Do Financial Frictions Explain Chinese Firms' Saving and Misallocation?*

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Abstract

This paper uses Chinese firm-level data to quantify financial frictions in China and asks to what extent they can explain firms' saving and capital misallocation. We first document features of the data, in terms of firm dynamics and financing. Relatively 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. We estimate the model using evidence on the firm size distribution and financing patterns and find that financial frictions can explain aggregate firm saving, the co-movement between saving and investment across firms, and around 60 percent of the dispersion in the marginal product of capital (MPK). The endogenous financial frictions, however, generate an opposite MPK-size relationship, which has important implications for total factor productivity losses.

Keywords: financial frictions, firms debt financing, capital misallocation, saving and investment

JEL classification: O16, F32, F37, F41, G33

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1 Introduction

The literature has emphasized that financial frictions can generate high saving rates and capital outflows, as well as capital misallocation and low total factor productivity (TFP) in less developed countries for example 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 for standard economic theories, which 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 by firms accounts for around 50 percent of total savings in China in the last two decades.

Financial frictions can lead to capital misallocation and low 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 literature on the effect of financial frictions on capital outflow and misallocation is large, however, it either use aggregate data or it ignores firms' financing patterns. Few works use micro-level Chinese data to quantify these frictions, and this paper fills this gap. We ask to what extent financial frictions, identified using firm-level behavior, can explain saving and capital misallocation in China.

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

To identify the magnitude of financial frictions in China, we build a heterogeneous-firm model

[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 savings vary with their ownership structure.

with endogenous default risk and a fixed cost of issuing loans. All firms produce with a decreasing return to scale technology subject to stochastic productivity shocks. They finance investment and dividend payouts from profits and taking bank loans. Firms may default on their loans and secretly operate in financial autarky, with penalized productivity. Banks provide loan price schedules that account for the default risks and a fixed cost of issuance. Thus, our model generates endogenous borrowing constraints, which are important for capital misallocation and the aggregate TFP loss.

In the model, the firm size distribution, leverage, and growth are all shaped by financial frictions. When considering external finance via bank loans, firms face a trade-off. On the one hand, borrowing involves a fixed cost, so that small loans have a high effective (average) interest rate. On the other hand, borrowing more is associated with a high default risk and thus 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 end up with low leverage. When they experience a good productivity shock, these small firms grow faster, due to their inefficient size. These predictions are consistent with the data.

We estimate the model using the firm size distribution and financing patterns and find that financial frictions can explain aggregate firm savings, the co-movement between saving and investment across firms, and around 60 percent of the dispersion in the marginal product of capital (MPK). However, the endogenous financial frictions generate a negative MPK-size relationship, which we show has important implications for TFP losses. Hsieh and Klenow (2009) argue that when firms productivity and MPK are jointly log-normal, the negative effect of misallocation on TFP can be summarized by the dispersion in MPK. However, in models with endogenous borrowing constraints like ours, productivity and MPK are not jointly log-normally distributed. We find that the dispersion in MPK is not sufficient to measure misallocation, and that the covariance between MPK and firm size matters. This is similar to the idea in Restuccia and Rogerson (2008): "large TFP losses must be associated with positively correlated taxes and firm productivity." Financial frictions, disciplined by our micro-level data and firm financing patterns, generate a positive relation between MPK and firm size, opposite to the data. This implies that other sources of distortions, such as taxes and labor market frictions, seem to be more important for capital misallocation.

Our paper is related to the literature on the international capital flows puzzle, and more specifically on the Chinese foreign surplus puzzle. Buera and Shin (2009) find that underdeveloped domestic financial markets are important in explaining the joint dynamics of TFP and capital flows. When an economic reform eliminates financial distortions, the TFP of a small open economy rises due to the more efficient allocation of resources. At the same time, saving rates surge while investment rates respond with a lag, resulting in capital outflows. Using a growth model, Song et al. (2011) show that during an economic transition high-productivity, non-state-owned firms outgrow low-productivity, state-owned firms if entrepreneurs have high enough savings. At the same time, the more financially-integrated SOE sector shrinks, forcing domestic savings 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 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 ignore 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 savings and the co-movement across firms of saving and investment, that can be explained by these frictions.

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 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 salient features of plant level data, and show that the model does not predict large aggregate TFP losses from misallocation, and that misallocation from financial constraints cannot explain the TFP gap between countries with little use of external finance and the US. Our quantitative exercise suggests that endogenous borrowing constraints are essential to explain the patterns in the 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 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 finding of positive size-leverage relation in China is consistent with their finding for the less developed countries. We, however, focus on the effect of financial frictions on Chinese capital misallocation measured by the covariance between MPK and firm size.

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, and growth. 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 manufacturing enterprises collected by the Chinese National Bureau of Statistics between 1998 and 2007. The dataset includes firms with sales over 5 million RMB (about 600,000 US dollars). It contains all information in the balance sheet, profit and loss statement, and cash flow statement.

We first describe overall patterns for firms' assets, leverage, interest rates, growth and the marginal product of capital. 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 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. We restrict our sample to firms with positive assets, non-negative total debt and positive sales, yielding 149,675 firms in 1998, and 251,018 firms in 2005. Value added measures are deflated using the GDP deflator.

