When Do Financial Frictions Matter for Misallocation?*

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Abstract

This paper reassesses the role of financial frictions in capital misallocation through a model disciplined by both firm-level borrowing costs and average revenue product of capital ($ARPK$). Using Chinese manufacturing data, we document substantial dispersion in $ARPK$, alongside a strong positive relationship between $ARPK$ and the borrowing costs firms face—patterns absent in U.S. data. We develop a heterogeneous-firm model with endogenous firm-specific borrowing costs and additional capital distortions modeled as exogenous wedges. In this model, eliminating financial frictions raises total factor productivity (TFP) by 25 percentage points. In contrast, without other capital distortions, removing financial frictions increases TFP by less than 2 percentage points. The stark difference arises from the interaction between financial frictions and permanent firm-level distortions, which generate endogenous financial heterogeneity and selection, making productive firms the most constrained. Our findings suggest that financial frictions can be highly distortionary when other sources of misallocation are present.

Keywords: financial frictions, firm debt financing, capital misallocation.

JEL classification: G3, E2

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1 Introduction

Since the seminal work of Hsieh and Klenow (2009), a large literature has documented substantial resource misallocation in developing economies such as China. A natural candidate explanation is underdeveloped financial markets, which distort firms' investment decisions and prevent capital from flowing to its most productive uses. Yet quantitative studies of financial frictions have produced mixed results regarding their aggregate importance. On the one hand, models such as Moll (2014) and Midrigan and Xu (2014) find that financial frictions generate only modest productivity losses, as constrained firms can accumulate internal funds and gradually relax borrowing constraints. On the other hand, studies such as Buera et al. (2011) and Song et al. (2011) argue that financial frictions play a central role in explaining misallocation and aggregate productivity gaps. This divergence raises a fundamental question: when do financial frictions matter quantitatively for misallocation?

This paper revisits this question by disciplining both financial frictions and other capital distortions using firm-level data. Using Chinese manufacturing data, we document substantial dispersion in firms' average revenue product of capital ($ARPK$), alongside a robust positive relationship between firms' borrowing costs and $ARPK$. That is, firms with higher $ARPK$—indicative of larger capital distortions—systematically face higher borrowing costs. This relationship is largely driven by persistent firm-level heterogeneity. In contrast, these patterns are absent in U.S. data, where dispersion in $ARPK$ is much smaller and borrowing costs are weakly or negatively correlated with $ARPK$.

To quantify the aggregate implications of this evidence, we develop a heterogeneous-firm model with endogenous firm-specific borrowing costs arising from state-noncontingent debt and default risk. Importantly, we allow financial frictions to interact with other permanent firm-level capital distortions, modeled as exogenous wedges following Hsieh and Klenow (2009), David and Venkateswaran (2019), and Bai et al. (2024). These wedges capture regulatory policies and differential treatment across firms.

This interaction fundamentally changes the quantitative importance of financial frictions: in the presence of exogenous wedges, financial frictions generate substantial total factor productivity (TFP) losses, far exceeding those in the canonical financial frictions model without such wedges (consistent with Moll (2014)). Moreover, the model with exogenous wedges replicates the observed dispersion in $ARPK$, the positive relationship between $ARPK$ and borrowing costs, and the persistence of this relationship within firms, whereas the canonical financial frictions model fails to do so. These results underscore the importance of incorporating other distortions when quantifying the role of financial frictions in misallocation, particularly in developing economies such as China.

We begin by documenting salient features of rich firm-level data from China spanning 1998 to 2007. Consistent with Hsieh and Klenow (2009), we find substantial dispersion in firms' average revenue products of capital in China, a pattern that persists throughout the sample period. To examine whether this dispersion relates to firm financing, we analyze firm-level borrowing costs, measured as the ratio of interest payments to total liabilities. We follow Gilchrist et al. (2013) and use this proxy for firms' financing conditions, as in a frictionless capital market, all firms would face the same borrowing costs and earn the same marginal return on capital.

Three key patterns emerge from our analysis. First, firms with higher $ARPK$ also face higher borrowing costs. Second, this positive relationship persists throughout the sample period (1998-2007) and holds within each ownership category, including privately owned enterprises (POEs), state-owned enterprises (SOEs), and other firm types. Third, permanent firm heterogeneity accounts for roughly half of the correlation between $ARPK$ and borrowing costs: when firm fixed effects are included, the regression coefficient declines from 0.16 to 0.07. These findings suggest the importance of persistent firm-specific distortions alongside financial frictions for misallocation in China.

For comparison, we examine the same relationship in the United States, an advanced economy with well-developed financial markets and fewer distortions. Using U.S. Compustat data, we find that borrowing costs are barely correlated with $ARPK$, contrasting with the strong positive relationship observed in China. To ensure this contrast is not driven by sample composition, we restrict both samples to firms with comparable asset sizes. The stark difference between the two countries remains.

To assess the aggregate implications, we develop a model with heterogeneous firms and endogenous borrowing constraints arising from state-noncontingent debt and default risk. Firms produce using a decreasing-returns-to-scale technology with capital and are subject to stochastic productivity and capital quality shocks. Firms finance investment and dividend payments from retained earnings and state-uncontingent bonds. They can default on their debt, and financial intermediaries incorporate this default risk into bond pricing. As a result, the model generates endogenous borrowing constraints and differential borrowing costs across firms.

The model incorporates three sources of misallocation: information frictions, financial frictions, and exogenous wedges. Information frictions arise because firms choose capital before productivity shocks are realized. Financial frictions—stemming from noncontingent debt and default risk—prevent firms from achieving optimal investment levels. Exogenous wedges act like taxes or subsidies on output and capture additional sources of misallocation, such as government policies and regulatory distortions. Together, these frictions generate cross-firm dispersion in the return to capital, resulting in inefficient allocation of resources.

The model generates large dispersion in $ARPK$, alongside a positive relationship between $ARPK$ and borrowing costs, through financial frictions and their interaction with exogenous wedges. Financial frictions imply that borrowing costs rise with default risk. Firms with limited net worth face tighter borrowing constraints and higher borrowing costs, which keep them inefficiently small and raise their $ARPK$. Exogenous wedges strengthen this mechanism. High-wedge firms face higher effective taxes, which directly increase their $ARPK$ by distorting capital downward. Wedges also amplify financial frictions—high-wedge firms are more prone to default, leading lenders to impose steeper bond-price schedules. This further tightens borrowing constraints, raising both borrowing costs and $ARPK$ for high-wedge firms.

We estimate the model by targeting the firm growth distribution, financing patterns, and $ARPK$ dispersion observed in Chinese data. These moments jointly identify the productivity process, the parameters governing financial frictions, and the exogenous wedges. The productivity process parameters primarily determine the distribution of value-added growth rates. Both the productivity process and capital quality shocks influence firm default risk, while the debt recovery rate shapes average leverage and borrowing costs across firms. We calibrate these parameters to match the empirical distributions of firm borrowing costs and leverage, and jointly calibrate the exogenous wedges to match the observed dispersion in $ARPK$. The model closely replicates these targeted moments. The model also matches the observed positive correlation between $ARPK$ and borrowing costs, although is not targeted in the estimation.

Using the calibrated model, we evaluate the magnitude of TFP losses attributable to financial frictions. In the benchmark model with exogenous wedges, eliminating financial frictions raises TFP by 25 percentage points, implying sizable misallocation due to financial frictions. For comparison, we recalibrate a reference model that excludes exogenous wedges. Consistent with the prior literature, the canonical financial frictions generates TFP losses of less than 2 percentage points. The contrast between the two models indicates that financial frictions can be quantitatively important for misallocation, but through the interaction with other distortions.

Why do financial frictions generate substantial misallocation only in the presence of exogenous wedges? Two mechanisms drive this amplification. First, in the absence of other wedges, productive firms grow large, accumulate internal funds, and gradually relax borrowing constraints, so that financial frictions generate only modest misallocation. In contrast, when permanent wedges are present, even highly productive firms are forced to operate at persistently smaller scales. As a result, they remain asset-poor, face higher default risk, and are subject to tighter borrowing constraints. Financial frictions therefore bind not only on unproductive firms, but on productive firms that would otherwise be large. By reshaping the distribution of firm size and financial conditions, wedges reallocate financial constraints toward productive firms, creating *persistent financial heterogeneity* and making financial frictions substantially more distortionary.

Second, *endogenous selection* further strengthens the amplification. Although wedges and productivity are independently drawn at entry, selection induces a positive correlation between them: among highly taxed firms, only the most productive survive, yet these survivors simultaneously face tighter financial frictions due to their high wedges. Capital is therefore systematically misallocated away from productive but constrained firms. Together, the two mechanisms explain why financial frictions can generate large aggregate productivity losses when they interact with other persistent distortions, even though they play a limited role in isolation.

Our model emphasizes the role of exogenous wedges in amplifying the impact of financial frictions on misallocation. To assess the empirical relevance of these wedges, we compare the benchmark model's predictions with those of a counterfactual model that excludes exogenous wedges, which reduces to the canonical firm financial friction model. We find that the benchmark model closely matches the observed $ARPK$ patterns along three dimensions, whereas the canonical financial friction model fails to do so.

First, the large dispersion in $ARPK$ observed in the Chinese data reflects substantial capital distortions and directly informs the estimation of exogenous wedges in the benchmark model. In contrast, the canonical financial friction model without exogenous wedges generates only 37% of the observed standard deviation of $ARPK$, even though it is recalibrated to match the dispersion in borrowing costs. This limited dispersion helps explain why the canonical financial friction model typically implies only modest capital misallocation in the literature.

Second, the data show that cross-firm heterogeneity in $ARPK$ is highly persistent. Regressing $ARPK$ on its lagged value yields a coefficient of 0.73, which declines to 0.16 after controlling for firm fixed effects. This sharp decline indicates that most of the observed persistence in $ARPK$ arises from permanent cross-firm heterogeneity.

Without exogenous wedges, the canonical financial friction model cannot replicate this pattern. In that model, high-$ARPK$ firms face larger returns on investment and have strong incentives to borrow and invest, so they reduce their $ARPK$ whenever possible. As a result, $ARPK$ persistence remains low in this model, and including firm fixed effects has little effect because firms are ex-ante identical.

In contrast, introducing permanent exogenous wedges enables the model to replicate the observed pattern. Firms facing permanently different exogenous wedges exhibit highly persistent differences in $ARPK$. At the same time, financial frictions continue to operate within firms, so once fixed effects are included, the autocorrelation coefficient declines sharply, consistent with the data. This evidence validates modeling exogenous wedges as permanent firm-level distortions.

Third, the data show a negative correlation between leverage and $ARPK$: firms with higher $ARPK$ borrow less. In the absence of exogenous wedges, the model predicts the opposite pattern. In this case, constrained firms have higher $ARPK$ and face stronger incentives to borrow, generating a positive correlation between leverage and $ARPK$. Introducing exogenous wedges resolves this discrepancy. Firms facing high wedges effectively pay higher taxes and face tighter bond price schedules than low-wedge firms. Thus, high-wedge firms exhibit higher $ARPK$ but lower leverage, allowing the model to reproduce the observed negative correlation.

Our paper makes two key contributions. First, we directly use firm-level borrowing costs and $ARPK$ to discipline financial frictions and other capital distortions. We document large dispersion in $ARPK$ and a positive correlation between borrowing costs and $ARPK$ among Chinese firms—patterns that are absent in the United States. Second, we reconcile conflicting findings in the literature regarding whether financial frictions generate substantial misallocation. Our analysis reveals that the quantitative importance of financial frictions depends critically on the presence of other distortions: in isolation, financial frictions generate modest losses, but when interacting with additional distortions common in developing economies like China, they become much more distortionary.

Literature. Our work contributes to the growing literature on capital misallocation. Following Hsieh and Klenow (2009), which documents substantial dispersion in the marginal products of capital across firms in China and India, subsequent studies have quantitatively evaluated various frictions that contribute to misallocation, including financial constraints (Midrigan and Xu, 2014; Moll, 2014), capital adjustment costs and information frictions (David and Venkateswaran, 2019), taxes (Glover and Levine, 2021), the allocation of financial liabilities (Whited and Zhao, 2021), mismeasurement (Bils et al., 2021), debt maturity (Karabarbounis and Macnamara, 2021), macroeconomic risk (David et al., 2022), and excess investor demand (Choi et al., 2025). The literature has established that financial frictions tend to generate only modest TFP losses, as constrained firms can accumulate internal funds and eventually self-finance their way out of constraints. Consistent with this result, our canonical financial frictions model—without exogenous wedges—also generates small TFP losses.

We complement these studies by using firm-level financing patterns to discipline financial frictions and by showing that their interaction with other distortions generates sizable capital misallocation.[1] We identify two mechanisms behind this amplification. First, exogenous wedges generate endogenous financial heterogeneity that cannot be undone through self-financing. Second, selection concentrates productive firms in the more financially constrained group. These mechanisms also help explain why capital misallocation is persistent, addressing the key puzzle raised by Banerjee and Moll (2010).

Our finding of large TFP losses arising from endogenous financial heterogeneity is related to prior literature that argues for a large role of financial frictions in misallocation. This includes financial heterogeneity due to sectoral fixed cost (Buera et al., 2011), differential access to credit between state-owned and private-owned firms (Song et al., 2011; Liu et al., 2021), and exogenous differences in bank intermediation costs (Cavalcanti et al., 2023; Faria-e-Castro et al., 2025). Complementing this literature, we introduce exogenous wedges that flexibly capture additional sources of distortions beyond financial or sectoral heterogeneity. This framework allows us to show that such persistent distortions interact with financial frictions and substantially amplify their impact on misallocation.

Our approach of using firm-level borrowing costs to discipline financial frictions is closely related to Gilchrist et al. (2013), who use a model with *exogenous* interest rates to match the dispersion in interest spreads among U.S. Compustat firms and find negligible implied TFP losses. In contrast, we examine not only borrowing costs but also the relationship between $ARPK$ and borrowing costs in both China and the United States, documenting stark cross-country differences. Moreover, our model features *endogenous* firm-level borrowing costs that interact with other distortions. We find that, for a developing economy such as China—where dispersion in both borrowing costs and $ARPK$ is large—introducing exogenous wedges greatly improves the model's fit to the data and amplifies the quantitative importance of financial frictions for misallocation.

Our paper is closely related to Arellano et al. (2012) and Bai et al. (2018), both of which quantify the impact of financial frictions on firm dynamics and TFP losses using firm-level financing data from Europe and China, respectively. In both studies, capital misallocation arises solely from financial frictions. We extend this class of models by introducing permanent exogenous wedges. We find that this enriched model better matches the observed dispersion in financing patterns and $ARPK$. We show that to explain China's

[1] Wu (2018) uses an empirical approach to disentangle the effects of firms' financial conditions and policy distortions on their $MPRK$, where policy distortions are proxied by firm ownership. She finds that both factors are important. We take a complementary approach by studying these forces in a quantitative model and focusing on their interaction.

capital misallocation, multiple sources of distortions are necessary, and incorporating exogenous wedges provides an empirically relevant and flexible approach.

Our paper relates to a large body of corporate finance literature on the impact of financial frictions on firm investment and financing. From the early work of Fazzari et al. (1988) to subsequent natural experiments and quantitative analyses,[2] we have learned that financial frictions affect investment and saving. Our analysis uses firm-level leverage, borrowing cost, and $ARPK$ data to discipline financial frictions, enabling our model to match the empirical distributions of value-added, leverage, borrowing costs, and $ARPK$ across firms. We show that financial frictions alone are insufficient to explain capital misallocation, but when they interact with other distortions, they account for a substantial share of misallocation with significant implications for aggregate productivity.

The rest of the paper is organized as follows. Section 2 presents the key empirical findings on debt financing, borrowing costs, and capital misallocation using Chinese firm-level data. Section 3 presents the model. Section 4 describes the estimation and validates the model. Section 5 presents the quantitative results. Section 6 concludes.

2 Empirical Motivation

This section documents our key empirical finding: firm-level borrowing costs in China are positively correlated with their marginal product of capital, which we proxy using the average revenue product of capital. This positive correlation suggests that financial frictions contribute to capital misallocation, since in a frictionless market, all firms would face the same borrowing cost and earn the same marginal return on capital. We begin by describing the data and then demonstrate the robustness of this relationship. Throughout our analysis, we use the United States as a benchmark for well-developed financial markets and compare Chinese patterns with those observed in the U.S. using Compustat data.

2.1 Data

The empirical analysis in this paper is based on rich firm-level data from an annual enterprise census conducted by the Chinese National Bureau of Statistics between 1998

[2]For example, see Chava and Roberts (2008), Gomes (2001), Cooley and Quadrini (2001), Hennessy and Whited (2005), Hennessy and Whited (2007), Gamba and Triantis (2008), Rampini and Viswanathan (2010), Korteweg (2010), Bolton et al. (2011), Eisfeldt and Muir (2016), Bocola and Bornstein (2023), Bau and Matray (2023), and Andreasen et al. (2023) among others.

and 2007.[3] The dataset covers all state-owned firms and non-state-owned firms with sales over 5 million RMB (about 700,000 US dollars) in the manufacturing sector. It contains detailed information from firms' balance sheets, profit and loss statements, and cash flow statements. We restrict the sample to firms with positive assets, non-negative total liabilities, and positive sales.

Our key variables include firm-level borrowing costs and the average revenue product of capital. We measure firm-level borrowing costs, r_{it}, by scaling the firm's interest payments using its total liabilities:

$$r_{it} \equiv \text{borrowing cost}_{it} = \frac{\text{interest payments}_{it}}{\text{total liabilities}_{it}}. \tag{1}$$

Observations with negative interest payments are treated as missing. As a robustness check, we also construct an alternative measure using the ratio of interest payments to the sum of current liabilities and long-term debt. This alternative measure contains slightly more missing observations, but our results are unchanged.

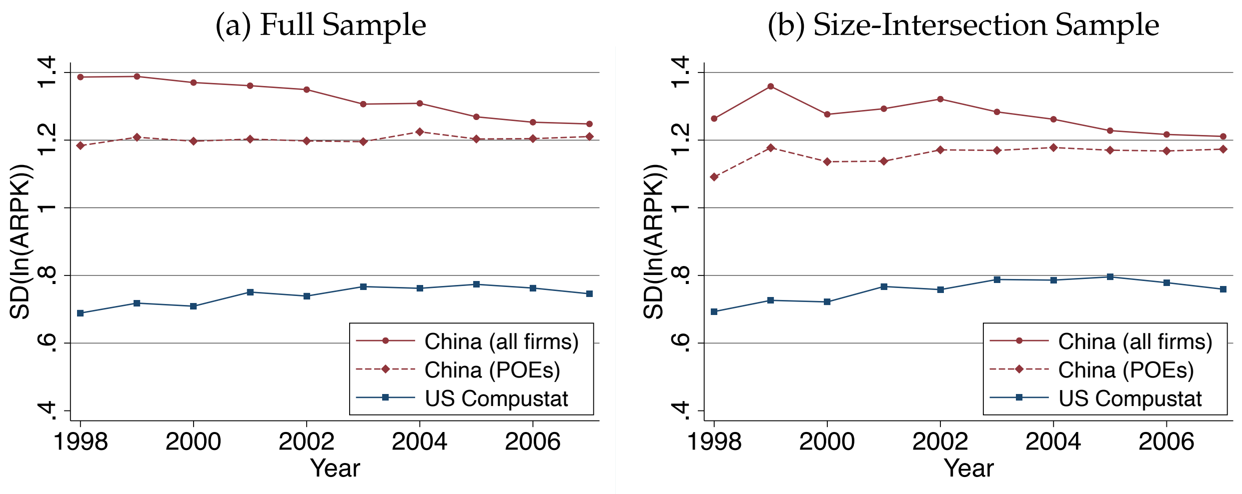
We compute $ARPK$ as firm value added divided by fixed assets. All variables are winsorized at the 1st and 99th percentiles within each year and industry. Because both borrowing costs and $ARPK$ can vary systematically across years and industries—and our model abstracts from such heterogeneity—we normalize each variable by removing year-industry means. Specifically, we use $y_{ijt} - \bar{y}_{jt}$, where y_{ijt} denotes either the borrowing cost or $\ln(ARPK)$ for firm i in industry j and year t.

