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ABSTRACT

We use firm-level data to identify financial frictions in China and explore the extent to which they can explain firms' saving and capital misallocation. We first document the features of the data in terms of firm dynamics and debt financing. State-owned firms have higher leverage and pay much lower interest rates than non-SOEs. Among privately owned firms, smaller firms have lower leverage, face higher interest rates, and operate with a higher marginal product of capital. We then develop a heterogeneous-firm model with two types of financial frictions, default risk, and a fixed cost of issuing loans. Our model generates endogenous borrowing constraints as banks consider the firm's productivity, asset, and debt when providing a loan. Using evidence on the firm size distribution and financing patterns, we estimate the model and find it can explain aggregate firms' saving and investment and around 50 percent of the dispersion in the marginal product of capital within private firms, which translates into a TFP loss as high as 12%.

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1 Introduction

A large body of literature has emphasized that financial frictions can generate high saving and capital misallocation in less-developed countries like China. China has been growing fast for decades and yet, despite this, it runs a current account surplus, accumulating a large stock of foreign reserves. This is puzzling, since standard economic theories predict that capital should flow to countries with fast-growing productivity and thus high returns. One explanation for this puzzle, advanced in the literature, is that Chinese financial markets are underdeveloped, leading to distorted financial allocations.[1] Privately owned firms, which are more productive than their state-owned counterparts, rely heavily on internal financing.[2] Indeed, saving among firms accounts for around 50 percent of the total saving in China in the last two decades. Financial frictions can also lead to capital misallocation and low total factor productivity (TFP). Hsieh and Klenow (2009) quantify the potential extent of misallocation in China, relative to the US: if capital and labor were hypothetically reallocated in a way that reduced dispersion of marginal products to US values, China would see a 30-50% increase in manufacturing TFP.

The existing literature tend to use aggregate data or micro-level firm dynamics to quantify the role of financial frictions on TFP. Most works, however, ignore firms' financing patterns. Our paper fills this gap. We ask to what extent financial frictions, quantified using firm dynamics and financing patterns, can explain saving and capital misallocation in China.

We start by documenting the salient features of rich, Chinese firm-level data. In particular, we are interested in how debt financing and firm growth vary across firms. We find that state-owned firms (SOE) have higher leverage and pay lower interest rates than non-SOEs. Among privately owned firms, small firms have lower leverage, pay higher interest rates, grow faster, and face a higher marginal product of capital (MPK) than large firms. Even though China has been undergoing significant reforms, like the state-owned-enterprise reforms and financial liberalization, these patterns of debt financing and firm dynamics are observed consistently over time.

To explain these salient features and quantify the magnitude of financial frictions in China, we build a heterogeneous-firm model with endogenous default risk and a fixed cost of issuing loans. All firms produce with a decreasing return to scale technology using capital. They face stochastic productivity shocks. Adjusting capital (size) is costly due to both adjustment cost and financing costs. Firms finance investment and dividend payouts from profits and bank loans. They may default on their loans and secretly operate in financial autarky, with

[1] Many papers have addressed this puzzle, for example, Buera and Shin (2009), Song, Storesletten, and Zilibotti (2011), Caballero, Farhi, and Gourinchas (2008), Quadrini, Mendoza, and Rios-Rull (2009).

[2] See Huang (2011), who shows that firms' saving vary with their ownership structure.

penalized productivity. Firms with lower productivity, smaller size, and larger amount of debt default more easily. Banks incorporate these default risk into the loan prices as well as the fixed cost of issuance. Hence, our model generates endogenous borrowing limits and differential leverage and interest rates across firms.

In the model, the firm's size, leverage, and growth are all affected by financial frictions. When considering external finance via bank loans, firms face a trade-off. On the one hand, borrowing more is associated with higher default risk and thus higher effective interest rate. On the other hand, borrowing involves a fixed cost, so that small loans have a high effective interest rate. In equilibrium, small firms with low assets tend to be more financially constrained, stay inefficiently small, pay high interest rate, and ultimately face low leverage. When they experience a good productivity shock, these small firms grow faster, due to their inefficient size. Our model thus has the potential to match the firm financing pattern in the data, namely low leverage and high interest rates faced by small firms.

The financial frictions in our model can not only explain the observed firm financing patterns, but also reflect the realistic frictions in China. According to a survey by Wagle (2000), around 70 percent of Chinese firms reported that paperwork and relationship with banks as major obstacles to their application for a formal bank loan. These overhead costs within the application process make it especially hard for small firms to access to external financing. Although China has made significant progress in reducing government intervention in the banking sector, there is still ample evidence that local governments continue to encourage banks to lend to state-owned banks by extending explicit or implicit government guarantees. With these guarantees, a bad loan to a state-owned enterprise is not considered as a bad loan for the banks, since the government will almost surely bail out the firm. By contrast, absent these government guarantees, privately owned enterprises are in general charged a much higher interest rate when they borrow from the banks.

We estimate the model using the firm size distribution, dynamics of sales, and financing patterns. These moments help us identify the productivity process, capital adjustment cost, and the parameters jointly governing financial frictions. In particular, the productivity process parameters are mostly related to the distribution of value added and its growth. We therefore target the shares of value added in the top 5, 10, and 20 percentiles, the mean autocorrelation of value added, and the standard deviation of growth. The capital adjustment cost affects how responsive a firm's investment to shocks. We discipline it with the regression coefficient of capital growth rate on value added. The fixed issuing cost and productivity loss after default determine the mean leverage and how leverage and interest rate vary with firm size. We thus include these moments in our estimation. Overall, the moments in our model closely match those in the data.

With the estimated parameters, we can explore the model implication on capital misallocation. Our model accounts for about 50% of MPK variation, which implies about a 12% of TFP loss. Hence we explain about one third of China's TFP loss measured in Hsieh and Klenow (2009). In the data, firms with low asset, low leverage, and high value added face higher MPK. The model produces a similar pattern, except regarding the MPK and asset relationship. Specifically, the correlation between MPK and value added is 0.38 in the model and 0.11 in the data. The MPK-leverage correlation is -0.05 in the model, which is close to that in the data, -0.01. The MPK-asset correlation is close to zero in the model, but -0.31 in the data. This implies that the relatively large MPK of small firms cannot be fully explained by financial frictions.

Additional statistics that can shed light on financial friction include the correlation of saving rate and investment rate. Financial frictions increase a firm's internal return and lead to a positive correlated saving and investment. The data correlation is 0.58 and the model correlation is 0.68, indicating a significant level of financial frictions. Our model closely matches the observed aggregate investment rate, and the ratio of aggregate investment to aggregate value added is 0.22 in the model versus 0.18 in the data. Our model also matches well how a firm's saving and investment co-move with its asset, value added, and leverage across time. In both the data and the model, larger firms reduce their debt and investment due to decreasing return to scale; high leverage firms reduce their debt; higher-productivity firms tend to have higher leverage and also invest more, leading to a positive relation between leverage and investment; and controlling for capital and debt, firms with larger output increase their debt and investment. In summary, our model successfully produces the observed cross-section and within-firm patterns on saving and investment.

Our benchmark model has two types of frictions distorting a firm's investment decision: financial frictions and capital adjustment cost. We conduct two analyses to decompose them. In the first one, we rerun our benchmark model with zero capital adjustment cost while keeping other parameters constant. In the second one, we shut down the financial frictions and compute a model with only capital adjustment cost. We find that financial frictions generate higher marginal returns and tend to distort the investment of less productive firms, while capital adjustment cost distorts the investment decision more among more productive firms. Either friction alone produces a large TFP loss, 9.5% under only financial frictions and 13% under only capital adjustment cost. Together, they interact and lead to larger but less dispersed MPKs across firms, hence a lower misallocation across firms. The model with only adjustment cost is apparently silent on firms' financing patterns.

Our paper is related to a large strand of literature in corporate finance which studies the impact of financial frictions on firm investment and financing patterns. From the early descriptive work of Fazzari, Hubbard, and Petersen (1988) to the natural experiments and quantitative exercises,[3] we have learned that financial frictions could affect investment and saving, and that these effects can be large. Our quantitative results show that the effects of financial frictions on saving and investment are indeed large for Chinese firms. Also, despite previous literature's success in matching the mean, standard deviation, or correlation of certain financial or real variables, they largely fail in matching the firm distribution. This could potentially lead to biased estimates in their counterfactual experiments due to firms' heterogeneous responses to the change of primitive parameters. Our analysis is differentiated by its consideration of a more realistic set of shock processes and financing features, which both generate a richer set of investment and financing predictions, and enable our model to do a markedly better job than previous models in matching the empirical firm distribution in sales, leverage, and interest rate. Furthermore, what is less well understood is the impact of financing frictions on the allocation of factors of productions across firms. We enter the picture by studying the impact of financial frictions through the lens of capital misallocation. We show that financial frictions could explain a large proportion of capital misallocation across heterogeneous firms, which has important implications for total factor productivity losses.

Our paper is closely related to the work of Whited and Zhao (2017) and David and Venkateswaran (2017). Whited and Zhao (2017) focus on the potential welfare gain from reallocating debt and equity among Chinese firms and estimate the distortion using a static model and observed data directly. Our paper uses a dynamic model to quantify the impact of financial frictions, including limited enforcement and credit intermediation cost, on firm saving and misallocation. David and Venkateswaran (2017) also quantify the contributions of capital adjustment cost, technology dispersion, and information friction to capital misallocation. We focus on identifying financial frictions with firm dynamics and financing patterns. The MPK dispersion is endogenous in our model, while it is exogenous in their work.

