Size-dependent Financial Frictions, Capital Misallocation and Aggregate Productivity *

Xiaolu Zhu†

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Abstract

This paper quantitatively examines the macroeconomic effects of size-dependent financial frictions on capital misallocation and aggregate total factor productivity. Based on panel data of China's manufacturing sector, I find that among non-state-owned enterprises, (i) the dispersion of marginal product of capital is large and persistent and (ii) large firms tend to have higher leverage, and lower mean and dispersion of marginal product of capital than their small counterparts. This paper analyzes a dynamic stochastic general equilibrium model with heterogeneous agents and size-dependent financial frictions under which larger firms face lower borrowing tightness. By calibrating the model to a Chinese firm-level dataset, I show that in addition to matching the aforementioned stylized facts, the economy with a size-dependent borrowing constraint is able to reproduce the observed negative correlation between firm size and the marginal product of capital, as well as generates quantitatively modest TFP loss.

Keywords: Financial Frictions, Productivity, Capital Misallocation

JEL Classification: E2, G3, O4

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†Department of Economics, 3120 Sproul Hall, University of California, Riverside, CA 92521, USA, E-mail:xzhu010@ucr.edu.

1 Introduction

Total factor productivity (TFP) is considered the dominant factor accounting for income per capita differences across countries.[1] Instead of focusing on the inefficiency within a representative firm, a growing strand of the literature emphasizes the role of factor allocation efficiency across heterogeneous firms in explaining the observed aggregate TFP differences.[2] Furthermore, the well-documented strong positive correlation between financial development and aggregate TFP[3] has driven recent work examining the role of financial frictions.[4] In this line of research, with imperfect financial markets, firms face the collateral-type borrowing constraint with homogeneous borrowing tightness.[5]

However, empirical evidence suggests that firms' financing ability depends largely on firm size, which is the fundamental firm characteristic. By analyzing the Chinese firm-level dataset for the period 1998-2007, I find that in the Chinese manufacturing sector, there exists a positive relationship between leverage and firm size. That is, large firms face lower borrowing tightness and tend to have higher leverage than small firms. Similar empirical evidence for the positive leverage-size slope can be found in Arellano et al. (2012), Gopinath et al. (2017) and Bai et al. (2018).[6] Since a firm's financing ability directly affects its capital decisions, failing to take into account the financial frictions disciplined by the observed firms' financing patterns may prevent salient features of capital misallocation from being captured.

This paper fills this gap by focusing on firms' financing patterns and studies the impacts of size-dependent financial frictions on capital misallocation and aggregate productivity.[7] To

[1]For example, Klenow and Rodriguez-Clare (1997), Hall and Jones (1999).

[2]See Hsieh and Klenow (2009), Restuccia (2011), among others.

[3]See Hopenhayn (2014), Arellano et al. (2012).

[4]See Buera et al. (2011), Midrigan and Xu (2014), Moll (2014), Itskhoki (2019), among others.

[5]In this paper, the borrowing tightness is defined as the maximum attainable leverage ratio.

[6]Using firm-level data of 27 European countries from 2004 to 2005, Arellano et al. (2012) show that there is a positive relationship between firm size and the leverage ratio and that as financial development increases, the leverage ratio of small firms relative to that of large firms increases. Gopinath et al. (2017) show that the regression coefficient of the leverage ratio on firm size is 0.15 using manufacturing data from Spain from 1999 to 2007. Bai et al. (2018) document financing patterns of manufacturing firms in China between 1998 and 2007 and suggest that among private firms, large firms have higher leverage than small firms, and the leverage-size slope is 0.2.

[7]Following Banerjee and Moll (2010), capital misallocation along the intensive margin is defined as the

capture the empirical fact that large firms have higher leverage than small firms, this paper builds a model of firm dynamics by incorporating the size-dependent borrowing constraint under which larger firms face lower borrowing tightness while enabling firms' capital decisions to be analytically tractable.

In the model, the optimal unconstrained capital increases in productivity. Under the collateral constraint with a size-invariant maximum leverage, the marginal product of capital increases in productivity, since given a certain net worth level, firms with higher productivity have higher financing needs and are more likely to be constrained. By contrast, with the size-dependent borrowing constraint, as the maximum attainable leverage ratio increases with firm size, the relationship between the marginal product of capital and productivity becomes non-monotonic. When productivity is sufficiently high, even firms without high net worth are able to accumulate adequate capital, grow large and relax the borrowing constraint. With this feature, firms with high productivity, large size or without high net worth are less impacted by financial frictions relative to the case under the homogeneous borrowing constraint.

To discipline the quantitative model, I document several facts on misallocation based on the Chinese firm-level dataset. Since policies may drive a wedge between factor prices and the marginal product of capital, the dispersion of the marginal product of capital as a measure of capital allocation efficiency is at the center of the analysis. First, the standard deviation of the marginal product of capital is persistent over the sample period, suggesting the existence of capital misallocation. In addition, the extent to which firms are distorted varies across different firm size groups. The mean and dispersion of marginal product of capital are smaller among large firms. The empirical findings suggest that the capital decisions of large firms are less distorted than those of their small counterparts. The implications of size-dependent financial frictions, under which large firms are more favored in the financial market than small ones, are in line with the observed facts.

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unequal marginal products of capital across agents with positive usage of capital.

This paper quantifies the impacts of the size-dependent borrowing constraint on capital misallocation and the aggregate TFP in the Chinese manufacturing sector. The parameters are jointly calibrated to match the moments of the firm-level and aggregate data in China. In particular, the borrowing tightness parameters are pinned down to match both financial development (the debt to GDP ratio) and firms' financing pattern (the positive leverage-size slope). The model with the size-dependent borrowing constraint matches well the firms' financing pattern, the skewed output distribution and other non-targeted moments. Moreover, the model with the size-dependent borrowing constraint explains approximately 35% of the dispersion of the marginal product of capital. The rationale for this result is that there are other forces in addition to financial frictions that contribute to capital misallocation, consistent with the findings of existing empirical work on Chinese manufacturing firms.[8] This model also generates the similar pattern of the mean and dispersion of marginal product of capital across size groups.

This paper focuses on the mechanism of the observed negative correlation between firm size and the marginal product of capital. Under the homogeneous borrowing constraint, which corresponds to the size-invariant maximum leverage, given a certain productivity, firms with higher net worth are able to grow larger and face lower marginal product of capital. In addition, given a net worth, firms with higher productivity tend to become larger and face higher marginal product of capital due to their larger financing needs for capital. These are two opposing forces affecting the correlation between firm size and the marginal product of capital. The model with the homogeneous borrowing constraint fails to reproduce the correlation between firm size and the marginal product of capital, as this correlation equals zero. By contrast, under the size-dependent borrowing constraint, when the productivity shock is large, firms without a high net worth are able to grow large, relax the borrowing constraint and face low marginal product of capital. Due to this feature, large firms are less distorted, and the model generates a negative correlation between firm size

[8] See Wu (2018).

and the marginal product of capital with a coefficient of -0.17, which is consistent with the data (-0.23).

In the model with the size-dependent borrowing constraint, the fraction of firms that are financially constrained at the steady state is 0.54, and the aggregate TFP loss is 3.98%, which implies that size-dependent financial frictions explain modest TFP loss along the intensive margin.[9] The rationale for this result is that self-financing undoes the impacts of the borrowing constraint on capital misallocation to some extent under persistent productivity shocks, as discussed in Moll (2014). Under the homogeneous borrowing constraint, the TFP loss is instead 5.12%. Without considering the size-dependent financial policy, we may not only fail to capture the relationship between firm size and misallocation but also overestimate the TFP loss since large firms, which contribute most to the economy, are actually less financially constrained.

To examine the important role of the borrowing tightness parameter in the financing patterns of firms, this paper conducts a sensitivity analysis. As the value of the borrowing tightness parameter increases, which corresponds to a larger leverage-size slope, the negative correlation between firm size and the marginal product of capital is stronger, and the dispersion of the marginal product of capital as well as the TFP loss decrease accordingly. Moreover, large firms benefit more from an increasing leverage-size slope than small firms. That is, compared with small firms, both the mean and dispersion of the marginal product of capital decrease further among large firms.

This paper closely relates to the growing strand of literature studying the impacts of financial frictions on misallocation and aggregate productivity. Moll (2014) develops a general equilibrium model with a collateral constraint to study the impacts of financial frictions

[9]Based on Chinese firm-level data from 1998 to 2007, Wu (2018) suggests that the annual average TFP loss is 27.5%, 8.3% of which is contributed by financial frictions. The significant TFP loss in China can be attributed to policy distortions. Midrigan and Xu (2014) measure the aggregate TFP losses in China as 22.5% based on the same dataset. Hsieh and Klenow (2009) quantify the role of misallocation in the aggregate manufacturing TFP using firm-level data in China and India by regarding the US as the efficiency benchmark. They show that if capital and labor are reallocated to equalize marginal products across firms to the extent of the US efficiency benchmark, then the aggregate TFP gains are 30%-50% for China.

on capital misallocation and aggregate TFP. Midrigan and Xu (2014) study a two-sector growth model of firm dynamics and show that financial frictions reduce the aggregate TFP by restraining firms' entry and technology adoption decisions, as well as by distorting capital allocation across existing firms. This paper differs from these previous works by considering firms' financing patterns and incorporating the size-dependent borrowing constraint. This paper shows that not considering firms' financing behavior fails to capture the patterns of capital misallocation and may overestimate the TFP loss. This paper is also closely related to Gopinath et al. (2017), which differs in that it studies the impacts of the decline in the real interest rate since the 1990s in South Europe on productivity and focuses on transitional dynamics. The present paper instead quantifies the impacts of size-dependent financial frictions on aggregate TFP at the steady state.

This paper is also related to the literature on firms' financing patterns. Arellano et al. (2012) show that there is a positive relationship between firm size and the leverage ratio based on a European dataset and that the leverage of small firms relative to large firms gets bigger as financial development increases. Bai et al. (2018) take firms' financing patterns, e.g. the positive leverage-size slope among Chinese private firms, into account and quantify the role of financial frictions on aggregate productivity. This paper differs from these works in the formulation of the borrowing constraint. In Arellano et al. (2012) and Bai et al. (2018), the borrowing limit is determined by taking default risks of firms and fixed cost of issuing loans. However, in Bai et al. (2018), the model with the endogenous borrowing constraint generates a slightly positive correlation between firm size and the marginal product of capital, which deviates from the Chinese data. In this paper, the model can reproduce the patterns of misallocation that both the mean and dispersion of marginal product of capital are lower among large firms than their small counterparts.

This paper also relates to the empirical findings on misallocation. David and Venkateswaran (2019) study various sources of capital misallocation in both China and US, e.g. capital adjustment costs, informational frictions and firm-specific factors. They find that in China, adjustment costs and uncertainty play a modest role, while other idiosyncratic factors, both productivity or size-dependent as well as permanent substantially contribute to misallocation. This paper focuses on one specific factor, size-dependent financial frictions, in capital misallocation. Ruiz-García (2019) finds that the average and dispersion of the marginal product of capital are higher for young, small and high-productivity firms based on a firm-level dataset from Spain. This paper reports similar findings in China. Bai et al. (2018) record that the marginal product of capital decreases with firm size based on a Chinese dataset. In addition to that relationship, this paper finds that the dispersion of the marginal product is also lower within large firms. Hsieh and Olken (2014) instead show that bigger firms have higher average product of capital in India, Indonesia and Mexico. However, their empirical findings are based on a dataset that includes both formal and informal firms. The present paper differs in focusing on the formal Chinese manufacturing sector.

The rest of this paper is organized as follows. Section 2 presents the firm-level dataset of the Chinese manufacturing sector. Section 3 introduces the model and discusses the implications of the size-dependent financial frictions on capital misallocation. Section 4 presents the model parameterization, and Section 5 analyzes the simulation results. Section 6 concludes the paper.

2 Data

This section describes the data and presents the empirical findings on capital misallocation in the Chinese manufacturing sector. Strong evidence for the relationship between firm size and the marginal product of capital as well as firms' financing patterns is found, which motivates the study of the impacts of size-dependent financial frictions on capital misallocation.

2.1 Data Description

The empirical findings are based on the firm-level dataset for the period 1998-2007 from the *Chinese Annual Survey of Industrial Firms*. This dataset includes all state-owned enterprises (SOEs) and all "above-scale" non-state-owned enterprises (non-SOEs) with annual sales above 5 million RMB (approximately 700,000 US dollars). Firms in this dataset account for the top 20% of manufacturing firms by industrial sales and contribute to more than 90% of the total industrial output in China.[10] This dataset reports abundant firm-level information and has been extensively studied in the existing literature related to Chinese firm behaviors.

To construct a panel for analysis purposes, I restrict the sample to the manufacturing sector and drop observations with negative key variables and observations with key variables that are not consistent with accounting standards.[11] Following Brandt et al. (2014), this paper creates a unique ID for each firm and constructs panel data based on the firm ID information. The output is measured by the value added and deflated by the GDP deflator. Following Brandt et al. (2014), capital is constructed by using the perpetual inventory method. Assets are measured by total assets, which serves as a proxy of firm size in this paper. To control differences in labor quality, labor is measured by the sum of wages and benefits and is then deflated by the CPI. Debt is measured by the sum of long-term and short-term debt. Leverage is defined as the ratio of total debt to total assets. The marginal product of capital is approximated by the average product of capital, which is the ratio of output to capital.

