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

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Abstract

We study the role of firm heterogeneity in state ownership and productivity in monetary policy transmission in China. We develop and estimate a dynamic model with heterogeneous firms—state-owned enterprises (SOEs) and privately owned enterprises (POEs)—featuring monetary supply shocks and financial frictions. We show that firms' responses to monetary supply shocks and risk premiums vary substantially both within and across SOEs and POEs, consistent with the data. Through counterfactual analysis, we show that more severe frictions in accessing debt markets for POEs exacerbate capital misallocation in times of contractionary monetary shocks, leading to sizable losses in aggregate productivity and output.

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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 SOEs and POEs respond differently to monetary supply shocks, both within and across sectors. These heterogeneous responses, manifested in firms' real decisions and equilibrium risk premia, are central to understanding 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 linked blocks: a firm investment block and a monetary block. In the firm block, monetary supply (MS) shocks and aggregate productivity shocks constitute the key sources of aggregate risk. Firm heterogeneity arises along two dimensions. First, SOEs and POEs differ in the magnitude of real investment frictions and financial frictions. Second, within each sector, firms differ in idiosyncratic productivity, which generates dispersion in risk premia and in firms' investment and financing responses to MS shocks. A central mechanism is that the cost of issuing debt is stochastic and varies with the aggregate MS shock, capturing the credit-supply effects of Chinese monetary policy: unlike the interest-rate-centered transmission typical of advanced

[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.

economies, monetary policy in China primarily moves the quantity of credit available to firms through the banking system, generating direct fluctuations in firms' debt-financing conditions.

The monetary block follows a canonical New Keynesian specification for nominal dynamics. It combines money demand, a Phillips curve, and an IS equation with a policy rule designed to reflect China's quantity-based framework and an exogenous process for money-supply growth. Given monetary and productivity shocks, the block delivers dynamics for inflation and the nominal interest rate, which we treat as inputs into the firm block. Integrating the two blocks allows us to quantify how monetary policy shocks affect firms' financing and investment decisions and why these effects propagate differently across SOEs and POEs through their distinct 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 relationship 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 premia and firms' 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; in the POE sector, this investment-return spread is close to zero. Second, MS shocks carry a positive price of risk. Periods in which monetary supply tightens are associated with investors' high marginal utility, that is, they are bad economic times, so that firms' return exposure to MS shocks is priced in financial markets and affects equilibrium expected returns. Third, high-investment SOE firms respond countercyclically to MS shocks: even when MS unexpectedly contracts, their stock returns, debt issuance, capital investment, and future profits still increase, making them less exposed to MS shocks, whereas low-investment SOE firms' stock returns are acyclical and their corporate policies are procyclical. In the POE sector, by contrast, stock return responses to MS shocks are procyclical, and corporate policy responses do not vary between high- and low-investment firms.

We then show that the model accounts for 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 less affected by monetary supply shocks due to the SOE sector's easier access to the 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 hits the economy, all firms find it more costly to issue debt. However, high-investment (high-productivity) SOEs 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. The most productive SOEs thus respond countercyclically to the contractionary MS shock, making them less exposed to MS shocks and explaining their relatively lower expected stock returns in equilibrium. By contrast, 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.

In contrast to SOEs, POEs face tighter financing conditions, reflected in higher marginal debt issuance costs, so their debt issuance responds weakly to contractionary MS shocks and is close to acyclical—especially for high-productivity firms—and limited debt capacity dampens the response of investment, profits, and continuation values. In easing states, however, high-productivity POEs experience larger value gains than low-productivity POEs; taken together, these forces imply that high-investment POEs have higher overall exposure to MS shocks. At the same time, low-investment POEs load slightly more on the market factor. The higher MS exposure of high-investment POEs and the higher market exposure of low-investment POEs offset, leading to similar expected returns across POE investment portfolios.

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-deviation 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 −4.9% and −5.1%, respectively.

To understand the economic forces driving these aggregate results, we conduct several counterfactual analyses. When we set the level of debt financing costs of POEs to the same lower level 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 equalize capital adjustment costs, collateralizability of capital, or equity issuance costs of POEs to SOE levels, the maximum drop in aggregate output and measured TFP remains roughly the same as in the baseline. These results imply that debt financing frictions are the key heterogeneity driving the differential response of measured TFP and sectoral output to MS shocks. This result has potential policy implications: leveling the playing field for SOEs and POEs in debt markets can lead to large economic gains. The table below reports that reducing POEs' debt frictions to SOE levels would increase measured TFP by 2 percentage points and aggregate output by 1 percentage point, due to better allocation of capital within the POE sector.

Aggregate impact of debt market frictions

	Drop in productivity	Drop in output
Baseline	−5.1%	−4.9%
Levelling up	−3.1%	−3.9%

Notes: Results from the average of 500 simulations of the calibrated model to a contractionary MS shock (see Section 3). In the Baseline, the level of real and financial frictions of POEs are different from that of SOEs. In the Levelling up, the level of debt market frictions of POEs are equalized to the level of SOEs.

Second, we conduct counterfactual monetary policy experiments to assess whether (i) a more hawkish policy that adjusts the money supply more aggressively in response to inflation pressures than the rule estimated by Chen et al. (2018), or (ii) more favorable nominal borrowing rates for POEs, can mitigate the effects of financing frictions on capital misallocation. We find that a more hawkish policy rule modestly attenuates the adverse effects of contractionary MS shocks on aggregate output and productivity, but the quantitative effects are limited. In comparison, granting POEs more favorable nominal interest rates than SOEs does not materially alleviate the structural financing constraints faced by POEs and therefore does not meaningfully reduce misallocation. Taken together, these experiments suggest that monetary policy transmission in China operates primarily through heterogeneous financing frictions across ownership types.

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] Related contributions include Hsieh and Klenow (2009), who show that if capital and labor were allocated as efficiently as in the U.S., China's manufacturing TFP could increase by 30% to 50%; Song et al. (2011), who model SOE-POE differences in productivity and access to capital; Chen et al. (2018), who study monetary policy and shadow banking; Whited and Zhao (2021), who estimate significant value-added losses from the misallocation of financial liabilities; and Geng and Pan (2024), who show that implicit government bailout protection makes SOE bond spreads resilient during liquidity stress, worsening outcomes for non-SOEs. Although we share with these papers the idea that frictions matter for understanding financial markets and the real economy in China, our work differs in three ways. First, we focus on both within- and cross-sectoral heterogeneity of SOEs and POEs in analyzing monetary transmission, whereas the existing literature mostly explores cross-sectoral differences; we show that within-sector heterogeneity in productivity plays a key role. Second, we document that monetary shocks affect firms' risk premia and corporate policies not only across but also within each sector, and we identify these effects through the cross-sectional risk premium associated with capital investment, whereas the existing literature primarily emphasizes quantities. Third, we quantify the effect of capital misallocation within sectors and show that leveling the playing field for POEs can lead to significant aggregate productivity gains.

This paper is also related to the broad literature on monetary policy transmission, primarily focused on the U.S. economy. Bernanke and Gertler (1995) and Kashyap and Stein (2000), among others, study the bank lending channel through banks' balance sheet conditions, while Drechsler et al. (2017) explore the deposits channel through banks' 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. However, we focus on monetary supply shocks, firms' risk premia, and corporate policies across firms with distinct state ownership in China. Our paper is also related to the investment-channel literature, including Ottonello and Winberry (2020) and Cloyne et al. (2023), but differs by emphasizing heterogeneity in state ownership and access to credit markets, rather than default risk or the

[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 China's economic growth using a tournament model, He et al. (2022), who examine the impact of a government-led staggered reform in the performance evaluation of Chinese SOEs, which replaced return on equity (ROE) with economic value added (EVA), Brunnermeier et al. (2022) who study China's unique approach to managing the financial system, where government plays an important role, Chen et al. (2023) who show how fiscal and monetary interventions affect credit allocation using loan-level data.

collateral channel, as the primary driver of differential responses to monetary policy shocks, and highlights the resulting impact on capital misallocation.

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 market failures and that the social benefits of SOEs may exceed the costs of inefficiency, while Shleifer and Vishny (1994) and Shleifer (1998) show that SOEs are inefficient because their objectives are not oriented toward shareholder-wealth maximization. Empirically, Dewenter and Malatesta (2001) and Alok and Ayyagari (2020), among others, find that SOEs are less efficient than POEs in terms of economic performance, and much of this literature argues that the costs of inefficiency associated with SOEs outweigh the benefits. Unlike this literature, which focuses 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 presents a dynamic model of the firm that we use to understand the empirical evidence. Section 3 solves and estimates the model. Section 4 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 5 discusses the aggregate implications of MS shocks and provides a detailed analysis of the economic mechanisms driving the results. Finally, Section 6 concludes. A separate appendix with additional results and robustness checks is posted online.

2 Model

We develop a dynamic heterogeneous-firm model with two linked blocks. The first is a firm investment block that delivers heterogeneous investment, financing, and return responses to monetary shocks through sector-specific real and financial frictions for SOEs and POEs. The second is a parsimonious New Keynesian monetary block, taken as given from firms' perspective, that disciplines the joint dynamics of the nominal interest rate and inflation. We embed these nominal dynamics in firms' problem to quantify how monetary policy differentially affects SOEs and POEs through their distinct frictions.

2.1 Investment block

The firm investment block features two sources of heterogeneity: cross-sectoral differences between SOEs and POEs in real and financial frictions and in the collateralizability of capital, and within-sector differences driven by idiosyncratic productivity. We structurally estimate the model for SOEs and POEs using asset pricing and quantity moments to identify the real and financial frictions.[4]

Firms choose investment to maximize market equity value, taking a stochastic discount factor (SDF) as given, and can issue debt and equity to finance operations. We do not model financial intermediation explicitly but instead use reduced-form cost functions for debt and equity issuance that capture the wedge between internal and external funds.

We incorporate MS shocks as a time-varying cost of issuing debt; in addition, MS shocks affect the SDF. This specification is motivated by China's quantity-based monetary policy framework, in which the People's Bank of China uses M2 growth as an intermediate target, implemented through instruments such as the required reserve ratio, open-market operations, and medium-term lending facilities, and thereby influences credit volumes in the banking system, making bank lending a key transmission channel. Modeling MS shocks as time-varying debt issuance costs thus captures this bank lending channel in a tractable way.

2.1.1 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 $Y_{j,t}$. We specify firm-level variables in real terms, after adjusting for the price level P_t. The production function is given by

$$Y_{j,t} = A_t Z_{j,t} K_{j,t}, \tag{1}$$

in which A_t is aggregate productivity and $Z_{j,t}$ is firm-specific productivity.[5] 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 $a_{t+1} \equiv \log(A_{t+1})$, ε^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:

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

in which $z_{j,t+1} \equiv \log(Z_{j,t+1})$, $\varepsilon^z_{j,t+1}$ is an i.i.d. standard normal shock that is uncorrelated across all firms in the economy and independent of ε^a_{t+1}. $\bar{z}$, ρ_z, and σ_z are the mean,

[4]Interest-rate differences are another possible source of heterogeneity. However, empirically we do not find significant differences in loan rates or their responses to monetary supply shocks between SOEs and POEs; adding a differential interest-rate channel in the model leaves the baseline results largely unchanged.

[5]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.

autocorrelation, and conditional volatility of (log) firm-specific productivity, respectively.

Physical capital accumulation is given by

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

where $I_{j,t}$ represents investment and δ denotes the capital depreciation rate.

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

$$G_{j,t}(\mathcal{O}) = \begin{cases} \frac{c_k^+(\mathcal{O})}{2}\left(\frac{I_{j,t}}{K_{j,t}} - \delta\right)^2 K_{j,t}, & I_{j,t} \geq \delta K_{j,t} \\ \frac{c_k^-(\mathcal{O})}{2}\left(\frac{I_{j,t}}{K_{j,t}} - \delta\right)^2 K_{j,t}, & I_{j,t} < \delta K_{j,t} \end{cases}, \tag{5}$$

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 processes. 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 with lemon problems can be different across SOEs and POEs. Production incurs a nonnegative fixed cost $f(\mathcal{O})K_{j,t}$ proportional to firm size to ensure that fixed costs are non-negligible as the firm grows.

2.1.2 Debt financing and monetary supply shocks

Firms use a mix of debt and equity to finance their operations. At time t, firms optimally choose the amount of borrowing $B_{j,t+1}$, which must be repaid at $t+1$. The firm's ability to borrow is bounded by 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 $K_{j,t+1}$. 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:

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

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 the nominal rate $r_f^\$$. Note that the collateralizability is allowed to differ between SOEs and POEs, which captures the fact that SOEs and POEs may face different treatment from banks for valuing the collateral in pledging for loans.