Our work also contributes to the growing literature on the effect of misallocation induced by financial frictions on aggregate TFP. Hsieh and Klenow (2009) use firm-level data to quantify the potential extent of misallocation in China and India relative to that of the US. They document sizable gaps in the marginal products of factors across plants in these emerging markets. Our paper emphasizes the misallocation in Chinese data, due to domestic financial frictions, by examining firms' debt financing choices and growth. Midrigan and Xu (2013) parameterize a financial frictions model to match the salient features of plant-level data and show that the model does not predict large aggregate TFP losses from misallocation and

[3] For example, Chava and Roberts (2008), Gomes (2001), Hennessy and Whited (2005), Hennessy and Whited (2007), Gamba and Triantis (2008), Rampini and Viswanathan (2010), Korteweg (2010), Bolton, Chen, and Wang (2011), Eisfeldt and Muir (2016), Armenter and Hnatkovska (2017) etc.

that misallocation from financial constraints cannot explain the TFP gap between countries with little use of external finance and the US. We examine firms' financing pattern combined with other salient features, and our exercise suggests that endogenous borrowing constraints are essential to explain firms' financing with Chinese data. Cooley and Quadrini (2001) show that the combination of persistent shocks with financial frictions can account for the dependence of firm dynamics on size and age.

Our paper is closely related to that of Arellano, Bai, and Zhang (2012), who use cross-country variations in financial market development to evaluate empirically and quantitatively the impact of financial frictions on firms' financing choices and growth rates, with a firm-level datasets for Europe. Our findings of positive size-leverage relation in China is consistent with their findings in the less-developed countries. We, however, focus on the effect of financial frictions on firms' saving and investment decisions and Chinese capital misallocation measured by the MPK dispersion and covariance between MPK and firm size.

Our paper is also related to the literature on the implications of financial frictions in China. Using a growth model, Song, Storesletten, and Zilibotti (2011) show that during an economic transition high-productivity, non-state-owned firms outgrow low-productivity, state-owned firms if entrepreneurs have high enough saving. At the same time, the more financially integrated SOE sector shrinks, forcing domestic saving to be invested abroad, leading to a foreign surplus. Wang, Wen, and Xu (2012) use two types of capital, financial and fixed capital, to explain two-way flows. In their model, underdeveloped financial market in China offer a high rate of returns to fixed capital but low rates of return to financial capital, relative to the US. As a result, households save abroad and FDI flows in. Most work uses either aggregate data or ignores firms' financing patterns. By comparison, our paper uses the debt financing features observed in the Chinese firm-level data to identify financial frictions and focuses on their consequences for firms. We quantify the saving and the co-movement across firms of saving and investment, which can be explained by these frictions.

The rest of the paper is organized as follows. Section 2 presents key empirical findings from our sample of Chinese firms, in terms of debt financing, interest rates, growth, and MPK. Section 3 introduces the model. Section 4 contains the quantitative analysis. Section 5 concludes.

2 Data

The empirical findings in this paper are based on rich firm-level data, an annual census of enterprises collected by the Chinese National Bureau of Statistics between 1998 and 2007. The dataset includes all state-owned firms and non state-owned firms with sales over 5 million

RMB (about 600,000 US dollars) in the manufacturing sector. It contains all information in the balance sheet, profit and loss statement, and cash flow statement. We restrict our sample to firms with positive assets, non-negative total debt, and positive sales, yielding 125,861 firms in 1998 and 306,299 firms in 2007.

In the following analysis, we focus on state-owned enterprises (henceforth SOEs) and privately owned manufacturing firms (henceforth POEs), since they are more likely to be impacted by the underdeveloped financial markets and distorted financial allocations in China, while foreign-owned firms, Hong Kong, Macau, and Taiwan owned firms are less likely to be affected by local financial conditions. We use information on registration type to classify SOEs and POEs. SOEs include solely state funded, state joint ownership, and state and collective joint ownership. In the appendix, we also show results with the least restrictive definition of SOE, which includes all the firms with positive state assets as well as collective enterprises. POEs include sole private enterprises, private partnership enterprises, private limited liability companies, and private shareholding corporations. In our sample, 29 percent of the firms in 1998 and 2.2 percent in 2007 are strictly defined SOEs, and 8 percent in 1998 and 54 percent in 2007 are POEs.

We first describe overall patterns for firms' assets, leverage, interest rates, growth, and the marginal product of capital. Nominal values are deflated using the GDP deflator and assets are measured by the book value of total assets. To measure the extent of a firm's debt financing, we use both leverage and the interest rate. Leverage is defined as the ratio of total debt to total assets, with total debt including short-term and long-term debt as well as short-term credit from suppliers. The firm-level interest rate is the ratio of interest payments to total debt. Firm growth is measured by the growth rate of value added. We use value added and firms' fixed assets to compute the marginal product of capital, which is affected by the capital intensity in each industry. We focus on firms' relative MPK and normalize each firm's value added to the capital ratio by the mean within each industry. Specifically, the relative MPK is calculated as $\log\left(\frac{Y_{ij}}{K_{ij}}\right) - \log\left(\overline{\frac{Y_j}{K_j}}\right)$ for a firm i in industry j.

Table 1 reports descriptive statistics, the mean and standard deviation of assets, value added, leverage, interest rates and growth rate for SOE and POE over time. Assets and value added are measured in terms of million RMB. SOE have much more assets than POEs on average. Both asset distributions are highly skewed, as the mean asset levels are much larger than the median. In terms of debt financing, SOEs have higher leverage, and they pay much lower interest rates than POEs. SOEs hold much more assets and have similar median value added, and its distribution is more dispersed than that for POEs'. POEs also grow faster, more than twice the rate of SOEs.

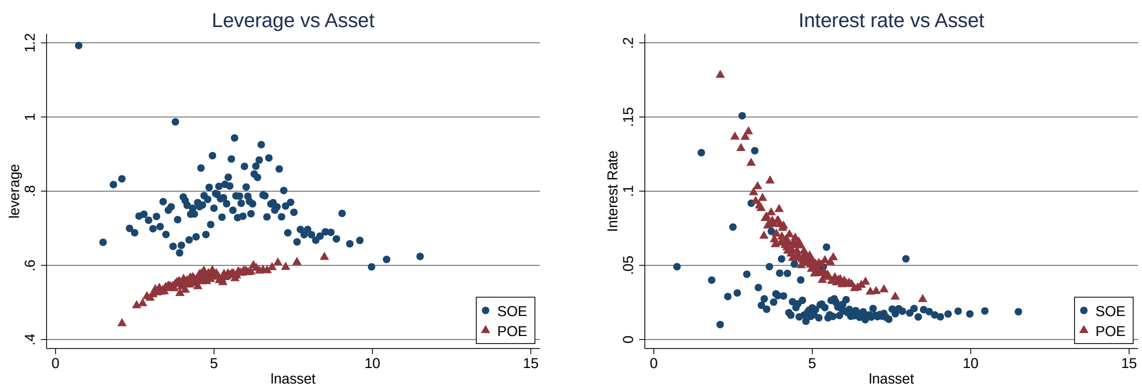
Do firms of different sizes finance their projects differently? Figure 1 shows the relation

Table 1: Statistics SOE vs POE

		Year 1999		Year 2007	
		SOE	POE	SOE	POE
Asset	Mean	143	17	623	42
		(1143)	(33)	(2911)	(174)
	Median	23	8	74	15
Value added	Mean	0.21	0.07	1.26	0.19
		(1.6)	(0.127)	(5.88)	(0.53)
	Median	0.03	0.03	0.18	0.08
Leverage	Mean	0.81	0.63	0.72	0.56
		(0.40)	(0.28)	(0.42)	(0.27)
	Median	0.78	0.64	0.67	0.58
Interest rate	Mean	0.03	0.08	0.03	0.09
		(0.33)	(0.28)	(0.13)	(0.69)
	Median	0.02	0.04	0.01	0.03
Growth rate	Mean	-0.01	0.16	0.12	0.23
		(0.71)	(0.62)	(0.59)	(0.56)
	Median	0.03	0.18	0.12	0.22

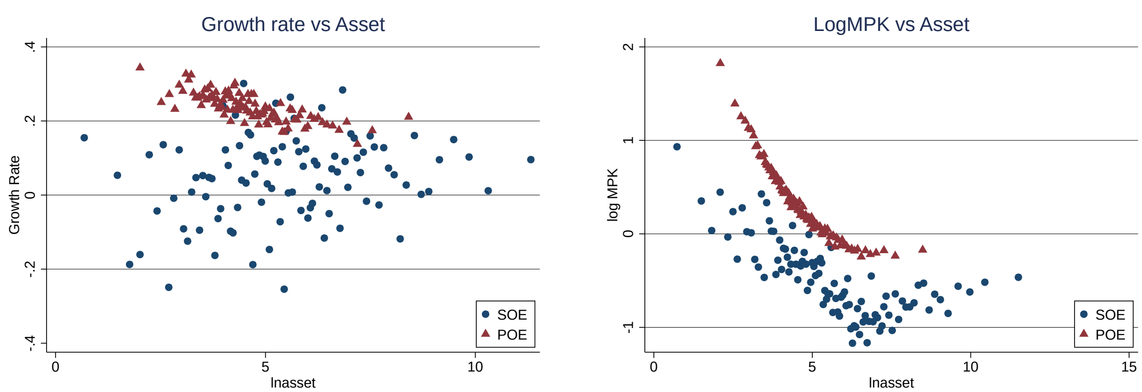
Notes: The table reports the descriptive statistics of assets, value added, leverage, interest rates, and growth rate for privately owned enterprises (POEs) and State-owned enterprises (SOEs) over time. Assets and value added are in terms of million RMB. Interest rate is constructed using interest payment over debt. Numbers in bracket are the standard deviations.

between leverage and interest rate with assets in Year 2006, and other years demonstrate similar patterns. Figure 1(a) depicts the mean leverage for different asset levels. The x-axis in the figure is the asset percentile of the SOEs and POEs in 2006, and on the y-axis, we plot mean leverage. On average, SOEs have higher leverage. Among POEs, leverage increases with firms assets. Figure 1(b) shows the relation between firms' interest rate and asset. On average, SOEs have lower interest rates. Among POEs, firms' interest rate decreases with their assets.