This paper further divides firms into SOEs and non-SOEs according to ownership considering that non-SOEs and SOEs in China are subject to different regulations. Following Hsieh and Song (2015) and Wu (2018), I identify firms' ownership by using the registered capital ratio. If the ratio of registered capital from the state to total registered capital is at least 50%, the firm is recognized as an SOE. Otherwise, the firm is a non-SOE. See Appendix

[10] See Brandt et al. (2012), Wang (2017).

[11] The information on accounting standards is based on the *Industrial Statistics Reporting System*, which is published by the NBS of China.

A.1 for details.

This paper focuses mainly on non-SOEs for the following reasons. First, SOEs compose a minor fraction of the dataset. The number of non-SOEs expanded rapidly over the sample period and accounts for 89% of the observations. Second, strong discrimination exists in the Chinese financial market across firms of different ownership, and non-SOEs are distorted by financial frictions. The banking system, which is dominated by the four state-owned banks, tends to lend to SOEs instead of non-SOEs, which lack political connections. Dollar and Wei (2007), Ayyagari et al. (2010) and Song et al. (2011) suggest that SOEs rely more on domestic bank loans to finance investments than non-SOEs. Poncet et al. (2010) and Curtis (2016) suggest that private Chinese firms are credit constrained, while SOEs are not. Furthermore, given that the focus of this paper is capital misallocation along the intensive margin, I study existing and ongoing non-SOEs with a sample covering 211,580 observations for the period 1998 to 2007.

2.2 Capital Misallocation

The marginal product of capital is at the center of the analysis. In the absence of distortions, the marginal product of capital across firms should be equal, and more resources are allocated to firms that are more productive. However, policies or institutions may drive a wedge between the factor prices and marginal products.[12] Thus, the dispersion of the marginal product of capital helps to measure the capital allocation efficiency. Intuitively, as discussed in Midirgan and Xu (2014) and Bai et al. (2018), the aggregate TFP loss is proportional to the dispersion of the marginal product of capital.

The standard deviation of $log(MP_k)$ is obtained at the industry level (4-digit) and then aggregated conditional on year. Figure 1 displays the evolution of the standard deviation of $log(MP_k)$ across non-SOEs for the period 1998-2007. As we can see, the dispersion of $log(MP_k)$ across years ranges from 0.86 to 0.92, with a mean of 0.89. These results indicate

[12] See Hsieh and Klenow (2009) and Restuccia (2011), among others.

that persistent capital misallocation does exist among non-SOEs over the sample period.

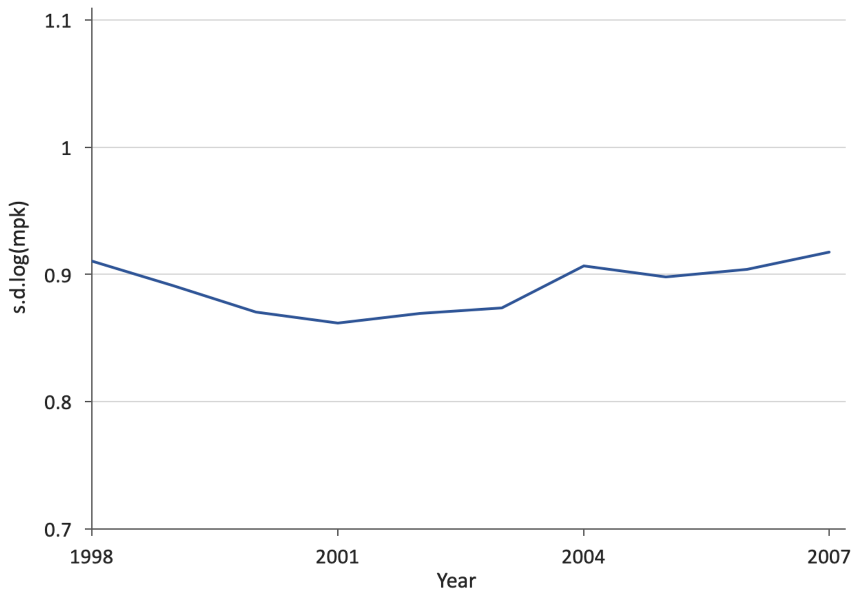
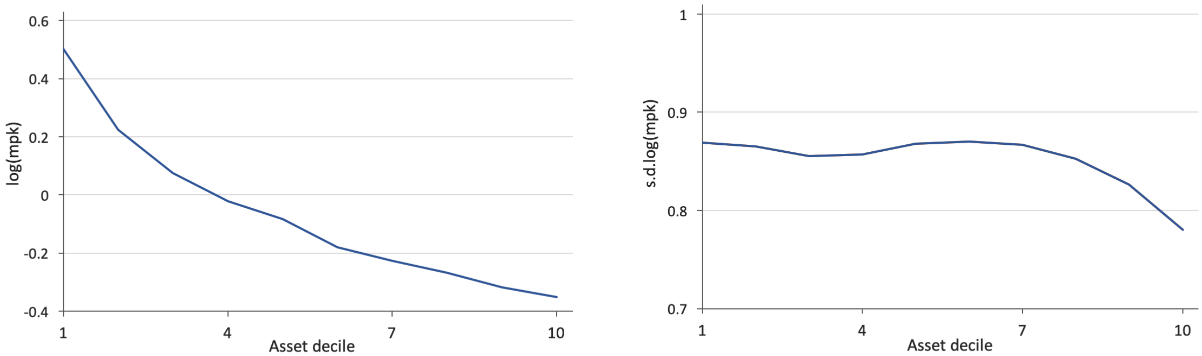


Figure 1: Dispersion of $log(MP_k)$ by Year

Note: This figure reports the standard deviation of $log(MP_k)$ among non-SOEs by year.

Policy distortions may drive capital misallocation through firm characteristics. In empirical corporate finance, firm size is a fundamental firm characteristic.[13] Next, I will examine how $log(MP_k)$ varies across different size groups. I obtain the mean of $log(MP_k)$ and the standard deviation of $log(MP_k)$ at the industry level and then aggregate them conditional on firm size. Firms are divided according to asset deciles. Figure 2 panel (a) shows the relationship between firm size and $log(MP_k)$ among non-SOEs. As we can see, $log(MP_k)$ decreases with firm size, which suggests that large firms are less distorted than small ones. Figure 2 panel (b) presents the variation of the dispersion of $log(MP_k)$ across firms of different sizes. The standard deviation of $log(MP_k)$ is also smaller within large firms.

[13] See Dang et al. (2018).



(a) Firm Size and $log(MP_k)$ (b) Firm Size and Standard Deviation of $log(MP_k)$

Figure 2: Firm Size and $log(MP_k)$

Note: This figure reports the relationship between firm size and $log(MP_k)$ in the data. The mean and standard deviation of $log(MP_k)$ are calculated in each asset decile.

To examine the robustness of the negative relationship between $log(MP_k)$ and firm size, I obtain the correlation between firm size and $log(MP_k)$ by industry. There are thirty 2-digit industries in the manufacturing sector according to the industry concordances provided by Brandt et al. (2014).[14] As shown in Table 1, the correlation between firm size and $log(MP_k)$ varies across different industries, and a negative correlation exists in each industry.

[14]Following the method of Brandt et al. (2014), this paper adopts a revision of the *China Industry Classification* (CIC) system of manufacturing with 593 four-digit industries and 30 two-digit industries.

Table 1: Correlation between Firm Size and $log(MP_k)$ by Industry

CIC	Industry	Corr.	CIC	Industry	Corr.
13	Agri-food processing	-0.21	28	Chemical fiber	-0.27
14	Food	-0.20	29	Rubber	-0.25
15	Beverage	-0.29	30	Plastic	-0.28
16	Tobacco	-0.43	31	Non-metallic Mineral	-0.31
17	Textile	-0.34	32	Ferrous metals	-0.22
18	Apparel	-0.19	33	Non-ferrous metal	-0.27
19	Leather	-0.10	34	Hardware	-0.20
20	Timber processing	-0.36	35	General equipment	-0.20
21	Furniture	-0.24	36	Professional equipment	-0.14
22	Paper	-0.29	37	Transportation	-0.19
23	Printing	-0.19	39	Electric machinery	-0.12
24	Stationery & sporting goods	-0.24	40	Communication device	-0.16
25	Petrochemical	-0.33	41	Instrument	-0.11
26	Chemistry	-0.25	42	Handicrafts & daily sundries	-0.28
27	Pharmaceutical	-0.08	43	Waste material recycling	-0.05

Note: This table reports the correlation between firm size and $log(MP_k)$ by the 2-digit industries. CIC denotes the *China Industry Classification Code*.

2.3 Financing Pattern

Financial frictions play a role in capital misallocation through firms' characteristics, on which firms' financing patterns depend. Ayyagari et al. (2010) find that bank financing is more prevalent among larger firms. Boyreau-Debray and Wei (2005) document that in China, all types of banks prefer to lend to SOEs and large private firms. Bai et al. (2018) document that among private firms, large firms are more leveraged. To see how the leverage ratio varies across different size groups, I calculate the average of leverage by asset quantiles. Figure 3 shows that the leverage ratio of firms fluctuates with firm size and large firms tend to face a higher leverage ratio than small ones with the upward-sloping fitted line (in red).

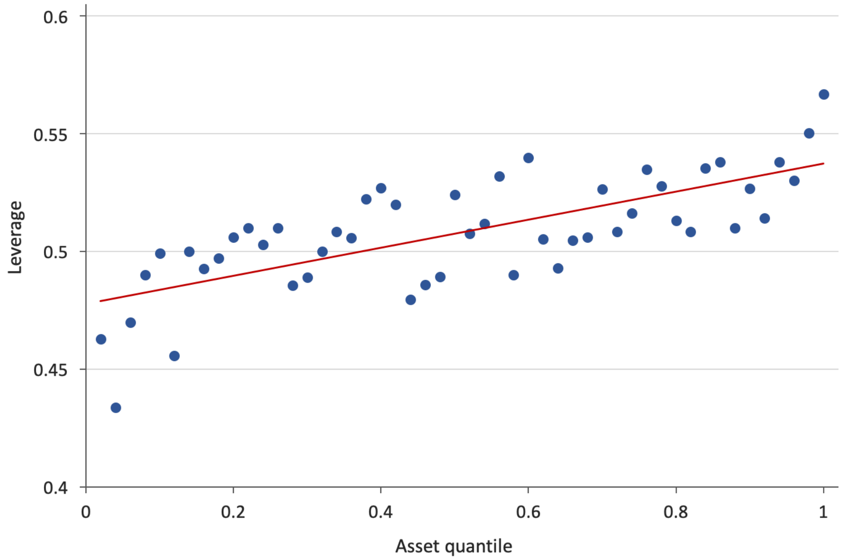


Figure 3: Firm Size and Leverage

Note: This figure reports the relationship between firm size and leverage. The mean leverage ratio is calculated in each asset quantile (50 quantiles).

I further examine the relationship between firm size and leverage by regression. I also re-examine the impacts of firm size on the marginal product of capital. The regression model is given by the following:

$$leverage_{ict}(or\, log(MP_{kict})) = \beta_0 + \beta_1 size_{ict} + dummy + u_{ict} \tag{1}$$

where i denotes the firm, c denotes the 4-digit industry and t denotes the year. The dependent variable is leverage in the leverage regression and $log(MP_k)$ in the marginal product of capital regression. In addition, $size_{ict}$ is measured by the logarithm of total assets. The term dummy includes the fixed effects of firm, year, and 4-digit industry. Moreover, u_{ict} is the error term.

Table 2 reports the regression results of leverage (or $log(MP_k)$) on firm size by considering the firm fixed effects, 4-digit industry fixed effects, and year fixed effects. Notably, the leverage-size slope is 0.026, which indicates that leverage increases with increasing firm size.

The regression coefficient of the marginal product of capital on firm size is a significant -0.039, which suggests that large firms are less distorted and tend to face a lower marginal product of capital.

Firms' financing ability affects their capital decisions directly. Financial frictions prevent firms from borrowing and investing, resulting in capital misallocation and aggregate productivity loss. In the rest of the paper, I examine how the financial frictions disciplined by the firms' financing patterns, which correspond to the size-dependent financial frictions, explain the observed capital misallocation in China.

Table 2: Regressions on Firm Size

	Leverage	$log(MP_k)$
Size	0.026***	-0.039***
(s.d.)	(0.0008)	(0.0033)
Constant	0.296***	0.056
(s.d.)	(0.0187)	(0.0799)
R-square	0.03	0.03
Firm FE	Yes	Yes
Year FE	Yes	Yes
4-digit Industry FE	Yes	Yes
Number of OBS	205,246	207,077

Note: This table reports the regression results for leverage (or $log(MP_k)$) on firm size. ***, ** and * denote statistically significant different from zero at the 1%, 5% and 10% levels.

3 The Model

This section provides a general equilibrium model with heterogeneous agents based on Midrigan and Xu (2014) and incorporates a size-dependent borrowing constraint in light of Gopinath et al. (2017). The economy is populated by a continuum of firms and a unit measure of workers. Firms are exogenously heterogeneous in their productivity and can finance investment through both internal funds and external borrowing. The amount of debt that firms can issue is limited, and the maximum attainable leverage increases in firm size.