In a robustness check, we classify Chinese firms into three ownership categories: privately owned enterprises (POEs), state-owned enterprises (SOEs), and firms with other ownership types, including foreign-owned firms. This classification is based on firms' registration-type information. POEs include sole private enterprises, private partnership enterprises, private limited liability companies, and private shareholding corporations. SOEs include solely state-funded, state joint ownership, and state and collective joint ownership. In our sample, POEs account for 8 percent of firms in 1998 and 54 percent in 2007, while SOEs account for 29 percent in 1998 and 2.2 percent in 2007.

For comparison, we also use U.S. Compustat data, representing an advanced economy with well-developed financial markets and relatively low misallocation. To maintain consistency with the Chinese data, we restrict the sample to manufacturing firms over the same period, 1998-2007. Following Whited and Zhao (2021), we compute firm-level value added as the sum of operating income before depreciation (OIBDP) and estimated wage

[3] We end the sample in 2007 because the Chinese National Bureau of Statistics stopped reporting value added in the firm-level data starting in 2008 (Brandt et al., 2014).

Figure 1: Misallocation in China and the U.S. Compustat Manufacturing



Note: This figure shows the standard deviation of ln($ARPK$) over time for China and the U.S. For each country, ln($ARPK$) is demeaned at the year-by-industry level. The left panel reports results using each country's full sample, while the right panel shows results based on the asset-size intersection sample between the two countries. The red solid lines represent all firms in the Chinese data, the red dashed lines represent Chinese private-owned enterprises (POEs), and the blue line represents U.S. Compustat manufacturing firms. Data sources: Chinese manufacturing firm-level data and U.S. Compustat manufacturing data, 1998 to 2007.

bills, where a firm's wage bill is constructed as the product of its employment (EMP) and industry-level wage rates obtained from the NBER-CES Manufacturing Industry Database. We measure fixed assets following Ottonello and Winberry (2020), constructing the capital stock using a perpetual inventory approach. Firm-level borrowing costs and $ARPK$ are then computed in the same manner as in the Chinese data. To facilitate a comparable analysis, in some specifications, we restrict both the U.S. and Chinese samples to the overlapping range of firm asset sizes after converting assets using exchange rates.

2.2 Empirical Evidence

Capital misallocation in China. Figure 1 shows the standard deviation of ln($ARPK$) over time for China and the U.S. The left panel reports results using each country's full sample. As shown in the graph, the dispersion in $ARPK$ is much higher in China than in the U.S., a pattern also documented in the existing literature (e.g., Hsieh and Klenow (2009)).[4] From 1998 to 2007, the dispersion in $ARPK$ in China declines modestly. This decline, however, is largely driven by the falling share of state-owned enterprises. When the sample is restricted

[4] Ziebarth (2013) documents similarly large dispersion in 19th century U.S. manufacturing and attributes it to poor transportation networks and limited competitive regulation.

to privately owned enterprises (POEs), the dispersion in $ARPK$ remains high and stable over time, suggesting persistently substantial capital distortions in China.

The higher dispersion in $ARPK$ in China is not driven by differences in sample composition between the two countries. Since Chinese data include more small firms than Compustat, one potential concern is that the observed differences reflect sample selection rather than underlying distortions. To address this concern, we follow Whited and Zhao (2021) and construct intersection samples for the two countries based on asset size. In each year, we first convert Chinese firms' asset values into U.S. dollars using the CNY-USD spot exchange rate, and then restrict both samples to the overlapping minimum and maximum asset values. The right panel of Figure 1 reports results based on these intersection samples. Excluding smaller firms slightly reduces the dispersion in $ARPK$ in the Chinese data, while the U.S. Compustat results are almost unchanged. Overall, even in the overlapping sample, the dispersion in $ARPK$ remains much larger in China than in the U.S., and this difference persists throughout the period from 1998 to 2007.

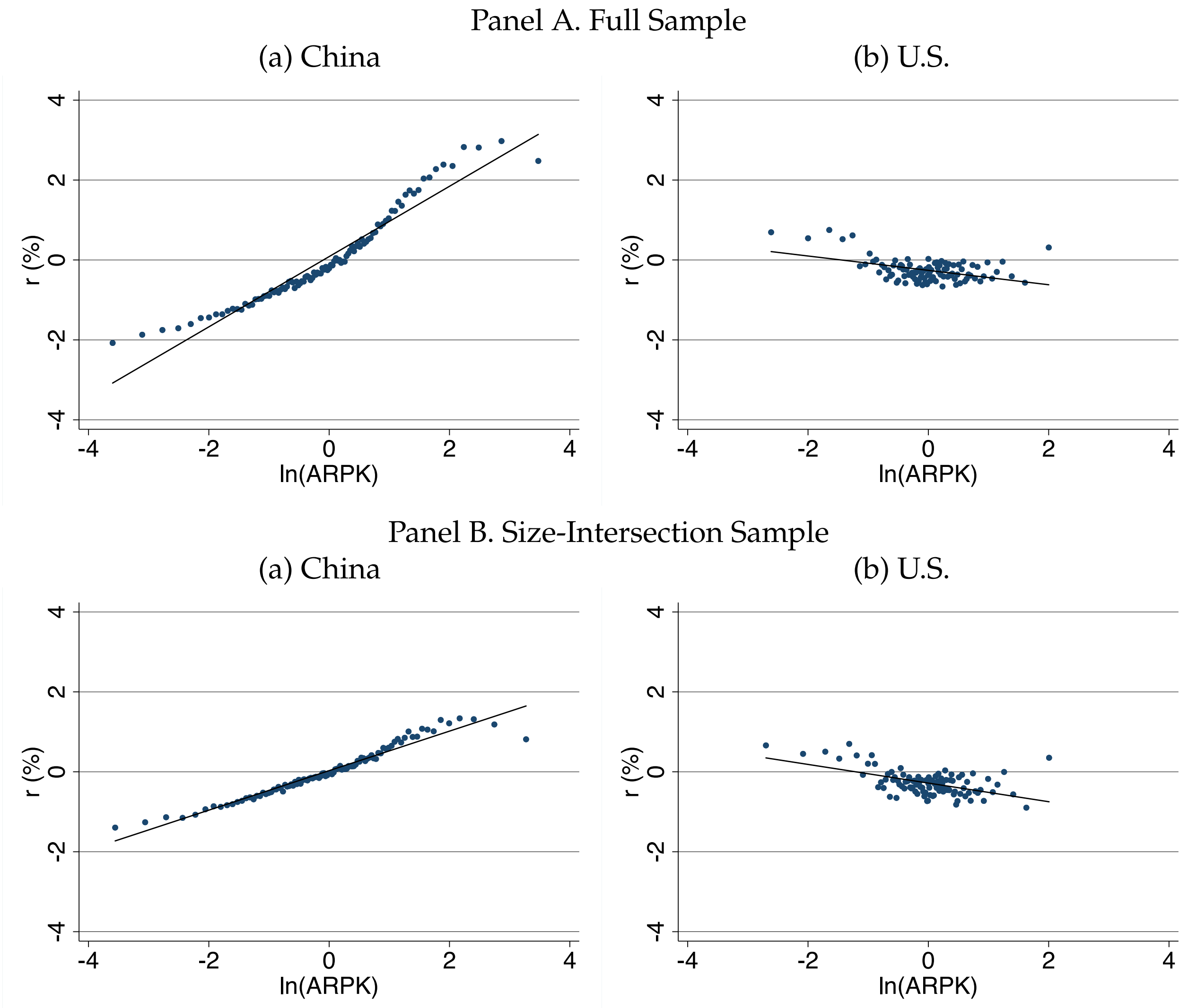
In addition to its standard deviation, the distribution of $\ln(ARPK)$ exhibits a persistent pattern across individual years. Figure E.1 in the appendix compares year-by-year histograms of $\ln(ARPK)$ for Chinese and U.S. Compustat manufacturing firms from 1998 to 2007. Every year, Chinese firms exhibit much greater dispersion than U.S. firms. Figure E.2 in the appendix re-draws the histograms using the size-intersection samples between the two countries. The patterns remain similar.

Misallocation and Borrowing Costs. We now explore the relationship between capital misallocation and financial frictions, which we proxy using firm-level borrowing costs, following Gilchrist et al. (2013). Figure 2 shows scatter plots of borrowing costs against $\ln(ARPK)$ for Chinese and U.S. manufacturing firms. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles based on $\ln(ARPK)$, and the mean values of the borrowing cost and $\ln(ARPK)$ are computed within each percentile. The scatter plot represents the average across years from 1998 to 2007. The solid line depicts the fitted linear relationship.

Panel A uses each country's full sample. In China, there is a strong positive correlation between borrowing costs and $\ln(ARPK)$, with a fitted slope of 0.88 (p-value < 0.001). In contrast, U.S. manufacturing firms show no positive correlation between borrowing costs and $\ln(ARPK)$; if anything, the slope is slightly negative. These patterns—positive in China and absent in the U.S.—hold consistently across all years from 1998 to 2007, as shown in Figure E.3 and E.5 in the appendix.

Panel B shows the results using the size-intersection sample. The dispersion in

Figure 2: Borrowing Costs and ln($ARPK$) in China and the U.S. Compustat Manufacturing



Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$) for Chinese and U.S. Compustat manufacturing firms. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$), and the mean values of the borrowing cost and ln($ARPK$) are computed within each percentile. The scatter plot represents the average across years from 1998 to 2007. The solid line depicts the fitted linear relationship. Panel A shows results using each country's full sample, while Panel B shows results based on the intersection sample by asset size between the two countries. Data sources: Chinese manufacturing firm-level data and U.S. Compustat manufacturing data, averaged over 1998–2007.

borrowing costs becomes smaller in the Chinese data, as smaller firms are excluded from the intersection sample, but the positive correlation between borrowing costs and ln($ARPK$) remains strong, with a fitted slope of 0.49 (p-value < 0.001). By contrast, the pattern for U.S. Compustat manufacturing firms changes little and continues to exhibit no positive correlation. Figures E.4 and E.6 in the appendix display the corresponding year-by-year

Table 1: Regressions of ln($ARPK$) on Financial Variables

Panel A. Full Sample

	China					U.S. Compustat				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
r_{it}	0.16***	0.15***	0.16***	0.073***	0.075***	-0.042***	-0.010	-0.0061	-0.011	-0.010
	(0.0014)	(0.0015)	(0.0015)	(0.0013)	(0.0013)	(0.016)	(0.016)	(0.016)	(0.010)	(0.010)
leverage$_{it}$		-0.023***	-0.015***	0.0066***	0.024***		-0.12***	-0.11***	-0.13***	-0.13***
		(0.0017)	(0.0017)	(0.0017)	(0.0017)		(0.017)	(0.018)	(0.016)	(0.016)
maturity$_{it}$			-0.13***	-0.049***	-0.044***			-0.020	0.023*	0.020*
			(0.0015)	(0.0012)	(0.0012)			(0.018)	(0.012)	(0.012)
Ns	1095521	1095521	1095521	1095521	1095521	15742	15742	15742	15742	15742
Adj. R^2	0.026	0.026	0.044	0.64	0.65	0.0017	0.014	0.014	0.72	0.72
Firm FE	×	×	×	✓	✓	×	×	×	✓	✓
Time FE	×	×	×	×	✓	×	×	×	×	✓

Panel B. Size-Intersection Sample

	China					U.S. Compustat				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
r_{it}	0.13***	0.12***	0.13***	0.069***	0.064***	-0.056***	-0.027	-0.022	-0.0091	-0.0090
	(0.0015)	(0.0016)	(0.0016)	(0.0015)	(0.0015)	(0.016)	(0.016)	(0.016)	(0.010)	(0.010)
leverage$_{it}$		-0.031***	-0.021***	-0.0070***	0.012***		-0.11***	-0.096***	-0.13***	-0.13***
		(0.0019)	(0.0019)	(0.0020)	(0.0020)		(0.018)	(0.019)	(0.017)	(0.017)
maturity$_{it}$			-0.15***	-0.054***	-0.051***			-0.023	0.025**	0.022*
			(0.0016)	(0.0014)	(0.0014)			(0.018)	(0.012)	(0.012)
Ns	862211	862211	862211	862211	862211	14416	14416	14416	14416	14416
Adj. R^2	0.017	0.018	0.040	0.63	0.63	0.0030	0.013	0.014	0.71	0.71
Firm FE	×	×	×	✓	✓	×	×	×	✓	✓
Time FE	×	×	×	×	✓	×	×	×	×	✓

Note: This table reports OLS regressions of ln($ARPK$) on borrowing costs, leverage, and debt maturity for Chinese and U.S. Compustat manufacturing firms. Borrowing costs, r_{it}, are computed as firms' interest payments divided by liabilities. Leverage is defined as liabilities divided by assets. Maturity is measured as the ratio of long-term debt to liabilities. All variables are demeaned at the year-by-industry level and standardized. Panel A uses each country's full sample, while Panel B uses the intersection sample based on asset size. Standard errors (reported in parentheses) are clustered at the firm level. Adj. R^2 denotes the adjusted coefficient of determination. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Data sources: Chinese manufacturing firm-level data and U.S. Compustat manufacturing data, 1998–2007.

scatter plots for the intersection sample from 1998 to 2007. The pattern still holds.

To assess whether the relationship between borrowing costs and ln($ARPK$) is driven by other financial variables, we estimate multivariate regressions that control for firms' leverage and debt maturity. Leverage is liabilities divided by assets, and maturity is the ratio of long-term debt to total liabilities. All variables are demeaned at the year-by-industry level and standardized to facilitate interpretation of the coefficients. Standard errors are clustered at the firm level in all regressions.

Table 1 reports the regression results from projecting ln($ARPK$) on borrowing costs, controlling for leverage, debt maturity, and fixed effects. Panel A uses each country's full sample, while Panel B uses the intersection sample based on asset size. Both panels deliver similar messages. The coefficients on borrowing costs are significantly positive for China, but either negative or statistically insignificant for U.S. firms, consistent with the patterns observed in the scatter plots.

Firm fixed effects account for a large part of the $ARPK$-borrowing-cost correlation in China. Consider column (3) of Panel A in Table 1. The coefficient on borrowing cost is 0.16 after controlling for leverage and maturity. However, after adding firm fixed effects in column (4), the coefficient falls to 0.07, remaining significant but becoming almost half the original magnitude. A similar pattern holds in Panel B for the size-intersection sample. These results indicate the importance of both financial frictions and firm-specific distortions in shaping firms' capital returns.[5]

Robustness Checks. Figure E.7 in the Appendix shows the scatter plot of borrowing costs against ln($ARPK$) separately by ownership type in China: private enterprises (POEs), state-owned enterprises (SOEs), and others. The pattern holds within each ownership group. POEs face the highest borrowing costs and tend to be associated with more positive ln($ARPK$) (relatively taxed), whereas SOEs face the lowest borrowing costs and are associated with more negative ln($ARPK$) (relatively subsidized).

We conduct additional robustness checks using an alternative measure of borrowing costs. Our benchmark measure defines the borrowing costs as the ratio of interest payments to total liabilities. The alternative measure uses the ratio of interest payments to the sum of current liabilities and long-term debt, which has slightly more missing values in the data. Figures E.8 and E.9 in the Appendix show the yearly scatter plots of this alternative borrowing cost measure against ln($ARPK$) for China and the U.S. The Chinese data display an even larger dispersion in borrowing costs, while the positive relationship with ln($ARPK$) remains strong. In contrast, the correlation in the U.S. data is barely affected and remains either insignificant or slightly negative.

[5]Adding time fixed effects barely changes the estimated coefficients, since all variables are already demeaned at the year level to net out aggregate shocks.

3 Model

We consider a small open economy with a continuum of heterogeneous firms. Financial markets are incomplete: firms can only issue state-uncontingent bonds and face the option to default; upon default, they exit the market, and lenders recover only a fraction of their assets. Resource misallocation can also arise from exogenous wedges. There are no aggregate shocks, and we will focus on the stationary equilibrium.

3.1 Technology

Firms produce using capital k with decreasing returns to scale. The output of firm i in period t is

$$y_{it} = z_{it}(\xi_{it}k_{it})^{\alpha}, \tag{2}$$

where z_{it} is the firm productivity and ξ_{it} captures the idiosyncratic capital-quality shock. Firm productivity z_{it} follows a log AR(1) process,

$$\log(z_{it}) = \rho_z \log(z_{it-1}) + \sigma_z \varepsilon_{it}, \varepsilon_{it} \sim N(0,1), \tag{3}$$

while the capital quality shock ξ_{it} is i.i.d., and $\log \xi_{it}$ follows a truncated normal distribution with support $[-4\sigma_{\xi}, 0]$, as in Ottonello and Winberry (2020). Let $F(\xi)$ denote its cumulative distribution function.

3.2 Sources of Misallocation

The model features three sources of capital misallocation: information frictions, exogenous wedges, and financial frictions.

First, *information frictions* are present in most capital accumulation models. Given the canonical timing assumption, firms choose capital one period in advance, before observing their realized productivity. Specifically, k_{it} is chosen in period $t-1$. As a result, ex post marginal products of capital differ across firms. This imperfect information on future productivity leads to a misallocation of capital across firms.

The second source of misallocation is *exogenous wedges*, modeled as firm-specific output wedges. For each unit of output produced, firms receive only $1/\tau_i$ units of it. The revenue received by firm i is therefore given by $y_{it}/\tau_i = z_{it}(\xi_{it}k_{it})^{\alpha}/\tau_i$. When $\tau_i > 1$, the wedge acts like a tax on output, while $\tau_i < 1$ corresponds to a subsidy. As emphasized by David and Venkateswaran (2019), firm-specific fixed distortions are an important source of capital misallocation in China. Motivated by this evidence, we model exogenous wedges as firm-level fixed effects. We assume that τ takes one of N_τ possible values with equal probabilities, and that different firms face different wedges. We calibrate the values of τ to match the empirical distribution of $ARPK$. These exogenous wedges provide a reduced-form representation of various distortions in the Chinese economy, such as subsidies, preferential policies, or institutional advantages faced by certain firms.

