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Essays on Macroeconomic Effects of Resource Misallocation

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ABSTRACT OF THE DISSERTATION

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by

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This dissertation consists of three essays that investigate the macroeconomic effects of resource misallocation. Chapter 1 provides an overview of this dissertation. Chapter 2 studies the macroeconomic effects of size-dependent financial frictions on capital misallocation and aggregate productivity. Based on the Chinese firm-level dataset, I find that among non-state-owned enterprises, (i) the dispersion of the marginal product of capital is significant and persistent and (ii) large firms tend to have higher leverage, and lower mean and dispersion of the marginal product of capital than their small counterparts. I analyze a dynamic stochastic general equilibrium model with heterogeneous agents and size-dependent financial frictions to match the stylized facts. I show that the economy with a size-dependent borrowing constraint can reproduce the observed negative correlation between firm size and the marginal product of capital and generate a TFP loss of 3.91%. Furthermore, ignoring firms' size-dependent financing patterns may lead to an overstatement of TFP loss due to financial frictions.

Chapter 3 studies the implications of financial development and financial reform policies on resource reallocation and aggregate productivity. I develop a general equilibrium model with heterogeneous private and state-owned firms, into which size-dependent financial frictions and equity issuance are incorporated. By calibrating the model to the Chinese economy, this chapter shows that financial reform has facilitated resource reallocation within and across the private and state sectors. The reallocation effects on the intensive margin due to reform policies account for most aggregate productivity and output gains. Besides, credit market development has played a more prominent role in promoting aggregate productivity and output than the equity market during the economic transition.

Chapter 4 investigates the impacts of factor market distortions on allocative efficiency by adopting a misallocation accounting framework with the gross output production structure and considering firm-specific distortions on capital, labor, and intermediate input. The empirical results suggest that the gross output gains by equalizing revenue productivity within sectors are 18.71% on average in the Chinese manufacturing sector. Despite the significant revenue share of gross output by intermediate input, reallocation gains from removing intermediate input distortion are smaller than that of capital and labor distortions. Although the wedge on intermediate input usage is not the primary source of misallocation, intermediate input possibly matters for the measured distortions and TFP gains.

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Chapter 1

Introduction

The allocation efficiency of factors across heterogeneous production units has played an essential role in the observed aggregate TFP and income per capita differences across countries. This dissertation consists of three essays that investigate the macroeconomic effects of resource misallocation, with a focus on the Chinese manufacturing firm-level dataset. Chapter 2 and Chapter 3 employ the direct approach assessing the importance of the specific source of misallocation, financial frictions, on the aggregate productivity and output. Chapter 4 adopts the indirect approach without specifying the underlying sources of misallocation to investigate the relative importance of all the potential factor market distortions on the aggregate economy.

Chapter 2 examines the effects of size-dependent financial frictions on capital misallocation and aggregate productivity. The well-documented positive correlation between financial development and aggregate TFP has driven recent work examining financial frictions' role in resource misallocation and aggregate productivity. In this line of research, firms face the collateral-type borrowing constraint with homogeneous borrowing tightness. Nevertheless, empirical evidence suggests a positive relationship between firm size and leverage. Since firms' financing abilities directly affect their capital decisions, failing to consider the financial frictions disciplined by firms' financing patterns may prevent salient features of capital misallocation from being captured.

Chapter 2 fills this gap by examining the importance of size-dependent financial frictions on misallocation. To capture the empirical features, this chapter 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). The model with a size-dependent borrowing constraint 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, and it generates a TFP loss of 3.91%. Moreover, ignoring firms' size-dependent financing patterns may lead to an overstatement of TFP loss since large firms are actually less distorted by financial frictions than their small counterparts.

Chapter 3 studies the implications of financial development on resource reallocation and aggregate productivity in the Chinese manufacturing sector. Over the past several decades, China has undergone rapid economic growth. Meanwhile, major reforms in the financial sector have taken place. Given the discriminatory financial policies and TFP gaps between the private and state sectors, Chapter 3 develops a model of firm dynamics with heterogeneous private and state-owned firms, and introduce size-dependent financial frictions as well as equity issuance to study the financial reform policies during this economic transition. Financial development, which is crucial for firms' fundraising capacity, affects private firms' entry and investment decisions. By calibrating the model to the Chinese economy, Chapter 3 shows that financial reform has promoted the reallocation of productive resources to more efficient use within and across the private and state sectors, resulting in an increase in the aggregate TFP and output by 8% and 35%. The decomposition along the margins suggests that the reallocation effects on the intensive margin account for the majority of efficiency gains. In addition, most efficiency gains can be attributed to the development of the credit market other than the equity market during the economic transition.

Chapter 4 investigates the impacts of all the factor market distortions on allocative efficiency and aggregate productivity in China's manufacturing sector from 1998 to 2007. By extending the misallocation accounting framework in Hsieh and Klenow (2009) and considering a gross output production structure, Chapter 4 finds that the gross output gains from eliminating all factor market distortions are 18.71% on average during the sample period. Although intermediate input accounts for a significant revenue share of gross output, the reallocation gains from removing intermediate input distortion (3.05%) are smaller on average relative to that of capital distortion (7.81%) and labor distortion (6.39%), implying that intermediate input distortion is less critical for resource misallocation in the Chinese manufacturing sector. In addition, a comparison of the summary statistics between the models with value-added and gross output production structures hints that intermediate input and the distortion on its usage will make a difference for the measurement of distortions and reallocation gains.

Chapter 2

Size-dependent Financial Frictions, Capital Misallocation and Aggregate Productivity

2.1 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

[1]For example, Klenow and Rodriguez-Clare (1997), and Hall and Jones (1999).
[2]See Hsieh and Klenow (2009), Restuccia and Rogerson (2008), among others.
[3]See Hopenhayn (2014), and Arellano et al. (2012).

financial frictions.[4] In this line of research with imperfect financial markets, firms face the collateral-type borrowing constraint with homogeneous borrowing tightness.

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 among private firms. 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).[5] 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.[6] To 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.

[4] In addition to financial frictions, labor market frictions also have important implications for aggregate TFP. See, for example, Lagos (2006), Petrosky-Nadeau (2013), Ortego-Marti (2017), among others.

[5] 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.

[6] Following Banerjee and Moll (2010), capital misallocation along the intensive margin is defined as the unequal marginal products of capital across agents with positive usage of capital.

In the model, the optimal unconstrained capital level 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 large, firms, even those without high net worth, are able to accumulate adequate capital, grow large and relax the borrowing constraint. With this feature, the marginal product of capital and productivity are less positively correlated and large firms 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 capital 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, non-state-owned enterprises (non-SOEs) face a higher dispersion of the marginal product of capital than state-owned enterprises (SOEs). Second, the extent to which firms are distorted varies across different firm size groups. The mean and dispersion of the marginal product of capital are smaller among large firms, suggesting that large firms are less distorted in capital decisions than their small counterparts. Regarding financing patterns, SOEs are not financially constrained, while non-SOEs have less access to bank loans and lower leverage. Moreover, a positive relationship between firm size and leverage exists for non-SOEs. The implications of size-dependent financial frictions faced by non-SOEs, under which large firms are more favored in financial market than small firms, are in line with the capital misallocation facts.

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 set 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.[7] This model also generates similar patterns of the mean and dispersion of the marginal product of capital across size groups as in the data.

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, the model fails to reproduce the negative correlation between firm size and the marginal product of capital, as the correlation equals zero. By contrast, under the size-dependent borrowing constraint, when

[7] See Wu (2018), and David and Venkateswaran (2019).

the productivity shock is sufficiently large, firms without a high net worth are able to accumulate adequate capital, relax the borrowing constraint and face a low marginal product of capital. Due to this feature, the positive correlation between the marginal product of capital and productivity is weaker, and large firms are less distorted than in the case under the homogeneous borrowing constraint. Hence, the model with the size-dependent borrowing constraint generates a negative correlation between firm size and the marginal product of capital with a coefficient of -0.16, consistent with the data (-0.23).

In the model with the size-dependent borrowing constraint, the aggregate TFP loss is 3.91%, which implies that size-dependent financial frictions explain modest TFP loss along the intensive margin.[8] One 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 5.08%. This indicates that without considering the size-dependent financial frictions, we may not only fail to capture the relationship between firm size and misallocation but also overstate 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,

[8] 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.

the positive correlation between productivity and the marginal product of capital becomes weaker, and the negative relationship between firm size and the marginal product of capital becomes stronger. The dispersion of the marginal product of capital as well as the TFP loss decrease accordingly. Moreover, compared with small firms, both the mean and dispersion of the marginal product of capital decrease further among large firms, suggesting that large firms benefit more from an increasing leverage-size slope than small 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 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 patterns may fail to capture the patterns of capital misallocation, and 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 the European dataset and that the leverage of small firms relative to large firms grows 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 in determining 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 considering the default risks of firms and the 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 whereby both the mean and dispersion of the 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 the 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 and 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 a 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 Chapter 2 is organized as follows. Section 2.2 presents the firm-level dataset of the Chinese manufacturing sector. Section 2.3 introduces the model and discusses the implications of the size-dependent financial frictions on capital misallocation. Section 2.4 presents the model parameterization, and Section 2.5 analyzes the simulation results. Section 2.6 concludes the paper.

2.2 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.

2.2.1 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 SOEs and the "above-scale" 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. 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.[9] 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 deflated by 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 firm ownership since non-SOEs and SOEs in China are subject to different regulations. Following Hsieh and Song (2015), 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

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

firm is recognized as an SOE. Otherwise, the firm is a non-SOE. See Appendix A.1.1 for more details.

2.2.2 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.[10] Thus, the dispersion of the marginal product of capital helps to measure the capital allocation efficiency. Intuitively, as discussed in Midirgan and Xu (2014), 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 4-digit industry level and then aggregated conditional on year. Figure 2.1 reports the evolution of the standard deviation of $\log(MP_k)$ over the period 1998-2007 for SOEs, non-SOEs and the full sample. The dispersion of $\log(MP_k)$ among SOEs increases after 1999, and the average is 0.82. In comparison, the dispersion of $\log(MP_k)$ among non-SOEs is higher than SOEs over time, and the average is 0.89. Since SOEs and non-SOEs differ in their capital allocation efficiency, the dispersion of $\log(MP_k)$ for the full sample over time is even larger, with a mean of 0.91. The above results suggest the presence of capital misallocation among Chinese firms over the sample period, and non-SOEs face larger distortions than SOEs. In addition, since SOEs compose only a minor fraction of the dataset (approximately 10% of the observations), the dispersion of $\log(MP_k)$ among non-SOEs and the full sample are quite close.

[10]See Hsieh and Klenow (2009), Restuccia and Rogerson (2008), among others.

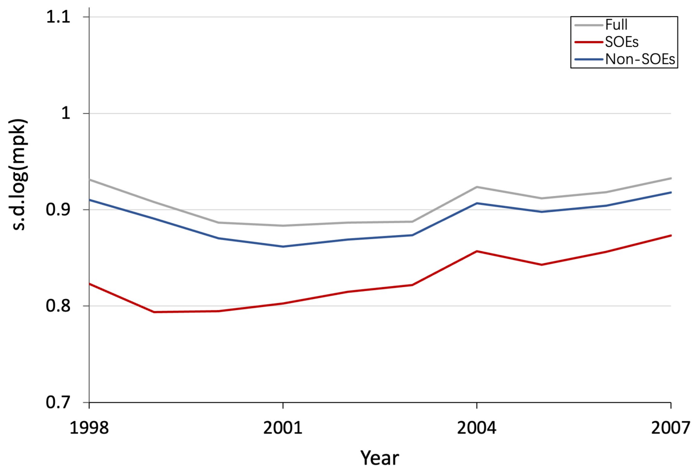


Figure 2.1: Dispersion of $\log(MP_k)$ by Year

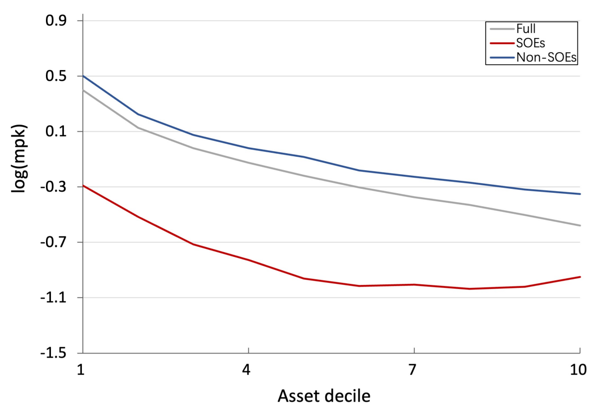
Note: This figure reports the standard deviation of $\log(MP_k)$ for SOEs, non-SOEs and the full sample by year.

Policy distortions may drive capital misallocation through firm characteristics. In empirical corporate finance, firm size is a fundamental firm characteristic.[11] 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 2.2 panel (a) shows the relationship between firm size and $\log(MP_k)$. As we can see, $\log(MP_k)$ decreases with firm size for non-SOEs, suggesting that large firms are less distorted in investment decisions than their small counterparts. For SOEs, $\log(MP_k)$ decreases with firm size first, and then increases for the top 20% of firms by assets. Furthermore, SOEs face lower $\log(MP_k)$ than non-SOEs across different firm sizes.

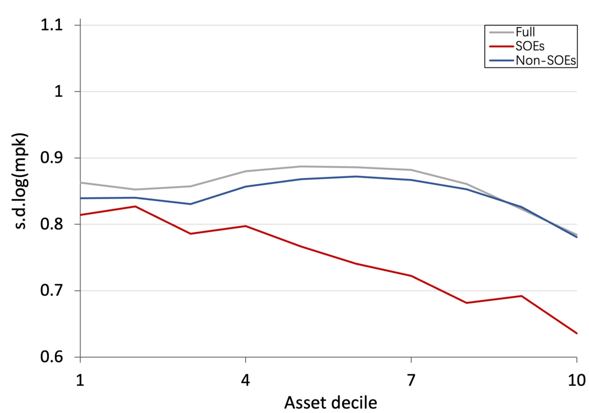
Figure 2.2 panel (b) presents the variation of the dispersion of $\log(MP_k)$ by firm size. The standard deviation of $\log(MP_k)$ among SOEs decreases with firm size and is lower

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

than non-SOEs in each asset decile. The standard deviation of $\log(MP_k)$ among non-SOEs is close to that for the full sample, and it is smaller among large firms, suggesting lower capital misallocation among large firms than small firms.



(a) Firm Size and Mean of $\log(MP_k)$



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

Figure 2.2: Firm Size and $\log(MP_k)$

Note: This figure reports the relationship between firm size and $\log(MP_k)$ for SOEs, non-SOEs and the full sample. The mean and standard deviation of $\log(MP_k)$ are calculated in each asset decile.

To further examine the relationship between $\log(MP_k)$ and firm size, I obtain the correlation between firm size and $\log(MP_k)$ by industry separately for non-SOEs and SOEs. There are thirty 2-digit industries in the manufacturing sector according to the industry concordances provided by Brandt et al. (2014).[12] As shown in Table 2.1, the correlation between firm size and $\log(MP_k)$ varies across different industries by ownership. A negative correlation exists in each industry for non-SOEs. For SOEs, except for the beverage, tobacco and waste material recycling industries, firm size and $\log(MP_k)$ are negatively correlated.

Table 2.1: Correlation between Firm Size and $\log(MP_k)$ by Industry

CIC	Industry	Correlation		CIC	Industry	Correlation	
		Non-SOEs	SOEs			Non-SOEs	SOEs
13	Agri-food processing	-0.21	-0.20	28	Chemical fiber	-0.27	-0.34
14	Food	-0.20	-0.26	29	Rubber	-0.25	-0.11
15	Beverage	-0.29	0.00	30	Plastic	-0.28	-0.49
16	Tobacco	-0.43	0.64	31	Non-metallic Mineral	-0.31	-0.37
17	Textile	-0.34	-0.19	32	Ferrous metals	-0.22	-0.25
18	Apparel	-0.19	-0.31	33	Non-ferrous metal	-0.27	-0.19
19	Leather	-0.10	-0.11	34	Hardware	-0.20	-0.18
20	Timber processing	-0.36	-0.42	35	General equipment	-0.20	-0.11
21	Furniture	-0.24	-0.46	36	Professional equipment	-0.14	-0.12
22	Paper	-0.29	-0.33	37	Transportation	-0.19	-0.14
23	Printing	-0.19	-0.24	39	Electric machinery	-0.12	-0.24
24	Stationery/sporting	-0.24	-0.51	40	Communication device	-0.16	-0.22
25	Petrochemical	-0.33	-0.25	41	Instrument	-0.11	-0.33
26	Chemistry	-0.25	-0.34	42	Handicrafts/daily sundries	-0.28	-0.41
27	Pharmaceutical	-0.08	-0.07	43	Waste material recycling	-0.05	0.96

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*.

2.2.3 Financing Patterns

Financial frictions play a role in capital misallocation through firms' characteristics, on which firms' financing patterns depend. To see how the leverage ratio varies across different size groups, I calculate the average of leverage by asset quantiles separately for SOEs and non-SOEs, which is shown in Figure 2.3. First, credit discrimination exists in the Chinese credit market across firms of different ownership types. As Figure 2.3 shows, SOEs

[12] 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.

have a higher leverage ratio than non-SOEs, since 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. The result is consistent with existing literature. For example, Dollar and Wei (2007) and Song et al. (2011) report that SOEs rely more on domestic bank loans to finance investments than non-SOEs. Poncet et al. (2010) and Curtis (2016) also suggest that private Chinese firms are credit constrained, while SOEs are not.

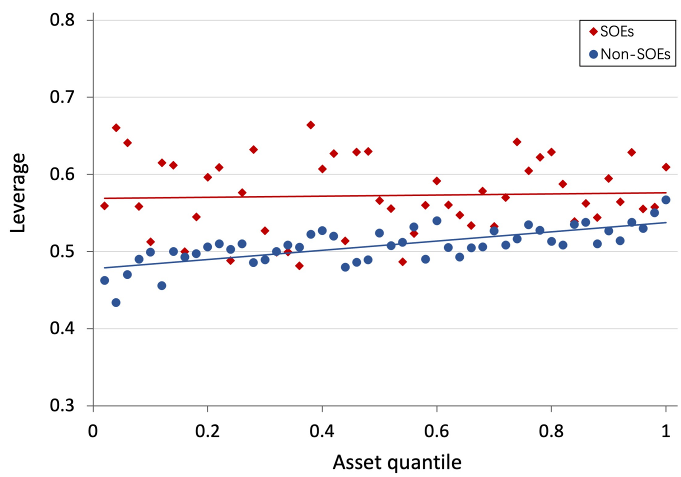


Figure 2.3: Firm Size and Leverage

Note: This figure reports the relationship between firm size and leverage for SOEs, non-SOEs and the full sample. The mean leverage ratio is calculated in each asset quantile (50 quantiles).

Second, SOEs and non-SOEs demonstrate different financing patterns. As Figure 2.3 shows, the leverage ratio of firms fluctuates with firm size, and large non-SOEs tend to have a higher leverage ratio than their small counterparts with an upward-sloping fitted line. In contrast, SOEs do not demonstrate a size-dependent leverage trend. Similarly, Bai et al. (2018) document that among private firms, large firms are more leveraged. Boyreau-

Debray and Wei (2005) also suggest that all types of banks prefer to lend to SOEs and large private firms in China.

To further compare the financing patterns between SOEs and non-SOEs, this paper examines the relationship between firm size and leverage by regression. The regression model is given by the following:

$$lev_{ict} = \beta_0 + \beta_1 size_{ict} + dummy + u_{ict} \tag{2.1}$$

where i denotes the firm, c denotes the 4-digit industry and t denotes the year. The dependent variable is leverage and measured by the debt-to-asset ratio. $size_{ict}$ 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 2.2 reports the regression results of leverage on firm size separately for non-SOEs and SOEs. The leverage-size slope among non-SOEs is significantly 0.026, implying that leverage increases with firm size within non-SOEs, consistent with the existing literature. In addition, the regression coefficient of leverage on firm size is insignificantly -0.003 among SOEs, suggesting that firm size has no statistically significant relationship with leverage for those firms.

Discussion. The above evidence suggests the presence of capital misallocation among Chinese manufacturing firms. Since SOEs have easy access to external finance and are not financially constrained, the dispersion of the marginal product of capital and the negative relationship between firm size and the marginal product of capital among those firms may mainly be attributed to factors other than financial frictions. In contrast, non-

Table 2.2: Regression Coefficients of Leverage on Firm Size

Variable	Leverage	
	Non-SOEs	SOEs
Size	0.026***	-0.003
	(0.0008)	(0.0028)
Constant	0.296***	0.640***
	(0.0187)	(0.0623)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
R-squared	0.03	0.04
Number of obs	205,246	32,554

Note: This table reports the regression results for leverage on firm size separately for non-SOEs and SOEs. ***, ** and * denote results significantly different from zero at the 1%, 5% and 10% levels. Standard errors are in parentheses.

SOEs face a more significant dispersion of the marginal product of capital, and have less access to bank loans and lower leverage than SOEs. Moreover, large non-SOEs face both a lower marginal product of capital and higher leverage than their small counterparts. Because firms' financing ability directly affects their capital decisions, the remainder of the paper will mainly focus on non-SOEs. I will examine how the financial frictions driven by firms' financing patterns, which correspond to the size-dependent financial frictions, explain the observed patterns of capital misallocation among non-SOEs.