3.1 Firms

Technology There is a continuum of firms indexed by $i \in [0,1]$, which adopt both labor l and capital k to produce homogeneous goods subject to a decreasing-return-to-scale technology. The production function for firm i is given by

$$y_{it} = z_{it}^{1-\eta}(l_{it}^{\alpha}k_{it}^{1-\alpha})^{\eta} \tag{2}$$

where η governs the span of control, which measures the degree of diminishing return to scale at the firm level as in Lucas (1978) and Atkeson and Kehoe (2005);[15] α is the labor elasticity. The idiosyncratic productivity shock z_{it} is independently and identically distributed across firms and follows a Markov switching process with transition density $\Pr(z_{it+1} = z'|z_{it} = z) = \pi(z'|z)$.

Timing Time is discrete. Following Moll (2014) and Midrigan and Xu (2014), exogenous productivity shocks z_{it+1} are known to firms at the end of the period t. Firms borrow d_{it+1} to finance capital k_{it+1} according to the new productivity z_{it+1}.[16] This convenient assumption makes capital measurable to productivity and enables this paper to focus on capital misallocation due to financial frictions.[17] In each period, firms choose consumption c_{it}, labor l_{it}, capital k_{it+1} and debt d_{it+1}. Firm i maximizes the present discounted lifetime utility:

$$\max_{\{c_{it},l_{it},k_{it+1},d_{it+1}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t log(c_{it}) \tag{3}$$

subject to the budget constraint given by

$$c_{it} + k_{it+1} - (1-\delta)k_{it} = y_{it} - \omega l_{it} - (1+r)d_{it} + d_{it+1} \tag{4}$$

[15] The assumption of decreasing-return-to-scale technology is reasonable since approximately 80 percent of Chinese manufacturing industries have a decreasing-return-to-scale value-added production function as estimated in Hao (2011).

[16] As discussed in Moll (2014), the model in which firms own and accumulate capital is equivalent to the setup with a rental market of capital.

[17] See Gopinath et al. (2017), which assumes that the productivity z_{it+1} is not revealed at the end of the period t and considers the risk in capital accumulation as the additional source of the dispersion of the marginal product of capital.

Size-dependent Borrowing Constraint Considering the empirical fact that large firms tend to face lower borrowing tightness and have higher leverage than small firms, the size-dependent borrowing constraint is introduced into this paper based on Gopinath et al. (2017):

$$d_{it+1} \leq \theta_0 k_{it+1} + \theta_1 \Phi(k_{it+1}) \tag{5}$$

where parameters θ_0 and θ_1 jointly govern the borrowing tightness. The borrowing constraint arises based on the microfoundation of limited commitment (the derivation of the borrowing constraint is shown in Appendix B.1). Suppose there exist default risks and debt is secured against capital as the collateral. In equilibrium, banks extend credit to the point that firms have no incentive to default. As a result, the amount of debt d_{it+1} that firm i can borrow is limited, which depends on the borrowing tightness parameters θ_0 and θ_1 and capital k. $\Phi(k)$ captures the disruption cost of production that firms have to pay in the event of default, which may occur due to loss of suppliers, market share, reputation, etc. Considering that larger firms lose more in the case of default, the disruption cost $\Phi(k)$ is assumed to be an increasing and convex function of capital k.

In this paper, the functional form for the disruption cost is assumed as $\Phi(k) = k^2$, which is analytically convenient in obtaining a closed-form solution for capital. The borrowing tightness, which corresponds to the maximum attainable leverage ratio $(d/k)_{max}$, is

$$(d/k)_{max} = \theta_0 + \theta_1 k \tag{6}$$

If $\theta_1 = 0$, all firms face a single borrowing tightness.[18] As long as θ_1 is positive, the maximum attainable leverage $(d/k)_{max}$ is an increasing function in capital k, which implies that large firms will face a lower borrowing tightness than small firms. In the rest of the paper, I call the borrowing constraint the homogeneous borrowing constraint if $\theta_1 = 0$ and the size-dependent borrowing constraint if $\theta_1 > 0$. I compare the implications of the two

[18] See Moll (2014), Buera and Moll (2015), Midrigan and Xu (2014), among others, in which firms face the same borrowing tightness.

cases.

Recursive Formulation and Decision Rules Net worth a is defined as $a = k - d \geq 0$. The firm's problem is rewritten recursively, and the Bellman equation is

$$V(a,z) = \max_{a',c} log(c) + \beta EV(a',z') \tag{7}$$

subject to the budget constraint given by

$$c + a' = \pi + (1+r)a \tag{8}$$

The borrowing constraint can be rewritten as

$$k' \leq \lambda_0 a' + \lambda_1 k'^2 \tag{9}$$

The firm solves the profit maximization problem

$$\pi(a,z) = \max_{k,l} z^{1-\eta}(l^{\alpha}k^{1-\alpha})^{\eta} - \omega l - (r+\delta)k \tag{10}$$

$$s.t. \quad k \leq \lambda_0 a + \lambda_1 k^2 \tag{11}$$

where $\lambda_0 = \frac{1}{1-\theta_0}$ and $\lambda_1 = \frac{\theta_1}{1-\theta_0}$. A larger λ_1 (or a smaller λ_0) corresponds to a higher leverage-size slope. When $\theta_1 = 0$, $\lambda_1 = 0$ accordingly, which implies that firms face homogeneous borrowing tightness. The parameter restrictions placed on the borrowing constraint are $\lambda_0 \geq 1$ and $\lambda_1 \geq 0$. Appendix B.2 presents the derivation of the parameter restrictions. Given a net worth a and productivity z, the firm maximizes its profit by choosing labor l and capital k subject to the borrowing constraint in equation (11).[19] Then, the firm chooses consumption c and net worth a' subject to the budget constraint in equation (8) and the borrowing constraint in equation (9).

The Euler equation can be solved as

$$\frac{1}{c(a,z)} = \beta E\left\{\frac{1}{c(a',z')}\left[(1+r) + \mu(a',z')\lambda_0\right]\right\} \tag{12}$$

[19] The net worth is split between capital and debt.

where $\mu(a,z)$ is the Lagrangian multiplier on the borrowing constraint. Since a' appears in the borrowing constraint in equation (9), the expectation of a binding borrowing constraint increases the net worth accumulation. Firms with high productivity tend to accumulate net worth, since productivity is persistent and firms expect a high demand for capital in the future. In addition, firms with low net worth accumulate internal funds to relax the future borrowing constraint.

Firms choose labor l and capital k to maximize their profit subject to the borrowing constraint in equation (11). $FOCs$ with respect to labor l and capital k are given by

$$\alpha\eta\frac{y(a,z)}{l(a,z)} = \omega \tag{13}$$

$$(1-\alpha)\eta\frac{y(a,z)}{k(a,z)} = r+\delta+\mu(a,z)\left[1-2\lambda_1 k(a,z)\right] \tag{14}$$

Capital Decisions Firms' capital decisions depend on both their productivity and financing ability. To obtain a closed-form solution of capital for financially constrained firms, I define the function $g(k)$ as the difference between the right-hand side and the left-hand side of the borrowing constraint in equation (11):

$$g(k) \equiv \lambda_0 a + \lambda_1 k^2 - k \tag{15}$$

When the borrowing constraint is binding, $g(k)=0$. The solution to $g(k)=0$ is

$$k_{1,2} = \frac{1 \pm \sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1},\ where\ k_1 \leq k_2 \tag{16}$$

The number of roots to $g(k)=0$ depends on the values of the borrowing tightness parameters λ_0 and λ_1 and the net worth a. Figure 4 presents the curve for the function $g(k)$.

Proposition 1 *Under the size-dependent borrowing constraint, the capital decisions for the financially unconstrained and constrained firms are as follows:*

1) When the borrowing constraint is slack, firms can achieve the optimal capital level k^u:

$$k^u = z\left(\frac{\alpha\eta}{\omega}\right)^{\frac{\alpha\eta}{1-\eta}}\left((1-\alpha)\eta\right)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}} \tag{17}$$

2) When the borrowing constraint is binding, firms can achieve a capital level of only k^c:

$$k^c = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}, \quad \textit{and} \quad k^c \leq k^u \tag{18}$$

Proof. *See Appendix B.3.*

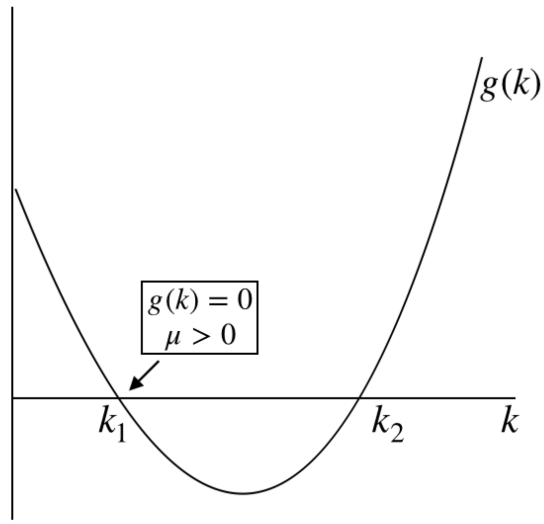


Figure 4: Graph for Function $g(k)$

Note: This figure presents the graph for $g(k)$. The number of intersections with the horizontal axis depends on borrowing tightness parameters λ_0 and λ_1, and net worth a.

According to Proposition 1, the optimal unconstrained level of capital k increases in productivity z; the constrained level of capital $k^c = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}$ depends on net worth a. Since $k^c \leq k^u$, the investment of financially constrained firms is insufficient. By comparison, under the homogeneous borrowing constraint ($\lambda_1 = 0$), the optimal unconstrained capital decision is also $k^u = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}}$; when the borrowing constraint is binding, the attainable capital level is $k^c = \lambda_0 a$, which is linear in net worth a.

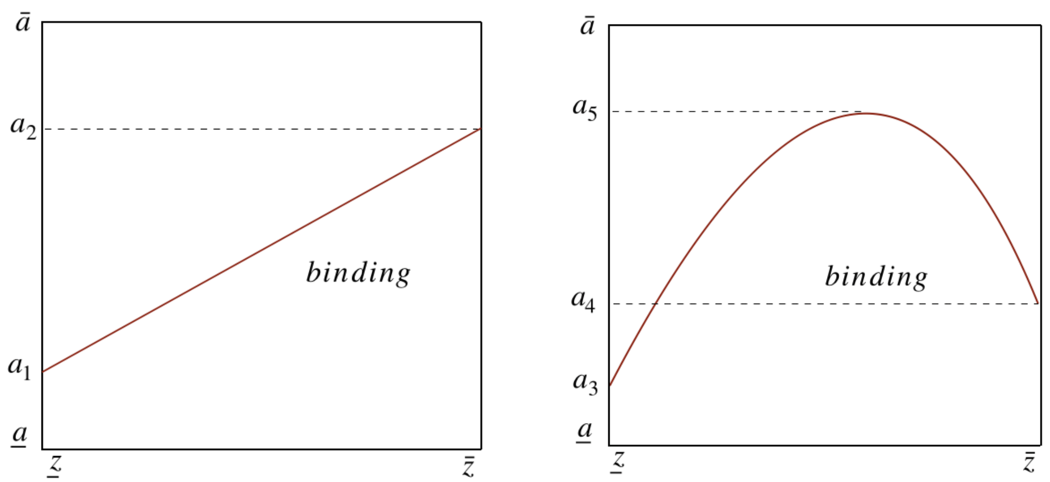
Firms are heterogeneous in their dependence on debt, and in each period, the borrowing constraint is binding only for some firms. The bindingness of the borrowing constraint depends on both firms' productivity and net worth and is different under the homogeneous borrowing constraint ($\lambda_1 = 0$) and the size-dependent borrowing constraint ($\lambda_1 > 0$), which is discussed as follows.

Proposition 2: *Under the homogeneous borrowing constraint, given a productivity* z*, the cutoff net worth for the bindingness of the borrowing constraint is* $a^* = \frac{k^u(z)}{\lambda_0}$*. When* $a \leq a^*$*, the borrowing constraint is binding; when* $a > \frac{k^u(\bar{z})}{\lambda_0}$*, the borrowing constraint is never binding.*

Proof. *See Appendix B.4.*

Proposition 3*: Under the size-dependent borrowing constraint, given a productivity* z*, the cutoff net worth for the bindingness of the borrowing constraint is* $a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1}$*. When* $a \leq a^*$*, the borrowing constraint is binding; when* $a > \frac{1}{4\lambda_0\lambda_1}$*, the borrowing constraint is never binding.*

Proof. *See Appendix B.5.*



(a) Homogeneous Borrowing Constraint (b) Size-dependent Borrowing Constraint

Figure 5: Bindingness of the Borrowing Constraint

Note: This figure depicts the bindingness of the borrowing constraint. For firms with state (a, z) below the red line, the borrowing constraint is binding.

