When Do Financial Frictions Matter for Misallocation?*

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Abstract

This paper revisits the impact of financial frictions on firm-level misallocation by disciplining them with firm-level financing patterns. Using firm-level data from 1998 to 2007, we document that Chinese firms with high average revenue products of capital face high interest rates, a pattern absent in US data. We develop a heterogeneous firm model with endogenous borrowing constraints to quantify aggregate implications. Financial frictions alone generate modest total factor productivity (TFP) losses of less than 2%. However, when interacting with other distortions prevalent in developing economies, removing financial frictions increases TFP by 25 percentage points. Our findings reveal that the interaction between financial frictions and other sources of misallocation drives substantial capital misallocation in China.

Keywords: financial frictions, firm debt financing, capital misallocation.
JEL classification: G3, E2

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1 Introduction

The seminal work of Hsieh and Klenow (2009) has spawned large studies on resource misallocation, particularly in developing countries such as China. Underdeveloped financial markets represent a natural source of such inefficiency in these economies. Yet quantitative studies of financial frictions have yielded mixed findings. Moll (2014) demonstrates that financial-friction-driven misallocation cannot be substantial when productivity shocks are persistent, as firms tend to save their way out of financial constraints. Similarly, Midrigan and Xu (2014) find that financial frictions generate large misallocation and TFP losses only through the entry margin. By contrast, Buera et al. (2011) and Song et al. (2011) argue that financial frictions substantially impact sectoral misallocation.

This paper revisits the role of financial frictions in misallocation by disciplining them with firm-level data on interest rates and borrowing, then quantifying their aggregate impact using heterogeneous-firm models with endogenous borrowing constraints. Empirically, we document that Chinese firms with high average revenue products of capital (ARPK) face high interest rates. Quantitatively, we find that models incorporating financial frictions alone generate modest TFP losses of 2%, consistent with Moll (2014), but fail to match the observed ARPK distribution. Introducing exogenous wedges, which capture other distortions such as regulatory policies and differential treatment across firm types, resolves this discrepancy by generating endogenous variation in borrowing constraints, thereby replicating the observed covariance between ARPK and interest rates. In this framework, financial frictions cause a 25% loss in TFP. Our analysis thus reveals that the interaction between exogenous wedges and financial frictions drives substantial capital misallocation in China.

We begin by documenting salient features of rich firm-level data from China spanning 1998 to 2007. We focus particularly on how debt financing and capital allocation vary across firms. Consistent with Hsieh and Klenow (2009), we find that China exhibits highly dispersed average revenue products of capital, and these patterns persist throughout the 1998-2007 period. To examine whether this dispersion relates to firm financing, we analyze firm-level interest rates, defined as the ratio of interest payments to total liabilities.

Several notable patterns emerge. First, firms with higher ARPK face higher interest rates, with a fitted slope of 0.88. Second, this positive relationship holds within each ownership category: state-owned enterprises, POEs, and other firm types all exhibit this pattern, even though POEs face higher interest rates on average. These patterns are also robust across time. We confirm these findings through regressions of ARPK on interest rates. Even after controlling for leverage and including firm fixed effects and year fixed

effects, the coefficient on interest rate remains positive and statistically significant. Firm fixed effects account for half of the observed correlation between interest rates and ARPK. Note that in a frictionless market, all firms would face the same interest rate and earn the same marginal return on capital. These findings suggest that capital allocation across firms in China is closely linked to financing patterns and firm-specific characteristics.

For comparison, we examine the same relationship in the United States, an advanced economy with well-developed financial markets. Using US Compustat data, we find that interest rates are barely correlated with ARPK, or even negatively correlated. This contrasts sharply with the patterns observed in China.

To assess the aggregate implications, we develop a model featuring 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 face stochastic productivity and capital quality shocks. Adjusting capital is costly due to financing frictions. 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 loan pricing. Our model thus generates endogenous borrowing constraints and differential interest rates across firms.

The model incorporates three sources of misallocation: information frictions, financial frictions, and exogenous wedges. Information frictions arise because firms must 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 operate like output taxes and capture various other sources of misallocation in China, such as government policies and regulatory distortions.

In the model, firm size, borrowing, and interest rates are all shaped by financial frictions. Higher borrowing increases default risk and thus raises the effective firm interest rate. In equilibrium, small firms with limited assets tend to be more financially constrained, remain inefficiently small, which raises their ARPK, and pay higher interest rates. When these firms experience positive productivity shocks, they grow faster due to their initially inefficient size. The model thus can generate the financing patterns observed in the data: firms with higher ARPK face higher interest rates.

We estimate the model by targeting the firm size distribution and financing patterns observed in Chinese data. These moments jointly identify the productivity process and the parameters governing financial frictions. The productivity process parameters primarily determine the distribution of value added and its growth rate. Both the productivity process and capital quality shocks influence firm default risk, while the debt recovery rate shapes average leverage and interest rates across firms. We calibrate these parameters to

match the empirical distributions of firm interest rates and leverage. We further calibrate the exogenous wedges to match the observed ARPK dispersion. Overall, the model closely replicates these targeted moments.

Using the calibrated model, we evaluate the magnitude of TFP losses attributed to financial frictions. Eliminating financial frictions would improve TFP by 25 percentage points. Of this gain, 7 percentage points stem from the direct effect of financial frictions, while 18 percentage points arise from endogenous selection: financial frictions force some productive firms to exit the market.

To isolate the role of financial frictions, we consider a case with only financial frictions and no exogenous wedges. Consistent with prior literature, financial frictions alone generate modest TFP losses of less than 2 percentage points. We further find that this specification replicates only 37% of the observed ARPK dispersion. However, these modest effects do not imply that financial frictions are unimportant. Rather, as demonstrated in our baseline case, other distortions interact with and amplify the impact of financial frictions, producing substantially large aggregate effects.

To unpack the interaction between exogenous wedges and financial frictions, we examine ARPK patterns in the data and assess how well the two models—with and without exogenous wedges—match these patterns. We find that the model incorporating both exogenous wedges and endogenous financial frictions aligns well with the data across multiple dimensions, whereas the model with financial frictions alone fails to replicate key empirical regularities. First, the data reveal a negative correlation between leverage and ARPK, indicating that firms with higher ARPK borrow less. Financial frictions alone generate the opposite prediction: a positive correlation, since higher-ARPK firms are more constrained and thus have stronger incentives to borrow. Introducing exogenous wedges resolves this tension. Firms facing high wedges effectively pay larger taxes and confront permanently tighter endogenous borrowing constraints than low-wedge firms. Thus, high-wedge firms exhibit higher ARPK but lower leverage, enabling the model to generate the observed negative correlation between leverage and ARPK.

Furthermore, ARPK shows substantial persistence over time. Firms with high ARPK tend to maintain high ARPK in subsequent periods. In the data, ARPK autocorrelation is 0.73 without firm fixed effects and falls to 0.16 after controlling for them. The model with financial frictions alone cannot replicate this pattern. Without permanent exogenous wedges, firms are ex-ante identical, so the autocorrelation of ARPK remains low regardless of whether firm fixed effects are included. In contrast, incorporating permanent exogenous wedges helps the model generate the same pattern observed in the data: ARPK autocorrelation is primarily driven by cross-firm heterogeneity captured through firm fixed effects.

Our paper makes two key contributions. First, we directly use firm-level financial variables—interest rates and leverage—to discipline financial frictions, and we document a positive correlation between interest rates and ARPK across Chinese firms, while such a relationship is 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 impact of financial frictions depends critically on the presence of other distortions: in isolation, financial frictions generate modest losses, but when interacting with other sources of misallocation common in developing countries, their effects are substantially amplified.

Our approach of using firm-level interest rates to measure financial frictions is similar to Gilchrist et al. (2013), who use a model with exogenous interest rates to match the dispersion of firm interest spread among US Compustat firms and find negligible implied TFP losses. In contrast, firm-level interest rates in our model are endogenous. Our quantitative analysis also focuses on a financially less developed country, China, which exhibits larger interest rate dispersions. We show that even when a model with only financial frictions matches the interest rate dispersion, it fails to generate the observed ARPK dispersion, which greatly limits the TFP losses that such a model can produce. Adding exogenous wedges resolves this discrepancy and amplifies the role of financial frictions.

Our paper is closely related to Arellano et al. (2012) and Bai et al. (2018). Arellano et al. (2012) use cross-country variations in financial market development to evaluate empirically and quantitatively the impact of financial frictions on firms' financing choices and growth rates using firm data from Europe. Bai et al. (2018) find a positive size-leverage relation in China, consistent with the finding in Arellano et al. (2012) for less-developed countries. In both studies, capital misallocation is solely driven by financial frictions. We introduce permanent exogenous wedges into a model with financial frictions similar to theirs. We find that this model better matches the observed dispersions in financing patterns and ARPK. Our key finding is that to explain China's capital misallocation, exogenous wedges are necessary, and these wedges interact with and amplify the role of financial frictions.

Our paper is closely related to the work of Whited and Zhao (2021) and David and Venkateswaran (2019a). Whited and Zhao (2021) focus on the potential welfare gain from reallocating debt and equity among Chinese firms and estimate the distortion using a static model and observed data directly. Our paper uses a dynamic model with limited enforcement to quantify the impact of financial frictions on capital misallocation. David and Venkateswaran (2019a) also quantify the contributions of capital adjustment cost, technology dispersion, and information friction to capital misallocation. We focus on identifying financial frictions with firm dynamics and financing patterns. A key difference

is that ARPK dispersion is endogenous in our model, whereas it is exogenous in their work.

Our work also contributes to the growing literature on financial frictions and misallocation. Hsieh and Klenow (2009) use firm-level data to quantify the extent of misallocation in China and India relative to the US, documenting sizable gaps in the marginal products of factors across plants. Midrigan and Xu (2014) parameterize a financial frictions model to match salient features of plant-level data and show that financial frictions alone do not predict large aggregate TFP losses. Cooley and Quadrini (2001) show that the combination of persistent shocks with financial frictions can account for the dependence of firm dynamics on size and age. Recent work by Bocola and Bornstein (2023) shows that default risk on trade credit can amplify output costs during recessions. Our paper complements 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.

Our paper is also related to the literature on the implications of financial frictions in China. Using a growth model, Song et al. (2011) show that during an economic transition, high-productivity, non-state-owned firms outgrow low-productivity, state-owned firms if entrepreneurs have high enough savings. At the same time, the more financially integrated SOE sector shrinks, forcing domestic savings to be invested abroad, leading to a foreign surplus. Wang et al. (2012) use two types of capital, financial and fixed capital, to explain two-way flows. In their model, the underdeveloped financial market in China offers a high rate of returns to fixed capital but low rates of return to financial capital, relative to the US. As a result, households save abroad, and FDI flows in. Most studies use either aggregate data or ignore firms' financing patterns. By comparison, our paper uses the debt financing features observed in the Chinese firm-level data on interest rates and leverage to discipline financial frictions and quantify their impact on capital misallocation.

Our paper relates to a large 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,[1] we have learned that financial frictions affect investment and saving. Our analysis uses firm-level leverage, interest rate, and ARPK data to discipline financial frictions, enabling our model to match the empirical distributions of value-added, leverage, interest rates, 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 the key empirical findings

[1]For example, Chava and Roberts (2008), Gomes (2001), Hennessy and Whited (2005), Hennessy and Whited (2007), Gamba and Triantis (2008), Rampini and Viswanathan (2010), Korteweg (2010), Bolton et al. (2011), Eisfeldt and Muir (2016), Choi et al. (2025), among others.

on debt financing, interest rates, 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 interest rates in China are positively correlated with the 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. In a frictionless market, all firms would face the same interest rate and earn the same marginal return on capital. We begin by describing the data, 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 US patterns derived from US Compustat data.

2.1 Data

The empirical findings in this paper are based on rich firm-level data from an annual enterprise census conducted by the Chinese National Bureau of Statistics between 1998 and 2007. The dataset includes all state-owned firms and non-state-owned firms with sales over 5 million RMB (about 600,000 US dollars) in the manufacturing sector. It contains all information in the balance sheet, profit and loss statement, and cash flow statement. We restrict our sample to firms with positive assets, non-negative total liabilities, and positive sales.

We classify Chinese firms into three ownership categories: state-owned enterprises (SOEs), privately-owned enterprises (POEs), and others, including foreign-owned firms. This classification draws on firms' registration type data. SOEs include solely state-funded, state joint ownership, and state and collective joint ownership. POEs include sole private enterprises, private partnership enterprises, private limited liability companies, and private shareholding corporations. In our sample, 29 percent of the firms in 1998 and 2.2 percent in 2007 are strictly defined SOEs, and 8 percent in 1998 and 54 percent in 2007 are POEs.