Table 1 reports descriptive statistics, the mean and median level of assets, value added, leverage, interest rates and growth rate for firms in 2005[3]. SOE[4] have more assets than non-SOEs on average.

[3]We drop the top 1 percent of firms for each variable to exclude outliers. Assets and value added are in terms of thousand RMB.

[4]SOE includes those with ownership codes 110, 141, 143, 149, 151. In the appendix, we also show results with the the least restrictive definition of SOE, which includes all the firms with positive state asset as well as collective enterprises. In our sample, 32.5 percent of the firms in 1998, and 5 percent in 2005 are SOEs.

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 non-SOEs. Even though they hold more assets, SOEs have similar average value added and its distribution is more dispersed than that for non-SOEs'. Non-SOEs also grow faster, more than twice the rate of SOEs.

Table 1: SOE vs Non-SOE, Year 2005

	Overall	SOE		Non-SOE	
	Average	Mean	Median	Mean	Median
Assets	37,220	70,022	21,399	35,826	12,959
Value Added	12,119	12,442	3,632	12,106	5,127
Leverage	0.58	0.77	0.72	0.56	0.58
Interest Rate	0.023	0.012	0.002	0.024	0.008
Growth Rate	0.21	0.10	0.08	0.21	0.18

In the following analysis, we focus on privately owned firms since they are more likely to be impacted by the underdeveloped financial markets and distorted financial allocations in China.[5]. We use information on registration type to classify POEs, which include sole private enterprises, private partnership enterprises, private limited liability companies and private shareholding corporations. For comparison, we also present statistics of SOEs.

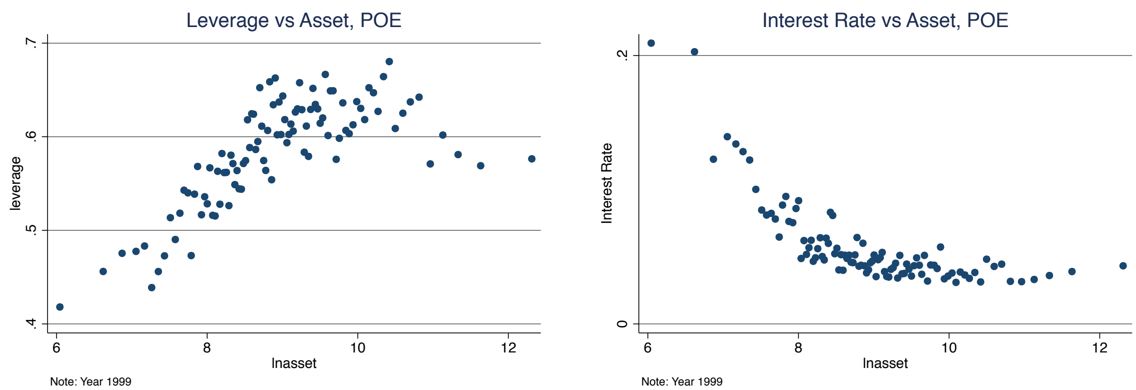
Do firms of different sizes finance their projects differently? Figure 1(a) depicts the mean leverage for different asset levels. The x-axis in the figure is the asset percentile for POEs in 1999, and on the y-axis, we plot mean leverage. Among POEs, leverage increases with firms assets[6]. Figure 1(b) shows that firms' interest rate decreases with their assets. Figure 2(a) illustrates the mean growth rate for POEs with different asset levels. As is well documented in the literature, small firms grow faster. Figure 2(b) depicts the relation between the marginal product of capital and asset levels. MPK has large dispersion and decreases with assets.

To study these patterns systematically, we regress the variables of interest on firms' asset level and an interaction of ownership and assets, controlling for industry fixed effects. Table 2 reports the regression results, with leverage, interest rate, growth and MPK in turn as the dependent

[5]State-owned firms in China receive favorable lending terms from state-owned banks and foreign-owned firms are less likely to be effected by local financial conditions. In the data appendix, we document the differences between SOE and POE in terms of firms dynamics and financing.

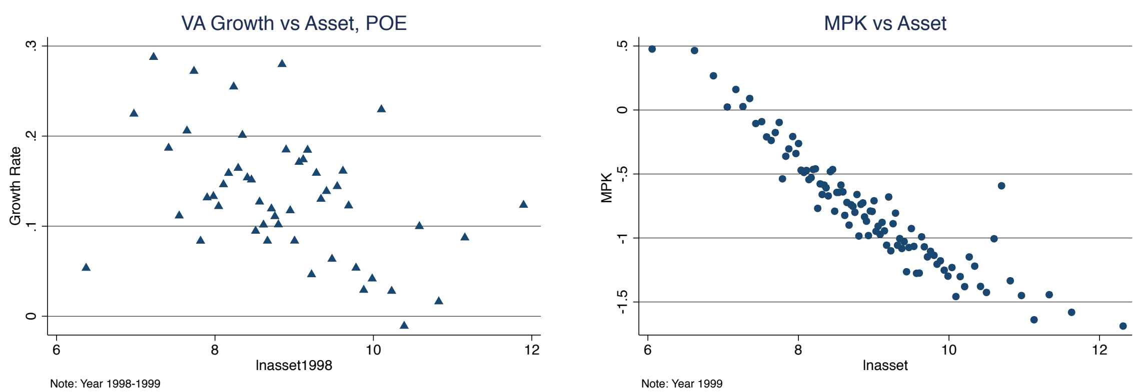
[6]In appendix Section 5 we include figures for other years and sectors.