Figure 5 reports the bindingness of the homogeneous borrowing constraint and the size-dependent borrowing constraint, respectively. The red line denotes the cutoff net worth a^*

for bindingness. In Figure 5 Panel (a), $a_1 = \frac{k^u(\underline{z})}{\lambda_0}$ and $a_2 = \frac{k^u(\bar{z})}{\lambda_0}$. Under the homogeneous borrowing constraint, the cutoff net worth $a^* = \frac{k^u(z)}{\lambda_0}$ increases fully with productivity z. That is, since firms with higher productivity z have a higher financing need for capital, the required net worth should be larger to not be constrained. Figure 5 Panel (b) shows the bindingness of the size-dependent borrowing constraint. In this figure, $a_3 = \frac{1-(1-2\lambda_1 k^u(\underline{z}))^2}{4\lambda_0\lambda_1}$, $a_4 = \frac{1-(1-2\lambda_1 k^u(\bar{z}))^2}{4\lambda_0\lambda_1}$ and $a_5 = \frac{1}{4\lambda_0\lambda_1}$. Notably, the cutoff net worth $a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1}$ is non-monotonic in productivity. That is, when productivity z is large, capital k^u with respect to productivity is high, which in turn enables those firms (even without a high net worth a) to relax the borrowing constraint. By contrast, under the homogeneous borrowing constraint, which corresponds to a size-invariant maximum leverage, firms with large productivity z are more likely to be financially constrained.

Marginal Product of Capital As financially constrained firms cannot fully adjust capital to the efficient level in response to the productivity shock, dispersion of MP_k endogenously arises across firms. The determination of the marginal product of capital is different under the homogeneous borrowing constraint and the size-dependent borrowing constraint.

Proposition 4: *Under the homogeneous borrowing constraint,*

1) Given productivity shock z, financially constrained firms with higher net worth a have larger $k^c(a)$ and lower MP_k; financially unconstrained firms with higher net worth a have constant $k^u(z)$, and $MP_k = r+\delta$.

2) Given net wealth a, financially unconstrained firms with higher productivity z have higher $k^u(z)$, and $MP_k = r+\delta$. Financially constrained firms with higher productivity z have constant $k^c(a)$ and higher MP_k.

Proof. *See Appendix B.6.*

Under the homogeneous borrowing constraint, $MP_k = r+\delta+\gamma$, where γ is the Lagrangian multiplier on the borrowing constraint (see Appendix B.4 for details). As discussed above, let $a_1 = \frac{k^u(\underline{z})}{\lambda_0}$, $a_2 = \frac{k^u(\bar{z})}{\lambda_0}$, the cutoff net worth for bindingness given z be $a^* = \frac{k^u(z)}{\lambda_0}$, and the cutoff productivity for bindingness given a be z^*. Given a productivity z, when $a \in [\underline{a}, a^*]$, firms are constrained. Firms with a larger net worth a have a higher capital $k^c(a)$ and a lower γ and MP_k. Given a net worth $a \in (a_1, a_2]$, when productivity $z \in [\underline{z}, z^*)$, firms are unconstrained. Firms with higher productivity z have higher $k^u(z)$; in addition, $\gamma = 0$, and $MP_k = r + \delta$. When productivity becomes large, e.g., $z \in [z^*, \bar{z}]$, firms are constrained. Since capital $k^c(a)$ does not change, firms with higher productivity z have higher γ and MP_k. More details can be seen in Appendix B.6 and Figure B.1. Overall, with the homogeneous borrowing constraint, given a productivity shock z, firms with higher net worth a are less likely to be constrained and tend to have higher k and lower MP_k. Given net wealth a, firms with higher productivity z tend to have higher k, are more likely to be constrained, and face higher MP_k.

Proposition 5: *Under the size-dependent borrowing constraint,*

1) Given productivity shock z, financially constrained firms with higher net worth a have larger $k^c(a)$ and lower MP_k; financially unconstrained firms with higher net worth a have constant $k^u(z)$, and $MP_k = r + \delta$.

2) Given net wealth a, financially unconstrained firms with higher productivity z have higher $k^u(z)$, and $MP_k = r + \delta$; financially constrained firms with higher productivity z have constant $k^c(a)$ and higher MP_k.

3) Firms with a sufficiently large productivity shock z, even without high net worth a, are financially unconstrained and have $MP_k = r + \delta$.

Proof. *See Appendix B.7.*

With the size-dependent borrowing constraint, $MP_k = r + \delta + \mu(1 - 2\lambda_1 k)$. As discussed in Proposition 3, let $a_3 = \frac{1-(1-2\lambda_1 k^u(\underline{z}))^2}{4\lambda_0\lambda_1}$, $a_4 = \frac{1-(1-2\lambda_1 k^u(\bar{z}))^2}{4\lambda_0\lambda_1}$, $a_5 = \frac{1}{4\lambda_0\lambda_1}$, the cutoff net worth for bindingness given z be $a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1}$, and the cutoff productivities for bindingness given a be z_1^* and z_2^*. Given a productivity z, when $a \in [\underline{a}, a^*]$, firms are constrained. Firms with a higher net worth have a higher capital $k^c(a)$, lower $\mu(1 - 2\lambda_1 k^c(a))$ and MP_k. Different from the homogeneous borrowing constraint, the relationship between productivity and marginal product of capital now is non-monotonic. That is, given a net worth $a \in (a_4, a_5]$, when $z \in [\underline{z}, z_1^*)$, firms are unconstrained. Firms with higher productivity z have a higher $k^u(z)$; in addition, $\mu = 0$, and $MP_k = r + \delta$. When $z \in [z_2^*, z_2^*]$, firms are constrained. Firms with higher productivity z have a higher μ and MP_k, as the capital $k^c(a)$ does not change. However, when the productivity is large enough, e.g., $z \in (z_2^*, \bar{z}]$, even firms without high net worth a are not financially constrained. That is because firms with high productivity z have high $k^u(z)$, which in turn enables those firms to eliminate the borrowing constraint and face a low MP_k. More details are given in Appendix B.7 and Figure B.2. By contrast, with the size-dependent borrowing constraint, firms with high productivity, large size, or even without high net worth are less impacted by financial frictions relative to the case with the homogeneous borrowing constraint.

3.2 Workers

There is a unit measure of workers in the economy. In each period, each worker consumes c_{it}^w, holds risk-free assets a_{it+1}^w and supplies v_{it} efficiency units of labor. The worker's problem in recursive form is as follows:

$$V(a^w, v) = \max_{c^w, a^{w'}} log(c^w) + \beta EV(a^{w'}, v') \tag{19}$$

subject to the budget constraint that

$$c^w + a^{w'} = \omega v + (1+r)a^w \tag{20}$$

where w is the real wage, r is the real interest rate, and β is the discount factor. The labor efficiency v_{it} follows a two-state Markov process. Since workers are heterogeneous in their labor efficiency v_{it}, they are also different in their assets a_{it}^w, which are endogenously determined in the model.

3.3 Equilibrium

A Stationary Recursive Competitive Equilibrium consists of value functions $V(a^w, v)$ for workers and $V(a,z)$ for firms; policy functions $c^w(a^w, v), a^{w'}(a^w, v)$ for workers and $c(a,z), a'(a,z)$ for firms; output, labor and capital decisions for firms, $y(a,z)$, $l(a,z)$ and $k(a,z)$; a stationary probability distribution $n(a,z)$ for firms over the state (a,z); constant factor prices ω, r and constant aggregate variables, such that:

1. Given the factor prices ω, r, the value functions and decision rules solve the workers' and firms' dynamic programming problems in equations (7) and (19);

2. Market clear

(i) Labor market

$$L = \int l(a,z)dn(a,z) \tag{21}$$

(ii) Asset market

$$A^{w'} + \int a'(a,z)dn(a,z) = \int k'(a,z)dn(a,z) \tag{22}$$

(iii) Goods market

$$C + I = Y \tag{23}$$

where L, I, and Y are the aggregate labor, investment and output. C is the aggregate consumption, which is the sum of total consumption by firms and workers. $A^{w'}$ is the aggregate assets supplied by workers.

3. The distribution $n(a,z)$ over state (a,z) is stationary, which is induced via the exogenous Markov chain for z and policy function $a'(a,z)$.

In the model, the exogenous productivity process and the policy function for the net worth $a'(a,z)$ jointly determine the endogenous Markov chain for (a,z) pairs on the state-space $A \times Z$. This "big" Markov chain has a stationary distribution $n(a,z)$. In the stationary equilibrium, firms' choices fluctuate over time in response to productivity shocks, whereas the aggregate variables and prices are constant.

3.4 TFP Loss

Since firms produce homogeneous goods, by integrating the output across firms, I obtain the aggregate production function given by

$$Y = \frac{\left(\int_i z_i {MP_{ki}}^{-\frac{(1-\alpha)\eta}{1-\eta}} di\right)^{1-\alpha\eta}}{\left(\int_i z_i {MP_{ki}}^{\frac{\alpha\eta-1}{1-\eta}} di\right)^{(1-\alpha)\eta}} (L^{\alpha} K^{1-\alpha})^{\eta} \tag{24}$$

The aggregate measured TFP is defined as

$$TFP = \frac{\left(\int_i z_i {MP_{ki}}^{-\frac{(1-\alpha)\eta}{1-\eta}} di\right)^{1-\alpha\eta}}{\left(\int_i z_i {MP_{ki}}^{\frac{\alpha\eta-1}{1-\eta}} di\right)^{(1-\alpha)\eta}} \tag{25}$$

which is endogenously determined by the firm-level productivity and the extent to which firms are financially constrained. Given the same amount of aggregate capital and labor, without financial frictions, resources are allocated efficiently. Then, the first-best aggregate TFP is

$$TFP^e = \left(\int_i z_i di\right)^{1-\eta} \tag{26}$$

The TFP loss due to misallocation is defined as the log difference between the efficient aggregate TFP and the aggregate TFP under financial frictions:

$$TFP\, loss \equiv log(TFP^e) - log(TFP) \tag{27}$$

In the rest of the paper, I will focus on the stationary equilibrium of the model and quantify the capital misallocation and TFP loss induced by the size-dependent financial frictions.

4 Calibration

The model is annual. Parameters are calibrated to match the Chinese economy. I set the capital depreciation rate δ to 0.06, which is within the range of empirical evidence on capital depreciation in China.[20] This paper assumes that the labor efficiency v follows a two-state Markov process. The ergodic distribution of the exogenous Markov chain for labor efficiency matches the employment ratio in China. As a result, the probability of staying unemployed p_u is 0.5, and the probability of staying employed p_e is 0.806, which implies that the fraction of workers that supply labor is 72% in any period.[21]

The rest of the parameters are jointly determined by adopting the simulated method of moments (SMM). The goal is to choose the set of parameters

$$\Theta = \{\eta, \beta, \rho, \sigma, \lambda_0, \lambda_1\} \tag{28}$$

such that the distance between the moments generated by the model and moments from the Chinese firm-level data, as well as moments from the aggregate data, is minimized. The efficiency of the SMM requires that the target moments should be sensitive to the variations in the structural parameters. Since each parameter affects more than one moment and some moments are more affected by certain parameters, the calibration procedures are as follows.

The discount factor β is set to match the aggregate capital-to-output ratio, as discussed in Guner et al. (2008). Based on the discussions in Li and Tang (2003) and Zhang and Zhang (2003), I choose an aggregate capital-to-output ratio of 2.3. As a result, the discount factor $\beta = 0.89$. As discussed in Buera et al. (2011), since in the data some of the payments to capital are actually payments to entrepreneurial input, it is difficult to obtain a capital share $(1-\alpha)\eta$ directly from the empirical work. To accommodate this difficulty, I first fix the labor share $\alpha\eta$ based on the existing literature and then calibrate η. Bai and Qian (2010)

[20] Wu et al. (2014) summarize selected published papers on capital stock estimation in Mainland China using the perpetual inventory method. The capital depreciation rate in those papers ranges from 2.2% to 17% in different periods, industries, and regions.

[21] According to the data of FRED, the employment-to-population ratio in China decreased over the period 1998-2007, and the average was 72%. Data source: https://fred.stlouisfed.org.

estimate that the labor share in the Chinese industry sector decreased from 0.49 in 1998 to 0.42 in 2004. In this paper, I set the labor share to 0.45. As discussed in Wang (2017), given that the span of control η affects the concentration of the output distribution, η is calibrated to match the fraction of output by the top 5 output percentiles. As a result, the span of control $\eta = 0.76$. Then, the labor elasticity α is recovered as 0.59.

This paper assumes that the idiosyncratic productivity z_{it} follows an AR(1) process,

$$log(z_{it}) = \rho log(z_{it-1}) + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \tag{29}$$

where ρ is the persistent component, ε_{it} stands for the transitory shock and σ_ε is the standard deviation of the transitory shock. Following the Rouwenhorst method (1995), I approximate this AR(1) process by a discrete Markov chain over a symmetric, evenly spaced state space. Considering that the productivity process is the primary determinant of the output, the moments that are used to identify the persistent component ρ and the standard deviation of the transitory shock σ_ε are (1) the standard deviation of the output growth rate, which equals 0.62, and (2) the first-order autocorrelation of the output, which is 0.87. The firm-level moments are based on the balanced panel of Chinese non-SOEs for the period 1998-2007, as discussed in Section 2. As a result, the persistent component ρ is 0.83, which is consistent with the existing literature. The standard deviation of the transitory shock $\sigma_\varepsilon = 0.79$, which is large to generate firm dynamics.

In addition, λ_0 and λ_1 jointly govern the borrowing tightness and determine firms' financing patterns. Primarily, λ_1 is closely related to the leverage-size slope.[22] The moments used to pin down parameters λ_0 and λ_1 are (1) the regression coefficient of the leverage ratio on firm size $log(asset)$, which is 0.03, and (2) the aggregate debt-to-output ratio $\frac{D}{Y}$.[23] Based on data from the World Bank, the average domestic credit to the private sector

[22]In the model, firm size is measured by total assets. If the firm borrows, debt $d > 0$, and the firm size equals the capital stock k. If the firm saves, debt $d < 0$, and the firm size is the sum of capital and saving, which equals $k - d$.