Since the presence of SOEs also contributes to the dispersion of the marginal product of capital, capital misallocation and TFP loss will be underestimated when only considering non-SOEs. Nonetheless, as discussed in Section 2.2.2, since SOEs account for only a minor fraction of the data, the dispersion of the marginal product of capital for non-SOEs is quite close to that of the full sample. This indicates that the majority of capital misallocation and TFP loss in China results from the distortions faced by non-SOEs.

2.3 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 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.

2.3.1 Firms

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

$$y_{it} = z_{it}^{1-\eta}(l_{it}^{\alpha}k_{it}^{1-\alpha})^{\eta} \tag{2.2}$$

where η governs the span of control, which measures the degree of diminishing return to scale at the firm level as in Lucas (1978); 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 period t. Firms borrow d_{it+1} to finance capital k_{it+1} according to the new productivity z_{it+1}.[13] This convenient

[13]As discussed in Moll (2014), the model in which firms own and accumulate capital is equivalent to the

assumption makes capital measurable to productivity and enables this paper to focus on capital misallocation due to financial frictions.[14] 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:

$$\max_{\{c_{it},l_{it},k_{it+1},d_{it+1}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \log(c_{it}) \tag{2.3}$$

subject to the budget constraint given by

$$c_{it} + k_{it+1} - (1-\delta)k_{it} = y_{it} - \omega l_{it} - (1+r)d_{it} + d_{it+1} \tag{2.4}$$

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

$$d_{it+1} \leq \theta_0 k_{it+1} + \theta_1 \Phi(k_{it+1}) \tag{2.5}$$

where parameters θ_0 and θ_1 jointly govern the borrowing tightness. The borrowing constraint arises because the contract has limited enforceability, and borrowers can choose to default. In the event of default, a firm reneges on a fraction μ_0 of its debt d_{it+1}; as a penalty, the bank seizes a fraction μ_1 of the undepreciated capital $(1-\delta)k_{it+1}$. In addition, there is a disruption cost $\Phi(k_{it+1})$ that the firm has to pay at default, which may arise due to a loss of suppliers, market share, reputation, etc. In equilibrium, banks extend their

setup with a rental market of capital.

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

credit only to the extent that no firm will renege on the contract. Therefore, the amount of debt that the firm can borrow is limited. The default-deterring borrowing limit satisfying the incentive compatibility constraint is endogenously given by the forgone revenues of firms at default. The derivation of the borrowing constraint is shown in Appendix A.2.1.[15]

Considering that larger firms lose more in the event of default, the disruption cost $\Phi(k)$ is assumed to be an increasing and convex function of capital k.[16] Because the disruption costs increase in capital, it is more costly for large firms to default than small firms, which makes debt redemption more valuable and relaxes the borrowing limit in the no-default equilibrium as firm size increases. The functional form of the disruption costs is assumed to be $\Phi(k) = k^2$, 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

$$(d/k)^{max} = \theta_0 + \theta_1 k \tag{2.6}$$

If $\theta_1 = 0$, all firms face a single borrowing tightness. As long as θ_1 is positive, the maximum attainable leverage $(d/k)^{max}$ is an increasing function of capital k, which

[15] Most of the existing literature on misallocation focuses on financial constraints that are motivated by a limited commitment problem, for example, Moll (2014) and Buera and Moll (2015). This paper extends the underlying logic of the borrowing constraint in the existing literature and obtains a default-deterring credit limit increasing with firm size. The underlying logic of the borrowing constraint in this paper is also similar to that in Azariadis, Kaas, and Wen (2016). In their paper, the greater expected payoff from access to unsecured credit in the future with a clean credit reputation makes debt redemption more valuable, which relaxes the default-deterring credit limit.

[16] The costs of default include both direct and indirect costs (Warner, 1977). Direct costs, such as legal and administrative costs, are straightforward to measure but relatively trivial for firms. Since firm size is a proxy for the complexity of a case at default, a positive relationship between direct costs and firm size has been reported (Deis et al., 1995). Indirect costs include the loss of sales and profits, disruptions in the customer-supplier relationship, a decline in market share, losses due to managerial distraction, etc. These are much more difficult to measure but nontrivial for firms (Davydenko et al., 2012). Bhabra and Yao (2011) find that firm size is also positively correlated with indirect default costs.

implies that large firms will face lower borrowing tightness than small firms. Since the borrowing constraint nests the most studied constraint with the size-invariant borrowing tightness as in Moll (2014) and Buera and Moll (2015), it facilitates the comparison of the size-dependent borrowing constraint with the existing literature and also simplifies some of the computation. 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 cases. Also, there may exist alternative specifications of size-dependent borrowing constraints, e.g., borrowing constraint with size-dependent pledgeability and earnings-based borrowing constraint, that also account for the cross-sectional moments in the data. The alternative borrowing constraints are discussed in Appendix A.3.

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

$$V(a, z) = \max_{a',c} \log(c) + \beta EV(a', z') \tag{2.7}$$

subject to the budget constraint given by

$$c + a' = \pi + (1 + r)a \tag{2.8}$$

The borrowing constraint can be rewritten as

$$k' \leq \lambda_0 a' + \lambda_1 k'^2 \tag{2.9}$$

The firm solves the profit maximization problem

$$\pi(a, z) = \max_{k,l} z^{1-\eta}(l^{\alpha}k^{1-\alpha})^{\eta} - \omega l - (r + \delta)k \tag{2.10}$$

$$s.t. \quad k \leq \lambda_0 a + \lambda_1 k^2 \tag{2.11}$$

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 A.2.2 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 (2.11).[17] Then, the firm chooses consumption c and net worth a' subject to the budget constraint in equation (2.8) and the borrowing constraint in equation (2.9).

The Euler equation can be solved as

$$\frac{1}{c(a, z)} = \beta E \left\{ \frac{1}{c(a', z')} \left[(1 + r) + \mu(a', z')\lambda_0 \right] \right\} \tag{2.12}$$

where $\mu(a, z)$ is the Lagrangian multiplier on the borrowing constraint. Since a' appears in the borrowing constraint in equation (2.9), the expectation of a binding borrowing constraint increases 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 also tend to accumulate internal funds.

[17] The net worth is divided between capital and debt.

Firms choose labor l and capital k to maximize their profit subject to the borrowing constraint in equation (2.11). $FOCs$ with respect to labor l and capital k are given by

$$\alpha\eta\frac{y(a,z)}{l(a,z)} = \omega \tag{2.13}$$

$$(1-\alpha)\,\eta\frac{y(a,z)}{k(a,z)} = r + \delta + \mu(a,z)\left[1 - 2\lambda_1 k(a,z)\right] \tag{2.14}$$

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 (2.11):

$$g(k) \equiv \lambda_0 a + \lambda_1 k^2 - k \tag{2.15}$$

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

$$k_{1,2} = \frac{1 \pm \sqrt{1 - 4\lambda_0\lambda_1 a}}{2\lambda_1},\ where\ k_1 \leq k_2 \tag{2.16}$$

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 2.4 presents the curve for the function $g(k)$.

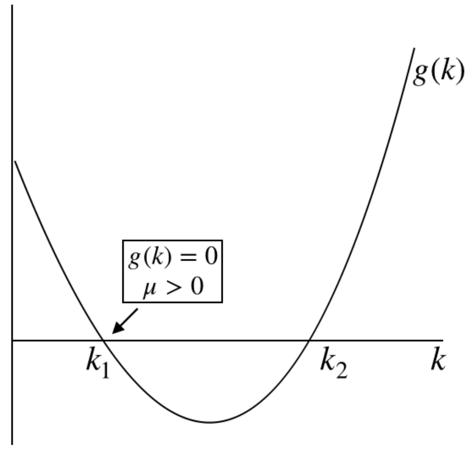


Figure 2.4: Graph for Function $g(k)$

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.

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:

$$k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}} z \tag{2.17}$$

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

$$k^c = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}, \quad \textit{and} \quad k^c \leq k^u \tag{2.18}$$

Proof. *See Appendix A.2.3.*

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.

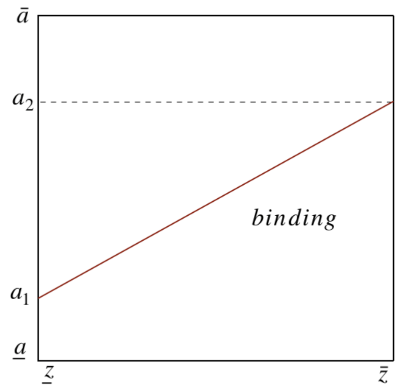
Proposition 2: *Under the homogeneous borrowing constraint, given productivity z, the cutoff net worth for the bindingness of the borrowing constraint is $a^* = \frac{k^u(z)}{\lambda_0}$. When $a \leq a^*$, the borrowing constraint is binding; when $a > \frac{k^u(\bar{z})}{\lambda_0}$, the borrowing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

Proof. *See Appendix A.2.4.*

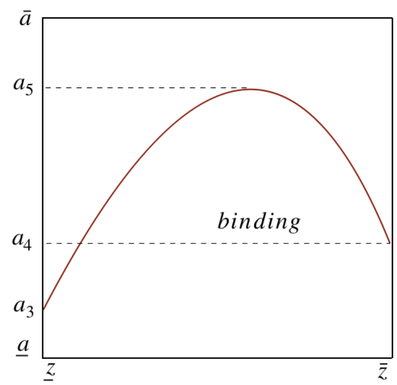
Proposition 3: *Under the size-dependent borrowing constraint, given productivity z, the cutoff net worth for the bindingness of the borrowing constraint is $a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1}$. When $a \leq a^*$, the borrowing constraint is binding; when $a > \frac{1}{4\lambda_0\lambda_1}$,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

Proof. *See Appendix A.2.5.*

Figure 2.5 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 2.5 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



(a) Homogeneous Borrowing Constraint



(b) Size-dependent Borrowing Constraint

Figure 2.5: 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.

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 2.5 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 sufficiently large, capital k^u with respect to productivity will be high, which in turn enables those firms (even without high net worth) 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 constrained by the financial frictions.

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 face a lower MP_k; financially unconstrained firms face a constant $MP_k = r + \delta$.

2) Given net wealth a, financially unconstrained firms with higher productivity z face a constant $MP_k = r + \delta$; financially constrained firms with higher productivity z face a higher MP_k.

Proof. *See Appendix A.2.6.*

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 a^* for bindingness given productivity z be $\frac{k^u(z)}{\lambda_0}$, and the cutoff productivity for bindingness given net worth a be z^*. Given productivity z, when $a \in [\underline{a}, a^*]$, firms are constrained. Firms with larger net worth face a lower MP_k. Given net worth $a \in (a_1, a_2]$, when productivity $z \in [\underline{z}, z^*)$, firms are unconstrained and $MP_k = r+\delta$; when productivity becomes large, e.g., $z \in [z^*, \bar{z}]$, firms are constrained, and firms with higher productivity face a higher MP_k. Further details can be seen in Appendix A.2.6. Overall, with the homogeneous borrowing constraint, given productivity, firms with higher net worth are less likely to be constrained and tend to face a lower MP_k. Given net wealth, firms with higher productivity are more likely to be constrained and face a higher MP_k.

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

1) Given productivity shock z, financially constrained firms with higher net worth a face a lower MP_k; financially unconstrained firms face a constant $MP_k = r + \delta$.

2) Given net wealth a, financially unconstrained firms with higher productivity z face a constant $MP_k = r + \delta$; financially constrained firms with higher productivity z face a higher MP_k.

3) Firms with sufficiently large productivity shock z are financially unconstrained and face a constant $MP_k = r + \delta$.

Proof. *See Appendix A.2.7.*

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 a^* for bindingness given productivity z be $\frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1}$, and the cutoff productivities for bindingness given net worth a be z_1^* and z_2^*. Different from the homogeneous borrowing constraint, the relationship between productivity and the marginal product of capital now is nonmonotonic. That is, given net worth $a \in (a_4, a_5]$, when $z \in [z_1^*, z_2^*]$, firms are constrained; firms with higher productivity z face a higher MP_k. However, when productivity is sufficiently large, e.g., $z \in (z_2^*, \bar{z}]$, firms even without high net worth a are financially unconstrained. This is because those highly productive firms will accumulate sufficient capital, which in turn enables them to relax the borrowing constraint and face a low MP_k. Further details are given in Appendix A.2.7.

2.3.2 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:

$$V(a^w, v) = \max_{c^w, a^{w'}} \log(c^w) + \beta EV(a^{w'}, v') \tag{2.19}$$

subject to the budget constraint that

$$c^w + a^{w'} = \omega v + (1+r)a^w \tag{2.20}$$

where ω 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.

2.3.3 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 (2.7) and (2.19);

2. Market clear

(i) Labor market

$$L = \int l(a,z)dn(a,z) \tag{2.21}$$

(ii) Asset market

$$A^{w'} + \int a'(a,z)dn(a,z) = \int k'(a,z)dn(a,z) \tag{2.22}$$

(iii) Goods market

$$C + I = Y \tag{2.23}$$

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 productivity 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.

2.3.4 TFP Loss

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

$$Y = \frac{\left(\int_i z_i MP_{ki}^{-\frac{(1-\alpha)\eta}{1-\eta}} di\right)^{1-\alpha\eta}}{\left(\int_i z_i MP_{ki}^{\frac{\alpha\eta-1}{1-\eta}} di\right)^{(1-\alpha)\eta}} (L^{\alpha} K^{1-\alpha})^{\eta} \tag{2.24}$$

The aggregate measured TFP is then defined as

$$TFP = \frac{\left(\int_i z_i MP_{ki}^{-\frac{(1-\alpha)\eta}{1-\eta}} di\right)^{1-\alpha\eta}}{\left(\int_i z_i MP_{ki}^{\frac{\alpha\eta-1}{1-\eta}} di\right)^{(1-\alpha)\eta}} \tag{2.25}$$

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

$$TFP^e = \left(\int_i z_i di\right)^{1-\eta} \tag{2.26}$$

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

$$TFP\ loss \equiv \log(TFP^e) - \log(TFP) \tag{2.27}$$

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

2.4 Calibration

The model is annual. Parameters are calibrated to match the Chinese economy. Table 2.3 presents the calibration results for the model with the size-dependent borrowing constraint. The labor efficiency v follows a two-state Markov process, and 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, implying that the fraction of workers that supply labor is 72% in any period.[18]

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

$$\Theta = \{\beta, \eta, \delta, \rho, \sigma_\varepsilon, \lambda_0, \lambda_1\} \tag{2.28}$$

such that the distance between the moments generated by the model and moments from the Chinese data, is minimized. The efficiency of the SMM requires the target moments to 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 real interest rate. Following Bai et al. (2018), I choose a targeted real interest rate of 5%, matching the average real interest rate of the US during the sample period. As a result, the discount factor $\beta = 0.889$. As discussed in

[18] 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.

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 the 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 the span of control η. Bai and Qian (2010) estimate that the labor share in the Chinese industrial sector decreased from 0.49 in 1998 to 0.42 in 2004. In this paper, I set the labor share to 0.45. 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 0.592. The capital depreciation rate δ is set to match the aggregate capital-to-output ratio. The discount factor $\delta = 0.061$, which is within the range of empirical evidence on capital depreciation in China.[19]

The idiosyncratic productivity z_{it} is assumed to follow an AR(1) process,

$$\log(z_{it}) = \rho \log(z_{it-1}) + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \tag{2.29}$$

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 first-order autocorrelation of the

[19] 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.

output, which is 0.87, and (2) the standard deviation of the output growth rate, which equals 0.62. The firm-level moments are based on the sample of Chinese non-SOEs for the period 1998-2007. As a result, the persistent component ρ is 0.831, which is consistent with the existing literature. The standard deviation of the transitory shock $\sigma_\varepsilon = 0.781$, which is large to generate firm dynamics.

Table 2.3: Calibration Results

Parameter	Description	Value	Source/target
p_u	Persistence zero state	0.5	Employment ratio
p_e	Persistence unit state	0.806	
β	Discount factor	0.889	Real interest rate
η	Span of control	0.760	Output share by top 5 output percentiles
α	Labor elasticity	0.592	Labor share $\alpha\eta$ equals 0.45
δ	Depreciation rate	0.061	Aggregate capital-to-output ratio
ρ	Persistent component	0.831	1-year autocorrelation of output
σ_ε	S.D. transitory shock	0.781	S.D. output growth
λ_0	Borrowing tightness	1.915	Aggregate debt-to-output ratio
λ_1	Borrowing tightness	0.010	Regression coefficient of leverage on firm size

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

Parameters λ_0 and λ_1 jointly govern the borrowing tightness and determine firms' financing patterns. In addition, λ_1 is primarily related to the leverage-size slope.[20] Thus, the moments used to pin down parameters λ_0 and λ_1 are (1) the regression coefficient of the leverage ratio on firm size, which is 0.03, and (2) the aggregate debt-to-output ratio.[21] Based on data from the World Bank, the average domestic credit to the private sector (% GDP) during the period 1998 to 2007 is 113%. As a result, λ_0 is 1.915, and λ_1 is

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

[21] 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.

0.01. Under the size-dependent borrowing constraint, the implied maximum leverage ratio is $(d/k)^{max} = 0.478 + 0.005k$, which increases in capital.[22]

Table 2.4 reports the values of the target moments used to calibrate the parameters in the data and in the model. The model fits the data quite closely.

Table 2.4: Model Fit

Moment	Data	Model
Real interest rate	0.05	0.05
Output share by top 5 output percentiles	0.39	0.39
Aggregate capital-to-output ratio	2.30	2.29
1-year autocorrelation output	0.87	0.88
S.D. output growth	0.62	0.62
Aggregate debt-to-output ratio	1.13	1.14
Regression coefficient of leverage on firm size	0.03	0.03

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

2.5 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.

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

2.5.1 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 2.6 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.

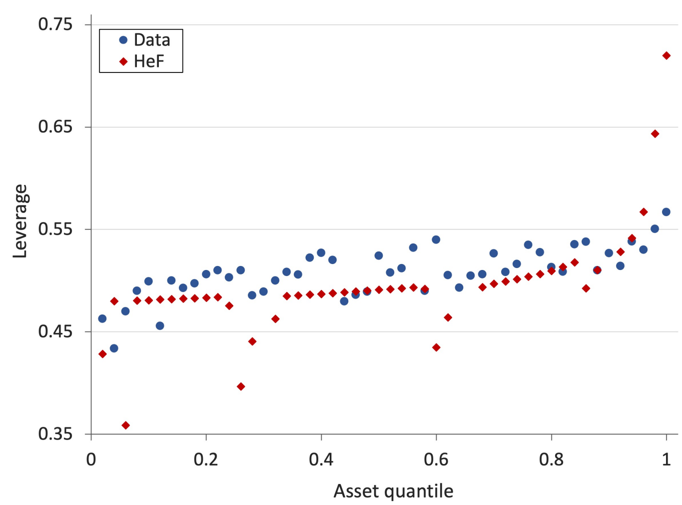


Figure 2.6: Firm Size and Leverage in the Data and HeF

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 2.7 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 47% and 62% of the total output. The output distribution is highly skewed, and the output is concentrated in large firms.

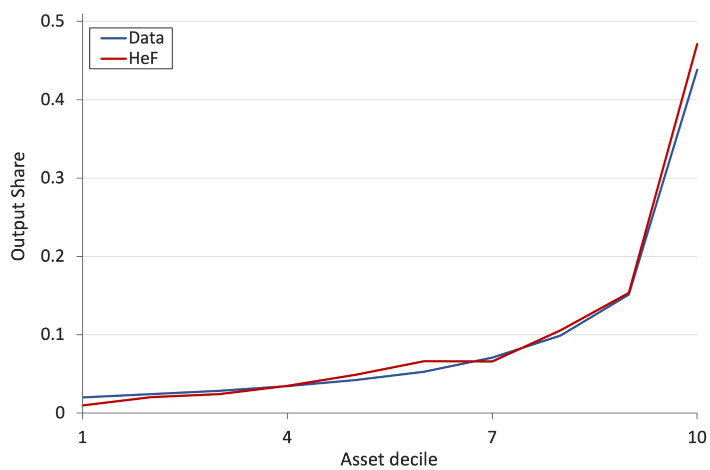


Figure 2.7: Output Distribution in the Data and HeF

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 2.5 reports non-targeted moments in the data and the 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 (1.24) 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 a 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 1.11, which is lower than the data. As discussed in Section

2.3, without distortions, the marginal product of capital across firms should be equal; 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, that contribute to capital misallocation.[23] 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 $\log(MP_k)$.

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. Thus, the model with the size-dependent borrowing constraint generates a negative correlation between $\log(MP_k)$ and net worth $\log(A)$. Since firms with higher productivity tend to have a larger financing need and are more likely to be financially constrained, the model generates a positive correlation between $\log(MP_k)$ and productivity $\log(Z)$ of 0.54. Moreover, since productivity is the primary determinant of output and firms with higher productivity tend to produce more, there is a positive correlation between $\log(MP_k)$ and $\log(Y)$. Furthermore, as large firms are less constrained under the size-dependent borrowing constraint, the correlation between $\log(MP_k)$ and firm size is -0.16, which is consistent with

[23] See David and Venkateswaran (2019), which studies the various sources of the measured capital misallocation in China and the US.