(a) Leverage and Assets (b) Interest Rate and Assets

Figure 1: Firm Size and Debt Financing



(a) Growth Rate vs Assets (b) MPK vs Assets

Figure 2: Firm Size, Growth, and MPK

Figure 2 shows the relation between growth rate and MPK with assets in Year 2006. Figure 2(a) illustrates the mean growth rate with different asset levels. As is well documented in the literature, small firms grow faster, and POEs have higher growth rates than SOEs. Figure 2(b) depicts the relation between the marginal product of capital and asset levels. SOEs have lower MPK. Among POEs, MPK has large dispersion and decreases with assets.

To study these patterns systematically, we regress the variables of interest on firms' asset levels and an interaction of ownership and assets, controlling for industry and year fixed effects. Table 2 reports the regression results, with leverage, interest rate, growth and MPK in turn as the dependent variable. The table shows that leverage ratios are significantly lower for POEs, that interest rates are significantly higher for POEs compared to SOEs, and that among POEs, smaller firms have a lower leverage, pay higher interest rates, experience faster growth, and operate with a higher MPK. Although there are sizable changes take place over time, for example the dramatic contraction of SOEs from 1998 to 2007 due to the SOE reform, the patterns we described above are consistently observed over time (see the data appendix).

Table 2: Regressions on Firm Ownership and Asset

	(1)	(2)	(3)	(4)
VARIABLES	Leverage	Interest Rate	Growth Rate	log MPK
Private	-0.358***	0.134***	0.354***	1.545***
	(-19.10)	(13.95)	(29.45)	(28.43)
Private*lnasset	0.0312***	-0.0203***	-0.0419***	-0.149***
	(11.21)	(-12.33)	(-19.81)	(-15.88)
lnasset	-0.0107***	-0.00343***	0.0142***	-0.211***
	(-4.320)	(-6.681)	(8.267)	(-25.27)
Constant	0.838***	0.0576***	-0.0570***	-0.859***
	(49.17)	(14.39)	(-4.413)	(-17.12)
Observations	859,619	587,621	562,938	859,619
R-squared	0.089	0.012	0.022	0.211
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: This table reports the regression results. The estimation sample includes all state-owned firms and privately owned firms in the manufacturing sector from 1998 to 2007 with sales over 5 million RMB, non-negative total debt, and positive assets. The dependent variables from columns 1 to 4 are leverage, interest rate, growth rate, and MPK, respectively. The explanatory variables include firm asset, a dummy variable which indicates firm ownership, and the interaction of ownership and assets. T-statistics reported in parentheses are calculated using robust asymptotic standard errors clustered at the four-digit industry level. All specifications control for both industry and year fixed effects. $***p < 0.01, **p < 0.05, *p < 0.1$.

Note that the observed firm financing patterns are not easily reconciled with models with exogenous borrowing constraints, for example collateral constraints, which generate negative correlation between firm size and leverage and fail to generate firm-specific interest rates. This calls for a model with endogenous borrowing constraints.

What type of financial frictions can generate these patterns and are realistic in China? In our setting, firms can default, and banks provide debt schedules, taking into account firms' default risk and fixed credit cost. The endogenous borrowing constraints model can explain the financing patterns across Chinese firms, and it also reflects the realistic financial frictions in China. Privately owned firms are more productive, but the state-owned banks have concerns that these firms can run away with their debt. The fixed credit cost captures banks' overhead cost and also the cost of obtaining necessary information for each deal. The model generates endogenous borrowing limits depending on firms' productivity, assets, and debt, as in reality banks consider these when providing loans.

How do financial frictions affect the capital allocation, hence the TFP? In addition to calculating the TFP loss from our estimated model with financial frictions, we show the distribution of MPK and the correlation between firms' MPK and productivity in our model. In general, both the dispersion of MPK and the covariance of z and MPK matter. Consider a continuum of heterogeneous firms, with production function $y_i = z_i^{1-\alpha} k_i^{\alpha}$. From the definition of MPK, $\quad k_i = (\alpha)^{\frac{1}{1-\alpha}} z_i \; MPK_i^{\frac{1}{\alpha-1}}$. We can therefore define TFP as

$$TFP = \frac{Y}{K^{\alpha}} = \frac{\int_i z_i \; MPK_i^{\frac{\alpha}{\alpha-1}} d_i}{\left(\int_i z_i \; MPK_i^{\frac{1}{\alpha-1}} d_i\right)^{\alpha}}. \tag{1}$$

In efficient allocations, the marginal product of capital is equalized across firms, $MPK_i = MPK_j$. The TFP would then be given by $TFP^e = (\int_i z_i d_i)^{1-\alpha}$. We can define the TFP loss by $\log(TFP^e) - \log(TFP)$.

If z_i and MPK_i are jointly log-normally distributed, Hsieh and Klenow (2009) show that the TFP loss $= \frac{1}{2}\frac{\alpha}{1-\alpha} var(logMPK_i)$, which implies that the loss only depends on dispersion of MPK. But in general, the covariance of z and MPK also matters, which can be seen from Equation (1). For example, suppose MPK is Pareto distributed with parameter μ, and $z = MPK^{\rho}$, so the correlation between z and MPK depends on ρ. In this case, the TFP loss is $\frac{\mu-\rho-\frac{\alpha}{\alpha-1}}{(\mu-\rho)^{1-\alpha}\left(\mu-\rho-\frac{1}{\alpha-1}\right)^{\alpha}}$. Figure 3 depicts the TFP loss for different μ and ρ values. The TFP loss increases with the variance in MPK. Furthermore, given the same dispersion in MPK, the TFP loss varies with the MPK-z correlation: a high correlation, i.e. more productive firms have higher MPK and lead to large losses, since larger z matters more for total output.

Meanwhile, the observed capital misallocation could also be due to other distortions. We therefore ask to what extent financial frictions disciplined by firm financing patterns can explain the saving and capital misallocation in China. In the next section, we construct a model that replicates firms' debt financing patterns, and then we estimate the model to match the financing patterns, dynamics, and distribution of sales within the firm-level data, and use those parameters to quantify firm saving, investment, capital misallocation, and the TFP loss generated by the frictions.

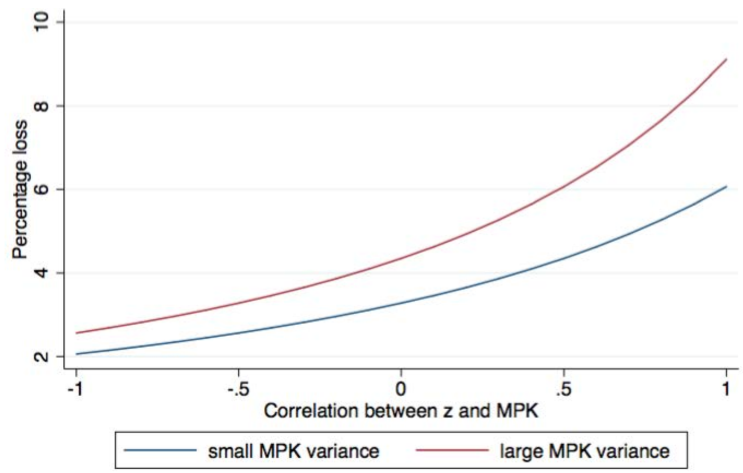


Figure 3: TFP Loss with different correlation between z and MPK

3 The Model

We consider a small open economy with a continuum of firms. Financial markets are imperfect in that firms can only borrow state-uncontingent bonds. Firms can default on their debt, albeit subject to certain drawbacks. Banks offer firm-specific debt contracts that compensate for default risk and a fixed cost of lending, as in Arellano, Bai, and Zhang (2012).

Firms produce with a decreasing return to scale technology using capital k as input. The output of firm i is given by $y_{it} = z_{it}^{1-\alpha} k_{it}^{\alpha}$, where α captures both the capital share and the return to scale, and z_{it} is a shock on the measured total factor productivity (TFP).

Firms use internal funds and external borrowings to finance the dividend payout, investment, and existing debt liabilities. The goal of firms is to maximize the life-time present value of dividends,

$$E_0 \sum_{t=0}^{\infty} (\beta(1-\eta))^t x_{it}$$

where β is the discount factor and η the exogenous exit rate. Firms have the option to default over their debt. If in default, firms' debt is being written off. Defaulting firms continue operating with some productivity loss but are denied access to international financial markets.

New firms enter with probability γ. A firm entering at period t starts with a productivity z_t^e and borrows b_{t+1}^e to finance initial size k_{t+1}^e. In the second period after entry, the new entrant becomes an incumbent. It will use the capital k_{t+1}^e to produce and repay b_{t+1}^e. New entrants' productivity in the second period follows the same process as that of incumbents.

