Shadow Banking, Financial Frictions and Firm Productivity

Zhiguo Xiao Kent Matthews *

December 30, 2023

Abstract

This paper investigates how Chinese firms' productivity is affected by financial frictions and firm-specific characteristics within an investment framework. We establish an equilibrium relationship that underscores the influence of firm type on the interplay between productivity and financial friction. Utilizing an unbalanced panel of data from the National Tax Statistics Database spanning 2005-2012, we test the predictions of our model. Our primary financial friction index is determined by the prevalence of shadow bank credit flows, calculated on a province-year basis through iterated least squares. To mitigate omitted variable bias, we include components of standard firm-level financial friction indexes, such as the Kaplan-Zingales index. Findings indicate that financial frictions intensify the productivity-finance sensitivity of firms, and this relationship weakens as the state's ownership share in the firm increases.

*Zhiguo Xiao, School of Management, Fudan University, Room 709 Siyuan Faculty Building, 670 Guoshun Rd., Shanghai 200433, China. Email: zhiguo_xiao@fudan.edu.cn. Kent Matthews: Cardiff Business School, Cardiff University, Wales, UK and Nottingham University Business School China, University of Nottingham Ningbo China, China. Email: MatthewsK@cardiff.ac.uk. The research is supported by the National Natural Science Foundation of China (NSFC grant: 71661137005), and ESRC-Newton Grant ES/P004199/1.

Keywords: Shadow banking; financial friction; firm type; total factor productivity.

JEL Classification: C13; C14

1 Introduction

The link between the productivity of the firm and its financial condition is a well-established area of economics and stems from an even wider research agenda relating to the link between financial development and economic growth. This latter area of research has spawned a vast literature – most recently reviewed by Heil (2018) – that provides a framework for the analysis of productivity and financial conditions. The empirical literature points to an ambiguity in the findings. Early studies suggest a monotonic positive relationship between finance and growth whereas more recent studies have exposed a non-linear relationship whereby beyond some threshold marginal finance results in lower growth.

A strand of this literature has focused on the implications of financial frictions on productivity at the level of the firm. The term "financial friction" is not itself unequivocal and means different things in different areas of the literature. The literature typically uses observable firm characteristics to arrive at a composite index of financial friction (for example, Hadlock and Pierce, 2009; Chen and Song, 2013). These firm characteristics are the endogenous reactions to financial constraints and are indirect indicators of financial frictions. Here, we can think of financial friction as formal or informal regulatory precept that acts as limits to the financing options of private firms. These impediments can manifest as regulatory credit quotas on the regular banks, or state directed bank credit, or distortionary factor prices in the form of subsidized discriminatory borrowing rates that drive other sectors towards alternative sources of finance. All three features describe the Chinese banking market. Despite increased competition, both internally and externally, the Chinese banking sector remains dominated by the five large state-owned banks. Up until recently the state-owned banks (SOBs) focused their lending on supporting the generally low productive state-owned sector. SMEs and the innovative industries of the private sector have been underserved by the mainstream Chinese banking sector. Around 99% of firms in China are SMEs, employing 70% of the labor force, contributing 60% of GDP and 50% of tax revenue, and yet they have access to only 20% of commercial bank credit (Sheng, et al 2013). Formal and informal regulations have seen this fast-growing productive private sector increasingly turn to the shadow banks for its finance (Tsai, 2017; Lu et al, 2015). In the two decades to 2018, the limits on bank interest rates, the use of high regulatory reserve ratios, loan-to-deposit caps, and window guidance by the Peoples Bank of China has provided the motive for the rapid growth in shadow banking.

The flow of shadow bank credit is symptomatic of the financial frictions faced by SMEs and the wider private sector in China. While it may be argued that driving firms to shadow bank financing is sub-optimal, it has the benefit of easing the financial frictions faced by them. This paper brings together shadow bank lending, financial frictions, and firm productivity.

The main objective of this paper is to cast shadow banking into the measurement of financial friction to investigate the latter's effects on firm productivity. We do this by utilizing a novel data sample from the National Tax Statistics Database for the period 2005-2012. An additional feature, is that we construct a measure of shadow bank credit flows at the provincial level using a novel econometric method, based on the time series of national level shadow banking size and provincial level covariates. We construct a measure of financial friction based on the shadow bank data and we match this measure with firm productivity data.

The rest of this paper is organized in the following way. The next section reviews the relevant literature on financial frictions and firm productivity. Section 3 outlines the theoretical model. Section 4 presents the firm level data and the constructed data on shadow bank credit flows. Section 5 sets out the econometric framework and empirical results. The final section concludes with a discussion of the results.

2 Literature Review

The link between financial frictions and firm level productivity is not unambiguous. In general, the literature suggests that financial frictions can slow economic growth and reduce productivity. But the mechanism that creates the friction varies across economies. These range from the inefficiency of the legal framework that creates obstacles to contract monitoring and enforcement; to collateral constraints; to differential borrowing rates and risk mispricing. A financial system that enables long-term contracts and efficient performance monitoring promotes the adoption of advanced technologies that generate higher productivity. In Cole et al, (2016) developing economies India and Mexico enable intermediate-level technology entrants that have shorter funding horizons than the advanced technology entrants as in the USA. Imperfect contract enforcement can skew firm entry decisions and distort the allocation of capital resulting in low TFP (Bruera, et al, 2011). Financial frictions can also raise the barriers to entry and distort the entry of SMEs when faced with high fixed costs. (Rajan and Zingales, 1998).

Collateral constraints and artificially determined borrowing rates act to impede the entry of high value-added firms resulting in the proliferation of low margin firms. Using a calibrated two-sector model of a high value-added and low value-added manufacturing economy for China, Midrigan and Xu (2014) show the potential TFP losses in the order of 22%. Particularly relevant to the low productive state-owned firms in China, Cabellero et al (2008) find that making easy credit available to persistently unprofitable Japanese firms drags down TFP. Similar findings are reported by Adalet McGowan et al, (2017) for a sample of firms from nine EU countries. Compared with the private sector, SOEs have low productivity and constitute most China's Zombie firms (Han, et al, 2019).

This line of literature finds that TFP is reduced by the constraints created by financial frictions. A more subtle view is put forward by Levine and Warusawitharana (2021). They show that a rise in financial frictions leads to fewer innovation investment resulting in an increased sensitivity of productivity growth to an increase in external finance. Using firm-level data for France, Italy, Spain, and UK, their main finding is that financial friction measured by various proxies, leads to reduced firm-level productivity growth, but that the sensitivity of the relation varies with the level of debt finance. Increased financial friction results in an increased sensitivity of productivity growth to debt growth. The interpretation is that the firm exhibits diminishing marginal returns to investment from external finance in the presence of less financial friction. In other words when financial friction is high, firms chose a lower of level of debt finance and its marginal impact is higher than in the case of lower financial friction, when a higher level of debt finance is chosen.