Table 2.5: Non-targeted Firm-level Moments in the Data and HeF

Moment	Data	HeF
A. Distributional Moment		
S.D. log output	1.22	1.24
Output share by top 10 output percentiles	0.54	0.52
Output share by top 20 output percentiles	0.70	0.67
3-year autocorrelation output	0.76	0.67
S.D. capital growth	0.46	0.55
S.D. log capital	1.41	1.2
1-year autocorrelation capital	0.95	0.89
3-year autocorrelation capital	0.87	0.72
B. Standard Deviation		
S.D. *leverage*	0.23	0.23
S.D. $\log(asset)$	1.24	1.11
S.D. $\log(MP_k)$	0.89	0.31
C. Correlation with $\log(MP_k)$		
Corr. of $\log(MP_k)$ and $\log(A)$	-0.21	-0.3
Corr. of $\log(MP_k)$ and $\log(Z)$	0.65	0.54
Corr. of $\log(MP_k)$ and $\log(Y)$	0.26	0.27
Corr. of $\log(MP_k)$ and $\log(asset)$	-0.23	-0.16

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 key variables. Panel C shows the correlations with marginal product of capital.

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 resources and the measure of producers as in the model, the planner allocates resources efficiently across firms. The marginal product of capital is equalized across firms in the efficient allocation. Table 2.6 reports the aggregate implications of both the efficient allocation and the model. The presence of financial frictions restrains capital allocation efficiency and aggregate output, as the aggregate capital-to-output ratio under financial frictions is higher than the first-best allocation with the same amount of aggregate capital. The fraction of firms that are financially constrained is 0.52, and the TFP loss in the model relative to the undistorted economy is 3.91%.

The TFP loss due to size-dependent financial frictions in the model 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.

Table 2.6: Aggregate Implications in the HeF

	Efficient	HeF
Capital-to-output ratio	2.19	2.29
Fraction constrained	0	0.52
TFP loss (%)	0	3.91

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

2.5.2 The Effect of Size-dependent Financial Frictions

To examine the effect 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 A.4 reports the calibration results and non-targeted moments. In the HoF model with the homogeneous borrowing constraint, $\lambda_0 = 2.498$, which implies that the maximum attainable leverage ratio[24] for any firm is 0.6.[25]

Non-targeted Moments. Table 2.7 reports the non-targeted moments. The standard deviations of leverage and $\log(MP_k)$ in both models are quite close. A negative correlation between $\log(MP_k)$ and net worth $\log(A)$ exists in both cases, since firms with higher net worth have stronger financing ability and are less likely to be affected by financial frictions. However, this negative correlation is strong in the HeF (-0.3) than the HoF (-0.19), as firms even without sufficient net worth are able to eliminate the borrowing constraint and face low marginal product of capital in the HeF case. A positive correlation between $\log(MP_k)$ and $\log(Z)$ also exists in the HoF case, since firms with higher productivity have a stronger financing need and are more likely to be constrained. However, since some highly productive firms in the HeF case will accumulate sufficient capital and relax the borrowing constraint, the HeF case generates a weaker correlation between $\log(MP_k)$ and $\log(Z)$ (which is 0.54) than the HoF case (0.58). Accordingly, the HeF model with the size-dependent borrowing constraint generates a smaller correlation between $\log(MP_k)$ and $\log(Y)$ than the HoF case.

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 2.7, the HoF model without taking into account firms' financing patterns fails to reproduce the correlation between firm size and $\log(MP_k)$, as it equals zero. The correlation is -0.16 instead in the HeF case with the size-dependent borrowing constraint.

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

Both firm size and marginal product of capital depend on firms' productivity and financing ability. When $\lambda_1 = 0$ with the homogeneous borrowing constraint, given productivity, firms with higher net worth tend to accumulate more capital and face a lower MP_k; given net worth, firms with higher productivity tend to be larger and face a higher MP_k. These two opposing forces shape 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 close to zero. By contrast, in the HeF model with positive λ_1, some highly productive firms accumulate sufficient capital and relax the borrowing constraint. Therefore, the positive correlation between the marginal product of capital and productivity is weaker, and large firms face a lower MP_k than in the case under the homogeneous borrowing constraint. This additional channel making large firms less distorted by financial frictions accounts for the negative correlation between firm size and $\log(MP_k)$ in the HeF.

Table 2.7: Non-targeted Firm-level Moments in the HeF and HoF

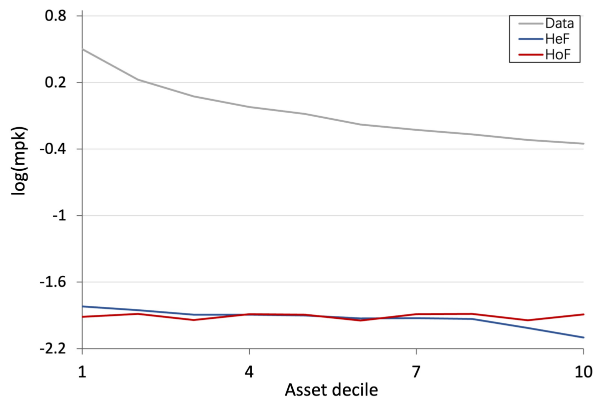
Moment	HeF	HoF
A. Standard deviation		
S.D. *leverage*	0.23	0.26
S.D. $\log(asset)$	1.11	1.28
S.D. $\log(MP_k)$	0.31	0.29
B. Correlation with $\log(MP_k)$		
Corr. of $\log(MP_k)$ and $\log(A)$	-0.3	-0.19
Corr. of $\log(MP_k)$ and $\log(Z)$	0.54	0.58
Corr. of $\log(MP_k)$ and $\log(Y)$	0.27	0.32
Corr. of $\log(MP_k)$ and $\log(asset)$	-0.16	0

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

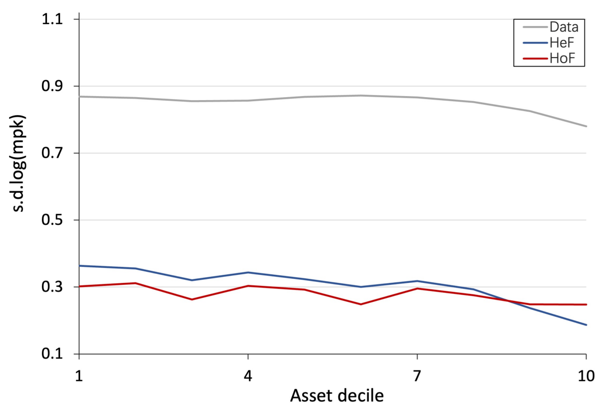
To further study the pattern of $\log(MP_k)$ across different size groups, I compute and compare the mean and standard deviation of $\log(MP_k)$ conditional on asset deciles.

Figure 2.8 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. 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. The standard deviations of $\log(MP_k)$ in the two models also vary across different size groups. As shown in Figure 2.8 panel (b), with the size-dependent borrowing constraint, the standard deviation of $\log(MP_k)$ decreases from 0.37 to 0.18 as firm size increases. The dispersion of $\log(MP_k)$ among large firms (top 20% by assets) is also smaller in HeF than in HoF.

Although the model with the size-dependent borrowing constraint is able to reproduce the patterns of the marginal product of capital by firm size, they are more muted than in the data. In panel (a), the downward trend of $\log(MP_k)$ in HeF is fatter than in the data, implying that other factors may also contribute to the negative relationship. The standard deviation of $\log(MP_k)$ in HeF is also smaller than in the data, suggesting the existence of other distortions in addition to financial frictions resulting in misallocation. As discussed in David and Venkateswaran (2019), adjustment and information frictions account for relatively modest fractions of the misallocation among Chinese firms, and the predominant drivers lie in firm-specific factors, especially the size/productivity-dependent policies. Therefore, other factors, e.g., adjustment and information frictions, and firm-specific distortions, in addition to size-dependent financial frictions may explain the gap in the marginal product of capital between the HeF case and data.



(a) Firm Size and Mean of log(MP_k)



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

Figure 2.8: 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 with the size-dependent borrowing constraint and the HoF with the homogeneous borrowing constraint. The mean and standard deviation of log(MP_k) are calculated in each asset decile.

Aggregate Implications. Table 2.8 reports the aggregate implications. As shown in the 7th row, the fractions of firms that are financially constrained at steady state in the two models are quite close. The fraction of firms that are constrained in each asset quartile is computed and compared (rows 3-6). In the HeF model, 60% of firms in the first asset quartile are constrained, which decreases to 49% in the fourth quartile. Large firms (the fourth asset quartile) are less likely to be financially constrained in HeF than in HoF.

Table 2.8 shows the TFP loss in the two models. Whether firms' financing pattern (the positive leverage-size slope) is considered affects the measured TFP loss. The TFP loss in the HeF model is 3.91%, which is smaller than in the HoF case (5.08%).[26] As discussed above, in the HeF model with the size-dependent borrowing constraint, some highly productive firms accumulate sufficient capital and eliminate the borrowing constraint. Thus, the marginal product of capital is less correlated with productivity than in the HoF case. Since large (or highly productive) firms, which contribute to the majority of output, are actually less distorted by financial frictions with both a lower mean and standard deviation of $\log(MP_k)$, the model generates a smaller TFP loss under the size-dependent financial frictions than in the HoF case.

Table 2.8: Aggregate Implications in the HeF and HoF

	HeF	HoF
Fraction Constrained		
Q1	0.60	0.46
Q2	0.54	0.59
Q3	0.51	0.47
Q4	0.49	0.58
Total	0.52	0.52
TFP loss (%)	3.91	5.08

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

Overall, the model with a size-dependent borrowing constraint is more suitable for matching the Chinese firm-level moments than the alternative. The model predicts a negative correlation between firm size and the marginal product of capital, which is a

[26] Instead of recalibrating λ_0 while setting λ_1 to zero as in the HoF case, I also calculate TFP loss by holding all other parameters fixed while setting λ_1 to zero. In this case, the standard deviation of $\log(MP_k)$ is 0.37, the correlation between $\log(MP_k)$ and $\log(Z)$ is 0.64. And the TFP loss is 5.54%, which is also larger than the HeF case.

feature lacking in the HoF model with the homogenous borrowing constraint. In addition, the model generates both a lower mean and standard deviation of the marginal product of capital among large firms than the HoF model. Without considering the size-dependent financial policy, the TFP loss may be overestimated, since large firms, which contribute the most to the economy, are more leveraged and less distorted by financial frictions.

2.5.3 Sensitivity Analysis

Since under the size-dependent borrowing constraint, the borrowing tightness parameter λ_1 plays an essential role in the firm's financing patterns, this subsection examines the impacts of λ_1 on capital misallocation. Table 2.9 reports the moments in terms of financing pattern and capital misallocation. Column 2 presents the moments in the baseline HeF model with $\lambda_1 = 0.01$, 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 2.9, 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 also 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.

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 net worth and $\log(MP_k)$ becomes stronger. Firms with high productivity are less likely to be constrained than previously,

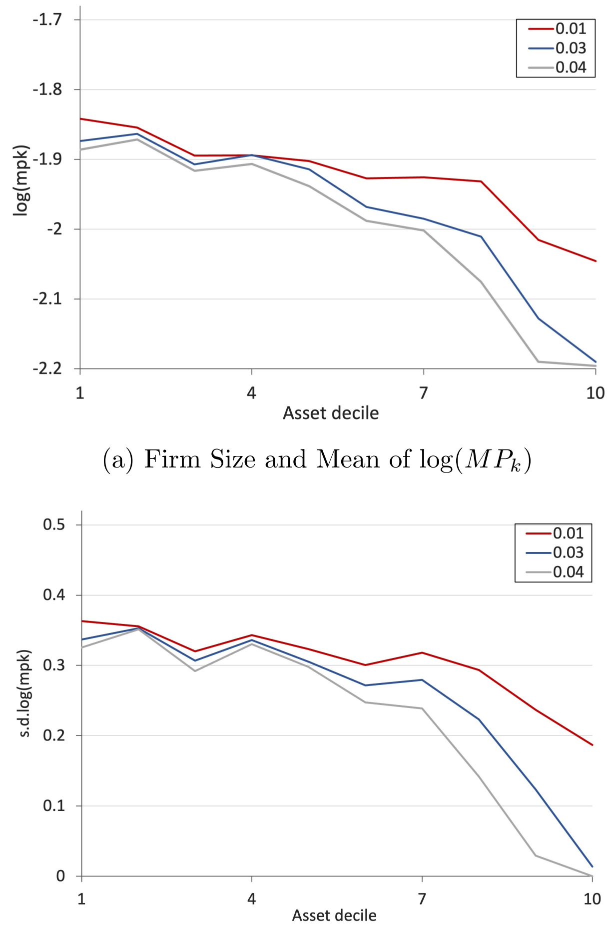
Table 2.9: Firm-level Moments in the Sensitivity Analysis

λ_1	0.01	0.03	0.04
A. Financing Pattern			
leverage-size slope	0.03	0.06	0.07
Debt-to-output ratio	1.14	1.57	1.67
B. Standard Deviation			
S.D. *leverage*	0.23	0.26	0.27
S.D. log($asset$)	1.11	1.25	1.28
S.D. log(MP_k)	0.31	0.29	0.28
C. Correlation with log(MP_k)			
Corr. of log(MP_k) and log(A)	-0.3	-0.42	-0.45
Corr. of log(MP_k) and log(Z)	0.54	0.34	0.28
Corr. of log(MP_k) and log(Y)	0.27	0.08	0.02
Corr. of log(MP_k) and log($asset$)	-0.16	-0.29	-0.32

Note: This table reports the firm-level moments in the baseline HeF model with $\lambda_1 = 0.01$ and for $\lambda_1 = 0.03$ and $\lambda_1 = 0.04$. Panel A reports financing patterns. Panel B presents the standard deviations of key variables. Panel C shows the correlations with the marginal product of capital.

and thus the positive correlation between productivity and log(MP_k) 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 2.9 presents the mean and standard deviation of log(MP_k) conditional on asset deciles in the baseline HeF model with $\lambda_1 = 0.01$ 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.



(a) Firm Size and Mean of $\log(MP_k)$

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

Figure 2.9: 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 $\lambda_1 = 0.01$ 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.

Table 2.10 reports the aggregate implications. As λ_1 increases, the fraction of firms that are constrained becomes smaller accordingly. In addition, the fraction constrained decreases more among large firms. When λ_1 increases from 0.01 to 0.03, the fraction constrained in the fourth asset quartile decreases from 0.49 to 0.21 (decreased by 57%), and when $\lambda_1 = 0.04$, only 12% of the firms are constrained in that size group. The TFP loss

Table 2.10: Aggregate Implications in the Sensitivity Analysis

λ_1	0.01	0.03	0.04
Fraction Constrained			
Q1	0.60	0.61	0.52
Q2	0.54	0.54	0.59
Q3	0.51	0.46	0.40
Q4	0.49	0.21	0.12
Total	0.52	0.46	0.41
TFP loss (%)	3.91	2.28	1.93

Note: This table reports the aggregate implications in the baseline HeF model with $\lambda_1 = 0.01$ 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).

decreases accordingly, as firms, especially large firms, are less financially constrained when the leverage-size slope increases.

2.6 Conclusion

This paper studies the impacts of financial frictions on capital misallocation and aggregate productivity 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 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 3.91%, which is modest and can be rationalized by firms' self-financing. Moreover, the TFP loss may be overstated 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 firms' entry and technology adoption decisions than on the intensive margin through capital misallocation. In addition, this paper studies resource misallocation among non-SOEs in the Chinese manufacturing sector. In the future, I will investigate the impacts of cross-sector resource misallocation on aggregate productivity.

Chapter 3

Financial Development, Resource Reallocation and Aggregate Productivity

3.1 Introduction

Over the past several decades, China has undergone rapid economic growth, the credit of which has been attributed mainly to the economic reform policies starting from 1978.[1] During the economic transition, the major reform in the financial sector, including the re-establishment of the central bank, the setup and reform of commercial banks, the emergence of non-bank financial institutions, and the development of the stock market, has taken place.[2] Despite the large expansion of the financial sector, the coexistence of

[1] See Borensztein and Ostry (1996), Young (2003), Song et al. (2011), among others.

[2] For example, Huang et al. (2013) review the financial reform in China and summarize the policy changes in central banking, banking sector, capital markets, and capital account.

misallocation of financial resources and rapid economic growth is puzzling,[3] which attracts substantial interest in the relationship between financial development and economic growth in China.[4]

This paper aims to quantitatively assess the impacts of financial development on aggregate productivity and output during the economic transition, focusing on the following two questions. First, as financial development impacts firms' entry and investment decisions, this paper studies how financial reform contributes to the aggregate economy along the intensive and extensive margins during the economic transition. Furthermore, since the reform process is gradual, despite the substantial financial development in China, the financial sector is still quite underdeveloped today, as suggested by the state sector's dominance of financial resources.[5] This paper also explores the extent to which the current repressive financial policies potentially restrain aggregate productivity and output.

This paper develops a general equilibrium model of firm dynamics based on Midrigan and Xu (2014) by introducing the heterogeneous state-owned enterprises and private firms. Given the strong discrimination in the credit market, SOEs are assumed to face no financial frictions. Meanwhile, this paper incorporates the size-dependent financial frictions faced by private firms, considering that among the private firms, large firms face lower borrowing tightness and have higher leverage than their small counterparts. In the model,

[3]See Boyreau-Debray (2003), among others.

[4]For example, among the empirical work, Hasan et al. (2009) suggest that capital market depth has a strong influence on growth, while the impact of bank lending is not significant and even negative. Chen (2006) shows that financial intermediation development promotes economic growth by substituting loans for state budget appropriation and the mobilization of savings, while loan distribution is inefficient. Boyreau-Debray (2003) finds that credit extended by the banking sector at the state level hurts local economic growth. Huang et al. (2011) find that the impacts of repressive financial policies turned from positive in the 1980s and the 1990s to averse in the 2000s, suggesting rising efficiency losses in recent years.

[5]See Dollar and Wei (2007), Ayyagari et al. (2010), among others.

private firms operate in the unproductive informal sector upon entry. Over time, they could choose to switch into the official manufacturing sector by paying entry costs and becoming more productive. SOEs operate in the official manufacturing sector upon entry. Except for the asymmetric financial policies across the private firms and SOEs in the manufacturing sector, they also differ in the sectoral-specific productivities, motivated by the empirical fact that private firms are, on average, more productive than SOEs.

The critical factors of the model are the inclusion of size-dependent financial frictions, equity issuance, endogenous entry, and the heterogeneity in sector-specific productivities. Financial development affects aggregate productivity and output through the following channels. Firstly, private firms who decide to switch from the informal sector to the official manufacturing sector finance the entry cost and physical capital through internal funds, equity issuance, and bank loans. Since the entry cost is non-trivial, financial frictions prevent private firms from entering the formal sector and adopting productive technology, restraining the aggregate TFP and output along the extensive margin. Besides, financial frictions may prevent the incumbent private firms in the manufacturing sector from investing efficiently in response to productivity shocks, which results in capital misallocation and efficiency loss.[6] Furthermore, since private firms are more productive than SOEs, financial frictions result in resource misallocation between the private and state sectors, as the productive private firms have less access to financial resources.

The model is calibrated to the firm-level and aggregate data in China. Firstly, the aggregate implications of financial reform are studied. During the pre-reform period,

[6]Financial frictions will also have an impact on the aggregate economy by influencing labor market activities. See, Wasmer and Weil (2004), Petrosky-Nadeau (2013), among others. This paper abstracts from distortion on the labor market and mainly focuses on the role of financial frictions on capital distortion.

private firms are assumed to have no access to external finance, e.g., no bank loans or equity issuance. The size of the informal sector as a percentage of manufacturing output is 45%, and the TFP loss among private firms is 6.65%. With the financial development in the credit market and equity market, more private firms are able to enter the manufacturing sector with the increasing financing ability. The size of the informal sector decreases to 16% consequently. Besides, as capital misallocation is alleviated among private firms in the manufacturing sector, the TFP loss decreases to 3.31%. With the entry of private firms and the market becoming more competitive with higher factor prices, resources are reallocated from the less productive SOEs to the productive private firms. The size of SOEs as a percentage of manufacturing output declines to 29%. With the reallocation of productive resources to more efficient use, the aggregate TFP and output in the manufacturing sector increases by 8% and 35%, respectively.

The reallocation effects induced by the financial reform on the aggregate TFP and output changes are further decomposed by the reform policies and extensive and intensive margins. As for the reform policies, the development in the credit market accounts for 81% and 83% of the TFP and output changes, respectively. The majority of the aggregate gains are attributed to the development in the credit market, which is consistent with the fact that bank loans, especially short-term loans, are the most critical financing source for private firms in China. Furthermore, the decomposition along the margins suggests that the reallocation effects on the intensive margin account for most of the TFP and GDP gains. That is because the credit market plays a limited role in funding entry costs, and the equity market is underdeveloped as a direct financing source for firms' entry.

The potential impacts of repressive financial policies are further studied. As for the credit market policies, by reducing the borrowing tightness, the capital misallocation among private firms in the manufacturing sector is alleviated, and the TFP loss declines consequently. Besides, with the entry and expansion of private firms, the sizes of the informal sector and state sector decrease accordingly. By eliminating the financial frictions faced by private firms, the aggregate TFP and output increase by 3% and 15%, respectively. When raising equity issuance, the capital misallocation, and TFP loss among private firms in the manufacturing sector become larger. Nonetheless, with the more massive entry of private firms, the aggregate productivity and output in the manufacturing sector increase considerably.

This paper is closely related to the work that studies the impacts of financial frictions on aggregate productivity. For example, Buera et al. (2011) focus on the relationship between financial frictions and the aggregate/sector-level total factor productivity across countries. Midrigan and Xu (2014) study a two-sector growth model of firm dynamics and show that financial frictions reduce the aggregate TFP mainly by restraining firms' entry and technology adoption decisions; capital misallocation among the existing firms plays a limited role in efficiency loss. This paper extends Midrigan and Xu (2014) while differing from their work in the following aspects. Firstly, Midrigan and Xu (2014) focus on the Korean economy, and this paper studies the Chinese manufacturing sector. Secondly, instead of adopting the borrowing constraint with the homogeneous borrowing tightness, this paper considers firms' financing patterns. It introduces the size-dependent financial frictions the private firms face, motived by the empirical fact that large private firms are more leveraged than their small counterparts. Furthermore, this paper divides firms in the manufacturing sector into SOEs and private firms. By introducing the state sector in which firms are financially unconstrained, this paper studies resource reallocation within and across sectors.