At period t, after the realization of the TFP shock z_t, a non-defaulting incumbent produces and uses its internal funds and external borrowings b_{t+1} to finance its new capital purchase k_{t+1}, capital adjustment cost $\Phi(k_t, k_{t+1})$, and dividend payout x_t. Given that the firm may default in the future, the borrowing price q_t reflects the firm's future default rate and depends on current productivity z_t, new capital stock for the next period k_{t+1}, and the borrowing b_{t+1}. Intuitively, high, persistent TFP shock z_t implies that the future repayment set is large, and large borrowings imply higher default probability. We assume the adjustment cost takes the quadratic specification

$$\Phi(k_t, k_{t+1}) = \frac{\phi}{2}\left(\frac{k_{t+1} - (1-\delta)k_t}{k_t}\right)^2 k_t. \tag{2}$$

The firm's dividend payout is given by

$$x_t = z_t^{1-\alpha}k_t^{\alpha} + (1-\delta)k_t - b_t + q_t(z_t, k_{t+1}, b_{t+1})b_{t+1} - k_{t+1} - \Phi(k_t, k_{t+1}). \tag{3}$$

There is limited liability and thus

$$x_t \geq 0. \tag{4}$$

Defaulting firms can only use their internal funds to pay out dividends and finance new investments. They are subject to a productivity loss λ and to the capital adjustment cost. Dividends are given by

$$x_t = (1-\lambda)z_t^{1-\alpha}k_t^{\alpha} + (1-\delta)k_t - k_{t+1} - \Phi(k_t, k_{t+1}). \tag{5}$$

Recursive problem A non-defaulting firm's state variables include its productivity z, current capital k, and current bond holding b. Upon observing its productivity shock, a firm in state (z, k, b) decides whether to default by comparing the default value V^d with the repayment value V^c,

$$V(z, k, b) = \max\{V^c(z, k, b), V^d(z, k)\}. \tag{6}$$

When $V^c(z, k, b) \geq V^d(z, k)$, the firm repays its debt, $d(z, k, b) = 0$. Otherwise, the firm defaults with $d(z, k, b) = 1$.

If it repays, the firm chooses its investment and new borrowings. In particular, it makes a decision on the next period's capital k', dividend payout x, and a loan b' to maximize the sum of the current dividend and discounted future values

$$V^c(z, k, b) = \max_{x, k', b'} \; x + \beta(1-\eta)EV(z', k', b') \tag{7}$$

subject to the budget constraint (3) and the non-negative dividend condition (4). Note the adjustment cost specified in (2).

If it defaults and continue to produce, the firm gets its debt written off but remains in financial autarky forever. In this case, the firm chooses dividends and new investments to maximizes its value,

$$V^d(z,k) \;=\; \max_{x,k'} \; x + \beta(1-\eta)EV^d(z',k') \tag{8}$$

subject to the budget constraint after default (5) and the non-negative dividend condition (4). Note that the non-negative dividend condition for sure can be satisfied in this case, since firms can always choose $k_{t+1} = (1-\delta)k_t$ and pays zero adjustment cost under the adjustment cost specification (2).

According to a survey by Wagle (2000), around 70 percent of firms reported that paperwork and relationships with banks were major obstacles to their application for a formal bank loan. These overhead costs of the application process make it especially hard for smaller firms to obtain the access to external financing. Although China has made significant progress in reducing government intervention in the banking sector, there is still ample evidence that local governments continue to encourage banks to lend to state-owned banks by extending explicit or implicit government guarantees. With these guarantees, a bad loan to a state-owned enterprise is not really considered a bad loan for the banks, since the government will almost surely bail out the firm. By contrast, absent these government guarantees, privately owned enterprises are in general charged a much higher interest rate when they borrow from the banks. These are consistent with our empirical findings in Section 2. To shed light on the key mechanisms that underlie these stylized facts, we model the Chinese bank lending in the following way.

We assume that banks are competitive and risk neutral. They have to pay a fixed credit cost ξ for every loan they issue. The fixed cost captures banks' overhead cost and also the cost of obtaining necessary information, building connection, or preparing the paperwork, for each deal. It is easy to see that, with a fixed cost and everything else constant, the effective interest rate is lower for larger loans. When $b' > 0$, the bond price schedule incorporates both the fixed cost and the future default probabilities,

$$q(z,k',b')b' + \xi = \frac{1}{1+r}E[1 - d(z',k',b')]b' \tag{9}$$

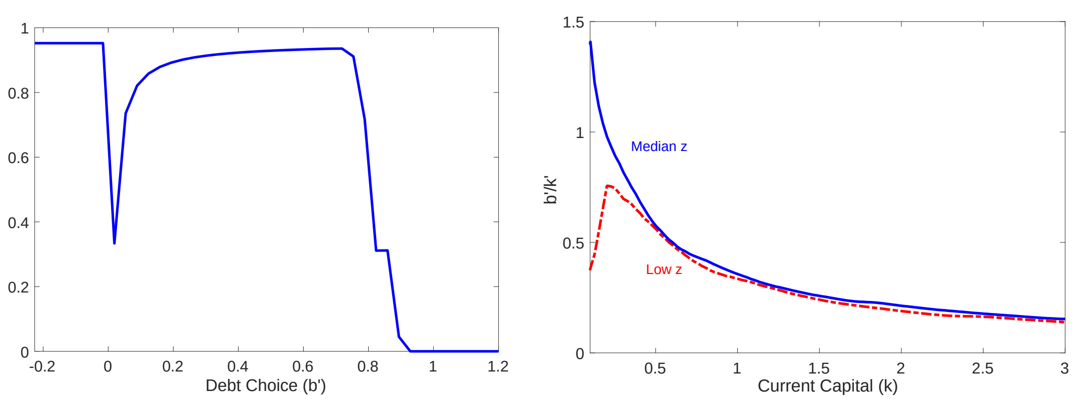
When firms save $b' \leq 0$, by making deposits $b' \leq 0$, banks pay the risk-free rate, $q = 1/(1+r)$. We intentionally keep the model as parsimonious as possible for tractability and clarity of the quantitative results. The key mechanism of the model, however, is likely to carry over to an alternative model with additional realistic features.

Definition 1. *A recursive equilibrium consists of decision rules, the value functions of firms,* *and the bond price schedule such that*

1. *Given the bond price schedule, the decision rules and value functions solve the firm's problem.*

2. *Given the decision rules and a risk-free rate, the bond price schedule satisfies (9) and banks break even in expected value.*

To understand how firms finance their investment when facing an endogenous borrowing limit, we plot the bond price schedule and the leverage choices in Figure 4 using the parameters estimated in the next section. Nonetheless, the features of the bond price schedule and leverage choices are quite generic. The left panel displays the price schedule as a function of debt choice, under the median productivity shock and the capital and debt with the largest mass in the invariant distribution. We scale the debt choice by the firm's average capital. When the chosen debt level is less than zero, the firm saves at the risk-free rate. For small loans, the fixed credit cost reduces the bond price and increases the effective interest rate. For high enough debt levels, the bond price decreases with the loan size, due to the increase in default risk. When debt is above 95 percent of the asset, the firm always defaults and the bond price is flat at zero. In summary, small and large loans are more expensive due to either the fixed credit cost or the high risk of default.



(a) Bond Price Schedule (b) Leverage Choice

FIGURE 4: BOND PRICE SCHEDULE AND LEVERAGE CHOICE

The right panel of Figure 4 depicts the choice of leverage, as a function of current capital k for two firms: one with a median level of productivity and one with a low productivity. Current debt levels have the largest mass in the invariant distribution of each productivity type. All variables are normalized by each firm's output. There are two prominent features. First, for the median-productivity firm, when capital increases, its leverage (b'/k') decreases. This is due to the decreasing return to scale; firms with higher capital stock have lower returns and thus have less incentive to borrow to finance investment. Second, for the firm of a low productivity, leverage first increases and then decreases with capital. The reason is because the fixed credit cost is relatively large for such firms, increasing the effective interest rate and dampening the incentive to borrow and invest. When the current capital level is high, the fixed cost effect becomes negligible, and the capital return effect dominates. Firms with high productivity tend to have higher leverage, since their capital returns are higher. Hence, the differential relationship between size (capital) and leverage in the decision rules for different firms helps us identify the magnitude of the fixed credit cost.

4 Quantitative Analysis

In this section, we present the quantitative analysis of the model. In Section 4.1, we estimate the shock process and key financial parameters using both cross-sectional and time-series data of sales distribution and financing patterns. Section 4.2 compares out-of-sample statistics in the model, with data moments to quantify the impact of financial frictions for firm saving, investment, and capital misallocation. In Section 4.3, we decompose the forces that distort capital allocations across firms: financial frictions versus capital adjusting friction. Lastly, Section 4.4 introduces state-owned firms into the model and compute the overall TFP losses.

4.1 Estimation

We assume that the TFP shock of firms has three components: a constant common growth rate g, a permanent component A, and an idiosyncratic component ν. Specifically, firm i's TFP shock at period t is given by $z_{it} = (1+g)^t A_i \nu_{it}$. The permanent component follows a Pareto distribution[4] with a shape parameter μ, i.e.

$$\Pr(A_i \leq a) = 1 - a^{-\mu}. \tag{10}$$

The idiosyncratic component ν follows an AR(1) process:

$$\log(\nu_{it}) = \rho \log(\nu_{it-1}) + \sigma \varepsilon_{it}, \tag{11}$$

where ε_{it} follows the standard normal distribution $N(0,1)$.