Figure 1: Firm Size and Debt Financing



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

Figure 2: Firm Size, Growth, and MPK



(a) Growth Rate vs Assets, Year 1999 (b) MPK vs Assets, Year 1999

variable. The table shows that leverage ratios are significantly higher for SOEs, that interest rates are significantly higher for POEs compared to SOEs, and that among POEs, smaller firms have a lower leverage, pay high interest rate, experience faster growth, and operate with a higher MPK. Although there are sizable changes over time, for example the dramatic contraction of SOEs from 1998 to 2005 due to the SOE reform, the patterns we described above are consistently observed (see the data appendix).

In general, whether it's the small or large firms that are most distorted has different implications for TFP losses, given a set level of MPK dispersion. Consider a continuum of heterogeneous firms,

Table 2: Regressions on Firms Asset, Year 1999

	Leverage	Interest Rate	Growth Rate	log MPK
lnasset	.036***	-.019***	-.029***	-.446***
	(6.65)	(-6.99)	(-3.87)	(-17.63)
SOE	.57***	-.215***	-.595***	-3.52***
	(9.38)	(-8.23)	(-7.63)	(-14.77)
SOE×lnasset	-.039***	.020***	.045***	0.261***
	(-7.35)	(7.36)	(5.4)	(9.94)
Observations	47,542	47,542	38,572	47,542
Industry FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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

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

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, as usually assumed in the literature, we can 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. Generally the correlation of z and MPK also matters. 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

$$\text{TFP loss} = \frac{\mu - \rho - \frac{\alpha}{\alpha-1}}{(\mu-\rho)^{1-\alpha}\left(\mu - \rho - \frac{1}{\alpha-1}\right)^{\alpha}}.$$

Figure 3 depicts the TFP loss for different μ and ρ values. Clearly, for a given ρ, the loss increases with the dispersion in MPK. Furthermore, given the same dispersion in MPK, the loss varies with the size-MPK correlation: a high ρ leads to large losses, since a high z matters more for total output.

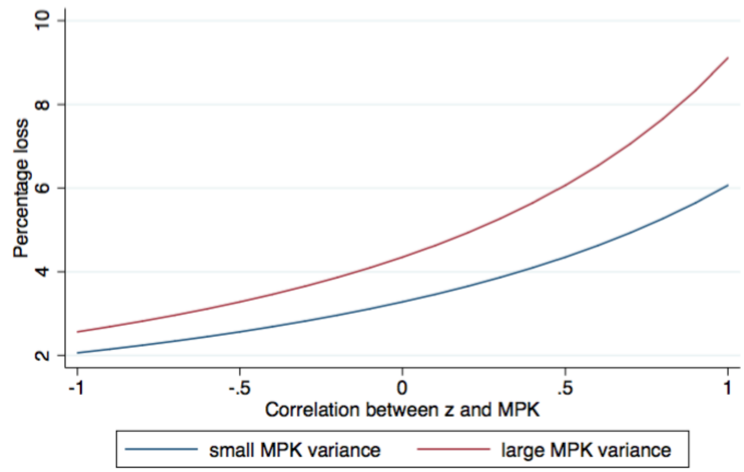


Figure 3: TFP Loss with different correlation between z and MPK

Note that the observed firm financing patterns are not easily reconciled with models with exogenous borrowing constraints, for example collateral constraints, which fail to generate firm-specific interest rates. This calls for a model with endogenous borrowing constraints. 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 savings and capital misallocation in China. In the next section, we construct a model that replicates firms debt financing patterns, then we estimate the model to match the firm-level data, and using those parameters we quantify firm savings, capital misallocation and the TFP loss generated by the frictions.

3 Model

We consider a small open economy with a continuum of firms. Financial markets are imperfect in that firms can only borrow state-uncontingent bond. 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 et al. (2012).

Firms produce with a decreasing return to scale technology using capital k as input,

$$y = z^{1-\alpha} k^{\alpha}$$

where z is the productivity with three components: a constant common growth rate g, a permanent component A, and an idiosyncratic component ν. In particular, in period t, firm i's productivity is given by

$$z_{it} = (1+g)^t A_i \nu_{it}.$$

Firms use their internal return and external borrowing to finance investment. Firms are indexed by their state variables, (z, k, b), with b denoting its initial debt level. If $b > 0$, the leverage of the firm is given by b/k, otherwise the leverage is zero. We assume that firms face limited liabilities.