This paper also relates to the literature on resource misallocation in China. Hsieh and Klenow (2009) quantify the role of distortions on aggregate manufacturing TFP using the firm-level dataset, and show that if the capital and labor were reallocated to equalize marginal products across firms to the extent of the efficiency benchmark US, the aggregate TFP gains in China would be 30 to 50 percent. This paper focuses on one specific source of distortion, e.g., financial frictions. This paper also relates to Song et al. (2011), which studies the economic transition in China and emphasizes the role of financial frictions on resource reallocation across manufacturing firms and productivity growth. Their work does not distinguish between reallocation along the extensive and intensive margins. This paper instead considers resource reallocation on both the extensive margin and the intensive margin. Liu et al. (2021) study the consequences of interest-rate liberalization in China on capital allocation and productivity based on a two-sector general equilibrium model. Their study suggests that the impacts of interest liberalization are ambiguous, because the policies improve productivity within the private and state sectors while worsening capital misallocation across sectors. My paper differs from Liu et al. (2021) by considering distinct aspects of financial development, e.g., the decline of borrowing tightness and the equity market development. This paper also relates to Curtis (2016) and Peng (2019), which study the impacts of economic reforms on the growth of China. This paper differs from them by focusing mainly on the financial reform.

The rest of Chapter 3 is organized as follows. Section 3.2 introduces the institutional background of the economic reform in China and discusses the main differences between the state and private sectors. Section 3.3 introduces the model setup, and Section 3.4 discusses the model parameterization. Section 3.5 presents model implications and conducts policy analysis. Section 3.6 concludes the paper.

3.2 Policy and Institutions

This section introduces the economic reform in China. Furthermore, it discusses the main differences between the private and state sectors in terms of the sectoral total factor productivity as well as financial policies, which are adopted as the essential features of the model presented in Section 3.3.

3.2.1 Overview

China has undergone rapid economic growth since the successive economic reform policies starting from 1978. The Chinese economy before 1978 was central planning, and SOEs dominated the economy in all the aspects (Lin et al., 1998). Since then, especially after the nominal legalization of private enterprises in 1986, private firms have reappeared and expanded. Since the economic reform was gradual, by 1992, the SOEs still consisted of the majority of the economy. It contributed to 64% of total industrial output and 68% of investment in fixed assets.[7] Despite the advantages of SOEs in undertaking social responsibilities and pursuing national policy objectives (Lin and Tan, 1999), SOEs were shown to have lower economic performance than non-SOEs, which also motivated the subsequent

[7] Data source: China Statistical Yearbook.

reform policies. In 1992, China declared the private sector as an essential part of the economy and made clear the private firms' legal status. In 1994, the modernization of corporate law and labor law became effective, and in 1997, the restructure and privatization of SOEs started.[8] With the rapid entry of private firms and the exit or privatization of SOEs, the state sector has primarily contracted. By 2007, it accounted for only 29.5% of total industrial output. The expansion of the private sector and the reallocation of resources between SOEs and private firms has driven China's economic growth (Hsieh and Song, 2015).

During the economic transition, the major reform and development in the financial sector have taken place. At the beginning of the economic reform in 1978, the only formal financial institution was the People's Bank of China (PBC), serving as both the central and commercial banks. Since then, with the re-establishment of the central bank, the setup and reform of commercial banks, the emergence of non-bank financial institutions, and the development of the stock market, the financial sector has significantly grown and played a bigger role in financial resource allocation.[9] This paper focuses on this economic transition period. It examines the impacts of resource reallocation within and across the private and state sectors induced by financial reform on the aggregate economy. The rest of this section presents the differences between SOEs and private firms in terms of sectoral productivity and financial policy, which motives the essential features of the model in this paper.

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[8] See Chen et al. (2020), among others, which summarize the historical background of economic reforms in China.

[9] See Huang and Wang (2013), among others.

3.2.2 Productivity Gaps

The productivity gap exists between private firms and SOEs, which is one of the main reasons for the differences in the two types of firms' performances. Brandt et al. (2008) suggest that from 1978 to 2007, the TFP levels in the state and non-state sectors diverged, and the level of TFP in the non-state sector is 80% higher than that in the state sector by 2004. The TFP gap between the state and non-state sectors peaked in 2000 at 125% in Brandt and Zhu (2010). Based on the same dataset, Du et al. (2014) show that the state sector firms are the least productive, although the state sector has been catching up with the private sector in recent years; the average TFP in the private sector has stayed at more or less the same level over the same period. They show that the average TFP of the surviving firms in the private sector (3.45) is 20% higher than that in the state sector (2.86). Since private firms are more productive than SOEs, the reallocation of resources from the less productive state sector to the productive private sector boosts aggregate productivity and output growth.

3.2.3 Financial Frictions

In China, the two most crucial financing channels are self-fundraising and bank loans (Allen et al., 2005). The intense discrimination exists in the Chinese financial market across firms of different ownership (Song et al., 2011). The banking system, which is dominated by the four state-owned banks, tends to lend to SOEs and discriminates against non-SOEs that 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, as for the private firms, banking financing is more prevalent with large firms than small ones. Boyreau-Debray and Wei (2005) find that all types of banks prefer lending to SOEs and large private firms in China. Bai et al. (2018) document that among private firms, large firms are more leveraged than their small counterparts in the Chinese manufacturing sector. The existence of financial frictions impedes private firms from entering the manufacturing sector and investing efficiently due to the limited access to external finance, resulting in resource misallocation among the private firms as well as across the private and state sectors.

3.3 The Model

The model is based on Midrigan and Xu (2014). In this economy, there is a measure N_t of private firms, a measure N_{st} of SOEs, and a unit measure of workers. The measure of firms and labor efficiency grow over time at a constant growth rate γ. The private firms operate in the informal sector upon entry. Over time, by paying an entry cost, they could switch to the formal manufacturing sector. Private firms in the formal sector face financial frictions as they have less access to external finance compared with SOEs. Since among the Chinese private firms, large are firms are more leverage than their small counterparts, this paper introduces the size-dependent borrowing constraint, under which large firms face lower borrowing tightness. SOEs operate in the formal manufacturing sector upon entry and are not subject to financial frictions.

3.3.1 Private Firms

Informal Private Firms. Private firms operate in the informal sector upon entry. Informal private firms are not registered with the government or subject to taxes. These firms adopt unproductive technology and only use labor to produce homogeneous goods.[10] The production function is given by

$$y_t = (Z^I z_t)^{1-\eta} l_t^{\eta} \tag{3.1}$$

where η governs the span of control and measures the degree of diminishing return to scale at the firm level; Z^I is the sector-specific productivity of informal private firms; z_t is the idiosyncratic productivity shock, which follows a Markov switching process with transition density $Pr(z_{t+1} = z'|z_t = z) = \pi(z'|z)$. New entrants draw their productivity z from the stationary distribution $\bar{G}(z)$.

As for the timing, the exogenous productivity shocks z_{t+1} are known to firms at the end of period t. In each period, informal firms produce, consume, and save. Firms can choose to enter the formal sector by paying a negligible entry cost c_e for the intangible investment and installing physical capital k_{t+1} for the next period's production. They can also issue equity to a fraction φ of their future profits. Using a to denote firms' net worth and primes to indicate next period variables, the Bellman equation for the informal private firms is

$$V^I(a, z) = \max_{a', c} \log(c) + \beta max \left\{ EV^I(a', z'), EV^P(a', z') \right\} \tag{3.2}$$

[10]Porta and Shleifer (2008) find that informal firms (not registered with the government) are small and extremely unproductive based on the World Bank firm-level surveys.

subject to the budget constraint

$$c + a' + 1_{\{\mu=1\}}(c_e - \varphi P_t) = \pi^I + (1+r)a \tag{3.3}$$

firms solve the profit maximization problem

$$\pi^I(a,z) = \max_l (Z^I z_t)^{1-\eta} l_t^\eta - \omega l \tag{3.4}$$

where β is the discount factor; r is the real interest rate; V^I and V^P are the values of the informal and formal private firms, respectively; $\mu \in \{0,1\}$ is the indicator of firms' entry decisions; P_t is the price of the sequence of firm profits in the future. The entry decisions depend on the expected values of switching to the formal sector or not. If a firm stays in the informal sector, the net worth for the next period a' is its saving. For those firms who choose to switch ($\mu = 1$), they must pay an entry cost c_e.

Due to the nontrivial entry cost and the low profitability in the informal sector, it is difficult for informal firms to only depend on the internal funds to finance the entry cost. Except for equity issuance, for firms who decide to enter the formal sector, they can borrow from banks to finance both of the entry cost and the physical capital of next period's production. Since the financial market is imperfect, the amount of debt that firms can issue is limited. The borrowing constraint is given by

$$k' \leq \lambda_0 a' + \lambda_1 \Phi(k') \tag{3.5}$$

where λ_0 and λ_1 are the borrowing tightness parameters. $\Phi(k)$ captures the disruption cost of production that firms have to pay in the case of default following Gopinath et al. (2017). Considering that large firms lose more in default, the disruption cost $\Phi(k)$ is assumed to be an increasing and convex function of capital k. In this paper, I assume that the functional form for the disruption cost is $\Phi(k) = k^2$, which is analytically convenient in obtaining the closed-form solution for capital. Under the borrowing constraint, the maximum leverage ratio (or the overall borrowing tightness) increases with capital k, capturing the empirical fact that large firms face lower borrowing tightness than small ones.

Formal Private Firms. Private firms in the official manufacturing sector adopt both labor l and capital k to produce homogeneous goods subject to a decreasing return to scale technology given by

$$y_t^P = (Z^P z_t)^{1-\eta}(l_t^\alpha k_t^{1-\alpha})^\eta \tag{3.6}$$

where α is the labor elasticity; Z^P is the sector-specific productivity of the formal private firms; z_t is the idiosyncratic productivity shock. This paper assumes that the productivity gap exists between informal and formal private firms. That is, formal private firms have a higher productivity on average $Z^P > Z^I$.

In each period, the private firms in the formal sector will consume c_t, produce y_t, pay a fraction φ of profits to equity holders, and borrow d_{t+1} to finance capital k_{t+1} with respect to the next period's productivity z_{t+1} accordingly. Net worth a is defined as $a = k - d$. Then, the Bellman equation for the formal private firms is given by

$$V^P(a, z) = \max_{a', c} \log(c) + \beta E V^P(a', z') \tag{3.7}$$

subject to the budget constraint

$$c + a' = (1 - \varphi)\pi^P + (1 + r)a \tag{3.8}$$

where the firms solve the profit maximization problem

$$\pi^P(a, z) = \max_{k,l} (Z^P z)^{1-\eta}(l^\alpha k^{1-\alpha})^\eta - \omega l - (r + \delta)k \tag{3.9}$$

subject to the the borrowing constraint

$$k \leq \lambda_0 a + \lambda_1 \Phi(k) \tag{3.10}$$

In the model, financial development impacts the investment of two types of capital: the intangible capital (or entry cost), which is productivity-improving, and the physical capital which is directly used as the input of production. Firstly, given the entry costs and productivity gaps between formal and informal private firms, financial frictions will dampen fundraising, prevent or delay entry decisions, and lower individual firms' productivity level. Besides, under financial frictions, private firms in the manufacturing sector may not be able to fully adjust capital to the efficient level in response to productivity shocks, which results in efficiency loss. Through the two channels, financial development plays a role in aggregate productivity and output.

3.3.2 SOEs

State-owned enterprises operate in the formal sector upon entry. SOEs adopt both labor l and capital k to produce homogeneous goods subject to a decreasing return to scale technology given by

$$y_t^S = (Z^S z_t)^{1-\eta}(l_t^\alpha k_t^{1-\alpha})^\eta \tag{3.11}$$

where Z^S is the sector-specific productivity of the SOEs. Following Song et al. (2011) and Liu et al. (2021), this paper assumes $Z^S < Z^P$ as TFP gap exits between SOEs and private firms; z_t is the idiosyncratic productivity shock. Since empirical evidence suggests that private firms are significantly more financially constrained than SOE, this paper adopts the convenient assumption that all the SOEs are not subject to any financial frictions. In each period, SOEs choose their consumption c_t, production y_t, capital stock k_{t+1}, and debt d_{t+1} accordingly. Net worth a is defined as $a = k - d$. Then, the Bellman equation for the SOEs is

$$V^S(a,z) = \max_{a',c} \log(c) + \beta E V^S(a',z') \tag{3.12}$$

subject to the budget constraint

$$c + a' = \pi^S + (1+r)a \tag{3.13}$$

where firm solves the profit maximization problem

$$\pi^S(a,z) = \max_{k,l}(Z^S z)^{1-\eta}(l^\alpha k^{1-\alpha})^\eta - \omega l - (r+\delta)k \tag{3.14}$$

3.3.3 Workers

There is a unit measure of workers in the economy. In each period, workers consume c_t^w, save a_{t+1}^w, work by supplying $\gamma^t v_t$ efficiency units of labor, and hold equity issued by private firms. The labor efficiency v_t follows a two-state Markov process with the probability of unemployed p_u and employed p_e. Since workers are heterogeneous in their labor efficiency v_{it}, they are also different in their asset a_t^w, which is endogenously determined in the model.

3.3.4 Equilibrium

A Recursive Competitive Equilibrium consists of value functions $V^w(a^w, v)$ for workers and $V^j(a,z)$ for firms, $j \in \{I, P, S\}$; policy functions $c^w(a,v), a_{t+1}^w(a,v)$ for workers, and $c^j(a,z)$, $a_{t+1}^j(a,z)$ for firms; output, labor and capital decisions for firms, $y^j(a,z)$, $l^j(a,z)$, $k^S(a,z)$ and $k^F(a,z)$; distributions for firms $n^j(a,z)$ such that:

1. The value functions and decision rules solve the firms' and workers' dynamic programming problems;

2. Market clear

(1) Labor Market

$$L = \sum_{j\in\{I,P,S\}} \int_{A\times Z} l^j(a,z)dn^j(a,z) \tag{3.15}$$

(2) Capital Market

$$\begin{aligned} A^w_{t+1} + \sum_{j\in\{I,P,S\}} \int_{A\times Z} a^j_{t+1}(a,z)dn^j_{t+1}(a,z) = & \int_{A\times Z} k^P_{t+1}(a,z)dn^P_{t+1}(a,z) \\ & + \int_{A\times Z} k^S_{t+1}(a,z)dn^S_{t+1}(a,z) \end{aligned} \tag{3.16}$$

(3) Goods Market

$$C_t + K_{t+1} - (1-\delta)K_t + C_{et} = Y_t \tag{3.17}$$

where

$$C_t = C^w_t + \sum_{j\in\{I,P,S\}} C^j_t \tag{3.18}$$

$$Y_t = \sum_{j\in\{I,P,S\}} Y^j_t \tag{3.19}$$

$$K_{t+1} = \sum_{j\in\{P,S)} K^j_{t+1} \tag{3.20}$$

$$C_{et} = c_e \int_{A\times Z} 1_{\{\mu(a,z)=1,a'\in A\}} dn^I_t(a,z) \tag{3.21}$$

where L_t is the aggregate labor supply; A^w_{t+1} is the the aggregate assets supplied by workers; C_t is the aggregate consumption, which is the sum of total consumption by workers C^w_t and by the three types of firms; Y_t is the aggregate output, which is the sum of total output by the three types of firms; K_{t+1} is the aggregate capital stock, which is the sum of total capital by private firms and SOEs; C_{et} is the aggregate entry costs paid by the private firms.

3. Distribution

(1) Informal Private Firms

$$n^I_{t+1}(a', z') = \int_A \int_Z 1_{\{\mu(a,z)=0, a' \in A\}} P(z'|z) dn^I_t(a, z) + \gamma N_t 1_{\{0 \in A\}} \bar{G}(z') \tag{3.22}$$

(2) Formal Private Firms

$$n^P_{t+1}(a', z') = \int_A \int_Z 1_{\{\mu(a,z)=1, a' \in A\}} P(z'|z) dn^I_t(a, z) + \int_A \int_Z 1_{\{a' \in A\}} P(z'|z) dn^P_t(a, z) \tag{3.23}$$

(3) SOEs

$$n^S_{t+1}(a', z') = \int_A \int_Z 1_{\{a' \in A\}} P(z'|z) dn^S_t(a, z) + \gamma N^S_t 1_{\{0 \in A\}} \bar{G}(z') \tag{3.24}$$

The decision rules of consumers c^w_t, a^w_t, the measures of firms $n^j_t(a, z)$, and the aggregate variables A^w_{t+1}, C_t, K_{t+1}, C_{et}, Y_t, L_t, all grow at a constant rate along a balanced growth path. In order to solve the model numerically, following Midrigan and Xu (2014), those variables are de-trended by $(1+\gamma)^t$. This paper then focuses on the resulting stationary system.

3.4 Calibration

The model is annual. Parameters are calibrated to match the Chinese economy. Table 3.1 presents the calibration results for the benchmark model. I set the capital depreciation rate δ to 0.06, which is within the range of empirical evidence on capital depreciation in China. This paper assumes that labor efficiency follows a two-state Markov process. The probability of staying unemployed p_u is 0.5, and the probability of staying employed p_e is 0.806, which matches the employment ratio (72%) in China. The growth rate γ is 8%, which is consistent with China's annual growth rate. I assume the same factor shares and span of control among SOEs and private firms in the manufacturing sector. Following Curtis (2016), the span of control η and labor share $\alpha\eta$ are set to 0.805 and 0.5, which implies that the labor elasticity parameter $\alpha = 0.62$.

I calibrate the sector-specific productivities of SOEs and private firms based on the Chinese manufacturing dataset from 1998 to 2007. The production function of manufacturing firms as discussed in Section 3.3 implies that firm-level productivity is

$$Z_{itc}^{j} = \left(\frac{y_{ict}}{(l_{ict}^{\alpha} k_{ict}^{1-\alpha})^{\eta}} \right)^{1/(1-\eta)}, \quad j \in \{P, S\} \tag{3.25}$$

where j, i, c and t denote ownership, firm, industry and year, respectively. Parameters η and α are set to the calibrated values above. Based on equation (3.25), firm-level productivity is calculated. Then, I obtain the average productivity grouped by ownership, year, and 4-digit industry; next, I get the average TFP across industry by ownership and year. Lastly, I calculate the average TFP for the SOEs and non-SOEs, respectively, by taking averages over the years. I find that private firms are, on average, 19% more efficient than SOEs. By normalizing the sector-specific productivity of SOEs, $Z^S = 1$, I set the sector-specific productivity of formal private firms $Z^{P(1-\eta)}$ to 1.19. It is consistent with the empirical finding in Du et al. (2014) and is at the lower end of the estimation of TFP gaps in the existing literature.[11] For simplicity, the sector-specific productivity of informal firms is set to $Z^I = 1$ in the benchmark economy.

The rest of the parameters are jointly pinned down by matching the aggregate and firm-level moments of the Chinese economy. The firm-level moments are based on the panel of the Chinese Annual Survey of Industrial Firms for the period 1998-2007. The discount factor β is set to match the capital-to-output ratio of the private firms, which is 2.3. As a result, the discount factor $\beta = 0.95$. Entry cost affects private firms' decisions of switching from the informal sector into the formal manufacturing sector directly. The higher the entry cost, the fewer the formal private firms. Thus, the entry cost is calibrated to match the size of the informal sector in the economy. According to Elign and Öztunali (2012), the size of the shadow economy as a percentage of official GDP in China is 13.56% on average from 1998 to 2007. This implies that $c_e = 0.81$.

This paper assumes that the idiosyncratic productivity z_t follows an AR(1) process, where ρ is the persistent component and σ_ε is the standard deviation of the transitory shock. Following the Rouwenhorst method (1995), I approximate the AR(1) process by a discrete Markov chain over a symmetric, evenly-spaced state space. Considering that the productivity process is the primary determinant for output, moments that are used

[11] Du et al. (2014) finds that the average TFP of the surviving firms in the private sector is 20% higher than that in the state sector based on the Chinese manufacturing firm-level dataset. As discussed in Section 3.2, the TFP gap between SOEs and private firms varies in the existing literature, and a TFP gap of 1.2 is at the lower end in the empirical findings.

to identify the persistent component ρ and the standard deviation of transitory shock σ_ε are (1) the standard deviation of output growth rate, which equals 0.79; (2) the first-order autocorrelation of output, which is 0.80 based on the Chinese manufacturing dataset. This yields the persistent component $\rho = 0.73$ and the standard deviation of transitory shock $\sigma_\varepsilon = 0.78$, which is large to generate firm dynamics.

Table 3.1: Calibration Results

Parameter	Description	Value	Source/target
δ	Depreciation rate	0.06	Wu et al. (2014)
γ	Growth rate	0.08	Annual growth rate
p_u	Persistence zero state	0.50	Employment ratio
p_e	Persistence unit state	0.805	
η	Span of control	0.805	Curtis (2016)
α	Labor elasticity	0.62	Labor share
(Z^S, Z^I, Z^P)	Sector-specific productivity	$(1, 1, 2.41)$	TFP gap
β	Discount factor	0.95	Capital to GDP
λ_0	Borrowing tightness	2.65	Private debt to GDP
λ_1	Borrowing tightness	0.017	Leverage-size slope
ρ	Persistent component	0.73	Autocorrelation output
σ_ε	S.D. transitory shock	0.78	S.D. output growth
c_e	Entry cost	0.81	Size of Informal economy
φ	Equity issuance	0.022	Stock market capitalization to GDP

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.