In this paper we explore this direction of research with the provision of shadow banking added to the standard proxies for financial friction used in the literature. But first we review the research in this area that is China specific. Capital misallocation and TFP distortions is a well-researched area in China (Dollar and Wei, 2007; Hsieh and Klenow, 2009). However, to our knowledge, there has been little published research on the effect of financial frictions on firm level productivity in China. Notable has been Ek and Wu (2018), Wu (2018), and Jin, Zhao, and Khumbahakar (2019). Using firm-level data from the Annual Survey of Industrial Enterprises for the period 1998-2007, Ek and Wu (2018) connect investment-cash flow sensitivity to capital misallocation and Wu (2018) identify the effects of financial frictions separately from that of policy distortions. The policy distortions relate to preferential credit treatment of state-owned enterprises by the state-owned banks or explicit or implicit subsidies to export oriented firms. Jin et al (2019) take a more nuanced approach by identifying a non-linear response of productivity in Chinese manufacturing firms to financial frictions measured by a financial constraint. The unobservable measure of financial friction is derived from observable firm characteristics (cash flow, leverage, and ownership identifiers). Productivity increases at low levels of financial constraint but increases at a decreasing rate as the constraint increases. Both papers take financial friction to arise from the problems of asymmetric information and costly state verification that give rise to an external finance premium. We have no problem with this interpretation. However, financial frictions and policy distortions relating to the banking sector are interrelated. Administered deposit interest rates have spawned an industry of wealth management products that has created the supply impetus for shadow banks and directed lending to state owned or favored enterprises that underprice risk have resulted in credit starvation to the SME sector. Shadow bank lending is the response to regulatory and market distortions and alleviates the funding tightness to the SMEs.

This paper constructs a measure of financial frictions that adds of the measure of shadow banking to the firm characteristics typically employed in the literature, and empirically evaluates the effects of financial frictions on productivity using firm level data from China.

3 The Model

In this section we set out the theoretical framework that underpins our empirical investigation. We follow Levine and Warusawitharana (2021) to start with a standard firm investment model, where firms use capital K and labor L to produce output Y. However, we depart from them by assuming that there are a continuum types of heterogeneous firms characterized by $\theta \in [0, 1]$. We can imagine that any firm's share can be held both privately and publicly, and θ represents the state share of the firm, where $\theta = 0$ corresponds to purely private firms and $\theta = 1$ corresponds to purely state-own firms. Firm θ operates with the Cobb-Douglas production function

$Y = A(\theta)K^{\alpha}L^{1-\alpha}$, where $A(\theta)$ is the productivity and α denotes capital share. The price of output is set to 1 and the wage rate for labor is w. The cash flow of the firm is

$$\Pi = \max_{L} \ Y - wL. \tag{1}$$

The capital depreciation rate is δ, and the adjustment cost of investment is $\lambda_C I^2/K$.

Assume that firms can choose to invest in innovative projects which promote their productivity $z = \ln(A)$. Denote by S the firm's expenditure on the innovative projects and z' the firm's productivity after the expenditure. We assume that the productivity growth rate can be presented as

$$z' - z = G(S, \theta) = \varphi(\theta)g(S, \epsilon), \tag{2}$$

where g is a concave function with $g(0, \cdot) = 0, \frac{\partial g(S,\cdot)}{\partial S} > 0, \frac{\partial^2 g(S,\cdot)}{\partial S^2} < 0, \frac{\partial^3 g(S,\cdot)}{\partial S^3} > 0$ and satisfies the standard Inada conditions,[1] and $\varphi(\theta) > 0, \varphi'(\theta) < 0$ for $\theta \in [0, 1]$.[2] We assume that firms follow the pecking order in financing, i.e., they use free cash flow first and then external resources when financing investment and innovative projects. We assume that firms face different external financial restrictions. Firms of type θ face financial friction $\phi\nu(\theta)$ with $\phi > 0$ being the aggregate component of the degree of financial friction, and $\nu(\theta)$ with $\nu(\theta) > 0, \nu'(\theta) < 0$ for $\theta \in [0, 1]$ being the firm type specific component of the degree of financial friction.[3] We can understand the financial friction $\phi\nu(\theta)$ as the additional proportional cost per unit of external finance.[4]

[1] A typical such function is $g(S) = S^{\sigma}$, with $0 < \sigma < 1$.

[2] Here we are assuming that private firms are more efficient in transforming innovation investment into productivity enhancement due to, e.g., competition and incentive structure. There is a large literature that has examined the productivity superiority of private firms in China that supports this assumption. See Driffield and Du (2007). A typical such function is $\varphi(\theta) = e^{-\lambda_G \theta}$, with $\lambda_G > 0$.

[3] A typical such function is $\nu(\theta) = e^{-\lambda_F \theta}$, with $\lambda_F > 0$.

[4] Essentially we are assuming that all firms are affected by the financial frictions, but firms with more state shares are less affected.

Denote the external finance requested by the firm by F, then the use of funds equation is then

$$F + \Pi = I + \lambda_C I^2/K + S. \tag{3}$$

The net profit of the firm is $-F(1 + \phi\nu(\theta)1_{\{F>0\}})$. We assume that in light of the political concern, the firm with positive state share (i.e., $\theta > 0$) will aim to maximize a discounted net profit $-D(\theta, F)F(1+\phi\nu(\theta)1_{\{F>0\}})$, with $D(\theta, F) = e^{\lambda_D \theta}, \lambda_D > 0$. Put it differently, the firms with state shares will be more risk averse in funding innovative projects, especially through external financing. The value of the firm, $V(K, z)$, is the solution to the following Bellman equation

$$\begin{aligned} V(K, z) &= \max_{I,K',S} \; - e^{\lambda_D \theta} F[1 + \phi\nu(\theta)1_{\{F>0\}}] + \beta E[V(K', z')], && (4) \\ K' &= K(1 - \delta) + I, && (5) \end{aligned}$$

where β is the firm's time discount rate and K' is its capital stock of next period. Define $H(S) = \frac{\partial}{\partial S} E[V(K', z')]$. Following Levine and Warusawitharana (2021) we assume that

$$H'(S) = \frac{\partial^2}{\partial S^2} E[V(K', z')] < 0. \tag{6}$$

The optimal choice of the firm has two scenarios. The firm may choose to secure no external finance due to the extra financial cost, and finance its investment and project within its budget constraint. Other than that, the firm's optimal choice on expenditure on innovative project is determined by the first order condition

$$e^{\lambda_D \theta}[1 + \phi\nu(\theta)1_{\{F>0\}}] = \beta \frac{\partial}{\partial S} E[V(K', z')]. \tag{7}$$

In the case of an interior solution (which is ensured by the Inada conditions and the concavity assumption), the first order condition can be written as

$$e^{\lambda_D \theta}[1 + \phi\nu(\theta)1_{\{F>0\}}] = \beta H(S). \tag{8}$$

The above equation characterizes the relationship between S, ϕ and θ.

Differentiate both sides of (8) we have

$$e^{\lambda_D \theta}\nu(\theta)d\phi + e^{\lambda_D \theta}\Big(\phi\nu'(\theta) + \lambda_D(1 + \phi\nu(\theta))\Big)d\theta = \beta H'(S)dS. \tag{9}$$

Thus

$$\frac{\partial S}{\partial \phi} = \frac{1}{\beta H'(S)} e^{\lambda_D \theta}\nu(\theta), \tag{10}$$
$$\frac{\partial S}{\partial \theta} = \frac{1}{\beta H'(S)} e^{\lambda_D \theta}\Big(\phi\nu'(\theta) + \lambda_D(1 + \phi\nu(\theta))\Big), \tag{11}$$

It is easy to see that $\frac{\partial S}{\partial \phi} < 0$ under our modeling assumptions, i.e., aggregate financial friction inhibits firms investment in innovation activities. Now how do firms differ in their investment in innovative projects? We introduction the following assumption:

Assumption 1 (A1) *We assume that the differential in burden caused by financial friction between different types of firms is not so large such that*

$$\phi\nu'(\theta) + \lambda_D(1 + \phi\nu(\theta)) > 0, \ \forall\theta. \tag{12}$$

It is easy to see that under Assumption A1, we have

$$\frac{\partial S}{\partial \theta} < 0, \tag{13}$$

i.e., state owned firms invest less in innovative projects than private firms as their relative advantage in financial burden is out-weighted by their risk averse attitude toward innovation investment.