To compute the model, we discretize the permanent component A into seven points (A_1, A_2, ..., A_6, A_7). We normalize A_1 as 1 and put equal spaces between A_1 to A_6. We then

[4] Comparing estimates with different processes, we find that a permanent Pareto distribution and an AR(1) idiosyncratic shocks combined with financial shocks best fit the data.

generate the respective probabilities of $\{\pi_1, \pi_2, ..., \pi_6, \pi_7\}$ consistent with (10). Hence there are three parameters to be determined for the permanent component: $\{A_6, A_7, \mu\}$.[5] We follow Tauchen and Hussey (1991) to discretize the idiosyncratic shock ν.

We assume a quadratic capital adjustment cost as in Equation (2). In the model, if a firm holds debt $b \geq 0$, we define the asset of the firm as its capital k and the leverage as b/k. Otherwise if $b < 0$, the asset is $k - b$ and the leverage is zero. The interest rate of the firm is $1/q(z, k'(z, k, b), b'(z, k, b))$ where $k'(z, k, b)$ and $b'(z, k, b)$ are the equilibrium capital and debt choices, respectively. The value added is given by $z^{1-\alpha}k^{\alpha}$. We solve the model using value function iteration and compute the invariant distribution of firms.

Table 3 presents two sets of parameters. The first set presents the chosen parameters independent of our model. The second set includes the parameters estimated jointly with the simulated method of moments (SMM), which chooses model parameters by matching the moments from a simulated panel of firms to their data counterparts. All data moments are the average of those between 1998 and 2007.

The first set of parameters is determined with external information and includes $\{r$, δ, g, $\alpha\}$. Specifically, we pick the annual risk-free rate $r = 5\%$ to match the real interest rate of the U.S during 1998 and 2007, as published by IMF. The capital depreciation rate δ is chosen to be ten percent annually. The annual growth rate g is 7%, consistent with China's average annual GDP growth rate. We choose a value of 0.4 for the production parameter α to capture both capital share and return to scale.

The second set consists of 13 parameters, discount factor β, fixed financing cost ξ, productivity loss after default λ, capital adjustment cost ϕ, persistence of idiosyncratic shock ρ, volatility of idiosyncratic shock σ, the Pareto parameters μ, A_6, A_7, the parameters related to entrants z_e, k_e, b_e, and the growth rate of number of firms γ. All of these parameters are estimated jointly to match firm financing pattern, sale distribution, and relative size of entrants, totaling 13 moments in total.

Panel B of Table 3 reports the simulated and actual moments. The model tightly matches the data moments. The success of SMM estimation depends on model identification, which requires that the chosen moments be sensitive to variations in the structural parameters. We now rationalize these moments.

We consider three moments related to firms' financing patterns: average leverage, the *leverage-asset slope*, and the *interest-asset slope*. To obtain these two slopes, we first classify firms into 100 bins according to their assets. We then calculate the average leverage and interest rates for each asset bin. We run the regressions of leverage or interest rate on asset

[5]We conduct sensitivity analysis to make sure our quantitative results are robust to the number of discretized points for the Pareto distribution.

bins. We call the coefficient in the leverage regression as the leverage-asset slope and the one in the interest rate regression as the interest-asset slope. In our dataset, the average leverage is 0.58, the leverage-asset slope is 0.17, and the interest-asset slope is -0.08. This implies that small firms use less debt financing but face a higher interest rate than large firms.

The discount factor β, credit fixed cost ξ, and default cost λ are mostly relevant for a firm's leverage decision. The more impatient the firm, the higher the leverage it will employ. The fixed credit cost ξ affects both mean leverage and the leverage-asset slope. A lower ξ implies a lower borrowing cost and thus a higher repayment capacity, which in turn raises leverage. Moreover, ξ affects firms differently. The fixed credit cost to sales is higher for small firms than for large firms. Facing the high borrowing cost, small firms choose to use less debt financing, which leads to a positive leverage-asset slope. The fixed credit cost also governs the interest-asset slope. A high credit cost leads to a high effective interest rate, particularly for small firms, and a negative interest-asset slope.

The productivity process parameters are mostly related to a firm's distribution in terms of value added. We therefore target the distribution, autocorrelation of value added, and the standard deviation of growth rate of value added. For the value-added distribution, we target the fractions of value added in the top 5, 10, and 20 percentiles. The distribution is skewed in that the top five percentile of firms accounts for about 34% of the total value added. The value-added distribution directly disciplines the permanent Pareto parameters μ, A_6, and A_7. These parameters would also indirectly change all other moments through their impacts on the firms' size distribution. The smaller the shape parameter and the higher the A_7, the fatter the right tail of firm size and the higher the concentration of market share. Although the leverage-asset slope within each type of permanent productivity might only be slightly positive or even negative, with enough heterogeneity in permanent components, the aggregate leverage-asset schedule can be upward-sloping as the fixed credit cost matters more for low A firms.

The cross-sectional autocorrelation of value-added is about 0.79, and the standard deviation of value-added growth is 0.4. The capital adjustment cost affects how responsive a firm's investment to shocks are. We thus consider the following regression of capital growth rate:

$$\log k_{t+1,i} - \log k_{t,i} = \gamma_i + \psi \log y_{t,i} + \alpha_0 X_{t,i} + \epsilon_{t,i}. \tag{12}$$

where $y_{t,i}$ and $k_{t,i}$ denotes firm i's value added and asset at period t, respectively. Control variable X includes log of assets and net worth. The estimated regression coefficient ψ is 0.11.

The productivity process parameters ρ and σ are most closely related to the persistence of value added and standard deviation of value-added growth. Capital adjustment cost also affects the volatility of the firms' value-added growth. The higher the adjustment cost, the smaller incentive to adjust capital, and the lower the volatility of value-added growth. Both financial frictions and capital adjustment cost affect ψ, the regression coefficient of capital growth on value added.

We also match the relative size of entrants to incumbents in terms of assets, value added, and leverage. In the data, entrants are smaller than incumbents, about 9% smaller in terms of value added, and 31% smaller in terms of asset. Their leverage is about 10% lower than than of the incumbent. We also match the fraction of entrants in our dataset, 20 percent on average.

Overall, the model closely matches the distribution of firms in terms of leverage, interest rates, and sales distribution: see Figures 5 and 6. In both the model and the data, small firms have lower leverage and face higher interest rates than larger firms. Value-added distribution is skewed and concentrated in large firms.

The estimated fixed credit cost is 0.01, about 1.3 percentage of aggregate output. After default, the productivity loss λ is 3%. The persistence parameter ρ is 0.72, which is within the range of values estimated in the literature. Foster, Haltiwanger, and Syverson (2008) estimate the persistence of traditional TFP about 0.8 using the U.S. Census of Manufactures data. The value is 0.59 in Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) for European firms, and 0.25 in Midrigan and Xu (2013) for Korean firms.

Note that we estimate the productivity parameters jointly with other parameters. A common practice in the literature, for example Wooldridge (2009), is to estimate firms' measured total factor productivity directly from data using firms' value added and inputs. We do not follow that approach here for two reasons. First, according to our model, firms' revenues, capital, and debt are jointly affected by the productivity process, costly capital adjustment, and most importantly financial frictions. Hence, it's not straightforward to apply the standard practice. Second, our panel data is very short. The estimated persistence parameter would be biased.

As is discussed in the literature (see Moll (2014) and Midrigan and Xu (2013) among others), the productivity process is important on the aggregate implications of financial frictions. Our estimation strategy therefore targets the cross-section sales distribution, autocorrelation of value added, and the volatility of value-added growth to greatly pin down the parameters in the productivity processes. Furthermore, Table 4 shows the out-of-sample moments of the transition matrix of value added in the model and the data. The estimated model also captures the transition well. A firm whose valued added is in the top five percentile has about 70% of probability remaining in this percentile, both in the model and in the data. In the data, firms in the lower 50th percentiles are also quite persistent, about 80% in the

Table 3: Model Parameters and Target Moments

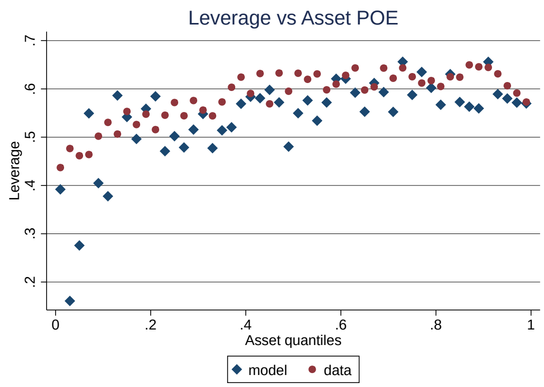
A. Parameter Estimates

Parameter	*Value*	*Identification*
	External Estimation	
Production parameter	$\alpha = 0.4$	Capital share and return to scale
Depreciation rate	$\delta = 0.1$	Standard
Risk free rate	$r = 0.05$	U.S. real interest rate
Annual growth rate	$g = 0.07$	China annual growth rate
	Internal Estimation	
Discount factor	$\beta = 0.96$	Mean leverage
Fixed credit cost	$\xi = 0.01$	Leverage-asset slope
Productivity loss after default	$\lambda = 0.03$	Interest-asset slope
Capital adjustment cost	$\phi = 1.03$	Capital growth-output regression
Shock standard deviation	$\sigma = 0.81$	Std (value-added growth)
Shock persistence	$\rho = 0.72$	Autocorrelation of value-added
Pareto shape parameter	$\mu = 1.32$	Share of value added of top-5%
Discretized A_6	$A_6 = 0.81$	Share of value added of top-10%
Discretized A_7	$A_7 = 0.99$	Share of value added of top-20%
Entrant productivity	$z_e = 0.20$	Relative output of entrants
Entrant capital	$k_e = 0.33$	Relative asset of entrants
Entrant debt	$b_e = 0.15$	Relative leverage of entrants
New entrant rate	$\gamma = 0.19$	Growth rate of number of firms