Firms incur adjustment costs when issuing new debt, denoted as $\Phi^B_{j,t}(\mathcal{O})$. 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). The cross-sectoral heterogeneity in debt financing frictions is consistent with several channels documented in the literature: 1) SOEs have implicit government guarantees 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 that of 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

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

The issuance rate of nominal debt $\frac{\Delta B^\$_{j,t+1}}{B^\$_{j,t}}$ is given by $\frac{\Delta B^\$_{j,t+1}}{B^\$_{j,t}} = \frac{B_{j,t+1}(1+\pi_t)-B_{j,t}}{B_{j,t}}$, where the inflation rate π_t captures the change in the price level between $t-1$ and t, i.e., $1+\pi_t = \frac{P_t}{P_{t-1}}$.[6] The monetary block, introduced later in Section 2.2, generates inflation π_t and the nominal interest rate $r^\$_{f,t}$ as functions of key exogenous state variables of aggregate productivity and money supply.

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

$$\xi_{t+1} = \rho_\xi \xi_t + \sigma_\xi \varepsilon^\xi_{t+1}, \quad (8)$$

in which ρ_ξ and σ_ξ are the first-order autocorrelation coefficient and conditional volatility of ξ_{t+1}. The aggregate shock ε^ξ_{t+1} is an i.i.d. standard normal shock independent of aggregate and firm-specific productivity shocks. We interpret ε^ξ_{t+1} as driven by MS shocks because, as discussed in detail in Section C.1 of Online Appendix, 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.[7] Furthermore, the parameter $\eta(\mathcal{O})$, which determines

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

[7] In appendix B.7, we explicitly study this channel in a simple model. We show that the asymmetry in debt issuance costs can be micro-founded using such a simple model that captures the transmission of

the sensitivity of the debt issuance costs to the monetary supply shock, is allowed to vary across SOEs and POEs (and hence these parameters will be estimated separately for each sector). This specification is consistent with the fact that SOEs and POEs respond to the MS shocks differently in the data.

2.1.3 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 resort.

Because external financing costs will be paid only if payouts are negative in real terms, we define the firm's real payout before financing cost ($E_{j,t}(\mathcal{O})$) as output minus investment in capital and change in debt, less investment adjustment costs and debt issuance costs,

$$E_{j,t}(\mathcal{O}) = (1-\tau)Y_{j,t} + \tau\delta K_{j,t} + \tau r^{\$}_{f,t}\frac{B_{j,t}}{1+\pi_t} - I_{j,t} - G_{j,t}(\mathcal{O}) + B_{j,t+1} - \left(1 + r^{\$}_{f,t}\right)\frac{B_{j,t}}{1+\pi_t} - \Phi^B_{j,t}(\mathcal{O}), \tag{9}$$

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

$$\Psi_{j,t}(\mathcal{O}) = \psi(\mathcal{O})\left|E_{j,t}(\mathcal{O})\right| \mathbf{1}_{\{E_{j,t}(\mathcal{O})<0\}}, \tag{10}$$

in which the 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 $D_{j,t}(\mathcal{O})$ distributed to shareholders is given by:

$$D_{j,t}(\mathcal{O}) = E_{j,t}(\mathcal{O}) - \Psi_{j,t}(\mathcal{O}) - f(\mathcal{O})K_{j,t}. \tag{11}$$

2.2 Monetary block

We augment the firm investment block with a parsimonious monetary block in the spirit of Woodford (2003) and Galí (2015), which delivers the joint dynamics of inflation and the nominal interest rate in response to monetary and productivity shocks. These nominal variables affect firms through the real rate and financing channels as in Gomes et al. (2016) and Corhay and Tong (2025), and from the perspective of the firm block, they are taken as given. We summarize the key components below.

quantity-based monetary policy to lenders when lenders face different levels of financial constraints.

Money-in-Utility-Function. To motivate a standard money-demand relation, we introduce a notional household that derives utility from real money balances, with σ and χ denoting the inverse intertemporal elasticity of substitution and the inverse Frisch elasticity of labor, and β the time-discount parameter. We use this preference specification only to discipline money demand within the monetary block; the stochastic discount factor that prices firm returns is specified separately in Section 2.3.

Nominal Rigidity. A final-goods sector aggregates differentiated intermediate goods into aggregate output $\mathcal{Y}_t$. Each intermediate-goods producer employs labor, faces aggregate productivity a_t as in (2), has monopolistic pricing power, and is subject to Calvo-style price rigidity with ϕ denoting the probability of price adjustment. Firms in the investment block are atomistic price takers: they take the aggregate price level as given, 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 steady state, according to policy coefficients ϕ_π and ϕ_x defined in (16).

The complete monetary block is detailed in Appendix B.8. After log-linearizing the full system, we obtain the standard linear representation of the New Keynesian framework which we feed into our heterogeneous firm block.

IS Curve. 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 $x_t \equiv \mathbf{y}_t - \mathbf{y}^f_t$ is the output gap, $\mathbf{y}_t$ is the log deviation of aggregate output $\mathcal{Y}_t$ from steady state, $r^{\$}_{f,t}$ is the nominal interest rate, and $\mathbf{y}^f_t$ and r^f_t are the natural level of output and the natural real interest rate under flexible prices.

New Keynesian Phillips Curve. Current inflation depends on the output gap (or real marginal cost) and expected future inflation:

$$\pi_t = \gamma x_t + \beta \mathbb{E}_t \pi_{t+1}, \quad \gamma = \frac{(1-\phi)(1-\beta\phi)}{\phi}(\sigma + \chi). \tag{13}$$

A higher Calvo price stickiness ϕ flattens the Phillips curve by reducing γ, increasing inflation persistence.

Money Demand. Real money balances 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 is (log) real money balances and $r^{\$} < 1$ is the steady-state nominal rate.

Real Money Growth. Money growth equals real money growth plus inflation:

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

Policy Rule for Money Growth. Money growth responds to deviations of inflation and the output gap from target, 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 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 a_t and ξ_t. The monetary block endogenously determines inflation and the nominal interest rate as functions of (a_t, ξ_t), which affect firms' decisions through the real interest rate and the real debt channel as in Gomes et al. (2016) and Corhay and Tong (2025):

$$\pi_t = \theta_\pi^a a_t + \theta_\pi^\xi \xi_t, \tag{17}$$

$$r_t^\$ = \theta_{r^\$}^a a_t + \theta_{r^\$}^\xi \xi_t, \tag{18}$$

where the coefficients depend on the structural parameters of the monetary block. Full derivations using the method of undetermined coefficients are provided in Section B.8 of the Online Appendix.

2.3 Firm's maximization problem and equilibrium risk and return

Firms take the SDF as given and choose investment and debt/equity issuance to maximize the present value of future dividends. For tractability, we specify the SDF directly 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 the real interest rate $r_{f,t} = r_{f,t}^\$ - \mathbb{E}_t\left[\pi_{t+1}\right]$ is the difference between the nominal rate and expected inflation. The prices of risk for both shocks (γ_A, γ_ξ) are positive: the positive price of risk for the MS shock is consistent with the empirical evidence reported here, and the positive price of risk for the aggregate productivity shock is consistent with Song et al. (2011), who show that positive TFP shocks are associated with higher consumption and output growth in China. This specification is broadly consistent with the SDF in Equation (23) used in the empirical analysis.

The firm's maximization problem is then:

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

subject to the capital accumulation equation (Eq. 4), the 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 receiving a death shock. Because the production technology (Eq. 1) has constant returns to scale (an AK technology), we introduce this shock to ensure the stationarity of the endogenous firm distribution through exogenous entry and exit. If a firm is hit by a death shock at time t, it immediately disappears and investors lose its future cash flows; new entrants of the same number replace exiting firms, starting with the median level of firm-level state variables and producing immediately upon entry.

In the model, risk and return relations are determined endogenously by firms' optimal decisions. The two-factor structure implies that a firm's exposures to aggregate productivity and MS shocks determine its risk and expected stock return:

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

where r^e_{t+1} is the excess return on the stock. With both prices of risk positive, assets whose returns covary positively with aggregate productivity or MS shocks are considered risky and therefore command higher average returns in equilibrium.

3 Model estimation and model implied monetary shocks

This section presents the model solution and estimation results, and shows how to use the model to recover the (unobserved) MS shocks in the data.

3.1 Structural estimation

We estimate the parameter vector θ by the simulated method of moments (SMM), which minimizes a distance criterion between key moments from the actual data of SOEs and POEs and simulated data,

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

where W is a weighting matrix. We solve the model at quarterly frequency (Online Appendix Sections B.1 and B.2 describe the solution algorithm and numerical implementation) and aggregate simulated firm-level data across firms and time as in the real data. We search the parameter space using an annealing algorithm with different initial values of θ to ensure convergence to the global minimum. Because the target moments span various categories with widely varying standard errors, we use the identity matrix as W to prevent any single moment from dominating the estimation and to focus on economically interesting moments.

Computational constraints limit the size of the estimated parameter space, so we focus the estimation on the 6 sector-specific parameters per sector (12 total) governing real and financial adjustment frictions for SOEs and POEs—the main parameters of interest for the economic mechanism—letting the data quantify their importance for the model fit. The remaining 19 parameters, common to both sectors, 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 0.025 following the literature on the Chinese economy in DSGE models (e.g., Song et al., 2011; Whited and Zhao, 2021), and the corporate tax rate τ is set to 0.13. Since we do not observe a significant difference between SOEs and POEs in the persistence of investment, we set $c_k^+(\mathcal{O})$ to 0 for both sectors so that the model-implied investment rate persistence is close to the data.

The middle panel in Table 1 reports parameters values regarding shocks at the quarterly level. The persistence ρ_a is set at 0.987, and the conditional volatility $\sigma_a = 0.03$ is set to match the persistence and volatility of aggregate profits, since the aggregate productivity shock is essentially a profitability shock in the model. The persistence of the MS shock, ρ_ξ, is set to match the persistence of annual M2 growth in the data, and its volatility σ_ξ is calibrated to match the aggregate debt growth rate volatility of approximately 5% per annum. For the idiosyncratic productivity process, we set $\rho_z = 0.899$ and $\sigma_z = 0.13$, consistent with data estimates. Given the AK technology, the long-run average firm-level productivity $\bar{z}$ pins down the average investment rate directly: we set $\bar{z}$ to 0.052 for SOEs and 0.055 for POEs to target the observed average investment rates of 12.1% and 16.5%. The fixed cost of production $f(\mathcal{O})$ is chosen to match the average book-to-market ratio for SOEs (0.53) and POEs (0.37). Quarterly exit rates are set to 2% for SOEs and 3% for POEs, consistent with the annual exit rates in Hsieh and Song (2015) and Brandt et al. (2012) for Chinese manufacturing firms.

To calibrate the stochastic discount factor, we set the real risk-free rate to 2.25% per annum consistent with the data. The prices of risk for productivity and MS shocks, $\gamma_a = 5.5$ and $\gamma_\xi = 25$, imply a market excess return and Sharpe ratio of 13.4% and 0.36, consistent with the Chinese equity market data counterparts of 13.8% and 0.45.

The monetary block endogenizes inflation and the nominal policy rate, which feed into firms' decisions in the investment block. As shown in Appendix B.8, the loadings of inflation and the nominal rate on aggregate productivity and monetary shocks are functions of the NK block's structural parameters, which we calibrate 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 to 2, and relative risk aversion to 1. We normalize steady-state inflation to zero, so nominal and real rates coincide in steady state, and choose the subjective discount factor β to match a 2.25% steady-state real rate. Under this calibration, Equations (17) and (18) imply that a tightening monetary shock (a decline in ξ_t) reduces money growth and inflation ($\theta_{\pi}^{\xi} > 0$) and raises the nominal policy rate ($\theta_{r^{\$}}^{\xi} < 0$), a classic liquidity effect under nominal rigidities (Galí, 2015).

Estimated parameters We estimate the capital adjustment cost, the collateralizability 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 $\Theta(\mathcal{O}) = \left(c_k^-(\mathcal{O}), \varphi(\mathcal{O}), f_B(\mathcal{O}), \phi_B(\mathcal{O}), \psi(\mathcal{O}), \eta(\mathcal{O})\right)$.

Panel A in Table 2, columns 1 and 3, presents 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 helps 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 identify the equity issuance cost parameter $\psi(\mathcal{O})$; the leverage ratio helps mainly identify the collateralizability parameter $\varphi(\mathcal{O})$, and investment-portfolio return spreads help identify the sensitivity of debt issuance costs to MS shocks $\eta(\mathcal{O})$.

3.2 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 documenting SOEs' preferential access to bank loans. SOEs also face lower marginal investment adjustment costs and have higher collateralizability. At the same time, the estimated sensitivity of debt issuance costs to MS shocks is higher for SOEs than for POEs, indicating that although SOEs face lower average debt-financing frictions, their borrowing costs vary more with aggregate monetary conditions.

The estimated adjustment cost parameters may appear large, but the implied ratio of capital adjustment costs to firm output is 0.62% when averaged across SOEs and POEs, close to the low end of Bloom (2009). The estimated debt and equity financing costs are 1.24% and 1.58%, respectively, close to the U.S. estimates in Altınkılıç and Hansen (2000).