Denote the equilibrium relationship between S and F by $\frac{\partial S}{\partial F} = m(S)$. Assume that $m(S) > 0$, $m'(S) \leq 0$,and $m''(S) \geq 0$. Define $h(S) = g'(S)m(S)$. Then $h(S) > 0$ and

$$\begin{aligned}
h'(S) &= g''(S)m(S) + g'(S)m'(S) < 0, && (14)\\
h''(S) &= g'''(S)m(S) + g''(S)m'(S) + g''(S)m'(S) + g'(S)m''(S) && (15)\\
&= g'''(S)m(S) + 2g''(S)m'(S) + g'(S)m''(S) && (16)\\
&> 0. && (17)
\end{aligned}$$

Our first proposition is the relationship between productivity growth and (aggregate) financial friction, external finance and their interactions:

Proposition 1 *(a) The productivity growth decreases with financial friction, i.e.,* $\frac{\partial G}{\partial \phi} < 0$*.*
(b) The productivity-finance sensitivity is positive, i.e., $\frac{\partial G}{\partial F} > 0$*. Intuitively, this means that firms use more external finance usually enjoys higher productivity growth.*
(c) The productivity-finance sensitivity reinforces with financial frictions, i.e., $\frac{\partial^2 G}{\partial \phi \partial F} > 0$*. Intuitively, this means that when the borrowing cost becomes higher, firms have to make better use of the fund.*

Our next two results are concerned with the interaction effects of state ownership on the productivity growth-financial friction relationship, and the three way interaction effect of state ownership, financial friction, external finance on the productivity growth.

Proposition 2 *(a) The productivity-finance sensitivity decreases with* θ*, the state share of the firm, i.e.,* $\frac{\partial^2 G}{\partial \theta \partial F} < 0$*, which means that private firms make better use of* *the external fund than the state owned firms, if and only of the following condition holds in equilibrium:*

$$\frac{d\ln\varphi(\theta)}{dS} = \frac{\varphi'(\theta)/\varphi(\theta)}{\partial S/\partial\theta} > -\frac{h'(S)}{h(S)}. \tag{18}$$

(b) The productivity growth-financial friction sensitivity increases with the state share of the firm, i.e., $\frac{\partial^2 G}{\partial\phi\partial\theta} > 0$, *which means that the inhibition of productivity growth by financial frictions is more severe for the private firms than the state-owned ones, if and only of the following condition holds in equilibrium:*

$$\frac{d\ln\eta(\theta)}{dS} = \frac{\eta'(\theta)/\eta(\theta)}{\partial S/\partial\theta} > -\frac{A'(S)}{A(S)} = \frac{g'(S)H''(S) - g''(S)H'(S)}{g'(S)H'(S)}, \tag{19}$$

where $\eta(\theta) = \varphi(\theta)e^{\lambda_D\theta}\nu(\theta)$ *and* $A(S) = \frac{g'(S)}{H'(S)}$.

Proposition 3 *The nexus between productivity-finance sensitivity and financial frictions declines with the state share of the firm, i.e.,*

$$\frac{\partial}{\partial\theta}\left(\frac{\partial^2 G}{\partial\phi\partial F}\right) < 0, \tag{20}$$

which means that when the borrowing cost rises, firms with state ownership are less compelled to make better use of the funds than those without state ownership, if and only of the following condition holds in equilibrium:

$$\frac{d\ln\eta(\theta)}{dS} > -\frac{B'(S)}{B(S)} = \frac{h'(S)H''(S) - h''(S)H'(S)}{h'(S)H'(S)}, \tag{21}$$

where $B(S) = \frac{h'(S)}{H'(S)}$.

Propositions 2 and 3 do not give a definitive answer to the sign of the interactions effects $\frac{\partial^2 G}{\partial\theta\partial F}$, $\frac{\partial^2 G}{\partial\phi\partial\theta}$ and $\frac{\partial}{\partial\theta}\left(\frac{\partial^2 G}{\partial\phi\partial F}\right)$, as all of them are contingent on the equilibrium relationship characterized by (18), (19) and (21), respectively.

Conditions in (18), (19), and (21) are requirements on the equilibrium value of S with respect to the exogeneous parameters of the model. To see how they play out, let's assume that $\varphi(\theta) = e^{-\lambda_G \theta}$ and $\nu(\theta) = e^{-\lambda_F \theta}$. Then $\eta(\theta) = e^{-\lambda\theta}$, hence

$$\ln \eta(\theta) = -\lambda\theta, \tag{22}$$

with $\lambda = \lambda_G + \lambda_F - \lambda_D > 0$.

After some algebra we can see that (19) is just

$$\frac{\partial S}{\partial \theta}\frac{A'(S)}{A(S)} < \lambda. \tag{23}$$

Now plug in the formula of $\frac{\partial S}{\partial \theta}$ in (11) we have that condition (19) can be represented as

$$\frac{g''(S)H'(S) - g'(S)H''(S)}{g'(S)[H'(S)]^2} > \frac{\beta\lambda}{\rho(\theta)} e^{-\lambda_D \theta}, \tag{24}$$

where $\rho(\theta) = \phi\nu'(\theta) + \lambda_D(1 + \phi\nu(\theta))$. The left hand side of (24) is a function of S, which can be solved (at least numerically), while the right hand side of (24) is a value determined by the exogenous parameters. Hence (24), or equivalently (19), is just a requirement on the range of the equilibrium value of S. Note that if we would assume a power functional form for g, i.e., $g(S) = S^\sigma$, with $0 < \sigma < 1$ (which is a plausible assumption), and if we would also like to assume a power functional form for the value function in terms of S (which is a strong assumption and only serves a heuristic purpose) [5], say $E[V(K', z')] = \Lambda S^\delta$, with $0 < \delta < 1$, then

$$\frac{g''(S)H'(S) - g'(S)H''(S)}{g'(S)[H'(S)]^2} = -\frac{1 + \sigma - \delta}{\Lambda\delta(1-\delta)} S^{1-\delta}, \tag{25}$$

[5] Abel and Eberly (1994) show that if both the adjustment cost function and the operating profit function are homogeneous functions, then the value function of the firm's dynamic optimization problem takes a power function form.

and (24) can be reduced to

$$S < \left[\frac{\Lambda\delta(1-\delta)\beta\lambda}{-\rho(\theta)(1+\sigma-\delta)}e^{-\lambda_D\theta}\right]^{\frac{1}{1-\delta}}. \tag{26}$$

How does shadow banking come into play in our modeling framework? As detailed by a numer of existing studies (Elliott and Yan, 2013; Le at al., 2014; Chen, Ren and Zha, 2018; Le et al., 2020), shadow banks in China are engaged in providing credit that otherwise would have been provided by the regulated commercial banks. SOEs in China could essentially borrow at the risk free rate from the commercial directly, while the majority of private firms have to obtain external finance through the shadow banking channel at additional cost. Without the shadow banking system, private firms have little alternatives for external financing except going listed with slim chance. So we can view shadow banking in China as leeway to the financial rigidity of the traditional SOE oriented financial system. The percentage of shadow banking finance out of total social finance indicates partially how easily credit is channel to the private sector. And we use one minus this percentage as a measure of aggregate financial friction in the economy. More specifically, since there is strong heterogeneity in financing conditions across different provinces of China, we'll calculate separate financial friction measures for different provinces.