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,

$$V(z, k, b) = \max_{d \in \{0,1\}} (1-d)\, V^c(z, k, b) + dV^d(z, k).$$

Let the optimal decision rule for default be $d(z, k, b)$ with $d(z, k, b) = 1$ denoting default.

If it repays, the firm chooses levels for investment and debt. In particular, it makes decision on next period's capital k', dividend x, and a loan b' with price $q(z, k', b')$ which, in equilibrium, will incorporating the default risk. The repaying value is given by

$$\begin{aligned} V^c(z, k, b) &= \max_{\{x, k', b'\}} \quad x + \beta E V(z', k', b') \\ \text{st} \quad x &= zk^\alpha + (1-\delta)k - b + q(z, k', b')b' - k' - \phi(k, k') \geq 0 \end{aligned}$$

where $\phi(k, k')$ is the capital adjustment cost. We assume limited liabilities and thus the dividend payment of the firm, x, has to be non-negative.

If it defaults, the firm gets its debt written off but it will be penalized with a productivity loss and be excluded from the credit markets for a random length of time. After default, the firm chooses dividend and new investment to maximizes its value,

$$\begin{aligned} V^d(z, k) &= \max_{x, k'} \quad x + \beta E\left[(1-\lambda)\, V^d(z', k') + \lambda V^c(z', k', 0)\right] \\ \text{st} \quad x &= \gamma z k^\alpha + (1-\delta)k - k' - \phi(k, k') \geq 0 \end{aligned}$$

where λ is the probability that the firm regains access to financial markets in the next period and γ is the fraction of productivity lost while in a state of default.

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 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. The bond price schedule incorporates both the fixed cost and the future default probabilities,

$$q(z,k',b')b' + \xi = \frac{b'}{1+r}\left[1 - \int d\left(z',k',b'\right) f\left(z';z\right) dz'\right].$$

When firms save, by making deposits $b' \leq 0$, banks pay the risk-free rate, $q = 1/(1+r)$.

Definition: A recursive equilibrium consists of decision rules, the value functions of firms, and the bond price schedule $q(z,k,b)$ such that

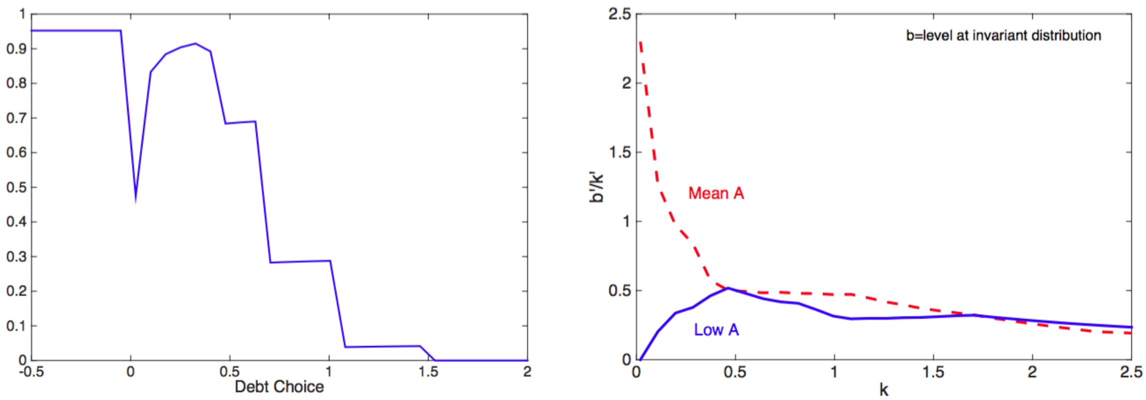
1. Given the bond price schedule, the decision rules and value functions solve the firm's problem.
2. Given the decision rules and a risk-free rate, the bond price schedule is such that banks break even in expected value.

To understand how firms finance their investment when facing an endogenous borrowing limit, we plot the bond price schedule and decision rules in Figure 4. [7] The left panel displays the price schedule as a function of debt choice, under the median productivity shock, capital and debt from the limiting distribution. We scale the debt choice by the firm's output. 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 150 percent of output, 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.

The right panel of Figure 4 depicts the choice of leverage, as a function of current capital k for two firms: one with an average level for the permanent component of productivity and one with a low permanent component of productivity. Current debt levels are taken from the limiting distribution of each permanent productivity type. All variables are normalized by each firm's output.

[7] Model parameters are estimated in the next section.

Figure 4: Bond Price Schedule and Leverage Choice



(a) Bond Price Schedule (b) Leverage Choice

There are two prominent features. First, for the average productivity firm, when capital increases, its leverage decreases. This is due to the decreasing return to scale, firms with higher capital stock have lower returns and thus have less of an incentive to borrow to finance investment. Second, for the firm of a low productivity type, 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 permanent 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. We choose parameters to replicate the firm size distribution of China, in 1999. We assume that the permanent component follows a Pareto distribution with a shape parameter μ, i.e.