Our key variables include firm-level interest rates and the average revenue product of capital (ARPK). We deflate all nominal values using the GDP deflator and measure assets by their book value. We define firm-level interest rates as the ratio of interest payments to total liabilities. We use value added and firms' fixed assets to compute the average revenue product of capital (ARPK). Since ARPK varies with industry-level capital intensity, we focus

on firms' relative ARPK by normalizing each firm's value-added-to-capital ratio against its industry mean. Specifically, the relative ARPK is calculated as $\log\left(\frac{Y_{ij}}{K_{ij}}\right) - \log\left(\frac{\overline{Y_j}}{K_j}\right)$ for a firm i in industry j.

2.2 Empirical Evidence

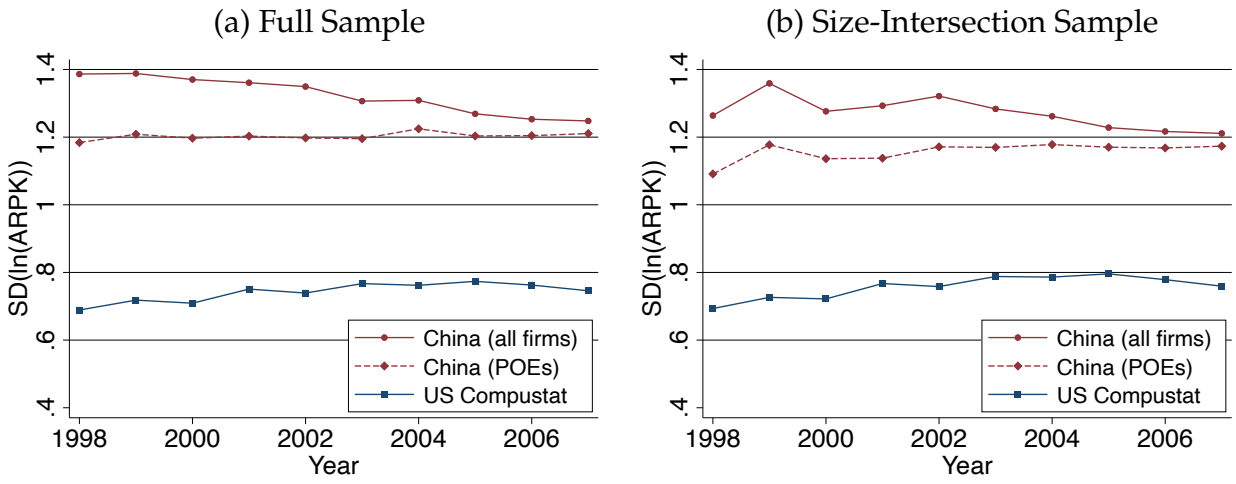
Capital misallocation in China. Figure 1 shows the standard deviation of $\ln(ARPK)$ over time for China and the U.S. The left panel reports results using each country's full sample. As shown in the graph, the dispersion of $ARPK$ is much higher in China than in the U.S., a pattern that has also been documented in other studies (e.g., Hsieh and Klenow (2009)). From 1998 to 2007, the dispersion of $ARPK$ in China declines. However, this decline is mainly driven by the falling share of state-owned firms in the economy. When focusing only on private enterprises, the dispersion of $ARPK$ remains high and stable over time, suggesting that there are substantial capital distortions in China.

The greater $ARPK$ dispersion in China does not stem from differences in sample composition between the two countries. Since China's data include more small firms than Compustat, one potential concern is that the differences are driven by sample selection. To address this concern, we follow Whited and Zhao (2021) and construct intersection samples for the two countries based on asset size. We first convert Chinese firms' asset values into U.S. dollars using the CNY-USD spot exchange rate, and then restrict both samples to their overlapping minimum and maximum asset values. The right panel of Figure 1 reports results based on this intersection sample. The dispersion of $ARPK$ becomes slightly lower in the Chinese data, while the U.S. Compustat results change very little. Overall, even in the overlapping sample, the dispersion of $ARPK$ remains much larger in China than in the U.S., and this difference is highly persistent over the entire period from 1998 to 2007.

This pattern persists across all individual years. Figure B.1 in the appendix compares the histograms of $\ln(ARPK)$ for China and U.S. Compustat manufacturing firms for each year from 1998 to 2007. Chinese firms exhibit much greater dispersion than U.S. firms in all years. Figure B.2 re-draws the histograms using the size-intersection sample between China and U.S. Compustat manufacturing. The patterns remain similar.

Misallocation and Interest Rates. We now explore the relationship between capital misallocation and financial frictions, which we proxy with firm-level interest rates. Figure 2 shows the scatter plot of interest rates 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

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.

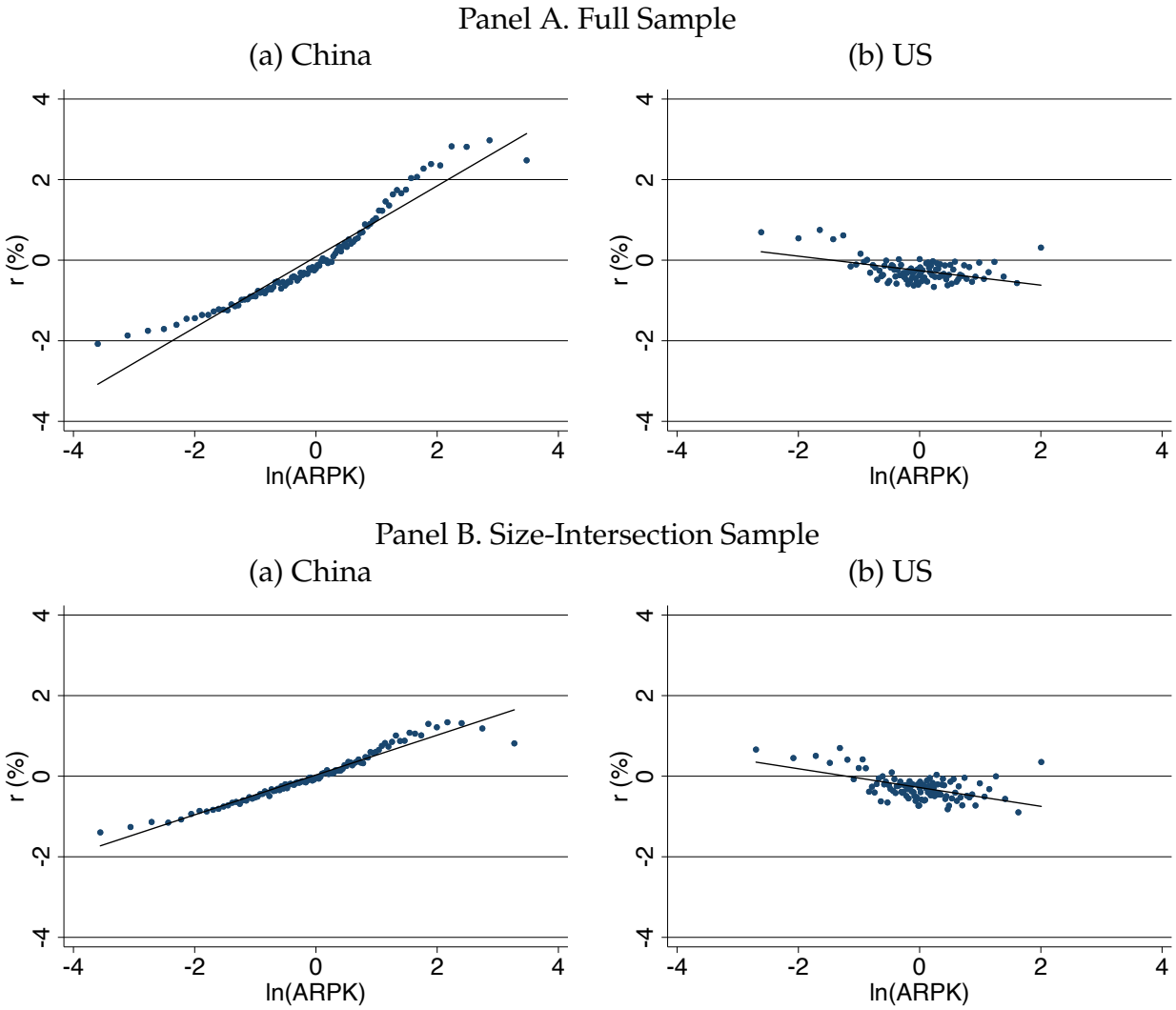
the interest rate and $\ln(ARPK)$ are computed within each percentile. The scatter plot represents the average across years from 1998 to 2007. The solid line depicts the fitted linear relationship.

Panel A uses each country's full sample. In China, there is a strong positive correlation between interest rates and $\ln(ARPK)$, with a fitted slope of 0.88 (p-value < 0.001). This pattern holds consistently across all years from 1998 to 2007, as shown in Figure B.3 in the appendix. In contrast, US Compustat manufacturing firms show no positive correlation between these variables. If anything, the slope is slightly negative. This absence of positive correlation persists throughout the entire 1998-2007 period, as Figure B.5 in the appendix demonstrates.

Panel B shows the results using the size-intersection sample. The dispersion of interest rates becomes smaller in China's data as smaller firms are excluded from the intersection sample, but the positive correlation between interest rates 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 is barely changed and still does not show a positive correlation. Figures B.4 and B.6 display the intersection-sample scatter plots for each year from 1998 to 2007. The pattern still holds.

To test whether the relationship between interest rates and $\ln(ARPK)$ is driven by other

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



Note: This figure shows the scatter plot of interest rates 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 interest rate 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.

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.

Table 1 reports the regression results. Panel A uses each country's full sample, while

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

Panel A. Full Sample

	China					US 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
	(0.00095)	(0.0010)	(0.0010)	(0.0010)	(0.00099)	(0.0080)	(0.0082)	(0.0085)	(0.0063)	(0.0063)
leverage$_{it}$		-0.023***	-0.015***	0.0066***	0.024***		-0.12***	-0.11***	-0.13***	-0.13***
		(0.00099)	(0.00099)	(0.0012)	(0.0012)		(0.0082)	(0.0089)	(0.0089)	(0.0089)
maturity$_{it}$			-0.13***	-0.049***	-0.044***			-0.020**	0.023***	0.020***
			(0.00092)	(0.00094)	(0.00094)			(0.0090)	(0.0076)	(0.0077)
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					US 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
	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0083)	(0.0086)	(0.0088)	(0.0067)	(0.0067)
leverage$_{it}$		-0.031***	-0.021***	-0.0070***	0.012***		-0.11***	-0.096***	-0.13***	-0.13***
		(0.0011)	(0.0011)	(0.0014)	(0.0014)		(0.0085)	(0.0093)	(0.0093)	(0.0094)
maturity$_{it}$			-0.15***	-0.054***	-0.051***			-0.023**	0.025***	0.022***
			(0.0010)	(0.0011)	(0.0011)			(0.0094)	(0.0081)	(0.0081)
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 interest rates, leverage, and debt maturity for Chinese and U.S. Compustat manufacturing firms. Interest rates 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 are in parentheses. 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.

Panel B uses the intersection sample based on asset size. Both panels deliver similar messages. First, the coefficients on interest rates are significantly positive for China, but either negative or insignificant for U.S. Compustat firms, consistent with the patterns in the scatter plots. Second, in China, interest rates appear to be the financial variable most strongly related to variations in ln($ARPK$), as the estimated coefficients on leverage and maturity are generally smaller. Third, the positive correlation between interest rates and ln($ARPK$) becomes much weaker when firm fixed effects are included, suggesting that

permanent firm heterogeneity plays an important role. In contrast, adding time fixed effects barely changes the estimated coefficients.

We also conduct additional robustness checks using an alternative measure of interest rates. Our benchmark measure defines the interest rates 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 B.7 and B.8 show the yearly scatter plots of this alternative interest rate measure against $\ln(ARPK)$ for China and the U.S. The Chinese data display an even larger dispersion of interest rates, 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.

Figure B.9 shows the scatter plot of interest rates against $\ln(ARPK)$ across three ownership types: state-owned enterprises (SOEs), private enterprises (POEs), and others. The pattern holds within each ownership group. POEs face the highest interest rates and tend to be associated with more positive $\ln(ARPK)$ (taxed), whereas SOEs face the lowest interest rates and tend to be associated with more negative $\ln(ARPK)$ (subsidized).

3 Model

We consider an 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 which they exit the market, and lenders receive some recovery value. Moreover, resource misallocation can also arise from exogenous wedges such as government regulatory distortions. There are no aggregate shocks in the economy.

3.1 Technology

Firms produce using a decreasing-returns-to-scale technology in capital, k. The output of firm i in period t is given by

$$y_{it} = z_{it}(\xi_{it} k_{it})^{\alpha}, \tag{1}$$

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

$$\log(z_{it}) = \rho_z \log(z_{it-1}) + \sigma_z \varepsilon_{it}, \varepsilon_{it} \sim N(0,1), \tag{2}$$

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

3.2 Sources of Misallocation

The model features three sources of 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 $t-1$. This imperfect information about future productivity leads to a misallocation of capital across firms.

The second source of misallocation is *exogenous wedges*, which we model using an output wedge. 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

$$\frac{y_{it}}{\tau_i} = \frac{z_{it}(\xi_{it}k_{it})^\alpha}{\tau_i}. \tag{3}$$

When $\tau_i > 1$, the wedge acts like a tax on output, while $\tau_i < 1$ corresponds to a subsidy. We assume that the exogenous wedges are not directly observable to economists in the data. Instead, only value added y_{it} is observed.