[23]The aggregate debt-to-output ratio is adopted to measure financial development as in Buera et al. (2011), Midrigan and Xu (2014), and Curtis (2016), among others.

(% GDP) during the period 1998 to 2007 is 113%. As a result, λ_0 is 1.916, and λ_1 is 0.012. Under the size-dependent borrowing constraint, the implied maximum leverage ratio is $(d/k)_{max} = 0.478 + 0.006k$, which increases in capital.[24]

Table 3 presents the calibration results for the model with the size-dependent borrowing constraint.

Table 3: Calibration Results

Parameter	Description	Value	Source/target
δ	Depreciation rate	0.06	Wu et al. (2014)
p_u	Persistence zero state	0.50	Match employment ratio in China
p_e	Persistence unit state	0.81	
β	Discount factor	0.89	Aggregate capital-to-output ratio
η	Span of control	0.76	Fraction of output by top 5 output percentiles
α	Labor elasticity	0.59	Labor share $\alpha\eta$ equals 0.45
ρ	Persistent component	0.83	S.D. output growth
σ_ε	S.D. transitory shock	0.79	1-year autocorrelation of output
λ_0	Borrowing tightness	1.916	Aggregate debt-to-output ratio
λ_1	Borrowing tightness	0.012	Regression coefficient of leverage on firm size

Note: This table reports the parameter values that are calibrated to match the empirical targets in the Chinese data, as discussed in the main text.

Table 4 reports the values of the target moments that are used to calibrate the parameters in the data and in the model. The model fits the data quite closely.

[24] The maximum leverage ratio is $(d/k)_{max} = \theta_0 + \theta_1 k$, $\lambda_0 = 1/(1-\theta_0)$ and $\lambda_1 = \theta_1/(1-\theta_0)$.

Table 4: Model Fit

Moment	Data	Model
S.D. output growth	0.62	0.62
1-year autocorrelation output	0.87	0.88
Aggregate debt-to-output ratio	1.13	1.14
Regression coefficient of leverage on firm size	0.03	0.03
Aggregate capital-to-output ratio	2.30	2.22
Output share by top 5 output percentiles	0.39	0.40

Note: This table reports the empirical and model values of the moments used to calibrate the parameters. Moments are based on the balanced sample of the Chinese non-SOEs for the period 1998-2007.

5 Quantitative Results

This section studies the quantitative impacts of size-dependent financial frictions on capital misallocation and the aggregate TFP. I first evaluate the performance of the model with the size-dependent borrowing constraint (termed "HeF" henceforth) and then examine the effects of the size-dependent financial frictions on capital misallocation. I also conduct a sensitivity analysis to examine the role of the borrowing tightness.

5.1 Model Validation

Financing Behavior To explore how well the HeF model with the size-dependent financial frictions matches the financing patterns of firms in the data, I first present the average leverage ratio conditional on asset quantiles. Figure 6 shows the relationship between leverage and firm size in the data and the model, respectively. As we can see, there is an increasing trend of leverage in both the model and the data, which suggests that large firms tend to have higher leverage.

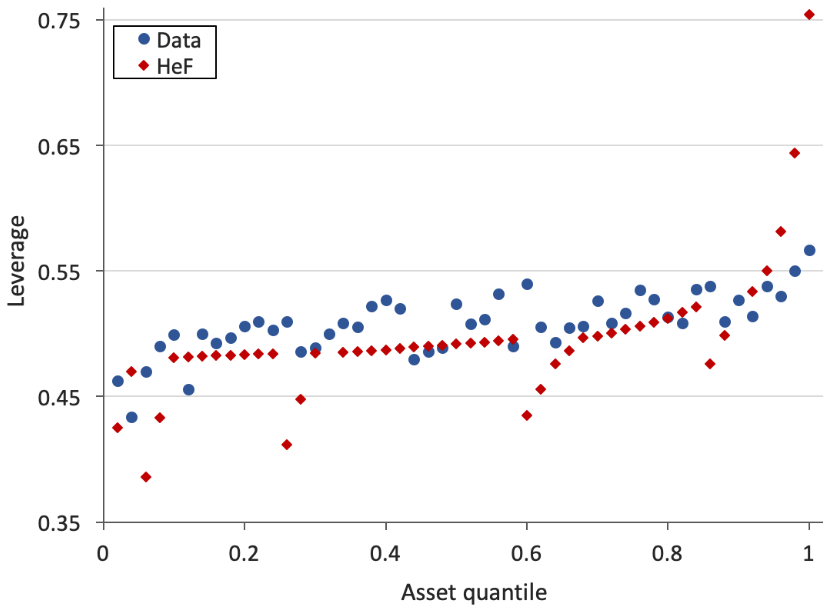


Figure 6: Firm Size and Leverage in the Data and HeF

Note: This figure reports the relationships between firm size and leverage in the model and in the data. The mean leverage ratio is calculated in each asset quantile (50 quantiles).

Output Distribution Figure 7 presents the output distribution by asset deciles in the data and in the model. The model reproduces the output distribution quite well. In the data, the top 10 and top 20 percentiles of firms by firm size account for 44% and 59% of the total output, and in the model, the top 10 and top 20 percentiles of firms contribute to 48% and 63% of the total output. The output distribution is highly skewed, and the output is concentrated in large firms.

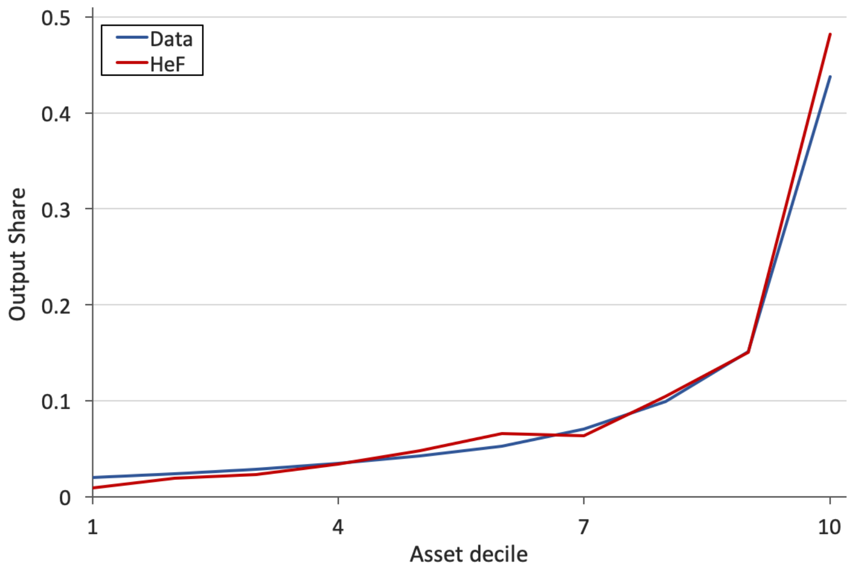


Figure 7: Output Distribution in the Data and HeF

Note: This figure reports the output share by asset deciles in the model and in the data. The fraction of output of the total output is calculated in each asset decile.

Non-targeted Moments Table 5 reports non-targeted moments in the data and model with the size-dependent borrowing constraint, respectively. As shown in Panel A, the standard deviations of $log(Y)$ in the data (1.22) and model (1.26) are quite close. The model also matches the distribution of output by output quantiles, although I target only the output share of the top 5 output percentiles in the calibration. The model generates larger standard deviation of capital growth, and the higher-order autocorrelations of capital and output in the model decay faster than those in the data.

Panel B presents the standard deviations of leverage, $log(asset)$ and $log(MP_k)$. The standard deviation of leverage in both the model and data is 0.23. The standard deviation of total assets is 1.14, which is lower than the data. As discussed in Section 3, without distortions, the marginal product of capital across firms should be equal, and the dispersion of the marginal product of capital endogenously arises in the model due to financial frictions. The standard deviation of $log(MP_k)$ generated by the model is 0.31, which explains 35% of the dispersion of $log(MP_k)$ in the data. The rationale for this result is that there are other forces in addition to financial frictions, such as taxes/subsidies, capital adjustment costs, and informational frictions,[25] that contribute to capital misallocation. The empirical work of Wu (2018) also suggests that significant capital misallocation in the Chinese manufacturing industry can be attributed to other policy distortions. Thus, this model, which focuses on financial frictions, does not generate a considerable dispersion of $log(MP_k)$.

Table 5: Non-targeted Firm-level Moments in the Data and HeF

	Data	HeF
A. Distributional Moments		
S.D. log output	1.22	1.26
Output share by top 10 output percentiles	0.54	0.53
Output share by top 20 output percentiles	0.70	0.68
3-year autocorrelation output	0.76	0.67
S.D. capital growth	0.46	0.56
S.D. log capital	1.41	1.22
1-year autocorrelation capital	0.95	0.89
3-year autocorrelation capital	0.87	0.73
B. Standard Deviations		
S.D. $leverage$	0.23	0.23
S.D. $log(asset)$	1.24	1.14
S.D. $log(MP_k)$	0.89	0.31
C. Correlations with $log(MP_k)$		
Corr. of $log(MP_k)$ and $log(A)$	-0.21	-0.32
Corr. of $log(MP_k)$ and $log(Y)$	0.26	0.25
Corr. of $log(MP_k)$ and $log(asset)$	-0.23	-0.17

Note: This table reports non-targeted moments in the data and model with the size-dependent borrowing constraint, respectively. Panel A presents the distributional moments of capital and output. Panel B reports the standard deviations of total assets, leverage, and the marginal product of capital. Panel C shows the correlations with the marginal product of capital.

The correlations with $log(MP_k)$ show how the extent to which firms are distorted varies with firm characteristics. Since firms with higher net worth have stronger financing ability and are less likely to be constrained, they tend to face a lower marginal product of capital.

[25] See David and Venkateswaran (2019), who study the various sources of the measured capital misallocation.

Thus, the model with the size-dependent borrowing constraint generates a negative correlation between $log(MP_k)$ and net worth $log(A)$ of -0.32. In addition, since productivity is the primary determinant of output, firms with higher productivity tend to produce more, have a stronger financing need for investment and are more likely to be financially constrained. As a result, there is a positive correlation between $log(MP_k)$ and $log(Y)$ of 0.25, consistent with the data (0.26). Furthermore, since large firms are less constrained under the size-dependent borrowing constraint, the correlation between $log(MP_k)$ and firm size is -0.17, which is consistent with the data (-0.23). Overall, the model with the size-dependent borrowing constraint matches the firm-level moments of the Chinese manufacturing sector well.

Aggregate Implications Given the same amount of aggregate capital and labor as in the model, the planner allocates resources efficiently across firms without any financial frictions, and the marginal product of capital is equalized across firms. Table 6 reports the aggregate implications of the efficient allocation and the model, respectively. The presence of financial frictions prevents firms from investing, as the aggregate capital-to-output ratio under financial frictions is 2.22, which is lower than the first-best allocation (2.70). The fractions of firms that are financially constrained is 0.54 and the TFP loss in the model relative to the undistorted economy is 3.98%.

Table 6: Aggregate Implications in the HeF

	Efficient	HeF
Capital-to-output ratio	2.70	2.22
Fraction constrained	0	0.54
TFP loss (%)	0	3.98

Note: This table reports the aggregate implications of the efficient allocation and the model with the size-dependent borrowing constraint, respectively.

The TFP loss due to size-dependent financial frictions in the Chinese manufacturing sector is modest, which is mainly due to two factors. First, financial friction is one of the potential sources of capital misallocation. In addition, as discussed in Moll (2014), as long as productivity shocks are relatively persistent, self-financing alleviates capital misallocation in the long run. The productivity process in the model with the size-dependent borrowing constraint is persistent with the persistent component $\rho = 0.83$, which enables firms to accumulate enough internal funds in prolonged high-productivity periods and eliminate financial frictions. As a result, modest TFP loss is observed at the steady state.

5.2 The Effects of Size-dependent Financial Frictions

To examine the effects of size-dependent financial frictions on capital misallocation, I compare the baseline HeF model to the model with the homogeneous borrowing constraint in which $\lambda_1 = 0$ (termed "HoF"). I calibrate the borrowing tightness parameter λ_0 in the HoF model by targeting the aggregate credit to the private sector (% GDP). Appendix C.1 reports the calibration results and non-targeted moments. In the HoF model with the homogeneous borrowing constraint, $\lambda_0 = 2.51$, which implies that the maximum attainable leverage ratio[26] for any firm is 0.6. [27]

Non-targeted Moments Table 7 reports the non-targeted moments. The standard deviations of leverage and $log(MP_k)$ in both models are quite close. In the HoF model, a negative correlation between $log(MP_k)$ and net worth $log(A)$ exists, since firms with higher net worth have stronger financing ability and tend to face a lower marginal product of capital. However, compared with the case under the size-dependent borrowing constraint, in which firms even without a high net worth are able to eliminate the borrowing constraint, the negative correlation between $log(MP_k)$ and $log(A)$ is weaker in HoF (-0.19) than HeF (-0.32). A positive correlation between $log(MP_k)$ and $log(Y)$ also exists, since firms with higher output, which corresponds to higher productivity, have a stronger financing need for investment and are more likely to be constrained. However, compared with the case under the size-dependent borrowing constraint, firms in HoF with higher productivity are more likely to be constrained. As a result, the HoF model with the homogeneous borrowing con-

[26]The maximum attainable leverage ratio in HoF is $(d/k)_{max} = \theta_0$, where $\theta_0 = (\lambda_0 - 1)/\lambda_0$.
[27]In the data, 20% of firms have leverage higher than 0.7.

straint generates a stronger correlation between $log(MP_k)$ and $log(Y)$ (which is 0.32) than HeF (0.25).