The third source of misallocation is *financial frictions*. Firms face limited liability and are subject to an equity issuance constraint that prevents them from raising new equity, which is captured by a non-negativity constraint on dividends. We abstract from external equity issuance for tractability. This assumption is appropriate for our setting, as bank loans dominated external financing for Chinese firms during our sample period (Allen et al., 2005). Financial markets are incomplete, and firms can borrow only through state-uncontingent debt. In addition, firms cannot commit to repayment and may default on their debt. Upon default, firms declare bankruptcy and exit the economy. Banks then liquidate the firm and recover a fraction of its assets. Banks serve as the lenders in the economy; they are competitive, risk-neutral, and take the risk-free interest rate $\bar{r}$ as given.

3.3 Firms' Problem

Upon entry, firm i draws an exogenous wedge τ_i, which remains fixed throughout its lifetime. Each period, firms draw two idiosyncratic shocks: productivity z_{it} and a capital-quality shock ξ_{it}. Firms inherit capital k_{it} and debt b_{it} from the previous period.

A non-defaulting firm's state variables are $(\tau_i, z_{it}, \xi_{it}, k_{it}, b_{it})$. After observing its shocks, the firm decides whether to default. If the firm defaults, we assume that its remaining value is transferred to lenders and the firm exits the market permanently; hence, the default value is zero. Therefore, the firm continues to operate as long as the repayment value V^c is positive:

$$V(\tau_i, z_{it}, \xi_{it}, k_{it}, b_{it}) = \max\{V^c(\tau_i, z_{it}, \xi_{it}, k_{it}, b_{it}), 0\}. \tag{4}$$

Conditional on repayment, the firm chooses current dividends div_{it}, next-period capital k_{it+1}, and next-period debt b_{it+1} to maximize the sum of current dividends and discounted expected future value, subject to a non-negativity constraint on dividends:

$$V^c(\tau_i, z_{it}, \xi_{it}, k_{it}, b_{it}) = \max_{div_{it}, k_{it+1}, b_{it+1}} div_{it} + \beta\, \mathbb{E}_{z_{it+1}|z_{it}} \int V(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1}) dF(\xi_{it+1}) \tag{5}$$

$$\text{s.t.} \quad div_{it} = \frac{1}{\tau_i} z_{it}(\xi_{it} k_{it})^\alpha + (1-\delta)\xi_{it} k_{it} - b_{it} - \zeta - k_{it+1} + q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} \geq 0, \tag{6}$$

where ζ is a fixed operating cost that firms must pay whenever they produce, and

$q(\tau_i, z_{it}, k_{it+1}, b_{it+1})$ is the bond price schedule, which reflects firm-specific default risk.

Since the firm's value becomes zero upon default, the firm chooses to default only if it cannot satisfy the non-negative dividend constraint in (6), that is, if there exists no contract (k_{it+1}, b_{it+1}, q) that delivers non-negative current dividends. As a result, default occurs when the firm draws a sufficiently unfavorable capital quality shock, conditional on other state variables. Specifically, the firm defaults if and only if

$$\xi_{it} < \xi^*_{it}(\tau_i, z_{it}, k_{it}, b_{it}), \tag{7}$$

where the default cutoff $\xi^*_{it}(\tau_i, z_{it}, k_{it}, b_{it})$ is characterized by the following equation:

$$\frac{1}{\tau_i} z_{it}(\xi^*_{it} k_{it})^\alpha + (1-\delta)\xi^*_{it} k_{it} - b_{it} - \zeta + \max_{k_{it+1}, b_{it+1}} \left\{-k_{it+1} + q\left(\tau_i, z_{it}, k_{it+1}, b_{it+1}\right) b_{it+1}\right\} = 0. \tag{8}$$

The firm's problem can then be reformulated using cash on hand x_{it} as a state variable:

$$V(\tau_i, z_{it}, x_{it}) = \max_{div_{it}, k_{it+1}, b_{it+1}} div_{it} + \beta\, \mathbb{E}_{z_{it+1}|z_{it}} \int_{\xi_{it+1} \geq \xi^*_{it+1}} V(\tau_i, z_{it+1}, x_{it+1}) dF(\xi_{it+1}), \tag{9}$$

$$\text{s.t.} \quad div_{it} = x_{it} - k_{it+1} + q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} \geq 0, \tag{10}$$

$$x_{it+1}(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1}) = \frac{1}{\tau_i} z_{it+1}(\xi_{it+1} k_{it+1})^\alpha + (1-\delta)\xi_{it+1} k_{it+1} - b_{it+1} - \zeta. \tag{11}$$

It is convenient to reformulate the firm's problem using cash on hand x_{it} as a state variable. Cash on hand summarizes the firm's internal funds available at the beginning of the period and is predetermined by past decisions and realized shocks. Financial frictions operate through cross-firm dispersion in x_{it}, which firms cannot freely adjust within the period. When a firm has low cash on hand, the non-negative dividend constraint (10) binds, restricting investment. The firm therefore operates below its unconstrained scale, raising its marginal product of capital. As a result, dispersion in cash on hand translates into dispersion in marginal products of capital, generating misallocation.

3.4 Bond Price Schedule

Since creditors are competitive, the bond price is determined to satisfy a zero-profit condition. Accordingly, the bond price q equals the discounted expected repayment, which takes into account the probability of full repayment and the expected recovery in the event of default:

$$q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) = \frac{1}{1+\bar{r}} \mathbb{E}_{z_{it+1}|z_{it}} \left[1 - F(\xi^*_{it+1}) + \int_{\xi_{it+1} < \xi^*_{it+1}} R(k_{it+1}, b_{it+1}, \xi_{it+1}) dF(\xi_{it+1}) \right]. \tag{12}$$

The recovery function is given by

$$R(k_{it+1}, b_{it+1}, \xi_{it+1}) = \min \left\{ \frac{\theta(1-\delta)\xi_{it+1} k_{it+1}}{b_{it+1}}, 1 \right\}, \text{if } b_{it+1} > 0. \tag{13}$$

A higher recovery rate θ allows creditors to recover a larger share of the firm's undepreciated capital following default. However, total recovery is bounded above by the face value of the debt.

Given the bond price schedule, we define the firm-specific borrowing cost:

$$r_{it} = \frac{1}{q(\tau_i, z_{it}, k_{it+1}, b_{it+1})} - 1. \tag{14}$$

3.5 Firm Entry and Equilibrium

We assume that potential entrants can finance capital using both internal equity and borrowing. As a result, the non-negative dividend constraint does not bind at entry. Given (τ_e, z_e), a potential entrant solves the following problem:

$$V^e(\tau_e, z_e) = \max_{k', b'} -k' + q(\tau_e, z_e, k', b')b' + \beta \mathbb{E}_{z'|z_e} \int_{\xi' \geq \xi'^*} V(\tau_e, z', x') dF(\xi'), \tag{15}$$

where x' is given by (11). Due to limited liability, the incumbent firm's value function V is non-negative. As a result, a potential entrant can always choose (k', b') such that $V^e(\tau_e, z_e) \geq 0$, implying that all potential entrants are willing to enter.[6]

Successful entry occurs only if $\xi' \geq \xi'^*$. Conditional on entry, the firm becomes an incumbent and solves the incumbent firm's problem (9). Let k'_e and b'_e denote the optimal capital and debt choices implied by the potential entrant's problem (15). In its first period as an incumbent, a surviving entrant produces using capital k'_e and repays debt b'_e.

Our entry process is designed to preserve a stationary distribution of exogenous wedges across firms. We assume that the economy has a fixed distribution of wedge types $\{\tau_j\}_{j=1}^{N_\tau}$, representing persistent differences in regulatory burden, market power, or other

[6] Midrigan and Xu (2014) show that financial frictions can generate sizable aggregate losses by distorting entry decisions. By assuming that potential entrants do not face a binding non-negative dividend constraint at entry, our quantitative results do not rely on this channel.

firm-specific distortions that remain constant over a firm's life cycle. To maintain this cross-sectional distribution in equilibrium, we impose that entrants are assigned wedges according to the same distribution as incumbents. Replacement entry ensures that exits from each wedge group are exactly offset by new entrants with the same wedge type. This approach generates endogenous selection: firms facing higher wedges τ must have higher productivity to survive, as low-productivity firms cannot remain viable when high wedges reduce profits. As a result, the equilibrium distribution exhibits a positive correlation between wedges and productivity, arising naturally from survival dynamics rather than being imposed ex ante. The following assumptions formalize this entry process.

First, the total mass of firms is normalized to one. Second, for each exogenous wedge value $\tau_k \in \{\tau_j\}_{j=1}^{N_\tau}$, the mass of firms in that wedge group remains constant over time, so exits are exactly offset by entry of firms facing the same wedge. In particular, when a firm with wedge τ_k exits, a new entrant with $\tau_e = \tau_k$ is drawn. Third, the entrant's initial productivity z_e is drawn from the ergodic distribution of z implied by equation (3), independently of τ_e. Fourth, we assume a sufficiently large pool of potential entrants so that, if an entrant does not survive, we continue drawing entrants of the same wedge type until one successfully enters.

Let $\Upsilon(\tau, z, x)$ denote the distribution of firms in the current period, satisfying $\int d\Upsilon(\tau, z, x) = 1$. Moving to the next period, the mass of non-defaulting firms with exogenous wedge τ' is given by

$$m(\tau') = \int_{\tau,z,x} \int_{z'} \int_{\xi' \geq \xi'^*} \mathbb{1}\{\tau' = \tau\} \pi_z(z'|z) dF(\xi') dz' d\Upsilon(\tau, z, x). \tag{16}$$

By the Law of Large Numbers, the mass of potential entrants that need to be drawn for group τ' is scaled by the probability that an entrant survives to become an incumbent:

$$m_e(\tau') = \frac{\pi_\tau(\tau') - m(\tau')}{\int_{z_e} \int_{z'} \int_{\xi' \geq \xi_e'^*} \mathbb{1}\{\tau' = \tau_e\} \pi_z(z'|z_e) dF(\xi') dz' dG(z_e)}, \tag{17}$$

where $G(z)$ denotes the ergodic distribution of productivity implied by equation (3).

The distribution of firms in the next period is the sum of surviving incumbents and entering firms:

$$\begin{aligned} \Upsilon(\tau', z', x') = & \int_{\tau,z,x} \int_{\xi' \geq \xi'^*} \mathbb{1}\{\tau' = \tau\} \pi_z(z'|z) \mathbb{1}\{x'(z', \xi'; \tau, z, x) = x'\} dF(\xi') d\Upsilon(\tau, z, x) \\ & + m_e(\tau') \int_{z_e} \int_{\xi' \geq \xi_e'^*} \mathbb{1}\{\tau' = \tau_e\} \pi_z(z'|z_e) \mathbb{1}\{x_e'(z', \xi'; \tau_e, z_e) = x'\} dF(\xi') dG(z_e). \end{aligned} \tag{18}$$

Definition 1. *Given the exogenous risk-free rate $\bar{r}$, an equilibrium consists of the decision rules* *and value functions of incumbent firms* $\{div(\tau,z,x), k'(\tau,z,x), b'(\tau,z,x), V(\tau,z,x)\}$ *and new entrants* $\{k'_e(\tau_e,z_e), b'_e(\tau_e,z_e), V^e(\tau_e,z_e)\}$*, bond price schedules* $q(\tau,z,k',b')$*, and a transition rule for the firm distribution such that:*

(i) Given the bond price schedules, the decision rules and value functions of incumbent firms and new entrants solve their respective problems in (9) *and* (15)*.*

(ii) The bond price schedules satisfy (12)*.*

(iii) The transition of the firm distribution is consistent with firms' decisions and follows (18)*.*

3.6 Decomposing Capital Distortions

Proposition 1 (Sources of Capital Distortions)**.** *The marginal product of capital for firm i at time $t+1$, denoted MPK_{it+1}, can be decomposed into four components: (i) an information friction term,* $\ln(z_{it+1}\xi^{\alpha}_{it+1}) - \ln \mathbb{E}(z_{it+1}\xi^{\alpha}_{it+1})$*, (ii) an exogenous wedge τ_i, (iii) the firm-specific interest rate $r_{it}+\delta$, and (iv) a shadow-cost term Λ_{it+1} capturing both marginal bond prices and the covariance between financial frictions and the marginal product of capital. Specifically,*

$$\ln MPK_{it+1} = \left[\ln(z_{it+1}\xi^{\alpha}_{it+1}) - \ln \mathbb{E}(z_{it+1}\xi^{\alpha}_{it+1})\right] + \ln \tau_i + \ln(r_{it}+\delta) + \Lambda_{it+1}, \tag{19}$$

where Λ_{it+1} is defined in Appendix A.

Proof. See Appendix A.

In a frictionless economy, the marginal product of capital would be equalized across firms. Here, MPKs differ across firms due to frictions in our model. Equation (19), derived from firms' first-order conditions for capital and borrowing, reveals how these frictions manifest in capital allocation. Information frictions create wedges between realized productivity shocks $z_{it+1}\xi^{\alpha}_{it+1}$ and expected productivity $\mathbb{E}(z_{it+1}\xi^{\alpha}_{it+1})$. Exogenous distortions enter through the firm-specific wedge τ_i. Financial frictions affect MPK through two channels. First, they generate firm-specific borrowing costs $r_{it} = 1/q_{it} - 1$, where default risk makes explicit interest rates vary across firms. Second, they create shadow costs Λ_{it+1} that distort capital allocation beyond observed interest rates.

The shadow cost Λ_{it+1} captures three forces. First, it reflects the extent to which the future non-negative dividend constraint binds, as well as the value losses from default when firms exit the market. Second, it incorporates how bond prices respond to marginal changes in capital and borrowing, capturing that financial frictions affect not only the level of interest rates but also marginal borrowing costs. Third, it captures the covariance between the marginal product of capital and future bindingness of the non-negative dividend constraint.

Two points are worth noting. First, exogenous wedges τ_i interact with financial frictions and affect both the financial friction term $\ln(r_{it} + \delta)$ and the shadow cost Λ_{it+1} through their impact on marginal bond prices and the bindingness of the non-negative dividend constraint. This occurs because permanent firm-specific wedges alter firms' default and saving incentives, thereby affecting their endogenous borrowing constraints. In our quantitative analysis, we find that high-wedge firms face tighter and steeper bond price schedules and exhibit greater MPK distortions. These patterns persist even after controlling for the direct effect of τ_i using firm fixed effects.

Second, financial frictions generate explicit cross-firm variation in interest rate r_{it}, which in turn affects MPK_{it}. This feature enables our model to match the observed positive relationship between borrowing costs and $ARPK$ across firms. In contrast, a common alternative approach models financial frictions through collateral constraints, where all firms pay the same explicit interest rate and only shadow costs vary across firms. Such models do not generate the cross-firm dispersion in interest rates observed in the data, nor the strong correlation between interest rates and $ARPK$. Our model instead incorporates both explicit interest rate variation through r_{it} and shadow costs captured by Λ_{it+1}.

Proposition 1 characterizes the capital distortions that affect each firm's MPK. Differences in MPK across firms—capital misallocation—then generate aggregate TFP losses (Hsieh and Klenow, 2009). Moreover, Restuccia and Rogerson (2008) show that the distribution of distortions across firms—whether high- or low-productivity firms face larger wedges—critically determines the magnitude of these losses. Intuitively, when more productive firms exhibit higher MPK, they are constrained from expanding to their efficient scale, amplifying misallocation and TFP losses. In our model, both the dispersion in MPK and its correlation with productivity arise endogenously from financial frictions. Quantifying the resulting TFP losses and isolating the contribution of financial frictions therefore requires a quantitative analysis, which we conduct in the next section.

4 Estimation

This section describes the estimation of the model. We first discuss how we use firm-level financing patterns to identify model parameters. We then validate the model by examining its ability to match untargeted moments related to financial frictions and capital misallocation. Appendix C describes the computational algorithm.

4.1 Parameterization

Table 2 presents two sets of parameters. The first set is calibrated externally, and the second set consists of parameters estimated jointly using moment matching, which selects model parameters by matching moments from a simulated panel of firms in the stationary distribution to their empirical counterparts. The model is calibrated at an annual frequency. All data moments are averages over the 1998-2007 period.

The first set of parameters is determined with external information and includes $\{\alpha, \delta, \bar{r}, \rho_z\}$. We set the production parameter α at 0.65 to capture both capital share and returns to scale. The capital depreciation rate δ is chosen to be six percent annually. We set the annual risk-free rate $\bar{r}$ at 2.25% to match China's average deposit rate during 1998 and 2007. Since our data covers only nine years, it is insufficient to reliably estimate the persistence of productivity shocks. We therefore follow the international business cycle literature and set ρ_z at 0.9.

The second set consists of 10 parameters: the standard deviations of productivity and capital quality shock $\{\sigma_z, \sigma_\xi\}$, fixed operating cost ζ, discount factor β, debt recovery rate θ, and five levels of exogenous wedges. These parameters are estimated jointly to match firm financing patterns and sales and $ARPK$ distributions, for a total of 10 moments.

Panel C of Table 2 reports the simulated and empirical moments. The model closely matches the data moments. The success of the estimation hinges on model identification, which requires that the chosen moments be sensitive to variations in the structural parameters. We now rationalize our choice of moments. First, the standard deviation of firm productivity shocks, σ_z, governs the dispersion in firms' growth rates. Accordingly, we target the standard deviation of firms' value-added growth rates.

We next target four moments related to firms' financing patterns: average leverage, the mean and standard deviation of firms' borrowing costs, and the correlation between borrowing costs and firm size (measured by log assets). In our dataset, the average leverage is 0.6, the mean borrowing cost is 4.3%, and its standard deviation is 6.7%. Moreover, borrowing costs are negatively correlated with firm size, with corr(ln(asset), borrowing costs) = −0.19, implying that smaller firms face higher borrowing costs.

Identification relies on the sensitivity of financing moments to structural parameters. The dispersion in firm growth rates identifies σ_z. Leverage and borrowing-cost moments jointly discipline β, ζ, θ, and σ_ξ. The correlation between firm size and borrowing costs is particularly informative about recovery rates, as larger firms offer higher expected recovery values in default. Finally, the five wedge values are calibrated to match the quintile means of $\ln(ARPK)$. By construction, these wedges capture persistent firm-level distortions.