As emphasized by David and Venkateswaran (2019b), firm-specific fixed factors 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 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 and preferential policies toward state-owned enterprises.

The third and final 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. 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 r as given.

3.3 Firms' problem

Upon entry, firm i draws an exogenous wedge τ_i, which remains fixed throughout the firm's 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. 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:

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

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

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

The mechanism through which financial frictions generate misallocation operates through the dispersion of cash on hand x_{it}. At a given point in time, firms cannot adjust x_{it}, as it is predetermined by past decisions and realized shocks. When a firm's cash on hand is low, the non-negative dividend constraint in (10) binds, limiting the firm's ability to invest. As a result, the firm operates with less capital than optimal, raising its marginal product of capital. Therefore, dispersion in cash on hand translates into dispersion in the marginal product of capital, generating misallocation.

3.4 Bond Price Schedule

Since creditors are competitive, the debt 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:

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

The recovery function is given by

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

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.

3.5 Firm Entry and Equilibrium

We assume that potential entrants can finance capital using both internal equity and borrowing. As a result, they do not face a binding financial constraint at entry. Given

(τ_e, z_e), a potential entrant solves the following problem:

$$V^e(\tau_e, z_e) = \max_{k', b'} -k' + q(\tau_e, z_e, k', b')b' + \beta \, \mathbb{E}_{z'|z_e} \int_{\xi' \geq \xi'^*} V(\tau_e, z', x') dF(\xi'), \tag{14}$$

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 is non-negative, implying that all potential entrants are willing to enter.

However, successful entry occurs only if $\xi' \geq \xi'^*$. Conditional on entry, the firm becomes an incumbent and solves the incumbent firm's problem in equation (9). Let k'_e and b'_e denote the optimal capital and debt choices implied by the potential entrant's problem in equation (14). In its first period as an incumbent, a surviving entrant produces using capital k'_e and repays debt b'_e.

The total mass of firms in the economy is normalized to one. We further assume that, for each exogenous wedge value $\tau_k \in \{\tau_j\}_{j=1}^{N_\tau}$, the mass of firms in that wedge group is constant over time. Thus, in the stationary equilibrium, the mass of exiting firms in each wedge group should be exactly offset by the mass of surviving entrants facing the same wedge. We assume that there is a sufficiently large pool of potential entrants to accommodate all exits.

Specifically, when a firm with exogenous wedge τ_k exits, a new entrant with $\tau_e = \tau_k$ is drawn from the pool of potential entrants. The entrant's initial productivity z_e is drawn from the ergodic distribution of z implied by equation (2). If the entrant does not survive to become an incumbent, we continue drawing entrants 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

$$m(\tau') = \int_{\tau, z, x} \int_{z'} \int_{\xi' \geq \xi'^*} \mathbb{1}\{\tau' = \tau\} \pi_z(z'|z) dF(\xi') dz' d\Upsilon(\tau, z, x). \tag{15}$$

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:

$$m_e(\tau') = \frac{\pi_\tau(\tau') - m(\tau')}{\int_{z_e} \int_{z'} \int_{\xi' \geq \xi'^*_e} \mathbb{1}\{\tau' = \tau_e\} \pi_z(z'|z_e) dF(\xi') dz' dG(z_e)}, \tag{16}$$

where $G(z)$ denotes the ergodic distribution of productivity implied by equation (2).

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

entering firms:

$$\begin{aligned}\Upsilon(\tau', z', x') = &\int_{\tau,z,x}\int_{\xi'\geq\xi'^{*}} \mathbb{1}\{\tau' = \tau\}\pi_z(z'|z)\mathbb{1}\{x'(z',\xi';\tau,z,x) = x'\}dF(\xi')d\Upsilon(\tau,z,x) \\ &+ m_e(\tau')\int_{z_e}\int_{\xi'\geq\xi'^{*}_e} \mathbb{1}\{\tau' = \tau_e\}\pi_z(z'|z_e)\mathbb{1}\{x'_e(z',\xi';\tau_e,z_e) = x'\}dF(\xi')dG(z_e).\end{aligned} \tag{17}$$

Definition 1. *Given the exogenous interest rate 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 (14).

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

(iii) The transition of the firm distribution is consistent with firms' decisions and follows (17).

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.

4.1 Identification

The model is calibrated at the annual frequency. We assume that the distribution of firms across wedge values $\tau_j \in \{\tau_k\}_{k=1}^{N_\tau}$ is uniform, with $\pi_\tau(\tau_j) = 1/N_\tau$. In the numerical exercise, we set $N_\tau = 5$ and calibrate the five values of τ to match the quintile means of $\ln(ARPK)$.

Table 2 presents two sets of parameters. The first set includes parameters chosen independent of our model. The second set consists of parameters estimated jointly using the simulated method of moments (SMM), which selects model parameters by matching moments from a simulated panel of firms to their data counterparts. All data moments are averages over the period 1998-2007.

The first set of parameters is determined with external information and includes $\{\alpha, \delta, r, \rho_z\}$. We set the production parameter α at 0.65 to capture both capital share and return to scale. The capital depreciation rate δ is chosen to be six percent annually. We set the

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 (%)	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 interest rate r (%)	4.32	5.92	4.90
Std interest rate (%)	6.72	6.19	6.31
Mean leverage	0.60	0.61	0.61
Corr(ln(asset), r)	-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.

annual risk-free rate 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 distribution, for a total of 10 moments.

Panel B of Table 2 reports the simulated and actual moments. The model tightly matches the data moments. The success of SMM estimation depends on model identification, which requires that the chosen moments be sensitive to variations in the structural parameters. We now rationalize these moments.

The standard deviation of firm productivity controls the distribution of firm value added. We therefore target the standard deviation of value-added growth rates. We consider four moments related to firms' financing patterns: average leverage, the mean and standard deviation of interest rates, and the correlation between interest rates and firm size (measured by log assets). In our dataset, the average leverage is 0.6, the mean interest rate is 4.3% and interest rate volatility is 6.7%. Furthermore, interest rates are negatively correlated with firm size, implying that smaller firms face higher borrowing costs.

The discount factor β, fixed operating cost, and debt recovery rate are mostly relevant for firm leverage decisions. Greater impatience, lower fixed costs, and higher debt recovery rates all contribute to higher leverage. The debt recovery rate has important implications for the correlation between firm size and interest rates. Larger assets imply greater debt recovery value in the event of default, which reduces interest rates. The exogenous wedges are calibrated jointly with other parameters to match the average $\ln(ARPK)$ by quintile. Overall, the model closely matches the distribution of firms in terms of leverage, interest rates, and sales and ARPK distribution, as shown in Panel C of Table 2.

For comparison, we also recalibrate the model without exogenous wedges by matching the same set of moments except for the ARPK distribution. The calibrated parameters and moments are shown in the last column of Table 2. The model fits these moments well in leverage, interest rates, and value added. However, without exogenous wedges, the model fails to replicate the observed ARPK distribution. The difference between the fifth and the first quintiles of ARPK is only 1.36, less than half the value of 3.70 observed in the data and in the baseline model with exogenous wedges.

Table 3: Untargeted Moments

Moments	Data	Model	
		Benchmark	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 the untargeted moments. All data moments—except the persistence of ln $ARPK$—are calculated as annual averages from 1998 to 2007, and the model moments are computed using the stationary distribution. $\hat{z}$ 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 steady state. Data moments are reported with 95% confidence intervals in brackets. Data source: Chinese manufacturing firm-level data, 1998–2007.

4.2 Model Validation

To validate the model, we examine untargeted moments related to financial frictions and capital misallocation in Table 3. First, the benchmark model generates a standard deviation of leverage (0.21) close to that in the data (0.29). However, financial frictions alone generate only half of the observed leverage variation, despite matching both mean leverage and interest rate dispersion. Second, leverage and ARPK are slightly negatively correlated in the data. The benchmark model replicates this pattern, whereas the model with financial frictions alone generates a counterfactually positive correlation of 19%.

Here is the intuition. With only financial frictions, two opposing forces are at work. 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 higher capital return (ARPK) and higher leverage. On the other hand, this correlation is also shaped by productivity differences. High-productivity firms face looser bond-price schedules and carry higher leverage, which reduces their capital distortions and lowers their ARPK. Thus,

cash-on-hand creates a positive correlation between leverage and ARPK, while productivity creates a negative one. In equilibrium, the cash-on-hand effect dominates, resulting in a positive correlation under financial frictions alone.

When exogenous wedges are introduced in our benchmark model, an additional force affects ARPK-leverage relationship. High-ARPK firms may also 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.

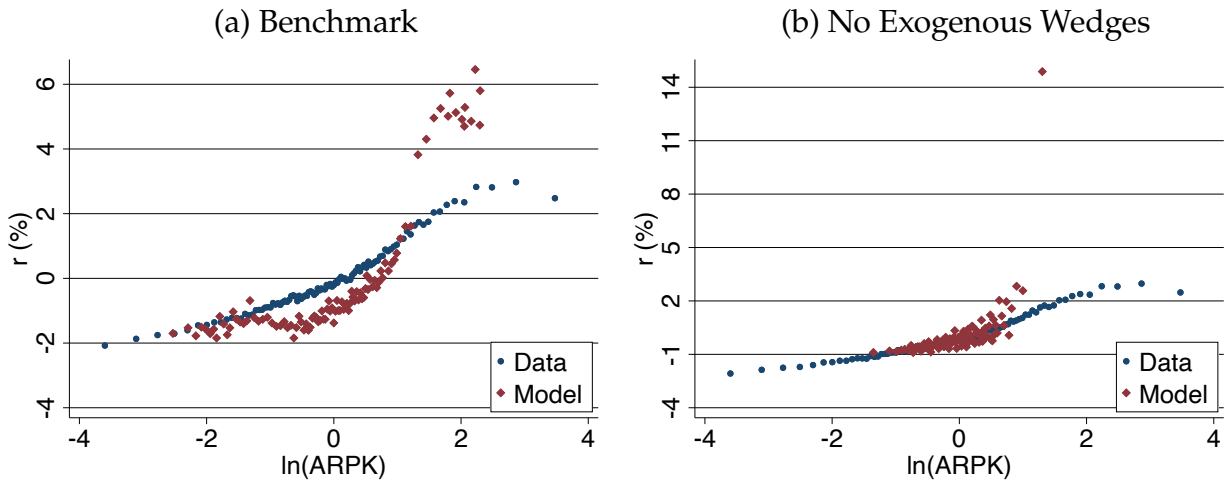
Table 3 further reports the autocorrelation of ARPK, which exhibits substantial persistence over time. Firms with high ARPK tend to maintain high ARPK in subsequent periods, with an autocorrelation of 0.73. This drops to 0.16 after controlling for firm fixed effects and further to 0.15 after additionally controlling for year fixed effects. These patterns indicate that ARPK persistence is mainly driven by firm-specific characteristics and not by time-varying aggregate factors. Our benchmark model with firm-specific permanent wedges replicates these patterns. In contrast, the model with financial frictions alone fails to do so. Firms are ex ante identical in that model, and persistent productivity shocks increase saving incentives, thereby allowing firms to relax their financial constraints. Thus, financial frictions alone cannot generate the persistent distortions observed in the data.

We now examine the relationship between interest rate and ARPK. Figure 3 plots interest rates against $\ln(ARPK)$ after grouping firms into 100 percentiles of $\ln(ARPK)$. Within each percentile, we compute the average interest rates and $\ln(ARPK)$. Panel (a) shows that the benchmark model closely matches the observed scatter plot, reproducing the wide range of $\ln(ARPK)$ from -4 to 4 by calibrating the values of exogenous wedges. Interest rates are positively correlated with these capital distortions. Panel (b) presents the same scatter plot for the model with only financial frictions. Although interest rates remain quite dispersed and positively correlated with $\ln(ARPK)$, the model generates only half the range of ARPK observed in the data and the benchmark model.

Table 4 reports OLS regressions of $\ln(ARPK)$ on interest rates and leverage using the model-simulated panel. The left panel presents results from the benchmark model. Consistent with the empirical findings in Table 1, interest rates are positively correlated with $\ln(ARPK)$, and this relationship is stronger than that of leverage. Moreover, the connection between interest rates and $\ln(ARPK)$ relies heavily on firm fixed effects. When firm fixed effects are included, the estimated coefficient on interest rates becomes much smaller, revealing the interaction between financial frictions and permanent firm heterogeneity in the model, again mirroring the empirical results in Table 1.

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

Figure 3: Interest Rates and ln($ARPK$): Model vs. Data



Note: This figure shows the scatter plot of interest rates 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 interest rate 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 steady state, 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.

