{t+1}, A_{t+1}, \xi_{t+1}, Z_{t+1})]$$

subject to the collateral constraint that comes in scaled form

$$b_{t+1} \leq \psi$$

Normalized earning is given by

$$e_t = (1 - \tau)y_t + \tau\delta + \tau r_f b_t - i_t - g_t + (1 - \delta + i_t)b_{t+1} - (1 + r_f)b_t - \Phi_t^B$$

Normalized dividend is therefore,

$$d_t = e_t - \phi \max(-e_t, 0)\mathbf{I}_{\{\max(-e_t,0)>0\}}$$

B.2 Numerical solution

We solve the firm's maximization problem numerical with a hybrid approach that combines value and policy function iteration approach. The value and policy functions are solved on a grid in a discrete state space. We specify 80 grids for leverage ratio b, and 15 grids for firm-level productivity Z. Stationary AR(1) processes, including Z, aggregate productivity A, and monetary supply ξ are all discretized using the approach as in Rouwenhorst (1995). Aggregate processes are discretized each with 5 grid points and out results are robust under finer discretization of aggregate states.

Once the discrete state space is constructed, we use a simple search routine in maximizing the firm's problem. To accelerate the convergence, we adopt a hybrid approach: we solve the Bellman operator (value function iteration) for 10 rounds and then use the most recent policy functions to update the firm value for another 50 rounds. And we continue this procedure until firm's value function fully converges. This iteration method is more efficient than the value function iteration alone because policy functions tend to converge faster than the value function itself.

B.3 Simulated Method of Moments Estimation

To generate the simulated data for the SMM estimation (used to create $\Psi^S(\theta)$ in Equation (22)), we simulate an economy with 3000 firms. This is run for 1000 quarters, with the first 800 quarters discarded to eliminate the effects of any assumptions on initial conditions. We use a simulated annealing algorithm for minimizing the criterion function in the estimation step in Equation (22). This starts with a predefined first. For the second guess onward it takes the best prior guess and randomizes from this to generate a new set of parameter guesses. That is, it takes the best-fit parameters and randomly "jumps off" from this point for its next guess. Over time the algorithm "cools," so that the variance of the parameter jumps falls, allowing the estimator to fine tune its parameter estimates around the global best fit. We restart the program with different initial conditions to ensure the estimator converges to the global minimum. The simulated annealing algorithm is extremely slow, which is an issue since it restricts the size of the parameter space which can be estimated. Nevertheless, we use this because it is robust to the presence of local minima and discontinuities in the criterion function across the parameter space.

To generate the standard errors for the parameter point estimates, we generate numerical derivatives of the simulation moments with respect to the parameters and weight them using the optimal weighting matrix. One practical issue with this is that the value of the numerical derivative, defined as $f'(x) = \frac{f(x+\varepsilon)-f(x)}{\varepsilon}$, is sensitive to the exact value of ε chosen. This is a common problem with calculating numerical derivatives using simulated data with underlying discontinuities, arising, for example, from grid-point-defined value functions. To address this, we calculate four values of the numerical derivative for an ε of +1%, +2.5%, +5%, and -1% of the midpoint of the parameter space and then take the median value of these numerical derivatives. This helps to ensure that the numerical derivative is robust to outliers arising from any discontinuities in the criterion function.

B.4 Robustness checks in model

Interest rate channel As is documented in the literature (Bai et al., 2018), the financing costs for SOEs tends to be lower than POEs, in particular, SOEs tend to pay 40-50 basis points lower than the POE counterparts in borrowing loans. We show that this difference doesn't change our main model findings. Figure **??** plots the response for SOEs with their interest rate 40 bps less than the baseline calibration. The drop in productivity and output is only 50 bps less than the baseline, suggesting the interest rate channel will not the main driving force in the model if the model does not have cross-sectoral heterogeneity in financial frictions.

General equilibrium Currently the model is in a partial equilibrium setting. A general equilibrium set-up would require a Krusell and Smith (1998) type of model with its additional loop and simulation to solve for prices and expectations. To investigate this we do run a pseudo-GE experiment, whereby we allow prices to change by an empirically realistic amount after a monetary shock. We solve the model by assuming that the interest rate depends on monetary policy stance. We discipline our procedure by matching the historical correlation between interest rate and monetary supply shock in China. We find broad robustness of our results on the impact of monetary supply shocks with a 10 bps bigger output drop and persistent recovery.

B.5 Credit supply and the transmission of monetary policy

In this section, we micro-found the debt adjustment cost function of firms and explain its heterogeneity between SOEs and POEs from the perspective of credit supply. This simple model captures the key transmission mechanism of quantity-based monetary policy in China and generates results that are observationally equivalent to our earlier assumption of heterogeneous debt adjustment costs on the credit demand side.

We assume that each firm is matched with a bank, where banks differ in the degree of financial frictions they face. Sun et al. (2021) adopt a similar matching framework to study firms' debt financing. Because we focus on short-term borrowing over two periods, we formulate the bank's optimization problem as a two-period profit maximization problem.

Each bank has three potential sources of funding. First, it collects deposits S from households, which are subject to the Required Reserve Ratio (RRR) set by the central bank of China. $\xi(m)$ denotes the RRR, i.e., the fraction of deposits held as reserves at the central bank. We use the same notation m as in our full model to denote the monetary policy stance. Second, the bank can borrow from the Medium-term Lending Facility (MLF), with quantity denoted by $L(m)$. Both sources are affected by monetary policy m. An accommodative policy shock either reduces the RRR, increases funding through the MLF, or both. Accordingly, we assume that $\xi(m)$ is decreasing in m and $L(m)$ is increasing in m. Finally, if these two sources are insufficient to meet funding needs, the bank resorts to costly external finance: each Chinese yuan raised externally incurs ϱ yuan in funding costs.

The composition of banks' funding sources and their sensitivity to monetary policy have been well documented in the literature. Luo et al. (2023) and Huang et al. (2019) show that the RRR and MLF are two key instruments of China's quantity-based monetary policy, motivating our explicit modeling of both. Costly external financing in China primarily arises from the interbank lending market. Bianchi and Bigio (2022) and Luo et al. (2023) demonstrate that frictions in this market play a crucial role in shaping the transmission of monetary policy in both the United States and China.

Bank's budget constraint at period one.

Bank's budget constraint at period one is given by

$$D_1^B(z_1) = \big(1-\xi(m_1)\big)S_1 + L(m_1) + \varrho\,\min\{0,\,D_1^B\} - b_1 - \frac{\eta}{2}\left(\frac{b_1}{b_0}-1\right)^2 b_0 - z_1. \tag{27}$$

The bank collects funds and extends credit to the firm it is matched with. The credit supply b_1 is endogenously chosen by the bank, subject to the supply adjustment cost $\frac{\eta}{2}\left(\frac{b_1}{b_0}-1\right)^2 b_0$, where $b_0 > 0$ is the previous period's credit supply and is treated as a predetermined variable. For example, such an adjustment cost can capture additional monitoring costs during credit expansion ($b_1 > b_0$) or downsizing costs during credit contraction ($b_1 < b_0$)[18]. Loan adjustment costs are a common feature in the banking literature to generate persistent variation in banks' balance sheets and leverage ratios (e.g., Begenau et al. (2025)).

Finally, the bank's profit is subject to an i.i.d. shock z_1 with CDF $\Phi(z_1)$ on the domain $[0, \bar{z}]$. The z shock generates external financing needs for banks at date 1 and lasts for one period only. The threshold realization of z above which the bank requires costly external financing is denoted z_1^* and satisfies

$$z_1^* = \big(1-\xi(m_1)\big)S_1 + L(m_1) - b_1 - \frac{\eta}{2}\left(\frac{b_1}{b_0}-1\right)^2 b_0. \tag{28}$$

In other words, $D_1^B(z_1^*) = 0$.

Bank's cash flow at date two.

$$D_2^B = L(m_2) - R^f S_1 + R^B b_1. \tag{29}$$

At date 2, the bank pays off its depositors at the risk-free rate R^f, receives the central bank liquidity injection $L(m_2)$, and collects revenues on the short-term loan contract with gross return R^B. We allow for potential spread between the lending rate and the deposit rate $R^B > R^f$.

Bank's value maximization problem.

Bank's value maximization problem, before observing the realization of shock z_1, is given by

$$V_1^B(b_0, S_1) = \max_{b_1}\left\{\int_0^{z_1^*} D_1^B(z_1)\,d\Phi(z_1) + \frac{1}{1-\varrho}\int_{z_1^*}^{\bar{z}} D_1^B(z_1)\,d\Phi(z_1) + \mathbb{E}\big[M_{1,2}D_2^B\big]\right\}, \tag{30}$$

where $D_1^B(z_1)$ is defined in the budget constraint and D_2^B denotes the bank's cash flow at date 2. $M_{1,2}$ is the stochastic discount factor between date 1 and date 2.

Next, we characterize the optimal credit supply decision of the bank and impose realistic parameter restrictions to make sure that bank's decision is an interior solution. We further analyze how potential heterogeneity in bank's financial frictions affects the bank's credit supply

[18]Note that we specify the bank adjustment cost to ensure that the bank's credit supply decision obtains an interior solution. Defaultable debt is an alternative modeling device to ensure an interior solution of the model. We have analyzed another model with defaultable debt and found that the results are similar. Details of the defaultable debt model are available upon request.

decision.