The borrowing tightness parameters λ_0 and λ_1 jointly determine the financing pattern of private firms. Since the model assumes that in the manufacturing sector only private firms are subject to financial frictions, moments used to pin down parameters λ_0 and λ_1 are (1) the regression coefficient of the leverage ratio on firm size among private firms, which is 0.03;[12] (2) the aggregate debt to output ratio $\frac{D}{Y}$. Based on data from the

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

World Bank, the average ratio of domestic credit to the private sector to GDP during the period 1998 to 2007 is 1.13. This yields a calibrated value of $\lambda_0 = 2.65$ and $\lambda_1 = 0.017$. For the fraction φ of equity claims that private firms could issue upon entry, I calibrate it to match the average of stock market capitalization to GDP in China from 1998 to 2007, which is 34.1%.[13] It generates a calibrated value of $\varphi = 0.022$.

3.5 Quantitative Results

This section quantitatively examines the impacts of financial reform on the aggregate economy. I present the implications of the model in the pre- and post-reform periods, and decompose the reallocation effects of financial reform by reform policies as well as by intensive and extensive margins. The impacts of current financial policies are also examined.

3.5.1 Model Implications

At the beginning of the economic reform in 1978, the only formal financial institution in China was the People's Bank of China (PBC), serving as central and commercial banks. Although a large number of financial institutions were established during the reform period,[14] the state sector demonstrates the dominance of financial resources. The bank system, which makes up the majority of the financial sector, is dominated by the four state-owned banks and serves as the prime lender to the state-owned enterprises. For a long period, private firms have almost no access to external finance.[15] Furthermore, the stock market was not established until 1990 and is strictly restricted by the government. To be

[13] Data source: https://fred.stlouisfed.org.

[14] By the end of 2008, there were 5,600 banking financial institutions (Huang et al. (2013)).

[15] See Dollar and Wei (2007), Ayyagari et al. (2010), among others.

consistent with these facts, I assume that the private firms have no access to the bank loans or equity market in the pre-reform period. In this case, borrowing tightness parameters $\lambda_0 = 1$, $\lambda_1 = 0$ and the fraction of equity issuance $\varphi = 0$. According to Section 3.4, the corresponding calibrated values in the post-reform period are $\lambda_0 = 2.65$, $\lambda_1 = 0.017$ and $\varphi = 0.022$. Table 3.2 reports the model implications in the pre- and post-reform periods, respectively.

Resource Reallocation among Private Firms. Different from state-owned enterprises, private firms in the manufacturing sector face financial frictions, resulting in capital misallocation and TFP loss along the intensive margin. During the pre-reform period, private firms have no access to external finance, and the debt to output ratio is zero. With the development of the credit market, the credit to the private sector (% GDP) increases to 104%. As firms have higher financing ability, the fraction of firms that are financially constrained declines from 72% to 43% consequently. The standard deviation of the marginal product of capital, as the measure of capital misallocation, reduces from 0.41 to 0.35. Accordingly, the TFP loss decreases from 6.65% to 3.31%. Financial development, especially in the credit market, promotes resource reallocation among private firms in the manufacturing sector.

Entry of Private Firms. Private firms who decide to switch from the informal sector to the official manufacturing sector finance the entry cost and physical capital through internal funds, equity issuance, and bank loans. Due to the low profitability of informal firms and non-trivial entry costs, financial frictions impede the entry of private firms. Without external finance, the selection effects of financial frictions are more substantial as only private firms who have accumulated enough net worth will enter the formal sector. The average net worth of entrants in the post-reform period is 0.82 of the pre-reform period. As private firms switch from the informal sector into the official manufacturing sector, the size of the informal sector as a fraction of manufacturing output decreases from 0.45 to 0.16.

Resource Reallocation between SOEs and Private Firms. Except for the SOEs having lower sector-specific productivity than formal private firms, this paper assumes that SOEs are not subject to financial frictions or entry barriers. As SOEs' productivity distribution remains unchanged in the pre- and post-reform period, financial reform does not affect the TFP of the state sector. Without external finance, SOEs take up all the debt, 60% of the capital stock, and 51% of the manufacturing output. With the entry of private firms and the market becoming more competitive with higher factor prices, resources are reallocated between the private and state sectors. The share of total debt by SOEs reduces to 34%, and the share of the total capital stock decreases to 30%. Accordingly, the share of manufacturing output by SOEs declines to 29%.

The entry and expansion of private firms result in a reallocation of resources to more efficient use in the manufacturing sector. As a result of the financial reform, the aggregate TFP in the manufacturing sector increases by 8%, and the aggregate output increases by 35%. The change in aggregate TFP and output induced by financial development can be attributed to the alleviation of capital misallocation among the private firms in the manufacturing sector, the entry of private firms which become more productive, as well as the resource reallocation between the less productive SOEs and productive private firms.

Table 3.2: Model Implications: Pre-/Post-Reform

	No External Finance	Post-Reform
Private		
Debt to output	0	1.04
S.D. $\log(MP_k)$	0.41	0.35
Fraction constrained	0.72	0.43
TFP loss (%)	6.65	3.31
Ave. net worth entrants	1	0.82
Size of informal economy	0.45	0.16
SOEs		
Debt share	1	0.34
Capital share	0.60	0.30
Output share	0.51	0.29
Aggregate		
TFP	1	1.08
Output	1	1.35

Note: This table reports the model implications of the pre-reform economy without external finance and the post-reform economy with bank loans and equity issuance, respectively.

3.5.2 Decomposition of Reallocation Effects

This subsection decomposes the reallocation effects induced by financial development on the aggregate productivity and output through the dimensions of financial policies, as well as the intensive and extensive margins.

Reform Policies. Starting with the pre-reform economy without external finance, I keep the fraction of equity issuance $\varphi = 0$, and set the borrowing tightness parameters λ_0 and λ_1 to the post-reform level. I calculate the total contribution of the credit market development to the aggregate TFP and output in the manufacturing sector as the difference between this experiment and the pre-reform economy. I then attribute the remaining TFP and output gains out of the total gains to the equity market development. As in Table 3.3, without equity issuance, the credit market development accounts for 81% and 83% of the changes in TFP and output.

I also decompose the reallocation effects of credit market policies (or the borrowing tightness parameters λ_0 and λ_1) by conducting the following two experiments, which are in a reverse sequence. In experiment (1), I keep the fraction of equity issuance $\varphi = 0$ and $\lambda_1 = 0$, and set λ_0 to the post-reform level. Since λ_0 mainly matters for the average leverage, an increase in λ_0 from 1 to the post-reform level at 2.65 enables the more massive entry of private firms. Also, it reduces capital misallocation among private firms in the manufacturing sector than the pre-reform economy. As shown in Table 3.3, an increase in λ_0 alone accounts for 61% and 48% of the changes in TFP and output. In experiment (2), I set the fraction of equity issuance $\varphi = 0$ and $\lambda_0 = 1$, and set λ_1 to the post-reform level at 0.017. Although the number of private firms entering the manufacturing sector is lower than in experiment (1), an increase in λ_1 which governs the leverage-size slope, enables the more massive entry of productive/large firms, and mainly reduces financial constraints faced by productive/large firms. Despite a smaller number of private firms operating in the manufacturing sector, as productive firms matter more for production, the increase in λ_1 alone accounts for 56% of the change in aggregate output, which is higher than in experiment (1) solely by λ_0 (48%).

The combination of the two credit market policies in total accounts for 81% and 83% of the changes in TFP and output, implying that the productivity and output gains are mainly driven by the development of the credit market other than the equity market.[16] This finding is consistent with the fact that although compared with SOEs, private firms are discriminated in the credit market, bank loans, especially the short term loans, are the

[16]The relative importance of credit market and equity market reform policies still holds by running the experiment in a reverse sequence.

most important source of funding for private firms. Furthermore, China's equity market is quite underdeveloped and only plays a minor role in financing. For example, the equity to GDP ratio from 1998 to 2007 is 34.1% on average in China, much lower than that in the US at 131.5%.[17]

Table 3.3: Decomposition: Financial Policy

	Credit Market			Equity market
	(1)	(2)	Total	
TFP	0.61	0.55	0.81	0.19
Output	0.48	0.56	0.83	0.17

Note: This table reports the decomposition of reallocation effects on aggregate productivity and output in the manufacturing sector by reform policies. "(1)" denotes experiment (1) by solely setting λ_0 to the post-reform level at 2.65; "(2)" denotes experiment (2) by solely setting λ_1 to the post-reform level at 0.017; "Total" denotes the experiment by setting λ_0 and λ_1 to the post-reform level,while keeping the fraction of equity issuance $\varphi = 0$.

Extensive and Intensive Margins. I next decompose the reallocation effects on aggregate productivity and output along the intensive and extensive margins. Since the equity market affects the economy mainly along the extensive margin, I first calculate the aggregate productivity and output in the manufacturing sector under the post-reform credit market policies, while with the same distribution of firms and equity issuance in the pre-reform economy. The differences between the resulting values and the pre-reform economy measure the reallocation effects along the intensive margin, consisting of both the private firms' efficiency gains and resource reallocation from SOEs to private firms. SOEs shrink due to higher factor prices, and private firms' output increases due to better access to external finance. I attribute the remaining effects to the extensive margin.

[17]Data source: https: fred.stlouisfed.org.

As shown in Table 3.4, the reallocation effects along the intensive margin account for 64% and 62% of the TFP and GDP gains. This finding is different from Midrigan and Xu (2014), which suggests small efficiency gains along the intensive margin and potentially substantial gains along the extensive margin in the Korean manufacturing sector. The assumption that intangible capital could also serve as collateral in their paper enables more massive entry to the manufacturing sector as well as smaller capital misallocation among incumbent firms. Considering that intangible capital as collateral is not prevalent among China's private firms, this paper instead allows only physical capital as collateral. As a result, the credit market has smaller impacts on firms' entry. Another reason for the limited role of financial development in resource reallocation on the extensive margin may be that the equity market is underdeveloped to serve as a direct financing source for firms' entry costs.

Table 3.4: Decomposition: Intensive/Extensive Margin

	Intensive	Extensive
TFP	0.64	0.36
Output	0.62	0.38

Note: This table reports the decomposition of total reallocation effects on aggregate productivity and output in the manufacturing sector by extensive and intensive margins.

3.5.3 Policy Analysis

Borrowing Tightness. Table 3.5 reports the implications of credit market policies, taking the post-reform economy as the benchmark. The maximum leverage ratio in the benchmark is $(d/k)_{max} = 0.62 + 0.006k$. When the borrowing tightness parameter λ_1 remains at 0.017 unchanged and λ_0 increases from 2.65 to 5, the maximum leverage becomes

$(d/k)_{max} = 0.8 + 0.006k$. As the intercept of the maximum leverage becomes larger, more smaller firms (with lower productivity) without enough net worth are less constrained and face lower marginal product of capital. As a result, the negative relationship between firm size and the marginal product of capital gets weaker compared with the benchmark. The debt to output ratio increases to 1.18 as private firms in the manufacturing sector have more excess to bank loans. The standard deviation of the marginal product of capital and the fraction of constrained firms decline to 0.30 and 0.32. Consequently, the TFP loss decreases from 3.31% to 2.44%. Moreover, the average net worth of entrants declines by 16% as the selection effects of financial frictions get weaker. With the expansion of the formal private firms, the sizes of the informal sector and the state sector decrease, and the aggregate TFP and output in the manufacturing sector increase by 2% and 6%, respectively.

As the borrowing tightness parameter λ_0 remains at 2.65 unchanged and λ_1 increases from 0.017 to 0.04, the maximum leverage ratio becomes $(d/k)_{max} = 0.62 + 0.015k$. As the slope of the maximum leverage increases, more larger firms (with higher productivity) without enough net worth could get rid of the borrowing constraint and face lower marginal product of capital. As a result, the negative correlation between firm size and the marginal product of capital gets stronger than the benchmark. With more external finance, the debt to output ratio increases to 1.24. The standard deviation of the marginal product of capital and the fraction of constrained firms decrease to 0.34 and 0.32. The aggregate TFP and output increase by 2% and 7%, respectively.

When the financial frictions are eliminated, the debt to output ratio increases to 1.47. The sizes of the informal sector and the state sector as percentage of manufacturing output decrease to 0.1 and 0.22. With the entry and expansion of private firms, the aggregate productivity and output in the manufacturing sector increase by 3% and 15%, respectively.

Table 3.5: Borrowing Tightness

	$\lambda_0 = 2.65$ $\lambda_1 = 0.017$	$\lambda_0 = 5$ $\lambda_1 = 0.017$	$\lambda_0 = 2.65$ $\lambda_1 = 0.04$	$\lambda_0 = \infty$ $\lambda_1 = \infty$
Private				
Debt to output	1.04	1.18	1.24	1.47
S.D. $\log(MP_k)$	0.35	0.30	0.34	0
Corr. $(\log(MP_k), size)$	-0.48	-0.40	-0.56	/
Fraction Constrained	0.43	0.32	0.32	0
TFP loss (%)	3.31	2.44	1.86	0
Ave. net worth entrant	1	0.84	0.86	0.73
Size of Informal economy	0.16	0.13	0.13	0.1
SOEs				
Output share	0.285	0.26	0.25	0.22
Aggregate				
TFP	1	1.02	1.02	1.03
Output	1	1.06	1.07	1.15

Note: This table reports the model implications in the benchmark with $\lambda_0 = 2.65$ and $\lambda_1 = 0.017$, and when $\lambda_0 = 5$; $\lambda_1 = 0.04$; $\lambda_0 = \infty$ and $\lambda_1 = \infty$, respectively.

Equity Issuance. I next vary the parameter φ that governs the equity issuance upon the entry of private firms, taking the post-reform economy where $\varphi = 0.022$ as the benchmark. As shown in Table 3.6, when φ gets larger, the equity to output ratio increases accordingly. Besides, the standard deviation of the marginal product of capital and the fraction of constrained firms increase with the larger equity issuance. This is mainly due to two reasons: firstly, as equity issuance φ gets larger, the selection effects of financial frictions gets weaker, as the average net worth of entrants decreases considerably. It then takes longer for those firms in the manufacturing sector to accumulate enough net worth and get rid of the borrowing constraint; second, since the private firms in the manufacturing need to pay back to the equity holders, they have less internal funds for investment. As a result, larger misallocation and TFP loss exist among private firms as equity issuance increases.

Table 3.6: Equity Issuance

	$\varphi = 0.022$	$\varphi = 0.05$	$\varphi = 0.08$
Private			
Equity to output	0.33	0.84	1.50
S.D. $\log(MP_k)$	0.353	0.367	0.369
Fraction Constrained	0.43	0.46	0.49
TFP loss (%)	3.31	3.77	3.89
Ave. net worth entrants	1	0.38	0.19
Size of informal economy	0.16	0.09	0.05
SOEs			
Output share	0.29	0.25	0.23
Aggregate			
TFP	1	1.03	1.05
Output	1	1.11	1.19

Note: This table reports the model implications in the benchmark with $\varphi = 0.02$ and when $\varphi = 0.05$ and $\varphi = 0.08$, respectively.

Meanwhile, the equity issuance promotes the entry of private firms significantly. When φ increases from 0.02 to 0.08, the sizes of the informal sector and state sector as a percentage of manufacturing output decrease to 0.05 and 0.23, respectively. Despite larger misallocation among private firms, the aggregate productivity and output in the manufacturing sector increase by 5% and 19%, with more massive entry of private firms.

3.6 Conclusion

Financial development has been regarded as one of the primary sources contributing to China's economic growth. This paper quantitatively examines the impacts of financial reform on resource reallocation and aggregate productivity by developing a general equilibrium model of firm dynamics. There are two types of firms in the model, private firms facing size-dependent financial frictions and state-owned enterprises without financial frictions. Financial development plays a role in aggregate productivity and output growth by affecting the entry and investment decisions of private firms, as well as the resource reallocation between the private and state sectors.

This paper finds that the entry and expansion of private firms induced by financial reform result in the reallocation of resources to more efficient use. With the alleviation of capital misallocation among the private firms in the manufacturing sector, the entry of private firms which become more productive, and the resource reallocation between the less productive state-owned enterprises and productive private firms, the aggregate TFP and output in the manufacturing sector increase by 8% and 35%, respectively. The decomposition of the reallocation effects suggests that credit market development plays a more critical role in promoting aggregate gains than the equity market. Furthermore, the reallocation effects on the intensive margin account for the majority of the TFP and output gains. By eliminating the financial frictions in the credit market, the aggregate TFP and output increase by 3% and 15%, respectively. The raising equity issuance also has large impacts on the aggregate output in the manufacturing sector.

Chapter 4

Factor Market Distortions and Aggregate Productivity: Evidence from China

4.1 Introduction

Resource misallocation among heterogeneous production units has significant adverse effects on the aggregate productivity and output in the Chinese manufacturing sector. Hsieh and Klenow (2009) find that if capital and labor are reallocated by equalizing marginal revenue products across firms to the extent of the US efficiency, the aggregate value-added gains will be 30%-50% for China. Based on the Chinese firm-level data from 1998 to 2007, Wu (2018) suggests that the annual average TFP loss is 27.5% due to capital distortions. Song and Wu (2015) estimate that capital misallocation alone may reduce aggregate TFP in China by 20% even in the later 2000s. Tombe and Zhu (2019) find that the decline of goods market frictions and labor market frictions accounts for 36% of the aggregate labor productivity growth between 2000 and 2005.

In addition to capital and labor, intermediate goods produced upstream in the production network are also important for the production process and growth accounting (Hulten, 1978). In China's manufacturing sector, the revenue share of intermediate inputs in gross output is 0.75 on average, much higher than that in other countries.[1] Meanwhile, the dispersion of marginal revenue product of intermediate input exists, suggesting the distortion in the usage of intermediate goods. Therefore, how the intermediate input distortion potentially affects the measured resource misallocation in the Chinese manufacturing sector in addition to capital and labor distortions is an essential question to be investigated.

This paper examines how the within-sector resource misallocation affects the aggregate productivity in the Chinese manufacturing sector by adopting a static model of monopolistic competition with heterogeneous firms. It extends the misallocation accounting framework in Hsieh and Klenow (2009) and Bils et al. (2020) by including the third factor of production, i.e., intermediate input, and considering the firm-specific distortions on the usage of capital, labor, and intermediate input. This paper adopts the Chinese Annual Survey of Industrial Firms for the period 1998-2007 for the empirical analysis. We calibrate the parameters to the Chinese manufacturing sector and investigate the impacts of the three types of distortions on aggregate productivity and output.

[1] For example, the revenue share of intermediate inputs in gross output is 0.495 on average for the US manufacturing sector according to the NBER productivity database.

First, the distribution of revenue productivity and capital, labor, and intermediate input distortions are less dispersed in 2007 than in 1998, suggesting the improvement of allocative efficiency during the sample period. The positive correlations between physical productivity and distortions imply that productive (unproductive) producers tend to be more (less) depressed by distortions. The allocative efficiency is further decomposed into the dispersions of capital, labor, and intermediate input wedges and the covariances between them. The dispersion of capital distortion, which decreases over time, accounts for the largest share of total misallocation. The second important factor is the dispersion of labor distortion. The dispersion of intermediate input distortion and the covariances between the three distortions only play a minor role in resource misallocation.

The reallocation gains from equalizing revenue products across firms within sectors are investigated. First, the gross output gain is 18.71% on average during the sample period by eliminating all the distortions. Second, by equalizing the marginal revenue product of one input within sectors while keeping the allocation of the other two factors unchanged, we can get the gross output gains due to capital, labor, and intermediate input wedges, respectively. The reallocation gains from removing capital and labor distortions are 7.81% and 6.39%, which are higher than that of intermediate input distortion (3.05%). The results are consistent with the decomposition of allocative efficiency, suggesting that although intermediate input accounts for a large revenue share of gross output, the distortion on its usage is less critical for resource misallocation in the Chinese manufacturing sector.

In the robustness check, input shares are alternately set to the values in the corresponding US manufacturing sectors since we could not distinguish between factor shares and distortions clearly from the data. As the factor shares in the two countries are quite different, the magnitude of gross output gains due to the three types of distortions changes significantly. However, the relative importance of the distortions does not change, and intermediate input distortion is not as important as capital and labor distortions for resource misallocation. Finally, a simple comparison of the summary statistics regarding productivity and distortions between the models with two and three factors of production is conducted, hinting that intermediate input and the distortion on its usage will make a difference for the measured aggregate TFP gains.

This paper contributes to the literature which studies the impact of resource allocative efficiency on aggregate productivity by employing the indirect approach and measuring the amount of misallocation without specifying the specific underlying source.[2] This paper differs from Hsieh and Klenow (2009) and its subsequent studies like Chen and Irarrazabal (2015) in considering a model with a gross output production structure instead of a value-added production structure. It thus examines the impact of intermediate input distortion on resource misallocation in addition to capital and labor distortions. This paper is closely related to the literature adopting a misallocation framework with a three-factor production function on gross output, such as Dias et al. (2016) and Bils et al. (2020). This paper differs in concentrating on the importance of intermediate input distortion on gross output loss and focusing on the Chinese manufacturing sector. This paper is also related to the recent literature investigating misallocation in a multi-sector framework by considering all the potential linkages between sectors. Jones (2011) and Bigio and La'O (2020) suggest

[2] Restuccia and Rogerson (2017) provide a summary of the literature on the direct and indirect approaches in measuring misallocation.

that sectoral distortions manifest at the aggregate level through production networks. This paper abstracts from intersectoral linkages and focuses on the misallocation within sectors due to the firm-level idiosyncratic distortions.