Table 4: 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
	(0.00045)	(0.00044)	(0.00018)	(0.00018)	(0.00046)	(0.00046)	(0.00049)	(0.00048)
leverage$_{it}$		-0.18	0.028	0.028		0.14	0.025	-0.0073
		(0.00044)	(0.00020)	(0.00020)		(0.00047)	(0.00056)	(0.00055)
Ns	4290895	4290895	4290895	4290895	4283781	4283781	4283781	4283781
Firm FE	×	×	✓	✓	×	×	✓	✓
Time FE	×	×	×	✓	×	×	×	✓

Note: This table reports OLS regressions of ln($ARPK$) on interest rates and leverage using the model-simulated panel. The simulations include 10,000 firms over 500 periods starting from the steady state. 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 are in parentheses.

exogenous wedges. The estimated coefficient on interest rates in this counterfactual model also remains significantly positive, as the financial friction embedded in the model can successfully generate this relationship. When firm fixed effects are not controlled for, the estimated coefficients are even closer to their empirical counterparts in Table 1. However, a key limitation of this model emerges when firm fixed effects are included. In the data, controlling for firm fixed effects substantially reduces the estimated interest-rate coefficient. In the reference model, by contrast, the last two columns of Table 4 show that the coefficient barely changes. This occurs because, in the model without exogenous wedges, financial frictions are the sole force driving the relationship between interest rates and $\ln(ARPK)$, leaving no role for permanent firm heterogeneity.

5 Quantitative Analysis

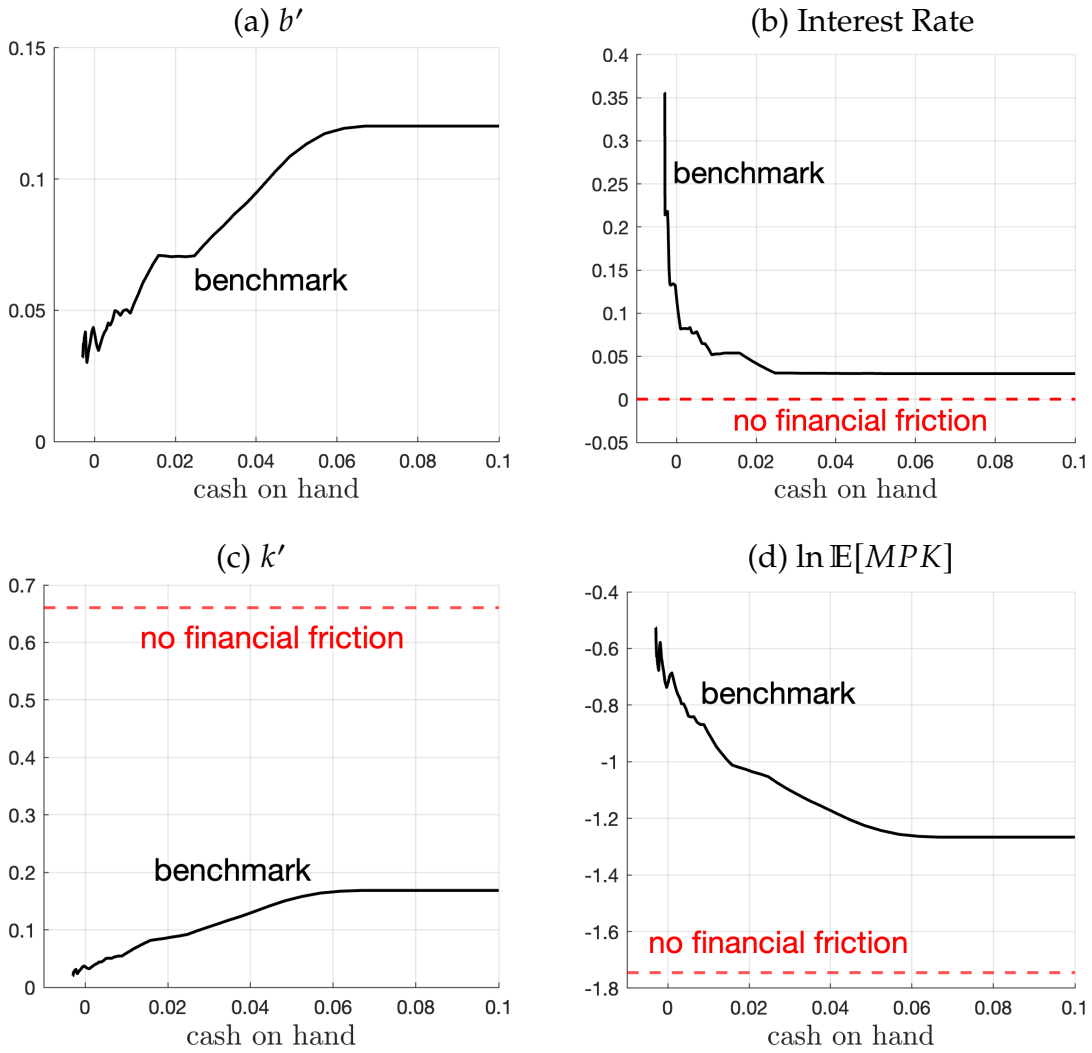
This section presents the quantitative results. We begin by examining decision rules to illustrate how financial frictions operate in the model. We then compute and decompose TFP losses to quantify the impact of financial frictions. The key finding is that while financial frictions alone generate modest 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 interest rate, 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 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, which is reflected in the increase in the interest rate shown in panel (b). Moreover, not only does the explicit interest rate 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). As a result, firms reduce both borrowing and capital investment, as illustrated in panels (a) and (c). For comparison, the red dashed lines represent the counterfactual decision rules in the absence of financial frictions. In this case, neither the interest rate, k', nor $\mathbb{E}[MPK]$ depends on firms' cash on hand.

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. Subplot (a) plots next-period debt b', subplot (b) displays the corresponding interest rate, 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'. 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.

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

$$TFP_t = \frac{Y_t}{K_t^\alpha} = \frac{\sum_i y_{it}}{(\sum_i k_{it})^\alpha} = \frac{\sum_i (z_{it}\xi_{it}^\alpha)^{\frac{1}{1-\alpha}} MPK_{it}^{\frac{\alpha}{\alpha-1}}}{\left(\sum_i (z_{it}\xi_{it}^\alpha)^{\frac{1}{1-\alpha}} MPK_{it}^{\frac{1}{\alpha-1}}\right)^\alpha}. \tag{18}$$

Under an efficient 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. Given the same set of firms, the corresponding efficient level of aggregate TFP is therefore

$$TFP_t^e = \frac{\sum_i (z_{it}\xi_{it}^\alpha)^{\frac{1}{1-\alpha}}}{\left(\sum_i (z_{it}\xi_{it}^\alpha)^{\frac{1}{1-\alpha}}\right)^\alpha} = \left(\sum_i (z_{it}\xi_{it}^\alpha)^{\frac{1}{1-\alpha}}\right)^{1-\alpha}. \tag{19}$$

We then define TFP losses as

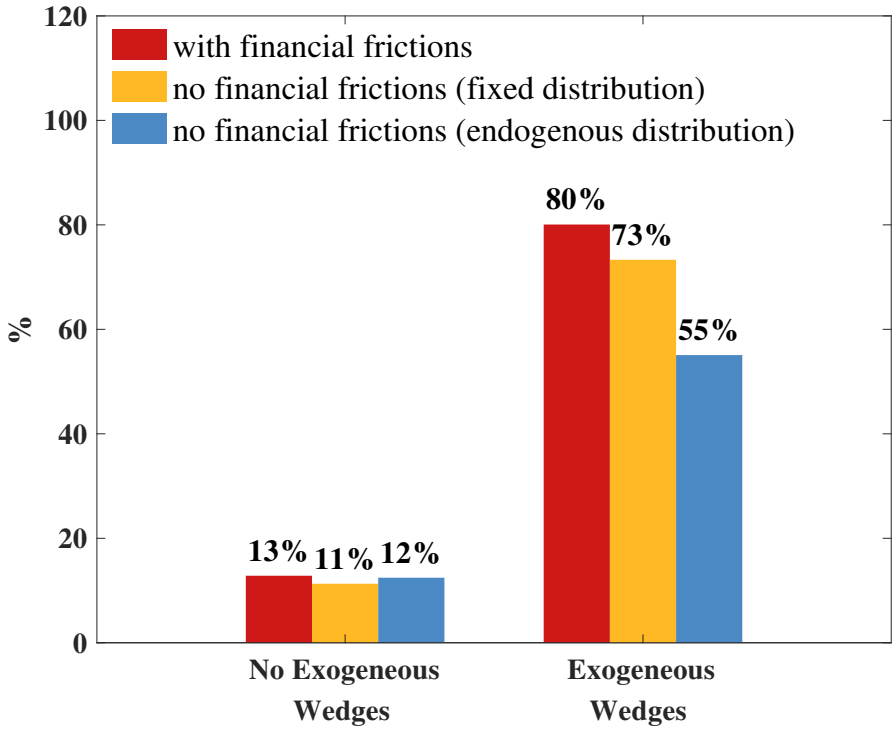
$$\log(TFP_t^e) - \log(TFP_t). \tag{20}$$

Figure 5 shows TFP losses across model specifications. The left three bars correspond to the model without exogenous wedges, and the numbers above the bars report TFP losses relative to their respective efficient TFP levels, as defined in equation (20). The red bar represents the baseline model with financial frictions, recalibrated as in Table 2. In the absence of exogenous wedges, the overall TFP loss is 13%. Recall that the model without exogenous wedges features two sources of TFP losses: financial frictions and informational frictions.

To isolate the contribution of financial frictions, we shut them down and recompute TFP losses. The yellow bar corresponds to this counterfactual economy, which shuts down financial frictions while holding fixed the parameters and firm distribution from the red bar. The TFP loss declines only slightly to 11%, indicating that financial frictions account for no more than 2 percentage points of misallocation. We further examine the role of the firm distribution by allowing it to adjust endogenously, shown by the blue bar. This specification also shuts down financial frictions and uses the same parameters as the red bar. Without financial frictions, firms face no borrowing constraints or default risk, so cash on hand is no longer a relevant state variable. In this counterfactual, we assume no entry or exit, and the firm distribution is given by the ergodic distribution of (τ, z, ξ). The resulting TFP loss is 12%, again differing from the baseline by only about 1 percentage point. Taken together, the left three bars 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.

The right three bars correspond to the model with exogenous wedges and are constructed

Figure 5: TFP Loss Decomposition



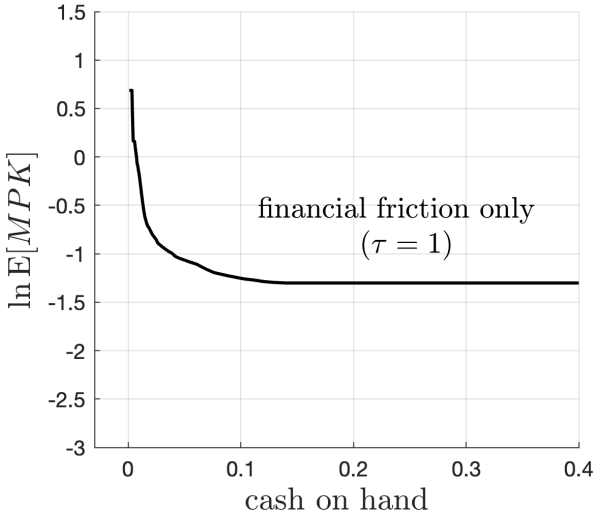
Note: This figure shows TFP losses across model specifications. The left three bars correspond to the model without exogenous wedges, while the right three bars correspond to the model with exogenous wedges. The numbers above the bars report TFP losses relative to their respective efficient TFP levels, as defined in equation (20). 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 firm distributions from the corresponding red bars. 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, ξ).

in the same way as the left three bars. The red bar shows that the benchmark model generates a sizable TFP loss of 80%, reflecting three sources of misallocation: exogenous wedges, financial frictions, and informational frictions. 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 to 73%, implying a direct effect of 7 percentage points. We then additionally allow the firm distribution to adjust to its new stationary distribution without financial frictions. The blue bar shows that TFP losses further decline 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. This finding suggests that financial frictions are an important source of misallocation and that endogenous firm distribution adjustments play a key role in amplifying their impact.