Panel A in Table 2 shows that the baseline model fits the data well across all targeted moments. The model-implied cross-sectional investment volatility (0.22 for SOEs and 0.28 for POEs), debt issuance spikes and cross-sectional volatility of debt issuance (0.14 and 0.15 for SOEs; 0.20 and 0.13 for POEs), fraction of firms issuing equity (0.12 for SOEs and 0.13 for POEs), and investment portfolio spreads (5.10% and 0.61%) all closely match their data counterparts. Overall, the model matches the target moments well with economically reasonable parameter values.

3.3 Model implied monetary supply shock proxy

We construct a model-based MS shock proxy to identify monetary supply shocks in the data, which we label as the 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 from a combination of equilibrium firm-level moments. We then map the model-implied relationship between these variables 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 issuance cost state variable ξ. Since variations in ξ impact the entire distributions of debt issuance and leverage, moments reflecting these distributions should be particularly informative. We find that *the first principal component* of four moments—the cross-sectional medians of firms' leverage ratios and new debt issuance, and the fractions of firms experiencing (abnormal) large leverage changes and debt growth—captures 85% of the variation in ξ. The first two moments capture average debt financing changes when aggregate debt financing cost varies; the last two capture the tails of the debt issuance and leverage distributions. We extract this principal component across SOEs because SOEs' debt-issuance margins are less constrained by sector-level financing frictions, allowing the MS shock to load more cleanly on their cross-sectional debt and leverage moments.[8]

We then apply the same methodology to the real data, extracting the first principal component of the four standardized moments to construct an empirical time series of the debt issuance cost state. A firm's leverage ratio is its total debt to total assets ratio at time t, and its debt growth equals the change in total debt from $t-1$ to t divided by average total assets over the same periods. The fraction of (abnormal) large leverage ratios at time t is the proportion of firms with leverage ratios above 60% in the entire pooled distribution, and the abnormal fraction of debt growth rate is the proportion of firms with absolute debt growth rate above 60% in the entire pooled distribution. We take the first difference of the fitted state to extract the empirical proxy for the MS shock ε^{ξ}.

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

3.4 Interpreting and validating the MS shock proxy

The model-implied MS shock proxy captures the sources of aggregate fluctuations that affect credit available to firms. We interpret the proxy as a monetary supply shock because of the tight institutional link between M2 growth and bank-credit conditions in China: M2 growth is the variable the People's Bank of China actively manages to support its annual GDP growth target, and bank credit is the principal channel through which M2 movements reach firms. Empirical proxies that capture variation in firms' aggregate debt-financing conditions should therefore track M2 closely, which we verify next. A negative MS shock proxy captures a contractionary monetary policy shock: less money circulating in the system, implying less credit available to (at least some) firms, as it is more costly to access. The converse is true for a positive MS shock. 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 this interpretation, we show that the MS shock proxy is highly correlated with several independent measures of monetary supply in China. Chen et al. (2018) develop and estimate an endogenously switching monetary policy rule in the spirit of Taylor (1993), using M2 growth as the intermediate tool of the People's Bank of China to obtain a time series of monetary supply shocks, which we denote as the M2 shock. The correlation of our model-implied MS shock proxy and the Chen et al. (2018) M2 shock is about 83.5%. Our proxy also closely follows variation in M2 growth itself (correlation is 80%) and captures significant variation in the bank-loan component of aggregate financing to the real economy (AFRE)—a broader intermediate target the People's Bank of China regulates that includes corporate bonds, equity financing, and foreign-currency loans—with correlation above 70%.

Relationship with other macroeconomic shocks. One concern is that, because the proxy relies on a simplified model of the real economy, it might be contaminated by other aggregate shocks, for example time-varying investment opportunities or credit risk (the latter absent from the model), that also drive the cross section of debt issuance and leverage decisions used to construct the MS shock. Table A.2 shows the proxy has small correlations with such measures: −5% with the aggregate TFP shock, 12% with investor sentiment, 8% with changes in the earnings-to-price ratio, respectively, and close to zero with the change in credit spread and book-to-market ratio. 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.

We focus on the model-based MS shock proxy in the empirical analysis because it provides a tight link between the model and the data—we can replicate the empirical procedures inside the model and analyze the role of SOEs and POEs in monetary transmission in a consistent manner. Results using the Chen et al. (2018) M2 shock are very similar (Online Appendix A.5).

4 Main findings

We investigate the link between MS shocks, asset prices, and corporate policies across SOEs and POEs in both the data and the model. To evaluate model fit, we replicate the empirical analyses on data simulated from the estimated model.

4.1 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. By 2019, the A-share market had 3,760 listed companies with a total market value of 59.2 trillion RMB, or 60% of China's GDP. The stock return data we use are from the 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 and includes publicly traded firms listed on both the Shanghai and Shenzhen stock exchanges. Following the literature, we exclude three types of firms: i) financial firms; ii) firms that are publicly listed for less than 6 months; and iii) the so-called "shell" firms.[9]

Following Liao et al. (2014), we classify a firm as an SOE or POE based on the ultimate controlling shareholders, which is disclosed in firms' annual financial reports. The state is identified as the ultimate controlling party under criteria issued by the China Securities Regulatory Commission (CSRC), which include majority share ownership, control of over 30% of voting rights, or the authority to elect more than half of the board (see Online Appendix A.1 for the full set of criteria and additional data construction details). Based on the nature of the property rights of ultimate controlling shareholders, firms split into SOEs, POEs, foreign-funded, and other firms, with SOEs and POEs accounting for more than 90% of all public firms. We exclude foreign-funded firms because their access to offshore capital markets places them outside the domestic monetary transmission channel central to our analysis. We pool the remaining "other" firms, predominantly widely-held companies without a controlling shareholder, with POEs: both groups face commercial financing terms and lack the implicit guarantees and preferential credit access associated with state control, and other firms account for only 2-3% of listed non-SOE firms over our sample period.

[9] As is shown in Liu et al. (2019), shell companies are attractive merger 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.

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 firms' debt growth (is the change in a firm's total debt, divided by the average assets of the current and previous fiscal years). Firm-level profit measure ΔCF_t is the change in a firm's total profit, divided by the average assets of the current and previous fiscal years. Table A.4 (columns Data) in the Online Appendix presents selected firm characteristics of SOEs and POEs. Overall, SOEs use more financial leverage and issue more debt, while POEs invest more and have higher TFP.

4.2 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. To characterize within-sector heterogeneity, we also investigate the relationship between firms' capital investment and expected stock returns within SOEs and POEs. We focus on capital investment because of its crucial role in driving economic growth in China and the well-established link between firms' investment and expected stock returns (the investment return spread) in the U.S. economy (Titman et al., 2004). Since capital investment is naturally positively correlated with firm productivity (which is more difficult to measure), this analysis also speaks to the link between firm-level productivity and expected stock returns within each sector.

Stock returns, state ownership, and capital investment. We use a portfolio approach. To investigate within-sector heterogeneity, we form three one-way sorted investment-rate (IK) portfolios (L: low IK, M: medium IK, and H: high IK) separately within SOEs and POEs. Panel A of Table 3 (Data columns) reports the average excess stock returns (r^e) and Sharpe ratios (SR) of these portfolios for SOEs (left columns) and POEs (right columns).

Panel A shows that the long low-IK, short high-IK portfolio (L-H), which we refer to as the *investment-return spread*, earns a sizable 5.5% per annum in the SOE sector, more than 2 standard errors from zero. The negative relation between firms' current investment and future stock returns within SOEs is consistent with the investment-return spread documented in U.S. data. Within POEs, by contrast, the spread is only 0.3% per annum, less than 0.1 standard errors from zero. The cross-sector difference is therefore economically large at 5.2% per annum, and the Sharpe ratio of the spread portfolio is also substantially higher in SOEs (0.48 versus 0.02). The sector-average excess return (not tabulated) is in fact significantly higher for POEs than for SOEs (18.1% versus 12.0%, a 6.1% per annum gap), so although

POEs appear riskier on average, the within-sector investment-return spread is concentrated entirely in the SOE 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 standard CAPM market factor) and the MS shock proxy as the two factors. 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 estimate the prices of risk (b_{MKT} and b_{MS}) by GMM using the standard moment condition $E\left[r^e_{it} M_t\right] = 0$, where r^e_{it} is the excess return of test asset i in year t. To help interpret the results, we rewrite 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 α_i is the pricing error associated with asset i. For comparison, we also estimate the one-factor CAPM (the restricted case in which $b_{MS} = 0$) to establish the marginal importance of the MS shock for capturing systematic risk.

Table 4 reports the GMM estimates of the prices of risk and the implied mean absolute pricing errors (MAE) across portfolios.[10] The estimated price of risk of the MS shock is positive and 2.1 standard errors from zero, and the two-factor model performs better than the CAPM in explaining portfolio returns (MAE of 1.4% versus 3.9% per annum). These results show that the MS shock is correlated with systematic risk and carries a positive price of risk: periods with negative MS shocks (monetary contractions) tend to occur when investors' marginal utility is high, that is, in bad economic times. By Equation (24), the impact of MS shocks on a firm's expected return is governed by its return covariance with the MS factor, with higher covariance commanding higher expected returns because such firms tend to underperform in bad economic times. The cross-sectional pattern of return covariances with the MS factor is therefore informative about differences in overall risk between SOEs and POEs, and about why the investment-return relationship differs across the two sectors.

Panel C in Table 3 reports the relative multivariate covariances (deviations from the within-sector mean) of each portfolio return with the MS factor and the market factor. We report demeaned covariances because the volatility of portfolio returns and the correlation between the market factor and the monetary shock differ between the data and the model,

[10] As test assets, we use the benchmark set of three SOE investment-rate portfolios and three SOE book-to-market (BM) portfolios. To improve the precision of the estimated price of risk for the MS shock given the small number of benchmark test assets, we also expand the real-data test-asset set by adding three SOE illiquidity portfolios and three SOE cash-flow-to-price (CFP) portfolios.

affecting the level of covariances but not their cross-sectional ranking. Demeaning therefore isolates relative factor exposures, the economically relevant objects for asset pricing. In the SOE sector, the cross-sectional variation in market factor exposure is economically small and statistically insignificant after demeaning, indicating that all portfolios load similarly on aggregate market risk. In contrast, the relative covariance with the MS factor *decreases* across investment portfolios, from positive (above-average exposure) for low-investment SOEs to negative (below-average exposure) for high-investment SOEs. Thus, high-investment SOEs are less exposed to MS shocks than low-investment SOEs (and the average SOE), and this cross-sectional variation in MS exposure, rather than differential market risk, explains the large investment-return spread in the SOE sector.

The pattern is markedly different in the POE sector. The relative covariance with the MS shock *increases* across investment portfolios, from negative for low-investment POEs to positive for high-investment POEs. At the same time, low-investment POEs have somewhat higher relative exposure to the market factor than high-investment POEs, although this difference is economically small and statistically insignificant. These two forces work in opposite directions and lead to similar average returns across high- and low-investment POEs, and hence to an insignificant investment-return spread in the POE sector.

The differential MS shock covariances also have implications for the asset pricing errors. Panel B in Table 3 shows that the CAPM alpha of the investment spread portfolio (L-H) is 5.4% per annum in the SOE sector, and this pricing error drops substantially in the two-factor model (Panel C) when the MS shock is included ($\alpha^{2F} = 2.0\%$, only 0.6 standard errors from zero).

Model implied result. Panel A of Table 3 (Model columns) shows that the baseline model reproduces the negative investment-excess return relation in the SOE sector and the insignificant pattern in the POE sector. The SOE investment return spread is 5.1% per year in the model versus 5.5% in the data, and the POE spread is statistically indistinguishable from zero, as in the data.[11]

The model also replicates the large dispersion in SOEs' relative covariances between stock returns and MS shocks across investment portfolios. In the Model columns of Panel C, this covariance declines with investment: high-investment SOEs have below-average MS exposure while low-investment SOEs have above-average exposure, with a statistically significant low-minus-high spread. As in the data, the cross-sectional variation in demeaned market-factor exposure is economically negligible and statistically insignificant. The model-implied CAPM alpha in Panel B is large and significant, while the two-factor alpha in Panel C is small and

[11] The model also matches average return levels and the SOE-POE gap: SOEs are 14.6% in the model versus 12.0% in the data, and POEs are 16.4% in the model versus 18.1% in the data.

insignificant, indicating that the negative investment-return relation within SOEs is driven primarily by heterogeneous MS exposure rather than differential market risk.

For POEs, the model also replicates the qualitative pattern in the data. Panel C shows that high-investment POEs have above-average MS exposure while low-investment POEs have below-average exposure, with a statistically significant low-minus-high difference. Low-investment POEs exhibit a slightly higher relative covariance with the market factor than high-investment POEs, though insignificant in the model as in the data. These offsetting forces (higher MS exposure but lower market exposure for high-investment POEs) lead to similar expected returns across POE investment portfolios, consistent with the data.

Finally, Table 4 shows that the model captures the empirical fact that a two-factor structure with the market and MS shocks prices the cross-section of equity returns reasonably well, while the CAPM fails with a large MAE and a low regression R^2.