The discount factor β, fixed operating cost ζ, and debt recovery rate θ are mostly relevant

Table 2: Moment Matching: Parameters and Moments

Panel A. Assigned Parameters

Parameters	Notations	All Models
Production function curvature	α	0.65
Depreciation rate	δ	0.06
Risk-free rate (%)	$\bar{r}$	2.25
Productivity persistence	ρ_z	0.90

Panel B. Parameters from Moment Matching

Parameters	Notations	Benchmark	No Exogenous Wedges
Std. of productivity shock	σ_z	0.41	0.49
Std. of capital quality shock	σ_ξ	0.43	0.35
Fixed operating cost	ζ	0.0014	0.019
Discount factor	β	0.76	0.80
Debt recovery rate	θ	0.04	0.052
Exogenous wedges	τ_1	0.14	—
	τ_2	0.49	—
	τ_3	0.88	—
	τ_4	1.36	—
	τ_5	5.05	—

Panel C. Moments

		Model	
Moments	Data	Benchmark	No Exogenous Wedges
Std($\triangle$value-added)	0.62	0.62	0.61
Mean borrowing cost (%)	4.32	5.92	4.90
Std borrowing cost (%)	6.72	6.19	6.31
Mean leverage	0.60	0.61	0.61
Corr(ln(asset), borrowing cost)	−0.19	−0.17	−0.14
Mean(ln $ARPK$) by quintile	−1.84	−1.84	-0.70*
	−0.64	−0.65	-0.26*
	−0.008	−0.003	0.02*
	0.64	0.64	0.27*
	1.86	1.85	0.66*

Note: This table reports the parameters and matched moments for both the benchmark model (with exogenous wedges) and the counterfactual model (without exogenous wedges). Panel A lists the assigned parameters, Panel B reports the estimated parameters, and Panel C presents the data and model moments. Moments marked with an asterisk (*) are not targeted in the calibration and are reported for comparison only. Data source: Chinese manufacturing firm-level data, averaged over 1998–2007 at an annual frequency.

for firms' leverage decisions. Greater impatience, lower fixed costs, and higher debt recovery rates all contribute to higher leverage. Conditional on leverage, fixed operating costs and the standard deviation of capital quality shocks, σ_ξ, govern the mean and dispersion in borrowing costs. The debt recovery rate also plays an important role in shaping the correlation between firm size and borrowing costs: larger asset holdings imply higher recovery values in the event of default, which reduces borrowing costs.

Finally, we assume that the distribution of firms across wedge values $\tau_j \in \{\tau_k\}_{k=1}^{N_\tau}$ is uniform, with $\pi_\tau(\tau_j) = 1/N_\tau$. We set $N_\tau = 5$ and calibrate the five wedge values of τ together with other parameters to match the quintile means of $\ln(ARPK)$. Overall, the model closely matches the distribution of firms in terms of value-added growth, leverage, borrowing costs, and $ARPK$ distribution, as shown in Panel C of Table 2.

For comparison, we also consider a reference model that excludes exogenous wedges, which reduces to a canonical financial friction model. We recalibrate this reference model to match the same set of moments, except those related to the $\ln(ARPK)$ distribution. The calibrated parameters and matched moments are reported in the last column of Table 2. The model continues to fit leverage, borrowing costs, and value-added moments well. However, in the absence of exogenous wedges, the reference model fails to replicate the observed $ARPK$ distribution. In particular, the difference between the fifth and the first quintiles of $\ln(ARPK)$ is only 1.36, less than half the value of 3.70 observed in the data and in the benchmark model with exogenous wedges.

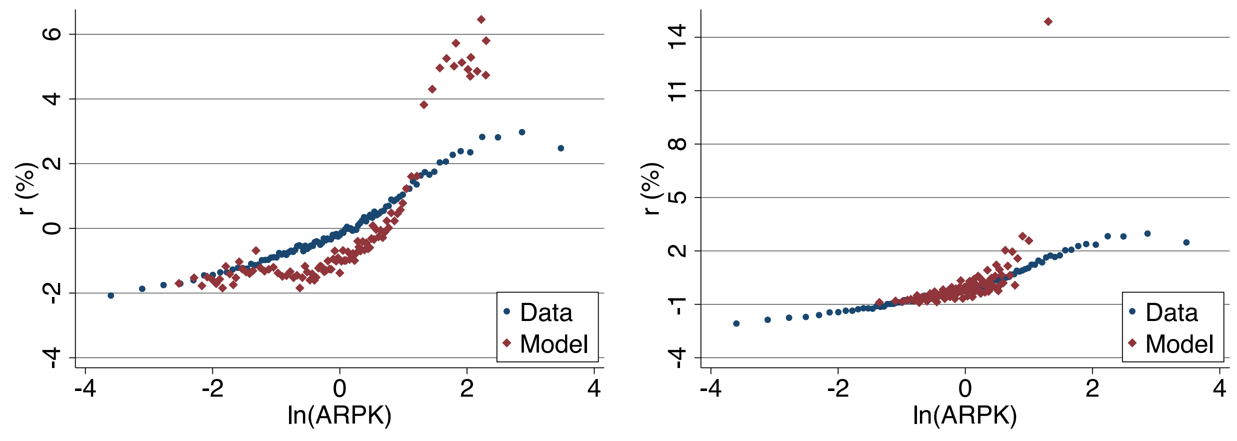
4.2 Model Validation

To validate the model, we first examine the relationship between borrowing costs and $\ln(ARPK)$, as in the empirical analysis in Section 2. We simulate 10,000 firms over 500 periods, starting from the stationary equilibrium. Figure 3 plots borrowing costs against $\ln(ARPK)$ after grouping firms into 100 percentiles of $\ln(ARPK)$. Within each percentile, we compute the average borrowing cost and average $\ln(ARPK)$. Panel (a) shows that the benchmark model closely matches the observed scatter plot, reproducing the wide range of $\ln(ARPK)$—approximately from −4 to 4—through the calibration of exogenous wedges. As in the data, borrowing costs are positively correlated with capital distortions, measured by $\ln(ARPK)$.

Panel (b) presents the corresponding scatter plot for the reference model without exogenous wedges (i.e., the canonical firm financial friction model). Although borrowing costs remain dispersed and positively correlated with $\ln(ARPK)$, this model generates only 37% of the empirical standard deviation of $\ln(ARPK)$. Moreover, although this model is

Figure 3: Borrowing Costs and ln($ARPK$): Model vs. Data

(a) Benchmark (b) No Exogenous Wedges



Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$). Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$), and the mean values of the borrowing cost and ln($ARPK$) are computed within each percentile. The blue round markers represent Chinese manufacturing firms, and the scatter plot reflects the average across years from 1998 to 2007. The red diamond markers represent model simulations of 10,000 firms over 500 periods starting from the stationary equilibrium, and the plotted points are averaged over all simulated periods. Model variables are demeaned at the year level. The left panel shows results from the benchmark model, while the right panel shows the reference model without exogenous wedges (recalibrated). Data sources: Chinese manufacturing firm-level data, averaged over 1998–2007.

recalibrated to match the same standard deviation of borrowing costs as the benchmark model, the scatter plot shows that this dispersion is driven primarily by a small mass of firms—roughly 1%—that face extremely high borrowing costs, while the majority of firms face relatively low borrowing costs. This pattern is inconsistent with the data.

Table 3 reports OLS regressions of ln($ARPK$) on borrowing costs using the model-simulated panel, controlling for firm leverage.[7] The left panel presents results from the benchmark model. Consistent with the empirical findings in Table 1, borrowing costs are positively correlated with ln($ARPK$). Moreover, the connection between borrowing costs and ln($ARPK$) relies heavily on firm fixed effects. When firm fixed effects are included, the estimated coefficient on borrowing costs becomes much smaller, while the adjusted R^2 increases substantially, revealing the interaction between financial frictions and permanent firm-level distortions in the model. These patterns closely mirror the empirical results shown in Table 1.

In contrast, the right panel reports results from the recalibrated reference model without

[7] All bonds are one-period in the model, so we do not control for debt maturity in the model-simulated regressions.

Table 3: Model-Simulated Regressions of ln($ARPK$) on Financial Variables

	Benchmark				No Exogenous Wedges			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
r_{it}	0.24	0.27	0.049	0.049	0.15	0.14	0.14	0.15
	(0.0063)	(0.0072)	(0.0010)	(0.0010)	(0.0075)	(0.0073)	(0.0072)	(0.0077)
leverage$_{it}$		-0.18	0.028	0.028		0.14	0.025	-0.0073
		(0.0017)	(0.0003)	(0.0003)		(0.0006)	(0.0008)	(0.0008)
Ns	4290895	4290895	4290895	4290895	4283781	4283781	4283781	4283781
Adj. R^2	0.066	0.10	0.87	0.87	0.024	0.045	0.055	0.10
Firm FE	×	×	✓	✓	×	×	✓	✓
Time FE	×	×	×	✓	×	×	×	✓

Note: This table reports OLS regressions of ln($ARPK$) on borrowing costs r_{it} and leverage using the model-simulated panel. The simulations include 10,000 firms over 500 periods starting from the stationary distribution. All variables are demeaned at the year level and standardized. The left panel presents results from the benchmark model, while the right panel presents results from the reference model without exogenous wedges (recalibrated). Standard errors (reported in parentheses) are clustered at the firm level. Adj. R^2 denotes the adjusted coefficient of determination.

exogenous wedges. In this counterfactual model, the estimated coefficient on borrowing costs remains significantly positive, as financial frictions alone can generate a positive relationship between borrowing costs and ln($ARPK$). When firm fixed effects are not included, the estimated coefficients are even closer to their empirical counterparts in Table 1. However, a key limitation of this model emerges once firm fixed effects are included. In the data, controlling for firm fixed effects substantially attenuates the estimated borrowing-cost coefficient and raises the adjusted R^2. By contrast, in the reference model, the last two columns of Table 3 show that neither the coefficient nor the adjusted R^2 changes meaningfully. This occurs because, in the model without exogenous wedges, financial frictions are the sole force driving the relationship between borrowing costs and ln($ARPK$), leaving no role for permanent firm heterogeneity.

Additionally, we report other untargeted moments related to financial frictions and capital misallocation in Table 4. First, the benchmark model generates a standard deviation of leverage (0.21) close to that in the data (0.29). However, in the absence of exogenous wedges, the canonical financial friction model accounts for only half of the observed leverage variation, despite matching both the mean leverage and borrowing cost dispersion.

Second, leverage and ln($ARPK$) are slightly negatively correlated in the data. The benchmark model successfully replicates this pattern, whereas the reference model without exogenous wedges generates a counterfactually positive correlation of 19%.

Table 4: Untargeted Moments

Moments	Data	Model: Benchmark	Model: No Exogenous Wedges
Std(leverage)	0.29 [0.285, 0.287]	0.21	0.15
Corr(leverage, $\ln ARPK$)	−0.04 [−0.049, −0.040]	−0.14	0.19
Corr($\ln \hat{z}$, $\ln ARPK$)	0.88 [0.878, 0.880]	0.61	0.79
Corr($\ln ARPK$, lagged $\ln ARPK$)			
No controls	0.73 [0.728, 0.730]	0.89	0.15
Control firm FEs	0.16 [0.154, 0.158]	0.05	0.05
Control firm FEs and year FEs	0.15 [0.145, 0.149]	0.05	0.02

Note: This table reports untargeted moments. All variables in the data are demeaned at the year-by-industry level. All data moments—except the persistence of $\ln ARPK$—are calculated as annual averages from 1998 to 2007, and the corresponding model moments are computed using the stationary equilibrium. The productivity proxy $\hat{z}$ is computed as value added divided by capital to the power α, $\hat{z} = y/k^{\alpha}$. The persistence, Corr($\ln ARPK$, lagged $\ln ARPK$), is calculated from the full firm-level panel from 1998 to 2007, both with and without controlling for firm or year fixed effects, while the model counterpart is computed from simulations of 10,000 firms for 500 periods starting from the stationary equilibrium. Data moments are reported with 95% confidence intervals in brackets. Data source: Chinese manufacturing firm-level data, 1998–2007.

The intuition is as follows. Without exogenous wedges, two opposing forces shape the relationship between leverage and $\ln(ARPK)$. On the one hand, firms with low cash on hand must borrow while reducing their capital to satisfy the non-negative dividend constraint. As a result, these firms exhibit both higher leverage and higher capital distortions, reflected in higher $ARPK$. On the other hand, productivity heterogeneity works in the opposite direction. High-productivity firms face looser bond-price schedules and carry higher leverage, which also means smaller distortions and lower expected marginal product of capital, $\mathbb{E}[MPK]$. Thus, cash-on-hand effects can induce a positive correlation between leverage and $ARPK$, while productivity differences generate a negative correlation. In equilibrium, the cash-on-hand effect dominates, resulting in a positive leverage-$ARPK$ correlation in the canonical financial friction model.

When exogenous wedges are introduced in the benchmark model, an additional force shapes the leverage-$ARPK$ relationship. Firms with high $ARPK$ are more likely to face larger exogenous distortions, which reduce their borrowing incentives and generate a negative relationship between leverage and $ARPK$. With this additional mechanism, the model produces a negative correlation consistent with the data.

Table 4 further reports the correlation between firms' $ARPK$ and productivity proxy $\hat{z}$. Because capital quality shocks are not directly observable in the data, we proxy firm productivity using $\hat{z} = y/k^{\alpha}$, and compute $\hat{z}$ in the model in the same manner. In the data, the correlation between the measured productivity $\ln \hat{z}$ and $\ln ARPK$ is strongly positive at 0.88, indicating that more productive firms face larger capital distortions. This pattern provides one explanation for the severity of aggregate misallocation in China.

The corresponding correlation in the benchmark model is also positive, at 0.61, and remains positive at 0.79 in the reference model without exogenous wedges. This similarity arises because both models feature financial frictions, which disproportionately force low-productivity firms to exit and thereby skew the firm distribution toward more productive firms. As a result, both models generate similar predictions for corr($\ln \hat{z}, \ln ARPK$), making it difficult to differentiate between them based on this moment.

Instead, Table 4 shows that the autocorrelation of $ARPK$ is informative in distinguishing between the two models. In the data, ln($ARPK$) exhibits substantial persistence over time: firms with high $ARPK$ tend to maintain high $ARPK$ in subsequent periods, with an autocorrelation of 0.73. Notably, this persistence falls sharply to 0.16 after controlling for firm fixed effects, and declines only slightly further, to 0.15, after additionally controlling for year fixed effects, as the data are already demeaned at the year-by-industry level.

The benchmark model with firm-specific permanent wedges successfully replicates these patterns, i.e., high raw persistence and low persistence once firm fixed effects are included. In contrast, the canonical financial friction model fails to generate the high unconditional persistence of $\ln ARPK$. In this reference model, firms are ex ante identical, and persistent productivity shocks increase saving incentives, thereby allowing firms to relax their financial constraints whenever possible. As a result, canonical financial frictions cannot generate the persistent capital distortions observed in the data, either with or without firm fixed effects included.

5 Quantitative Analysis

This section presents the quantitative results. We begin by examining firms' decision rules to illustrate how financial frictions operate in the model. We then compute and decompose total factor productivity (TFP) losses to quantify the impact of financial frictions on capital misallocation. Our key finding is that while canonical financial frictions generate only modest TFP losses, their interaction with exogenous wedges leads to substantial misallocation.

5.1 Decision Rules

Figure 4 shows firms' decision rules as functions of cash on hand for firms with median productivity and the median exogenous wedge. Panel (a) plots next-period debt, b'. Panel (b) displays the corresponding borrowing cost, defined as $1/q(\tau, z, k', b') - 1$. Panel (c) presents next-period capital k', and panel (d) shows the logged expected marginal product of capital, $\ln \mathbb{E}[MPK]$, conditional on the choice of k'.

The black solid lines correspond to the benchmark model. In this model, as cash on hand declines, firms face tighter financial constraints, reflected in the increase in the borrowing cost shown in panel (b). Moreover, not only does the explicit borrowing cost rise, but the shadow cost of borrowing also increases. Together, they lead firms to operate at a higher expected marginal product of capital, as shown in panel (d). Consequently, firms reduce both borrowing and capital investment, as illustrated in panels (a) and (c).

For comparison, the red dashed lines depict the counterfactual decision rules in the absence of financial frictions. Appendix B provides a detailed description of this counterfactual economy. In this model, the borrowing cost, capital choice k', and $\mathbb{E}[MPK]$ are independent of firms' cash on hand.

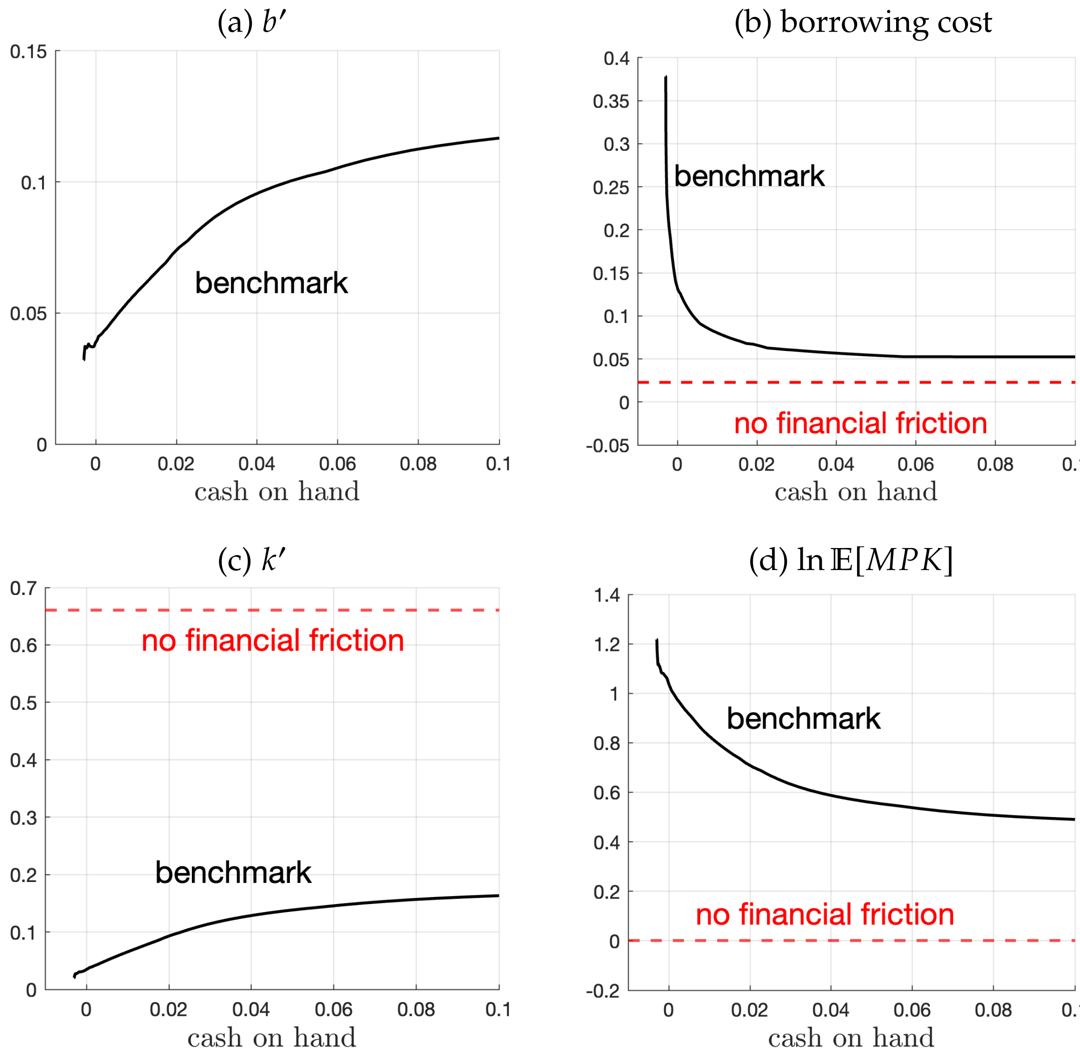
5.2 Decomposing TFP Losses

We measure misallocation using TFP losses relative to the efficient allocation. Given the production function, $y_{it} = z_{it}(\xi_{it} k_{it})^{\alpha}$, the relationship between firm i's capital and its marginal product of capital is $k_{it} = (\alpha z_{it} \xi_{it}^{\alpha})^{\frac{1}{1-\alpha}} MPK_{it}^{\frac{1}{\alpha-1}}$. We define aggregate TFP as

$$TFP_t = \frac{Y_t}{K_t^{\alpha}} = \frac{\sum_i y_{it}}{(\sum_i k_{it})^{\alpha}} = \frac{\sum_i (z_{it}\xi_{it}^{\alpha})^{\frac{1}{1-\alpha}} MPK_{it}^{\frac{\alpha}{\alpha-1}}}{\left(\sum_i (z_{it}\xi_{it}^{\alpha})^{\frac{1}{1-\alpha}} MPK_{it}^{\frac{1}{\alpha-1}}\right)^{\alpha}}. \tag{20}$$