Lemma 1 (Characterization of optimal credit supply) *Assume that $\varrho \in (0,1)$. Solving bank's maximization problem (30) delivers a condition that any interior maximizer b_1 must satisfy:*

$$\frac{1-\varrho\Phi(z_1^*)}{1-\varrho}\left[1+\eta\Big(\frac{b_1}{b_0}-1\Big)\right] = \mathbb{E}[M_{1,2}R^B]\,. \tag{31}$$

Proof. Since $D_1^B(z_1) = z_1^* - z_1$ by construction of z_1^*, we can write

$$V_1^B = \int_0^{z_1^*}(z_1^* - z_1)\,d\Phi(z_1) + \frac{1}{1-\varrho}\int_{z_1^*}^{\bar{z}}(z_1^* - z_1)\,d\Phi(z_1) + \mathbb{E}\big[M_{1,2}\big(L(m_2) - R^f S_1 + R^B b_1\big)\big]\,.$$

Differentiating with respect to b_1 and applying Leibniz's rule gives

$$\frac{\partial V_1^B}{\partial b_1} = \frac{\partial z_1^*}{\partial b_1}\left[\Phi(z_1^*) + \frac{1-\Phi(z_1^*)}{1-\varrho}\right] + \mathbb{E}[M_{1,2}R^B].$$

From the definition of z_1^*, we have

$$\frac{\partial z_1^*}{\partial b_1} = -1 - \eta\Big(\frac{b_1}{b_0} - 1\Big).$$

The first-order condition $\frac{\partial V_1^B}{\partial b_1} = 0$ then yields

$$\left[1+\eta\Big(\frac{b_1}{b_0}-1\Big)\right]\left[\Phi(z_1^*) + \frac{1-\Phi(z_1^*)}{1-\varrho}\right] = \mathbb{E}[M_{1,2}R^B].$$

Simplifying the term in brackets,

$$\Phi(z_1^*) + \frac{1-\Phi(z_1^*)}{1-\varrho} = \frac{(1-\varrho)\Phi(z_1^*) + 1 - \Phi(z_1^*)}{1-\varrho} = \frac{1-\varrho\,\Phi(z_1^*)}{1-\varrho},$$

which gives the key equation (31). ■

Note that the optimal credit supply (31) implicitly characterizes b_1. Clearly, bank's financial frictions generates a wedge between credit supply on the left hand side and the return of credit on the right hand side. Such a wedge depends on the unit financing cost ϱ and the probability of requiring external financing $\Phi(z_1^*)$. An increase in ϱ or $\Phi(z_1^*)$ widens the wedge, making it more difficult for the bank to supply credit. We next provide a proposition that studies the monetary policy transmission in this simple model.

Proposition 1 (Monetary policy and credit supply) *Let the optimal b_1 solve (31). Assume an interior solution with $0 < \Phi(z_1^*) < 1$, $\xi'(m_1) < 0$, and $L'(m_1) > 0$. Then, a contractionary monetary policy shock at date one*

1. *increases the probability of bank's external financing need: $\frac{\partial(1-\Phi(z_1^*))}{\partial m_1} < 0$.*

2. decreases the bank's credit supply: $\frac{\partial b_1}{\partial m_1} > 0$.

Proof. Differentiate the first-order condition with respect to m_1:

$$\frac{\eta}{b_0}\frac{\partial b_1}{\partial m_1} = \mathbb{E}[M_{1,2}R^B]\,(1-\varrho)\,\frac{\varrho\,\phi\big(z_1^*\big)}{\big(1-\varrho\,\Phi\big(z_1^*\big)\big)^2}\cdot\frac{\partial z_1^*}{\partial m_1}. \tag{32}$$

From the definition of z_1^*,

$$\begin{aligned}\frac{\partial z_1^*}{\partial m_1} &= \frac{\partial}{\partial m_1}\Big[(1-\xi(m_1))S_1 + L(m_1) - b_1 - \frac{\eta}{2}\left(\frac{b_1}{b_0}-1\right)^2 b_0\Big]\\ &= -\xi'(m_1)S_1 + L'(m_1) - \frac{\partial b_1}{\partial m_1} - \eta\left(\frac{b_1}{b_0}-1\right)\frac{\partial b_1}{\partial m_1}.\end{aligned}$$

Plug this into the previous line and define

$$\kappa \equiv \mathbb{E}[M_{1,2}R^B]\,(1-\varrho)\,\frac{\varrho\,\phi\big(z_1^*\big)}{\big(1-\varrho\,\Phi\big(z_1^*\big)\big)^2},$$

to get

$$\frac{\eta}{b_0}\frac{\partial b_1}{\partial m_1} = \kappa\Big(-\xi'(m_1)S_1 + L'(m_1) - \frac{\partial b_1}{\partial m_1} - \eta\left(\frac{b_1}{b_0}-1\right)\frac{\partial b_1}{\partial m_1}\Big).$$

Note that the constant κ is non-negative since the financing cost ϱ is less than 1. Collect the $\partial b_1/\partial m_1$ terms on the left:

$$\left[\frac{\eta}{b_0} + \kappa\left(1+\eta\left(\frac{b_1}{b_0}-1\right)\right)\right]\frac{\partial b_1}{\partial m_1} = \kappa\,[-\xi'(m_1)S_1 + L'(m_1)].$$

Divide both sides to obtain the stated expression. Under $\xi'(m_1) < 0$ and $L'(m_1) > 0$, the LHS is positive, the RHS is positive, hence $\partial b_1/\partial m_1 > 0$.

Equation (32) shows that b_1 and z_1^* respond to monetary policy shocks in the same direction,

$$\frac{\partial z_1^*}{\partial m} = \frac{\eta/b_0}{\kappa}\frac{\partial b_1}{\partial m} > 0.$$

By the chain rule,

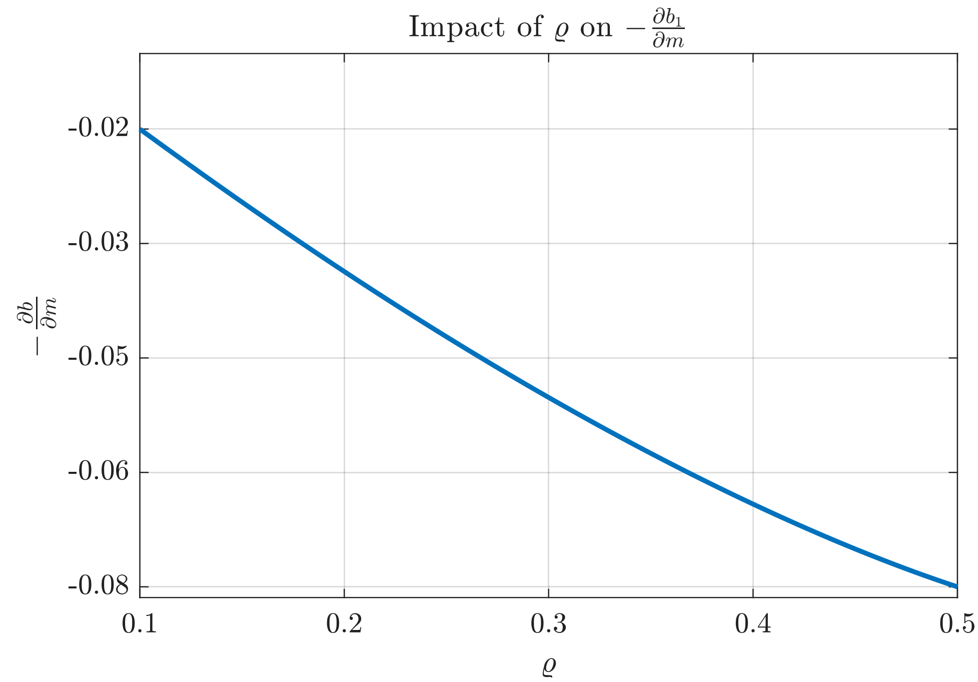
$$\frac{\partial}{\partial m}\Big(1-\Phi(z_1^*)\Big) = -\phi(z_1^*)\frac{\partial z_1^*}{\partial m} < 0,$$

since $\phi(z_1^*) > 0$ and $\partial z_1^*/\partial m > 0$. ■

Heterogeneous effects of monetary policy shocks on credit supply. Finally, we examine the heterogeneous effects of monetary policy shocks on credit supply when banks differ in their external financing cost ϱ. Consider an SOE and a POE that are otherwise identical except for the bank with which they are matched. We assume that the bank's financing cost ϱ is higher for POEs than for SOEs, i.e., $\varrho^{\mathcal{P}} > \varrho^{\mathcal{S}}$. We examine how the elasticity of credit supply to monetary policy shocks varies with ϱ, i.e., $\partial(\frac{\partial b_1}{\partial m_1})/\partial\varrho$.

Since we cannot characterize the relationship between ϱ and credit supply elasticity analytically, we apply numerical methods to solve for the optimal credit supply decision in equation (31) for different values of ϱ. We then compute the elasticity of credit supply to monetary policy shocks as $\frac{\partial b_1}{\partial m_1}$ and investigate how it varies as ϱ changes within a realistic range of $(0, \frac{1}{2})$.[19] We hold all other parameters constant at their baseline values: the initial leverage b_0, bank adjustment cost parameter η, deposits S_1, the range of shock $\bar{z}$, and monetary policy level m_1 are all normalized to unity for simplicity. Additionally, we impose linear functional forms for $L(m)$ and $\xi(m)$ with slope coefficients of 0.1 and -0.1, respectively. Our results are robust to alternative parameter values and functional forms.