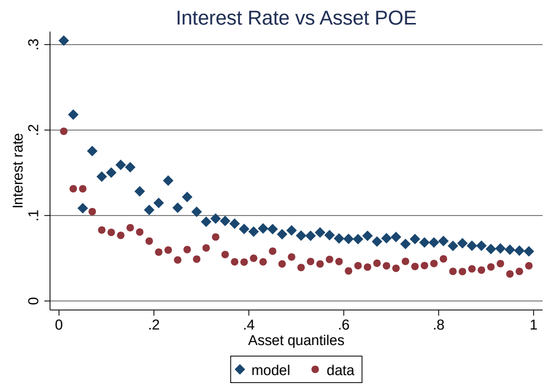
B. Moments

Target Moments	Data	Model
Average leverage	0.58	0.55
Leverage-asset slope	0.17	0.20
Interest-asset slope	-0.08	-0.08
Standard deviation of value-added growth	0.40	0.48
Serial correlation of value added	0.79	0.85
Capital growth-output coefficient	0.11	0.18
Distribution of value added		
Frac. of value added in the top 5 Percentiles	0.34	0.37
Frac. of value added in the top 10 Percentiles	0.46	0.48
Frac. of value added in the top 20 Percentiles	0.61	0.62
Entrant (%)		
Relative value added	-9.3	-9.3
Relative asset	-31	-20
Relative leverage	-10	-21
Growth rate of number of firms (%)	20	20

Notes: Calculations are based a sample of Chinese firms from 1998 to 2007 at annual frequency. The estimation is done with SMM, which chooses model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Panel A reports the estimated parameters, Panel B reports the simulated and actual moments.



(a) Leverage



(b) Interest Rate

Figure 5: Leverage, Interest Rate, and Asset

Notes: Panels (a) and Panel (b) depict the mean leverage ratio and mean interest rate over 50 asset quantiles respectively. The firm leverage is calculated as the ratio of total debt to total assets. The firm-level interest rate is the ratio of interest payments to total debt.

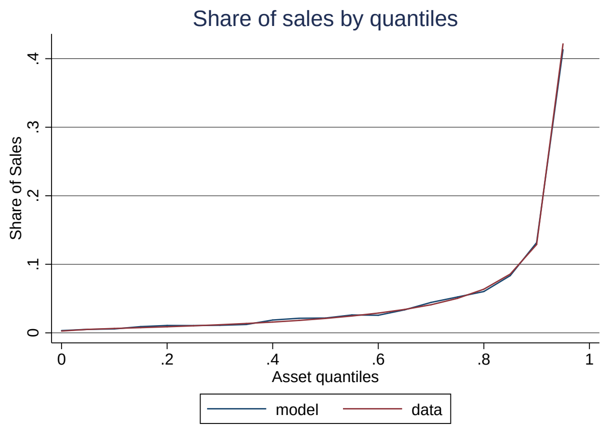


Figure 6: Sale Distribution

Notes: This figure depicts the sale distribution in the data and in the model respectively. For each asset quantile, we calculate the fraction of sales produced by firms in that quantile.

Table 4: Non-Targeted Transition matrix of value added, data and model

Data	Top 5% at t+1	5-10	10-20	20-50	50-100
Top 5% at t	0.69	0.19	0.07	0.04	0.01
5-10	0.16	0.39	0.32	0.11	0.03
10-20	0.04	0.12	0.43	0.35	0.06
20-50	0.01	0.02	0.10	0.60	0.27
50-100	0.00	0.00	0.02	0.15	0.82

Model	Top 5% at t+1	5-10	10-20	20-50	50-100
Top 5% at t	0.71	0.14	0.06	0.007	0.08
5-10	0.23	0.28	0.31	0.07	0.12
10-20	0.03	0.22	0.38	0.28	0.10
20-50	0.00	0.03	0.15	0.54	0.29
50-100	0	0	0.00	0.21	0.79

Notes: This table reports the transition matrix of value added in the model and the data. Each entry reports the probability of a firm on each row quantile to transit to each column quantile.

same percentile next period, as is observed similarly in the model. Both the model and the data have the feature that firms in the middle have much larger mobilities.

4.2 Model Implications over Capital Misallocation and Saving

We now answer the following question: to what extent is the model with financial frictions able to account for capital misallocation, as measured by the variation in MPK across firms and firm-saving and investment behavior?

The upper panel of Table 5 shows the out-of-sample moments of cross-sectional volatilities of asset, leverage, and MPK in the data and model. In the data, the standard deviation of asset is 1.14, of leverage is 0.28, and of MPK is 1.21. The model accounts for about 60% of the observed variations of asset and leverage and 50% of MPK variation. The model implied TFP loss is around 11.57% in which the efficient TFP is calculated with the productivity distribution of the incumbent firms in the benchmark, assuming no risk of capital accumulation and a constant capital return of $r + \delta$. TFP loss in China from misallocation is about 30-50% in Hsieh and Klenow (2009), hence, our model with endogenous financial frictions explains about one third of the total misallocation of their estimates. Note that the benchmark model only includes privately owned firms; the TFP losses are greater when we incorporate SOEs in Section 4.4.

We also examined which types of firms are more distorted and have higher MPK by studying the cross-sectional correlations of MPK with lagged observed variables of asset, leverage, and value added. In the data, firms with low assets, low leverage, and high value added face higher MPK. The model produces a similar pattern except the MPK and asset relationship. Specifically, the MPK-asset correlation is close to zero in the model, but -0.31 in the data. The correlation between MPK and value added is 0.38 in the model and 0.11 in the data. The MPK-leverage correlation is -0.05 in the model, close to that in the data, -0.01.

Further statistics that shed light on financial friction include the correlation of saving rate and investment rate. Without financial frictions, the Modigliani-Miller theorem holds. Thus, capital structure is irrelevant for firm value, and saving rate is not well defined. Financial frictions increase a firm's internal return and lead to a positive correlation between saving and investment. We therefore explore this correlation in both our model and data. In the model, firms either save with financial intermediaries or save in their own capital. Hence firms' gross saving is the difference between the value added and the sum of dividend payout and interest payment, i.e. $saving = z^{1-\alpha}k^{\alpha} - x + (qb' - b')$, which also equals the sum of equity growth and capital depreciation. Our saving in the data is constructed using the second method: i.e. the sum of change in equity and capital depreciation. The data correlation of saving rate and investment rate is 0.58 and the model correlation is 0.68, indicating a significant level of financial frictions. Our model also closely matches the observed aggregate investment rate: the ratio of aggregate investment to aggregate value added is 0.22 in the model versus 0.18 in the data.

We also study how a firm's saving and investment co-move with its asset, value added, and leverage across time. We run the regression of debt growth and capital growth on the logged asset, leverage, and logged value added, controlling for industry and year effect in both the model and the data. Table 6 presents the model and data regression coefficients. All coefficients are significant, with p-values less than 0.01. Our model effectively matches the sign and size of the observed regression coefficients. In both the data and model, large firms reduce their debt and investment due to the decreasing return to scale; high leverage firms reduce their debt. Across firms, firms with higher permanent productivity tend to have higher leverage and also invest more, leading to a positive relation between leverage and investment; controlling for capital and debt, firms with larger output increase their debt and investment. In summary, our model successfully produces the observed cross-section and within-firm patterns of saving and investment.

Table 5: Across-Firm Saving, Investment, and MPK

	Data	Model
Standard Deviations		
Asset	1.14	0.70
Leverage	0.28	0.17
MPK	1.21	0.59
TFP loss (%)		11.57
Cross-sectional correlations with MPK_{t+1}		
Asset	-0.31	0.02
Leverage	-0.01	-0.05
Value added	0.11	0.38
Saving and Investments		
corr(saving, investment)	0.58	0.68
Investment rate	0.18	0.22

Notes: The upper panel reports the out-of-sample moments of cross-section volatilties of asset, leverage, and MPK in the model and data. The middle panel reports the cross-sectional correlation of asset, leverage, and MPK with MPK_{t+1} in the data and the model. The lower panel reports the statistics about saving and investment in the data and the model.

Table 6: Within-Firm Saving and Investment

	Debt growth		Capital growth	
VARIABLES	Data	Model	Data	Model
Asset	-0.08***	-0.05***	-0.13***	-0.19***
Leverage	-0.71***	-0.28***	0.04***	0.11***
Value added	0.03***	0.09***	0.07***	0.17***

Notes: This table reports the regression results of debt growth and capital growth on logged asset, leverage, and logged value added controlling for industry and year effect in both the model and the data.

4.3 Decomposing Mechanism: Financial Frictions or Capital Adjusting Friction

Our benchmark model has two types of frictions that distort a firm's investment decision: financial frictions and capital adjustment cost. Financial frictions include a fixed credit cost of issuing debt and default risk from limited enforcement. The capital adjustment cost captures both financial and technology constraints in augmenting or reducing capital. On the one hand, capital adjustment cost is part of financial frictions, as it captures cost to sell used capital as in (Cui (2014)). This cost is in particularly large in China, since it has less-developed secondary markets for capital and less-developed stock market for merger and acquisition. On the other hand, we can also view the capital adjustment cost as some technology restrictions: it takes time and materials to install machines and build plants. Not taking a stand on the intrinsic property of adjustment cost, we decompose two mechanisms, financial frictions and capital adjustment cost, in preventing firms from choosing efficient capital: financial frictions and capital adjusting frictions.