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

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

$$\log(\nu_{it}) = \rho \log(\nu_{it-1}) + \sigma\varepsilon_{it}, \qquad \varepsilon_{it} \sim N(0,1).$$

The idiosyncratic shock is discretized using the Hussey-Tauchen (1992) method. We discretize the Pareto distribution into seven points $(A_1, A_2, ..., A_6, A_7)$ with the respective probabilities $\{\pi_1, \pi_2, ..., \pi_6, \pi_7\}$ consistent with (1). We normalize $A_1 = 1$ and equally spaces A_1 to A_6. We are thus left with two parameters to estimate, A_6 and A_7.[8] Finally, we assume a quadratic capital adjustment cost as

$$\Phi(k, k') = \frac{\phi}{2}\left(\frac{k' - (1-\delta)k}{k}\right)^2 k.$$

4.1 Estimation

Table 3 presents two sets of parameters. The first set is calibrated or set independently of our model. This set includes the risk-free rate r, the capital depreciation rate δ, the persistence of the idiosyncratic shock ρ, the production function parameter α, and the annual growth rate g. The second set are 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.

The annual risk-free rate is picked to match a deposit rate of four percent per year. The capital depreciation rate is chosen to be 10% annually. We set ρ to 0.85, which is in line with Foster, Haltiwanger, and Syverson's (2008) estimated value. The annual growth rate is 7 percent. We choose a value of 0.33 for the decreasing returns parameter α.[9]

The other eight parameters, discount factor β, productivity loss γ, fixed financing cost ξ, capital adjustment cost ϕ, volatility of idiosyncratic shock σ, and Pareto parameters μ, A_6, A_7 are jointly estimated to match the following eight moments in the data: mean leverage, mean and standard deviation of growth rate of value added, persistence and volatility of firms sales, the slope of the leverage schedule over assets, the slope of the interest rate schedule over assets, and the distribution of value added. Table 4 reports the simulated and actual moments. The model tightly matches the eight data moments.

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

[9] This can be viewed as a rigid labor market friction.

Table 3: Model Parameters and Target Moments

	Value	Description
Calibrated Parameters		
α	0.33	Production function curvature
λ	0.1	Reentry probability
δ	0.1	Depreciation rate
r	0.05	Risk-free rate
ρ_z	0.85	Persistence of productivity shock
Estimated Parameters		
β	0.94	Discount factor
γ	0.3	Productivity loss in default
ξ	0.012	Fixed credit cost
ϕ	1.3	Capital adjustment cost
σ	0.76	Productivity shock standard deviation
μ_A	1.30	Shape parameter for permanent distribution
A_6	0.8	The second largest value of A
A_7	0.92	The largest value of A

The success of SMM estimation depends on model identification, which requires that we choose moments that are sensitive to variations in the structural parameters. We now describe and rationalize the moments that we choose to match. The discount factor β, credit fixed cost ξ and adjustment cost ϕ are most relevant for the firm's leverage decision. The more impatient the firm, the higher the leverage it would employ. The fixed credit cost affects both the mean and the slope of leverage ratios. A lower ξ increases mean leverage. When ξ is big, borrowing is very costly for small firms, and thus they have lower leverage, resulting in an upwards sloping schedule. When ξ is relatively small, smaller firms would employ higher leverage. The fixed credit cost ξ also governs the mean interest rate and the slope of the interest schedule over assets. A high credit cost leads to a higher mean interest rate. Also, when the fixed cost is high, small firms tend to borrow very little, due to the high effective interest rate. This would result in a downward-sloping interest schedule over assets. σ, which governs the volatility of firm productivity, is most closely related to the persistence, mean, and standard deviation of firm sale growth. Capital adjustment cost also impacts firm sale growth variance. The higher the adjustment cost, the lower the standard deviation of sale growth. The value added distribution directly disciplines the permanent Pareto parameters μ_A, A_6, A_7. These parameters, which govern the type distribution, would also indirectly change all other moments through their impacts on the firms' size distribution. The smaller the shape parameter, the fatter the right tail of firm size, and the higher the concentration of market share. Although the leverage schedule slope within each type of permanent productivity might only be slightly positive or even negative, with enough heterogeneity in permanent components, the aggregate leverage schedule can be upward-sloping.

We find that in our estimates firms face a high fixed credit cost, resulting in an upward-sloping leverage schedule, across asset quantile. For this fixed cost value, small firms face higher mean interest rates, because of their lower amount of external debt issuance and higher default probability. Sale growth is greater for small firms. Facing financial friction, small firms face expensive external financing and do not operate at their optimal scale.