Figure A.1: Bank's financing cost and credit supply elasticity to monetary policy shocks



This figure shows how the elasticity of bank credit supply to monetary policy shocks varies with the bank's external financing cost ϱ. The elasticity is computed as $\frac{\partial b_1}{\partial m_1}$ from the bank's optimal credit supply decision, under different financing costs ϱ. Other parameters, including the initial leverage b_0, bank adjustment cost parameter η, deposit S_1, the range of shock $\bar{z}$, and monetary policy level m_1 are held constant and normalize to ones for simplicity. Additionally, we impose linear functional forms for $L(m)$ and $\xi(m)$ with slope coefficients of 0.1 and -0.1, respectively. Our results are robust to alternative parameter values and functional forms

The main results are illustrated in Figure A.1. To connect with the quantitative model, we focus on the elasticity of credit supply with respect to a *negative* monetary policy shock and invert its sign for comparability. The figure shows that as financial frictions rise, the elasticity of credit supply to a negative monetary policy shock declines. When monetary policy tightens, the

[19]When the financing cost ϱ is too high, banks will not extend any credit to firms. Instead, they would require negative debt from firms, which represents an unrealistic form of bank savings from firms.

central bank raises the required reserve ratio on deposits and reduces liquidity injections, both of which constrain banks' funding capacity and limit their ability to extend credit to firms. These adverse effects of monetary tightening are further amplified when banks face higher external financing costs, captured by a larger ϱ. Consequently, credit supply among POEs is more adversely affected by tightening shocks than that of SOEs, since POE-affiliated banks typically bear higher external financing costs by assumption. While our quantitative model does not explicitly incorporate this mechanism, the assumed debt-adjustment-cost specification is designed to capture its reduced-form implications.

B.6 Monetary Block

The monetary block follows a canonical New Keynesian framework in the spirit of Woodford (2003) and Galí (2015).

Households. Preferences feature money-in-utility (MIU):

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-1/\sigma}}{1-1/\sigma} - \frac{N_t^{1+\chi}}{1+\chi} + \upsilon \ln\left(\frac{M_t}{P_t}\right) \right],$$

where $0 < \beta < 1$ is the discount factor, $\sigma > 0$ the inverse intertemporal elasticity of substitution, $\chi > 0$ the inverse Frisch elasticity of labor supply, and $\upsilon > 0$ the weight on real money balances. The household's nominal budget constraint is

$$P_t C_t + B_{t+1} + M_t - M_{t-1} \leq W_t N_t + P_t D_t - P_t T_t + \left(1 + i_{t-1}^{\$}\right) B_t,$$

which states that total nominal expenditures—consumption, new bond purchases, and money accumulation—cannot exceed available nominal income, consisting of labor income $W_t N_t$, dividend income $P_t D_t$, net of taxes $P_t T_t$, and the returns on previously held bonds $(1 + i_{t-1}^{\$}) B_t$. Here, P_t denotes the aggregate price level, C_t consumption, B_t nominal bond holdings, M_t nominal money balances, N_t labor supply, and $i_t^{\$}$ the nominal interest rate.

Firms and Pricing. Final output aggregates a continuum of differentiated intermediate goods via a Dixit–Stiglitz aggregator:

$$\mathbf{Y}_t = \left(\int_0^1 \mathbf{Y}_t(i)^{\frac{\varepsilon-1}{\varepsilon}} \, di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \qquad \varepsilon > 1,$$

where ε denotes the elasticity of substitution across intermediate goods. The corresponding demand for each intermediate variety is

$$\mathbf{Y}_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\varepsilon} \mathbf{Y}_t,$$

and the aggregate price index satisfies the usual relationship implied by cost minimization.

Intermediate firm i produces according to a linear technology,

$$\mathbf{Y}_t(i) = A_t N_t(i),$$

where $a_t \equiv \ln A_t$ follows the process in (2). Each firm sets its price subject to Calvo-type nominal rigidity: in each period, it can reset its price with probability $1-\phi$. A firm that can reset at time t chooses $P_t^{\#}$ to maximize the expected discounted stream of real profits subject to the demand constraint, where period-t nominal profits are

$$P_t(i)\mathbf{Y}_t(i) - W_t N_t(i).$$

The optimal pricing decision under Calvo stickiness leads to the standard New Keynesian Phillips Curve (NKPC) after log-linearization.

Policy and Money Dynamics. The growth rate of real money balances is defined as

$$g_t = m_t - m_{t-1} + \pi_t,$$

where $m_t = \ln M_t - \ln P_t$ denotes the (log) real money balance and π_t the inflation rate. The monetary authority adjusts the growth rate of real money balances g_t in response to deviations of inflation and the output gap from their steady states, subject to a persistent monetary policy shock ξ_t. The money-growth rule is given by

$$g_t = \phi_\pi \pi_t + \phi_x x_t + \xi_t,$$

where ϕ_π and ϕ_x are policy response coefficients, and ξ_t evolves according to the process specified in (8).

Since this framework is standard, we omit the full set of equilibrium conditions, log-linearization steps, and system reduction, and refer interested readers to Galí (2015) and Woodford (2003) for details. We present below only the resulting endogenous inflation and nominal interest rate processes obtained after log-linearization.

Proposition 2 (Endogenous Inflation and Nominal Rate Processes) *Under the New Keynesian block in Section B.6, the output gap admits a two–state representation:*

$$x_t = \theta_x^a\, a_t + \theta_x^\xi\, \xi_t, \tag{33}$$

with loadings

$$\theta_x^a = \frac{\sigma(1+\chi)\big(1+\rho_a(r^\$-1)\big)}{\sigma(r^\$-1)(\sigma+\chi)} \left\{ \frac{1}{1-r^\$} - \left[1 + \frac{r^\$\,\phi_x}{\sigma(1-r^\$)(\rho_a-1)}\right]\rho_a - \frac{r^\$(\phi_\pi-\rho_a)-(1-\rho_a)}{\sigma(1-r^\$)(\rho_a-1)}\, \frac{\gamma\,\rho_a}{1-\beta\rho_a} \right\}^{-1},$$

$$\theta_x^\xi = \frac{r^\$\,\rho_\xi}{\sigma(1-r^\$)(\rho_\xi-1)} \left\{ \frac{1}{1-r^\$} - \left[1 + \frac{r^\$\,\phi_x}{\sigma(1-r^\$)(\rho_\xi-1)}\right]\rho_\xi - \frac{r^\$(\phi_\pi-\rho_\xi)-(1-\rho_\xi)}{\sigma(1-r^\$)(\rho_\xi-1)}\, \frac{\gamma\,\rho_\xi}{1-\beta\rho_\xi} \right\}^{-1}.$$

Inflation and the nominal interest rate are linear in the state variables (a_t, ξ_t):

$$\pi_t = \theta_\pi^a\, a_t + \theta_\pi^\xi\, \xi_t, \qquad r_t^\$ = \theta_{r^\$}^a\, a_t + \theta_{r^\$}^\xi\, \xi_t, \tag{34}$$

with coefficients

$$\theta_\pi^a = \frac{\gamma}{1-\beta\rho_a}\,\theta_x^a, \qquad \theta_\pi^\xi = \frac{\gamma}{1-\beta\rho_\xi}\,\theta_x^\xi,$$

$$\theta_{r^\$}^a = \sigma\theta_x^a(\rho_a-1) + \rho_a\theta_\pi^a + 1, \qquad \theta_{r^\$}^\xi = \sigma\theta_x^\xi(\rho_\xi-1) + \rho_\xi\theta_\pi^\xi.$$

Proof. We solve the log-linearized New Keynesian system using the method of undetermined coefficients. Start from money demand (14), expressed in terms of the output gap and the natural real rate:

$$m_t = \sigma\big(x_t + \mathbf{y}_t^f\big) + \frac{r^\$ - 1}{r^\$}\, r_t^\$ = \sigma\left(x_t + \frac{1+\chi}{\sigma+\chi}\, a_t\right) + \frac{r^\$ - 1}{r^\$}\, r_t^\$,$$

and, using the standard relationship between the natural real rate and productivity (see, e.g., Galí (2015)),

$$r_t^f = \frac{\sigma(1+\chi)(\rho_a - 1)}{\sigma+\chi}\, a_t,$$

we obtain the convenient form:

$$m_t = \sigma\left(x_t + \frac{1}{\sigma(\rho_a - 1)}\, r_t^f\right) + \frac{r^\$ - 1}{r^\$}\, r_t^\$. \tag{35}$$

We conjecture linear laws of motion in the state variables (r_t^f, ξ_t):

$$\pi_t = \theta_\pi^f r_t^f + \theta_\pi^\xi \xi_t, \qquad x_t = \theta_x^f r_t^f + \theta_x^\xi \xi_t, \qquad m_t = \theta_m^f r_t^f + \theta_m^\xi \xi_t.$$

From the New Keynesian Phillips Curve (13), we have:

$$\theta_\pi^f(1 - \beta\rho_a) = \gamma\theta_x^f, \qquad \theta_\pi^\xi(1 - \beta\rho_\xi) = \gamma\theta_x^\xi,$$

implying

$$\theta_\pi^f = \frac{\gamma}{1 - \beta\rho_a}\, \theta_x^f, \qquad \theta_\pi^\xi = \frac{\gamma}{1 - \beta\rho_\xi}\, \theta_x^\xi. \tag{36}$$