The rest of Chapter 4 is organized as follows. Section 4.2 presents the misallocation accounting framework. Section 4.3 introduces the dataset and presents the model parameterization, and Section 4.4 analyzes the main empirical results. Section 4.5 concludes the paper.

4.2 The Model

The misallocation accounting framework in this paper is based on Hsieh and Klenow (2009), and Bils at al. (2020) by adopting a static model of monopolistic competition with heterogeneous firms. This paper introduces intermediate inputs as the third production factor in addition to capital and labor. It examines how the three types of distortions on the usage of capital, labor, and intermediate input at the firm level affect aggregate productivity.

The single final good Y is produced by a representative firm in the perfectly competitive final output market by combing the intermediate goods Y_s produced by the S manufacturing sectors. The Cobb-Douglas production technology for the final good is,

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}, \quad \sum_{s=1}^{S} \theta_s = 1 \tag{4.1}$$

where θ_s is the sector revenue share of gross output. The final good producer maximizes its profits,

$$\max_{Y_s} PY - \sum_{s=1}^{S} P_s Y_s \tag{4.2}$$

The first order condition associated with this problem implies that $P_s Y_s = \theta_s PY$, where P_s is the price index of industry output Y_s, and P is the price index of final output Y. We can note that the final good Y can be further divided into intermediate goods M used by firms and the aggregate value added V.

The gross output in sector s is produced according to the following CES function,

$$Y_s = \left(\sum_{i=1}^{N_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{4.3}$$

where N_s is the number of varieties (or firms) in sector s, and σ is the elasticity of substitution between the differentiated goods. The profit maximization problem for the firm producing the intermediate goods Y_s is

$$\max_{Y_{si}} P_s Y_s - \sum_{i=1}^{N_s} P_{si} Y_{si} \tag{4.4}$$

Under the assumption of monopolistic competition, we can get the inverse demand function for the differentiated goods Y_{si} such that $P_{si} = P_s Y_s^{\frac{1}{\sigma}} Y_{si}^{-\frac{1}{\sigma}}$.

Suppose each firm produces one variety. Firm i in sector s produces the gross output Y_{si} by adopting the Cobb-Douglas production technology with capital, labor, and intermediate inputs,

$$Y_{si} = A_{si} \left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \right)^{\eta_s} M_{si}^{1-\eta_s} \tag{4.5}$$

where A_{si} is the idiosyncratic productivity at the firm level; capital share of value added α_s and intermediate inputs share of gross output $1-\eta_s$ are sector-specific. Suppose firms are monopolistic competitive. They face three types of idiosyncratic distortions, which are modeled for simplicity, as wedges τ_{si}^K, τ_{si}^L, and τ_{si}^M to capital, labor, and intermediate inputs purchases. The wedges measure the extent to which marginal revenue products deviate from the corresponding factor prices. The profits of firms i in sector s is given by

$$\pi_{si} = P_{si}Y_{si} - (1+\tau_{si}^K)RK_{si} - \left(1+\tau_{si}^L\right)\omega L_{si} - \left(1+\tau_{si}^M\right)P_M M_{si} \tag{4.6}$$

The profit maximization problem implies that the gross output price P_{si} is a fixed markup over its marginal cost, which is given by

$$P_{si} = \frac{\sigma}{\sigma-1}\frac{1}{A_{si}}\left[\frac{(1+\tau_{si}^K)R}{\alpha_s\eta_s}\right]^{\alpha_s\eta_s}\left[\frac{(1+\tau_{si}^L)\omega}{(1-\alpha_s)\eta_s}\right]^{(1-\alpha_s)\eta_s}\left[\frac{(1+\tau_{si}^M)P_M}{1-\eta_s}\right]^{1-\eta_s} \tag{4.7}$$

The first order conditions associated with the profit maximization problem also implies that the marginal revenue products of capital, labor, and intermediate inputs are

$$MRPK_{si} = \frac{\sigma-1}{\sigma}\alpha_s\eta_s\frac{P_{si}Y_{si}}{K_{si}} = \left(1+\tau_{si}^K\right)R \tag{4.8}$$

$$MRPL_{si} = \frac{\sigma-1}{\sigma}(1-\alpha_s)\eta_s\frac{P_{si}Y_{si}}{L_{si}} = \left(1+\tau_{si}^L\right)\omega \tag{4.9}$$

$$MRPM_{si} = \frac{\sigma-1}{\sigma}(1-\eta_s)\frac{P_{si}Y_{si}}{M_{si}} = \left(1+\tau_{si}^M\right)P_M \tag{4.10}$$

Following Hsieh and Klenow (2009), the physical productivity (or firm level TFP) $TFPQ_{si}$ is defined as

$$TFPQ_{si} \equiv A_{si} = \frac{Y_{si}}{\left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\eta_s} M_{si}^{1-\eta_s}} \tag{4.11}$$

And the revenue productivity $TFPR_{si}$ is defined as

$$TFPR_{si} \equiv A_{si} P_{si} = \frac{P_{si} Y_{si}}{\left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\eta_s} M_{si}^{1-\eta_s}} \tag{4.12}$$

The distinction between physical productivity $TFPQ_{si}$ and revenue productivity $TFPR_{si}$ is important because identifying $TFPQ_{si}$ requires firms' real output Y_{si} and the firm-specific prices are lack in the data. In contrast, $TFPR_{si}$ can be inferred using sector-specific deflators and firms' nominal output $P_{si}Y_{si}$. The revenue productivity $TFPR_{si}$ can be further expressed as a function of idiosyncratic distortions faced by each firm,

$$TFPR_{si} = \frac{\sigma}{\sigma - 1} \left[\frac{(1+\tau_{si}^{K})R}{\alpha_s \eta_s}\right]^{\alpha_s \eta_s} \left[\frac{(1+\tau_{si}^{L})\omega}{(1-\alpha_s)\eta_s}\right]^{(1-\alpha_s)\eta_s} \left[\frac{(1+\tau_{si}^{M})P_M}{1-\eta_s}\right]^{1-\eta_s} \tag{4.13}$$

We can see from equation (4.13) that the revenue productivity $TFPR_{si}$ is independent of the idiosyncratic productivity A_{si}, and it is proportional to the wedges on the inputs purchases. A high $TFPR_{si}$ implies that firms face barriers which shift away resource allocation from the optimal level. In addition, the revenue productivity will be equalized across firms within a sector in the absence of distortions.

The gross output Y_s in sector s is defined as

$$Y_s \equiv TFP_s \left(K_s^{\alpha_s} L_s^{1-\alpha_s}\right)^{\eta_s} M_s^{1-\eta_s} \tag{4.14}$$

where $K_s = \sum_{i=1}^{N_s} K_{si}$, $L_s = \sum_{i=1}^{N_s} L_{si}$, and $M_s = \sum_{i=1}^{N_s} M_{si}$. And the sectoral-level TFP is expressed as

$$TFP_s = \left[\sum_{i=1}^{N_s} \left(A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{4.15}$$

where $\overline{TFPR}_s$ is the geometric average of the average marginal revenue products of capital, labor, and intermediate inputs in sector s.

4.3 Data and Calibration

The empirical findings are based on the Chinese Annual Survey of Industrial Firms for the period 1998-2007. This dataset includes all state-owned enterprises and the "above-scale" non-state-owned enterprises with annual sales over 5 million RMB, and it reports rich firm-level information. This paper restricts the sample to the manufacturing sector. Observations with negative/missing key variables, or observations with key variables that are not consistent with accounting standards are omitted.

The variables are recorded in nominal terms. The gross output (measured by the total industrial output) and intermediate input are deflated using the sector-level producer price index with 1998 as the base year. To control the differences in labor quality, labor input is measured by the sum of wages and benefits. Since the labor share reported in the firm-level dataset is much lower than the aggregate labor share of the Chinese manufacturing sector reported in the national accounts, following Hsieh and Klenow (2009), labor compensation at the firm level is adjusted such that the aggregate adjusted labor compensation across firms is 50% of the aggregate value added. Labor compensation is then deflated by employing the province-level consumer price index with 1998 as the base year. Following Brandt et al. (2014), the real capital stock is constructed by adopting the perpetual inventory method. An alternative measure of real capital stock is the fixed assets net of depreciation deflated using the province-level fixed asset price index with 1998 as the base year, which will be examined in the robustness check. To rule out the extreme values, the top and bottom 1% of the above key variables in each year are omitted.

The output elasticity of substitution between differentiated goods σ is set to 3. The rental price R is set to 10%. The labor share is measured as the share of labor income in industrial value added, and capital share α_s is set to be one minus labor share. The intermediate input share is calculated as the ratio of intermediate costs to the gross output at the 2-digit sector level. Since the input shares in the Chinese manufacturing sector vary over time, I employ the averages of the input shares in each sector over the sample period 1998-2007. Therefore, capital share of value added α_s and intermediate input share of gross output $1 - \eta_s$ are sector-specific and time-invariant.

By setting the parameters, we can now identify distortions in the usage of capital, labor, and intermediate inputs from the data,

$$1 + \tau_{si}^K = \frac{\sigma - 1}{\sigma} \alpha_s \eta_s \frac{P_{si} Y_{si}}{R K_{si}} \tag{4.16}$$

$$1 + \tau_{si}^L = \frac{\sigma - 1}{\sigma} (1 - \alpha_s) \eta_s \frac{P_{si} Y_{si}}{\omega L_{si}} \tag{4.17}$$

$$1 + \tau_{si}^M = \frac{\sigma - 1}{\sigma}(1 - \eta_s)\frac{P_{si}Y_{si}}{P_M M_{si}} \tag{4.18}$$

We can identify the physical productivity using

$$A_{si} = \kappa_s \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{\left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\eta_s} M_{si}^{1-\eta_s}} \tag{4.19}$$

where $\kappa_s = \left(P_s Y_s^{\frac{1}{\sigma}}\right)^{-\frac{\sigma}{\sigma-1}}$ is a sector-specific scalar and set to 1 for simplicity. The revenue productivity $TFPR_{si}$ can be calculated by using equation (4.12). To rule out extreme values, the 1% tails of the dispersion of revenue productivity $TFPR_{si}$ $(\log(TFPR_{si}/\overline{TFPR_s}))$ and the dispersion of physical productivity $(\log(A_{si}N_s^{\frac{1}{\sigma-1}}/\overline{A_s}))$ across industries are trimmed. The sector shares of gross output θ_s is then calculated.

4.4 Empirical Results

This section presents the main results regarding resource allocation efficiency in the Chinese manufacturing sector. The summary statistics of productivity, distortions, and firm size over time are reported. The allocative efficiency is decomposed to study the relative importance of different distortion components. Finally, we explore the potential reallocation gains by removing the input distortions within sectors.

4.4.1 Dispersion of Productivity, Distortions and Firm Size

To characterize the dynamics of the distributions of productivity, distortions and firm size, Table 4.1 reports the summary statistics by pooling $\log(TFPQ_{si})$, $\log(TFPR_{si})$, $\log(1 + \tau_{si}^K)$, $\log(1 + \tau_{si}^L)$, and $\log(1 + \tau_{si}^M)$ in the two years of the sample, 1998 and 2007, and Figure 4.1 plots the corresponding distributions. In Table 4.1, the standard deviation of physical productivity $\log(TFPQ_{si})$ decreases from 0.71 in 1998 to 0.66 in 2007. Figure 4.1 panel (a) plots the distribution of the rescaled physical productivity relative to the corresponding mean value in each sector, i.e., $\log(A_{si}N_s^{\frac{1}{\sigma-1}}/\overline{A}_s)$. Consistent with Table 4.1, the distribution of physical productivity gets less dispersed. Besides, the left tail of the distribution of physical productivity becomes thinner, suggesting the exit of inefficient firms or the increased idiosyncratic productivity.

Table 4.1: Summary Statistics for Productivity and Distortions

1998	$\log(TFPQ_{si})$	$\log(TFPR_{si})$	$\log(1+\tau_{si}^K)$	$\log(1+\tau_{si}^L)$	$\log(1+\tau_{si}^M)$
S.D.	0.71	0.26	1.27	0.97	0.21
75-25	0.85	0.32	1.67	1.24	0.19
90-10	1.73	0.66	3.20	2.42	0.40
Corr.$\log(TFPQ_{si})$	1.00	0.55	0.46	0.57	0.03
2007	$\log(TFPQ_{si})$	$\log(TFPR_{si})$	$\log(1+\tau_{si}^K)$	$\log(1+\tau_{si}^L)$	$\log(1+\tau_{si}^M)$
S.D.	0.66	0.22	1.11	0.89	0.18
75-25	0.95	0.28	1.48	1.15	0.17
90-10	1.72	0.55	2.83	2.23	0.37
Corr.$\log(TFPQ_{si})$	1.00	0.58	0.38	0.53	0.14

Note: This table reports the summary statistics for productivity and distortions in the year 1998 and 2007. S.D. is standard deviation; 75-25 is the difference between the 75th and 25th percentiles; 90-10 is the difference between 90th and 10th percentiles; Corr.$\log(TFPQ_{si})$ is the correlations with $\log(TFPQ_{si})$.

Figure 4.1 panel (b) plots the distribution of the rescaled revenue productivity relative to the corresponding mean value in each sector, i.e., $\log(TFPR_{si}/\overline{TFPR}_s)$. The distribution of revenue productivity gets less dispersed in 2007 than in 1998, suggesting less misallocation of resources across firms over time. In addition, the left tail has become much thinner, suggesting an improvement in resource allocation efficiency. The statistics in Table 4.1 regarding $\log(TFPR_{si})$ are consistent with the panel (b). As in Table 4.1 and panels (c), (d), and (e), although the intermediate input distortion $\log(1+\tau_{si}^{M})$ is significantly less dispersed than capital distortion $\log(1+\tau_{si}^{K})$ and labor distortion $\log(1+\tau_{si}^{L})$, these three types of distortions demonstrate similar dynamics. That is, they display a decreasing standard deviation, a smaller difference between 75th and 25th percentiles, as well as less difference between 90th and 10th percentiles in 2007 than in 1998. It implies fewer impacts of factor market distortions on resource misallocation across firms.

To further explore the relationship between firm characteristics and distortions, Table 4.1 reports the correlations with physical productivity $\log(TFPQ_{si})$. Physical productivity $\log(TFPQ_{si})$ are positively correlated with $\log(1+\tau_{si}^{K})$, $\log(1+\tau_{si}^{L})$, $\log(1+\tau_{si}^{M})$, and $\log(TFPR_{si})$, which means firms with higher productivity are subject to larger distortions. The correlations with $\log(1+\tau_{si}^{K})$ and $\log(1+\tau_{si}^{L})$ decreases slightly over time, whereas the correlation with $\log(1+\tau_{si}^{M})$ gets larger in 2007. David and Venkateswaran (2019) suggest that the predominant drivers of capital misallocation in the Chinese manufacturing sector lie in firm-specific factors, especially the size/productivity-dependent policies. Table 4.1 implies that labor and intermediate input are also subject to productivity-dependent distortions. As discussed in Restuccia and Rogerson (2008), distortions correlated with productivity will potentially do much more damage than uncorrelated distortions.

Firm size in this paper is approximated by the gross revenue output $P_{si}Y_{si}$. The actual firm size $Y_{si}P_{si} \propto \left[A_{si}/\left(1+\tau_{si}^{K}\right)^{\alpha_s\eta_s}\left(1+\tau_{si}^{L}\right)^{(1-\alpha_s)\eta_s}\left(1+\tau_{si}^{M}\right)^{1-\eta_s}\right]^{\sigma-1}$; when all the distortions are eliminated, the efficient firm size $Y_{si}^{*}P_{si}^{*} \propto A_{si}^{\sigma-1}$. Thus, in the absence of distortions, the more productive firms tend to be larger; positive input distortions τ_{si}^{K}, τ_{si}^{L} or τ_{si}^{M} will reduce firm size. As discussed above, physical productivity A_{si} and input

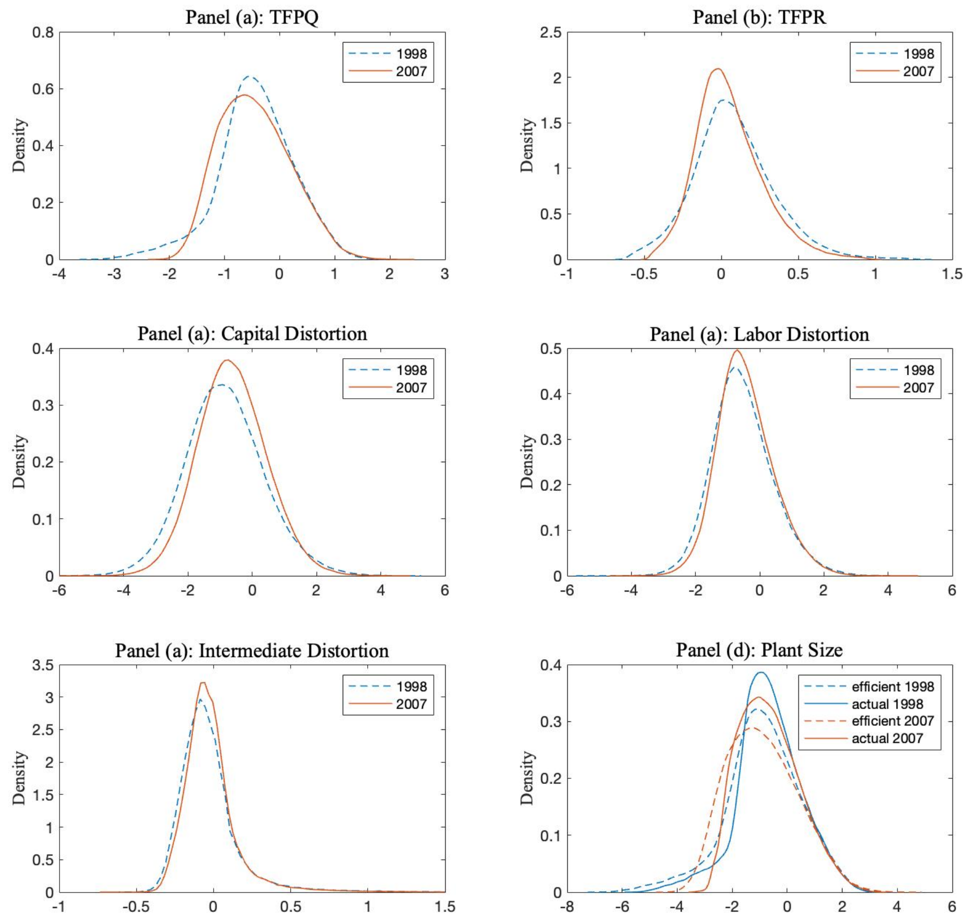

Figure 4.1: Distribution of Productivity, Distortions and Firm Size

Note: Panel (a) plots the distribution of physical productivity, $\log(A_{si}N_s^{\frac{1}{\sigma-1}}/\overline{A}_s)$. Panel (b) plots the distribution of revenue productivity, $\log(TFPR_{si}/\overline{TFPR}_s)$. Panel (c) plots the distribution of capital distortion, $\log(1+\tau_{si}^K/\overline{1+\tau_s^K})$. Panel (d) plots the distribution of labor distortion, $\log(1+\tau_{si}^L/\overline{1+\tau_s^L})$. Panel (e) plots the distribution of intermediate distortion, $\log(1+\tau_{si}^M/\overline{1+\tau_s^M})$. Panel (f) plots the distribution of actual firm size, $\log(P_{si}Y_{si}/\overline{P_sY_s})$ and efficient firm size, $\log(Y_{si}^*P_{si}^*/\overline{Y_s^*P_s^*})$. All the variables are rescaled to the corresponding mean value in each sector.

distortions are positively correlated. Therefore, more (less) productive firms tend to be smaller (larger) than efficient. Panel (f) reports the distributions of rescaled actual firm size, i.e., $\log(P_{si}Y_{si}/\overline{P_sY_s})$ and efficient firm size, i.e., $\log(Y^*_{si}P^*_{si}/\overline{Y^*_sP^*_s})$. The distribution of actual firm size is less dispersed than the efficient firm size. Tails, especially the left tails, get thicker for the efficient firm size than the actual firm size, suggesting less productive firms are subsidized and tend to be larger than the efficient firm size. In addition, the efficient firm size gets less dispersed in 2007 than in 1998, which is consistent with the decreasing dispersion of physical productivity A_{si} over time. We also find that the left tail of efficient firm size becomes thinner, suggesting that the exit of inefficient plants or an increase in idiosyncratic productivity.