Table 4: Baseline Model v.s Data

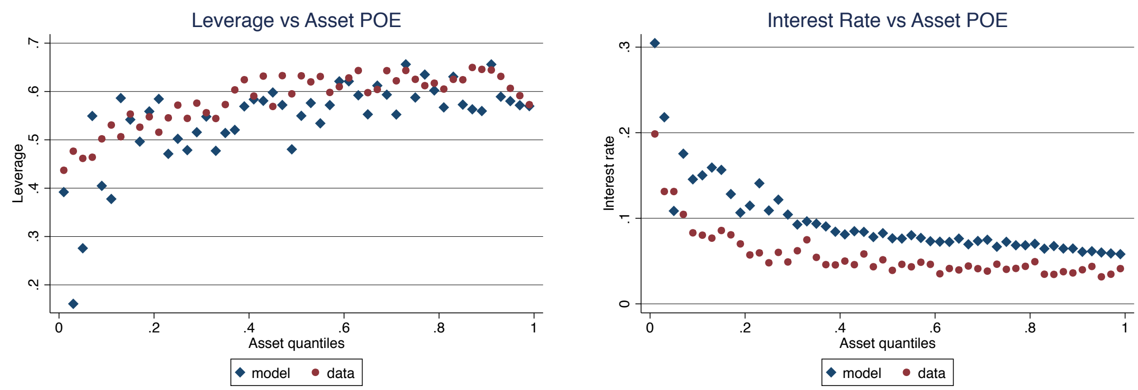
Target Moments	Model	Data POE 1999
Mean Leverage	0.56	0.58
Leve-Asset pct Slope	0.17	0.17
Interest-Asset pct Slope	-0.12	-0.08
Growth of Value Added		
Mean	0.14	0.13
Var	0.40	0.40
Distribution of VA		
TOP Percentiles	Fraction of VA	
5	0.34	0.34
10	0.48	0.46
20	0.66	0.62

Overall, the model matches well the distribution of firms in terms of leverage, interest rates, and sales distribution, see Figure 5 and 6. In both the model and the data, small firms have lower leverage and face higher interest rates than larger firms.

4.2 Model Implications over Saving and Capital Misallocation

Given the estimation results for our model with financial frictions, disciplined using firm financing data, we ask to what extent the model is able to account for firm saving and investment behavior and capital misallocation, as measured by variation in MPK across firms. Saving in the data is the sum of change of equity and capital depreciation. Saving in the model is defined consistent with

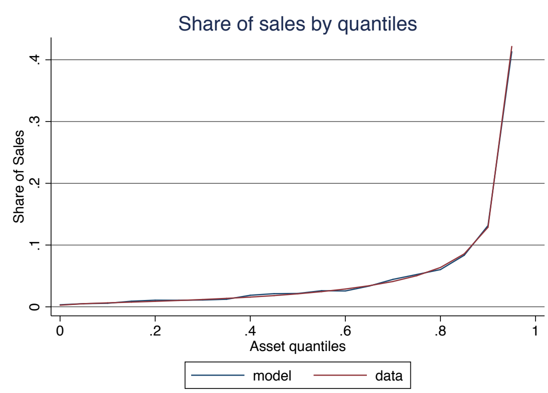
Figure 5: Leverage, Interest Rate, and Asset



(a) Leverage

(b) Interest Rate

Figure 6: Sale Distribution



the data, saving $= z^{1-\alpha}k^{\alpha} - x + (qb' - b')$. [10] The results shown in Table 5 can be viewed as an out-of-sample test of the model, given that they are not targeted in the estimation. The model matches well the gross saving rate, 0.15 in the model and 0.18 in the data. Saving and investment co-move across firms with a correlation of 28 percent in the model and 31 percent in the data. The model accounts for around 60 percent of variation in MPK, but fails to generate the size-MPK relationship. Specifically, in the data, large firms have a lower marginal return while the opposite is true in the model.

It is useful to study firms' first order condition for capital to understand how MPK varies with firm

[10] It is easy to see that in the model saving $=$ value added $-$ dividend payout $-$ interest payment, which can be reorganized as (value added-interest payment-depreciation)-dividend payout+depreciation. We thus have that saving is also the sum of equity change and capital depreciation.

Table 5: Model Implication on Savings and MPK

Non-Targeted Moments	Model	Data
Aggregate Statistics		
Gross saving rate	0.15	0.18
Dispersion of MPK	0.67	1.12
Correlations		
Saving rate, Investment rate	0.28	0.31
MPK, asset	0.20	-0.36
MPK, leverage	0.36	0.01

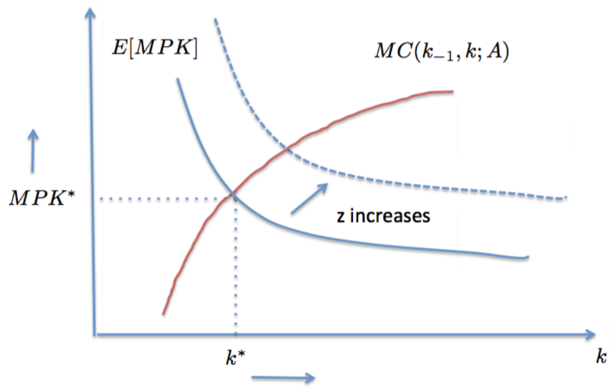
size. The optimal capital stock equates the expected future marginal return and current marginal cost. Roughly speaking, the following holds

$$E[MPK] = r + \delta + \underbrace{\phi f(k_{-1}, k)}_{\text{adjustment cost}} + \underbrace{\mu(A, k)}_{\text{financial frictions}} \equiv MC(k_{-1}, k; A). \tag{2}$$