4.3 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, and Pj_t is the investment portfolio quintile dummy for $j = 2, 3$.

The relevant regression coefficients are c and e_j. The coefficient e_j measures the differential exposure of firms in investment-rate portfolio $j = 2$ or 3 relative to firms in the low ($j = 1$) portfolio. When $h = 0$, these coefficients give the contemporaneous responses to the MS shock, and when $h = 1$, the one-year-ahead responses. We estimate the equation separately for SOEs and POEs. For debt and investment, we focus on the contemporaneous responses since these variables can change immediately, while for profits we report both contemporaneous and one-year-ahead responses since shocks may take time to affect profits through other channels (such as investment).

Debt issuance. Table 5 reports the estimates for the change in debt issuance (ΔD_t). The contemporaneous response decreases across investment portfolios in the SOE sector: high-investment SOEs respond negatively (countercyclically) to the MS shock while low-investment SOEs respond positively, with $c = 0.61$ and $e_3 = -0.87$, both statistically significant. This implies that high-investment (high-productivity) SOEs can still increase debt issuance despite a negative MS shock (bad economic times). For POEs, $c = 0.54$ and $e_3 = 0.47$ (statistically insignificant), implying that high- and low-investment POEs exhibit broadly similar debt issuance responses to changes in aggregate credit market conditions.

Investment. Table 5 shows a similar pattern for the change in investment (ΔIK_t): the contemporaneous response decreases across investment portfolios in the SOE sector ($c = 0.86$, $e_3 = -1.39$, both statistically significant), implying that high-investment SOEs can still increase their investment rate despite a negative MS shock. For POEs, the response across high- and low-investment firms is not monotonic and the relevant coefficients are statistically insignificant.

Profits. Table 5 shows that the one-year-ahead change in profits (ΔCF_{t+1}) of low-investment SOEs responds to the MS shock positively while high-investment SOEs respond negatively ($c = 0.03$, $e_3 = -0.15$ at $t + 1$), implying that high-investment SOEs produce more cash flows going forward despite a current negative MS shock. For POEs, profit responses are uniform across portfolios as the e_2 and e_3 slopes are statistically insignificant.

Taken together, these results show that MS shocks have a strong and systematic effect on firms' asset prices and corporate policies, with effects that vary meaningfully within and across SOEs and POEs. Two robustness checks in the Online Appendix support this conclusion. First, replacing the model-implied MS shock with the M2 shock of Chen et al. (2018) yields very similar results, consistent with the high correlation between the two series. Second, tests of the interest-rate and shadow-banking channels confirm that neither drives the differential exposures we document.

Model-implied results. We replicate the panel regressions using simulated data. Table 5 (columns "Model") shows that, consistent with the data, high-investment (more productive) SOEs increase current investment, debt issuance, and one-period-ahead profits in response to an adverse MS shock (which raises debt issuance costs and corresponds to the high marginal utility state for investors). Across POEs, the responses do not vary much across portfolios, also consistent with the data.

5 Monetary policy transmission

We use the model as a laboratory to study monetary policy transmission in China. We first examine impulse response functions of key variables to a negative MS shock (a credit contraction) for both SOEs and POEs to understand the underlying economic mechanisms. We then quantify the effects of MS shocks on aggregate outcomes, such as aggregate and sectoral output and productivity, emphasizing the capital-misallocation channel, both in the model and in direct empirical tests. Finally, we conduct counterfactual experiments to assess how these effects depend on the model's key features.

5.1 Impulse responses to MS shocks

To understand how firms adjust to monetary supply (MS) shocks in the model, Figure 1 reports impulse responses of debt issuance, investment, profits, and continuation values to a negative MS shock (i.e., a credit contraction) for SOEs and POEs. To illustrate within-sector heterogeneity, we compare two firms whose idiosyncratic productivity is set one standard deviation above and below the median, which we label "high-productivity" and "low-productivity". For each sector, we plot each variable relative to a firm with median level of productivity that experiences the same shock. These high- and low- productivity firms correspond closely to the high- and low-investment firms in both the SOE and POE sectors. While productivity is not the only dimension along which firms differ, it is a key state variable that maps naturally into differences in corporate policies, including investment and debt issuance.

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 the steady state levels despite the tightening shock, implying that their equity is less exposed to MS shocks. By contrast, low-productivity SOEs reduce investment, cut back on debt issuance, and experience declines in profits and firm values, making them riskier.

For POEs, the cyclicality of their financing adjustments is distinct from that of SOEs. Following a contractionary MS shock (a tightening in credit conditions), high-productivity SOEs expand debt issuance sharply, consistent with countercyclical financing that sustains investment when credit conditions worsen. By contrast, POEs' debt issuance responds much less and is close to acyclical, especially among high-productivity firms. This muted financing response carries over to real decisions. While high-productivity POEs continue to adjust investment countercyclically, the increase is substantially smaller than for high-productivity SOEs because limited debt capacity dampens the response of profits and continuation values. Consequently, high-productivity POEs provide little hedging against contractionary MS shocks.

Under expansionary MS shocks (easing states; not tabulated), however, high-productivity POEs experience larger value gains than low-productivity POEs (when the marginal utility is low). Therefore, the weak differential response in tightening states and the stronger differential response in easing states imply higher unconditional MS exposure for high-productivity POEs. This asymmetry maps directly into the cross section: high-investment (high-productivity) POEs load more on the MS factor because they benefit disproportionately in easing states while showing little relative resilience in tightening states.

These model-implied patterns on real and financial decisions align closely with our empirical findings in Section 4.3. In the data, high-productivity SOEs exhibit strongly countercyclical debt issuance and investment following negative MS shocks, whereas high-productivity POEs respond much more weakly and, in most specifications, insignificantly. Consistent with this evidence, when we apply the same panel-regression specifications to simulated model data as in the empirical analysis (Table 5), the model reproduces the differential sensitivity across ownership types.

5.2 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 aggregate level. Following Khan and Thomas (2013), 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 2 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 2 shows that measured TFP and aggregate output decrease by -5.1% and -4.9%, respectively, after a negative MS shock.[12]

[12] 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

5.3 Inspecting the mechanism

To understand the model mechanism in generating the aggregate effects of MS shocks, we investigate two channels in the model: (i) cross-sectoral heterogeneity in financial and real frictions, and (ii) monetary policy stance. Two additional channels, the price of risk of MS shocks and within-sector heterogeneity in productivity, are discussed in the Appendix.

5.3.1 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 2 reports the impulse responses of sectoral measured TFP and output to a one-standard-deviation negative MS shock.[13] 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 POEs have the same (higher than in the baseline) debt collateralizability $\varphi(\mathcal{O})$ or the same (lower than in the baseline) equity issuance costs $\psi(\mathcal{O})$ as SOEs, the responses of sectoral measured TFP and output remain largely unchanged relative to the baseline. However, when we level the playing field by equalizing 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 2 shows

China's GDP to be 60% and 40%, respectively .

[13]For completeness, we report the target moments and the investment portfolio spreads of these counterfactual analyses in Table A.14 of the Online Appendix.

that giving POEs the same access to debt markets significantly improves aggregate measured TFP by 2 percentage points, and increases aggregate output by 1 percentage point.

5.3.2 The role of monetary policy stance

Incorporating the monetary block enables 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: whether alternative policy stances can mitigate the effects of financing frictions, and the impact of a policy reducing the nominal interest rate specifically for POEs.

In the first experiment, we implement a more hawkish policy than Chen et al. (2018) by doubling their policy response coefficient and doubling the sticky price parameter to make the transmission mechanism more pronounced. The upper-left panel of Figure 3 shows that a more hawkish central bank mitigates capital misallocation only marginally: the initial drop in measured TFP is slightly smaller for SOEs (-2.6% versus -2.9% in the baseline) and for POEs (-6.3% versus -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, so a hawkish policy that responds quickly to inflation helps stabilize real debt burdens and mitigates 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 upper-right panel of Figure 3 shows that, surprisingly, this modestly exacerbates capital misallocation: the initial drop in measured TFP worsens to -6.8% from -6.5% in the baseline. A lower nominal interest rate incentivizes POEs to borrow more, increasing their leverage and amplifying financial frictions when a negative MS shock hits the economy.

Taken together, the sticky-leverage and nominal-rate channels both shape the differential effects of monetary policy on SOEs and POEs, but their quantitative contributions are modest. The first-order transmission mechanism in our framework operates primarily through heterogeneous financing frictions, and the model's main quantitative results remain robust. These experiments are intended to be illustrative; a full analysis of optimal policy design would require a general-equilibrium framework in which firms' real decisions feed back into nominal dynamics and policy tradeoffs, which we leave for future research.

The Online Appendix examines two additional mechanisms. A higher price of risk of MS shocks raises the average risk premium and leads to larger declines in output and TFP, while lower idiosyncratic productivity dispersion within SOEs and POEs reduces capital misallocation, output losses, and the difference in output and TFP responses across the two sectors after a contractionary MS shock.

5.4 Tests of capital misallocation and MS Shocks

This section tests the model's predictions on capital misallocation and monetary supply (MS) shocks using the data. We first examine how industry-level TFP growth responds to MS shocks in the SOE and POE sectors, and then study how MS shocks affect within-industry dispersion in the marginal revenue product of capital (MRPK) across sectors, our proxy for misallocation.

We construct industry-level TFP growth separately for SOEs and POEs in each year by aggregating firm-level TFP growth within industry using net property, plant, and equipment (PPENT) as weights. We then regress the change in industry-level TFP growth on the negative of the MS shock (so higher values correspond to contractionary shocks), focusing on the interaction between the POE dummy and the shock.

Columns (1)–(2) of Panel A in Table 6 show that contractionary MS shocks are associated with a significant decline in the change in TFP growth for POEs but not for SOEs. Adding controls leaves the estimates essentially unchanged (Columns (3)–(4) of Panel A), confirming robustness. More importantly, the interaction coefficient between the POE dummy and the negative MS shock (Column (5)) is significantly negative, implying that tightening shocks reduce TFP growth more in the POE sector, consistent with the model.

In addition to the TFP growth analysis, we also test the misallocation mechanism using dispersion in the marginal revenue product of capital (MRPK). Following Hsieh and Klenow (2009), we proxy for capital misallocation by the dispersion of MRPK across firms within each industry and ownership sector (SOE vs. POE). We measure firm-level MRPK as revenue divided by net property, plant, and equipment (PPENT). To remove industry-level differences in MRPK, we first demean each firm's MRPK by its industry-year mean. We then compute, for each sector, the standard deviation of the demeaned MRPK within each industry-year, and regress this dispersion measure on the negative of the MS shock, focusing on the interaction between the POE dummy and the MS shock.

Panel B of Table 6 show that contractionary MS shocks are associated with a more significant increase in MRPK dispersion for POEs compared to SOEs, both with and without controls. More importantly, the interaction between the POE dummy and the negative MS shock is significantly positive as shown in Column (5), indicating that tightening shocks exacerbates misallocation more in the POE sector, consistent with the model.

6 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 cyclicality 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. 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 linked blocks: a monetary block that generates MS-driven interest-rate and inflation dynamics, and a firm investment block in which firms choose investment and financing subject to sector-specific real and financial frictions. SOEs and POEs differ in these frictions, while within each sector firms differ in idiosyncratic productivity, generating dispersion in investment, debt issuance, and risk premia. MS shocks shift credit supply by moving firms' stochastic debt-issuance costs. Quantitatively, SOEs' preferential access to debt markets generates sizable misallocation: equalizing POEs' debt-market access to that of SOEs raises aggregate productivity and output by about 1–2 percentage points.

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

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Table 1: Calibration–Pre-determined parameters

parameter	Symbol	Value
Technology		
Corporate tax rate	τ	0.13
Capital depreciation rate	δ	0.025
Upward capital adjustment cost	$c_k^+(\mathcal{O})$	0
Fix cost SOE/POE	$f(\mathcal{O})$	$2.0/1.0\times10^{-3}$
Death rate SOE/POE	$\kappa(\mathcal{O})$	0.02/0.03
Stochastic processes		
Conditional volatility of aggregate productivity	σ_a	0.03
Persistence of aggregate productivity	ρ_a	0.987
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	0.899
Conditional volatility of firm-specific productivity	σ_z	0.13
Persistence coefficient of debt issuance cost	ρ_ξ	0.943
Conditional volatility of debt issuance cost	σ_ξ	0.04
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	0.75
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	0.23	0.22	0.29	0.28
Spikes in debt issuance	0.16	0.14	0.20	0.20
Cross-sectional debt issuance volatility	0.15	0.15	0.16	0.13
Equity issuance fraction	0.10	0.12	0.12	0.13
Leverage ratio	0.52	0.52	0.46	0.45
Investment return spread (in %)	5.48	5.10	0.25	0.61
Panel B: Estimated parameters				
$c_k^-(\mathcal{O})$: Downward capital adjustment cost		9.84		12.52
		(0.22)		(0.28)
$f_B(\mathcal{O})$: Fixed debt issuance cost		0.009		0.011
		(0.000)		(0.000)
$\phi_B(\mathcal{O})$: Quadratic debt issuance cost		6.31		7.61
		(0.14)		(0.17)
$\eta(\mathcal{O})$: Sensitivity to monetary shock		18.86		12.26
		(0.32)		(0.19)
$\psi(\mathcal{O})$: Equity issuance cost		0.17		0.22
		(0.00)		(0.01)
$\varphi(\mathcal{O})$: Tightness of collateral constraint		0.69		0.57
		(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 the corresponding moments from the simulated panel. The cross-sectional firm-level moments are computed quarter by quarter (using rolling four-quarter windows wherever annual aggregation is required) and then averaged across the simulated time series. The results for the model part (columns "Model") are obtained from a long sample of 1,000 firms for each ownership type over 10,000 quarterly periods, with the first 2,500 quarters discarded as burn-in (7,500 usable 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 parentheses.