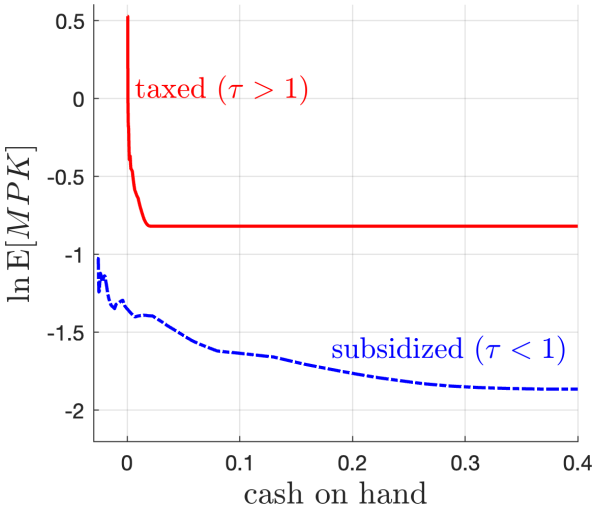
Figure 6: Endogenous Financial Heterogeneity

Panel A. Policy Functions for Expected MPK

(a) No Exogenous Wedges

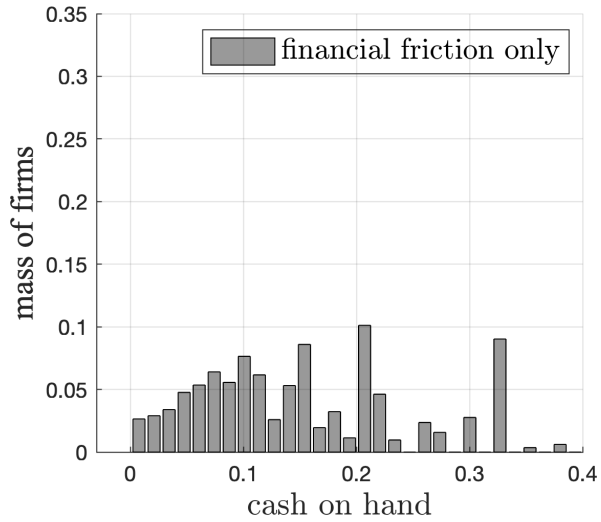


(b) Benchmark

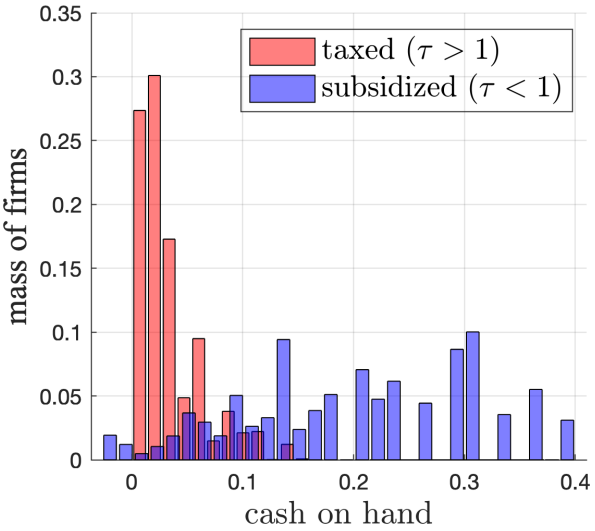


Panel B. Distribution of Cash on Hand

(a) No Exogenous Wedges

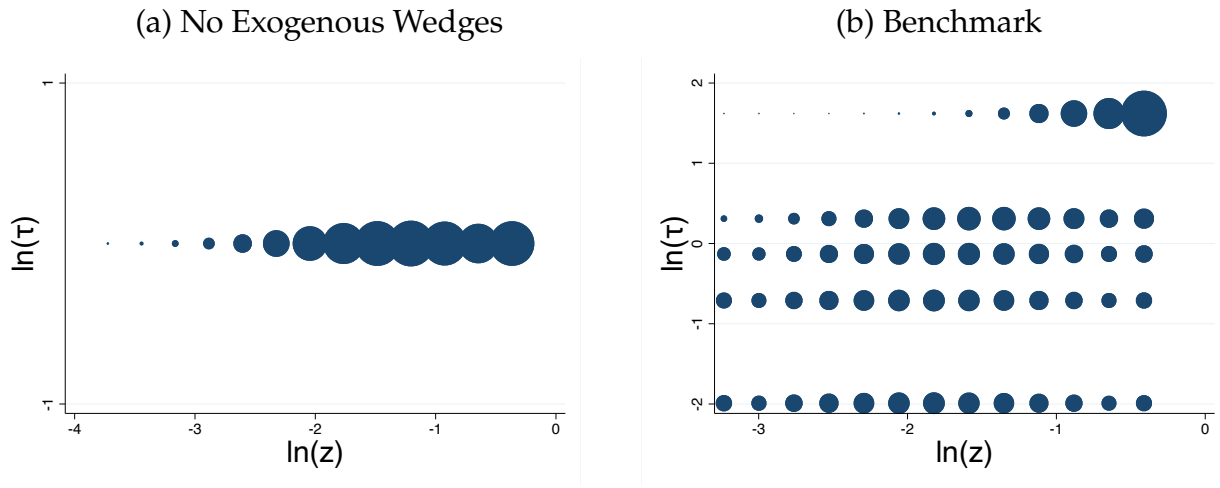


(b) Benchmark



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 subplot corresponds to the recalibrated reference model without exogenous wedges (i.e., $\tau = 1$ for all firms), while the right subplot shows the benchmark model with exogenous wedges. In the right subplot of Panel A, the red solid line represents taxed firms ($\tau > 1$), and the blue dashed line represents subsidized firms ($\tau < 1$).

Figure 7: Joint Distribution of Exogenous Wedges and Productivity



Note: This figure shows the 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 recalibrated reference model without exogenous wedges (i.e., $\tau = 1$ for all firms), while the right subplot shows the benchmark model with exogenous wedges.

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

Figure 6 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. The left subplot corresponds 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. As cash on hand declines, financial constraints become binding: both the interest rate and the shadow cost of borrowing increase, leading firms to operate at a higher marginal product of capital.

Therefore, in this canonical model of firm financial frictions, misallocation depends on the distribution of cash on hand.[2] However, as emphasized by Midrigan and Xu (2014), firms can self-finance. The left 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.

[2]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.

The right subplot of Panel A shows the benchmark model with exogenous wedges. The red solid line represents taxed firms ($\tau > 1$), while the blue dashed line represents subsidized firms ($\tau < 1$). Introducing exogenous wedges adds an additional dimension of heterogeneity: taxed firms face more severe financial frictions 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 right subplot of Panel B displays the stationary distributions 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.

The second amplification mechanism operates through *endogenous selection*. Panel B of Figure 7 shows the 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 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.

The right subplot presents 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 between $\ln(z)$ and $\ln(\tau)$ of 0.20 in the stationary equilibrium. Since high-τ firms also face tighter financial constraints, selection concentrates productive firms in the more financially constrained group. Although 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.

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 interest rates 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 canonical financial frictions but also exogenous wedges that proxy for other distortions prevalent in developing economies. Our quantitative results show that, financial frictions alone generate modest misallocation, but their interaction with exogenous wedges leads to sizable TFP losses. Two mechanisms drive this amplification: exogenous wedges generate endogenous financial heterogeneity that cannot be undone through self-financing, and selection concentrates productive firms in the more financially constrained group. These findings suggest that a key difference between developing and developed economies lies not only in financial frictions themselves, but also in the other distortions that interact with them.

References

Arellano, Cristina, Yan Bai, and Jing Zhang, "Firm dynamics and financial development," *Journal of Monetary Economics*, 2012, *59* (6), 533–549.

Bai, Yan, Dan Lu, and Xu Tian, "Do financial frictions explain Chinese firms' saving and misallocation?," Technical Report, National Bureau of Economic Research 2018.

Bocola, Luigi and Gideon Bornstein, "The macroeconomics of trade credit," Technical Report, National Bureau of Economic Research 2023.

Bolton, Patrick, Hui Chen, and Neng Wang, "A unified theory of Tobin's q, corporate investment, financing, and risk management," *Journal of Finance*, 2011, *66* (5), 1545–1578.

Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin, "Finance and development: A tale of two sectors," *American economic review*, 2011, *101* (5), 1964–2002.

Chava, Sudheer and Michael R. Roberts, "How does financing impact investment? The role of debt covenants," *Journal of Finance*, 2008, *63* (5), 2085–2121.

Choi, Jaewon, Xu Tian, Yufeng Wu, and Mahyar Kargar, "Investor demand, firm investment, and capital misallocation," *Journal of Financial Economics*, 2025, *168*, 104039.

Cooley, Thomas F. and Vincenzo Quadrini, "Financial Markets and Firm Dynamics," *American Economic Review*, 2001, *91* (5), 1286–1310.

David, Joel M. and Venky Venkateswaran, "The sources of capital misallocation," *American Economic Review*, 2019, *109* (7), 2531–2567.

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Eisfeldt, Andrea L. and Tyler Muir, "Aggregate external financing and savings waves," *Journal of Monetary Economics*, 2016, *84*, 116–133.

Fazzari, Steven M., R. Glenn Hubbard, Bruce C. Petersen, Alan S. Blinder, and James M. Poterba, "Financing constraints and corporate investment," *Brookings Papers on Economic Activity*, 1988, *1988* (1), 141–206.

Gamba, Andrea and Alexander Triantis, "The value of financial flexibility," *Journal of Finance*, 2008, *102* (61), 2263—2295.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek, "Misallocation and financial market frictions: Some direct evidence from the dispersion in borrowing costs," *Review of Economic Dynamics*, 2013, *16* (1), 159–176.

Gomes, Joao F., "Financing investment," *American Economic Review*, 2001, *91* (5), 1263–1285.

Hennessy, Christopher A. and Toni M. Whited, "Debt dynamics," *Journal of Finance*, 2005, *60* (3), 1129–1165.

Hennessy, Christopher and Toni Whited, "How Costly is External Financing? Evidence from a Structural Estimation," *Journal of Finance*, 2007, *62* (1), 58–64.

Hsieh, Chang-Tai and Peter J Klenow, "Misallocation and manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Judd, Kenneth L., *Numerical methods in economics*, MIT press, 1998.

Korteweg, Arthur, "The net benefits to leverage," *Journal of Finance*, 2010, *65* (6), 2137–2170.

Midrigan, Virgiliu and Daniel Yi Xu, "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, 2014, *104* (2), 422–458.

Moll, Benjamin, "Productivity losses from financial frictions: Can self-financing undo capital misallocation?," *American Economic Review*, 2014, *104* (10), 3186–3221.

Ottonello, Pablo and Thomas Winberry, "Financial heterogeneity and the investment channel of monetary policy," *Econometrica*, 2020, *88* (6), 2473–2502.

Rampini, Adriano A. and S. Viswanathan, "Collateral, risk management, and the distribution of debt capacity," *Journal of Finance*, 2010, *65* (6), 2293–2322.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, "Growing like china," *The American Economic Review*, 2011, *101* (1), 196–233.

Wang, Pengfei, Yi Wen, and Zhiwei Xu, "Two-way capital flows and global imbalances: a neoclassical approach," *Federal Reserve Bank of St. Louis Working Paper Series*, 2012, (2012-016).

Whited, Toni M. and Jake Zhao, "The misallocation of finance," *Journal of Finance*, 2021, *76* (5), 2359–2407.

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

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

A Computation Algorithm

This section explains the 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

$$M(\tau_i, z_{it}) = \max_{k_{it+1}, b_{it+1}} \left\{ q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} - k_{it+1} \right\}. \tag{21}$$

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

$$q^{\{0\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) = \beta, \qquad M^{\{0\}}(\tau_i, z_{it}) = \beta\, b_{\max}, \tag{22}$$

   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

$$\frac{1}{\tau_{it}} z_{it} (\xi_{it} k_{it})^{\alpha} + (1-\delta)\xi_{it} k_{it} - b_{it} - \zeta + M^{\{n\}}(\tau_i, z_{it}) < 0. \tag{23}$$

   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:

$$q^{\{n+1\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) = \frac{1}{1+r} \sum_{z_{it+1}} \pi_z(z_{it+1}|z_{it}) \sum_{\xi_{it+1}} \pi_\xi(\xi_{it+1})$$
$$\left[(1 - d(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1})) + d(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1}) R(k_{it+1}, b_{it+1}, \xi_{it+1}) \right]. \tag{24}$$

The recovery function is given by

$$R(k_{it}, b_{it}, \xi_{it}) = \min\left\{\frac{\theta(1-\delta)\xi_{it}k_{it}}{b_{it}}, 1\right\}, \text{if } b_{it} > 0. \tag{25}$$

(d) Update the borrowing limit:

$$M^{\{n+1\}}(\tau_i, z_{it}) = \max_{k_{it+1}, b_{it+1}} \left\{q^{\{n+1\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1})b_{it+1} - k_{it+1}\right\} \tag{26}$$

(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:

$$\begin{aligned} G^{\{n\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}) &= \mathbb{E}_{z_{it+1}|z_{it}} \int_{\xi_{it+1} \geq \xi^*_{it+1}} V^{\{n\}}(\tau_i, z_{it+1}, x_{it+1}) dF(\xi_{it+1}) \\ &= \sum_{z_{it+1}} \pi(z_{it+1}|z_{it}) \sum_{\xi_{it+1}} \pi_\xi(\xi_{it+1})(1 - d(\tau_i, z_{it+1}, \xi_{it+1}, k_{it+1}, b_{it+1}))V^{\{n\}}(\tau_i, z_{it+1}, x_{it+1}). \end{aligned} \tag{27}$$

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:

$$\hat{V}(\tau_i, z_{it}) = \max_{k_{it+1}, b_{it+1}} -k_{it+1} + q(\tau_i, z_{it}, k_{it+1}, b_{it+1})b_{it+1} + \beta G^{\{n\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}). \tag{28}$$