Under an efficient (first-best) allocation—i.e., in the absence of frictions or distortions—the marginal product of capital is equalized across firms, so that $MPK_i = MPK_j$, for all i and j (Hsieh and Klenow, 2009). Given the same set of firms, the corresponding efficient

Figure 4: Firm's Decision Rules

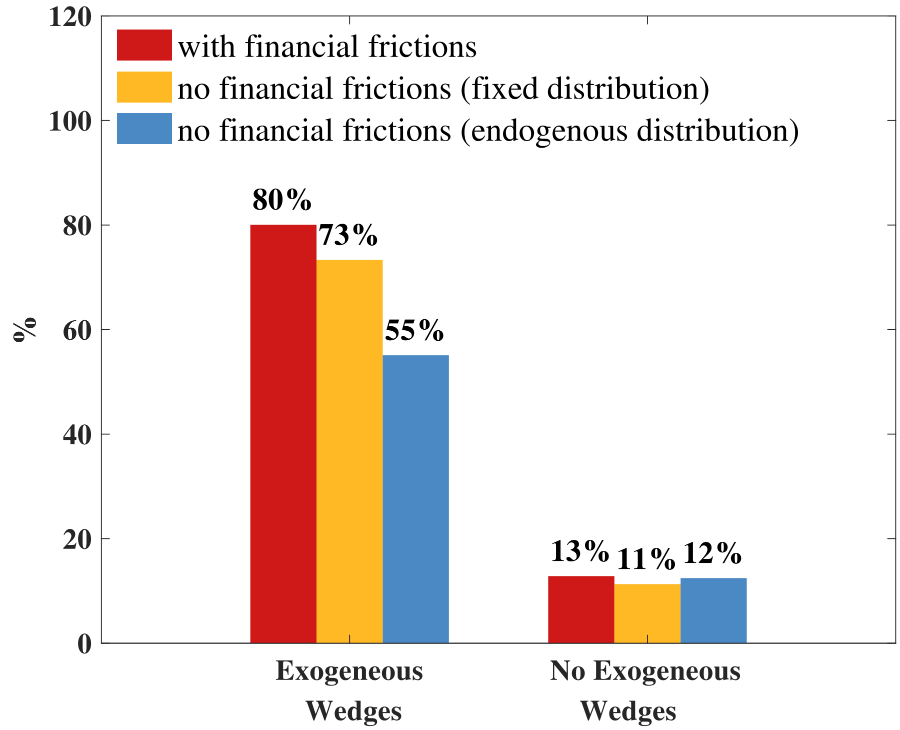


Note: This figure shows firms' decision rules as functions of cash on hand for firms with median productivity and the median exogenous wedge. The black solid lines correspond to the benchmark model, while the red dashed lines represent the counterfactual decision rules in the absence of financial frictions. Subplot (a) plots next-period debt b', subplot (b) displays the corresponding borrowing cost, defined as $1/q(\tau, z, k', b') - 1$, subplot (c) presents next-period capital k', and subplot (d) shows the logged expected marginal product of capital conditional on the choice of k', expressed as deviations from the no-financial-friction case.

level of aggregate TFP is therefore

$$TFP_t^e = \frac{\sum_i (z_{it}\xi_{it}^{\alpha})^{\frac{1}{1-\alpha}}}{\left(\sum_i (z_{it}\xi_{it}^{\alpha})^{\frac{1}{1-\alpha}}\right)^{\alpha}} = \left(\sum_i (z_{it}\xi_{it}^{\alpha})^{\frac{1}{1-\alpha}}\right)^{1-\alpha}. \tag{21}$$

Figure 5: TFP Loss Decomposition



Note: This figure shows TFP losses across model specifications. The left three bars correspond to the model with exogenous wedges, while the right three bars correspond to the model without exogenous wedges. The numbers above the bars report TFP losses relative to their respective efficient TFP levels in log points, as defined in equation (22). The red bars represent the baseline models with financial frictions, recalibrated as in Table 2. The yellow bars correspond to counterfactual models that shut down financial frictions while holding fixed the parameters and the benchmark model's stationary distribution $\Upsilon(\tau, z, x)$. The blue bars also shut down financial frictions and use the same parameters as the corresponding red bars, but allow the firm distribution to adjust endogenously; in this case, there is no entry or exit, so the endogenous distribution is given by the joint ergodic distribution of (τ, z).

We then define TFP losses as

$$\text{TFP loss} = \log(TFP_t^e) - \log(TFP_t). \tag{22}$$

Figure 5 shows TFP losses in log points across model specifications. The three bars on the left correspond to the benchmark model with both financial frictions and exogenous wedges, and the numbers above the bars report TFP losses relative to their respective efficient TFP levels, as defined in equation (22). The red bar represents the benchmark TFP losses: around 80%, reflecting all three sources of misallocation: exogenous wedges, financial frictions, and informational frictions.

To isolate the contribution of financial frictions, we eliminate them, solve the counterfactual model, and recompute TFP losses.[8] The yellow bar corresponds to this exercise, which removes financial frictions while holding fixed both the parameters and the firm distribution underlying the red bar. Specifically, we take the benchmark model's stationary distribution $\Upsilon(\tau, z, x)$ as given, solve for firms' capital choices k' and the implied $MRPK'$ in the absence of financial frictions, and compute the resulting TFP losses.

The yellow bar shows that TFP losses decline from 80% to 73%, implying that financial frictions account for 7 percentage points of TFP losses, holding the firm distribution fixed. This result indicates that financial frictions play a quantitatively meaningful role in generating misallocation by distorting firms' capital choices.

We next examine how allowing the firm distribution to adjust endogenously affects the role of financial frictions, as shown by the blue bar. This specification also shuts down financial frictions and uses the same parameters as the red bar, but allows the firm distribution to converge to its stationary equilibrium. In the absence of financial frictions, firms face neither borrowing constraints nor default risk, so cash on hand is no longer a relevant state variable. Moreover, there is no entry or exit. As a result, the firm distribution is given by the joint ergodic distribution of (τ, z). The blue bar shows that the resulting TFP loss further declines to 55%.

Taken together, these results imply that financial frictions account for 25 percentage points of TFP losses (80%–55%) in the presence of exogenous wedges. Of this loss, 7 percentage points reflect the effect of financial frictions on firms' capital decisions at the benchmark distribution, while the remaining 18 percentage points arise from endogenous selection that alters the firm distribution. This finding suggests that financial frictions are an important source of misallocation and that endogenous adjustments in the firm distribution play a key role in amplifying their impact.

The three bars on the right correspond to the reference model without exogenous wedges and are constructed in the same way as the three bars on the left. In this model, there are two sources of misallocation: financial frictions and informational frictions. The red bar represents the TFP loss calculated using equation (22) in the reference model that is recalibrated as shown in Table 2. In the absence of exogenous wedges, the overall TFP loss is 13%.

To disentangle the role of financial frictions, we again shut them down while holding fixed the same parameters and firm distribution. The yellow bar shows that TFP losses decline only slightly to 11%, indicating that financial frictions account for no more than 2 percentage points of misallocation. We then additionally allow the firm distribution to adjust to its new stationary equilibrium in the absence of financial frictions. The blue bar

[8] Appendix B describes this counterfactual model.

shows that TFP losses are 12%, again differing from the baseline by only about 1 percentage point. Taken together, the three bars on the right indicate that financial frictions account for less than 2 percentage points of TFP losses, consistent with the existing literature that finds only modest misallocation effects from financial frictions.[9]

The natural question, then, is why exogenous wedges make financial frictions more distortionary. Two mechanisms are at work: endogenous persistent financial heterogeneity and endogenous selection. Both mechanisms amplify the misallocation generated by financial frictions.

Figure 6 illustrates how exogenous wedges generate *endogenous financial heterogeneity*. The left subplots show the benchmark model with exogenous wedges. Panel A displays the policy functions for $\ln \mathbb{E}[MPK]$ of median-productivity firms as a function of cash on hand. As cash on hand declines, financial constraints become binding: both the borrowing cost and the shadow cost of borrowing increase, leading firms to operate at a higher marginal product of capital.

Introducing exogenous wedges adds an additional dimension of heterogeneity. The red solid line represents taxed firms ($\tau > 1$), while the blue dashed line represents subsidized firms ($\tau < 1$). Taxed firms face tighter effective financial constraints than subsidized firms. When $\tau > 1$, firms are taxed and operate with fewer internal resources, making financial constraints more binding. In contrast, when $\tau < 1$, firms are subsidized and relatively cash-rich, so financial frictions matter less for them.

The left subplot of Panel B displays the stationary distribution of cash on hand for the two groups of firms. The two distributions are clearly distinct: taxed firms are more concentrated in the constrained region, where $\mathbb{E}[MPK]$ rises steeply, while subsidized firms are more dispersed in regions where $\mathbb{E}[MPK]$ is relatively flat. As a result, firms become more dispersed along the financial dimension in the presence of exogenous wedges, and the heterogeneity induced by these wedges cannot be undone through self-financing. In this sense, exogenous wedges endogenously generate heterogeneity in financial frictions, and this additional layer of dispersion makes financial frictions more distortionary.

In contrast, the right subplots correspond to the recalibrated reference model without exogenous wedges (i.e., $\tau = 1$). In this counterfactual model, the only source of variation in $\mathbb{E}[MPK]$ is financial frictions. That is, as in canonical models of firm financial frictions, misallocation depends primarily on the distribution of cash on hand (or collateral).[10] However, as emphasized by Midrigan and Xu (2014), firms can self-finance. The right

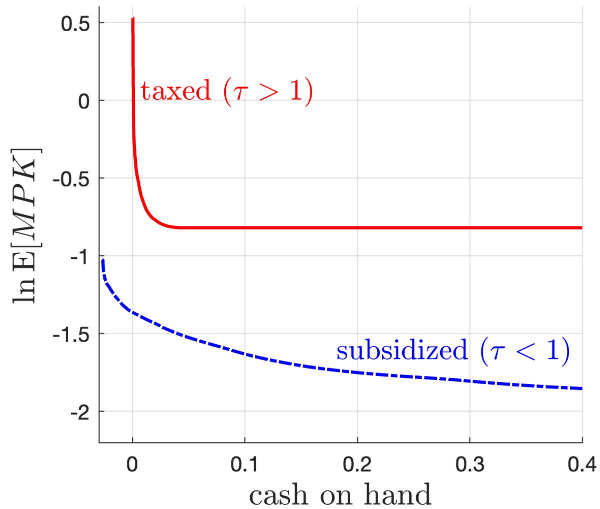
[9]Table D.1 in the appendix reports results for the non-recalibrated models without exogenous wedges, and TFP losses due to financial frictions are also below 2%.

[10]In the absence of financial frictions, the expected marginal product of capital is equalized across firms and does not depend on firms' cash on hand.

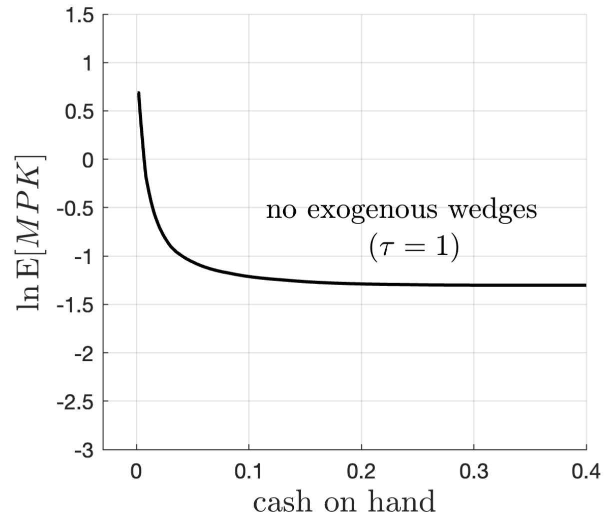
Figure 6: Endogenous Financial Heterogeneity

Panel A. Policy Functions for Expected MPK

(a) Benchmark

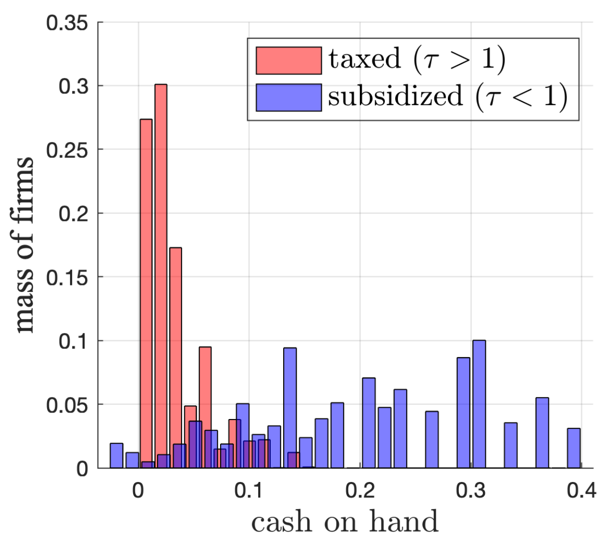


(b) No Exogenous Wedges

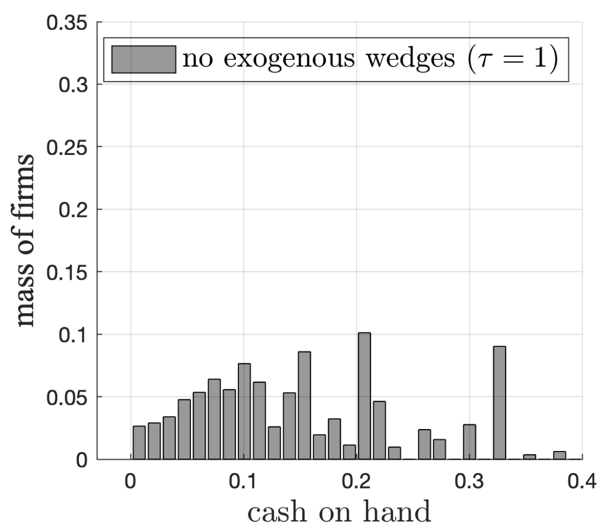


Panel B. Distribution of Cash on Hand

(a) Benchmark



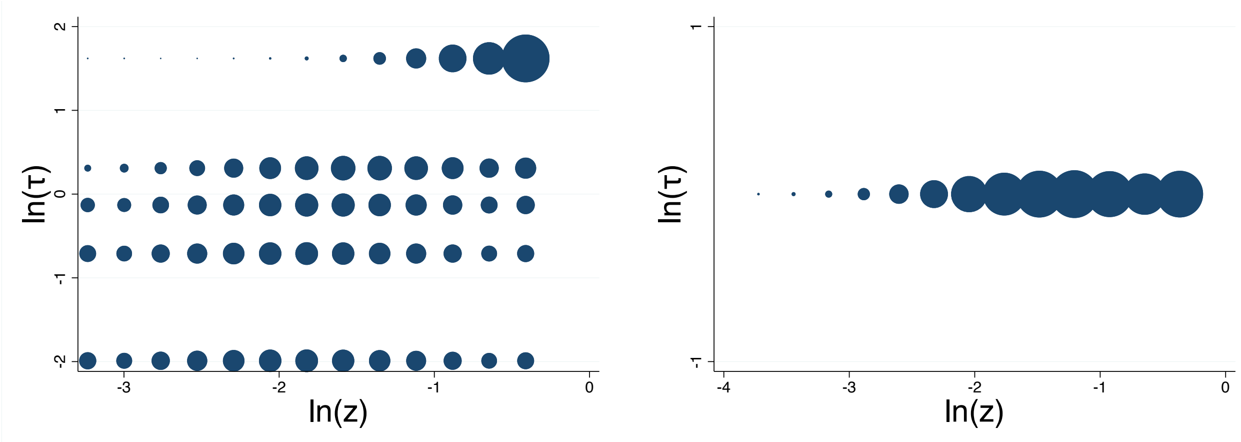
(b) No Exogenous Wedges



Note: This figure illustrates how exogenous wedges generate endogenous financial heterogeneity. Panel A displays the policy functions for $\ln \mathbb{E}[MPK]$ of median-productivity firms as a function of cash on hand. Panel B presents the corresponding stationary distribution of cash on hand, also for median-productivity firms. In both panels, the left subplots correspond to the benchmark model with exogenous wedges, where red represents taxed firms ($\tau > 1$) and blue denotes subsidized firms ($\tau < 1$). The right subplots show the recalibrated reference model without exogenous wedges (i.e., $\tau = 1$ for all firms).

Figure 7: Ex-Post Joint Distribution of Exogenous Wedges and Productivity

(a) Benchmark (b) No Exogenous Wedges



Note: This figure shows the ex-post joint distribution of exogenous wedges (τ) and productivity (z) in the stationary equilibrium, where each dot represents the mass of firms. The left subplot corresponds to the benchmark model with exogenous wedges, while the right subplot shows the recalibrated reference model without exogenous wedges (i.e., $\tau = 1$ for all firms).

subplot of Panel B plots the distribution of cash on hand and shows that this self-financing mechanism prevents firms from operating at very low levels of cash on hand, concentrating the distribution in regions where $\mathbb{E}[MPK]$ is relatively flat. As a result, the implied misallocation is quantitatively small in canonical models of financial frictions.

The second amplification mechanism operates through *endogenous selection*. Figure 7 shows the ex-post joint distribution of exogenous wedges (τ) and productivity (z) in the stationary equilibrium, where each dot represents the mass of firms.

As before, the left subplot corresponds to the benchmark model with exogenous wedges, which features heterogeneity along two dimensions: both τ and z. Although wedges and productivity are independently drawn for potential entrants, equilibrium selection through entry and exit induces a positive correlation between them. High-τ firms face larger distortions and are more likely to exit; among them, only the most productive survive. This generates a positive correlation of 0.20 between $\ln(z)$ and $\ln(\tau)$ in the stationary equilibrium. Since high-τ firms also face tighter financial constraints, selection concentrates productive firms in the more financially constrained group. While selection ensures that productive firms survive, it creates a systematic pattern: the most productive surviving firms are disproportionately those facing tight financial constraints. Capital is therefore misallocated away from these productive but constrained firms, amplifying the distortionary effects of financial frictions.