Table 7: Non-targeted Firm-level Moments in the HeF and HoF

	HeF	HoF
A. Standard deviations		
S.D. *leverage*	0.23	0.27
S.D. $log(asset)$	1.14	1.28
S.D. $log(MP_k)$	0.31	0.29
B. Correlations with $log(MP_k)$		
Corr. of $log(MP_k)$ and $log(A)$	-0.32	-0.19
Corr. of $log(MP_k)$ and $log(Y)$	0.25	0.32
Corr. of $log(MP_k)$ and $log(asset)$	-0.17	0

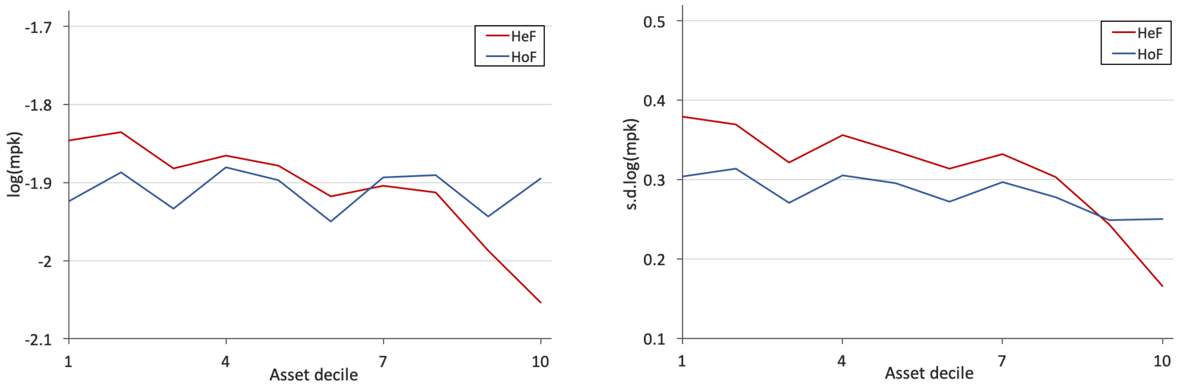
Note: This table reports non-targeted moments in the HeF model with the size-dependent borrowing constraint and the HoF with the homogeneous borrowing constraint, respectively. Panel A reports the standard deviations of total assets, leverage, and the marginal product of capital. Panel B shows the correlations with the marginal product of capital.

Firm Size and Capital Misallocation The critical difference between HeF and HoF lies in the correlation between firm size and $log(MP_k)$. As shown in Table 7, the HoF model without taking into account firms' financing pattern (the positive leverage-size slope) fails to reproduce the correlation between firm size and $log(MP_k)$, as it equals zero. The correlation is instead -0.17 in the HeF model with the size-dependent borrowing constraint. Both firm size and the marginal product of capital depend on firms' productivity and financing ability. When $\lambda_1 = 0$ with the homogeneous borrowing constraint, on the one hand, given a productivity z, firms with higher net worth a are able to afford more capital, become large and face a lower MP_k. Moreover, given a net worth a, firms with higher productivity z tend to be larger and face a higher MP_k due to the higher financing need for capital. These two opposing forces affect the correlation between firm size and the marginal product of capital. Based on the calibration of the HoF model, the correlation between $log(MP_k)$ and firm size is 0. By contrast, in the HeF model with positive λ_1, when productivity z is large enough, even firms without high net worth are able to have sufficient capital, grow large and relax the borrowing constraint. This additional channel makes large firms less distorted by financial frictions and thus face a lower marginal product of capital. Due to this feature, the HeF model predicts a negative relationship between firm size and $log(MP_k)$, which is consistent with the data.

To further study the pattern of $log(MP_k)$ across different size groups, I compute and compare the mean and standard deviation of $log(MP_k)$ conditional on asset deciles in HeF and HoF. Figure 8 panel (a) reports the relationship between firm size and $log(MP_k)$. In HeF under the size-dependent borrowing constraint, $log(MP_k)$ decreases with firm size, which is consistent with the pattern in the data. In HoF under the homogeneous borrowing constraint, $log(MP_k)$ fluctuates slightly and does not demonstrate a downward trend. Moreover, the mean of $log(MP_k)$ among large firms (top 20% by assets) is lower in HeF than in HoF. Although the standard deviations of $log(MP_k)$ in the two models are close (As shown in Table 7, 0.31 in HeF and 0.29 in HoF), they vary across different size groups. As shown in Figure 8 panel (b), the standard deviation of $log(MP_k)$ decreases slightly in the HoF model. By contrast, with the size-dependent borrowing constraint, the standard deviation of $log(MP_k)$ decreases from 0.38 to 0.16 as firm size increases. And the dispersion of $log(MP_k)$ among large firms (top 20% by assets) is also smaller in HeF than in HoF.

The model with the size-dependent borrowing constraint is able to reproduce both the patterns of the mean and standard deviation of $log(MP_k)$ by firm size; however, these patterns are more muted than those in the data because factors other than financial frictions also contribute to capital misallocation.

Aggregate Implications Table 8 reports the aggregate implications. As shown in the 3rd row, the fraction of firms that are financially constrained at the steady state in the two models are quite close (0.54 in HeF and 0.52 in HoF). Then, the fraction of firms that are constrained in each asset quartile is computed and compared (rows 4-7). In the HeF model with the size-dependent borrowing constraint, 62% of firms in the second asset quartile are constrained, which decreases to 48% in the fourth quartile. Large firms (the fourth asset



(a) Firm Size and $log(MP_k)$ (b) Firm Size and Standard Deviation of $log(MP_k)$

Figure 8: Firm Size and $log(MP_k)$ in the HeF and HoF

Note: This figure reports the relationships between firm size and $log(MP_k)$ in the HeF model with the size-dependent borrowing constraint and the HoF model with the homogeneous borrowing constraint. The mean and standard deviation of $log(MP_k)$ are calculated in each asset decile.

quartile) are less likely to be financially constrained in HeF than in HoF.

Table 8 shows the TFP loss in the two models. Whether firms' financing pattern (the positive leverage-size slope) is taken into account or not affects the generated aggregate TFP loss. The TFP loss in the HeF model is 3.98%, which is smaller than in the HoF model (5.12%). As discussed above, although firms' capital decisions are distorted in both models due to financial frictions, in the HeF model with the size-dependent borrowing constraint, large firms, which contribute to the majority of output, are actually less distorted with both the lower mean and standard deviation of $log(MP_k)$ than small firms. Thus, we generate a smaller TFP loss under the size-dependent financial frictions.

Overall, the model with a size-dependent borrowing constraint is suitable for matching the Chinese firm-level moments compared with the alternative. The model predicts a negative correlation between firm size and the marginal product of capital, which is a feature lacking in the HoF model with the homogenous borrowing constraint. In addition, the model generates both the lower mean and standard deviation of the marginal product of capital among large firms compared with the HoF model. Without considering the size-dependent financial

Table 8: Aggregate Implications in the HeF and HoF

	HeF	HoF
Fraction Constrained		
Total	0.54	0.52
Q1	0.55	0.48
Q2	0.62	0.58
Q3	0.52	0.49
Q4	0.48	0.56
TFP loss (%)	3.98	5.12

Note: This table reports the aggregate implications in the HeF model with the size-dependent borrowing constraint and the HoF model with the homogeneous borrowing constraint. The fraction of firms that are constrained is calculated in each asset quartile (Q1-Q4).

policy, the TFP loss may be overestimated, since large firms, which contribute more to the economy, are actually more leveraged and less distorted by financial frictions.

5.3 Sensitivity Analysis

Since under the size-dependent borrowing constraint, the borrowing tightness parameter λ_1 plays an important role in the firm's financing pattern, this subsection examines the impacts of λ_1 on capital misallocation.

Table 9 reports the moments in terms of financing pattern and capital misallocation. Column 2 presents the moments in the baseline HeF model with $\lambda_1 = 0.012$, and columns 3-4 report the corresponding moments as λ_1 increases. When $\lambda_1 = 0.03$, the maximum attainable leverage ratio $(d/k)_{max} = 0.478 + 0.016k$, and when $\lambda_1 = 0.04$, $(d/k)_{max} = 0.478 + 0.021k$. As shown in Table 9, when λ_1 increases, the leverage-size slope increases accordingly, since large firms are more favored in the financial market. As the increasing λ_1 implies a decreasing borrowing tightness, the aggregate debt-to-output ratio increases, leverage and $log(asset)$ become more volatile with the higher standard deviations, and the dispersion of $log(MP_k)$ decreases consequently.

Table 9: Firm-level Moments in the Sensitivity Analysis

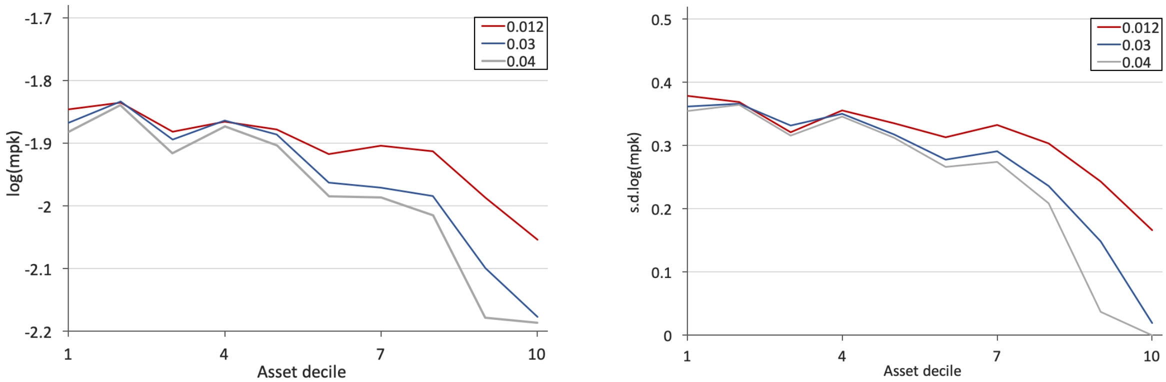
λ_1	0.012	0.03	0.04
A. Financing Patterns			
leverage-size slope	0.03	0.06	0.07
Debt-to-output ratio	1.14	1.5	1.58
B. Standard Deviations			
S.D. $leverage$	0.23	0.25	0.26
S.D. $log(asset)$	1.14	1.26	1.29
S.D. $log(MP_k)$	0.31	0.27	0.25
C. Correlations with $log(MP_k)$			
Corr. of $log(MP_k)$ and $log(A)$	-0.32	-0.42	-0.44
Corr. of $log(MP_k)$ and $log(Y)$	0.25	0.09	0.04
Corr. of $log(MP_k)$ and $log(asset)$	-0.17	-0.29	-0.32

Note: This table reports the firm-level moments in the baseline HeF model with $\lambda_1 = 0.012$ and for $\lambda_1 = 0.03$ and $\lambda_1 = 0.04$. Panel A reports financing patterns. Panel B presents the standard deviations of total assets, leverage, and the marginal product of capital. Panel C shows the correlations with the marginal product of capital.

The changes in financing patterns affect capital misallocation accordingly. As λ_1 increases, firms without high net worth are more likely to eliminate the borrowing constraint than before. As a result, the negative correlation between firm size and $log(A)$ becomes stronger. Firms with high productivity are less likely to be constrained than before, and thus the positive correlation between firm size and $log(Y)$ weakens. As large firms are even more favored in the financial market, the negative correlation between firm size and $log(MP_k)$ becomes stronger.

Although as λ_1 increases the maximum attainable leverage ratio for all firms increases compared with the baseline HeF model, large firms benefit more from the increasing leverage-size slope than small firms. Figure 9 presents the mean and standard deviation of $log(MP_k)$ conditional on asset deciles in the baseline HeF model with $\lambda_1 = 0.012$ and when $\lambda_1 = 0.03$ and $\lambda_1 = 0.04$. As we can see from panels (a) and (b), as λ_1 increases, the average and standard deviation of $log(MP_k)$ decrease. Moreover, both the mean and dispersion of $log(MP_k)$ decrease further among large firms.

Table 10 reports the aggregate implications. As λ_1 increases, the fraction of firms that



(a) Firm Size and $log(MP_k)$ (b) Firm Size and Standard Deviation of $log(MP_k)$

Figure 9: Firm Size and $log(MP_k)$ in the Sensitivity Analysis

Note: This figure reports the relationship between firm size and $log(MP_k)$ in the baseline HeF model with $\lambda_1 = 0.012$ and when $\lambda_1 = 0.03$ and $\lambda_1 = 0.04$, respectively. The mean and standard deviation of $log(MP_k)$ are calculated in each asset decile.

are constrained becomes smaller accordingly. In addition, the fraction constrained decreases more among large firms. When λ_1 increases from 0.012 to 0.03, the fraction constrained in the fourth asset quartile decreases from 0.48 to 0.23 (decreased by 54%), and when $\lambda_1 = 0.04$, only 14% of the firms are constrained in that size group. The TFP loss decreases accordingly, as firms, especially large firms, are less constrained when the leverage-size slope increases.