Table 3: Investment portfolios across SOEs and POEs

	SOE								POE							
	Data				Model				Data				Model			
	L	M	H	L-H	L	M	H	L-H	L	M	H	L-H	L	M	H	L-H
	Panel A. Excess Returns															
r^e	14.77	11.83	9.28	5.48	17.15	14.54	12.06	5.10	18.07	18.39	17.82	0.25	17.11	15.46	16.50	0.61
[t]	1.34	1.06	0.86	2.35	34.35	29.12	17.17	9.56	1.43	1.62	1.60	0.07	25.18	26.64	36.19	0.71
SR	0.46	0.37	0.29	0.48	0.48	0.41	0.35	0.31	0.49	0.51	0.49	0.02	0.58	0.60	0.62	0.03
	Panel B. CAPM															
α	3.78	1.31	-1.60	5.37	-1.47	-4.15	-5.07	3.60	5.41	5.87	5.22	0.19	2.87	1.78	2.29	0.57
[t]	1.54	0.43	-0.70	2.35	-2.18	-6.49	-5.89	5.60	1.60	1.92	1.72	0.06	6.03	3.64	5.80	0.84
b	0.97	0.93	0.96	0.01	1.29	1.29	1.19	0.10	1.12	1.11	1.11	0.01	0.99	0.95	0.98	0.00
[t]	27.02	21.54	26.32	0.25	31.07	37.22	24.24	1.99	26.38	36.19	30.55	0.13	23.99	42.90	32.69	0.04
R^2	0.87	0.80	0.86	0.00	0.85	0.88	0.77	0.03	0.87	0.90	0.90	0.00	0.74	0.88	0.89	0.00
	Panel C. Asset pricing tests															
α^{2F}	0.01	1.86	-2.03	2.04	0.58	0.19	-1.27	1.85	-0.50	-0.56	-3.64	3.14	0.92	-0.07	0.28	0.65
[t]	0.00	1.16	-0.93	0.63	0.66	0.86	-2.03	1.60	-0.57	-0.68	-1.14	0.93	4.06	-0.54	0.76	1.37
$\widetilde{\text{Cov}}^{MKT}$	-1.34	0.94	0.40	-1.74	0.21	0.25	-0.45	0.66	1.89	-0.72	-1.17	3.06	0.09	-0.16	0.07	0.03
[t]	-0.12	0.08	0.03	-1.04	0.26	0.30	-0.57	1.94	0.16	-0.07	-0.11	1.87	0.15	-0.28	0.11	0.07
$\widetilde{\text{Cov}}^{MS}$	4.04	-2.58	-1.46	5.50	1.76	-0.66	-1.10	2.86	-2.71	-0.57	3.28	-5.99	-0.87	-1.25	2.12	-2.99
[t]	1.68	-0.72	-0.49	1.85	1.65	-0.59	-0.78	1.75	-0.79	-0.17	1.05	-2.87	-0.87	-1.75	2.88	-1.45

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. 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 price of risk of the market factor. b_{MS} denotes the price of risk 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, $\widetilde{\text{Cov}}^{MKT}$ is the demeaned multivariate covariance (deviations from the within-group mean) between the portfolio returns and the market factor, and $\widetilde{\text{Cov}}^{MS}$ is the demeaned multivariate covariance (deviations from the within-group mean) 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 2005 to 2018 in panel C. The results for the model part (column "Model") are obtained from 1,000 firms of simulated data for both types.

Table 4: The price of risk of MS shocks

	Data		Model	
	CAPM	2-Factor	CAPM	2-Factor
MKT	0.45	0.25	1.84	-0.19
[t]	1.80	0.99	9.29	-0.29
MS		0.85		0.94
[t]		2.10		3.19
R^2	-1.48	87.29	89.86	96.12
MAE	3.86	1.38	1.79	0.87

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 price of risk of the market factor. b_{MS} denotes the price of risk of the monetary supply shocks.The test assets include three SOE investment-rate (IK) portfolios, three SOE book-to-market (BM) portfolios, three SOE illiquidity portfolios, and three SOE cash-flow-to-price (CFP) portfolios. The model results are based on the IK and BM portfolios due to simulated-data availability. 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 2005 to 2018. The results for the model part (column "Model") are obtained from 1,000 firms of simulated data.

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	0.61	0.86	0.13	0.03	-0.03	-0.08	0.03	0.03
$[t]$	3.31	2.80	2.09	0.52	-0.78	-1.29	5.07	6.14
$P2 \times MS$	-0.52	-0.46	-0.08	-0.10	-0.07	-0.09	-0.01	-0.05
$[t]$	-2.12	-1.20	-0.97	-1.14	-1.70	-1.74	-3.21	-14.01
$P3 \times MS$	-0.87	-1.39	0.10	-0.15	-0.11	-0.19	0.00	-0.06
$[t]$	-3.24	-3.05	1.21	-1.68	-2.20	-2.93	0.32	-12.85
N	11468	11771	11772	10595	12530	12530	12530	11309
R^2	0.22	0.30	0.12	0.02	0.47	0.59	0.57	0.51
	Panel B: POE							
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
MS	0.54	0.68	0.49	0.43	-0.04	-0.12	0.01	0.02
$[t]$	2.32	1.66	4.54	3.37	-0.65	-1.20	3.74	4.46
$P2 \times MS$	-0.33	0.65	-0.15	-0.21	-0.02	-0.03	-0.01	-0.03
$[t]$	-1.14	1.23	-1.20	-1.41	-0.52	-0.52	-1.52	-10.72
$P3 \times MS$	0.47	-0.54	0.03	0.04	-0.05	-0.12	0.01	-0.03
$[t]$	1.36	-0.88	0.22	0.25	-0.92	-1.15	0.91	-7.88
N	9781	11146	11146	9277	12958	12958	12958	11922
R^2	0.22	0.30	0.11	0.05	0.57	0.62	0.56	0.46

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

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

$\Pi_{i,t+h}$ is either (i) the first difference of debt growth (is the change in firm i's total debt at time t, divided by the average of total assets at t and $t-1$) (ΔD_t); (ii) the first difference of firm i's investment rate at time t (ΔIK_t); or (iii) the change in firm i's total profit at time t, divided by the average of total assets at t and $t-1$ (ΔCF_t), and ΔCF_{t+1} at time $t+1$. MS is the monetary supply shock series. Pj_t is the investment rate portfolio $j = 2, 3$ dummy. The control variables include firms' physical capital to market equity ratio (KM), Tobin Q, size, and leverage; μ_k denotes industry fixed effects. $[t]$ denotes Newey–West heteroscedasticity and autocorrelation consistent t-statistics for the real data, and the t-statistic for whether the estimated slope coefficient differs from zero for the simulated data. N is the total number of firm-year observations. R^2 is the adjusted R^2. All dependent variables are winsorized at the top and bottom 1 percent in each year to reduce the influence of outliers. The real-data sample period is 2005 to 2018. The model results (columns "Model") are obtained from 125 samples of simulated data, each containing 1,000 firms for both types and 15 annual observations for both POE and SOE firms.

Table 6: Tests of capital misallocation and MS shocks

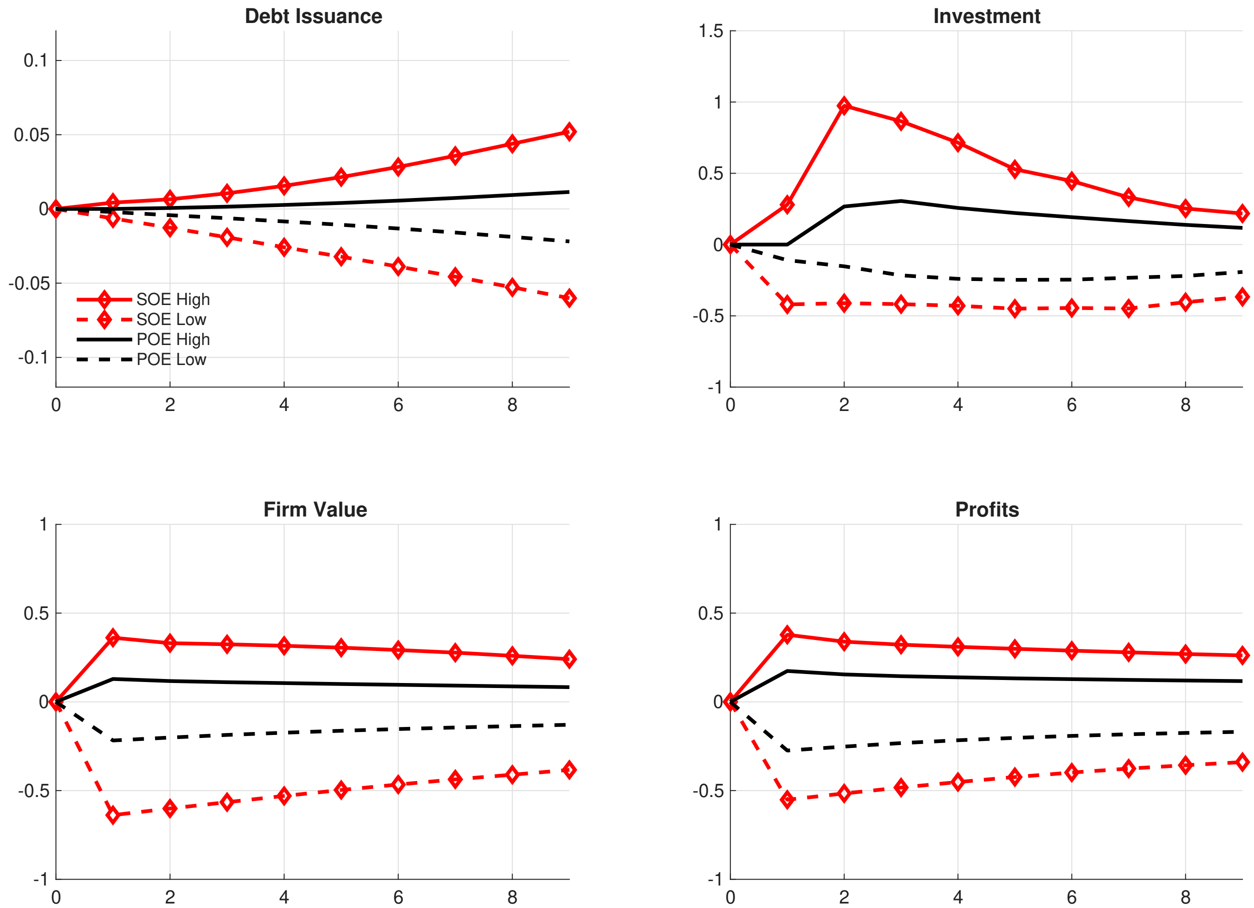
	(1) SOE	(2) POE	(3) SOE	(4) POE	(5) Both
Panel A: TFP growth and MS shocks					
MS	0.00	-0.03	0.05	-0.02	0.03
[t]	0.26	-2.73	2.32	-2.20	1.53
MS $\times$ POE					-0.04
[t]					-1.67
Controls	No	No	Yes	Yes	Yes
N	612	594	612	593	1205
R^2	0.00	0.00	0.12	0.01	0.04
Panel B: MRPK dispersion and MS shocks					
MS	0.14	1.74	0.19	1.59	0.24
[t]	0.43	2.02	0.62	2.10	0.77
MS $\times$ POE					1.38
[t]					1.69
Controls	No	No	Yes	Yes	Yes
N	683	643	683	642	1325
R^2	0.00	0.03	0.02	0.05	0.05

Panel A reports industry-level regressions of the industry-level TFP growth on MS monetary policy shocks, estimated separately for SOEs, POEs, and the pooled sample, with and without industry-level controls. Panel B reports analogous regressions using industry-level measures of MRPK dispersion. In both panels, the specifications are of the form

$$\begin{aligned}\Delta\text{TFP}_{i,j,t} \text{ or } \text{Disp(MRPK)}_{i,j,t} = \alpha + b\,\text{MS}_{t-1} + c\big(\text{POE}_{j,t-1} \times \text{MS}_{t-1}\big) \\ + d\,\text{POE}_{j,t-1} + \beta X_{i,j,t} + \mu_{i,j} + \varepsilon_{i,j,t}.\end{aligned}$$