4 Empirical Analysis

4.1 Data and variables

Our firm level productivity and characteristics data come from China's National Tax Statistics Database (NTSD), jointly developed by China's State Administration of Taxation and Ministry of Finance in 1985 for the purpose of collecting tax-related information from firms across the country. NTSD provides essential information about firms' characteristics and performance, which allows us to accurately identify variables and then calculate their values needed in our empirical study, such as TFP, investment (i.e., current increase in fixed assets), and so forth. NTSD's data before 2005, however, are not so useful because both the sampling methods and the indicators were experimental and changed frequently. In 2005, NTSD finally settled down with a fixed sampling method and a set of indicators. We therefore use the data in NTSD from 2005 to 2012. During this period, nearly 120,000 firms are randomly sampled from the nationwide pool of taxpayers every year, using stratified random sampling. These firms represent about 10% of the annual total output and tax revenues in China, and 48% of the firms sampled are in the manufacturing sector; 45% in the service sector; and the rest in agriculture (1%), mining (2%), and construction (4%). The NTSD dataset is different from the more widely used China Industrial Enterprise Database (CIED) or the China Economic Census Database (CECD) produced by the National Bureau of Statistics (NBS). The NTSD dataset provides several key advantages over the CIED dataset. First, whereas the CIED dataset covers only manufacturing firms, the NTSD dataset covers all sectors, including service sectors with high technological entry barriers such as satellite data transmission, which is of critical interest to our study. Second, the CIED dataset is a censored dataset: it includes all SOEs but only non-SOEs with five million RMB annual sales or more. As shown by Bai, Mao, and Zhang (2014), a censored dataset has important drawbacks for statistical estimation. In contrast, the NTSD dataset is compiled by a stratified random sampling method and covers firms of all sizes. The NTSD dataset is thus much more representative than the CIED dataset. Third, the NTSD dataset is an annual dataset that covers 2005 to 2012, which is the critical period for our empirical investigation. In contrast, most scholars use the CIED data only from 1998 to 2007, even though the CIED dataset is an annual dataset, because its quality after 2007 is suspect. Finally, the CECD dataset is reported every five years, which renders it far less fine-grained.

For productivity, we use TFP values calculated via the Olley-Pakes (OP) method (Olley and Pakes, 1996) in our baseline models, with TFP values calculated via the Levinsohn-Petrin (LP) method (Levinsohn and Petrin, 2003) and OLS (i.e., Solow residuals) methods in robustness checks.

For financial friction, we use two levels of information to account for the financial frictions faced by individual firms. From the firm level perspective, a number of financial friction indexes have been proposed, such as the KZ index (Kaplan and Zingales, 1997), the WW index (Whited and Wu, 2006), the SA index (Hadlock and Pierce, 2009; Chen and Song, 2013), and the JZK index (Jin, Zhao and Kumbhakar, 2019), all of which linearly combine certain firm characteristics such as size, age, ownership types, etc. into a summarizing number. To account for financial frictions at the firm level, we take a slightly different route. Instead of constructing a financial friction index using a list of underlying firm characteristics and use the index in the regressions, we use the underlying characteristics directly in the regressions. [6]

The shadow banking system in China provides another way to measure financial friction at the aggregate level. The measure as defined above captures how much credit out of the pool has actually been allocated to the state sector. According to the *Annual Report on Chinese Enterprises 2018*, compiled by the State Administration for Market Regulation of China, 88% of Chinese firms are of private nature in 2017. When the aggregate measure increases, more credit will be channeled to the state own firms, and it will be more difficult for the vast majority of firms to obtain external finance, in which sense the aggregate measure indeed serves the purpose of indicating the degree of financial friction.

[6] It is clear that in linear regression models, if the true model is a model with a linear combination of certain variables, say $Z_i = \sum_{i=1}^{K} \alpha_i X_i$ as the covariate, with coefficient estimate γ, then in the regression where Z_i is replaced with $X_1, \ldots, X_K$, the corresponding coefficient estimates of $X_1, \ldots, X_K$ are $\gamma\alpha_1, \ldots, \gamma\alpha_K$ respectively, with the same level of statistical significance.

One of China's main development strategies is learning-by-doing from regional experiments. Hence the local environment, in particular the local financing environment, plays important roles in firms' investment in R&D and innovative projects hence productivity upgrading. Thus, in constructing the aggregate measure of financial friction we opt for the provincial level. To calculate provincial level financial friction indexes, we need to have provincial level shadow banking data. However, due to the complex nature of the shadow banking system, only the national aggregate shadow banking data are available. We therefore need to decompose the national aggregate into provincial components. Our idea is to use a semi-supervised learning algorithm based on the panel data regression framework to estimate the weights for decomposition. The algorithm is described in Appendix B.

We also follow Levine and Warusawitharana (2021) to use debt as the measure of external financing. The summary statistics of the key variables are displayed in Table 1 below.

Table 1: Summary Statistics of Key Variables

Variable	No. Obs	Mean	SD	Min	Max
ln_tfp_op	106342	2.699	1.602	-0.792	6.845
lnage	106963	1.960	0.664	0.693	3.296
lnassets	106348	9.566	2.623	5.136	15.537
lnoutput	106978	9.569	2.677	4.518	14.937
lnRD	76604	0.453	1.783	0.000	8.919
SOE	106986	0.086	0.280	0.000	1.000
debt	93200	3.376	777.954	-262.681	237437.000
lndebt	88798	8.925	2.892	3.195	15.194
ff	106977	0.774	0.227	0.178	0.996

ln_tfp_op is logarithm of the TFP calculated by the OP method, lnage is logarithm of firm's age, lnassets is logarithm of firm's total assets, lnoutput is logarithm of firm's output, lnRD is logarithm of firm's R&D investment, SOE is the dummy for State-Owned Enterprise, debt is firm's debt, lndebt is logarithm of firm's debt, and ff is the financial friction index.

The variable definitions in Table 1 are: ln_tfp_op is logarithm of TFP calculated by the OP method, tfp_op_gr is the growth rate of TFP, lnage is logarithm of age, lnassets is logarithm of total assets in millions of RMB, lnoutput is logarithm of total output in millions of RMB, lninvest is logarithm of total investment in millions of RMB, lnRD is logarithm of R&D spending in millions of RMB, SOE is State Owned Enterprise dummy, debt is liabilities to assets ratio, debt_gr is growth rate of liabilities, and ff is financial friction index, which is defined as 1 minus the shadow banking flow divided by 2 times the total social finance flow. All variables are winsorized at 2 percentile.

4.2 Econometric models

Our estimation strategy follows closely in the footsteps of Levine and Warusawitharana (2021)[7]. The baseline econometric model to test the hypothesis is

$$\begin{aligned} \Delta \ln(TFP_{ijpt}) = &\alpha \Delta \ln(Debt_{i,t}) + \beta Financial\ Frictions_{p,t} \\ &+ \gamma Financial\ Frictions_{p,t} \times \Delta \ln(Debt_{i,t}) \\ &+ \tau_j + \nu_t + \lambda_p + \varepsilon_{i,t}, \end{aligned} \tag{27}$$

where i, j, p, t are indices for firm, industry, province and year respectively, with $X_{i,t}$ a list of control variables such as firm age, firm size (the log assets), output growth, physical investment and so on, τ_j, ν_t, λ_p are industry, time and province fixed effects, respectively. *Financial Friction* is measured as 1 minus the ratio of shadow banking finance and 2 times total social finance. Hence an increase in this variable is interpreted as a tightening in financial friction.

[7] A dynamic panel specification is adopted to allow for inertia in the productivity process.