Table 10: Aggregate Implications in the Sensitivity Analysis

λ_1	0.012	0.03	0.04
Fraction Constrained			
Total	0.54	0.47	0.44
Q1	0.55	0.63	0.63
Q2	0.62	0.53	0.52
Q3	0.52	0.47	0.45
Q4	0.48	0.23	0.14
TFP loss (%)	3.98	2.40	2.15

Note: This table reports the aggregate implications in the baseline HeF model with $\lambda_1 = 0.012$ and when $\lambda_1 = 0.03$ and $\lambda_1 = 0.04$, respectively. The fraction of firms that are constrained is calculated in each asset quartile (Q1-Q4).

6 Conclusion

This paper studies the impacts of financial frictions on capital misallocation and the aggregate TFP based on the Chinese manufacturing dataset. To capture the empirical feature that large firms have a higher leverage ratio than small firms, this paper formulates a general equilibrium model of firm dynamics based on Midrigan and Xu (2014) and introduces size-dependent financial frictions in light of Gopinath et al. (2017). With the size-dependent borrowing constraint, the borrowing tightness decreases with firm size. I calibrate the model by using the Chinese firm-level dataset to identify the productivity process and borrowing tightness parameters. Under the size-dependent borrowing constraint, since larger firms are less likely to be distorted by financial frictions, this paper predicts a negative correlation between firm size and the marginal product of capital, which is a feature that the model with a homogeneous borrowing constraint fails to capture. The model with a size-dependent borrowing constraint predicts a TFP loss of 3.98%, which is modest and can be rationalized by firms' self-financing. The TFP loss may be overestimated without considering the size-dependent financial policy, since large firms are actually less distorted by financial frictions.

This paper can be extended in several directions. For example, since the fixed costs of entry and technology adoption are nontrivial, financial frictions may play a more substantial role along the extensive margin by distorting the entry and technology adoption decisions of individual firms than on the intensive margin through capital misallocation. Severe borrowing tightness dampens fundraising and restrains entry and technology adoption, which reduces the aggregate TFP. In addition, this paper studies resource misallocation within the manufacturing sector. In the future, I will investigate the impacts of cross-sector resource misallocation on aggregate productivity.

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A Data

A.1 Data Cleaning

This paper focuses on the firm-level dataset from the *Chinese Annual Survey of Industrial Firms*, which is published by the National Bureau of Statistics (NBS) of China. This dataset includes all state-owned firms and all "above-scale" non-state-owned firms with annual sales exceeding 5 million RMB. This dataset covers the industries of manufacturing, mining, and public utilities and includes a wealth of firm-level information, such as firms' balance sheets, output, and revenues. The sample period is 1998-2007. As shown in Table A.1, there are more than 2 million observations in this sample.

1. Dropping Invalid Observations

First, observations with negative key variables are deleted. I drop observations with a negative industrial value added, employment, fixed assets at the original price, total assets, and total liabilities. Next, I drop observations that violate the accounting standards required by the *China Industrial Statistics Reporting System* because (1) the fixed asset at the original price is smaller than the accumulated depreciation; (2) the fixed asset at the original price is smaller than the net fixed asset; (3) the accumulated depreciation is smaller than the current depreciation; (4) the total assets are smaller than the sum of current assets, long-term investments, fixed assets, and intangible assets; (5) the total debt is smaller than the sum of short-term and long-term debt; (6) the industrial output is smaller than the industrial value added or smaller than the intermediate input. Furthermore, I restrict the sample within the manufacturing sector.

2. Industry Classification

Since there was a change in the *China Industry Classification* (CIC) system starting in 2003, another task when dealing with this dataset is to unify the industry classification over the years. Following the method of Brandt et al. (2014), this paper adopts a revision of the CIC system of manufacturing with 593 four-digit industries and 30 two-digit industries.

Each firm is classified into one particular industry.

3. Firm ID

Another challenge when dealing with this dataset is that although the firm ID information is reported in the original dataset, there is no unique firm ID to identify the same firm that exists in multiple years. For example, a firm may be assigned to different IDs over the years due to a change in the firm name. Following Brandt et al. (2014), this paper identifies the same firms by combining information on the firm ID, legal identity, region, phone number, industry, founding year, product, and so on and then assigns a unique ID to each firm in this dataset.

4. Firm Ownership

Considering that in China, SOEs have easier access than non-SOEs to external finance, this paper divides firms into SOEs and non-SOEs according to their ownership. According to the *Chinese Annual Survey of Industrial Firms*, two indicators help identify ownership: (1) registered ownership and (2) registered capital. One problem of using registered ownership is that in China, actual ownership may not be consistent with registered ownership. For example, if the ratio of Hong Kong, Macau, Taiwan (HMT) or foreign capital to total registered capital is larger than 25%, then the firm can be legally registered as a non-SOE, even though this firm is actually controlled by the state. Thus, following Wu (2018), Fang (2019), and Hsieh and Song (2015), this paper identifies firm ownership by using registered capital. As long as the ratio of state capital to total registered capital is no less than 50%, the firm is identified as an SOE. Otherwise, the firm is a non-SOE.

A.2 Variable Definition

This part describes the definitions and measures of the variables.

Output. The output is measured by the value added, which is directly reported in the dataset, and is then deflated by the GDP deflator.

Capital Stock. There is a lack of a good measure of capital stock in the dataset. Following

Brandt et al. (2014), the real capital stock series is constructed by adopting the perpetual inventory method.

Labor. There are two measures of labor: (1) employment and (2) wage and welfare compensation. To control the differences in the quality of labor within and across firms, following Gopinath et al. (2017), this paper uses the sum of wages and welfare payments as the measure of labor.

Total Assets. Total assets are defined as the sum of current assets, long-term investments, fixed assets and intangible assets. This parameter is directly reported in the dataset.

Total Debt. Total debt is the sum of long-term and short-term debt. This variable is directly reported in the dataset.

Leverage. Leverage is defined as the ratio of total debt to total assets. In this paper, leverage is restricted within the range of $[0, 1]$.

B Derivations and Proofs

B.1 Microfoundation of the Size-dependent Borrowing Constraint

The size-dependent borrowing constraint arises from the microfoundation of limited commitment. If the firm does not default, the budget constraint is

$$c_{it} + k_{it+1} - (1-\delta)k_{it} = y_{it} - \omega l_{it} - (1+r)d_{it} + d_{it+1} \tag{B.1}$$

Following Gopinath et al. (2017), this paper assumes that in the case of default, the firm can default on a fraction μ_0 of its debt d_{it}. As a penalty, the bank sizes a fraction μ_1 of the undepreciated capital stock $(1-\delta)k_{it}$. There exists a disruption cost of production $\Phi(k_{it})$ in the case of default, where $\Phi(k) = k^2$ is an increasing and convex function of capital. Other default benefits are summarized in the term $\mu_3 k_{it}$. In addition, this paper assumes that firms that default still have access to the financial market in the next period. Then, the budget constraint is

$$c_{it} + k_{it+1} - (1-\delta)k_{it} = y_{it} - \omega l_{it} - (1+r-\mu_0)d_{it} - \mu_1(1-\delta)k_{it} - \mu_2\Phi(k_{it}) + \mu_3 k_{it} + d_{it+1} \tag{B.2}$$

Due to the issue of limited commitment, the bank extends credit to the point that firms have no incentive to default in equilibrium. That is, for firms, the value of not defaulting is no less than the value of defaulting. The resulting borrowing constraint is

$$d_{it} \leq \underbrace{\left(\frac{\mu_1(1-\delta)-\mu_3}{\mu_0}\right)}_{\theta_0} k_{it} + \underbrace{\left(\frac{\mu_2}{\mu_0}\right)}_{\theta_1} \Phi(k_{it}) \tag{B.3}$$

Define net worth $a_{it} = k_{it} - d_{it} \geq 0$. Then, the borrowing constraint is rewritten as

$$k_{it} \leq \underbrace{\left(\frac{\mu_0}{\mu_0 - \mu_1(1-\delta)+\mu_3}\right)}_{\lambda_0} a_{it} + \underbrace{\left(\frac{\mu_2}{\mu_0 - \mu_2(1-\delta)+\mu_3}\right)}_{\lambda_1} \Phi(k_{it}) \tag{B.4}$$

where $\lambda_0 = \frac{1}{1-\theta_0}$ and $\lambda_1 = \frac{\theta_1}{1-\theta_0}$.

B.2 Parameter Restrictions on the Size-dependent Borrowing Constraint

Parameter restrictions are placed to ensure that defaulting is costly. The default cost is

$$\begin{aligned} C(k) &= \mu_1(1-\delta)k + \mu_2\Phi(k) - \mu_3 k \\ &= (\mu_1(1-\delta)-\mu_3)\,k + \mu_2 k^2 \end{aligned} \tag{B.5}$$

As long as $\mu_1(1-\delta)-\mu_3 \geq 0$, $C(k)\geq 0$. To ensure that both λ_0 and λ_1 are nonnegative, another appropriate restriction is $\mu_0-\mu_1(1-\delta)+\mu_3 \geq 0$. Based on the expressions for λ_0 and λ_1 in Appendix B.1, the resulting parameter restrictions are $\lambda_0 \geq 1$ and $\lambda_1 \geq 0$.

If $\mu_2 = 0$, then $\theta_1 = 0$, and $\lambda_1 = 0$. In this case, the size-dependent financial friction channel is closed.

B.3 Proof of Proposition 1

Under the size-dependent borrowing constraint, $FOCs$ with respect to labor l and capital k are given by

$$\alpha\eta\frac{y(a,z)}{l(a,z)} = \omega \tag{B.6}$$

$$(1-\alpha)\,\eta\frac{y(a,z)}{k(a,z)} = r+\delta+\mu(a,z)\,[1-2\lambda_1 k(a,z)] \tag{B.7}$$

where $\mu(a,z)$ is the Lagrangian multiplier on the borrowing constraint:

$$\mu(a,z) = \begin{cases} 0 & if\ k(a,z) < \lambda_0 a + \lambda_1 k(a,z)^2 \\ \frac{1}{(1-2\lambda_1 k(a,z))}[(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(1-\alpha)\,\eta\left(\frac{z}{k(a,z)}\right)^{\frac{1-\eta}{1-\alpha\eta}} - r-\delta] & if\ k(a,z) = \lambda_0 a + \lambda_1 k(a,z)^2 \end{cases} \tag{B.8}$$

Then, l and k can be jointly solved as

$$l(a,z) = z^{\frac{1-\eta}{1-\alpha\eta}}(\frac{\alpha\eta}{\omega})^{\frac{1}{1-\alpha\eta}} k^{\frac{(1-\alpha)\eta}{1-\alpha\eta}} \tag{B.9}$$

$$k(a,z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}[r+\delta+\mu(a,z)(1-2\lambda_1 k(a,z))]^{\frac{\alpha\eta-1}{1-\eta}} \tag{B.10}$$

To obtain a closed-form solution for capital, I define the function $g(k)$ as the difference between the RHS and LHS of the borrowing constraint:

$$g(k) \equiv \lambda_0 a + \lambda_1 k^2 - k \tag{B.11}$$

When the borrowing constraint is slack, the capital decision k^u is

$$k^u(a,z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}} \tag{B.12}$$

which satisfies both $\mu = 0$ and $g(k) > 0$. In this case, k^u increases in productivity z.

When the borrowing constraint is binding, $g(k) = 0$. As long as $1 - 4\lambda_0\lambda_1 a \geq 0$, there are two real roots k_1 and k_2 for $g(k) = 0$ (where $k_1 \leq k_2$). Since when $k = \frac{1}{2\lambda_1}$, $g(k)$ achieves its minimum value, the relative relationship between k_1 and k_2 is

$$0 \leq k_1 \leq \frac{1}{2\lambda_1} \leq k_2 \tag{B.13}$$

Only when capital $k^c = k_1$ are both $\mu > 0$ and $g(k) = 0$ satisfied. Thus, firms that face a binding borrowing constraint can achieve a capital level of only $k^c(a,z)$, which is the smaller root k_1 of $g(k) = 0$:

$$k^c(a,z) = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1} \tag{B.14}$$

B.4 Proof of Proposition 2

When $\lambda_1 = 0$, the borrowing constraint is

$$k \leq \lambda_0 a \tag{B.15}$$

The $FOCs$ with respect to labor l and capital k are

$$\alpha\eta \frac{y(a,z)}{l(a,z)} = \omega \tag{B.16}$$

$$(1-\alpha)\eta \frac{y(a,z)}{k(a,z)} = r + \delta + \gamma(a,z) \tag{B.17}$$

where $\gamma(a,z)$ is the Lagrangian multiplier on the borrowing constraint given by

$$\gamma(a,z) = \begin{cases} 0 & if\ k(a,z) < \lambda_0 a \\ \left(\frac{\alpha\eta}{\omega}\right)^{\frac{\alpha\eta}{1-\eta}} (1-\alpha)\eta \left(\frac{z}{k(a,z)}\right)^{\frac{1-\eta}{1-\alpha\eta}} - r - \delta & if\ k(a,z) = \lambda_0 a \end{cases} \tag{B.18}$$

Then, l and k can be jointly solved as

$$l(a,z) = z^{\frac{1-\eta}{1-\alpha\eta}} (\frac{\alpha\eta}{\omega})^{\frac{1}{1-\alpha\eta}} k^{\frac{(1-\alpha)\eta}{1-\alpha\eta}} \tag{B.19}$$

$$k(a,z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}} ((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}} [r + \delta + \gamma(a,z)]^{\frac{\alpha\eta-1}{1-\eta}} \tag{B.20}$$

When the borrowing constraint is slack, the capital decision k^u is

$$k^u(a,z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}} ((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}} (r+\delta)^{\frac{\alpha\eta-1}{1-\eta}} \tag{B.21}$$

In this case, capital k^u increases in productivity z.