Next, combining the money-growth identity (15) with the policy rule (16) yields:

$$\mathbb{E}_t\pi_{t+1} = \phi_\pi \mathbb{E}_t\pi_{t+1} + \phi_x \mathbb{E}_t x_{t+1} + \mathbb{E}_t\xi_{t+1} - \big(\mathbb{E}_t m_{t+1} - m_t\big),$$

which, after substituting the linear conjectures and rearranging, gives:

$$\big[(\phi_\pi - 1)\tfrac{\gamma\rho_a}{1-\beta\rho_a} + \phi_x\rho_a\big]\theta_x^f = (\rho_a - 1)\theta_m^f, \tag{37}$$

$$\big[(\phi_\pi - 1)\tfrac{\gamma\rho_\xi}{1-\beta\rho_\xi} + \phi_x\rho_\xi\big]\theta_x^\xi = (\rho_\xi - 1)\theta_m^\xi - \rho_\xi. \tag{38}$$

Using the IS curve (12) and substituting for $r_t^\$$ via (35) yields two linear equations in (θ_x^f, θ_m^f) and $(\theta_x^\xi, \theta_m^\xi)$, respectively:

$$\left[\frac{1}{1 - r^\$} - \rho_a\left(1 + \tfrac{\phi_x}{\sigma}\right) - \tfrac{\phi_\pi}{\sigma}\tfrac{\gamma\rho_a}{1-\beta\rho_a}\right]\theta_x^f = \tfrac{1}{\sigma}\left(1 - \rho_a - \tfrac{r^\$}{r^\$-1}\right)\theta_m^f + \tfrac{1+\rho_a(r^\$-1)}{\sigma(r^\$-1)(\rho_a-1)}, \tag{39}$$

$$\left[\frac{1}{1 - r^\$} - \rho_\xi\left(1 + \tfrac{\phi_x}{\sigma}\right) - \tfrac{\phi_\pi}{\sigma}\tfrac{\gamma\rho_\xi}{1-\beta\rho_\xi}\right]\theta_x^\xi = \tfrac{1}{\sigma}\left(\tfrac{1}{1-r^\$} - \rho_\xi\right)\theta_m^\xi + \tfrac{\rho_\xi}{\sigma}. \tag{40}$$

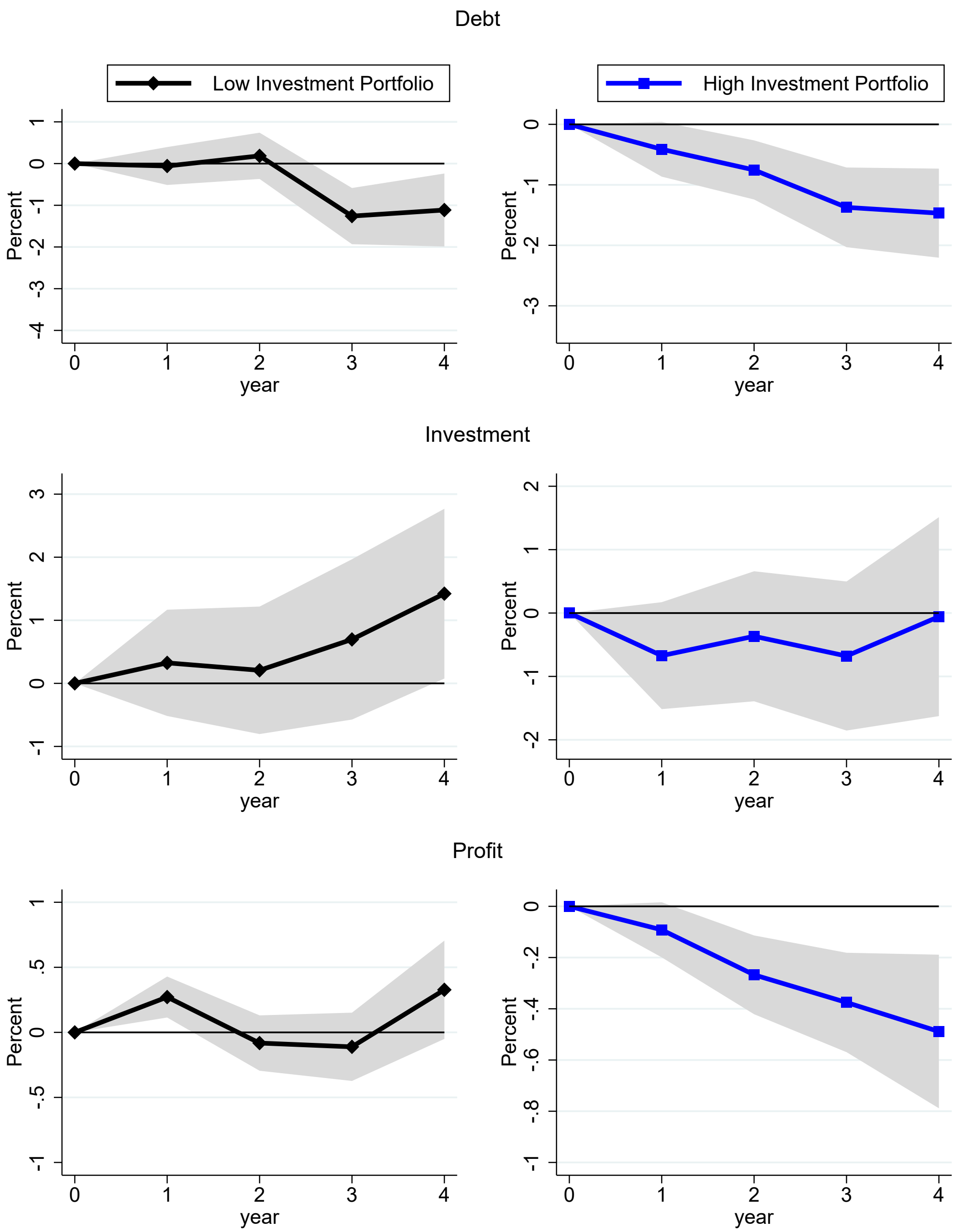
Solving equations (37)–(39) yields θ_x^f, and equations (38)–(40) yield θ_x^ξ. Converting from r_t^f to productivity using $r_t^f = \frac{\sigma(1+\chi)(\rho_a-1)}{\sigma+\chi} a_t$ provides the stated expression for θ_x^a, while θ_x^ξ is already expressed in terms of ξ_t. Equation (36) then gives $(\theta_\pi^a, \theta_\pi^\xi)$.

Finally, from the IS curve,

$$r_t^\$ = \sigma\big(x_t - \mathbb{E}_t x_{t+1}\big) + \mathbb{E}_t\pi_{t+1} + r_t^f,$$

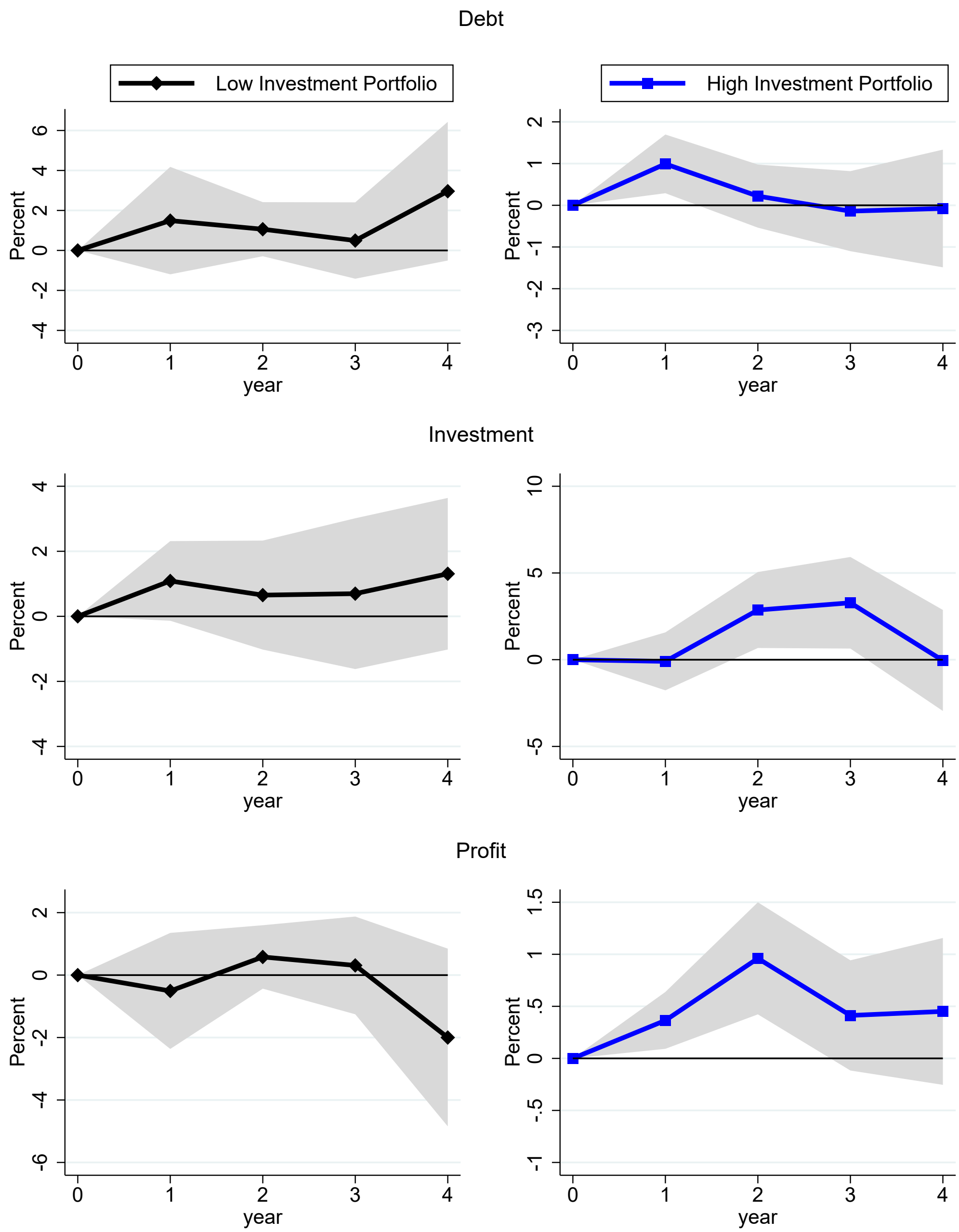
collecting the coefficients on a_t and ξ_t yields the stated $(\theta_{r^\$}^a, \theta_{r^\$}^\xi)$. ∎