For a robustness check we also estimate the following models:

$$
\begin{aligned}
\Delta \ln(TFP_{ijpt}) = {} & \rho \ln(TFP_{ijp,t-1}) + \alpha \Delta \ln(Debt_{i,t}) \\
& + \beta Financial\ Frictions_{p,t} \\
& + \gamma Financial\ Frictions_{p,t} \times \Delta \ln(Debt_{i,t}) \\
& + \tau_j + \nu_t + \lambda_p + \varepsilon_{i,t},
\end{aligned} \tag{28}
$$

$$
\begin{aligned}
\Delta \ln(TFP_{ijpt}) = {} & \rho \ln(TFP_{ijp,t-1}) + \alpha \Delta \ln(Debt_{i,t}) \\
& + \beta Financial\ Frictions_{p,t} \\
& + \gamma Financial\ Frictions_{p,t} \times \Delta \ln(Debt_{i,t}) \\
& + \psi X_{i,t} + \tau_j + \nu_t + \lambda_p + \varepsilon_{i,t},
\end{aligned} \tag{29}
$$

To check whether the results are related to firm characteristics such as ownership, we include the SOE dummy and its interactions with the main variables of interest

$$
\begin{aligned}
\Delta \ln(TFP_{ijpt}) = {} & \rho \ln(TFP_{ijp,t-1}) + \alpha \Delta \ln(Debt_{i,t}) + \beta Financial\ Frictions_{p,t} \\
& + \gamma Financial\ Frictions_{p,t} \times \Delta \ln(Debt_{i,t}) \\
& + \delta SOE_{it} + \theta SOE_{it} \times \Delta \ln(Debt_{i,t}) \\
& + \vartheta SOE_{it} \times Financial\ Frictions_{p,t} \\
& + \zeta SOE_{it} \times \Delta \ln(Debt_{i,t}) \times Financial\ Frictions_{p,t} \\
& + \psi X_{i,t} + \tau_j + \nu_t + \lambda_p + \varepsilon_{i,t},
\end{aligned} \tag{30}
$$

The 4 Trillion Stimulus Package started in November 2008 changed the nature of China's shadow banking sector fundamentally. To check whether the results are related to the nature and composition of shadow banks, we include a time dummy

$SP = 1$ being time after 2008, and its interactions with the main variables of interest

$$\begin{aligned}\Delta \ln(TFP_{ijpt}) = &\rho \ln(TFP_{ijp,t-1}) + \alpha\Delta \ln(Debt_{i,t}) + \beta Financial\ Frictions_{p,t} \\ &+ \gamma Financial\ Frictions_{p,t} \times \Delta \ln(Debt_{i,t}) \\ &+ \delta SP_t + \theta SP_t \times \Delta \ln(Debt_{i,t}) \\ &+ \vartheta SP_t \times Financial\ Frictions_{p,t} \\ &+ \zeta SP_t \times \Delta \ln(Debt_{i,t}) \times Financial\ Frictions_{p,t} \\ &+ \psi X_{i,t} + \tau_j + \lambda_p + \varepsilon_{i,t},\end{aligned} \tag{31}$$

4.3 Empirical results

We present two sets of estimations results with the above econometric specifications. The first set of results are obtained by panel least squares regressions with fixed effects (FE). As is well-known (Nickell, 1981; Cheng, Wang and Xiao, 2021; Levine and Warusawitharana, 2021), conventional panel estimation with a lagged dependent variable gives rise to biased estimates. As a consequence, we undertake an additional set of dynamic panel estimation with Arellano and Bond (1991)'s GMM method.

Table 2 reports FE regression results where firm owership (the SOE dummy) is introduced as the conditioning variable. The corresponding GMM estimation results are reported in Table 3. For both Table 2 and Table 3, columns 1-4 report the results for models specified by (27)-(30), respectively. Specifically, column 1 shows the results from the baseline equation, column 2 examines the interaction with the SOE dummy, and columns 3-4 adds firm characteristic control variables with the final column adding firm level expenditure on R&D investment. Since column 4 of Table 3 allows for the full panoply of firm characteristics and investment in R&D and is estimated with the GMM method that can correct the potential bias of FE estimators, we will mainly discuss the implications of this results and view results in other columns as accompanying evidence.

First, we can confirm that there is significant inertia in firm-level TFP. The lag log of TFP is negative and significant, indicating convergence of productivity growth. Second, the results of column 4 of Table 3 provide strong support for proposition 1(a) that financial friction inhibits productivity growth, and statistically insignificant support for proposition 2(a) that private firms suffer more from financial friction than state-owned firms.

The coefficients of debt growth in all columns of Table 3, including column 4 are all statistically insignificant, indicating that the claim in proposition 1(b) is not firmly endorsed by the data. The positive, and in particular positive and significant in column 4, sign of the interaction of our measure of financial friction and external finance shows that the negative impact of financial friction on the firm-level TFP is muted with its external debt, a result predicted in proposition 1(c) and resonating with the main finding of Levine and Warusawitharana (2021).

The triple interaction of SOE, debt growth, and financial friction, is negative, although insignificant, which suggest that the sensitivity of productivity growth to the interaction of the SOE dummy and debt growth declines with increasing debt as in proposition 2(b).

However, our findings may have been distorted by the post-GFC credit easing policy of the Chinese authorities. The 4 trillion RMB stimulus package in 2008 saw a 37% rise in bank credit in 2009 from an increase of 21% in 2008, and M2 growth of 28% over an increase of 18% in 2008. In Tables 4-5 we show the results of bringing in a dummy variable (SP), which reflects this sharp rise in the stock of money and credit. For both Tables 4-5, column 2 reports the results estimated with model (31), and column 1 reports the results without control variables. The result shows that the stimulus dummy absorbs a large part of the variation in firm-level TFP. However, digging deeper into the interactions to decompose the effects of the stimulus action, a more nuanced picture emerges from column 2.

First, inertia in the process of TFP evolution is retained. Second, financial friction in its raw state continues to exert a negative impact on productivity as per proposition 1(a). External finance has an insignificant effect but its effect is conditional on the strong conditions of 17 and 19. The stimulus effect absorbs the external finance effect which shows a weakening of the negative effect of financial friction (at the 10% level), in the triple interaction of the stimulus dummy, debt growth and financial friction. The stimulus effect works to offset the negative effects of financial frictions on firm-level productivity . The impact of the stimulus is to weaken the financial constraints of firms and increase productivity. Of the control variables, older firms are less productive than younger ones. Investment and R&D appears to have independent positive effects.

5 Conclusions

Our findings are tentative but also tantalizing. Using a unique dataset, we have addressed the role of financial frictions in the determination of firm-level productivity. We have taken the research direction pointed by Levine and Warusawitharana (2021) but we contribute to the literature in three ways.

First, we argue that in the China context, the role of shadow banks in financing the private sector in general and SMEs in particular has to be considered as "shadows" of financial frictions. The financial frictions that Chinese firms face stem from the regulatory environment that has traditionally favored state-owned enterprises. Shadow banks are the market outcome of restrictive state-owned bank activity that feeds SOEs at the cost of starving SMEs.

Second, we use "signal extraction" methods to estimate the scale of shadow bank flows at the provincial level for the time period under investigation. This estimate is used as an additional indicator of financial frictions and matched against firms located in the specific province. Third, we find that isolating the period of the stimulus package produces strong support for the role of financial frictions in the determination of productivity at the firm level.

Our empirical findings are a "mixed bag" that invites deeper investigation. The results need to be able to stand up against alternative measures of productivity, which is a necessary robustness test. In the China context, the ownership effect of financial frictions on productivity requires careful dissection. It is a part of proposition 1 that has yet to be fully identified.

Appendix A: Proofs of results

Proof of Proposition 1. We first note that $\frac{\partial S}{\partial \phi} < 0$ and $\frac{\partial S}{\partial \theta} > 0$. By the chain rule,

$$\frac{\partial G}{\partial \phi} = \frac{\partial G}{\partial S}\frac{\partial S}{\partial \phi} = \varphi(\theta)g'(S)\frac{1}{\beta H'(S)}e^{\lambda_D \theta}\nu(\theta) = \frac{g'(S)}{\beta H'(S)}\varphi(\theta)e^{\lambda_D \theta}\nu(\theta) < 0, \quad (32)$$

as $g'(S) > 0$, $H'(S) < 0$ and $\varphi(\theta) > 0, \nu(\theta) > 0$.