For comparison, the right subplot presents the recalibrated reference model without exogenous wedges. Since there is only a single value, $\tau = 1$, the dots align horizontally. The distribution is concentrated toward higher productivity levels, reflecting the fact that more productive firms are more likely to survive. However, selection operating solely along the productivity dimension is quantitatively weak, as firms can largely self-finance. Therefore, the resulting TFP losses are small in this canonical firm financial friction model.

To summarize, exogenous wedges amplify the misallocation effects of financial frictions through two mechanisms: endogenous financial heterogeneity and endogenous selection. Through these channels, financial frictions generate quantitatively sizable misallocation.

6 Conclusion

The existing literature reaches mixed conclusions on whether firm-level financial frictions generate substantial capital misallocation. In this paper, we revisit this question. Using firm-level data, we first document that borrowing costs and capital distortions are strongly correlated in China, whereas this relationship is largely absent in U.S. data. We then build and estimate a model that incorporates not only financial frictions but also exogenous wedges that proxy for other distortions prevalent in developing economies. Our quantitative results show that the interaction between financial frictions and exogenous wedges generates sizable TFP losses, whereas the canonical financial frictions model implies only modest misallocation.

Two mechanisms drive this amplification. First, exogenous wedges generate endogenous and persistent financial heterogeneity that cannot be undone through self-financing. Second, endogenous selection concentrates more productive firms in the more financially constrained group. These findings suggest that a key difference between developing and developed economies lies not only in the severity of financial frictions, but also in the presence of other distortions that interact with them.

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Appendix to "When Do Financial Frictions Matter for Misallocation?"

by Yan Bai, Dan Lu, Xu Tian, and Yajie Wang

A Sources of Capital Distortions

This section proves Proposition 1, which characterizes how the marginal product of capital depends on three frictions: information, exogenous wedges, and financial frictions.

First, we write the first-order conditions with respect to capital and borrowing:

$$(1+\gamma)\left(1-\frac{\partial q}{\partial k'}b'\right) = \beta\,\mathbb{E}_{z'|z}\left\{\int_{\xi'\geq\xi^*}\left[\alpha\frac{1}{\tau}z'\xi'^{\alpha}k'^{\alpha-1}+(1-\delta)\xi'\right](1+\gamma')dF(\xi')\right\} - \beta\,\mathbb{E}_{z'|z}\left\{f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial k'}\right\}, \quad (23)$$

$$(1+\gamma)\left(q+\frac{\partial q}{\partial b'}b'\right) = \beta\,\mathbb{E}_{z'|z}\left\{\int_{\xi'\geq\xi^*}(1+\gamma')dF(\xi')+f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial b'}\right\}, \quad (24)$$

where γ is the Lagrange multiplier on the non-negativity dividend constraint (10).

Dividing (23) by (24) yields

$$\frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)} = \frac{\mathbb{E}_{z'|z}\left\{\int_{\xi'\geq\xi^*}[\alpha\frac{1}{\tau}z'\xi'^{\alpha}k'^{\alpha-1}+(1-\delta)\xi'](1+\gamma')dF(\xi')-f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial k'}\right\}}{\mathbb{E}_{z'|z}\left\{\int_{\xi'\geq\xi^*}(1+\gamma')dF(\xi')+f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial b'}\right\}}$$
$$= \frac{\mathbb{E}_{z',\xi'|z}\left[[\alpha\frac{1}{\tau}z'\xi'^{\alpha}k'^{\alpha-1}+(1-\delta)\xi'](1+\gamma')\mathbb{1}\{\xi'\geq\xi^*\}\right]-\mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial k'}\right]}{\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi'\geq\xi^*\}\right]+\mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial b'}\right]}. \quad (25)$$

Rearranging yields

$$\frac{1}{\tau}\,\mathbb{E}_{z',\xi'|z}\left[(\alpha z'\xi'^{\alpha}k'^{\alpha-1})(1+\gamma')\mathbb{1}\{\xi'\geq\xi^*\}\right]$$
$$= \frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)}\,\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi'\geq\xi^*\}\right]-(1-\delta)\,\mathbb{E}_{z',\xi'|z}[\xi'(1+\gamma')\mathbb{1}\{\xi'\geq\xi^*\}]$$
$$+\frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)}\,\mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial b'}\right]+\mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial\xi^*}{\partial k'}\right]. \quad (26)$$

Define $MPK' = \alpha z' \xi'^{\alpha} k'^{\alpha-1}$. The left-hand side of (26) can be decomposed as

$$\begin{aligned}
&\frac{1}{\tau}\,\mathbb{E}_{z',\xi'|z}\left[(\alpha z'\xi'^{\alpha}k'^{\alpha-1})(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right] \\
&= \frac{1}{\tau}\,\mathbb{E}_{z',\xi'|z}\left(\alpha z'\xi'^{\alpha}k'^{\alpha-1}\right)\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right] + \frac{1}{\tau}\,\mathrm{Cov}_{z',\xi'|z}(\alpha z'\xi'^{\alpha}k'^{\alpha-1}, (1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}) \\
&= \frac{1}{\tau}\alpha k'^{\alpha-1}\,\mathbb{E}_{z',\xi'|z}\left(z'\xi'^{\alpha}\right)\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right] + \frac{1}{\tau}\,\mathrm{Cov}_{z',\xi'|z}(MPK', (1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}).
\end{aligned} \tag{27}$$

which implies

$$\begin{aligned}
&\frac{1}{\tau}\alpha k'^{\alpha-1}\,\mathbb{E}_{z',\xi'|z}\left(z'\xi'^{\alpha}\right)\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right] \\
&= \frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)}\,\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right] - (1-\delta)\,\mathbb{E}_{z',\xi'|z}[\xi'(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}] \\
&\quad + \frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)}\,\mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial \xi^*}{\partial b'}\right] + \mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial \xi^*}{\partial k'}\right] \\
&\quad - \frac{1}{\tau}\,\mathrm{Cov}_{z',\xi'|z}(MPK', (1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}).
\end{aligned} \tag{28}$$

Let $\mathcal{X}$ denote the right-hand side of (28). A first-order Taylor expansion of $\ln \mathcal{X}$ gives

$$\ln \mathcal{X} = \ln\left[(r+\delta)\left(1+\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right)\right] \tag{29}$$

$$= \ln(r+\delta) + \ln\left(1+\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right) \tag{30}$$

$$= \ln(r+\delta) + \frac{\mathcal{X}-(r+\delta)}{r+\delta} + o\left(\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right), \tag{31}$$

where $r = 1/q(\tau,z,k',b') - 1$, and we assume $|\frac{\mathcal{X}-(r+\delta)}{r+\delta}|$ is small.

Taking logs on both sides of (28) and using the first-order expansion for $\ln \mathcal{X}$ yields:

$$\ln\left\{\frac{1}{\tau}\alpha k'^{\alpha-1}\,\mathbb{E}_{z',\xi'|z}\left(z'\xi'^{\alpha}\right)\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right]\right\} = \ln(r+\delta) + \frac{\mathcal{X}-(r+\delta)}{r+\delta} + o\left(\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right). \tag{32}$$

Rearranging and adding $\ln(z'\xi'^{\alpha})$ to both sides yields

$$\begin{aligned}
\ln(\alpha k'^{\alpha-1}) + \ln(z'\xi'^{\alpha}) &= \ln(z'\xi'^{\alpha}) - \ln\left(\mathbb{E}_{z',\xi'|z}\left(z'\xi'^{\alpha}\right)\right) + \ln\tau + \ln(r+\delta) \\
&\quad - \ln\left(\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right]\right) + \frac{\mathcal{X}-(r+\delta)}{r+\delta} + o\left(\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right).
\end{aligned} \tag{33}$$

The left-hand side equals $\ln MPK'$ by the definition of MPK':

$$\ln MPK' = \ln(z'\xi'^{\alpha}) - \ln\left(\mathbb{E}_{z',\xi'|z}\left(z'\xi'^{\alpha}\right)\right) + \ln\tau + \ln(r+\delta) + \Lambda', \tag{34}$$

where Λ' is given by

$$\Lambda' = -\ln\left(\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right]\right) + \frac{\mathcal{X}-(r+\delta)}{r+\delta} + o\left(\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right) \tag{35}$$

$$\begin{aligned}
=&\frac{1}{r+\delta}\frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)}\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right] \\
&-\frac{1}{r+\delta}\left\{(r+\delta)\left[1+\ln\left(\mathbb{E}_{z',\xi'|z}\left[(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}\right]\right)\right] + (1-\delta)\,\mathbb{E}_{z',\xi'|z}[\xi'(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}]\right\} \\
&+\frac{1}{r+\delta}\left\{\frac{\left(1-\frac{\partial q}{\partial k'}b'\right)}{\left(q+\frac{\partial q}{\partial b'}b'\right)}\mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial \xi^*}{\partial b'}\right] + \mathbb{E}_{z'|z}\left[f(\xi^*)V(\tau,z',\xi^*,k',b')\frac{\partial \xi^*}{\partial k'}\right]\right\} \\
&-\frac{1}{r+\delta}\frac{1}{\tau}\mathrm{Cov}_{z',\xi'|z}(MPK',(1+\gamma')\mathbb{1}\{\xi' \geq \xi^*\}) + o\left(\frac{\mathcal{X}-(r+\delta)}{r+\delta}\right).
\end{aligned} \tag{36}$$

B Counterfactual Model: Eliminating Financial Frictions

This section describes the counterfactual economy in which financial frictions are eliminated. In this environment, the firm's problem reduces to

$$\max_{k_{it+1}} -k_{it+1} + \frac{1}{1+r}\left\{\frac{1}{\tau_i}\,\mathbb{E}[z_{it+1}k_{it+1}^{\alpha}|z_{it}] + (1-\delta)k_{it+1}\right\} \tag{37}$$

The first-order condition with respect to k_{it+1} is

$$\alpha\frac{1}{\tau_i}\,\mathbb{E}[z_{it+1}|z_{it}]k_{it+1}^{*\alpha-1} = r+\delta, \tag{38}$$

$$\Rightarrow k_{it+1}^{*} = \left(\frac{\alpha\frac{1}{\tau_i}\,\mathbb{E}[z_{it+1}|z_{it}]}{r+\delta}\right)^{\frac{1}{1-\alpha}}. \tag{39}$$

Because financial constraints are absent and there is no entry or exit in this counterfactual economy, the stationary distribution of (τ, z) coincides with the ergodic distribution:

$$\Upsilon(\tau, z) = \pi_\tau(\tau)\,g_z(z), \tag{40}$$

where $\pi_\tau(\tau_j) = 1/N_j$ and $g_z(z)$ denotes the invariant distribution implied by equation (3).

C Computational Algorithm

This section provides the detailed computational algorithm for solving the model using value function iteration.

1. We construct grids for z_{it} using the Tauchen method and discretize ξ_{it} using a quadrature method. Capital grids are centered around the efficient choice, so the grid for k_{it+1} depends on (τ_i, z_{it}). The grid for b_{it+1} is constructed around k_{it+1} and therefore depends on $(\tau_i, z_{it}, k_{it+1})$.

2. Iterate on the bond price schedule $q(\tau_i, z_{it}, k_{it+1}, b_{it+1})$ and the associated borrowing limit. The borrowing limit is defined as

$$M(\tau_i, z_{it}) = \max_{k_{it+1}, b_{it+1}} \left\{ q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} - k_{it+1} \right\}. \tag{41}$$

   (a) Make initial guesses for the bond price schedule and the borrowing limit:

$$q^{\{0\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) = \beta, \qquad M^{\{0\}}(\tau_i, z_{it}) = \beta\, b_{\max}, \tag{42}$$

   where $b_{\max}$ is the largest grid point for b_{it+1}.

   (b) Given $M^{\{n\}}(\tau_i, z_{it})$ and the state $(\tau_i, z_{it}, k_{it}, b_{it})$, the firm defaults for a given ξ_{it} if

$$\frac{1}{\tau_{it}} z_{it} (\xi_{it} k_{it})^{\alpha} + (1-\delta)\xi_{it} k_{it} - b_{it} - \zeta + M^{\{n\}}(\tau_i, z_{it}) < 0. \tag{43}$$

   Let $d(\tau_i, z_{it}, \xi_{it}, k_{it}, b_{it}) = 1$ indicate default in period t (and $d = 0$ otherwise).

   (c) Update the bond price schedule:

$$q^{\{n+1\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) = \frac{1}{1+r} \sum_{z_{it+1}} \pi_z(z_{it+1}|z_{it}) \sum_{\xi_{it+1}} \pi_{\xi}(\xi_{it+1})$$
$$\left[(1 - d(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1})) + d(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1}) R(k_{it+1}, b_{it+1}, \xi_{it+1}) \right]. \tag{44}$$

   The recovery function is given by

$$R(k_{it}, b_{it}, \xi_{it}) = \min \left\{ \frac{\theta(1-\delta)\xi_{it} k_{it}}{b_{it}}, 1 \right\}, \text{if } b_{it} > 0. \tag{45}$$

   (d) Update the borrowing limit:

$$M^{\{n+1\}}(\tau_i, z_{it}) = \max_{k_{it+1}, b_{it+1}} \left\{ q^{\{n+1\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} - k_{it+1} \right\} \tag{46}$$

(e) Repeat steps (b)–(d) until convergence: the relative distance between $M^{\{n+1\}}$ and $M^{\{n\}}$ is below 10^{-7}, and the relative distance between $q^{\{n+1\}}$ and $q^{\{n\}}$ is below 10^{-10}. Following Judd (1998), we measure the relative distance as $\text{dist}(f^{\{n+1\}}, f^{\{n\}}) = \frac{(\sum_x (f^{\{n+1\}}(x) - f^{\{n\}}(x))^2)^{\frac{1}{2}}}{1+(\sum_x f^{\{n\}}(x)^2)^{\frac{1}{2}}}$.

3. Make an initial guess for the firm's value function $V^{\{0\}}(\tau_i, z_{it}, x_{it})$ on the grid for x_{it}.

4. Given $V^{\{n\}}(\tau_i, z_{it}, x_{it})$, compute the expected future value by numerical integration:

$$\begin{aligned} G^{\{n\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) &= \mathbb{E}_{z_{it+1}|z_{it}} \int_{\xi_{it+1} \geq \xi^*_{it+1}} V^{\{n\}}(\tau_i, z_{it+1}, x_{it+1}) dF(\xi_{it+1}) \\ &= \sum_{z_{it+1}} \pi(z_{it+1}|z_{it}) \sum_{\xi_{it+1}} \pi_\xi(\xi_{it+1})(1 - d(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1}))V^{\{n\}}(\tau_i, z_{it+1}, x_{it+1}). \end{aligned} \tag{47}$$

For next-period cash on hand x_{it+1} that does not lie on the grid, we use linear interpolation between the two nearest grid points to obtain the firm's value V.

5. For each (τ_i, z_{it}), we solve the following relaxed problem to determine the cutoff value of cash on hand at which the non-negative dividend (NND) constraint (10) becomes binding:

$$\hat{V}(\tau_i, z_{it}) = \max_{k_{it+1}, b_{it+1}} -k_{it+1} + q(\tau_i, z_{it}, k_{it+1}, b_{it+1})b_{it+1} + \beta G^{\{n\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}). \tag{48}$$

Let $\{\hat{k}_{it+1}(\tau_i, z_{it}), \hat{b}_{it+1}(\tau_i, z_{it})\}$ denote the optimal policies that solve the relaxed problem. We then define the cash-on-hand cutoff as

$$\hat{x}_{it}(\tau_i, z_{it}) = -[q(\tau_i, z_{it}, \hat{k}_{it+1}(\tau_i, z_{it}), \hat{b}_{it+1}(\tau_i, z_{it}))\hat{b}_{it+1}(\tau_i, z_{it}) - \hat{k}_{it+1}(\tau_i, z_{it})]. \tag{49}$$

When $x_{it} < \hat{x}_{it}(\tau_i, z_{it})$, the NND condition binds. For any $x_{it} \geq \hat{x}_{it}(\tau_i, z_{it})$, firms are unconstrained by the NND condition, and the optimal policies coincide with the solution to the relaxed problem (48):

$$k^*_{it+1}(\tau_i, z_{it}, x_{it}) = \hat{k}_{it+1}(\tau_i, z_{it}), \qquad b^*_{it+1}(\tau_i, z_{it}, x_{it}) = \hat{b}_{it+1}(\tau_i, z_{it}). \tag{50}$$

In this region, the firm's value function is linearly increasing in cash on hand:

$$V^{\{n+1\}}(\tau_i, z_{it}, x_{it}) = V^{\{n\}}(\tau_i, z_{it}, \hat{x}_{it}(\tau_i, z_{it})) + x_{it} - \hat{x}_{it}(\tau_i, z_{it}), \forall x_{it} \geq \hat{x}_{it}(\tau_i, z_{it}). \tag{51}$$

6. Update the grid for x_{it} on the interval $[\underline{x}_{it}(\tau_i, z_{it}), \bar{x}_{it}(\tau_i, z_{it})]$, where

$$\underline{x}_{it}(\tau_i, z_{it}) = -M(\tau_i, z_{it}), \qquad \bar{x}_{it}(\tau_i, z_{it}) = \hat{x}_{it}(\tau_i, z_{it}). \tag{52}$$

7. Using grid search, update the firm's value function for $x_{it} \in [\underline{x}_{it}(\tau_i, z_{it}), \bar{x}_{it}(\tau_i, z_{it})]$:

$$V^{\{n+1\}}(\tau_i, z_{it}, x_{it}) = \max_{div_{it}, k_{it+1}, b_{it+1}} div_{it} + \beta G^{\{n\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}), \tag{53}$$

$$\text{s.t. } div_{it} = x_{it} - k_{it+1} + q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} \geq 0. \tag{54}$$

   Let $k^*_{it+1}(\tau_i, z_{it}, x_{it})$ and $b^*_{it+1}(\tau_i, z_{it}, x_{it})$ denote the associated optimal policy functions.

8. Apply Howard's improvement algorithm three times to update V and G using the optimal policies $k^*_{it+1}(\tau_i, z_{it}, x_{it})$ and $b^*_{it+1}(\tau_i, z_{it}, x_{it})$.