Figure A.2: Responses of SOEs to MS shock



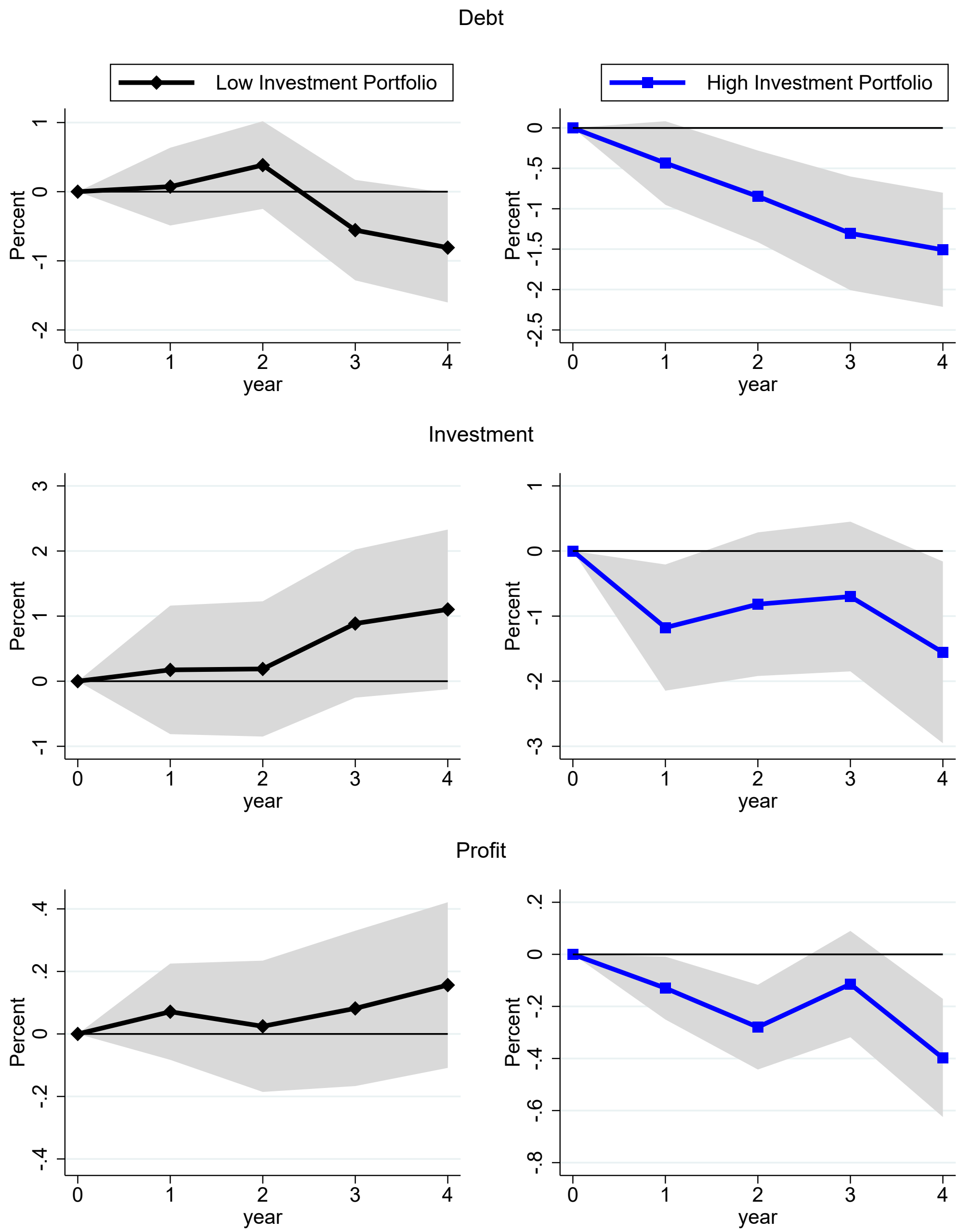
This figure reports the coefficient b over years t from a panel OLS regressions $\Pi_{i,t+h} = a + b \times M2_t + \varepsilon_{i,t},\ h = 0,1,2,3,4$ using SOEs sample. Where $\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t, or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). MS is the monetary supply shocks. The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. Dashed areas represent 90% confidence intervals.

Figure A.3: Responses of POEs to MS shock



This figure reports the coefficient b over years t from a panel OLS regressions $\Pi_{i,t+h} = a + b \times M2_t + \varepsilon_{i,t},\ h = 0, 1, 2, 3, 4$ using POEs sample. Where $\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t, or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). MS is the monetary supply shocks. The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. Dashed areas represent 90% confidence intervals.

Figure A.4: Responses of SOEs to M2 shock



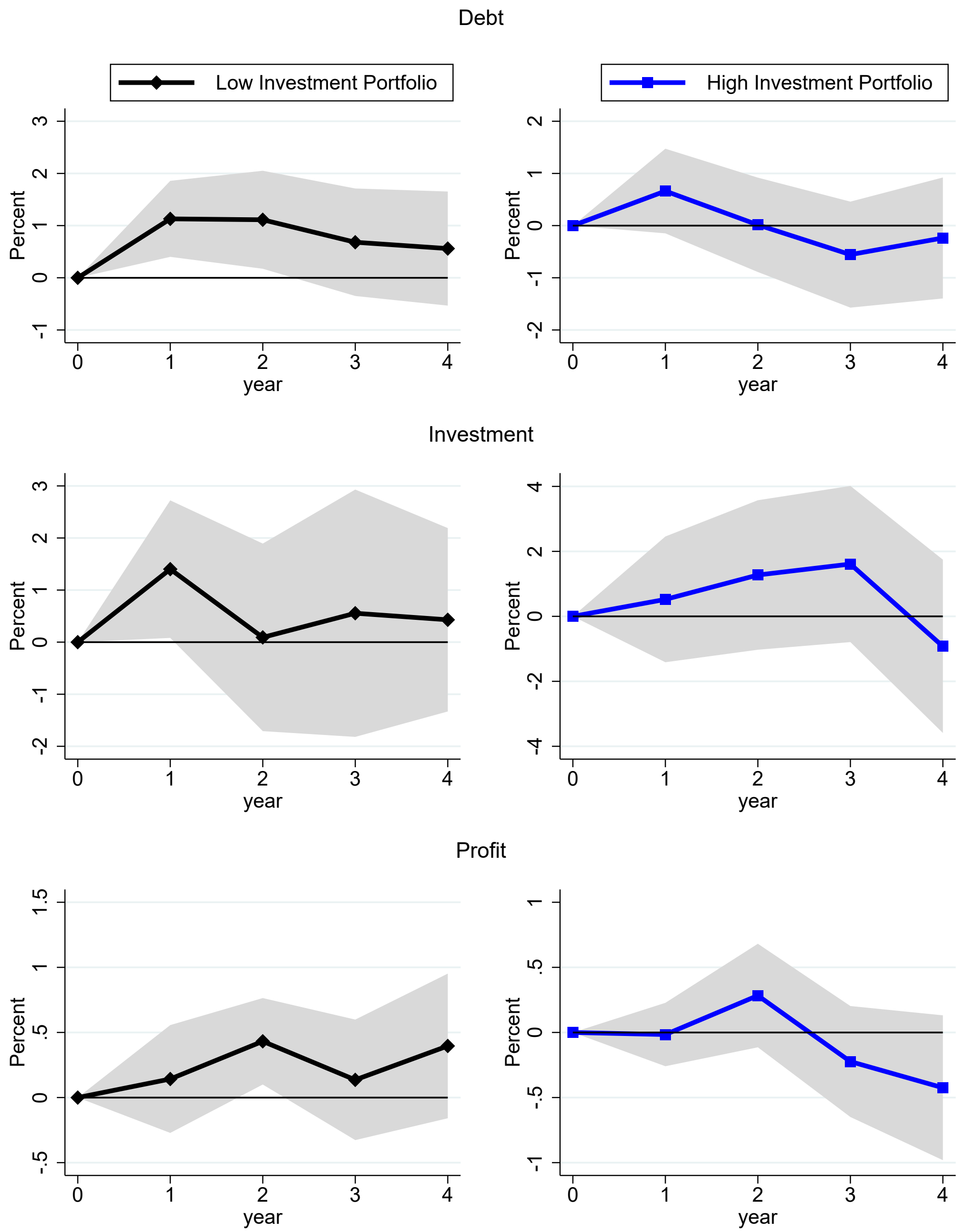
This figure reports the coefficient b over years t from a panel OLS regressions $\Pi_{i,t+h} = a + b \times M2_t + \varepsilon_{i,t},\ h = 0, 1, 2, 3, 4$ using SOEs sample. Where $\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t, or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). $M2$ is the monetary supply shock constructed by CRZ. The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. Dashed areas represent 90% confidence intervals.