Now since both θ and ϕ are exogenous parameters of the model, and in equilibrium both S and F are functions of θ and ϕ, we have that

$$\frac{\partial G}{\partial F} = \frac{\partial G}{\partial S}\frac{\partial S}{\partial F} = \varphi(\theta)g'(S)\frac{\partial S}{\partial F} = \varphi(\theta)g'(S)m(S) > 0, \quad (33)$$

as $g'(S) > 0$ and $\frac{\partial S}{\partial F} = m(S) > 0$.

Therefore,

$$\begin{aligned}
\frac{\partial^2 G}{\partial\phi\partial F} &= \frac{\partial}{\partial\phi}\left(\frac{\partial G}{\partial F}\right) = \frac{\partial}{\partial\theta}\Big(\varphi(\theta)g'(S)m(S)\Big) \\
&= \varphi(\theta)\frac{\partial S}{\partial\phi}\Big(g''(S)m(S) + g'(S)m'(S)\Big) \\
&= \varphi(\theta)\frac{\partial S}{\partial\phi}h'(S) \\
&= \frac{1}{\beta}\varphi(\theta)e^{\lambda_D\theta}\nu(\theta)\frac{h'(S)}{H'(S)} > 0
\end{aligned}$$

as $g''(S) < 0$, $\frac{\partial S}{\partial\phi} < 0$ and $h'(S) < 0$. ■

Proof of Proposition 2.

$$\begin{aligned}
\frac{\partial^2 G}{\partial\theta\partial F} &= \frac{\partial}{\partial\theta}\left(\frac{\partial G}{\partial F}\right) = \frac{\partial}{\partial\theta}\Big(\varphi(\theta)g'(S)m(S)\Big) \\
&= \frac{\partial}{\partial\theta}\Big(\varphi(\theta)h(S)\Big) \\
&= \varphi'(\theta)h(S) + \varphi(\theta)h'(S)\frac{\partial S}{\partial\theta} \\
&= \varphi(\theta)h(S)\left(\frac{\varphi'(\theta)}{\varphi(\theta)} + \frac{h'(S)}{h(S)}\frac{\partial S}{\partial\theta}\right) \\
&< 0,
\end{aligned}$$

as $\varphi'(\theta) < 0, h(S) > 0, \varphi(\theta) > 0, h'(S) < 0$, and $\frac{\partial S}{\partial\theta} > 0$.

Define $\eta(\theta) = \varphi(\theta)e^{\lambda_D\theta}\nu(\theta)$ and $A(S) = \frac{g'(S)}{H'(S)}$. Then

$$\begin{aligned}
\frac{\partial^2 G}{\partial\phi\partial\theta} &= \frac{\partial}{\partial\theta}\left(\frac{\partial G}{\partial\phi}\right) = \frac{\partial}{\partial\theta}\left(\frac{g'(S)}{\beta H'(S)}\varphi(\theta)e^{\lambda_D\theta}\nu(\theta)\right) \\
&= \frac{\partial}{\partial\theta}\left(\frac{1}{\beta}\eta(\theta)A(S)\right) \\
&= \frac{1}{\beta}\left(\eta'(\theta)A(S) + \eta(\theta)A'(S)\frac{\partial S}{\partial\theta}\right)
\end{aligned}$$

Hence $\frac{\partial^2 G}{\partial\phi\partial\theta} > 0$ is equivalent to

$$\eta'(\theta)A(S) + \eta(\theta)A'(S)\frac{\partial S}{\partial\theta} > 0, \tag{34}$$

which is

$$\frac{\eta'(\theta)/\eta(\theta)}{\frac{\partial S}{\partial\theta}} < -\frac{A'(S)}{A(S)}, \tag{35}$$

and is just

$$\frac{d\ln\eta(\theta)}{dS} < -\frac{A'(S)}{A(S)} = \frac{g'(S)H''(S) - g''(S)H'(S)}{g'(S)H'(S)}. \tag{36}$$

■

Proof of Proposition 3. The proof of Proposition 3 is similar to that of Proposition 2 part (b) above, with just $A(S)$ replaced by $B(S) = \frac{h'(S)}{H'(S)}$. ■

Appendix B: A semi-supervised learning algorithm for construction of the shadow banking data

Suppose an entity consists of N subdivisions (such as a country consists of different states or provinces), indexed by $i = 1, \ldots, N$. Let $(Y_{it}, \mathbf{X}_{it})$ be a set of characteristic variables for subdivision i at time $t = 1, \ldots, T$, where $Y_{it} \in \mathbb{R}$ is the key variable of interest while unfortunately unavailable, and $\mathbf{X}_{it} = (X_{i1t}, \ldots, X_{iKt})' \in \mathbb{R}^K$ is a vector of auxiliary variables which are linearly related with Y_{it}.

Though Y_{it}'s are not observable, we do have time series observations of the aggregate levels $Y_t = \sum_{i=1}^N Y_{it}$. We assume that $\{Y_t\}_{t=1,\ldots,T}$ and $\{X_{ikt}\}_{t=1,\ldots,T}$ are all stationary processes. In the case of nonstationarity, we can model the first differences of Y_t and X_{ikt}, respectively.

Our aim is to estimate the values ofY_{it} based on Y_t and X_{ikt}. A simple model is

$$Y_{it} = \alpha + \mathbf{X}_{it}'\beta + \epsilon_{it}, \tag{37}$$

where $\mathbf{X}_{it} = (X_{i1t}, \cdots, X_{iKt})'$. Since we don't observe Y_{it}, we can not estimate the parameters α and β directly. The problem falls to the category of semi-supervised learning, or more specifically, the aggregate learning problem (Musicant et al., 2007; Kotzia et al., 2015; Law et al., 2018). In this part, I'll propose an innovative method to predict the values of Y_{it}.

Let $w_{it} = \frac{E[Y_{it}]}{E[Y_t]}$. By the stationarity of $\{Y_{it}\}_t$, w_{it} is a time-invariant constant for each i, i.e., $w_{it} = w_i$. And since $E[Y_{it} - w_i Y_t] = 0$, a natural unbiased estimator of Y_{it} is $w_i Y_t$. Our problem therefore moves to the estimation of the $w_i's$.

We propose obtaining the estimates of the $w_i's$ from the following optimization problem:

$$\min_{w_i>0,\sum w_i=1} \left\{ \min_{\alpha,\beta} \sum_t \sum_i (w_i Y_t - \alpha - \mathbf{X}_{it}'\beta)^2 + \lambda \sum_t (Y_t - N\alpha - \mathbf{X}_t'\beta)^2 \right\}, \tag{38}$$

where $\mathbf{X}_t = \sum_i \mathbf{x}_{it}$, and λ is the tuning parameter. The objective function above tries to balance the individual level prediction error and group level prediction error. An optimization with only the first term $\sum_t \sum_i (w_i Y_t - \alpha - \mathbf{X}_{it}'\beta)^2$ in the objective function tends to overfit the data. The second term $\lambda \sum_t (Y_t - N\alpha - \mathbf{X}_t'\beta)^2$ serves as a test data to reduce the model's out of sample prediction error.

The optimization taget function in (38) is quadratic in all parameters, and since we have no restrictions on α and β, we can solve (38) in two steps. In the first step, for fixed value of w_i's, we solve for α and β as functions of w_i's. In the second step, we plug in the estimate of α and β and solve the constrained optimization for w_i's. The idea of using penalized regression such as in (38) is appealing for controlling bias-variance tradeoff. However, the implementation of such widely used optimization methods often suffers from many practical issues, such as the choice of tuning parameter γ. Therefore, an explicit solution, even if being only approximately reliable, is largely desirable.