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

$$\hat{x}_{it}(\tau_i, z_{it}) = -[q(\tau_i, z_{it}, \hat{k}_{it+1}(\tau_i, z_{it}), \hat{b}_{it+1}(\tau_i, z_{it}))\hat{b}_{it+1}(\tau_i, z_{it}) - \hat{k}_{it+1}(\tau_i, z_{it})]. \tag{29}$$

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 (28):

$$k^*_{it+1}(\tau_i, z_{it}, x_{it}) = \hat{k}_{it+1}(\tau_i, z_{it}), \qquad b^*_{it+1}(\tau_i, z_{it}, x_{it}) = \hat{b}_{it+1}(\tau_i, z_{it}). \tag{30}$$

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

$$V^{\{n+1\}}(\tau_i, z_{it}, x_{it}) = V^{\{n\}}(\tau_i, z_{it}, \hat{x}_{it}(\tau_i, z_{it})) + x_{it} - \hat{x}_{it}(\tau_i, z_{it}), \forall x_{it} \geq \hat{x}_{it}(\tau_i, z_{it}). \tag{31}$$

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

$$\underline{x}_{it}(\tau_i, z_{it}) = -M(\tau_i, z_{it}), \qquad \bar{x}_{it}(\tau_i, z_{it}) = \hat{x}_{it}(\tau_i, z_{it}). \tag{32}$$

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

$$V^{\{n+1\}}(\tau_i, z_{it}, x_{it}) = \max_{div_{it}, k_{it+1}, b_{it+1}} div_{it} + \beta G^{\{n\}}(\tau_i, z_{it}, k_{it+1}, b_{it+1}), \tag{33}$$

$$\text{s.t. } div_{it} = x_{it} - k_{it+1} + q(\tau_i, z_{it}, k_{it+1}, b_{it+1}) b_{it+1} \geq 0. \tag{34}$$

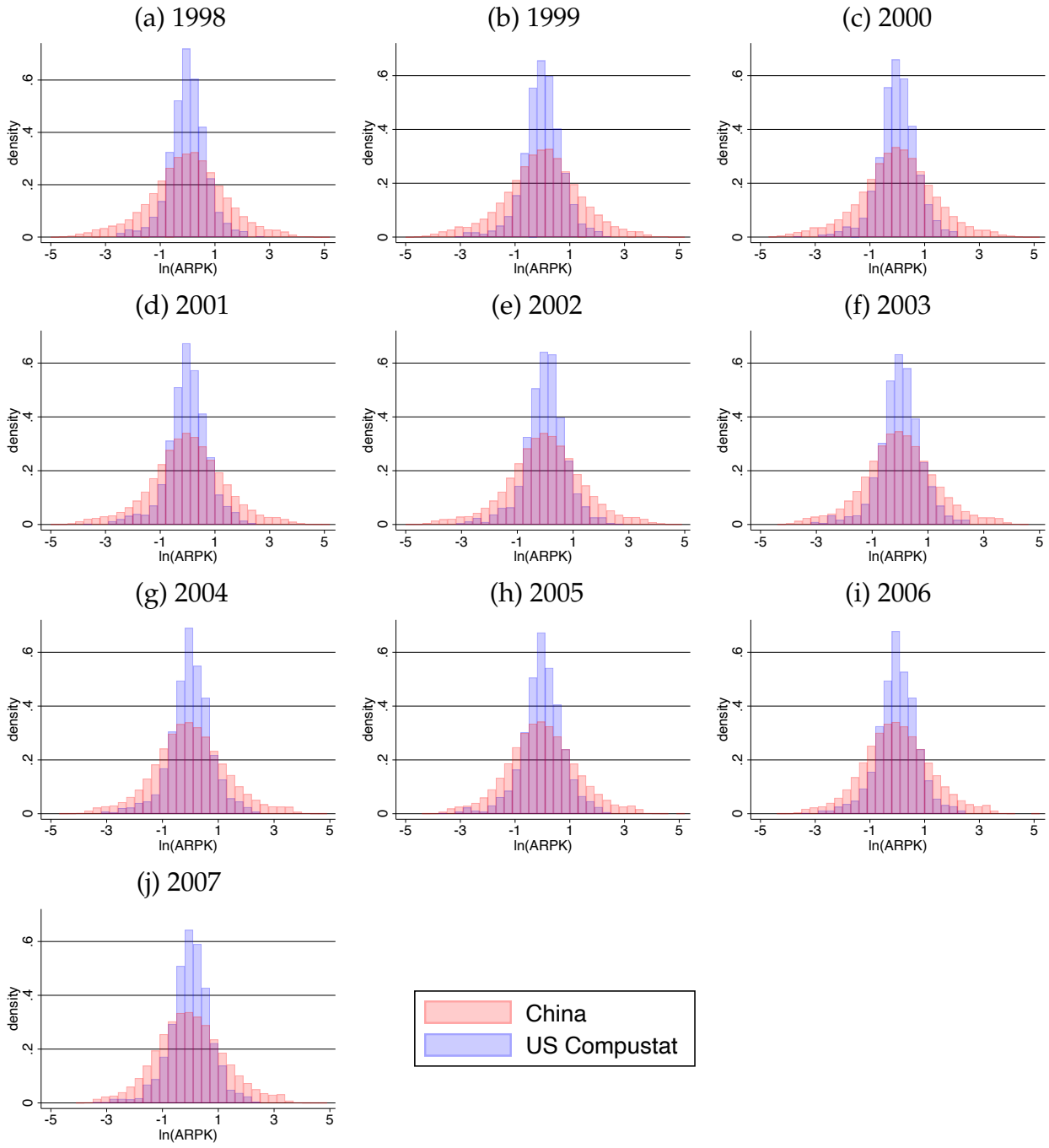
Let $k^*_{it+1}(\tau_i, z_{it}, x_{it})$ and $b^*_{it+1}(\tau_i, z_{it}, x_{it})$ denote the associated optimal policy functions.

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}.

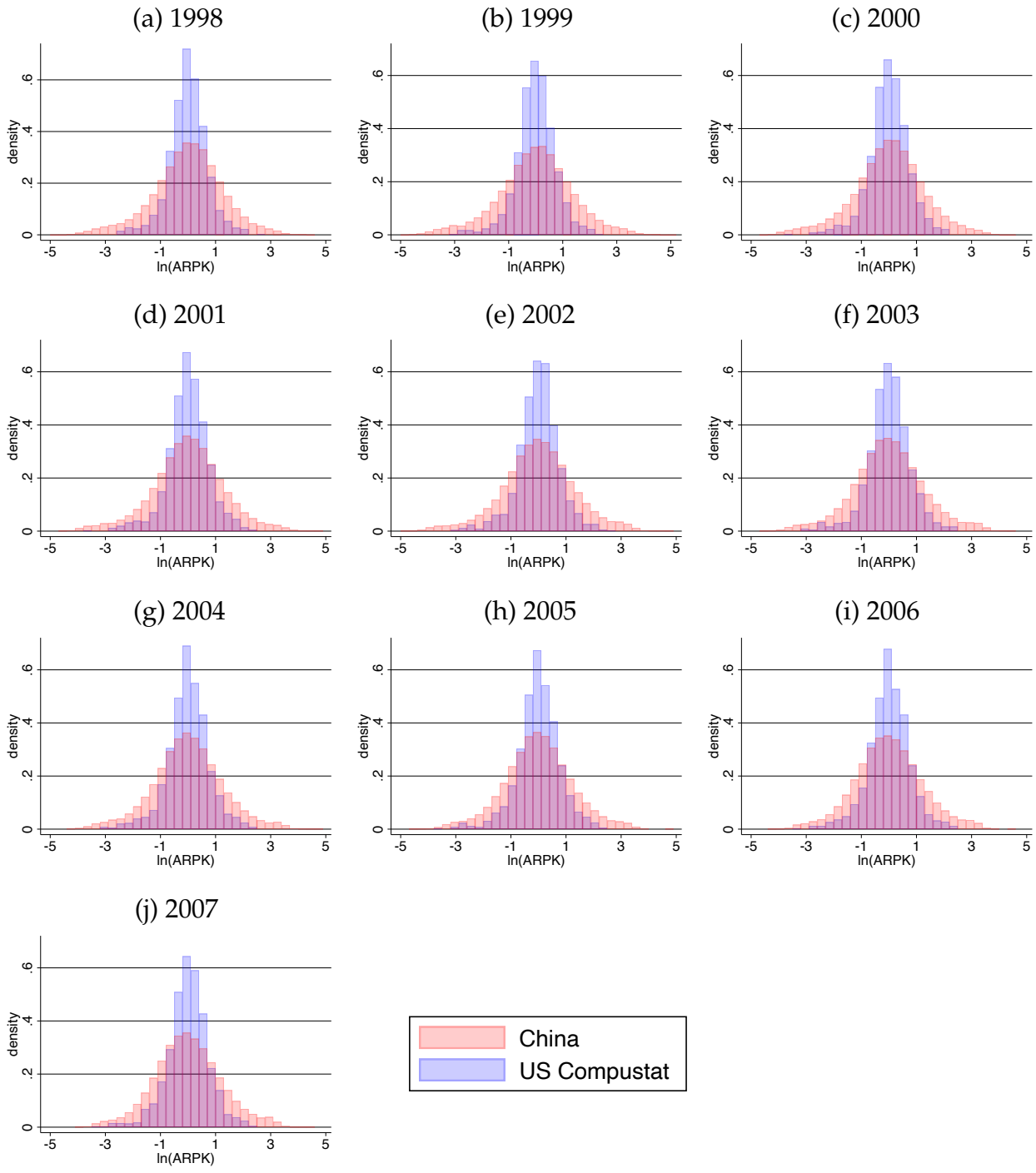
B Additional Tables and Figures

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



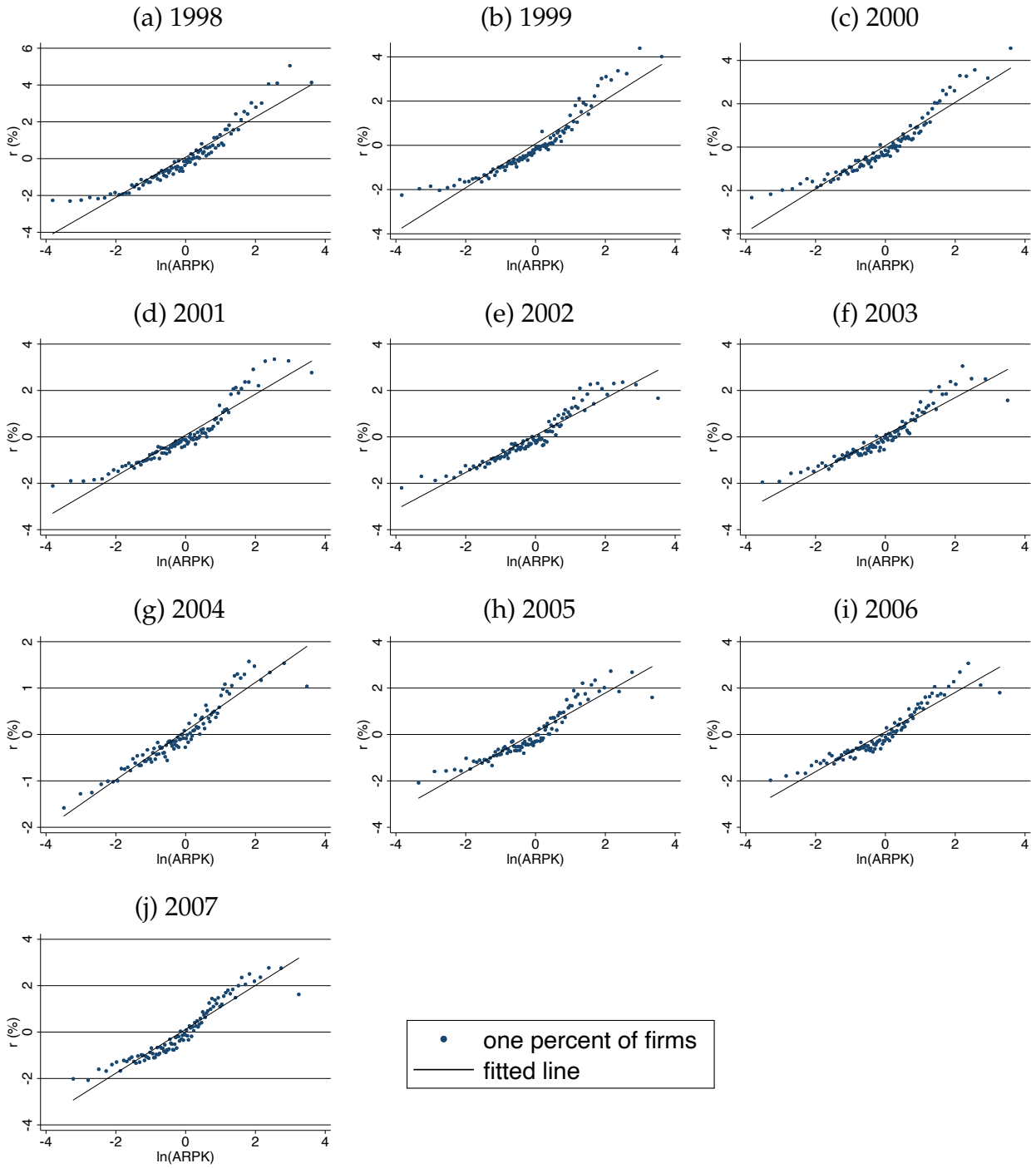
Note: This figure shows the histograms of ln($ARPK$) for Chinese and U.S. Compustat manufacturing firms. The variable is demeaned at the year-by-industry level. Red bars denote China, and blue bars denote the United States. Data sources: Chinese manufacturing firm-level data and U.S. Compustat manufacturing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