Table A.1: Statistics of the aggregate variables

	STD	AR(1)
GDP	2.36	0.96
Investment	8.85	0.89
Consumption	2.80	0.98
Debt	5.56	0.80
M2	5.47	0.87
M2 shock	1.53	0.75
MS shock	1.68	0.99

This table reports the statistics of the aggregate variables. GDP is the real year-on-year growth rate of Gross National Product. Investment is the real year-on-year growth rate of the completed investment in fixed assets of the whole society. Consumption is the real year-on-year growth rate of total retail sales of consumer goods. Debt is the real year-on-year growth rate of the sum of the total debt of the firms used in our paper. STD is standard deviation, and AR(1) is the regression coefficient of the first order autoregressive.

Figure A.5: Responses of POEs to M2 shock



This figure reports the coefficient b over years t from a panel OLS regressions $\Pi_{i,t+h} = a + b \times M2_t + \varepsilon_{i,t},\ h = 0, 1, 2, 3, 4$ using POEs sample. Where $\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t, or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). $M2$ is the monetary supply shock constructed by CRZ. The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. Dashed areas represent 90% confidence intervals.

Table A.2: Correlation of the aggregate variables

	GDP	Investment	Consumption	Debt	M2	M2 shock	MS shock
GDP	1.00						
Investment	0.66	1.00					
Consumption	0.57	0.85	1.00				
Debt	0.50	0.76	0.81	1.00			
M2	0.40	0.84	0.82	0.88	1.00		
M2 shock	0.48	0.74	0.83	0.61	0.65	1.00	
MS shock	0.61	0.78	0.86	0.67	0.61	0.83	1.00

This table reports the correlation of the aggregate variables. GDP Growth is the real year-on-year growth rate of Gross National Product. Investment Growth is the real year-on-year growth rate of the completed investment in fixed assets of the whole society. Consumption Growth is the real year-on-year growth rate of total retail sales of consumer goods. Debt Growth is the real year-on-year growth rate of the sum of the total debt of the firms used in our paper.

Table A.3: Relationship with macroeconomic shocks

	ΔTFP	ΔISI	ΔCS	ΔEP	ΔBM	ΔTQ
MS shock	-0.08	0.11	-0.02	-0.13	-0.15	0.05
p-value	0.78	0.70	0.95	0.66	0.62	0.86
M2 shock	-0.11	-0.14	0.14	0.02	0.05	-0.16
p-value	0.72	0.62	0.66	0.95	0.87	0.59

This table reports the correlation of other shocks. We consider the following proxies of time-varying investment opportunities: the change in the aggregate TFP of the firms used in our paper (ΔTFP), the change in China investor sentiment index (ΔISI), the change in credit spread between corporate bond yields and China government bonds yield (ΔCS), the changes in the aggregate earnings-to-price ratio, book-to-market ratio, and Tobin's Q of the firms used in our paper (ΔEP, ΔBM, and ΔTQ) .

Table A.4: Stock return predictability and ownership structure

	1	2	3	4
IK	-0.23		-0.11	-0.36
[t]	-1.53		-0.68	-2.54
IK× SOE			-0.39	-0.44
[t]			-2.12	-2.45
SOE		-0.54	-0.24	-0.49
[t]		-2.82	-1.08	-2.59
Constant	1.95	-8.38	2.09	-8.69
[t]	2.17	-2.98	2.23	-3.11
N	285,891	285,477	285,891	285,477
R^2	0.00	0.06	0.01	0.06
Controls	No	Yes	No	Yes

The table reports the estimated average slopes in the equation below from Fama-MacBeth (1973) cross-sectional regressions:

$$r_{i,t} = a + b \times IK_{i,t-1} + c \times IK_{i,t-1} \times SOE_{i,t-1} \\ + d \times SOE_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

in which $r_{i,t}$is the firm i monthly stock return and $IK_{i,t-1}$ is the lagged values of firm i's investment, $SOE_{i,t-1}$ is a dummy variable that is equal to one if firm i is state-owned firm at time $t-1$. $Controls_{i,t-1}$ are firm-level control variables including size, ROA, leverage ratio, wage-to-profit ratio, and industry dummy × time. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). R^2 is the average of regression R-squares. The investment rate is winsorized at the top and bottom 0.5 percent in each cross section to decrease the influence of outliers. The estimates of the control variables' coefficients are omitted. The coefficients b and c are multiplied by 100. N is the total number of firm-month observations. The sample is from July 2004 to June 2019.

Table A.5: Characteristics of investment portfolios across SOEs and POEs

	Data					Model				
	Panel A. SOE									
	L	M	H	L-H	Avg	L	M	H	L-H	Avg
IK_t	0.051	0.124	0.178	-0.126	0.118	0.021	0.155	0.232	-0.211	0.136
TFP_t	0.391	0.454	0.472	-0.082	0.439	0.704	1.002	1.473	-0.769	1.060
ΔD_t	0.023	0.045	0.063	-0.040	0.043	0.012	0.058	0.077	-0.065	0.049
Leverage_t	0.514	0.527	0.551	-0.037	0.531	0.270	0.275	0.293	-0.023	0.279
	Panel B. POE									
	L	M	H	L-H	Avg	L	M	H	L-H	Avg
IK_t	0.051	0.165	0.223	-0.171	0.146	0.025	0.144	0.325	-0.300	0.165
TFP_t	0.423	0.490	0.512	-0.089	0.475	0.668	1.012	1.659	-0.991	1.113
ΔD_t	0.022	0.056	0.067	-0.045	0.048	0.022	0.035	0.073	-0.051	0.043
Leverage_t	0.470	0.445	0.438	0.033	0.451	0.318	0.329	0.323	-0.005	0.323

This table reports the averages of the 3 portfolios one-way sorted on investment rate for SOE and POE firms. IK is the investment rate; TFP is the total factor productivity estimated following Imrohoroglu and Tuzel (2014); ΔD is the change in total debt at time t divided by the average of total capital at time t and $t-1$; Leverage ratio is total-debt-to-total-asset ratio; L, M, and H stand for the low, median, and high investment portfolios, respectively. L-H stands for the low-minus-high investment portfolio. Avg refers to the average value for a particular characteristic across L, M, H portfolios. The subscripts t stands for portfolio-level characteristics measured at the time of portfolio formation. This table constructs the average characteristics for each portfolio by first computing the median of each characteristic across all firms in the portfolio in a given year, and then reports the corresponding time series averages.

Table A.6: The price of risk of M2 shock

	Data		Model	
	CAPM	2-Factor	CAPM	2-Factor
MKT	0.36	0.68	1.21	0.84
[t]	1.54	1.47	31.81	4.87
M2		0.70		0.17
[t]		2.19		4.48
R^2	5.41	35.22	19.24	96.03
MAE	4.32	3.35	2.56	0.56

This table reports the GMM asset pricing tests of the following two-factor model $E[r_{i,t}^e] = \alpha_i + b_{MKT}Cov(MKT_t, r_{i,t}^e) + b_{M2}Cov(M2_t, r_{i,t}^e)$, in which MKT is the market factor, and M2 is the monetary supply shock constructed by CRZ (the CAPM model is the restricted case in which b_M2 =0). b_{MKT} denotes the risk factor loading of the market factor. b_{M2} denotes the risk factor loading of M2 shock. The test assets are SOE 3-IK portfolios, five SOE size, and five SOE BM portfolios. MAE denotes the mean absolute error of the pricing errors. All the portfolio returns are annual returns. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). R^2 is the regression R-squares adjusted for the degree of freedom. The sample is from 2004 o 2018. The results for the model part (column "Model") are obtained from 500 samples of simulated data, each with 3,000 firms for both types and 100 quarterly observations.

Table A.7: Asset pricing tests of M2 shock

	SOE										POE									
	Data					Model					Data					Model				
	L	M	H	L-H	All	L	M	H	L-H	All	L	M	H	L-H	All	L	M	H	L-H	All
α^{2F}	2.01	1.93	-0.27	2.28	0.16	0.10	-1.01	-0.23	0.33	-0.38	-0.85	1.84	2.48	-3.33	0.33	2.37	2.61	2.35	0.02	2.44
[t]	0.67	0.80	-0.17	0.67	0.70	0.06	-1.20	-0.41	0.30	-0.52	-0.20	1.11	0.97	-0.52	0.78	4.54	5.75	3.29	0.03	4.54
Cov^{MKT}	22.42	22.53	22.94	-0.52	22.50	13.92	11.25	9.51	4.41	11.56	27.78	24.30	24.14	3.64	25.17	6.69	6.29	6.52	0.17	6.50
[t]	1.98	1.76	1.83	0.40	1.81	3.30	3.35	3.45	-2.81	3.37	2.03	2.09	2.09	-1.60	2.08	7.52	7.61	7.53	-0.73	7.55
Cov^{M2}	-0.16	-4.83	-5.11	4.95	-4.19	3.96	-2.11	-2.37	6.33	-0.17	7.26	7.38	6.63	0.63	6.90	-0.25	-0.77	0.91	-1.16	-0.04
[t]	-0.04	-1.69	-1.62	2.15	-1.44	2.27	-2.99	-1.57	1.96	-0.76	1.89	2.42	2.82	0.17	2.53	-0.42	-4.13	1.52	-0.99	-1.01

This table reports the asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}Cov(MKT_t, r^e_{i,t}) + b_{M2}Cov(M2_t, r^e_{i,t})$, in which MKT is the market factor, and M2 is the monetary supply shock constructed by CRZ (the CAPM model is the restricted case in which b_{M2} =0). b_{MKT} denotes the risk factor loading of the market factor. b_{M2} denotes the risk factor loading of M2 shock. Estimation is by GMM, and the test assets are the six 2-sectors × 3-IK portfolios. α^{2F} is the two-factor model alpha, Cov^{MKT} is the multivariate covariance between the portfolio returns and the market factor, and Cov^{M2} is the covariance between the portfolio returns and M2 shock. The data sample is annual from 2004 to 2018. The results for the model part (column "Model") are obtained from 1500 samples of simulated data, each with 3,000 firms for both types and 100 quarterly observations. L-H stands for the low-minus-high investment portfolio.