We conduct two analyses. First, we rerun our benchmark model with zero capital adjustment cost while keeping other parameters the same. We call this analysis the *Only-Financial model*. Then, we shut down the financial frictions and compute a model with only capital adjustment cost by solving recursively the following first-order condition for a firm with (z, k):

$$1 + \Phi_2(k, k') = \frac{1}{1+r} E\left[\alpha z'^{1-\alpha} k'^{\alpha-1} + 1 - \delta - \Phi_1(k', k'')\right] \tag{13}$$

where Φ_1 and Φ_2 denote the derivatives of the capital adjustment cost Φ over k and k', respectively. The adjustment cost function is given by (2). We call this analysis the *Only-Adjustment model*. In the latter analysis, none of the financial parameters matter, and we use the same productivity parameters and capital adjustment cost ϕ as the benchmark model.

Table 7 shows comparison between our benchmark model and the two comparative statics. The capital adjustment cost does not significantly affect the average leverage in that the only-financial-friction model has a leverage of 0.57 close to benchmark number. The capital adjustment cost, however, affects firms differently in terms of leverage and interest. It amplifies the effect of the fixed credit cost in the benchmark model. Without it, we need an even higher fixed credit cost to generate a positive leverage-asset slope or a more negative interest-asset slope. Capital adjustment cost also greatly matters for the firms' investment response to shocks. Without it, firms' capital growth is quite responsive to the value added with a coefficient of 1.21, about 7 times larger than the benchmark and the data. This also demonstrates how we identify the capital adjustment cost. The firms' value-added distribution remains almost the same when the adjustment cost is set to zero. With only financial friction,

Table 7: Decomposing Mechanism: Financial Friction versus Adjustment Friction

Moments	Benchmark	Only-Financial	Only-Adjustment
Leverage	0.55	0.57	-
Leverage-asset slope	0.20	-0.21	-
Interest-asset slope	-0.08	-0.04	-
Capital growth-output coefficient	0.18	1.21	0.16
Std(value-added growth)	0.48	0.50	0.49
Autocorr(value added)	0.85	0.88	0.87
Share of VA in top 5 %	0.37	0.39	0.41
Share of VA in top 10 %	0.48	0.47	0.59
Share of VA in top 20 %	0.62	0.60	0.74
Implications on distortion			
Investment rate	0.21	0.33	0.23
Mean MPK	0.27	0.26	0.16
Std log(MPK)	0.58	0.53	0.61
TFP loss (%)	11.57	9.46	13.03

Notes: This table shows the comparison between the benchmark model, and two alternative models: one has only financial frictions, the other has only adjustment cost. To calculate the moments for the only-financial model, we rerun our benchmark model with zero capital adjustment cost while keeping other parameters the same. To calculate the moments for only-adjustment model, we shut down the financial frictions and compute a model with only capital adjustment cost.

the firm investment rate is higher, 0.33 versus 0.21 in the benchmark. Firms are thus less distorted. Nonetheless, financial friction alone generates sizable misallocation and TFP losses in that the standard deviation of log MPK is 0.53 and TFP loss is 9.46%, compared to 0.58 and 11.57% in the benchmark.

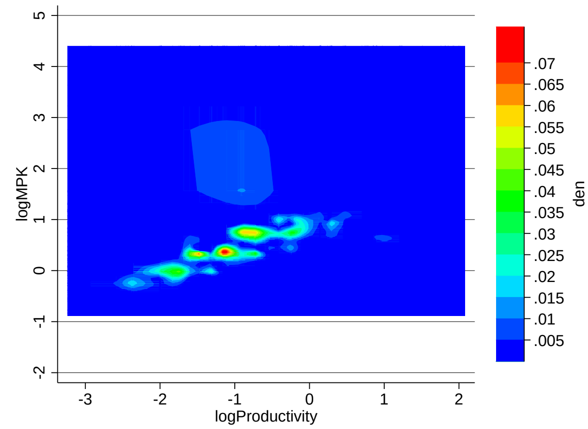
The model with only capital adjustment cost shows larger capital distortion than the benchmark, see the last column of Table 7. Firms reluctantly increase their size in response to positive productivity shock, and the regression coefficient ψ is only 0.16. Although the average investment rate is higher and average capital return is close to $r+\delta$, there are larger variations in MPK across firms, 0.61, and thus higher TFP loss (13.03%) than the benchmark case.

To better understand the distortions across models, we also graph the heat maps for the joint distribution of the expected MPK and productivity. In each subfigure of Figure 7, the x-axis is the log productivity of firms and the y-axis is the log of expected MPK, demeaned with the undistorted return of $\log(r+\delta)$. The graphs depict the density of each combination of MPK and productivity in the invariant distributions. The brighter the color, the larger the density. In both the benchmark and the only-adjustment friction, larger productivity firms face higher distortion due to higher MPK. With only financial frictions, small firms face higher MPK due to the fixed credit cost.

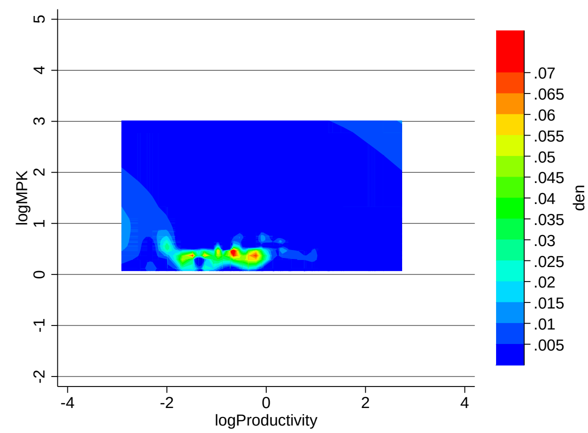
Overall, both financial friction and capital adjustment cost distort firms' investment decisions. Financial frictions generate higher marginal returns and tend to distort the investment of less productive firms, while capital adjustment cost distorts more the investment decision of more productive firms. Either friction alone produces a large TFP loss. Together, they interact and lead to larger but less dispersed MPKs across firms, hence a smaller misallocation among firms. The total TFP loss in the benchmark is in between those generated by the two frictions alone.

4.4 Introducing SOE

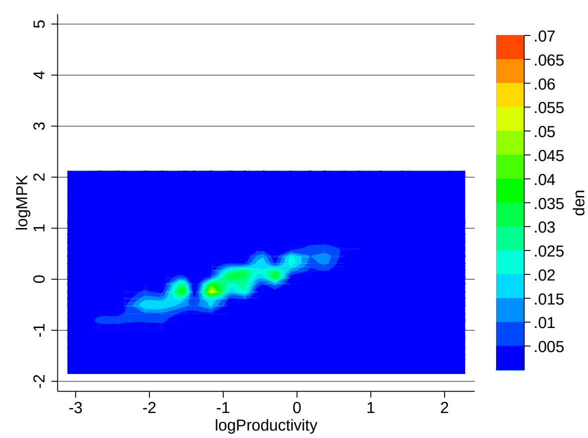
So far we have focused on the privately owned firms and shown that financial frictions can explain 50% of the dispersion of MPK and generate about 12% of TFP loss within privately owned firms. Next we quantify the misallocation between POEs and SOEs. SOEs in China can access financial resources easily; we therefore assume they do not face any financial frictions and solve the model with only adjustment cost as in (13). We estimate SOE productivity processes and capital adjustment cost to match the SOE distributions. The upper panel of Table 8 shows the data and model moments for SOEs. The value added of SOEs is more skewed than that of POEs, and the top 5 percentile of firms accounts for about 72% of the



(a) Benchmark



(b) Only-Financial Friction



(c) Only-Adjustment Friction

Figure 7: Distortion Comparison Across Models

Notes: This figure depicts the heat maps for the joint distribution of expected MPK and productivity for the benchmark model, only-financial model, and only-adjustment model. In each subfigure, the x-axis is the log productivity of firms and the y-axis is the log of expected MPK, demeaned with the undistorted return of $\log(r+\delta)$. The brighter color, the higher density of each combination of MPK and productivity.

total SOE value added. In addition, SOEs are 40% less productive than POEs, which captures other distortions within SOEs and between SOEs and POEs.

To calculate the total TFP loss for all firms, we pool the firms from the benchmark model and the calibrated SOEs. The share of SOEs is taken from the data, 20% average between 1999 and 2007. The overall TFP loss increases to 15%. Note that there are distortions within SOEs, so adding a fraction of undistorted firms tends to reduce dispersion, but the dispersion between POEs and SOEs increases the overall TFP loss. Table 8 also shows that the aggregate TFP is 35% lower with the existence of SOEs, as SOEs are much less productive.

Table 8: Misallocation between POE and SOE

Target Moments	SOE-Data	SOE-Model
Capital growth-output coefficient	0.18	0.14
Std(value-added growth)	0.54	0.54
Autocorr(value added)	0.92	0.92
Share of VA in top 5%	0.72	0.60
Share of VA in top 10%	0.82	0.81
Share of VA in top 20%	0.90	0.93
	POE only	POE+SOE
TFP loss(%)	11.57	15
Aggregate TFP	1	0.65

Notes: We estimate the SOE model using SMM. The upper panel of table shows the data and model moments for SOE. In the lower panel, we calculate the TFP losses and aggregate TFP for POE firms and for the whole sample with both POEs and SOEs.