9. Repeat steps 4–8 until the relative distance between $G^{\{n+1\}}$ and $G^{\{n\}}$ falls below 10^{-6}.

D Additional Tables

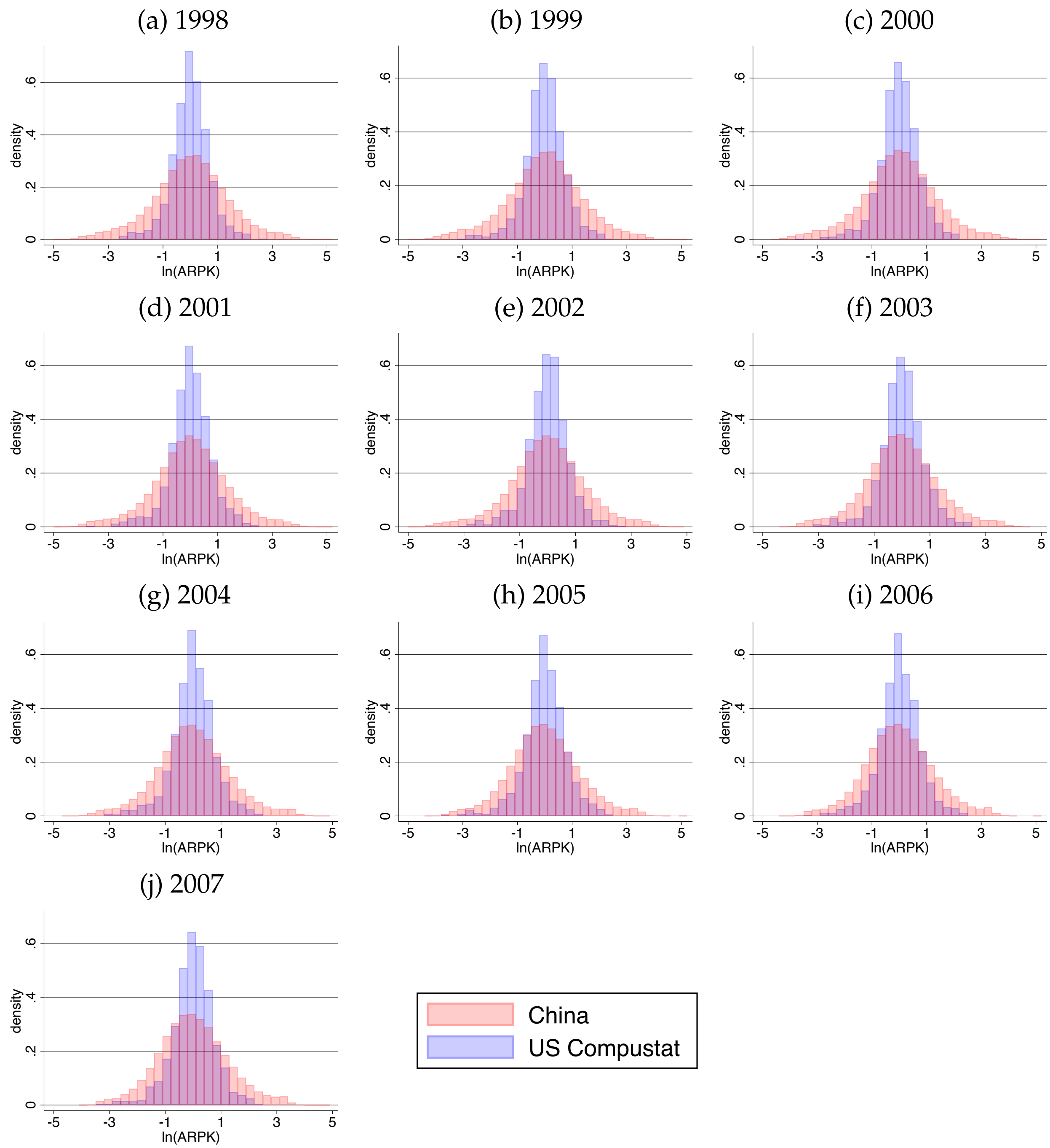
Table D.1: Results from Non-Recalibrated Models without Exogenous Wedges

Moments	Data	Models without Exogenous Wedges		
			No Financial Frictions	
		Financial Frictions	Fixed Dist.	Endogenous Dist.
Std(△value-added)	0.62	0.63	0.66	0.66
Mean borrowing cost (%)	4.32	5.04	—	—
Std borrowing cost (%)	6.72	7.41	—	—
Mean leverage	0.60	0.56	—	—
Corr(ln(asset), borrowing cost)	−0.19	0.02	—	—
	−1.84	−0.61	−0.56	−0.56
	−0.64	-0.24	−0.21	−0.22
Mean(ln $ARPK$) by quintile	−0.008	0.00	0.00	−0.01
	0.64	0.23	0.21	0.22
	1.86	0.61	0.53	0.54
TFP losses (%)	—	11.17	9.57	9.75
⇒ Relative to financial frictions	—	—	1.60	1.42

Note: This table reports data moments and TFP losses for non-recalibrated counterfactual models without exogenous wedges. The "Data" column shows the data moments for comparison. The "Financial Frictions" column reports outcomes from the baseline model with financial frictions. The "No Financial Frictions – Fixed Distribution" column shuts down financial frictions while holding the firm distribution fixed at the stationary distribution $\Upsilon(\tau, z, x)$ of the "Financial Frictions" model. The "No Financial Frictions – Endogenous Distribution" column also shuts down financial frictions, but allows the firm distribution to adjust endogenously; in this case, there is no entry or exit, so the endogenous distribution is given by the joint ergodic distribution of (τ, z, ξ). All models are computed given the same parameters as in the benchmark model reported in Table 2. Data source: Chinese manufacturing firm-level data, averaged over 1998–2007 at an annual frequency.

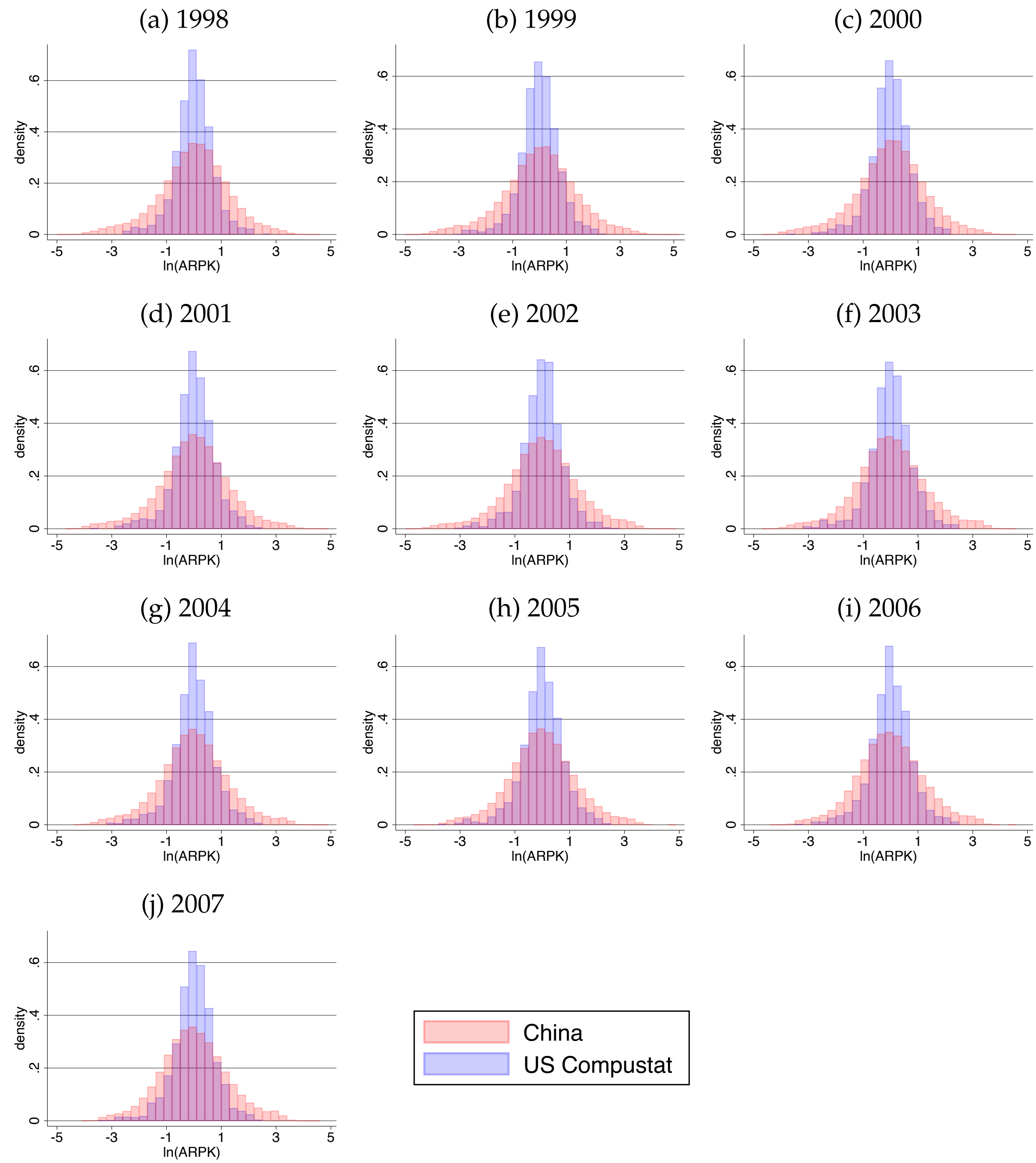
E Additional Figures

Figure E.1: Histograms of ln($ARPK$) in China and U.S. Compustat Manufacturing, 1998–2007



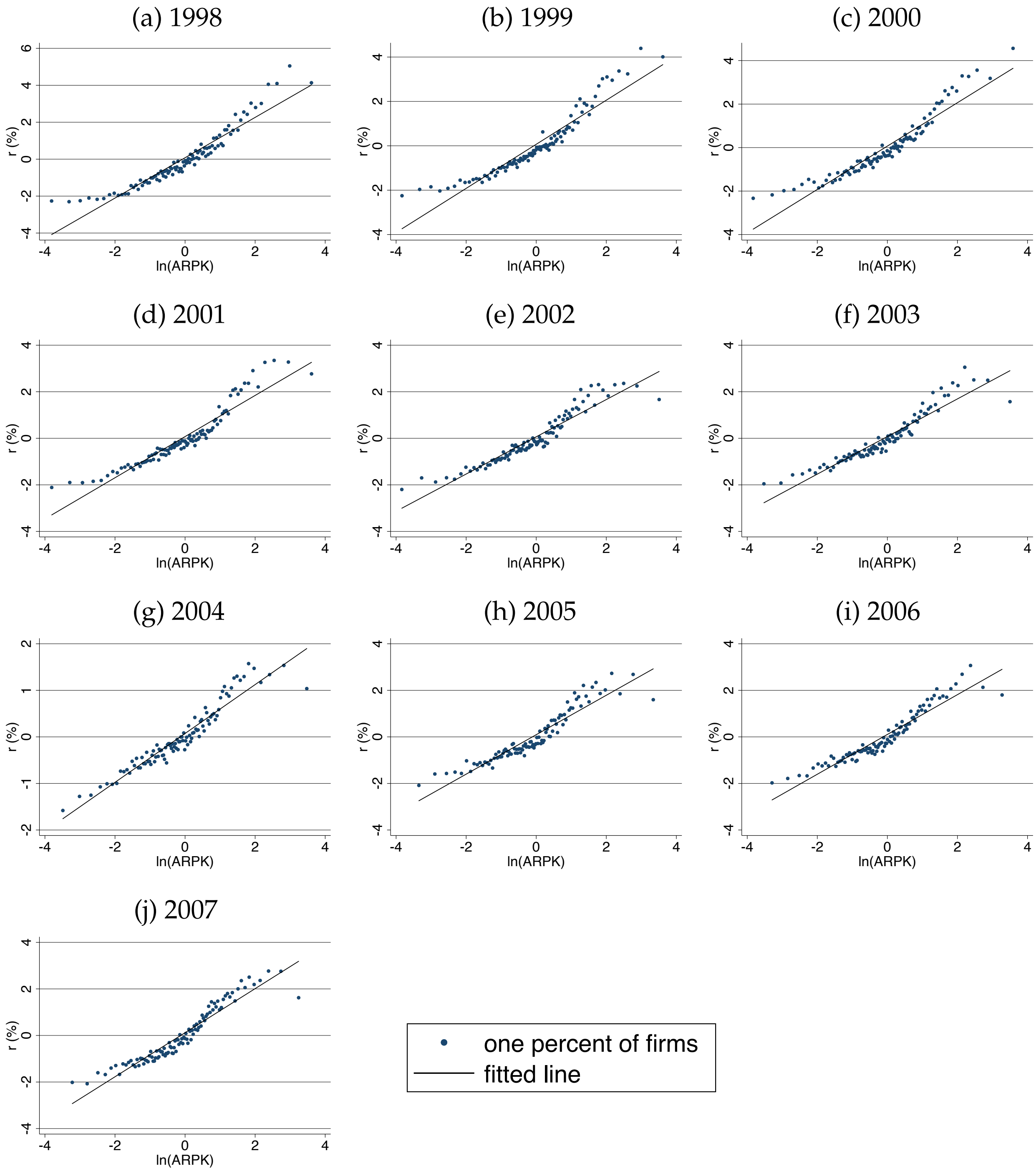
Note: This figure shows the histograms of ln($ARPK$) for Chinese and U.S. Compustat manufacturing firms. The variable is demeaned at the year-by-industry level. Red bars denote China, and blue bars denote the United States. Data sources: Chinese manufacturing firm-level data and U.S. Compustat manufacturing data, 1998–2007.

Figure E.2: Histograms of ln($ARPK$) in China and U.S. Compustat Manufacturing, Size-Intersection Sample with U.S. Compustat Manufacturing, 1998–2007



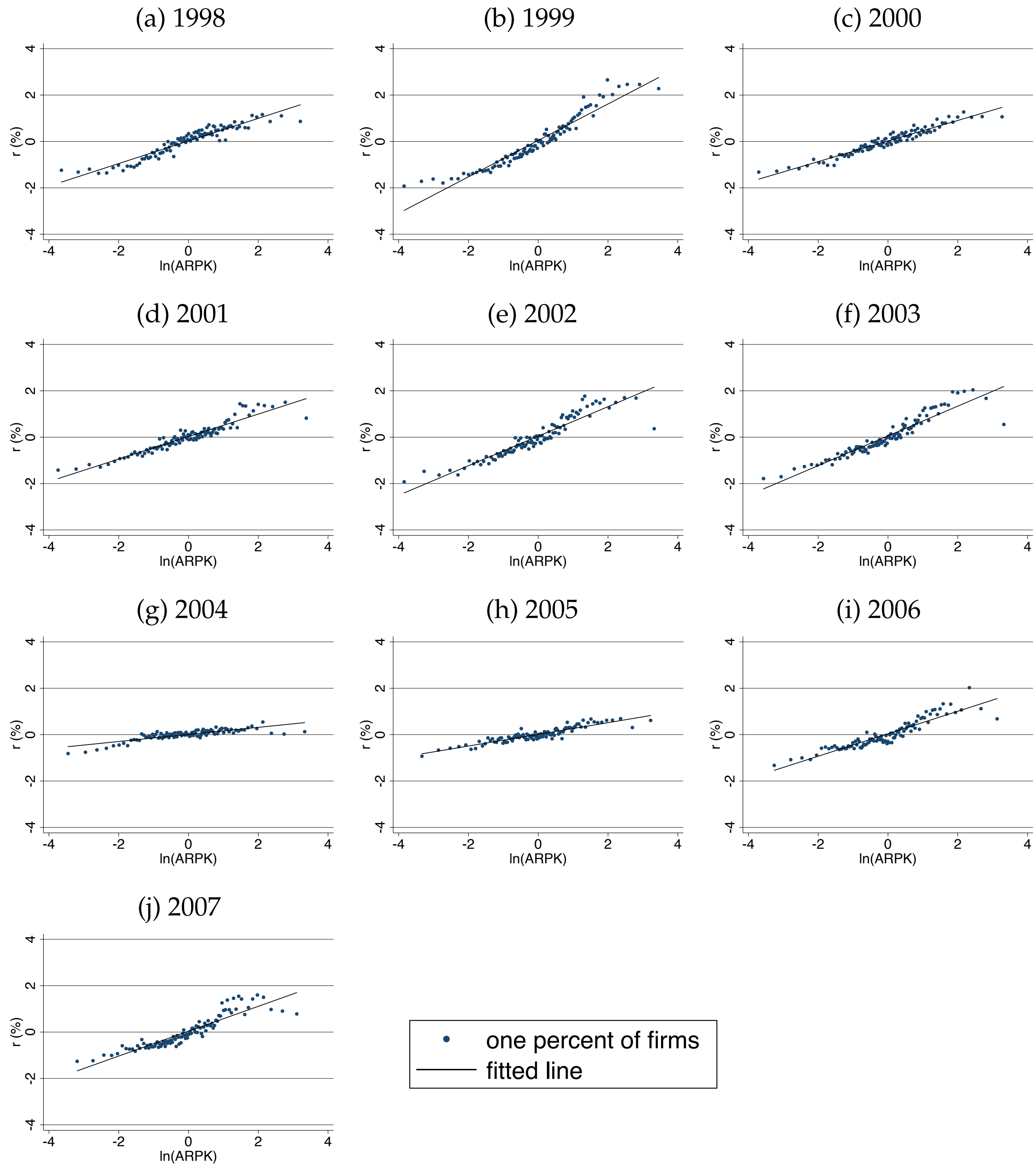
Note: This figure shows the histograms of ln($ARPK$), using the intersection sample by asset size between China and U.S. Compustat manufacturing. The variable is demeaned at the year-by-industry level. Red bars denote China, and blue bars denote the United States. Data sources: Chinese manufacturing firm-level data and U.S. Compustat manufacturing data, 1998–2007.

Figure E.3: Borrowing Costs and ln($ARPK$) in China, 1998–2007



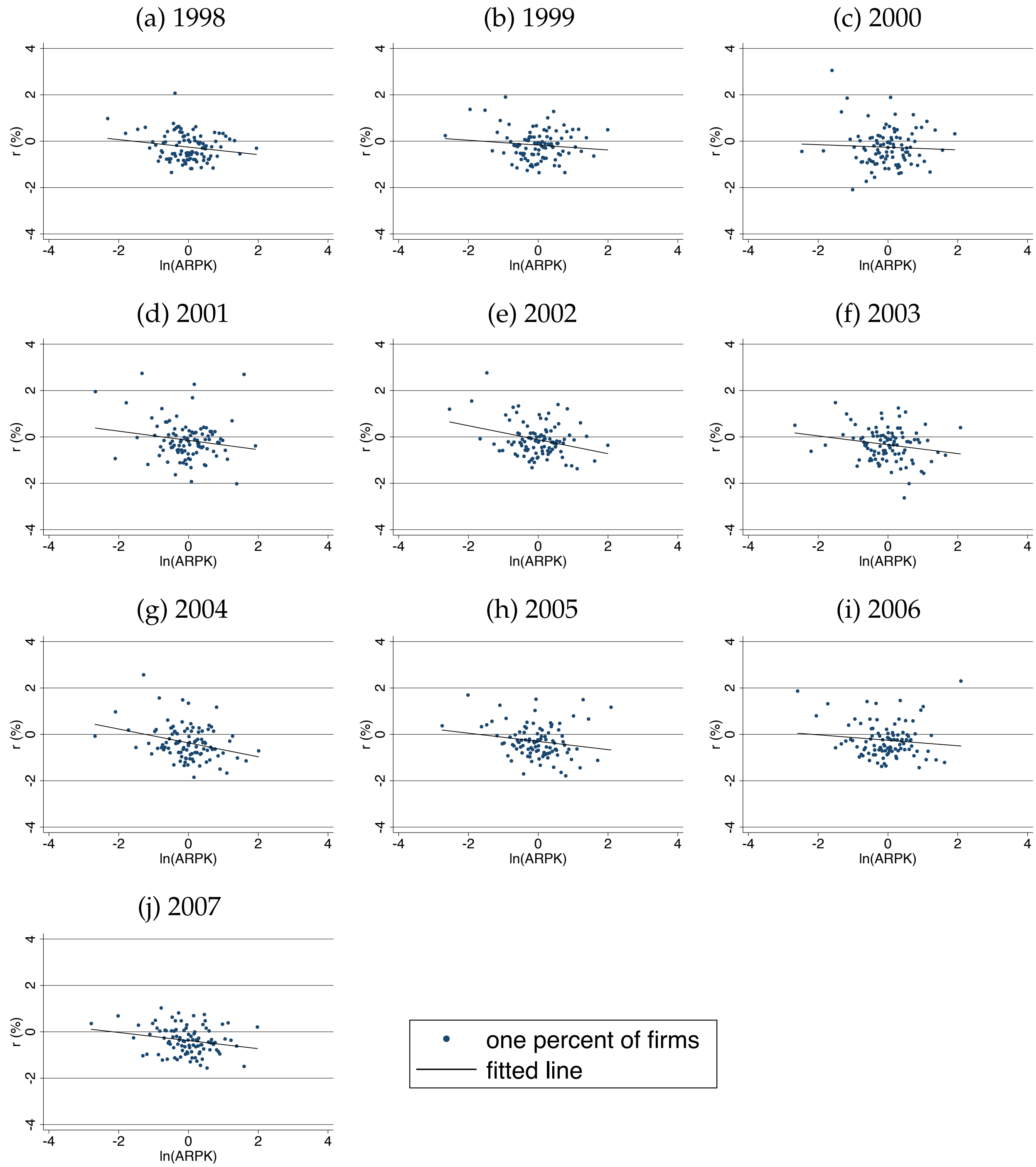
Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$). Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: Chinese manufacturing firm-level data, 1998–2007.