Table A.8: Debt growth, investment, and profits responses to M2 shock

	Panel A. SOE			
	$\Delta \mathrm{D}_t$	$\Delta \mathrm{IK}_t$	$\Delta \mathrm{CF}_t$	$\Delta \mathrm{CF}_{t+1}$
$M2$	0.54	0.86	0.09	0.17
[t]	2.17	1.97	1.12	1.95
$P2 \times M2$	-0.66	-0.79	-0.08	-0.08
[t]	-2.04	-1.48	-0.84	-0.69
$P3 \times M2$	-0.77	-1.78	0.06	-0.22
[t]	-2.23	-2.84	0.59	-2.01
N	11,413	11,406	11,163	10,016
R^2	0.21	0.29	0.07	0.02
	Panel B. POE			
	$\Delta \mathrm{D}_t$	$\Delta \mathrm{IK}_t$	$\Delta \mathrm{CF}_t$	$\Delta \mathrm{CF}_{t+1}$
$M2$	0.79	0.33	0.37	0.46
[t]	2.51	0.55	2.13	3.13
$P2 \times M2$	-0.49	0.55	-0.03	-0.02
[t]	-1.21	0.71	-0.18	-0.11
$P3 \times M2$	-0.02	-0.15	0.24	-0.01
[t]	-0.05	-0.17	1.24	-0.05
N	9,387	9,385	9,260	7,662
R^2	0.09	0.31	0.04	0.02

This table reports the relevant slope coefficients from a panel ols regressions of the form:

$$\Pi_{i,t+h} = a + b \times \Pi_{i,t-1} + c \times M2_t + \sum_{j=2}^{3} (d_j \times Pj_t + e_j \times Pj_t \times M2_t) + \varepsilon_{i,t}, \;\; h = 0, 1,$$

$\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t,or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). $M2$ is the monetary supply shock constructed by CRZ. $Pj_t$is the investment rate portfolios $j = 2,\ 3$ quintile dummy, respectively; The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). N is the total number of firm-year observations. R^2 is the regression R-squares adjusted for degree of freedom. All dependent variables are winsorized at the top and bottom 1 percent in each year to decrease the influence of outliers. The sample period in the real data is 2004 to 2018.

Table A.9: Interest rate responses to MS and M2 shocks

	MS		M2	
	Panel A. SOE			
	R_t	R_t	R_t	R_t
S	-0.01	-0.01	-0.07	-0.13
[t]	-0.91	-1.30	-0.59	-1.17
$P2 \times S$	0.01	0.01	0.26	0.22
[t]	0.51	0.65	1.60	1.37
$P3 \times S$	-0.00	0.00	-0.25	-0.11
[t]	-0.09	0.43	-1.58	-0.77
N	619	594	619	594
R^2	0.02	0.13	0.03	0.13
Controls	No	Yes	No	Yes
	Panel B. POE			
	R_t	R_t	R_t	R_t
S	-0.00	-0.01	-0.25	-0.40
[t]	-0.24	-0.36	-1.09	-1.61
$P2 \times S$	-0.01	-0.02	0.11	0.22
[t]	-0.38	-0.73	0.39	0.73
$P3 \times S$	0.01	0.00	0.25	0.48
[t]	0.27	0.17	0.79	1.51
N	619	594	619	594
R^2	0.02	0.12	0.03	0.13
Controls	No	Yes	No	Yes

This table reports the relevant slope coefficients from a panel ols regressions of the form:

$$R_{i,t+h} = a + b \times S_t + \sum_{j=2}^{3} (c_j \times Pj_t + d_j \times Pj_t \times S_t) + \varepsilon_{i,t},\ h = 0, 1,$$

$R_{i,t}$ is the difference between firm's i loan interest rate and the bank benchmark interest rate at time t. S is MS shock or M2 shock. Pj_t is the investment rate portfolios $j = 2,\ 3$ quintile dummy, respectively; The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). N is the total number of firm-year observations. R^2 is the regression R-squared adjusted for degree of freedom. All dependent variables are winsorized at the top and bottom 1 percent in each year to decrease the influence of outliers.

Table A.10: Debt growth, investment, and profits responses to shadow banking (SB) shock

		Panel A. SOE		
	$\Delta \mathrm{D}_t$	$\Delta \mathrm{IK}_t$	$\Delta \mathrm{CF}_t$	$\Delta \mathrm{CF}_{t+1}$
SB	0.04	0.03	0.03	-0.01
[t]	2.67	1.05	6.01	-2.59
$P2 \times SB$	0.02	0.00	-0.01	0.02
[t]	1.03	0.09	-1.85	2.56
$P3 \times SB$	-0.02	-0.03	0.00	0.01
[t]	-1.28	-0.80	-0.53	1.92
N	11,413	11,406	11,163	10,016
R^2	0.21	0.29	0.08	0.02
		Panel B. POE		
	$\Delta \mathrm{D}_t$	$\Delta \mathrm{IK}_t$	$\Delta \mathrm{CF}_t$	$\Delta \mathrm{CF}_{t+1}$
SB	0.08	-0.02	0.06	-0.02
[t]	3.56	-0.37	5.43	-1.68
$P2 \times SB$	-0.01	-0.02	-0.03	0.01
[t]	-0.20	-0.35	-2.49	0.74
$P3 \times SB$	0.00	0.07	-0.01	-0.01
[t]	0.09	1.09	-0.94	-0.67
N	9,387	9,385	9,260	7,662
R^2	0.09	0.31	0.04	0.01

This table reports the relevant slope coefficients from a panel ols regressions of the form:

$$\Pi_{i,t+h} = a + b \times \Pi_{i,t-1} + c \times SB_t + \sum_{j=2}^{3} (d_j \times Pj_t + e_j \times Pj_t \times SB_t) + \varepsilon_{i,t},\ \ h = 0, 1,$$

$\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t,or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). SB is the first difference of the growth rate of China's shadow banking. $Pj_t$is the investment rate portfolios $j = 2,\ 3$ quintile dummy, respectively; The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). N is the total number of firm-year observations. R^2 is the regression R-squares adjusted for degree of freedom. All dependent variables are winsorized at the top and bottom 1 percent in each year to decrease the influence of outliers. The sample period in the real data is 2004 to 2018.

Table A.11: Investment portfolios across SOEs and POEs using 5-IK portfolios

	SOE							POE						
	L	2	M	4	H	L-H	All	L	2	M	4	H	L-H	All
							Panel A. Excess Returns							
r^e	13.71	15.63	11.45	11.11	9.53	4.17	11.71	18.83	17.55	18.03	19.08	16.45	2.38	18.62
[t]	1.27	1.40	1.00	1.00	0.88	2.07	1.04	1.53	1.35	1.62	1.74	1.44	0.61	1.55
SR	0.44	0.47	0.34	0.35	0.29	0.37	0.37	0.49	0.47	0.50	0.54	0.46	0.16	0.52
							Panel B. CAPM							
α	3.15	4.59	0.81	0.94	-1.61	4.76	1.22	6.16	4.87	5.85	7.00	4.03	2.13	6.24
[t]	1.28	1.67	0.21	0.29	-0.70	2.33	0.49	1.67	1.38	1.68	2.19	1.36	0.54	2.45
b	0.94	0.99	0.95	0.91	1.00	-0.05	0.94	1.13	1.13	1.09	1.08	1.11	0.02	1.11
[t]	21.27	27.21	21.05	19.75	26.63	-1.14	24.21	29.28	26.24	30.67	33.06	34.07	0.62	41.43
R^2	0.88	0.83	0.76	0.77	0.89	0.02	0.85	0.83	0.88	0.88	0.89	0.91	0.00	0.91

Panels A and B report the average excess stock returns and the CAPM alphas (abnormal returns) of five one-way sorted on investment rate portfolios of the SOE sector (left panel) and the POE sector (right panel). r^e is the average annualized ($\times$1200) portfolio excess stock return; [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). SR is the portfolio Sharpe ratio; α and b are the portfolio average CAPM alpha (reported in annual percentage($\times$1200)) and market beta, obtained as the intercept and slope coefficient from monthly CAPM regressions. L, 2, M, 4, and H stand for the low, second, median, fourth, and high investment portfolios, respectively. L-H stands for the low-minus-high investment portfolio.