4.4.2 Decomposition of Allocative Efficiency

The sector-level productivity TFP_s in equation (4.15) can be also expressed as a function of firm-level productivity and distortions (see Appendix B.1 for details),

$$TFP_s = \frac{\left[\sum_{i=1}^{N_s}(\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{N_s}\frac{1}{1+\tau_{si}^K}(\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{\alpha_s}\left[\sum_{i=1}^{N_s}\frac{1}{1+\tau_{si}^L}(\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{(1-\alpha_s)\eta_s}\left[\sum_{i=1}^{N_s}\frac{1}{1+\tau_{si}^M}(\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{1-\eta_s}} \tag{4.20}$$

where τ_{si} is the total distortion at the firm-level, which is summarized by the geometric weighted average using factor shares as weights,

$$\tau_{si} \equiv \left(1+\tau_{si}^K\right)^{\alpha_s\eta_s}\left(1+\tau_{si}^L\right)^{(1-\alpha_s)\eta_s}\left(1+\tau_{si}^M\right)^{1-\eta_s} \tag{4.21}$$

To understand the relative importance of the distortions in resource misallocation, TFP_s is further decomposed, following the method in Chen and Irarrazabal (2015). Suppose that A_{si}, $\left(1+\tau_{si}^K\right)$, $\left(1+\tau_{si}^L\right)$, and $\left(1+\tau_{si}^M\right)$ follow a joint log-normal distribution in each sector and N_s tends to infinity, by using the corresponding moment generating function, the sector-level productivity TFP_s can be decomposed based on equation (4.20) into the following equation,

$$\begin{aligned}
\log(\frac{TFP_s^e}{TFP_s}) &= \frac{1}{2}\alpha_s\eta_s[1+\alpha_s\eta_s(\sigma-1)]Var[\log(1+\tau_{si}^K)] \\
&+ \frac{1}{2}(1-\alpha_s)\eta_s[1+(1-\alpha_s)\eta_s(\sigma-1)]Var[\log(1+\tau_{si}^L)] \\
&+ \frac{1}{2}(1-\eta_s)[1+(1-\eta_s)(\sigma-1)]Var[\log(1+\tau_{si}^M)] \\
&+ \alpha_s(1-\alpha_s)\eta_s^2(\sigma-1)Cov\left[\log(1+\tau_{si}^K),\log(1+\tau_{si}^L)\right] \\
&+ \alpha_s\eta_s(1-\eta_s)(\sigma-1)Cov\left[\log(1+\tau_{si}^K),\log(1+\tau_{si}^M)\right] \\
&+ (1-\alpha_s)\eta_s(1-\eta_s)(\sigma-1)Cov\left[\log(1+\tau_{si}^L),\log(1+\tau_{si}^M)\right]
\end{aligned} \tag{4.22}$$

As shown in equation (4.22), the sector-level productivity TFP_s can be decomposed into the dispersions and the covariances of capital, labor, and intermediate input wedges. Figure 4.2 plots the $\log(TFP_s^e/TFP_s)$ and its components. Capital distortion contributes the most to the allocative efficiency in the Chinese manufacturing sector, and the dispersion of capital distortion decrease over time. The dispersion of labor distortion reduces first, and then increases slightly. The dispersion of intermediate input distortion, as well as the covariances between capital, labor and, intermediate input wedges only account for a minor fraction of allocative efficiency in the Chinese manufacturing sector.

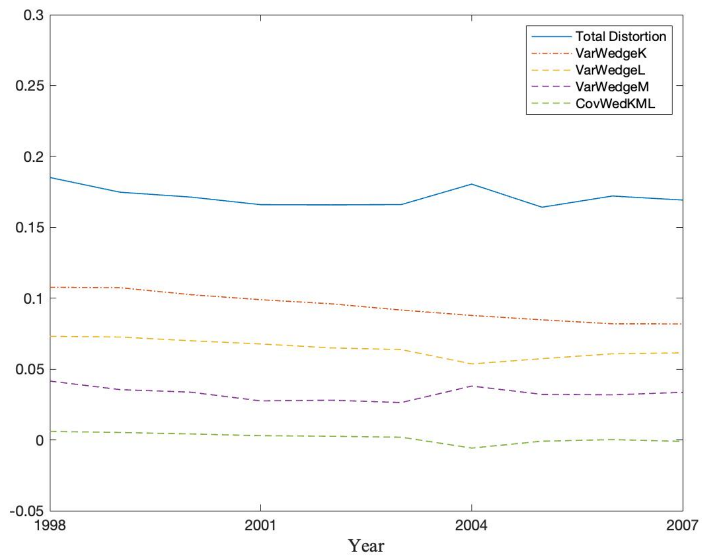

Figure 4.2: Decomposition of Allocative Efficiency

Note: This figure plots the components of the total TFP gains. VarWedgeK is the dispersion of $\log(1+\tau_{si}^K)$; VarWedgeL is the dispersion of $\log(1+\tau_{si}^L)$; VarWedgeM is the dispersion of $\log(1+\tau_{si}^M)$; CovWedgeKML is the sum of all the covariances between $\log(1+\tau_{si}^K)$, $\log(1+\tau_{si}^L)$ and $\log(1+\tau_{si}^M)$. Variances and covariances on this figure are the weighted mean across sectors using the sector shares of gross output θ_s as the weights.

4.4.3 Reallocation Gains

1. Reallocation Gains and the Relative Importance of Distortions

Given the same amount of resources, we can get the efficient level of sectoral productivity TFP_s^e when the planer reallocates factors such that the marginal revenue products of capital, labor, and intermediate input are equalized across firms within each sector. The efficient level of TFP in sector s is given by

$$TFP_s^e = \left(\sum_{i=1}^{N_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}} = \overline{A}_s \tag{4.23}$$

By aggregating the ratio of actual TFP to the efficient TFP in each sector according to the Cobb-Douglas aggregator, we can obtain the gross output gains for the whole manufacturing sector by removing all the distortions, which is given by

$$\frac{Y^e}{Y} = \prod_{s=1}^{S} \left[\sum_{i=1}^{N_s} \left(\frac{\overline{A}_s}{A_{si}} \frac{TFPR_{si}}{\overline{TFPR_s}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{4.24}$$

Table 4.2 reports the gross output gains from equalizing the marginal revenue products of factors of production within sectors. Column 5 implies that the gross output gains $((\frac{Y^e}{Y} - 1) * 100\%)$ by removing all the capital, labor, and intermediate input distortions in the Chinese manufacturing sector will be 18.71% on average during the sample period.

By singly reallocating capital such that the marginal revenue products of capital are equalized within sectors, we can get the gross output Y^K. The gross output gains from eliminating capital distortion can then be calculated as $(\frac{Y^K}{Y} - 1) * 100\%$. Column (2) implies that the gross output in the Chinese manufacturing sector will increase by 7.81% on average by removing the capital wedge. The gross output gains due to capital distortion decrease over time, implying the alleviation of capital distortion. Similarly, the gross output gains from eliminating labor distortion, i.e., $(\frac{Y^L}{Y} - 1) * 100\%$, is 6.39% on average. The gross output gains from reallocating intermediate inputs, i.e., $(\frac{Y^M}{Y} - 1) * 100\%$, is smaller than that of capital and labor, and it is 3.05% on average. The above results suggest that capital distortion is the most essential type of distortions, despite its decreasing importance over the sample period. Besides, labor market distortion is also important for misallocation and aggregate productivity.[3] Although intermediate input takes up a large share of gross output

[3] See, for example, Lagos (2006) uses a Mortensen-Pissarides model studying how labor market policies affect the level of measured TFP through selection effects; Petrosky-Nadeau (2013) explains the unusual

compared to capital and labor, the distortion on its usage has a relatively small negative impact on the aggregate TFP.

Table 4.2: Reallocation Gains by Year (%)

	Capital wedge	Labor wedge	Intermediate wedge	Total output gains
1998	8.34	6.58	3.30	20.34
1999	8.18	6.43	2.78	19.10
2000	7.98	6.40	2.66	18.69
2001	7.96	6.35	2.39	18.05
2002	7.98	6.21	2.49	18.04
2003	7.85	6.44	2.38	18.06
2004	7.67	5.98	5.28	19.78
2005	7.43	6.14	3.04	17.84
2006	7.38	6.71	3.14	18.78
2007	7.30	6.69	3.08	18.44
Average	7.81	6.39	3.05	18.71

Note: This table reports the gross output gains over time by eliminating capital distortion (column 2), labor distortion (column 3), intermediate distortion (column 4), and all the three types of distortions (column 5) within sectors respectively.

The reallocation gains from equalizing the marginal revenue products of factors are heterogeneous across sectors. Table 4.3 reports the reallocation gains by sector for the year 2007. The gross output gains from reallocating capital range from 2.98% in the Stationery & sporting sector to 35.20% in the Tobacco sector. The gross output gains from reallocating labor range from 1.77% in the Tobacco sector to 11.32% in the Apparel sector. Except for the Tobacco sector, Petrochemical sector, and Communication device sector, the reallocation gains of eliminating intermediate input distortion are smaller than both the capital and labor distortions.

increase in aggregate TFP after the financial crisis of 2008 by modeling creation and destruction of jobs in the presence of credit and labor market frictions; Ortego-Marti (2017) quantifies the TFP differences among developed countries due to skill losses during unemployment with search and matching frictions.

Table 4.3: Reallocation Gains by Sector in 2007 (%)

CIC	Industry	Capital wedge	Labor wedge	Intermediate wedge	Total output gains
13	Agri-food processing	11.92	3.78	2.64	19.87
14	Food	9.38	5.70	3.04	20.07
15	Beverage	13.43	4.15	3.38	22.38
16	Tobacco	35.20	1.77	6.53	37.12
17	Textile	5.08	5.82	2.06	13.85
18	Apparel	2.69	11.32	3.65	17.30
19	Leather	2.98	10.60	2.71	16.04
20	Timber processing	9.31	5.66	2.37	19.11
21	Furniture	5.39	7.76	2.49	17.28
22	Paper	7.18	4.54	2.31	15.83
23	Printing	6.11	8.97	3.75	20.28
24	Stationery & sporting	2.94	10.89	3.04	16.57
25	Petrochemical	8.03	2.65	3.29	14.96
26	Chemistry	8.57	5.65	3.06	18.92
27	Pharmaceutical	9.81	6.48	5.19	23.24
28	Chemical fiber	6.07	2.83	2.25	11.49
29	Rubber	7.16	8.24	2.84	20.00
30	Plastic	6.60	7.26	2.79	18.29
31	Non-metallic mineral	7.83	9.24	2.62	22.67
32	Ferrous metals	7.13	5.07	2.51	15.71
33	Non-ferrous metal	10.64	6.42	2.78	21.23
34	Hardware	6.54	7.64	3.15	19.00
35	General equipment	5.40	8.20	2.89	18.23
36	Professional equipment	4.68	7.77	3.51	16.76
37	Transportation	6.64	5.90	3.17	17.03
39	Electric machinery	7.82	6.60	2.64	18.93
40	Communication device	9.32	4.19	5.04	18.38
41	Instrument	5.68	8.93	4.65	19.96
42	Handicrafts & daily sundries	4.76	10.42	3.04	17.90

Note: This table reports the gross output gains for the 2-digit sectors in 2007 by eliminating capital distortion (column 3), labor distortion (column 4), intermediate distortion (column 5), and all the three types of distortions (column 6) within sectors, respectively. CIC denotes the *China Industry Classification code.*

2. Robustness Check

The empirical results above are based on the parameters α_s and η_s that are calibrated to the Chinese manufacturing sector. However, one issue in using the Chinese factor shares directly is that we could not distinguish between factor shares and distortions easily from the data. In this robustness check, following Hsieh and Klenow (2009), factor shares are set to the values of the corresponding manufacturing sectors in the US, which is considered a relatively undistorted economy. The 2-digit sector-level input shares in the US are calculated based on the NBER productivity database.[4] Similarly, the labor share is measured as the share of labor income in industrial value added, and capital share α_s^{us} is set to be one minus labor share. The intermediate input share $1-\eta_s^{us}$ is calculated as the ratio of intermediate costs to the gross output in the corresponding 2-digit sectors. Table 4.4 reports the gross output gains over time adopting the US factor shares by eliminating capital distortion, labor distortion, intermediate distortion, and all the three distortions within sectors.

Table 4.4: Robustness Check: Reallocation Gains with the US Factor Shares (%)

	Capital wedge	Labor wedge	Intermediate wedge	Total output gains
1998	23.55	12.72	2.97	48.77
1999	23.08	12.70	2.23	46.69
2000	22.36	12.60	2.16	45.21
2001	22.18	12.44	1.94	43.94
2002	22.01	12.21	2.04	43.21
2003	21.11	12.72	1.84	42.57
2004	21.17	11.40	3.44	41.22
2005	20.48	11.98	2.26	40.80
2006	20.35	12.98	2.30	42.41
2007	19.80	13.39	2.14	41.61
Average	21.61	12.51	2.33	43.64

Note: This table reports the gross output gains over time with the US factor shares by eliminating capital distortion (column 2), labor distortion (column 3), intermediate distortion (column 4), and all the three types of distortions (column 5) within sectors, respectively.

Compared to Table 4.2 with the Chinese factor shares, gross output gains due to capital distortion and labor distortion now get larger, whereas the gross output gains due to intermediate input distortion become smaller. That is because the average intermediate input share of gross output across the US manufacturing sectors is 0.495, which is much

[4] Data source: https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.

smaller than that in the China manufacturing sector with 0.747. Therefore, the lower intermediate input share in the US amplifies the measured gross output gains due to capital and labor distortions and reduces that due to intermediate distortion. Although the magnitude of gross output gains due to distortions varies when adopting the US factor shares, the relative importance of distortions still holds. That is, capital distortion contributes the most to the TFP loss, and intermediate input distortion is the least important factor.

4.4.4 Value-added Production Structure Revisited

The above empirical study is based on the misallocation accounting framework with the three factors of production. Therefore, we focus on the gross output gains by reallocating capital, labor, and intermediate input within sectors. Despite the empirical results suggesting that intermediate input distortion is not the primary source of the overall misallocation, taking the intermediate input and the distortion on its usage into the misallocation accounting framework may potentially influence the measured TFP gains quantitatively.

Table 4.5 reports the summary statistics for productivity and distortions in the model with two factors of production as in Hsieh and Klenow (2009), and the model with three factors of production respectively in the year 2007. In obtaining Table 4.5, the gross output elasticity of substitution between differentiated goods σ in the model with three factors of production is set to 3 as in the above; the value added elasticity of substitution between differentiated goods σ^{va} in the model with two factors of production is also set to 3 for simplicity. Compared to the model with three factors of production, the model with two factors of production generates much higher dispersions of physical productivity $\log(TFPQ_{si})$ and revenue productivity $\log(TFPR_{si})$, as well as larger positive correlations with physical productivity $\log(TFPQ_{si})$. The above results suggest that the measured firm-level misallocation is larger in the model with two factors of production than the model with three factors of production.

However, to further compare the differences between the two specifications on the measured distortions and TFP gains more precisely, we need to carefully calibrate the parameters, e.g., the value added elasticity of substitution between differentiated goods σ^{va}, and the sector shares of value added θ_s^{va}. Besides, to make the TFP gains under two specifications comparable, we should also focus on the value added gains instead of the gross output gains in the model with three factors of production. That is an essential question to be studied further.

Table 4.5: Comparison: Summary Statistics for Productivity and Distortions in 2007

	$\log(TFPQ_{si})$		$\log(TFPR_{si})$		$\log(1+\tau_{si}^K)$		$\log(1+\tau_{si}^L)$		$\log(1+\tau_{si}^M)$	
	2	3	2	3	2	3	2	3	2	3
S.D.	1.20	0.66	0.82	0.22	1.12	1.11	0.91	0.89	\	0.18
75-25	1.66	0.95	1.11	0.28	1.51	1.48	1.20	1.15	\	0.17
90-10	3.12	1.72	2.12	0.55	2.87	2.83	2.30	2.23	\	0.37
Corr.$\log(TFPQ_{si})$	1.00	1.00	0.89	0.58	0.68	0.38	0.77	0.53	\	0.14

Note: This table reports the summary statistics for productivity and distortions in 2007 for the model with two factors of production (denoted by "2") and the model with three factors of production (denoted by "3"). S.D. is standard deviation; 75-25 is the difference between the 75th and 25th percentiles; 90-10 is the difference between 90th and 10th percentiles; Corr.$\log(TFPQ_{si})$ is the correlations with $\log(TFPQ_{si})$.

4.5 Conclusion

This paper investigates how factor market distortions affect aggregate productivity in the Chinese manufacturing sector from 1998 to 2007 by extending the misallocation accounting framework in Hsieh and Klenow (2009). This paper finds that by equalizing revenue productivity within sectors, the gross output gains are 18.71% on average during the sample period. Although intermediate input accounts for a significant revenue share of gross output, the reallocation gains from removing intermediate input distortion (3.05%) are smaller on average relative to that of capital distortion (7.81%) and labor distortion (6.39%), implying limited importance of intermediate input distortion on resource misallocation in the Chinese manufacturing sector. Although the wedge on intermediate input usage is not the primary source of misallocation, considering intermediate input may potentially matter for the measured distortions and TFP gains.

These findings have policy implications and will also guide future research. First, despite decreasing capital misallocation over time, investigating the origins of capital misallocation and policies in reducing it is crucial since capital distortion is the most significant source of resource misallocation in China's manufacturing sector. Second, labor distortion is also essential for aggregate productivity, and the effects of labor market frictions on labor misallocation can be further investigated (Lagos, 2006; Petrosky-Nadeau, 2013; Ortego-Marti, 2017; Hsieh et al., 2019). Third, although this paper introduces intermediate input, the model abstracts from inter-sectoral production linkage as in the recent literature like Jones (2011) and Bigio and La'O (2020), and only focuses on resource misallocation within sectors. Therefore, examining the impact of intermediate input for misallocation in China through the input-output structure will be an interesting area for future research. Finally, mismeasurement may result in a biased measure of distortions and TFP losses (Bils et al., 2020). Thus, identifying the true marginal products in the presence of measurement error will be another important issue to be investigated.

Chapter 5

Conclusions

This dissertation consists of three essays, each investigating the macroeconomic effects of resource misallocation from different aspects, with a focus on the Chinese manufacturing firm-level dataset.

Chapter 2 adopts the direct approach assessing the importance of the specific source of distortion, financial frictions, on capital misallocation along the intensive margin. The model is featured by a size-dependent borrowing constraint among heterogeneous firms, under which the borrowing tightness decreases with firm size. Since larger firms are less likely to be distorted by financial frictions, the model reproduces a negative correlation between firm size and the marginal product of capital as in the data. In addition, this essay estimates a TFP loss of 3.91% due to capital misallocation across firms induced by the size-dependent financial frictions.

Chapter 3 focuses on how financial development contributes to the aggregate economy along both the intensive and extensive margins by extending the model presented in

Chapter 2. The introduction of the private firms' entry decisions and the financially unconstrained state sector enables us not only to study capital misallocation within incumbent private firms but also to examine resource reallocation within and across private and state sectors. The quantitative results show that financial development in China promotes aggregate productivity and output by 8% and 35%, with productive resources reallocated to the more efficient use.

Chapter 4 employs the indirect approach without specifying underlying sources of misallocation to examine the effects of all potential factor market distortions on the aggregate economy. The empirical results suggest that capital market distortion is the most essential contributor to the total misallocation, despite its decreasing importance that may be partially explained by the financial development studied in Chapter 3. Although intermediate input makes up a large fraction of gross output compared to capital and labor in China, the distortion on its usage has a relatively small impact on the within-sector resource misallocation. These findings have important policy implications and will guide future research.

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Appendix A

Appendix for Chapter 2

A.1 Data

A.1.1 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.

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, industry, founding year, product, and then assigns a unique ID to each firm.

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.1.2 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 $[0, 1]$.

A.2 Derivations and Proofs

A.2.1 Microfoundation of the Size-dependent Borrowing Constraint

The paper extends the underlying logic of the borrowing constraint in the existing literature motived by limited commitment (e.g., Moll, 2014; Buera and Moll, 2015; Midrigan and Xu, 2014). Suppose that contract enforcement is limited and default risks exist. If the firm redeems its debt, the firm solves the problem

$$V^N(k,d,z) = \max_{k',d',c} \log(c) + \beta EV(k',d',z') \tag{A.1}$$

Subject to the budget constraint

$$c_{it} + k_{it+1} - (1-\delta)k_{it} = y_{it} - \omega l_{it} - (1+r)d_{it} + d_{it+1} \tag{A.2}$$

In case of default, the firm defaults on a fraction μ_0 of its debt d_{it}. As a penalty, the bank seizes a fraction μ_1 of the undepreciated capital $(1-\delta)k_{it}$. There is a disruption cost in the event of default that the firm has to pay $\Phi(k_{it})$, following Gopinath et al. (2017). Other default benefits are summarized in the term $\mu_3 k_{it}$. In addition, we assume that firms that default still have access to the financial market in the next period for simplification. Thus, the firm solves the problem

$$V^D(k,d,z) = \max_{k',d',c} \log(c) + \beta EV(k',d',z') \tag{A.3}$$

Subject to the budget constraint

$$c_{it}+k_{it+1}-(1-\delta)k_{it} = y_{it}-\omega l_{it}-(1+r-\mu_0)d_{it}-\mu_1(1-\delta)k_{it}-\mu_2\Phi(k_{it})+\mu_3 k_{it}+d_{it+1} \quad \text{(A.4)}$$

The firm chooses not to default if and only if

$$V^N \geq V^D \quad \text{(A.5)}$$

Therefore, we can obtain the incentive compatibility constraint so that there is no default in the equilibrium as follows:

$$d_{it} \leq \underbrace{\left(\frac{\mu_1\left(1-\delta\right)-\mu_3}{\mu_0}\right)}_{\theta_0} k_{it} + \underbrace{\left(\frac{\mu_2}{\mu_0}\right)}_{\theta_1} \Phi(k_{it}) \quad \text{(A.6)}$$

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

$$k_{it} \leq \underbrace{\left(\frac{\mu_0}{\mu_0-\mu_1\left(1-\delta\right)+\mu_3}\right)}_{\lambda_0} a_{it} + \underbrace{\left(\frac{\mu_2}{\mu_0-\mu_2\left(1-\delta\right)+\mu_3}\right)}_{\lambda_1} \Phi(k_{it}) \quad \text{(A.7)}$$

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

A.2.2 Parameter Restrictions on the Size-dependent Borrowing Constraint

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

$$\begin{aligned} C(k) &= \mu_1(1-\delta)k + \mu_2\Phi(k) - \mu_3 k \\ &= (\mu_1(1-\delta) - \mu_3)\, k + \mu_2 k^2 \end{aligned} \tag{A.8}$$

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 A.2.1, 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.