The left-hand side of equation (2) is the expected marginal return of capital and the right-hand side of equation (2) is the marginal cost of capital, $MC(k_{-1}, k; A)$. The marginal cost has three components: the usual one given by the risk-free and depreciation rates, the marginal adjustment cost of capital, and the part reflecting frictions. To have MPK increasing with size, it has to be the case that MC is upward sloping. Otherwise, MPK always decreases with size, see Figure 7. The marginal adjustment cost part increases with size, thus the adjustment cost helps generate an upward-sloping MPK-size relation. Financial frictions, however, have two opposing effects. On the one hand, a choice of more capital increases output next period and thus relaxes tomorrow's non-negative dividend condition, which reduces marginal cost. On the other hand, high capital also increases the outside value of the firm, which boosts firms' default incentive. Lenders take this into consideration and charge a high interest rate for larger capital stocks, generating a higher marginal cost. Hence, whether financial frictions lead to an upward or downward relation between MPK and size hinges on which effect dominates, the limited liability effect or the default effect.

We show the MPK-size relation from the model's limiting distribution in Figure 8. The figure shows that within each permanent productivity type A, there is a strong positive correlation between MPK and the transitory productivity shock z. While across different permanent productivity levels, this correlation is significantly reduced, as firms with high permanent productivity accumulate capital

Figure 7: MPK and Firm Size



and are less constrained.

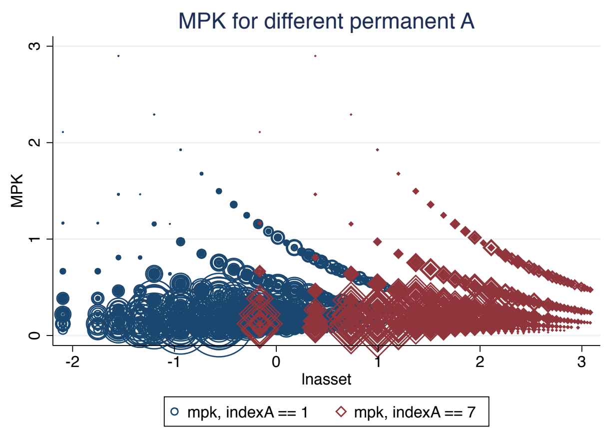


Figure 8: Marginal Product of Capital (Model Simulation)

To further understand how each force, adjustment cost and financial frictions, affects the MPK-size relation, we conduct experiments over the adjustment cost and financial frictions in Table 6. In the first experiment, we eliminate the capital adjustment cost by setting $\phi = 0$. Without adjustment cost, MPK dispersion decreases from 0.67 to 0.53. Most importantly, there is almost no difference in MPK between small and large firms. TFP losses are reduced from around seven percent to less than three percent, due to both a lower dispersion of MPK and less distorted large firms. The leverage and size relation, however, becomes counterfactual. Small firms have higher leverage. This means that if we were to increase the fixed credit cost, the MPK-size relation may become more positive.

The next two experiments are about financial frictions: reducing the fixed credit cost and

Table 6: Counterfactual Experiments

	Benchmark	$\phi = 0$	$\xi = 0$	$\gamma = 0.5$
Leverage-size	0.23	-0.34	-0.49	0.06
Dispersion of MPK	0.67	0.53	0.67	0.72
MPK-size	0.20	-0.05	0.22	-0.02
MPK-leverage	0.36	0.05	0.18	0.29
TFP loss (%)	6.87	2.72	7.91	7.72

increasing the punishment for default. The fixed credit cost affects small firms more whereas default punishment matters more for large firms. A decrease in the fixed credit cost, from the benchmark level to zero, also has no impact on MPK dispersion, but reduces the distortion in small firms and thus the MPK-size relation becomes more upward-sloping. This small increase in slope from, 0.2 to 0.22, turns out to have a large impact on TFP losses, which increase from 6.87% to 7.91%. The last experiment increases the default punishment γ from 30 percent to 50 percent. Under such a larger default cost, firms have more of an incentive to repay, particularly larger firms. This reduces the slopes of the size-leverage and size-MPK relations. There is also an increase in MPK dispersion and TFP losses become greater.

5 Conclusion

This paper first presented evidence on firm dynamics and financing decisions, from a Chinese firm-level dataset. 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 a heterogeneous-firm model with financial frictions captured by endogenous default risk and a fixed cost of issuing loans.

We then quantified the magnitude of financial frictions in China, and ask to what extent firms' saving and capital misallocation can be explained by these frictions. We found that financial frictions can explain aggregate firm savings, the co-movement between savings and investment, and around 60 percent of the dispersion in the marginal product of capital. The endogenous financial frictions, however, generate a negative MPK-size relationship, which we show has important implications for measured TFP losses. On the one hand, financial friction distortions positively related to firm sizes tend to lead to larger TFP losses. On the other hand, our work implies that the observed distortions to 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. [11] 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.

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

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Appendix

C Data

Table 7 shows firms leverage, interest rate and growth rate for other years and sectors in our sample.