When the borrowing constraint is binding, the attainable capital level k^c is

$$k^c = \lambda_0 a \tag{B.22}$$

In this case, k^c is linear in net worth a.

Given a productivity z, when the borrowing constraint is exactly binding, $k^u = k^c$. Then, the cutoff net worth a^* is

$$a^* = \frac{k^u(z)}{\lambda_0} \tag{B.23}$$

If $a \leq a^*$, the borrowing constraint is binding. If $a > a^*$, the borrowing constraint is slack. When the net worth a is large enough, e.g., $a > \frac{k^u(\bar{z})}{\lambda_0}$, the borrowing constraint is never binding.

B.5 Proof of Proposition 3

Under the size-dependent borrowing constraint ($\lambda_1 > 0$), according to Proposition 1, $k^u(z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}}$, and $k^c(a) = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}$. Given productivity z, when the borrowing constraint is exactly binding, $k^u = k^c$. Then, the cutoff net worth a^* is

$$a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1} \tag{B.24}$$

If $a \leq a^*$, the borrowing constraint is binding. If $a > a^*$, the borrowing constraint is slack. When the net worth a is large enough, e.g., $a > \frac{1}{4\lambda_0\lambda_1}$, the borrowing constraint is never binding.

B.6 Proof of Proposition 4

Based on Appendix B.4, the marginal product of capital MP_k under the homogeneous borrowing constraint is equal to

$$MP_k = r+\delta+\gamma \tag{B.25}$$

The capital decisions for the financially unconstrained and constrained firms are $k^u(z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}}$ and $k^c(a) = \lambda_0 a$, respectively. Let $a^* = \frac{k^u(z)}{\lambda_0}$, $a_1 = \frac{k^u(\underline{z})}{\lambda_0}$, $a_2 = \frac{k^u(\bar{z})}{\lambda_0}$, $c = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}}$, and $z^* = \frac{k^c(a)}{c}$, where z^* is the cutoff productivity for bindingness given a. Then, the relationship between the net worth a, productivity z, capital k and marginal product of capital MP_k is the following:

1. Given a productivity z:

(1) firms are constrained, as $a \in [\underline{a}, a^*]$. Firms with a larger net worth a have higher capital $k^c(a)$ and lower γ and MP_k;

(2) firms are unconstrained, as $a \in (a^*, \bar{a}]$. The capital $k^u(z)$ is constant; in addition, $\gamma = 0$, and $MP_k = r + \delta$.

2. Given a net worth a:

(1) when $a \in [\underline{a}, a_1]$, firms are constrained, as $z \in [\underline{z}, \bar{z}]$. Firms with higher productivity z have higher γ and MP_k, as capital $k^c(a)$ does not change;

(2) when $a \in (a_1, a_2]$, 1) firms are unconstrained, as $z \in [\underline{z}, z^*)$. Firms with higher productivity z have higher $k^u(z)$; in addition, $\gamma = 0$, and $MP_k = r + \delta$; 2) firms are constrained, as $z \in [z^*, \bar{z}]$. Firms with higher productivity z have higher γ and MP_k, as the capital $k^c(a)$ does not change;

(3) when $a \in (a_2, \bar{a}]$, firms are unconstrained, as $z \in [\underline{z}, \bar{z}]$. Firms with higher productivity z have higher $k^u(z)$; in addition, $\gamma = 0$, and $MP_k = r + \delta$.

Figure B.1 reports the relationships between net worth a, productivity z and MP_k under the homogeneous borrowing constraint. The idiosyncratic productivity is discretized into nine equally spaced states, and a brighter color corresponds to a higher MP_k. Given a productivity shock z, firms with a higher net worth a tend to face a lower MP_k, since the higher net worth helps relax the borrowing constraint. In addition, given a net worth a, the marginal product of capital MP_k increases fully with increasing productivity. That is, firms with a higher productivity accordingly have a higher financing need for capital. As a result, those firms are more constrained and face a higher MP_k.

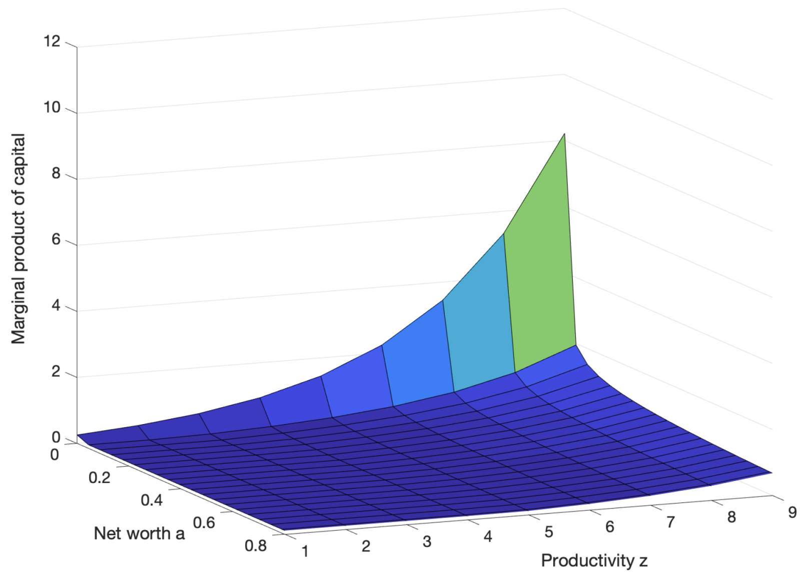

Figure B.1: Determination of the Marginal Product of Capital ($\lambda_1 = 0$)

Note: This figure reports the relationship between the state (a, z) and the marginal product of capital MP_k under the homogeneous borrowing constraint.

B.7 Proof of Proposition 5

The marginal product of capital MP_k under the size-dependent borrowing constraint is equal to

$$MP_k = r + \delta + \mu(1 - 2\lambda_1 k) \tag{B.26}$$

According to Proposition 1, $k^u(z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}}$, $k^c(a) = k_1(a) = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}$ and $k_2(a) = \frac{1+\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}$. Let $a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1}$, $a_3 = \frac{1-(1-2\lambda_1 k^u(\underline{z}))^2}{4\lambda_0\lambda_1}$, $a_4 = \frac{1-(1-2\lambda_1 k^u(\bar{z}))^2}{4\lambda_0\lambda_1}$, $a_5 = \frac{1}{4\lambda_0\lambda_1}$, $c = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}(r+\delta)^{\frac{\alpha\eta-1}{1-\eta}}$, $z_1^* = \frac{k_1(a)}{c}$, and $z_2^* = \frac{k_2(a)}{c}$, where z_1^* and z_2^* are the cutoff productivities for bindingness given a. The relationship among the net worth a, productivity z, capital k and marginal product of capital MP_k under the size-dependent borrowing constraint is as follows:

1. Given a productivity z:

(1) firms are constrained, as $a \in [\underline{a}, a^*]$. Firms with a larger net worth a have larger

capital $k^c(a)$ and lower $\mu(1-2\lambda_1 k^c(a))$ and MP_k ;

(2) firms are unconstrained, as $a \in (a^*, \bar{a}]$. The capital $k^u(z)$ is constant; in addition, $\gamma = 0$, and $MP_k = r + \delta$.

2. Given a net worth a:

(1) when $a \in [\underline{a}, a_3]$, firms are constrained, as $z \in [\underline{z}, \bar{z}]$. Firms with higher productivity z have higher μ and MP_k, as the capital $k^c(a)$ does not change;

(2) when $a \in (a_3, a_4]$, 1) firms are unconstrained, as $z \in [\underline{z}, z_1^*)$. Firms with higher productivity z have higher $k^u(z)$; in addition, $\mu = 0$, and $MP_k = r + \delta$; 2) firms are constrained, as $z \in [z_1^*, \bar{z}]$. Firms with higher productivity z have higher μ and MP_k, as the capital $k^c(a)$ does not change;

(3) when $a \in (a_4, a_5]$, 1) firms are unconstrained, as $z \in [\underline{z}, z_1^*)$. Firms with higher productivity z have higher $k^u(z)$; in addition, $\mu = 0$, and $MP_k = r + \delta$; 2) firms are constrained, as $z \in [z_1^*, z_2^*]$. Firms with higher productivity z have higher μ and MP_k, as the capital $k^c(a)$ does not change; 3) firms are unconstrained, as $z \in (z_2^*, \bar{z}]$. Firms with higher productivity z have higher $k^u(z)$; in addition, $\mu = 0$, and $MP_k = r + \delta$;

(4) when $a \in (a_5, \bar{a}]$: firms are unconstrained, as $z \in [\underline{z}, \bar{z}]$. Firms with higher productivity z have higher $k^u(z)$; in addition, $\mu = 0$, and $MP_k = r + \delta$.

Different from the case under the homogeneous borrowing constraint, now firms with a sufficiently large productivity shock z ($z \in (z_2^*, \bar{z}]$, even without a high net worth a) are not financially constrained. Those firms tend to have a higher k and face a lower MP_k.

Figure B.2 depicts the relationship among the net worth a, productivity z and marginal product of capital MP_k for the size-dependent borrowing constraint. Given a productivity shock z, firms with a higher net worth a tend to face a lower MP_k due to the stronger financing ability. Given a net wealth a, as productivity z increases, MP_k increases accordingly due to the higher financing need. However, when productivity z is large enough, firms (even those without high net worth a) are able to accumulate sufficient capital k and relax the borrowing constraint. As a result, MP_k becomes low for high-productivity firms.

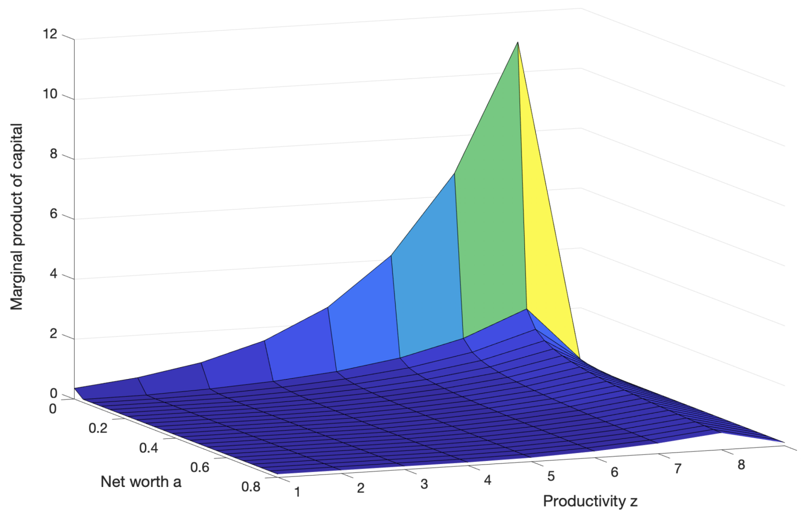

Figure B.2: Determination of the Marginal Product of Capital ($\lambda_1 > 0$)

Note: This figure reports the relationship between the state (a, z) and the marginal product of capital MP_k under the size-dependent borrowing constraint.

C Calibration Results

C.1 Calibration Results under the Homogeneous Borrowing Constraint

Table C.1 presents the calibration results in the model with the homogeneous borrowing constraint. The target moment for the borrowing tightness parameter λ_0 is the aggregate credit to the private sector (% GDP), which is 113%.

Table C.1: Calibration Results

Parameter	Description	Value	Source/target
δ	Depreciation rate	0.06	Wu et al. (2014)
p_u	Persistence zero state	0.50	Match employment ratio in China
p_e	Persistence unit state	0.81	
β	Discount factor	0.88	Aggregate capital-to-output ratio
η	Span of control	0.80	Fraction of output by the top 5 output percentiles
α	Labor elasticity	0.56	Labor share $\alpha\eta$ equals 0.45
ρ	Persistent component	0.87	S.D. output growth
σ_ε	S.D. transitory shock	0.84	1-year autocorrelation of output
λ_0	Borrowing tightness	2.512	Aggregate debt-to-output ratio

Note: This table reports the parameter values that are calibrated to match the empirical targets in the Chinese data, as discussed in the main text.

Table C.2 reports the non-targeted moments in the model with the homogeneous borrowing constraint.

Table C.2: Non-targeted Firm-level Moments in the Data and HoF

	Data	HeF
S.D. log output	1.22	1.49
Output share by top 10 output percentiles	0.54	0.54
Output share by top 10 output percentiles	0.70	0.71
3-year autocorrelation output	0.76	0.75
S.D. capital growth	0.46	0.58
S.D. log capital	1.41	1.42
1-year autocorrelation capital	0.95	0.92
3-year autocorrelation capital	0.87	0.78

Note: This table reports non-targeted moments in the data and the model with the homogeneous borrowing constraint, respectively.