Figure E.4: Borrowing Costs and ln($ARPK$) in China, 1998–2007
Size-Intersection Sample with U.S. Compustat Manufacturing



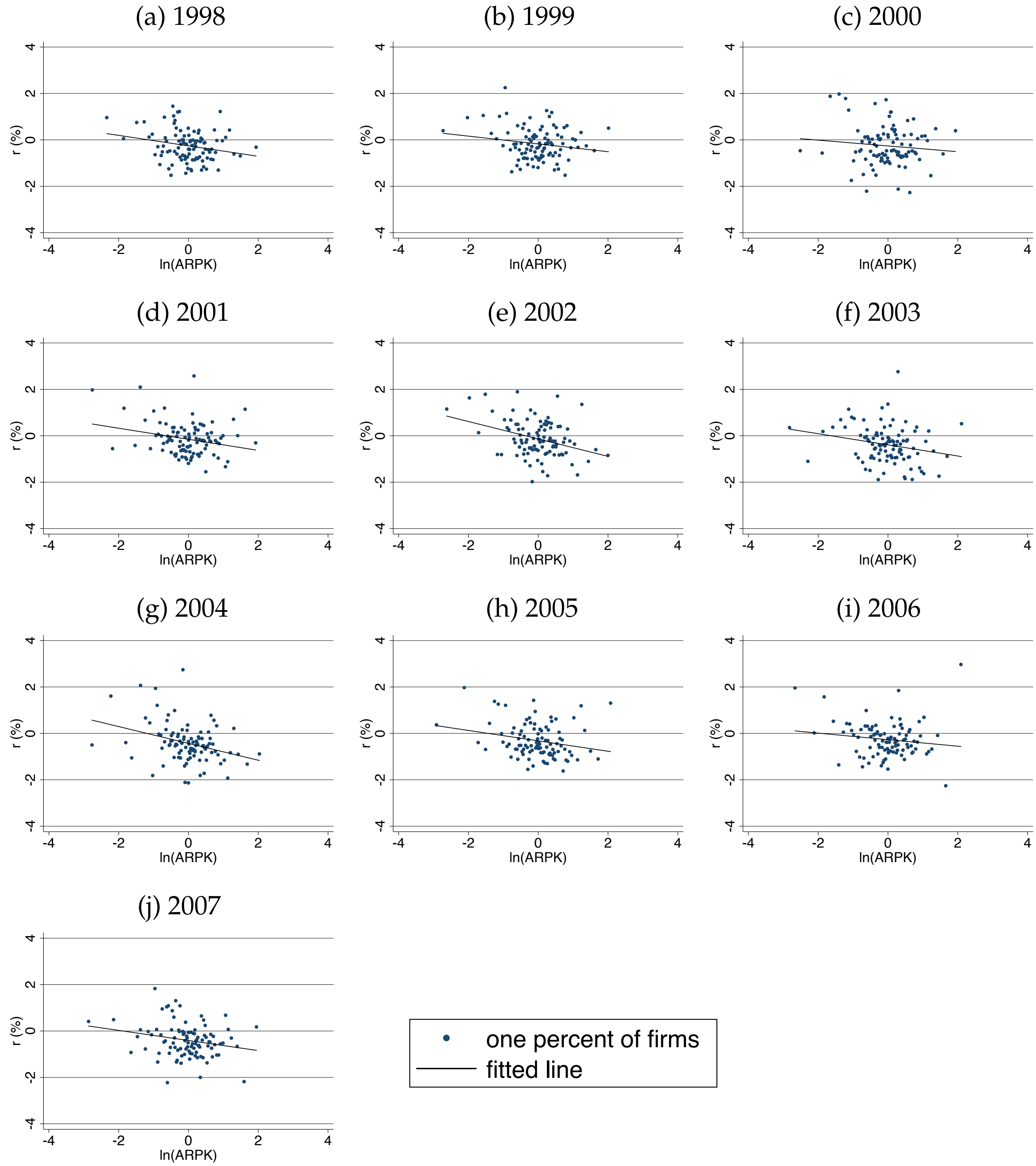
Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$) for Chinese manufacturing firms, using the intersection sample by asset size between China and U.S. Compustat manufacturing. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: Chinese manufacturing firm-level data and U.S. Compustat manufacturing firm-level data, 1998-2007.

Figure E.5: Borrowing Costs and ln($ARPK$) in U.S. Compustat Manufacturing, 1998–2007



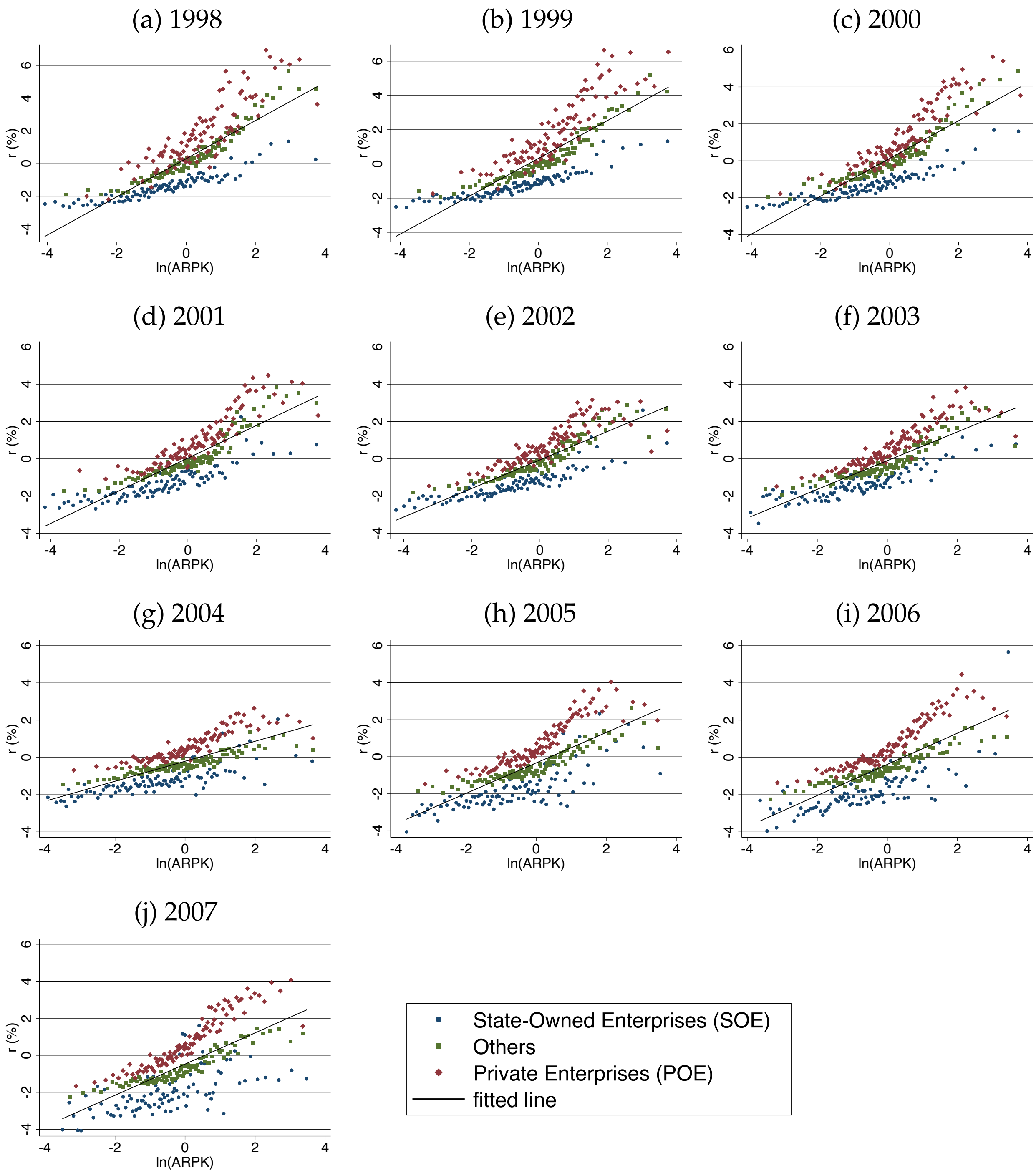
Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$). Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: U.S. Compustat manufacturing firm-level data, 1998–2007.

Figure E.6: Borrowing Costs and ln($ARPK$) in U.S. Compustat Manufacturing, 1998–2007
Size-Intersection Sample with China



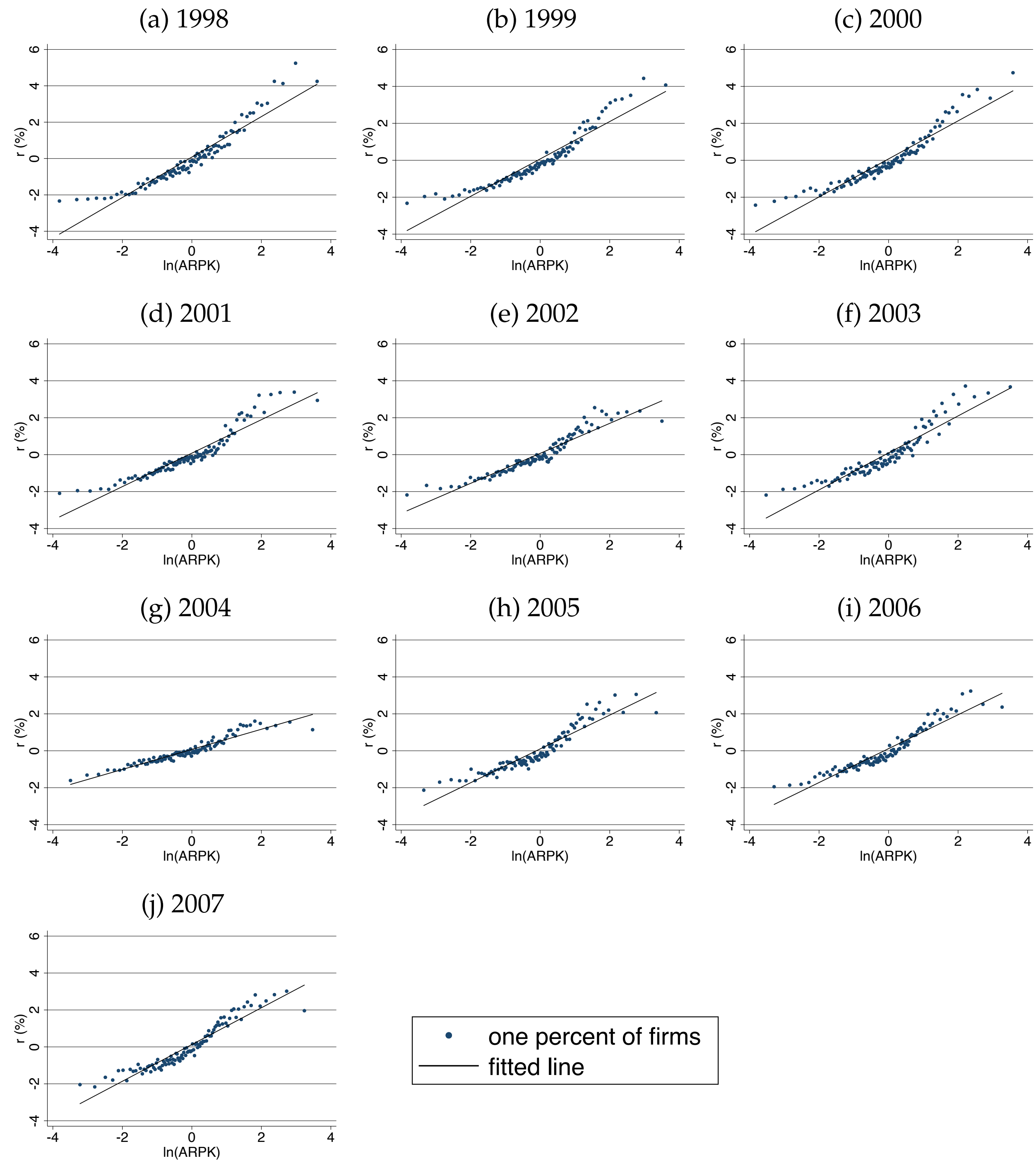
Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$) for U.S. Compustat manufacturing firms, using the intersection sample by asset size between China and U.S. Compustat manufacturing. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: Chinese manufacturing firm-level data and U.S. Compustat manufacturing firm-level data, 1998-2007.

Figure E.7: Borrowing Costs and ln($ARPK$) in China by Ownership, 1998–2007



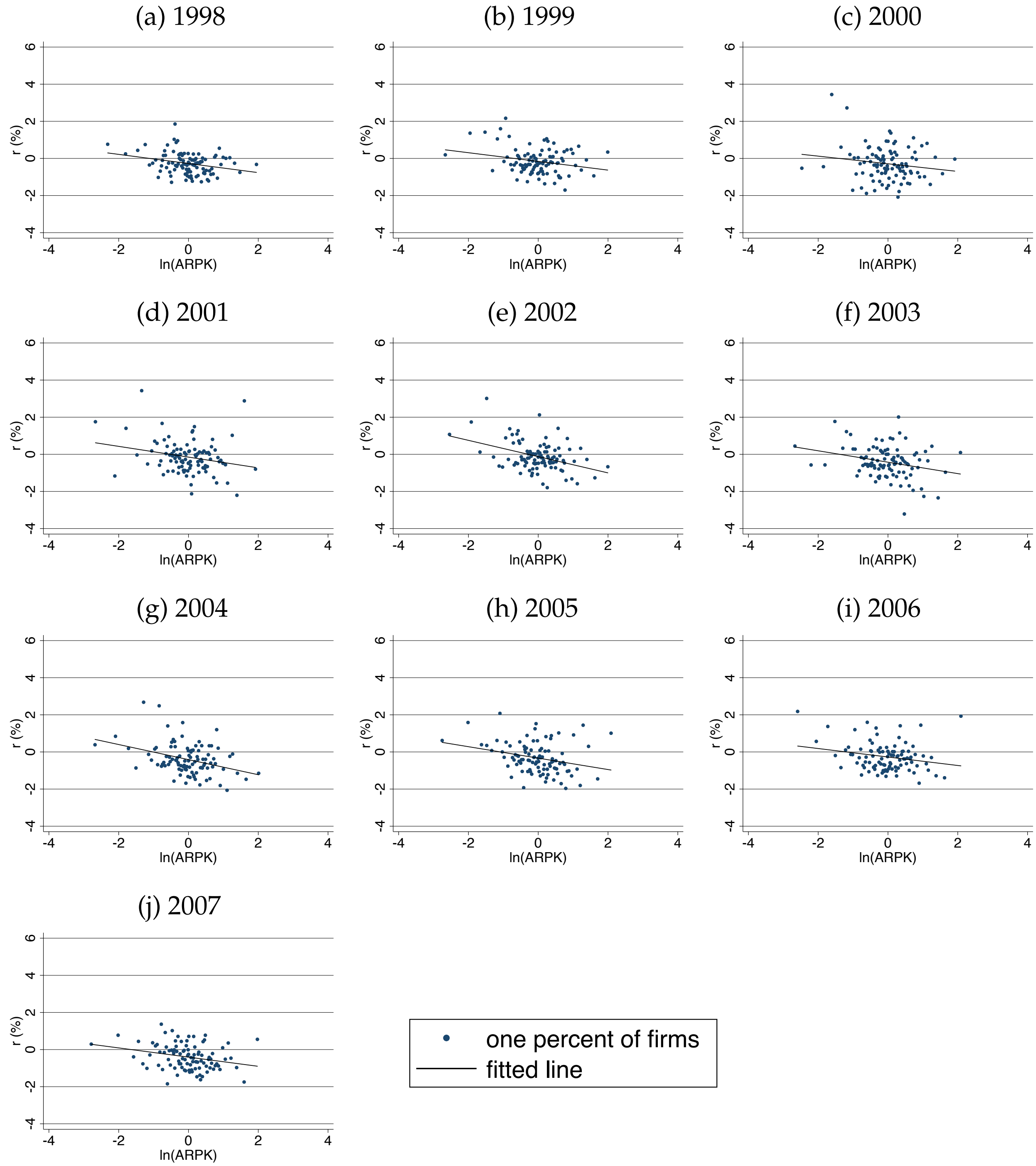
Note: This figure shows the scatter plot of borrowing costs against ln($ARPK$) across three ownership types: state-owned enterprises (SOEs), private enterprises (POEs), and others. Both variables are demeaned at the year-by-industry level. For each ownership type in each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms within that ownership type and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: Chinese manufacturing firm-level data, 1998–2007.

Figure E.8: Borrowing Costs (Alternative Measure) and ln($ARPK$) in China, 1998–2007



Note: This figure shows the scatter plot of borrowing costs (alternative measure) against ln($ARPK$), where borrowing costs are calculated as the ratio of interest payments to the sum of current liabilities and long-term debt. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: Chinese manufacturing firm-level data, 1998–2007.

Figure E.9: Borrowing Costs (Alternative Measure) and ln($ARPK$) in U.S. Compustat Manufacturing, 1998–2007



Note: This figure shows the scatter plot of borrowing costs (alternative measure) against ln($ARPK$), where borrowing costs are calculated as the ratio of interest payments to the sum of current liabilities and long-term debt. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the borrowing cost and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: U.S. Compustat manufacturing firm-level data, 1998–2007.