Table A.12: Asset pricing tests across SOEs and POEs–5-IK portfolios

	MS Shock							M2 Shock						
	L	2	M	4	H	L-H	All	L	2	M	4	H	L-H	All
Panel A. SOE														
α^{2F}	0.95	4.21	3.66	-0.45	-0.08	1.03	0.16	1.96	1.5	2.31	-1.19	-0.11	2.06	0.16
[t]	0.53	0.99	1.43	-0.19	-0.06	0.5	0.41	0.91	0.48	0.97	-0.41	-0.07	1.37	0.70
Cov^{MKT}	23.30	25.00	25.57	26.11	25.15	-1.85	24.63	21.63	23.11	22.60	23.55	22.74	-1.11	22.50
[t]	1.91	1.94	1.75	1.76	1.88	-1.53	1.78	1.95	1.96	1.73	1.78	1.91	-1.25	1.81
Cov^{S}	1.18	-2.11	-8.92	-2.97	-6.99	8.17	-5.78	0.38	1.26	-6.59	-1.15	-4.79	5.17	-4.19
[t]	0.61	-0.74	-1.74	-0.94	-2.16	3.48	-0.77	0.10	0.35	-2.14	-0.31	-1.66	3.55	-1.44
Panel B. POE														
α^{2F}	3.37	0.17	2.2	2.98	-0.96	4.33	0.58	-0.01	1.54	3.38	2.18	-0.44	0.43	0.33
[t]	1.48	0.09	1.32	1.56	-0.63	1.22	1.09	0	0.84	1.46	1.1	-0.84	0.09	0.78
Cov^{MKT}	27.14	28.80	24.69	24.67	26.62	0.52	25.94	27.05	26.56	24.06	23.02	25.75	1.30	25.17
[t]	2.09	1.89	2.09	1.99	1.92	0.47	1.97	2.26	2.15	2.30	2.32	2.20	2.21	2.08
Cov^{S}	-0.49	5.11	7.16	7.94	8.48	-8.97	5.23	11.98	10.05	11.92	11.04	12.45	-0.47	6.90
[t]	-0.11	1.22	1.47	2.11	2.99	-3.15	0.65	2.94	2.64	2.95	3.04	3.44	-0.28	2.53

This table reports the asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}Cov(MKT_t, r^e_{i,t}) + b_S Cov(S_t, r^e_{i,t})$, in which MKT is the market factor, and S refers to MS or M2 shock. α^{2F} is the two-factor model alpha, Cov^{MKT} is the multivariate covariance between the portfolio returns and the market factor, and Cov^S is the covariance between the portfolio returns and M2 or MS shock. The data sample is annual from 2004 to 2018 for both panel A (five investment sorted portfolios for SOEs) and B (five investment sorted portfolios for POEs). L, 2, M, 4, and H stand for the low, second, median, fourth, and high investment portfolios, respectively. L-H stands for the low-minus-high investment portfolio.

Table A.13: The price of risk of 5-IK portfolios

	MS shock		M2 shock	
	CAPM	2-Factor	CAPM	2-Factor
MKT	0.29	0.24	0.39	0.68
[t]	1.11	0.93	1.67	1.50
S		0.63		0.68
[t]		1.93		2.20
R^2	0.02	29.22	3.94	35.70
MAE	2.97	2.49	4.31	3.11

This table reports the GMM asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}Cov(MKT_t, r^e_{i,t}) + b_S Cov(S_t, r^e_{i,t})$, in which MKT is the market factor, and S is MS shock or M2 shock (the CAPM model is the restricted case in which b_S =0). b_{MKT} denotes the risk factor loading of the market factor. b_S denotes the risk factor loading of S is MS shock or M2 shock. The test assets are SOE 5-IK portfolios, five SOE size, and five SOE BM portfolios. MAE denotes the mean absolute error of the pricing errors. All the portfolio returns are annual returns. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). R^2 is the regression R-squares adjusted for the degree of freedom. The sample is from 2004 o 2018.

Table A.14: Debt growth, investment and profits responses to MS or M2 shocks using 5-IK portfolios

	MS shock				M2 shock			
	Panel A. SOE							
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
S	0.80	0.61	0.16	0.20	0.83	0.65	0.10	0.27
[t]	3.33	1.49	2.10	2.40	2.56	1.14	0.95	2.34
$P2 \times S$	-0.40	-0.15	-0.06	-0.29	-0.59	-0.25	-0.09	-0.23
[t]	-1.23	-0.27	-0.58	-2.29	-1.39	-0.34	-0.66	-1.49
$P3 \times S$	-0.98	-0.30	-0.09	-0.21	-1.44	-0.34	-0.11	-0.21
[t]	-2.97	-0.58	-0.89	-1.87	-3.30	-0.47	-0.84	-1.47
$P4 \times S$	-0.76	-0.87	0.04	-0.23	-0.76	-0.98	-0.03	-0.16
[t]	-2.41	-1.74	0.39	-2.18	-1.84	-1.40	-0.22	-1.17
$P5 \times S$	-1.03	-1.45	0.07	-0.27	-1.12	-2.20	0.09	-0.28
[t]	-3.01	-2.39	0.66	-2.48	-2.49	-2.67	0.67	-1.93
N	11,413	11,406	11,163	10,016	11,413	11,406	11,163	10,016
R^2	0.21	0.32	0.07	0.01	0.21	0.32	0.07	0.01
	Panel B. POE							
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
S	0.48	0.44	0.53	0.32	1.08	0.30	0.38	0.28
[t]	1.52	0.80	3.65	2.09	2.58	0.40	1.67	1.46
$P2 \times S$	-0.48	-0.62	-0.14	0.23	-1.00	-0.21	-0.04	0.44
[t]	-1.12	-0.81	-0.71	1.05	-1.79	-0.20	-0.15	1.68
$P3 \times S$	0.19	0.56	-0.27	-0.05	-0.31	0.87	-0.11	0.02
[t]	0.45	0.77	-1.55	-0.25	-0.56	0.88	-0.45	0.10
$P4 \times S$	-0.51	-0.25	-0.05	0.06	-1.32	-0.14	0.12	0.27
[t]	-1.23	-0.34	-0.27	0.33	-2.44	-0.14	0.48	1.09
$P5 \times S$	0.43	-0.52	0.08	0.14	0.06	-0.18	0.22	0.17
[t]	0.93	-0.61	0.40	0.67	0.10	-0.16	0.85	0.69
N	9,387	9,385	9,260	7,662	9,387	9,385	9,260	7,662
R^2	0.09	0.34	0.04	0.02	0.09	0.34	0.04	0.02

This table reports the relevant slope coefficients from a panel OLS regressions of the form:

$$\Pi_{i,t+h} = a + b \times \Pi_{i,t-1} + c \times S_t + \sum_{j=2}^{5} (d_j \times Pj_t + e_j \times Pj_t \times S_t) + \varepsilon_{i,t},\ h = 0, 1,$$

$\Pi_{i,t+h}$ is the first difference of the change in firm's i total debt at time t divided by the average of total capital at time t and $t-1$ (the first difference of firm's i investment rate at time t,or the change in firm's i EBIT at time t divided by the average of total capital at time t and $t-1$). S is MS shock or M2 shock. $Pj_t$is the investment rate portfolios $j = 2, 3, 4,\ 5$ quintile dummy, respectively; The control variables include firm's physical capital to market equity ratio (KM), book capital to market equity ratio (BM), Tobin Q, size and leverage. [t] is heteroscedasticity and autocorrelation consistent t-statistics (Newey-West). N is the total number of firm-year observations. R^2 is the regression R-squares adjusted for degree of freedom. All dependent variables are winsorized at the top and bottom 1 percent in each year to decrease the influence of outliers.

Table A.15: Selected data versus model-implied moments across alternative calibrations

	Inv vol	debt iss spikes	Debt iss vol	Equity iss fraction	Leverage	Inv spread	$\mathbb{E}(R^e)$
Panel A: Counterfactual analysis on POE							
0. Data POE	0.28	0.20	0.18	0.13	0.45	0.00	18.62
1. Baseline POE	0.28	0.19	0.13	0.14	0.44	-0.15	18.46
2. Same investment cost as SOE	0.34	0.13	0.12	0.16	0.41	2.05	8.09
3. Same debt iss cost as SOE	0.21	0.07	0.10	0.09	0.38	-2.64	16.36
4. Same collateralizability as SOE	0.30	0.28	0.21	0.27	0.61	-3.05	16.29
5. Same equity iss. cost as SOE	0.31	0.15	0.12	0.18	0.42	1.39	15.86
6. High MS risk	0.08	0.05	0.06	0.02	0.44	1.78	23.03
7. Low firm vol.	0.04	0.14	0.04	0.06	0.45	0.37	13.39
8. Pseudo GE	0.24	0.22	0.12	0.16	0.43	-1.51	18.65
Panel B: Counterfactual analysis on SOE							
9. Data SOE	0.20	0.15	0.14	0.16	0.53	5.58	11.71
10. Baseline SOE	0.20	0.16	0.14	0.14	0.54	5.37	11.01
11. High MS risk	0.19	0.10	0.14	0.09	0.55	7.64	14.76
12. Low firm vol.	0.05	0.10	0.05	0.07	0.56	1.59	10.19
13. Pseudo GE	0.23	0.14	0.15	0.14	0.54	5.57	12.34

This table presents selected moments of the cross-sectional investment, debt, and equity issuance dynamics, and return spread between high vs low investment rate sorted portfolios. The table reports the following moments: the cross-sectional standard deviation of the debt issuance rate and that of the firm-level investment rate, the spikes in debt issuance, and equity issuance frequency, leverage, the difference in the return between the portfolios of high and low investment rates (Inv spread), and the value-weighted sector average returns ($\mathbb{E}(R^e)$) . Panel A reports the model fit and counterfactual analysis on POEs. Cases 0 and 1 illustrate the fit of the model compared to the data. Cases 2 to 5 relax the investment and financing frictions of POEs, in which we assume that POEs have the same investment adjustment cost (case 2), identical debt adjustment cost (case 3), the same collateralizability of capital (case 4), and the same equity issuance cost (case 5) as SOEs. Cases 6 to 8 report moments under three experiments: increasing MS risks, reducing cross-sectional volatility of firm productivity, and countercyclical interest rate rule. Panel B conducts similar exercises for SOEs under the same three experiments.