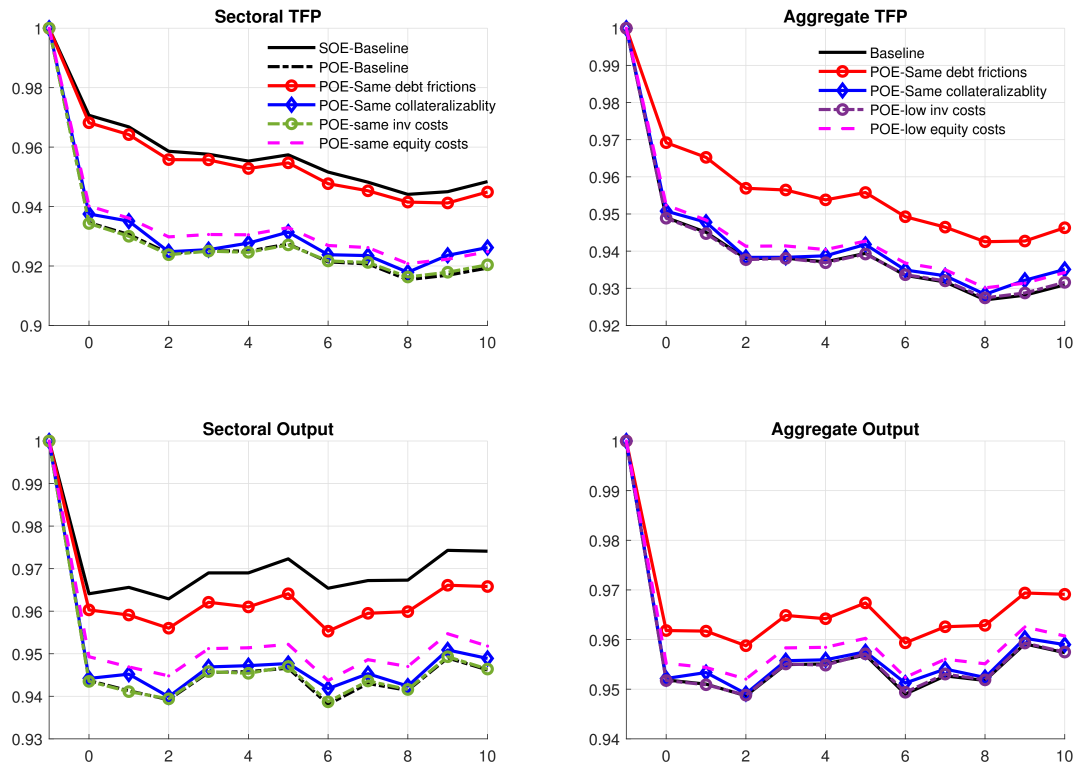
where $\Delta\text{TFP}_{i,j,t}$ is the change in industry $i's$ total factor productivity (TFP) growth in either POE or SOE sectors (j), and $\text{Disp(MRPK)}_{i,j,t}$ is the dispersion of the marginal revenue product of capital (MRPK) in industry $i's$ and sector (j). MS_{t-1} is the lag of the opposite of the MS shock, and $\text{POE}_{j,t-1}$ is a dummy variable equal to one if TFP or MRPK is for the POE sector, and zero otherwise. The control variables $X_{i,j,t}$ include the industry's physical capital-to-market equity ratio (KM), Tobin's Q, and leverage. μ_i is industry $\times$ POE dummy fixed effects. Industry classifications follow the Industry Classification Guidelines for Listed Companies issued by the China Securities Regulatory Commission (CSRC). t-statistics, reported in parentheses, are heteroskedasticity- and autocorrelation-consistent (Newey–West). R^2 values are within-R^2 values for the panel regressions. We exclude industry-year observations that contain only one firm. To account for variation in industry size, we weight the panel regressions by the number of firms in each industry-year. The sample covers the period from 2005 to 2018.

Figure 1: Firms' responses to the monetary supply (MS) shock: SOE vs. POE



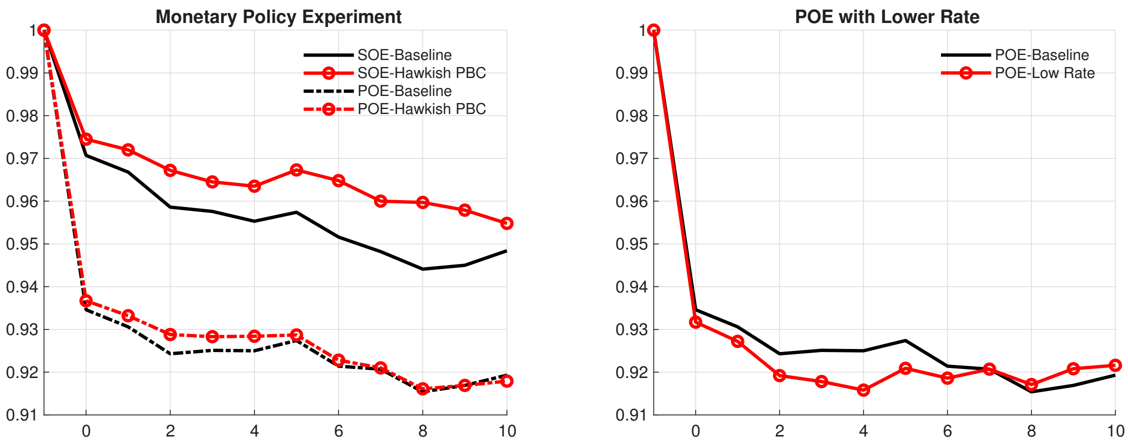
This figure plots impulse responses of key endogenous variables under the baseline calibration to a one-standard-deviation contractionary monetary-supply shock, which raises the marginal cost of debt issuance and corresponds to a high–marginal-utility state. Responses are reported as percent deviations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

Figure 2: 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 3: Measured TFP: the role of monetary policy



This figure plots impulse responses of sectoral output and measured TFP to a one-standard-deviation contractionary MS shock under two alternative specifications: (i) a more hawkish policy rule with a stronger response to inflation, (ii) a lower nominal rate for POEs. 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.

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 three 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, which is obtained from the Wind database.

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. China's monetary supply shocks (M2 shocks) data are downloaded from the Center for Macro Finance (CMF) in 2020 (`https://en.cmf.cafr.cn/`).

A.2 Measuring investment and portfolio returns

Physical capital investment at time t is constructed from accounting identities as follows. By definition, the change in gross fixed assets from $t-1$ to t equals the purchase of gross fixed assets minus the gross value of sales of gross fixed assets. The gross value of sales in turn equals the net value of sales plus the decrease in accumulated depreciation. Combining these gives:

$$\text{Physical capital investment}_t = \text{Change in gross fixed assets}_t + \text{Decrease in accumulated depreciation}_t.$$

Following Fama and French (1992), at the end of June of year t we sort all firms within each sector into three portfolios based on their investment rate at the end of year $t-1$, using the within-sector tercile breakpoints. Portfolio returns are value-weighted by net fixed assets

(PPENT) and tracked from July of year t to June of year $t+1$, with the procedure repeated annually.

To implement annual rather than monthly rebalancing, we fix each firm's portfolio weight at its lagged PPENT (K_{t-1}) at portfolio formation in July of year t, and update the weight each subsequent month by the cumulative return since formation. For example, the September weight is $K_{t-1} \times Return_{July,t} \times Return_{August,t}$, and so on through June of the following year. Using PPENT rather than market equity as weights helps avoid extreme outliers in the cross-sectional market equity distribution, especially in the SOE sector.

A.3 Regression analysis of investment-return relationship

We also examine the link between firms' 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 (physical capital to market equity ratio (KM), Tobin Q, size, leverage, and industry dummy).

Table A.3 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 2, the slope coefficient on the interaction of investment rate and the SOE dummy is -0.43. This difference is large in economic terms: A 10% increase in the firm's investment rate, is associated with a decrease of 0.043% 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.4 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.4 shows that the model matches basic firm characteristics of chinese SOEs and POEs. low investment (high investment) SOEs as well as POEs are associated with low (high) productivity, low (high) investment rate, and low (high) debt issuance, both in the data and in our model. However, the book leverage ratios of SOEs and POEs show opposite trends, and the real data and simulated data are consistent.

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. Tables A.5 to A.7 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 (MS 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 results imply that the M2 shock and the MS shock capture a common component of monetary growth in 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 insignificant. All these responses to the M2 shock are consistent with those to the MS shock.

A.6 Interest rates across SOEs and POEs

One alternative channel driving the differential exposures to MS shocks is the interest-rate channel: high- and low-investment SOEs and POEs may respond differently to MS shocks because their loan interest rates respond differently. To test this channel, we collect firm-level interest-rate data and compute each firm's interest rate as its loan rate minus the bank benchmark rate.[14] Table A.8 reports the results. While we cannot fully rule out a role for interest rates, most of the responses of SOEs' and POEs' interest rates to MS shocks are statistically insignificant, and the responses do not vary systematically across high- and low-investment SOE firms. This is perhaps unsurprising given that, as noted in Section 2, China's monetary policy uses M2 growth as the intermediate target, with interest rates playing a limited role in policy implementation.

[14]The sample size for this analysis is significantly smaller: only about 5% of firms in our data report the interest rates on their loans. However, the key firm-level characteristics, including investment rate, debt growth, and profitability, are similar to those of the full sample.

A.7 Shadow banking

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[15] and redo the empirical analyses. Table A.9 reports the result. We find the responses of investment, debt issuance and profit growth to the shadow banking growth shocks do not exhibit 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.10 to A.13 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 one. We first convert the nominal variables into one in real term and then exploit the homogeneity property of the model and scale all variables 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

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

subject to the collateral constraint that comes in scaled form

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

Normalized earning is given by

$$e_t = (1-\tau)y_t + \tau\delta + \tau r^{\$}_{f,t}\frac{b_t}{1+\pi_t} - i_t - g_t + (1-\delta+i_t)b_{t+1} - (1+r^{\$}_{f,t})\frac{b_t}{1+\pi_t} - \Phi^B_t$$

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

Normalized dividend is therefore,

$$d_t = e_t - \psi|e_t|\mathbf{I}_{\{e_t<0\}} - f$$

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 Decreasing return to scale production function

We examine the robustness of our capital misallocation results by considering an alternative production function with decreasing returns to scale (DRS). We modify Equation (1) as follows:

$$Y_{j,t} = A_t Z_{j,t} K_{j,t}^{\alpha},$$

where $0 < \alpha < 1$ is the output elasticity of capital. This assumption breaks the homogeneity of the firm's optimization problem, introducing capital as an additional state variable. We set $\alpha = 0.85$ while keeping all other parameters of the benchmark SOE and POE models unchanged.

With DRS technology, the ratio of sectoral aggregate output to capital no longer serves as a direct measure of sectoral productivity. Instead, we compute two alternative measures. First, we calculate the average firm-level productivity $Z_{j,t}$, weighted by firm size (capital) within each sector. Intuitively, if capital is allocated efficiently, more productive firms should operate with more capital, thereby raising this weighted average. Second, we compute the Solow residual using aggregate sectoral output and capital.

Figure A.3 presents the dynamics of both productivity measures following a negative monetary supply shock. The POE sector experiences a significantly more pronounced decline in productivity compared to the SOE sector. The magnitude of the implied capital misallocation is quantitatively similar across the two measures. Overall, these results confirm our benchmark findings under CRS technology, although the magnitudes of the responses are somewhat larger.

B.5 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_ξ 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 3.

Figure 3 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.14 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.

B.6 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 0.13 to 0.013. The results are displayed in the lower-right panel of Figure 3.

Figure 3 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.14 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.

B.7 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 ($b_1 < b_0$)[16]. 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 decision.

[16]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.

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

$$V_1^B = \int_0^{z_1^*}(z_1^*-z_1)\,d\Phi(z_1) + \frac{1}{1-\varrho}\int_{z_1^*}^{\bar{z}}(z_1^*-z_1)\,d\Phi(z_1) + \mathbb{E}\big[M_{1,2}\big(L(m_2)-R^fS_1+R^Bb_1\big)\big]\,.$$

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:

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

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,

$$\frac{\partial z_1^*}{\partial m_1} = \frac{\eta/b_0}{\kappa}\frac{\partial b_1}{\partial m_1} > 0.$$

By the chain rule,

$$\frac{\partial}{\partial m_1}\Big(1-\Phi(z_1^*)\Big) = -\phi(z_1^*)\frac{\partial z_1^*}{\partial m_1} < 0,$$

since $\phi(z_1^*) > 0$ and $\partial z_1^*/\partial m_1 > 0$. ■

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 $(0, \frac{1}{2})$.[17] We hold all other parameters constant at their baseline values: the initial

[17]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.

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.