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



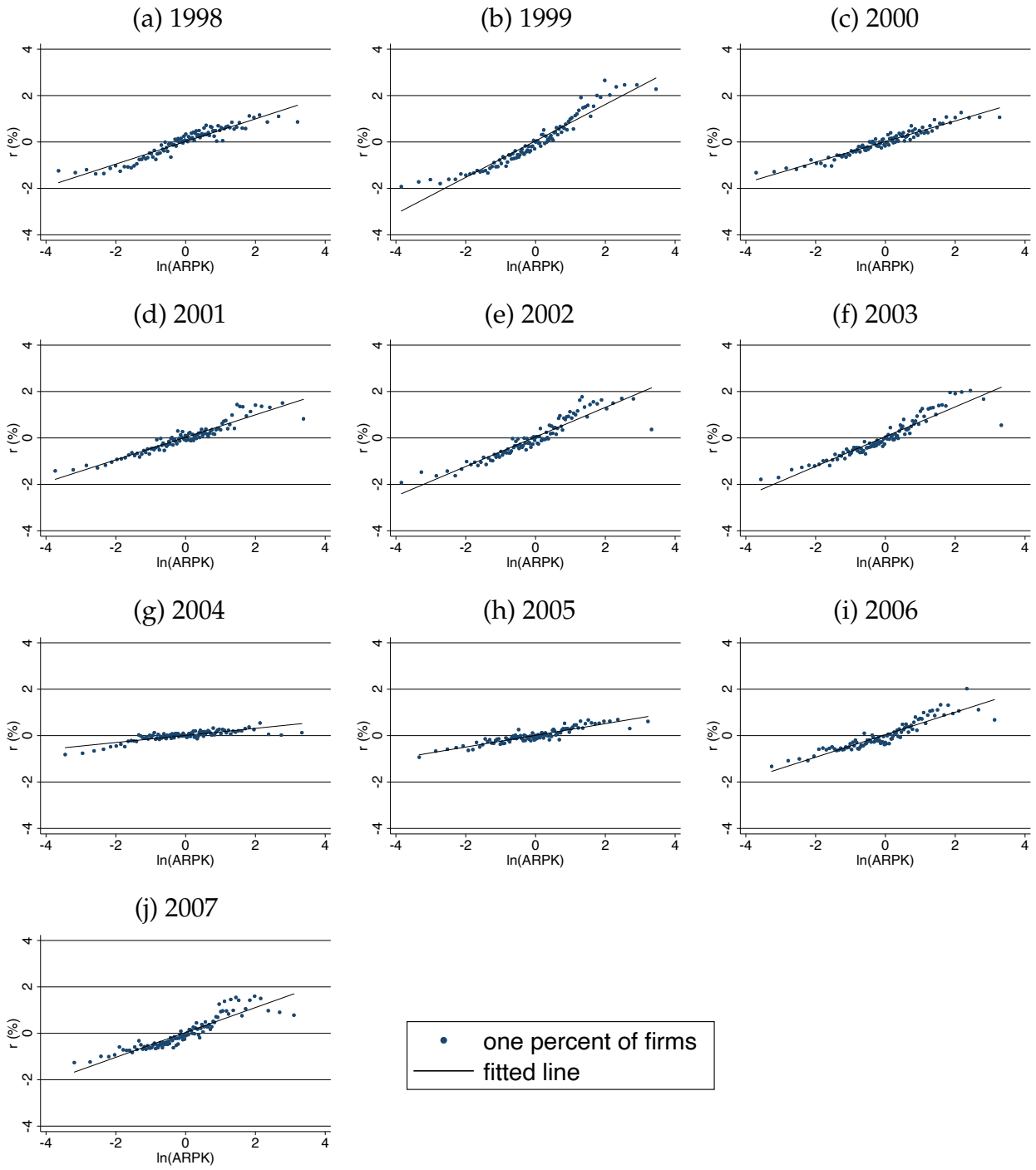
Note: This figure shows the histograms of ln($ARPK$), using the intersection sample by asset size between China and U.S. Compustat manufacturing. The variable is demeaned at the year-by-industry level. Red bars denote China, and blue bars denote the United States. Data sources: Chinese manufacturing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

Figure B.3: Interest Rates and ln($ARPK$) in China, 1998–2007



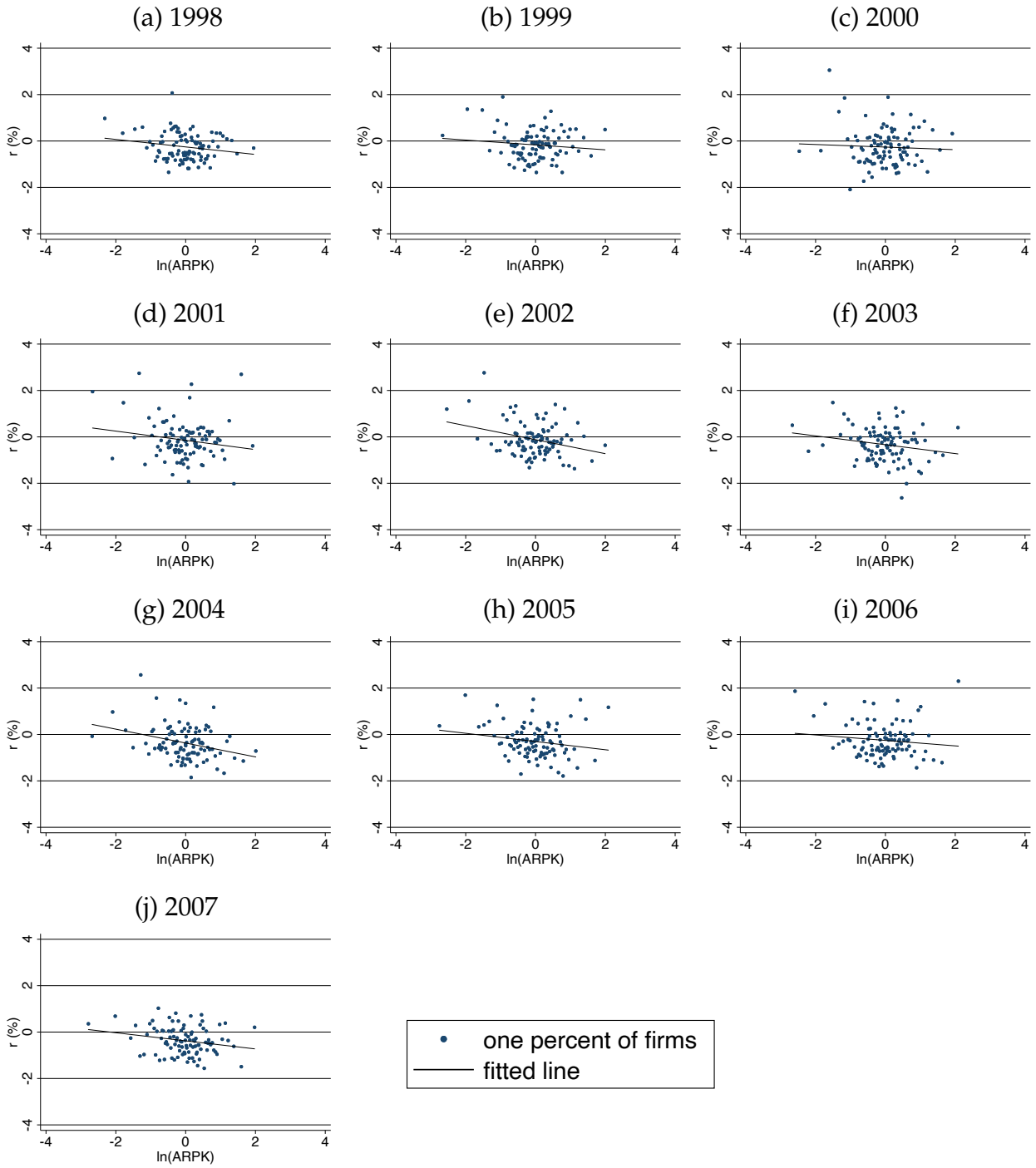
Note: This figure shows the scatter plot of interest rates against ln($ARPK$). Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the interest rate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

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



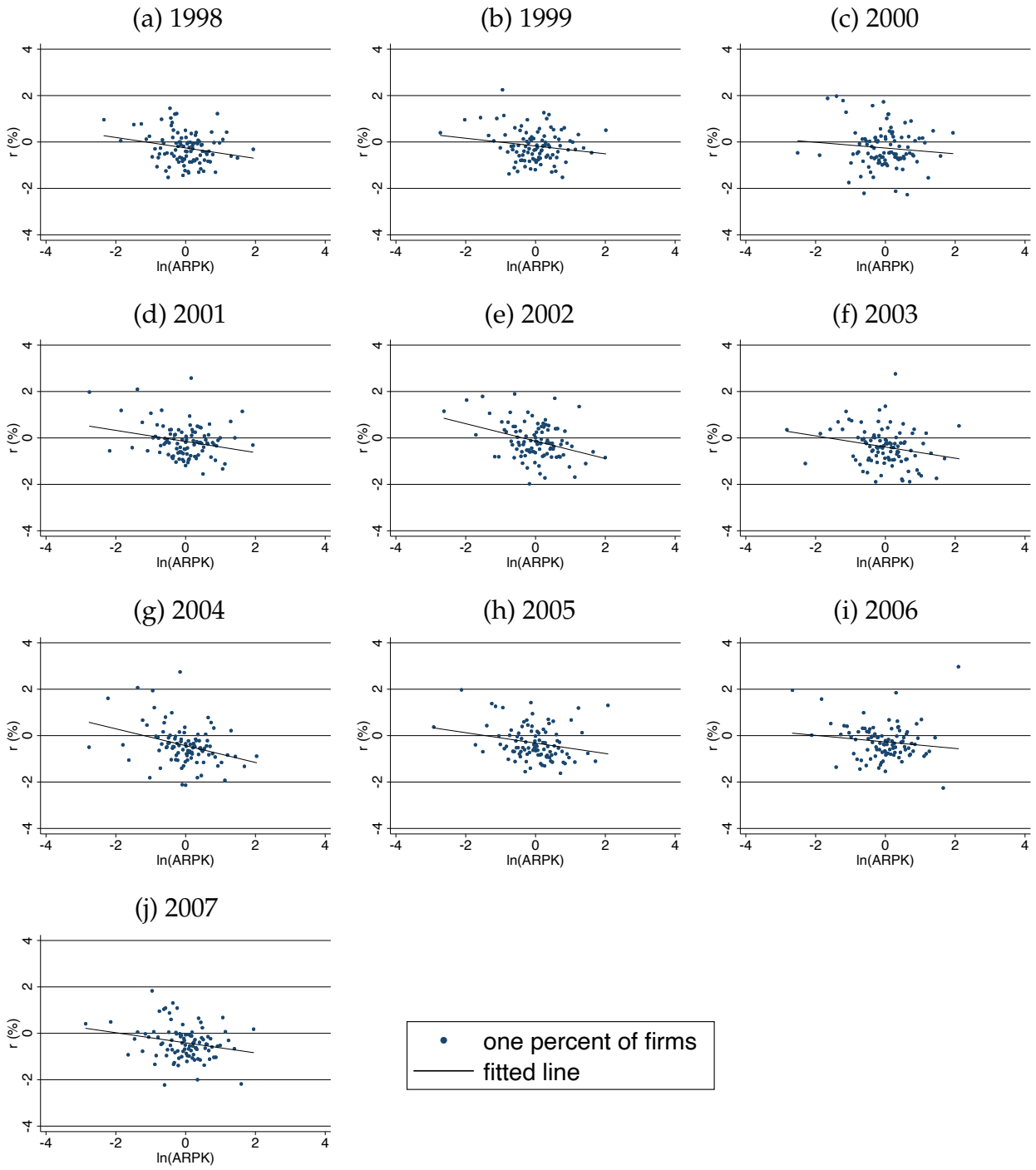
Note: This figure shows the scatter plot of interest rates against ln($ARPK$) for Chinese manufacturing firms, using the intersection sample by asset size between China and U.S. Compustat manufacturing. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the interest rate 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 B.5: Interest Rates and ln($ARPK$) in U.S. Compustat Manufacturing, 1998–2007