In the case that γ is large, the two step optimization problem described above produces estimators that are asymptotically equivalent to that are produced by the following iterated least squares (ILS) procedure. In the first step, we obtain estimates of α and β on the time aggregated data Y_t and $\mathbf{X}_t = \sum_{i=1}^{N} \mathbf{X}_{it}$ though least squares:

$$(\hat{\alpha}_{aols}, \hat{\beta}_{aols}) = \arg\min_{\alpha,\beta} \sum_t (Y_t - N\alpha - \mathbf{X}_t'\beta)^2. \tag{39}$$

In the second step, we obtain estimates of the w_i's, denoted by $\hat{w}_i$, by solving the following optimization problem:

$$\min_{w_i \geq 0, \sum w_i = 1} \sum_t \sum_i (w_i Y_t - \hat{\alpha}_{aols} - \mathbf{X}_{it}'\hat{\beta}_{aols})^2. \tag{40}$$

Our estimates of Y_{it} is then defined as $\hat{Y}_{it} = \hat{w}_i Y_t$. Xiao (2023) proved that the above ILS estimators for w_i's are consistent and lead to unbiased prediction of Y_{it}'s.

Our aggregate China Shadow Banking size are from two sources:

1. Goldman Saches, 2013: This data contain series from 2000-2012.

2. Moody's quarterly reports: This data contain series from 2010-2017.

In our data, 2000-2009 are from GS, 2013-2017 are from Moody's, and 2010-2012 are the averages of GS and Moody's. Since these two data source have different definition of shadow banking in China, in compiling our aggregate shadow banking data, we retain the original number when there is only one data source available, and we take the average when both data source are available. Therefore, the year 2000-2009 data are from GS, year 2013-2018 data are from Moody's, and year 2010-2012 data are the averages of GS and Moody's figures.

Our set of auxiliary variables including the provincial yearly time series of the following indicators:

1. Total Social Financing
2. GDP
3. Real Estate Investment
4. Total Assets of Private Enterprises
5. Total Production of Cement

All the data for auxiliary variables come from China's National Bureau of Statistics.

Appendix C: Empirical results

Table 2: Financial Frictions and TFP Growth-Debt Sensitivity: Multi-way FE Regressions

	(1)	(2)	(3)	(4)
	$\Delta \ln(TFP)$	$\Delta \ln(TFP)$	$\Delta \ln(TFP)$	$\Delta \ln(TFP)$
ff_{t-1}	-0.6943*	-0.6839**	-0.5308	-0.6982
	(0.3573)	(0.3483)	(0.3698)	(0.4383)
lndebt_{t-1}	-0.0506*	0.0149	0.0282	-0.0537
	(0.0265)	(0.0252)	(0.0274)	(0.0345)
$\text{lndebt}_{t-1} \times \text{ff}_{t-1}$	0.0416	0.0419	0.0254	0.0310
	(0.0284)	(0.0272)	(0.0294)	(0.0357)
lnTFP_{t-1}		-0.3387***	-0.3386***	-0.3472***
		(0.0101)	(0.0101)	(0.0119)
SOE			1.0460*	0.9662
			(0.5423)	(0.6394)
$\text{SOE} \times \text{lndebt}_{t-1}$			-0.0964**	-0.0944*
			(0.0447)	(0.0545)
$\text{SOE} \times \text{ff}_{t-1}$			-1.3019**	-1.0758
			(0.6170)	(0.6996)
$\text{SOE} \times \text{lndebt}_{t-1} \times \text{ff}_{t-1}$			0.1275**	0.1131*
			(0.0529)	(0.0606)
lnage_{t-1}				-0.0390**

				(0.0167)
lnassets_{t-1}				0.0923***
				(0.0154)
lnoutput_{t-1}				0.0236*
				(0.0121)
lnRD_{t-1}				0.0014
				(0.0073)
_cons	0.7486**	1.0138***	0.8848***	0.7049*
	(0.3293)	(0.3187)	(0.3396)	(0.4136)
N	13560	13560	13560	10144
R^2	0.053	0.191	0.192	0.205

Standard errors clustered by industry are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Financial Frictions and TFP Growth-Debt Sensitivity: GMM

	(1)	(2)	(3)	(4)
	$\Delta\ln(TFP)$	$\Delta\ln(TFP)$	$\Delta\ln(TFP)$	$\Delta\ln(TFP)$
ff_{t-1}	-2.1541	-2.3888	-10.8924***	-9.0635*
	(3.5601)	(2.5276)	(4.1608)	(5.2227)
lndebt_{t-1}	-0.0679	0.0663	-0.3528	-0.8187*
	(0.1904)	(0.1358)	(0.2250)	(0.4295)
$\text{lndebt}_{t-1} \times \text{ff}_{t-1}$	0.0446	0.1175	0.7003**	0.5593
	(0.2286)	(0.1624)	(0.2860)	(0.3595)
lnTFP_{t-1}		-0.8033***	-0.7963***	-0.9275***
		(0.0764)	(0.0835)	(0.1071)
SOE			-19.6203***	-10.9751
			(7.5207)	(8.0273)
SOE $\times$ lndebt_{t-1}			1.4889**	0.8011
			(0.6042)	(0.6338)
SOE $\times$ ff_{t-1}			24.7583**	22.5440*
			(9.8648)	(12.0354)
SOE $\times$ $\text{lndebt}_{t-1} \times \text{ff}_{t-1}$			-1.8782**	-1.8898*
			(0.8092)	(1.0226)
lnage_{t-1}				-0.4313
				(0.4370)

lnassets_{t-1}				0.6525*
				(0.3502)
lnoutput_{t-1}				0.0166
				(0.2945)
lnRD_{t-1}				0.1464
				(0.1001)
_cons	2.0956	2.9299	9.7444***	7.9862*
	(2.9570)	(2.2045)	(3.4985)	(4.6262)
N	13699	13699	13699	10287
R^2				

Standard errors clustered by industry are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Financial Frictions and TFP Growth-Debt Sensitivity: Multi-way FE Regressions & SP Dummy

	(1)	(2)
	$\Delta \ln(TFP)$	$\Delta \ln(TFP)$
lnTFP_{t-1}	-0.3395***	-0.3474***
	(0.0103)	(0.0122)
SP	-1.0431*	-0.4297
	(0.6058)	(0.8261)
lndebt_{t-1}	-0.1650***	-0.1008
	(0.0572)	(0.0875)
SP$\times$ lndebt_{t-1}	0.1886***	0.0480
	(0.0687)	(0.0973)
ff_{t-1}	-1.6772***	-0.8617
	(0.4569)	(0.6780)
SP$\times$ ff_{t-1}	1.3582*	0.9132
	(0.7992)	(1.0750)
$\text{lndebt}_{t-1} \times \text{ff}_{t-1}$	0.2350***	0.0828
	(0.0619)	(0.0918)
SP$\times$ $\text{lndebt}_{t-1} \times \text{ff}_{t-1}$	-0.1902**	-0.0668
	(0.0824)	(0.1157)
lnage_{t-1}		-0.0390**
		(0.0167)

lnassets_{t-1}		0.0938***
		(0.0158)
lnoutput_{t-1}		0.0224*
		(0.0123)
lnRD_{t-1}		0.0008
		(0.0072)
_cons	1.9058***	0.8325
	(0.4220)	(0.6429)
N	13560	10144
R^2	0.190	0.203

Standard errors clustered by industry are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Financial Frictions and TFP Growth-Debt Sensitivity: GMM & SP Dummy