Table 7: SOE vs Non-SOE, Year 1998 and 2005

	1998			2005		
	Average	SOE	Non-SOE	Average	SOE	Non-SOE
Leverage	.666	.772	.622	.579	0.769	.564
Interest Rate	.056	.042	.062	.023	0.012	.024
Growth Rate	.014	-.066	.046	0.208	.10	.214

Figure 9, 10, 11, 12 plot the relations between leverage, interest rate, growth rate and MPK with firms asset level for state-owned firms and private-owned firms in year 2006. Table 8 shows regressions of the interested variables on firms asset level, and interaction of ownership and firms asset, controlling for industry fixed effects, for year 2006. Similar to what we show in Section 2, among POE, small firms have a lower leverage, pay high interest rate, have a larger growth rates and higher MPK.

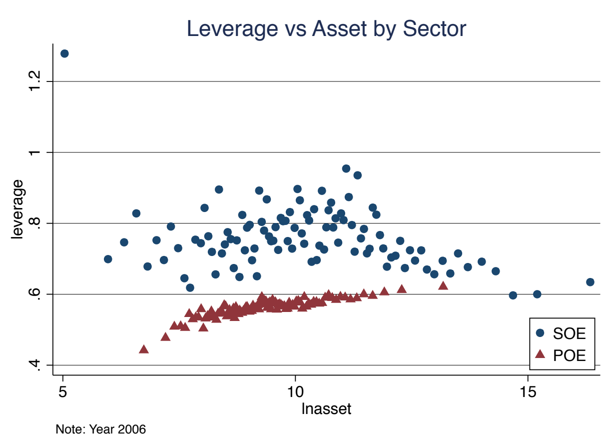

Figure 9: Leverage vs Asset, by Sector, Year 2006

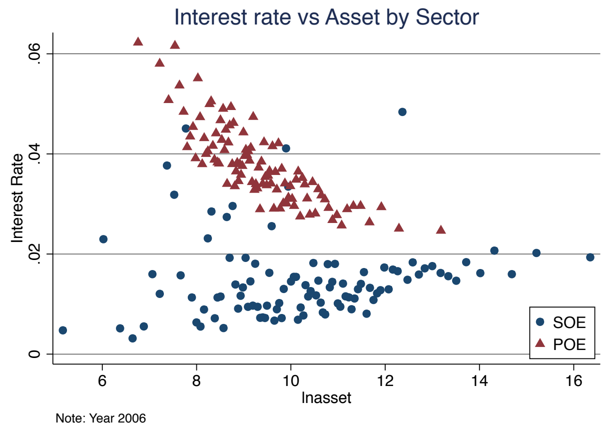

Figure 10: Interest Rate vs Asset, by Sector, Year 2006

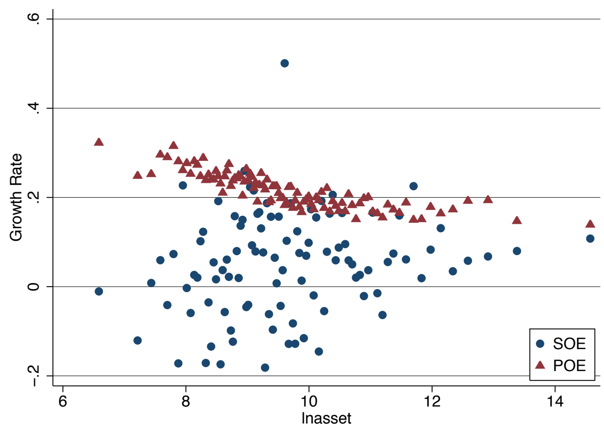

Figure 11: Growth Rate vs Asset, by Sector, Year 2006

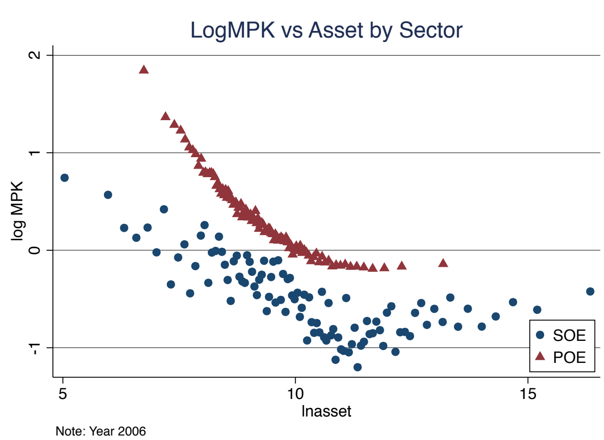

Figure 12: MPK vs Asset, by Sector, Year 2006

Table 8: Regression of Leverage, Interest Rate, Growth and MPK on Firms Asset and Ownership, Year 2006

	Leverage	Interest Rate	Growth Rate	log MPK
lnasset	.018***	-.006***	-.021***	-.341***
	(8.17)	(-3.68)	(-6.92)	(-26.59)
SOE	.566***	-.089***	-.475***	-2.37***
	(11.58)	(-5.07)	(-7.13)	(-10.63)
SOE×lnasset	-.036***	.006***	.033***	0.181***
	(-7.92)	(4.20)	(5.02)	(8.49)
Observations	142,009	142,009	112,368	142,009
Industry FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$