5 Conclusion

To what extent do financial frictions matter for Chinese firm saving and capital misallocation? Most previous papers use either aggregate data or ignore firm-level financing patterns. Our paper uses the debt financing features observed in the Chinese firm-level data to identify financial frictions and focuses on their consequences for firms. Using a Chinese firm-level dataset , we first present evidences on firm dynamics, financing decisions, and capital misallocation. We find that SOEs have higher leverage, lower interest rates, and lower MPK. Within POEs, small firms have lower leverage, face higher interest rates, and operate with a higher marginal product of capital relative to large firms. These patterns are not easily reconciled with exogenous borrowing constraints. We develop and estimate a heterogeneous-firm model with financial frictions captured by endogenous default risk and a fixed cost of issuing loans. Using the model, we examine firms' financing pattern combined with other salient features and find that endogenous borrowing constraints are essential to explain firms' financing in Chinese data. Despite previous literature's success in matching the mean, standard deviation, or correlation of certain financial or real variables, they largely fail in matching the firm distribution. This could potentially lead to biased estimates in their counterfactual experiments due to firms' heterogeneous responses to the change of primitive parameters. Our analysis is differentiated from previous literature by its consideration of a more realistic set of shock processes and financing features, which both generate a richer set of investment and financing predictions and enable our model to do a markedly better job than previous models in matching the empirical firm distribution in sales, leverage, and interest rate.

Our estimated model can explain aggregate firm saving, the co-movement between saving and investment, the co-movement between firms saving, investment and size, and around 50 percent of the dispersion in the marginal product of capital. Overall, our model generates a 12% TFP loss. Our work also implies that the observed high MPK of small firms cannot be fully explained by financial frictions. Other sources of distortions, such as taxes, subsidies, and labor market frictions seem to be important.[6] It would be worthwhile to further explore the contributions of other frictions to firm saving, misallocation, and TFP losses. Future research along these lines should be fruitful.

[6] Yang (2012) argues that these frictions could be important for high Chinese saving.

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Appendix

Data

Table A1 shows firms median leverage, interest rate, and growth rate for some other years in our sample. The numbers and differences between SOE and POE are quite stable over time.

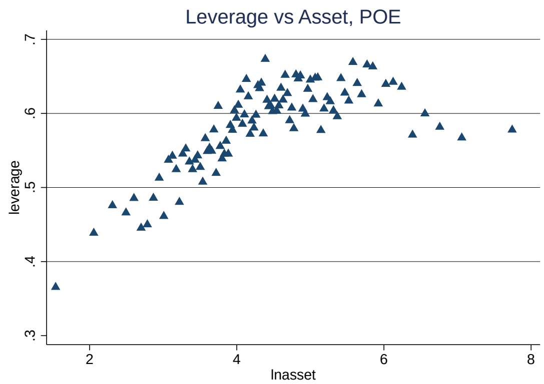
Table A1: SOE vs Non-SOE, Years 2002 and 2005

	2002			2005		
	Average	SOE	Non-SOE	Average	SOE	Non-SOE
Leverage	.657	.752	.609	.612	0.717	.603
Interest Rate	.023	.017	.027	.024	0.014	.026
Growth Rate	.014	-.049	.175	0.226	.09	.238

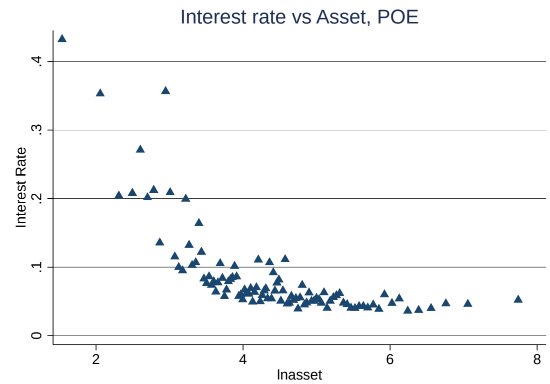
Notes: The table reports the descriptive statistics of leverage, interest rates, and growth rate for nonstate-owned enterprises and state-owned enterprises (SOEs) for some sample years. Interest rate is constructed using interest payment over debt.

Figure A1 and Figure A2 depict the relations between leverage, interest rate, growth rate, and MPK with firms asset level for state-owned firms and privately owned firms in year 1999. These patterns at the beginning of the sample are very similar to the pattern at the end of the sample, shown in Section 2.

Table A2 and Table A3 show regressions of the interested variables on firms' asset level, and the interaction of ownership and firms' assets, controlling for industry fixed effects, for year 1999 and 2006, respectively. Similar to the panel regression we show in Section 2, POEs have lower leverage, higher interest rates, higher growth rate and higher MPK than SOEs. Among POEs, small firms have a lower leverage, pay high interest rate, and have a larger growth rates and higher MPK.

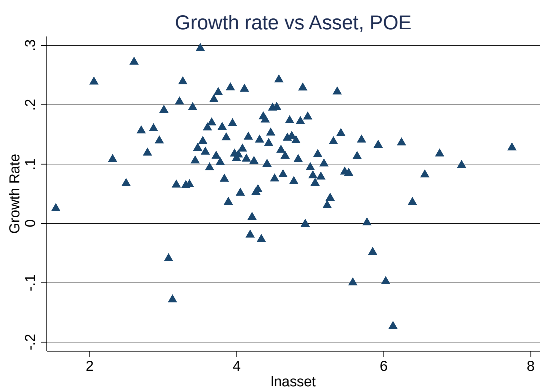


(a) Leverage and Assets, Year 1999

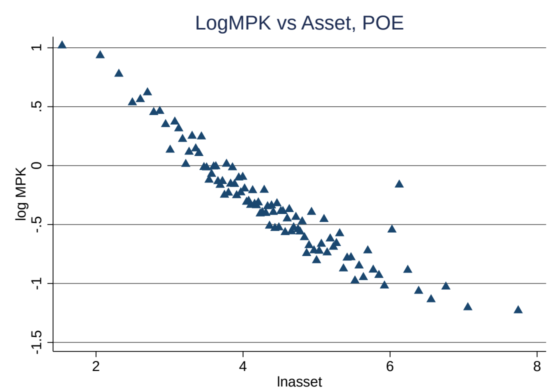


(b) Interest Rate and Assets, Year 1999

Figure A1: Firm Size and Debt Financing



(a) Growth Rate vs Assets, Year 1999



(b) MPK vs Assets, Year 1999

Figure A2: Firm Size, Growth, and MPK

Table A2: Regressions on Firm Ownership and Asset, Year 1999

VARIABLES	(1) Leverage	(2) Interest Rate	(3) Growth Rate	(4) log MPK
Private	-0.424***	0.154***	0.501***	2.221***
	(-16.66)	(10.81)	(8.829)	(24.10)
Private*lnasset	0.0467***	-0.0258***	-0.0601***	-0.233***
	(9.789)	(-9.045)	(-5.379)	(-10.70)
lnasset	-0.00926***	-0.00276***	0.0166***	-0.222***
	(-3.728)	(-9.105)	(3.745)	(-18.76)
Constant	0.838***	0.0462***	-0.129***	-0.348***
	(63.29)	(26.72)	(-5.513)	(-5.714)
Observations	47,152	36,468	33,122	46,592
R-squared	0.093	0.139	0.033	0.271
Industry FE	Yes	Yes	Yes	Yes

Notes: This table reports the regression results. The estimation sample includes all state-owned firms and non state-owned firms in the manufacturing sector in 1999 with sales over 5 million RMB, non-negative total debt, and positive assets. The dependent variables from columns 1 to 4 are leverage, interest rate, growth rate, and marginal product of capital (MPK) respectively. The explanatory variables are firm ownership, asset and an interaction of ownership and assets. T-statistics reported in parentheses are calculated using robust asymptotic standard errors clustered at the four-digit industry level. All specifications control for industry fixed effects. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A3: Regressions on Firm Ownership and Asset, Year 2006

VARIABLES	(1) Leverage	(2) Interest Rate	(3) Growth Rate	(4) log MPK
Private	-0.395***	0.0968***	0.441***	1.238***
	(-13.56)	(8.609)	(9.910)	(16.04)
Private*lnasset	0.0347***	-0.0133***	-0.0481***	-0.138***
	(7.210)	(-7.798)	(-6.959)	(-11.32)
lnasset	-0.0189***	-0.00272***	0.0177***	-0.193***
	(-4.185)	(-2.971)	(2.926)	(-17.68)
Constant	0.880***	0.0410***	-0.0632	-0.371***
	(32.40)	(5.886)	(-1.551)	(-5.186)
Observations	141,702	91,236	106,008	139,302
R-squared	0.070	0.040	0.016	0.147
Industry FE	Yes	Yes	Yes	Yes

Notes: This table reports the regression results. The estimation sample includes all state-owned firms and non state-owned firms in the manufacturing sector in 2006 with sales over 5 million RMB, non-negative total debt, and positive assets. The dependent variables from column 1 to 4 are leverage, interest rate, growth rate, and marginal product of capital (MPK) respectively. The explanatory variables are firm ownership, asset, and an interaction of ownership and assets. T-statistics reported in parentheses are calculated using robust asymptotic standard errors clustered at the four-digit industry level. All specifications control for industry fixed effects. $***p < 0.01, **p < 0.05, *p < 0.1$.