	(1)	(2)
	$\Delta \ln(TFP)$	$\Delta \ln(TFP)$
lnTFP_{t-1}	-0.7988***	-0.9080***
	(0.0811)	(0.0899)
SP	1.4494	27.7371
	(9.7106)	(23.9402)
lndebt_{t-1}	-0.0264	2.4376
	(1.0532)	(2.6315)
SP $\times$ lndebt_{t-1}	0.5312	-2.3090
	(1.0351)	(2.5841)
ff_{t-1}	5.4613	27.4158
	(11.6725)	(24.6939)
SP $\times$ ff_{t-1}	-0.1646	-21.6496
	(11.4625)	(24.3208)
lndebt_{t-1} $\times$ ff_{t-1}	0.3607	-2.1248
	(1.2519)	(2.6666)
SP $\times$ lndebt_{t-1} $\times$ ff_{t-1}	-0.7008	1.7302
	(1.2476)	(2.6446)
lnage_{t-1}		-0.2242
		(0.4086)

lnassets_{t-1}		0.4978
		(0.3515)
lnoutput_{t-1}		-0.3426
		(0.3963)
lnRD_{t-1}		0.0592
		(0.0800)
_cons	-4.7414	-27.2162
	(9.9837)	(23.1919)
N	13699	10287
R^2		

Standard errors clustered by industry are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

References

[1] Abel, A. B., Eberly, J. C., (1993), "A unified model of investment under uncertainty," *American Economic Review*, 84(5), 1369–1384.

[2] Alessi, L., Barigozzi, M. and Capasso, M., (2011), "Non-fundamentalness in structural econometric models: A review," *International Statistical Review* 79, 16-47.

[3] Arellano, M. , Bond, S. , (1991), "Some tests of specification for panel data: Monte carlo evidence and an application to employment equations," *Review of Economic Studies*, 58, 277–297.

[4] Bai, Chong-En, Jie Mao, and Qiong Zhang, (2014), "Measuring market concentration in China: The problem with using censored data and its rectification," *China Economic Review* 30, 432–47.

[5] Bruera, F., Kaboski, J., and Shin, Y., (2011), "Finance and development: A tale of two sectors", *American Economic Review*, 101, 1964-2002.

[6] Cabellero, R., Hoshi, T., and Kashayap, A (2008), "Zombie lending and depressed restructuring in Japan," *American Economic Review*, 84, 1350-1368.

[7] Chen, K., Ren, J., & Zha, T. (2018), "The nexus of monetary policy and shadow banking in China," *American Economic Review*, 108(12), 3891–3936.

[8] Cheng, D., Wang, J., & Xiao, Z., (2021), "Global value chain and growth convergence: Applied especially to China," *Pacific Economic Review*, 26(2), 161-182.

[9] Cole, H., Greenwood, J., and Sanchez, J., (2016), "Why doesn't technology flow from rich to poor countries?", *Econometrica*, 84, 1477-1521.

[10] Dollar, D., and Wei, S., (2007), Das (wasted) kapital: Firm ownership and investment efficiency in China, NBER Working Paper No 13103, Cambridge, MA: National Bureau of Economic Research.

[11] Driffield, N., Du, J., (2007), Privatisation, state ownership and productivity: Evidence from China. *International Journal of The Economics of Business*, 14(2), 215–239.

[12] Elliott, D. and Yan K., 2013, The Chinese financial system: An introduction and overview, John L. Thornton China Center Monograph Series, The Brookings Institution.

[13] Ek, C., and Wu, G., (2018), "Investment-cash flows sensitivities and capital misallocation," *Journal of Development Economics*, 133, 220-230.

[14] Hadlock, C., and Pierce, J., (2009), "New evidence on measuring financial constraints: Moving beyond the KZ index," *Review of Financial Studies*, 23, 909-1940.

[15] Han, S., You, W. and Nan, S., (2019), "Zombie firms, external support and corporate environmental responsibility: Evidence from China," *Journal of Cleaner Production*, 212, 1499-1517.

[16] Heil, M., (2018), "Finance and productivity: A literature review," *Journal of Economic Surveys*, 32, 5, 1355-1383.

[17] Hsieh, C., and Klenow, P., (2009), "Misallocation and manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124, 4, 1403-1448.

[18] Jin, M., Zhao, S., and Kumbhakar, S C., (2019), "Financial constraints and firm productivity: Evidence from Chinese manufacturing," *European Journal of Operational Research*, 275, 1139-1156.

[19] Kaplan, S.N., and Zingales, L. (1997), "Do investment-cash flow sensitivities provide useful measures of financing constraints?" *Quarterly Journal of Economics*, 112, 1, 196-215.

[20] Kotzias, D., Denil, M., De Freitas, N., Smyth, P., (2015), "From group to individual labels using deep features," *KDD '15: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.*

[21] Law, H. C. L., Sejdinovic, D., Cameron, E., Lucas, T., Flaxman, S., Battle, K., Fukumizu, K., (2018), "Variational Learning on Aggregate Outputs with Gaussian Processes," *2018 Neural Information Processing Systems* Volume: 31, pp 6081-6091.

[22] Le, V.P.M., Matthews, K., Meenagh, D., Minford, P., Xiao, Z., (2014), "Banking and the macroeconomy in China: A banking crisis deferred?" *Open Economies Review*, 25, (1), 123–161.

[23] Le, V. P. M., Matthews, K., Meenagh, D., Minford, P., & Xiao, Z., (2020), "China's market economy, shadow banking and the frequency of growth slowdown," *The Manchester School*, in press.

[24] Levine, O., and Warusawitharana, M., (2021), "Finance and productivity growth: Firm-Level evidence," *Journal of Monetary Economics*, 117, 91-107.

[25] Levinson, J., and Petrin, A. (2003), "Estimating production function using inputs to control for unobservables," *Review of Economic Studies*, 70, 2, 317-341.

[26] Lu, Y., Guo, H., Kao, E.H. and Fung, H.G., (2015), "Shadow banking and firm financing in China," *International Review of Economics & Finance*, 36, 40-53.

[27] Midrigan, V., and Xu, D.Y., (2014), "Finance and misallocation: Evidence from plant level data," *American Economic Review*, 104, 422-458.

[28] Musicant, D. R., Atlas, R., Christensen, J. M., Olson, J. F., Rzeszotarski, J. M., Turetsky, E. R. D., 2009, "Supervised Learning by Training on Aggregate Outputs," Working paper.

[29] Nickell, S, (1981), "Biases in dynamic models with fixed effects," *Econometrica*, 49, 1417–1426.

[30] Olley, S., and Pakes, A. (1996), "The dynamics of productivity in the telecommunications equipment industry," *Econometrica*, 64, 6, 1263-1297.

[31] Rajan, R., and Zingales, L., (1998), "Financial dependence and growth," *American Economic Review*, 88, 559-686.

[32] Sheng, A., Soon Ng, C., and Edelmann, C., (2013). Asia Finance 2020: Framing a New Asian Finance Architecture, Oliver Wyman, Fung Global Institute.

[33] State Administration for Market Regulation of China, (2018), *Annual Report on Chinese Enterprises 2018*. China Industry and Commerce Press: Beijing.

[34] Tsai, K.S., (2017), "When shadow banking can be productive: Financing small and medium enterprises in China," *The Journal of Development Studies*, 53(12), 2005- 2028.

[35] Whited, T., and Wu, G. (2006), "Financial constraints risk," *Review of Financial Studies*, 19, 2, 531-559.

[36] Wu, G., (2018), "Capital misallocation in China: Financial frictions or policy distortions?" *Journal of Development Economics*, 130, 203-223.

[37] Xiao, Z., (2023), "Semi-supervised learning with aggregate and auxiliary data," Working paper.