The main results are illustrated in Figure A.4. 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 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.8 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):

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

where $0 < \beta < 1$ is the discount factor, $\sigma > 0$ is 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.8, 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

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

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

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,

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

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

C 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 firms' private vs. state ownership structure.

C.1 Monetary policy overview

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.[18] 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 and 2018 also witnessed investment-driven economic growth in which credit and bank loans were used to finance investment in SOEs and POEs. Since 2017, monetary policy has still adhered 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, the PBC has used two key intermediate targets to implement the quantity-based monetary policy approach. The first is M2 growth, and the second is bank credit. The PBC outlines the targets for M2 growth and 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 monetary policy, the bank lending channel is also one of the key channels in implementing 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 the PBC to implement monetary policy include the required reserve ratio (RRR), central bank lending, rediscounting, open market operations, etc. Changes in the RRR are 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-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 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.

C.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

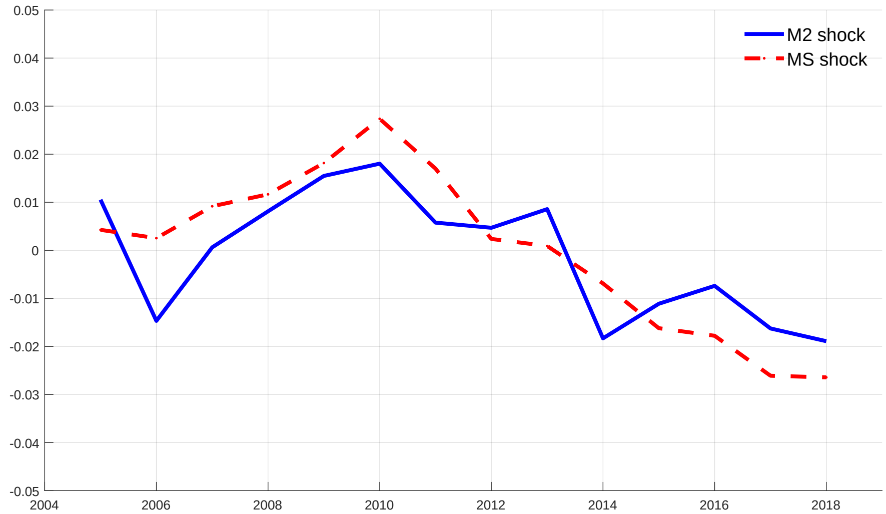
[18] Refer to Huang et al. (2019), "Monetary policy framework and transmission mechanisms", chapter 2 of the Handbook of China's Financial System, for a detailed discussion of the transition of monetary policy in China from 1949, and Chen and Zha (2018), "Macroeconomic effects of China's financial policies",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

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 ordered state-owned banks to lend directly to SOEs.

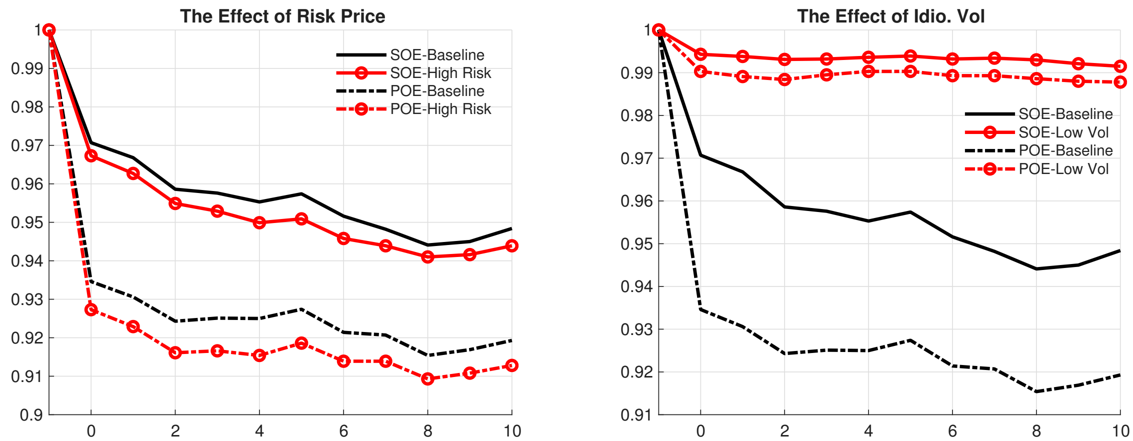
Since implementing the quantity-based framework after 1998, the PBC has focused on M2 growth and credit as the intermediate targets. As a result, the PBC's monetary policy stopped direct credit allocation to SOEs. However, the bank lending channel is still an important policy mechanism that drives investment-led 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 the fact 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 that of POEs because it is easier for SOEs to access debt financing.

Figure A.1: Time series of the M2 and MS shocks



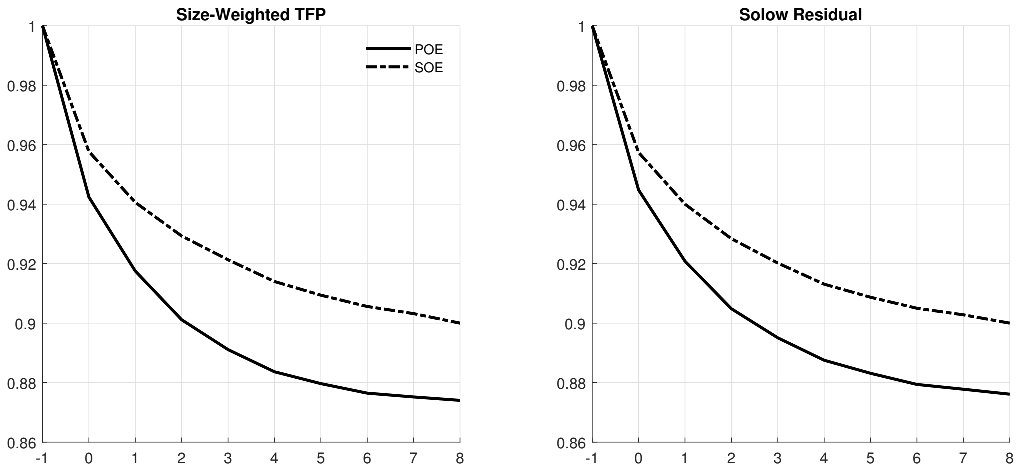
This figure reports the time series of two monetary supply shocks: 1) the M2 shock (solid line) that we construct following CRZ and extend to a longer sample which ranges from 2005 to 2018, and 2) the MS shock (dashed line) that we estimate in the data with the identification guided by our structural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

Figure A.2: Measured TFP-the role of risk and firm heterogeneity



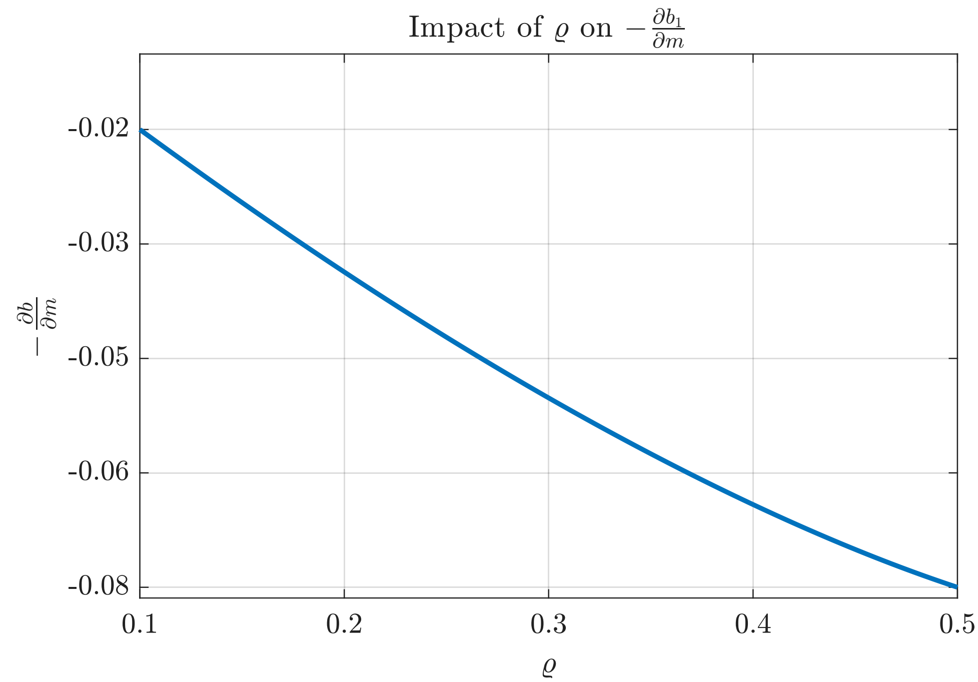
This figure plots impulse responses of sectoral output and measured TFP to a one-standard-deviation contractionary MS shock under four alternative specifications: (i) a higher market price of MS risk, and (ii) lower firm-level productivity volatility for both SOE and POE firms. Responses are reported 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 output-to-capital ratio.

Figure A.3: Measured TFP losses under DRS production technology



This figure plots impulse responses of sectoral measured TFP to a one-standard-deviation contractionary monetary supply shock under the assumption of decreasing returns to scale (DRS) production technology ($Y = AZK^{\alpha}$, with $\alpha = 0.85$). We report two measures of sectoral productivity: (i) the capital-weighted average of firm-level productivity Z, and (ii) the Solow residual computed using aggregate sectoral output and capital. The solid lines represent the responses for POEs, while the dashed lines represent those for SOEs. The y-axis shows the ratio between post shock and pre-shock levels of measured TFP, normalized to one at the time of the shock.

Figure A.4: 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 one 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

Table A.1: Correlation of the aggregate variables

	GDP	Investment	Consumption	Debt	M2	M2 shock	MS shock
GDP	1.00						
Investment	0.61	1.00					
Consumption	0.53	0.86	1.00				
Debt	0.42	0.74	0.89	1.00			
M2	0.61	0.90	0.90	0.84	1.00		
M2 shock	0.37	0.70	0.76	0.71	0.64	1.00	
MS shock	0.64	0.80	0.87	0.79	0.80	0.84	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 year-on-year growth rate of social financing scale.

Table A.2: Relationship with macroeconomic shocks

	ΔTFP	ΔISI	ΔCS	ΔEP	ΔBM	ΔTQ
MS shock	-0.05	0.12	-0.04	0.08	-0.02	-0.03
p-value	0.86	0.69	0.90	0.78	0.95	0.92
M2 shock	0.27	-0.10	0.14	0.38	0.27	-0.17
p-value	0.38	0.73	0.67	0.18	0.35	0.57

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.3: Stock return predictability and ownership structure

	1	2	3
IK	-0.24	-0.10	0.05
[t]	-1.55	-0.63	0.35
IK× SOE		-0.43	-0.49
[t]		-2.24	-3.32
SOE		-0.19	0.02
[t]		-0.86	0.10
N	315267	315267	309779
R^2	0.00	0.01	0.14
Controls	No	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 firms' physical capital to market equity ratio (KM), Tobin Q, size,leverage, and industry dummy. [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 1 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.4: 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	0.052	0.128	0.183	-0.131	0.121	0.056	0.124	0.262	−0.206	0.146
TFP_t	0.496	0.584	0.609	-0.114	0.563	0.737	1.009	1.403	−0.666	1.070
ΔD_t	0.023	0.045	0.062	-0.039	0.044	0.018	0.031	0.062	−0.044	0.038
$Leverage_t$	0.514	0.524	0.548	-0.034	0.529	0.518	0.534	0.530	−0.012	0.524
	Panel B: POE									
	L	M	H	L-H	Avg	L	M	H	L-H	Avg
IK_t	0.062	0.187	0.246	-0.185	0.165	0.083	0.176	0.349	−0.266	0.194
TFP_t	0.532	0.627	0.660	-0.128	0.607	0.834	1.005	1.546	−0.712	1.116
ΔD_t	0.023	0.052	0.067	-0.044	0.047	0.023	0.052	0.067	-0.044	0.047
$Leverage_t$	0.452	0.416	0.415	0.037	0.428	0.465	0.458	0.435	0.030	0.449

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); Note that the TFP measures have been normalized to have a mean of one, respectively for SOEs and POEs. ΔD is the change in total debt at time t divided by the average of total assets 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 subscript 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.5: The price of risk of M2 shocks

	Data		Model	
	CAPM	2-Factor	CAPM	2-Factor
MKT	0.45	0.82	1.84	-0.19
[t]	1.80	1.43	9.29	-0.29
M2		0.91		0.94
[t]		2.70		3.19
R^2	-1.48	73.14	89.86	96.12
MAE	3.86	1.94	1.79	0.87

This table reports the GMM asset pricing tests of the following two-factor model $E[r^e_{i,t}] = \alpha_i + b_{MKT}Cov(MKT_t, r^e_{i,t}) + b_{M2}Cov(M2_t, r^e_{i,t})$, 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 $b_M 2$ =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 include three SOE investment-rate(IK) portfolios, three SOE book-to-market (BM) portfolios, three SOE illiquidity portfolios, and three SOE cash-flow-to-price (CFP) 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 to 2019. The results for the model part (column "Model") are obtained from 1,000 firms of simulated data.