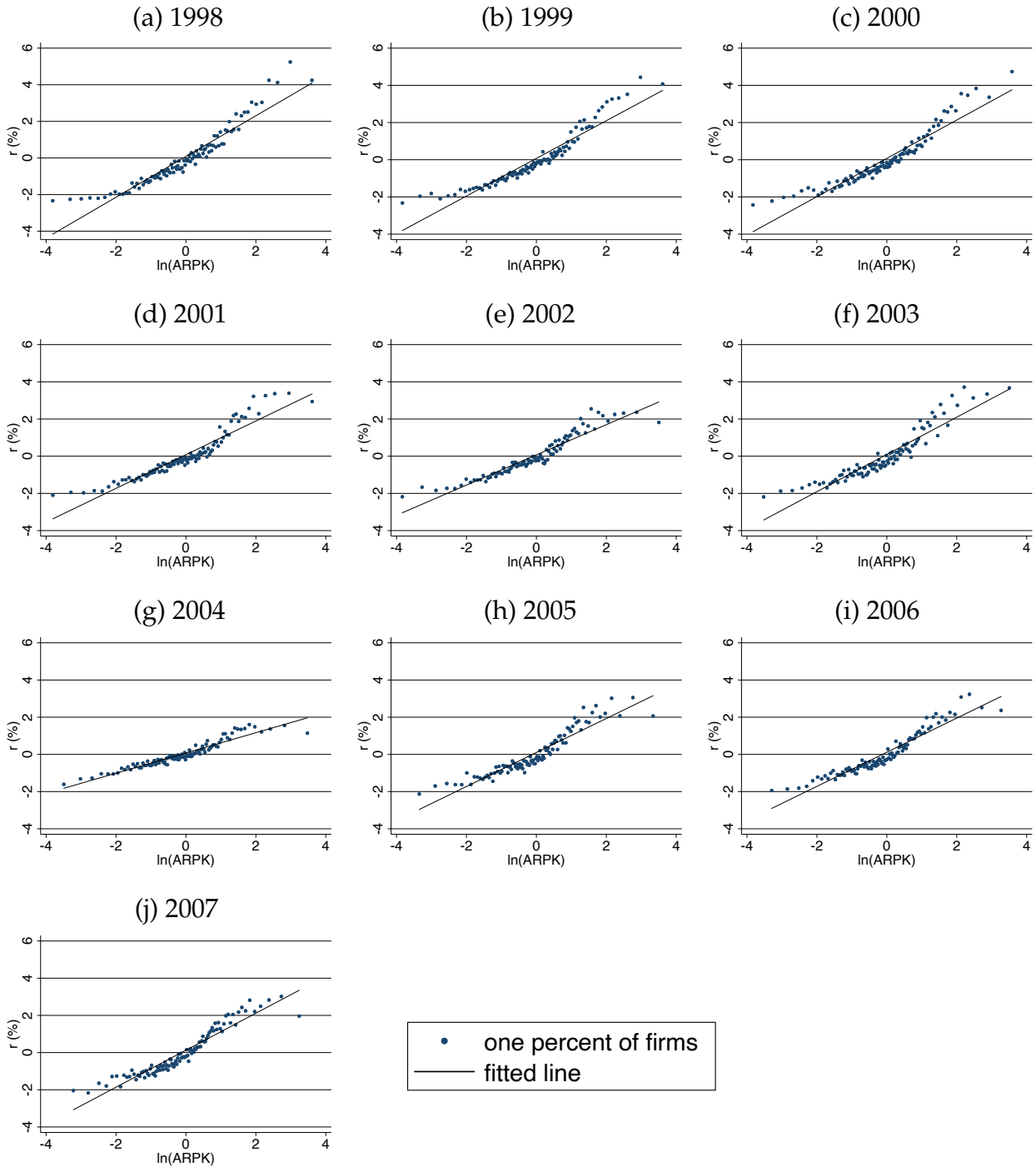
Note: This figure shows the scatter plot of interest rates against ln($ARPK$). Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the interest rate 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 B.6: Interest Rates and ln($ARPK$) in U.S. Compustat Manufacturing, 1998–2007
Size-Intersection Sample with China



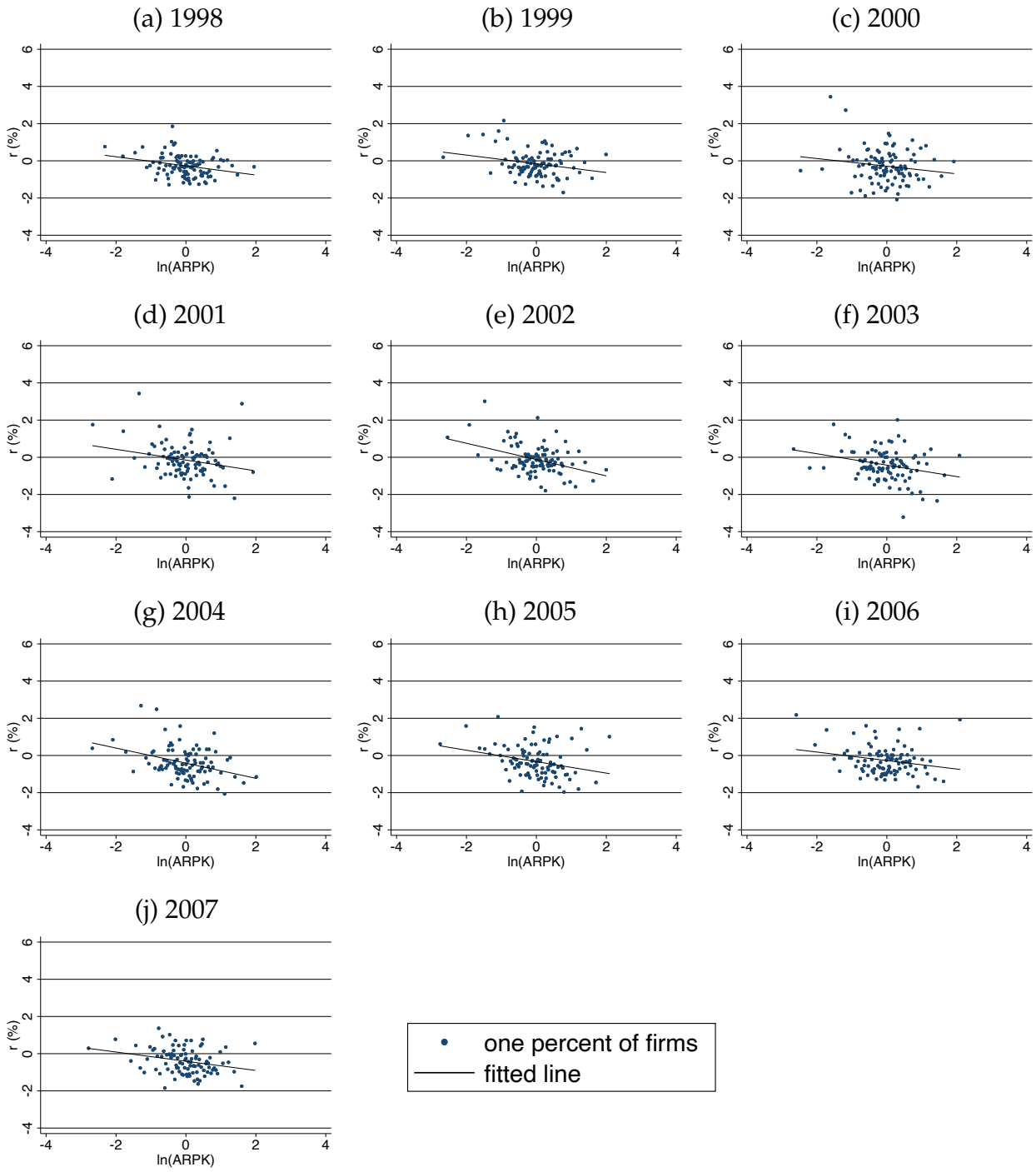
Note: This figure shows the scatter plot of interest rates against ln($ARPK$) for U.S. Compustat manufacturing firms, using the intersection sample by asset size between China and U.S. Compustat manufacturing. Both variables are demeaned at the year-by-industry level. For each year, firms are grouped into 100 percentiles of ln($ARPK$). Each dot represents one percent of firms and the corresponding mean values of the interest rate 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 B.7: Interest Rates (Alternative Measure) and ln($ARPK$) in China, 1998–2007



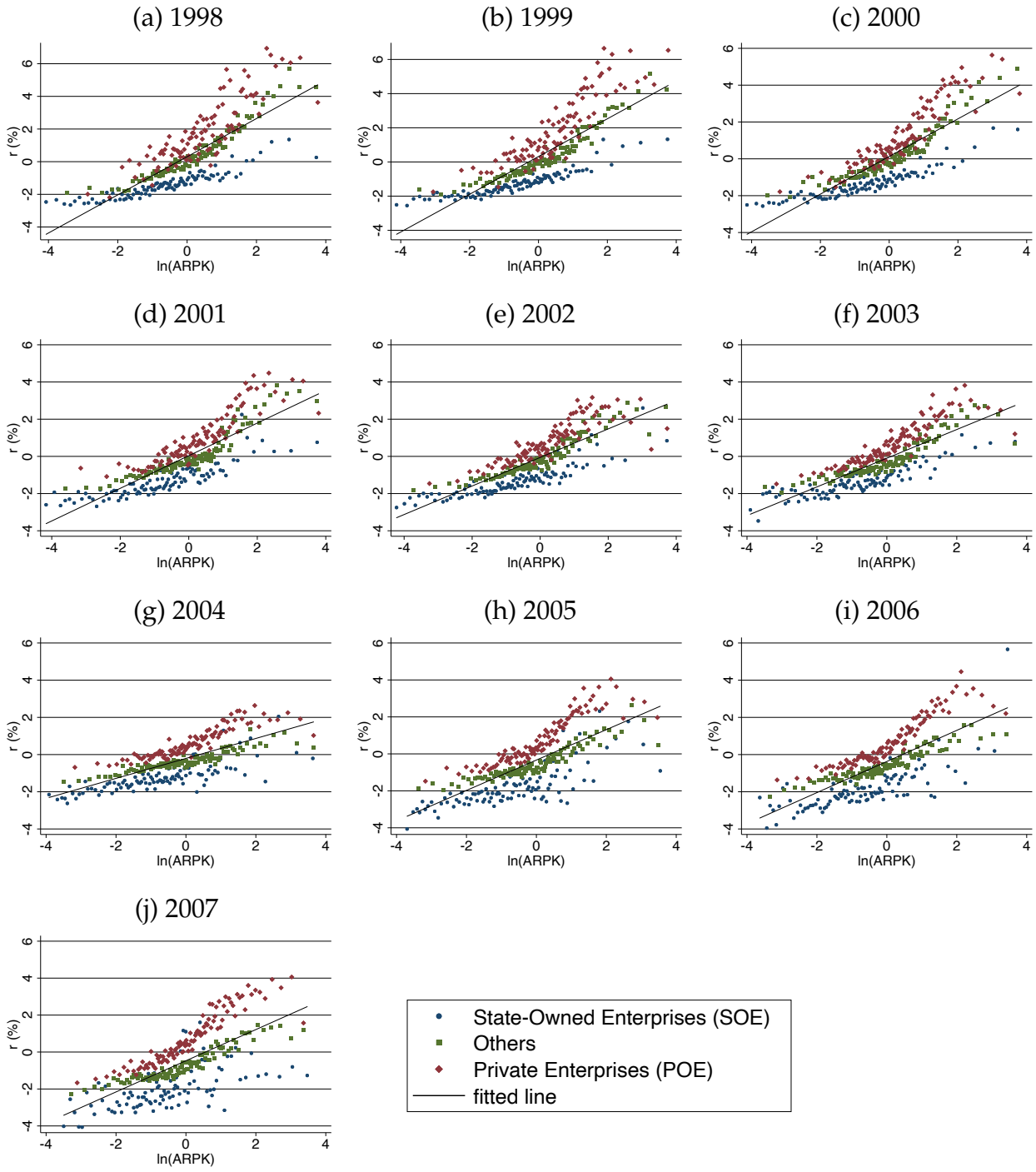
Note: This figure shows the scatter plot of interest rates (alternative measure) against ln($ARPK$), where interest rates are calculated as the ratio of interest payments to the sum of current liabilities and long-term debt. Both variables are demeaned at the year-by-industry level. For each year, firms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

Figure B.8: Interest Rates (Alternative Measure) and ln($ARPK$) in U.S. Compustat Manufacturing, 1998–2007



Note: This figure shows the scatter plot of interest rates (alternative measure) against ln($ARPK$), where interest rates 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 interest rate 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 B.9: Interest Rates and ln($ARPK$) in China by Ownership, 1998–2007



Note: This figure shows the scatter plot of interest rates 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 interest rate and ln($ARPK$) in that percentile. The solid line depicts the fitted linear relationship. Data source: Chinese manufacturing firm-level data, 1998–2007.