A.2.3 Proof of Proposition 1

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

$$\alpha\eta\frac{y(a,z)}{l(a,z)} = \omega \tag{A.9}$$

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

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

$$\mu(a,z) = \begin{cases} 0 & if\ k < \lambda_0 a + \lambda_1 k^2 \\ \frac{1}{(1-2\lambda_1 k(a,z))}[\left(\frac{\alpha\eta}{\omega}\right)^{\frac{\alpha\eta}{1-\eta}}(1-\alpha)\,\eta\left(\frac{z}{k(a,z)}\right)^{\frac{1-\eta}{1-\alpha\eta}} - r - \delta] & if\ k = \lambda_0 a + \lambda_1 k^2 \end{cases} \tag{A.11}$$

Then, l and k can be jointly solved as

$$l(a,z) = z^{\frac{1-\eta}{1-\alpha\eta}}(\frac{\alpha\eta}{\omega})^{\frac{1}{1-\alpha\eta}}k^{\frac{(1-\alpha)\eta}{1-\alpha\eta}} \tag{A.12}$$

$$k(a,z) = z(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}}[r+\delta+\mu(a,z)(1-2\lambda_1 k(a,z))]^{\frac{\alpha\eta-1}{1-\eta}} \tag{A.13}$$

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:

$$g(k) \equiv \lambda_0 a + \lambda_1 k^2 - k \tag{A.14}$$

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

$$k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}}z \tag{A.15}$$

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

$$0 \leq k_1 \leq \frac{1}{2\lambda_1} \leq k_2 \tag{A.16}$$

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 $g(k) = 0$:

$$k^c(a,z) = \frac{1 - \sqrt{1 - 4\lambda_0\lambda_1 a}}{2\lambda_1} \tag{A.17}$$

A.2.4 Proof of Proposition 2

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

$$k \leq \lambda_0 a \tag{A.18}$$

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

$$\alpha\eta \frac{y(a,z)}{l(a,z)} = \omega \tag{A.19}$$

$$(1-\alpha)\,\eta \frac{y(a,z)}{k(a,z)} = r + \delta + \gamma(a,z) \tag{A.20}$$

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

$$\gamma(a,z) = \begin{cases} 0 & if\ k(a,z) < \lambda_0 a \\ \left(\frac{\alpha\eta}{\omega}\right)^{\frac{\alpha\eta}{1-\eta}} (1-\alpha)\,\eta \left(\frac{z}{k(a,z)}\right)^{\frac{1-\eta}{1-\alpha\eta}} - r - \delta & if\ k(a,z) = \lambda_0 a \end{cases} \tag{A.21}$$

Then, l and k can be jointly solved as

$$l(a,z) = z^{\frac{1-\eta}{1-\alpha\eta}} \left(\frac{\alpha\eta}{\omega}\right)^{\frac{1}{1-\alpha\eta}} k^{\frac{(1-\alpha)\eta}{1-\alpha\eta}} \tag{A.22}$$

$$k(a,z) = z\left(\frac{\alpha\eta}{\omega}\right)^{\frac{\alpha\eta}{1-\eta}} ((1-\alpha)\eta)^{\frac{1-\alpha\eta}{1-\eta}} \left[r + \delta + \gamma(a,z)\right]^{\frac{\alpha\eta-1}{1-\eta}} \tag{A.23}$$

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

$$k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}} z \tag{A.24}$$

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

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

$$k^c = \lambda_0 a \tag{A.25}$$

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

$$a^* = \frac{k^u(z)}{\lambda_0} \tag{A.26}$$

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.

A.2.5 Proof of Proposition 3

Under the size-dependent borrowing constraint ($\lambda_1 > 0$), according to Proposition 1, $k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}} z$, 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

$$a^* = \frac{1-(1-2\lambda_1 k^u(z))^2}{4\lambda_0\lambda_1} \tag{A.27}$$

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.

A.2.6 Proof of Proposition 4

Based on Appendix A.2.4, the marginal product of capital MP_k under the homogeneous borrowing constraint is equal to

$$MP_k = r + \delta + \gamma \tag{A.28}$$

The capital decisions for the financially unconstrained and constrained firms are $k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}} z$ 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 A.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 higher productivity accordingly have a higher financing need for capital. As a result, those firms are more constrained and face a higher MP_k.

A.2.7 Proof of Proposition 5

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

$$MP_k = r + \delta + \mu(1 - 2\lambda_1 k) \tag{A.29}$$

According to Proposition 1, $k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}}(\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}} z$, $k^c(a) = k_1(a) = \frac{1-\sqrt{1-4\lambda_0\lambda_1 a}}{2\lambda_1}$ 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^*

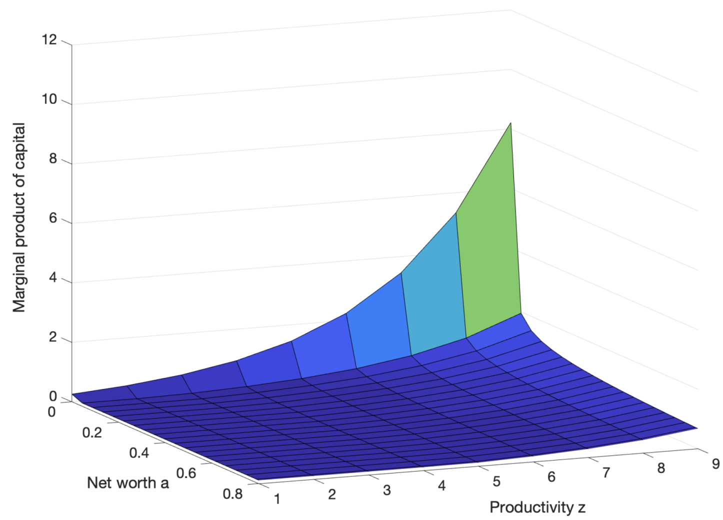

Figure A.1: Determination of the Marginal Product of Capital ($\lambda_1 = 0$)

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

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 a 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 a 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 a 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 a 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 a 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 a 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 a 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 face a low MP_k.

Figure A.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 their greater 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 highly productive firms.

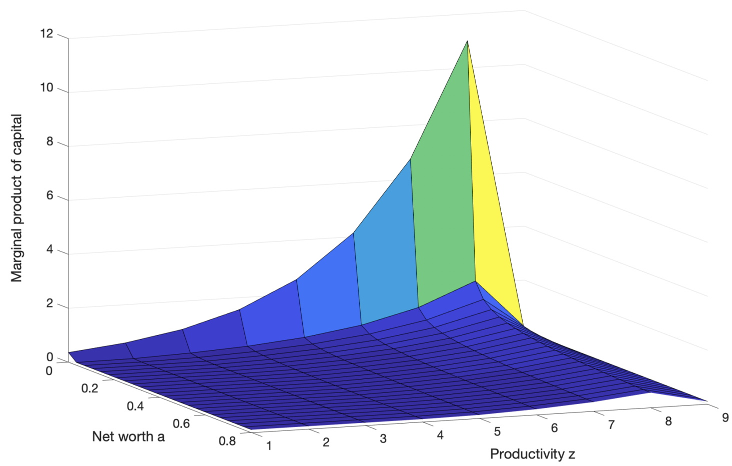

Figure A.2: Determination of the Marginal Product of Capital ($\lambda_1 > 0$)

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.

A.3 Alternative Specifications of the Size-dependent Borrowing Constraint

The positive relationship between leverage and firm size has been found in various countries; however, the determinants of the leverage-size correlation are still largely unresolved due to lacking empirical studies on the underlying mechanism and conflicting theoretical predictions (Rajan and Zingales, 1995). To capture the positive leverage-size relationship, this paper models a size-dependent borrowing constraint by following Gopinath et al. (2017) and introducing default costs that increase in firm size. Alternative specifications of size-dependent borrowing constraints, e.g., borrowing constraint with size-dependent pledgeability and borrowing constraint based on earnings, may also capture the leverage-size correlation and the other cross-sectional moments. The alternative borrowing constraints are discussed as follows.

1. Borrowing Constraint with Size-dependent Pledgeability

Collateral matters as it could mitigate the enforcement frictions between firms and banks. Intuitively, larger firms have more collateralizable capital proportionally, resulting in a positive leverage-size relationship. Therefore, the general form of a borrowing constraint with size-dependent pledgeability can be given by

$$d \leq \Psi(k)k \tag{A.30}$$

where the function $\Psi(k)$ represents the overall pledgeability of the installed capital, and its range is $[0, 1]$. In order to capture the size-dependent pledgeability, $\Psi(k)$ is assumed to be an increasing function in capital. Since large firms can pledge more capital proportionally, they have higher leverage than small firms. For example, in Ruiz-García (2020), the function $\Psi(k)$ is set to $\theta\left(\frac{k}{k^u}\right)^{\psi}$, where θ denotes the maximum level of pledgeability, ψ governs the heterogeneity in pledgeability among firms, and k^u is the optimal capital level at a given productivity. Firms with higher internal funds will install more capital and therefore exhibit larger pledgeability. In Ruiz-García (2020), the model adopting a borrowing constraint with size-dependent pledgeability can reproduce the cross-sectional moments observed in the Spanish firm-level dataset.

2. Borrowing Constraint Based on Earnings

Instead of focusing on an asset-based borrowing constraint, there is growing literature studying the role of financial frictions in macroeconomics by adopting an earnings-based borrowing constraint (Lian and Ma, 2021; Drechsel, 2020; Greenwald, 2019).[1] As discussed in Drechsel (2020), an earnings-based borrowing constraint can be derived as a solution to the limited enforcement of contract problem. Suppose there exist default risks, and the lender has the right to seize the ownership of the entire firm in the event of default. Since the lender is uncertain about the firm value, the firm ownership is then evaluated using a fixed multiple of the firm's cash flows. Therefore, the firm's debt is limited by a function of the cash flows (usually measured using operating earnings). Furthermore, loan covenants

[1]For example, Lian and Ma (2021) find that borrowing against cash flows accounts for the majority of US non-financial corporate debt; and cash flow-based lending is less common among small firms, young firms, and low-profit firms.

in debt contracts, e.g., a maximum of debt-to-earnings ratio that should not be violated, are an important way to impose earnings-based borrowing constraints.

There exists heterogeneity in the covenant limits by firm. Drechsel (2020) reports that the most frequent loan covenant is the maximum ratio of debt to EBITDA (earnings before interest, taxes, depreciation, and amortization). The mean of its value is 4.6, while the 25th and 75th percentile are 3 and 5. Since small firms have less stable or verifiable cash flows, it is difficult for creditors to count on those firms' continuing operations. By contrast, large firms have lower volatility of sales and employment, which allows them to have higher leverage (Chatterjee and Eyigungor, 2020). Therefore, the earnings-based borrowing constraint with heterogeneous covenant limits can be given by

$$d \leq \Phi(k)\pi^n \tag{A.31}$$

where the function $\Phi(k)$ represents the maximum ratio of firms' debt against the operating earnings. It governs the overall borrowing tightness of the earnings-based borrowing constraint. As lenders value large firms' cash flows more than small firms, they discount the future firm value with the function $\Phi(k)$ that increases in firm size. As noted in Lian and Ma (2021), leverage typically refers to the debt-to-earnings ratio under the earnings-based borrowing constraint.

The function π^n denotes the operating earnings measured by EBITDA and is defined as

$$\pi^n \equiv y - \omega l \tag{A.32}$$

The solution to labor choice l that maximizes the operating earnings π^n after learning productivity z is given by

$$l = (\frac{\alpha\eta}{\omega})^{\frac{1}{1-\alpha\eta}} z^{\frac{1-\eta}{1-\alpha\eta}} k^{\frac{(1-\alpha)]\eta}{1-\alpha\eta}} \tag{A.33}$$

Therefore, the operating earnings π^n can be rewritten as

$$\pi^n = (1-\alpha\eta)(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\alpha\eta}} z^{\frac{1-\eta}{1-\alpha\eta}} k^{\frac{(1-\alpha)]\eta}{1-\alpha\eta}} \tag{A.34}$$

The optimal capital level k^u for financially unconstrained firms is

$$k^u = (\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\eta}} (\frac{(1-\alpha)\eta}{r+\delta})^{\frac{1-\alpha\eta}{1-\eta}} z \tag{A.35}$$

The marginal product of capital for these unconstrained firms equals to $r+\delta$. For financially constrained firms, the attainable capital level k^c is given by

$$k^c = a + (1-\alpha\eta)(\frac{\alpha\eta}{\omega})^{\frac{\alpha\eta}{1-\alpha\eta}} z^{\frac{1-\eta}{1-\alpha\eta}} (k^c)^{\frac{(1-\alpha)\eta}{1-\alpha\eta}} \Phi(k^c) \tag{A.36}$$

Suppose the functional form for the maximum debt-to-earnings ratio $\Phi(k)$ is ϕk^{ψ}, where parameters ϕ and ψ jointly govern the borrowing tightness. Under the parameter restriction that $\psi < \frac{1-\eta}{1-\alpha\eta}$, for financially constrained firms, given productivity z, since $\frac{dk^c}{da} > 0$, firms with higher net worth will be able to purchase more capital, and have higher leverage $\Phi(k^c)$; the marginal product of capital decreases accordingly. Given net worth a, since $\frac{dk^c}{dz} > 0$, constrained firms with higher productivity will have higher borrowing capacity.

Thus, they install more capital and have higher leverage $\Phi(k^c)$; in addition, the marginal product of capital increases first and then declines with productivity. Compared to an asset-based borrowing constraint, productivity enlarges firms' borrowing capacity directly with the earnings-based borrowing constraint. The TFP loss due to financial frictions therefore may be overstated without considering the pledgeable operating earnings.

A.4 Calibration Results under the Homogeneous Borrowing Constraint

Table A.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 A.1: Calibration Results in the HoF

Parameter	Description	Value	Source/target
p_u	Persistence zero state	0.5	Employment ratio
p_e	Persistence unit state	0.806	
β	Discount factor	0.887	Real interest rate
η	Span of control	0.806	Output share by top 5 output percentiles
α	Labor elasticity	0.558	Labor share $\alpha\eta$ equals 0.45
δ	Depreciation rate	0.069	Aggregate capital-to-output ratio
ρ	Persistent component	0.873	1-year autocorrelation of output
σ_ε	S.D. transitory shock	0.834	S.D. output growth
λ_0	Borrowing tightness	2.498	Aggregate debt-to-output ratio

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

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

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

Moment	Data	HeF
S.D. log output	1.22	1.48
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	0.57
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.

Appendix B

Appendix for Chapter 4

B.1 Derivations Omitted from the Main Text

This section provides the derivation of equation (4.20) in the main text as follows.

Plug the inverse demand function $P_{si} = P_s Y_s^{\frac{1}{\sigma}} Y_{si}^{-\frac{1}{\sigma}}$ into equation (4.8) and by rearrangement, we can get

$$\frac{\sigma-1}{\sigma}\alpha_s\eta_s P_s Y_s^{\frac{1}{\sigma}}\left[A_{si}\left(\frac{L_{si}}{K_{si}}\right)^{(1-\alpha_s)\eta_s}\left(\frac{M_{si}}{K_{si}}\right)^{1-\eta_s}\right]^{\frac{\sigma-1}{\sigma}} K_{si}^{-\frac{1}{\sigma}} = \left(1+\tau_{si}^K\right)R \tag{B.1}$$

Plug the expressions for $\frac{L_{si}}{K_{si}}$ and $\frac{M_{si}}{K_{si}}$ (which are obtained based on equations (4.8), (4.9) and (4.10)) into equation (B.1), we can get

$$\begin{aligned} K_{si} = &\left(\frac{\sigma-1}{\sigma}\right)^{\sigma} P_s^{\sigma} Y_s A_{si}^{\sigma-1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s\eta_s(1-\sigma)-1}\left(\frac{\omega}{\beta_s}\right)^{(1-\alpha_s)\eta_s(1-\sigma)} \\ &\left(\frac{P_M}{\gamma_S}\right)^{(1-\eta_s)(1-\sigma)}\left(1+\tau_{si}^K\right)^{-1}\tau_{si}^{1-\sigma} \end{aligned} \tag{B.2}$$

where the total distortion at the firm-level τ_{si} is defined as the geometric weighted average using factor shares as weights,

$$\tau_{si} \equiv \left(1+\tau_{si}^{K}\right)^{\alpha_s \eta_s} \left(1+\tau_{si}^{L}\right)^{(1-\alpha_s)\eta_s} \left(1+\tau_{si}^{M}\right)^{1-\eta_s} \tag{B.3}$$

The corresponding aggregate capital K_s in sector s then can be expressed as

$$\begin{aligned} K_s &= \sum_{i=1}^{N_s} K_{si} \\ &= \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} P_s^{\sigma} Y_s \left(\frac{R}{\alpha_s}\right)^{\alpha_s\eta_s(1-\sigma)-1} \left(\frac{\omega}{\beta_s}\right)^{(1-\alpha_s)\eta_s(1-\sigma)} \\ &\left(\frac{P_M}{\gamma_S}\right)^{(1-\eta_s)(1-\sigma)} \sum_{i=1}^{N_s} \left(\frac{A_{si}}{\tau_{si}}\right)^{\sigma-1} \left(1+\tau_{si}^{K}\right)^{-1} \end{aligned} \tag{B.4}$$

Similarly, we can obtain the aggregate labor L_s in sector s,

$$\begin{aligned} L_s &= \sum_{i=1}^{N_s} L_{si} \\ &= \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} P_s^{\sigma} Y_s \left(\frac{R}{\alpha_s}\right)^{\alpha_s\eta_s(1-\sigma)} \left(\frac{\omega}{\beta_s}\right)^{(1-\alpha_s)\eta_s(1-\sigma)-1} \\ &\left(\frac{P_M}{\gamma_S}\right)^{(1-\eta_s)(1-\sigma)} \sum_{i=1}^{N_s} \left(\frac{A_{si}}{\tau_{si}}\right)^{\sigma-1} \left(1+\tau_{si}^{L}\right)^{-1} \end{aligned} \tag{B.5}$$

And aggregate intermediate inputs M_s in sector s,

$$\begin{aligned} M_s &= \sum_{i=1}^{N_s} M_{si} \\ &= \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} P_s^{\sigma} Y_s \left(\frac{R}{\alpha_s}\right)^{\alpha_s\eta_s(1-\sigma)} \left(\frac{\omega}{\beta_s}\right)^{(1-\alpha_s)\eta_s(1-\sigma)} \\ &\left(\frac{P_M}{\gamma_S}\right)^{(1-\eta_s)(1-\sigma)-1} \sum_{i=1}^{N_s} \left(\frac{A_{si}}{\tau_{si}}\right)^{\sigma-1} \left(1+\tau_{si}^{M}\right)^{-1} \end{aligned} \tag{B.6}$$

The firm level gross output Y_{si} is

$$Y_{si} = A_{si} \left(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}\right)^{\eta_s} M_{si}^{1-\eta_s} \tag{B.7}$$

Plug the above expressions for K_{si}, L_{si} and M_{si} into equation (B.7), we can get the expression for Y_{si} as

$$Y_{si} = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} P_s^{\sigma} Y_s A_{si}^{\sigma} \left(\frac{R}{\alpha_s \eta_s}\right)^{-\alpha_s \eta_s \sigma} \left(\frac{\omega}{\beta_s}\right)^{-(1-\alpha_s)\eta_s \sigma} \left(\frac{P_M}{\gamma_S}\right)^{-(1-\eta_s)\sigma} \tau_{si}^{-\sigma} \tag{B.8}$$

The gross output Y_s in sector s is

$$\begin{aligned} Y_s &= \left(\sum_{i=1}^{N_s} Y_{si}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \\ &= \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} P_s^{\sigma} Y_s \left(\frac{R}{\alpha_s \eta_s}\right)^{-\alpha_s \eta_s \sigma} \left(\frac{\omega}{\beta_s}\right)^{-(1-\alpha_s)\eta_s \sigma} \\ &\left(\frac{P_M}{\gamma_S}\right)^{-\gamma_s \sigma} \left[\sum_{i=1}^{N_s} \left(\frac{A_{si}}{\tau_{si}}\right)^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{B.9}$$

The sector-level productivity TFP_s is defined as

$$TFP_s \equiv \frac{Y_s}{\left(K_s^{\alpha_s} L_s^{1-\alpha_s}\right)^{\eta_s} M_s^{1-\eta_s}} \tag{B.10}$$

Plug equations (B.4), (B.5), (B.6) and (B.9) into equation (B.10), we get the expression for TFP_s as

$$TFP_s = \frac{\left[\sum_{i=1}^{N_s} (\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{N_s} \frac{1}{1+\tau_{si}^K} (\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{\alpha_s\eta_s} \left[\sum_{i=1}^{N_s} \frac{1}{1+\tau_{si}^L} (\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{(1-\alpha_s)\eta_s} \left[\sum_{i=1}^{N_s} \frac{1}{1+\tau_{si}^M} (\frac{A_{si}}{\tau_{si}})^{\sigma-1}\right]^{1-\eta_s}} \tag{B.11}$$

TFP_s in equation (B.11) depends on idiosyncratic productivity A_{si} and distortions τ_{si}^K, τ_{si}^L, and τ_{si}^M. In addition, the expression for TFP_s in equation (B.11) and equation (4.15) are equivalent.