Table A.6: Asset pricing tests of M2 shock

	SOE				POE			
	L	M	H	L-H	L	M	H	L-H
α^{2F}	0.21	0.87	-3.40	3.61	-0.27	-0.70	-3.17	2.90
[t]	0.07	1.06	-1.69	0.92	-0.25	-0.68	-1.08	0.85
Cov^{MKT}	-1.00	0.69	0.31	-1.31	1.73	-0.73	-1.00	2.74
[t]	-0.09	0.06	0.03	-0.98	0.15	-0.07	-0.09	1.61
Cov^{M2}	4.24	-3.25	-0.98	5.22	-1.63	0.00	1.62	-3.25
[t]	1.43	-1.40	-0.39	2.31	-0.62	0.00	0.81	-1.11

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 2019. L-H stands for the low-minus-high investment portfolio.

Table A.7: Debt growth, investment, and profits responses to M2 shock

	Panel A. SOE			
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
$M2$	0.54	0.99	0.08	0.07
[t]	2.18	2.31	0.93	0.77
$P2 \times M2$	-0.70	-0.80	-0.11	-0.03
[t]	-2.19	-1.52	-1.12	-0.26
$P3 \times M2$	-0.79	-1.77	0.06	-0.14
[t]	-2.30	-2.87	0.55	-1.23
N	11468	11771	11772	10595
R^2	0.22	0.30	0.11	0.02
	Panel B. POE			
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
$M2$	0.88	0.84	0.12	0.48
[t]	2.89	1.49	0.53	3.04
$P2 \times M2$	-0.77	0.61	0.18	-0.19
[t]	-2.04	0.84	0.87	-0.94
$P3 \times M2$	0.28	-0.41	0.38	0.01
[t]	0.65	-0.50	1.58	0.03
N	9781	11146	11146	9277
R^2	0.22	0.30	0.10	0.05

This table reports the relevant slope coefficients from panel 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 debt growth (is the change in firm's i total debt at time t divided by the average of total assets at time t and $t-1$) (or the first difference of firm's i investment rate at time t; or the change in firm's i total profit at time t, divided by the average of total assets 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), Tobin Q, size, leverage, and industry fixed effects. [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 2005 to 2018.

Table A.8: Interest rate responses to MS and M2 shocks

	SOE		POE	
	MS	M2	MS	M2
	R_t	R_t	R_t	R_t
S	-0.09	-0.13	-0.31	-0.46
[t]	-1.20	-1.64	-2.21	-2.41
$P2 \times S$	0.11	0.13	0.14	0.22
[t]	1.12	1.23	0.79	0.93
$P3 \times S$	-0.09	-0.11	0.18	0.40
[t]	-0.99	-1.01	0.97	1.63
N	788	788	395	395
R^2	0.17	0.17	0.24	0.24

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

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

$R_{i,t}$ is the difference between firm i's 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), Tobin Q, size, leverage, and industry fixed effects. [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.9: Debt growth, investment, and profits responses to shadow banking (SB) shock

	Panel A. SOE			
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
SB	0.03	0.03	0.03	-0.02
[t]	2.18	1.18	5.64	-3.52
$P2 \times SB$	0.02	0.01	-0.01	0.01
[t]	0.95	0.23	-2.45	2.25
$P3 \times SB$	-0.03	-0.03	-0.01	0.01
[t]	-1.58	-0.97	-1.34	2.12
N	11468	11771	11772	10595
R^2	0.22	0.30	0.12	0.02
	Panel B. POE			
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
SB	0.06	0.01	0.06	-0.02
[t]	3.06	0.21	5.39	-1.69
$P2 \times SB$	-0.02	-0.06	-0.04	0.00
[t]	-0.73	-1.24	-2.93	0.11
$P3 \times SB$	0.01	0.02	-0.03	0.00
[t]	0.50	0.33	-1.95	-0.34
N	9781	11146	11146	9277
R^2	0.22	0.30	0.11	0.05

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

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

$\Pi_{i,t+h}$ is the first difference of debt growth (is the change in firm's i total debt at time t divided by the average of total assets at time t and $t-1$) (or the first difference of firm's i investment rate at time t; or the change in firm's i total profit at time t, divided by the average of total assets 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), Tobin Q, size, leverage, and industry fixed effects. [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 2005 to 2018.

Table A.10: Investment portfolios across SOEs and POEs using 5-IK portfolios

	SOE						POE					
	L	2	M	4	H	L-H	L	2	M	4	H	L-H
Panel A. Excess Returns												
r^e	13.91	15.07	10.65	10.63	9.64	4.28	20.46	16.46	16.99	19.53	16.38	4.08
[t]	1.31	1.36	0.93	0.94	0.90	2.16	1.67	1.33	1.47	1.74	1.50	1.15
SR	0.45	0.45	0.32	0.33	0.30	0.38	0.53	0.46	0.47	0.53	0.46	0.32
Panel B. CAPM												
α	3.33	3.79	-0.11	0.24	-1.71	5.03	7.61	4.08	4.43	6.89	3.93	3.67
[t]	1.43	1.43	-0.03	0.08	-0.81	2.58	2.06	1.27	1.36	1.96	1.29	1.05
b	0.94	1.00	0.95	0.92	1.00	-0.07	1.14	1.10	1.11	1.12	1.10	0.04
[t]	20.99	28.25	22.36	20.84	27.65	-1.36	26.93	27.26	29.49	28.17	34.83	0.86
R^2	0.88	0.84	0.77	0.79	0.90	0.03	0.84	0.89	0.89	0.87	0.90	0.01

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.11: Asset pricing tests across SOEs and POEs–5-IK portfolios

	MS Shock						M2 Shock					
	L	2	M	4	H	L-H	L	2	M	4	H	L-H
Panel A. SOE												
α^{2F}	0.33	2.09	1.50	-1.92	-1.86	2.19	1.25	1.73	1.58	-1.95	-2.44	3.69
[t]	0.33	0.91	1.17	-0.85	-1.18	0.98	1.10	1.07	1.52	-0.96	-1.75	1.59
Cov^{MKT}	-2.02	-0.58	1.02	2.02	-0.43	-1.59	-1.70	-0.31	0.47	2.04	-0.51	-1.19
[t]	-0.17	-0.05	0.08	0.15	-0.04	-1.65	-0.14	-0.03	0.04	0.15	-0.04	-1.57
Cov^{S}	4.58	2.24	-5.44	0.17	-1.56	6.14	3.82	3.71	-7.18	0.39	-0.74	4.56
[t]	1.99	0.82	-1.10	0.05	-0.54	2.74	1.17	1.26	-2.61	0.13	-0.29	2.62
Panel B. POE												
α^{2F}	0.44	-1.84	0.05	1.98	-0.42	0.87	1.28	-2.27	0.05	1.81	-0.68	1.97
[t]	0.71	-1.37	0.08	1.17	-0.36	1.03	1.06	-1.34	0.07	1.07	-0.60	1.32
Cov^{MKT}	1.11	1.75	-0.64	-1.52	-0.69	1.80	0.83	1.65	-0.54	-1.49	-0.46	1.29
[t]	0.09	0.13	-0.05	-0.13	-0.06	2.78	0.07	0.12	-0.04	-0.13	-0.04	1.77
Cov^{S}	-5.25	-0.46	1.31	0.89	3.51	-8.76	-2.72	-1.49	1.23	0.31	2.68	-5.40
[t]	-1.22	-0.12	0.33	0.23	1.05	-3.18	-0.76	-0.50	0.50	0.11	1.22	-2.16

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.12: The price of risk of 5-IK portfolios

	MS shock		M2 shock	
	CAPM	2-Factor	CAPM	2-Factor
MKT	0.43	0.26	0.43	0.79
[t]	1.68	0.99	1.68	1.45
S		0.82		0.87
[t]		2.22		2.71
R^2	-1.93	85.99	-1.93	70.02
MAE	3.77	1.50	3.77	2.05

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 five SOE investment-rate(IK) portfolios, three SOE book-to-market (BM) portfolios, three SOE illiquidity portfolios, and three SOE cash-flow-to-price (CFP) 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.

Table A.13: 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	0.81	0.89	0.14	0.12	0.78	0.96	0.12	0.15
[t]	3.39	2.19	1.71	1.40	2.43	1.71	1.07	1.24
$P3 \times S$	-1.00	-0.27	-0.08	-0.22	-1.37	-0.41	-0.13	-0.20
[t]	-3.05	-0.51	-0.72	-1.93	-3.20	-0.59	-0.95	-1.37
$P5 \times S$	-1.10	-1.68	0.06	-0.21	-1.09	-2.33	0.03	-0.20
[t]	-3.17	-2.76	0.64	-1.91	-2.43	-2.88	0.19	-1.35
N	11468	11771	11772	10595	11468	11771	11772	10595
R^2	0.22	0.32	0.12	0.02	0.22	0.32	0.12	0.02
	Panel B. POE							
	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}	ΔD_t	ΔIK_t	ΔCF_t	ΔCF_{t+1}
S	0.66	0.83	0.60	0.44	1.17	0.79	0.09	0.47
[t]	2.21	1.64	4.44	2.85	2.97	1.15	0.31	2.20
$P3 \times S$	-0.35	0.37	-0.34	-0.18	-0.96	0.53	0.12	-0.25
[t]	-0.91	0.54	-2.15	-0.94	-1.89	0.58	0.44	-0.97
$P5 \times S$	0.71	-0.63	-0.03	0.02	0.44	-0.36	0.46	0.01
[t]	1.55	-0.80	-0.20	0.08	0.77	-0.35	1.43	0.02
N	9781	11146	11146	9277	9781	11146	11146	9277
R^2	0.22	0.33	0.11	0.05	0.22	0.33	0.10	0.05

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

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

$\Pi_{i,t+h}$ is the first difference of debt growth (is the change in firm's i total debt at time t divided by the average of total assets at time t and $t-1$) (or the first difference of firm's i investment rate at time t; or the change in firm i's total profit at time t, divided by the average of total assets 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), Tobin Q, size, leverage, and industry fixed effects. [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.14: Selected data versus model-implied moments across alternative calibrations

	Inv vol	Debt iss spikes	Debt iss vol	Equity iss frac	Leverage	Inv spread	$\mathbb{E}(R^e)$
Panel A: Counterfactual analysis on POE							
0. Data POE	0.28	0.19	0.15	0.13	0.46	0.43	18.62
1. Baseline POE	0.28	0.20	0.13	0.13	0.45	0.61	17.80
2. Same investment cost as SOE	0.35	0.20	0.15	0.17	0.45	−0.25	13.27
3. Same debt iss cost as SOE	0.23	0.20	0.16	0.16	0.45	1.36	16.63
4. Same collateralizability as SOE	0.26	0.28	0.18	0.19	0.55	2.05	16.57
5. Same equity iss. cost as SOE	0.31	0.24	0.16	0.20	0.46	2.70	15.43
6. Low firm vol.	0.06	0.11	0.06	0.07	0.47	0.44	13.25
7. High MS risk	0.28	0.22	0.15	0.14	0.45	−0.90	24.37
8. Lower rate	0.31	0.35	0.17	0.18	0.48	−2.72	19.37
9. Hawkish policy	0.25	0.13	0.10	0.11	0.38	0.97	19.93
Panel B: Counterfactual analysis on SOE							
10. Data SOE	0.23	0.15	0.14	0.10	0.53	5.58	11.71
11. Baseline SOE	0.22	0.14	0.15	0.12	0.52	5.57	11.73
12. High MS risk	0.21	0.13	0.14	0.11	0.55	7.24	14.76
13. Low firm vol.	0.05	0.08	0.05	0.07	0.56	2.61	8.03
14. Hawkish policy	0.30	0.30	0.24	0.20	0.61	3.71	17.46

This table presents selected moments of the cross-sectional investment, debt, and equity issuance dynamics, and return spread between low minus high 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, equity issuance frequency, leverage, the difference in the return between the portfolios of low and high 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. Row 0 presents the data moments for POEs, and row 1 shows the baseline model fit. Rows 2 to 5 relax the investment and financing frictions of POEs, in which we assume that POEs have the same investment adjustment cost (row 2), identical debt issuance cost (row 3), the same collateralizability of capital (row 4), and the same equity issuance cost (row 5) as SOEs. Rows 6 to 9 report moments under four additional experiments: reducing cross-sectional volatility of firm productivity (row 6), increasing monetary shock's risk price (row 7), lowering the interest rate (row 8), and implementing hawkish monetary policy (row 9). Panel B conducts counterfactual analysis for SOEs. Row 10 presents the data moments for SOEs, and row 11 shows the baseline model fit. Rows 12 to 14 report moments under three experiments: increasing monetary shock risk (row 12), reducing cross-sectional volatility of firm productivity (row 13), and implementing hawkish monetary policy (row 14).