

Capital Misallocation in China: Financial Frictions or Policy Distortions?*

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Abstract

Policy distortions and financial frictions are two leading candidates in generating capital misallocation. This paper designs an identification strategy to separate their effects on average MRPK dispersion across firm ownership, as the average treatment effect on the treated and the selection bias from a policy intervention. Financial frictions are estimated to cause an aggregate TFP loss of 8.3 percent on the intensive margin, which accounts for 30 percent of the capital misallocation observed in China. Using the counterfactual MRPK from a matching procedure, some popular hypotheses on what drive the policy distortions are tested in the matched samples.

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Keywords: capital misallocation, financial frictions, policy distortions, propensity score matching, Chinese economy

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1 Introduction

A new and growing literature, as surveyed in Restuccia and Rogerson (2013), argues that resource misallocation across heterogeneous firms in an economy lowers its aggregate total factor productivity (TFP). This makes the efficiency of resource allocation a new perspective to understand the cross-country income differences. Among various production factors, capital misallocation has been documented as a prevailing empirical phenomenon, both in less developed economies in general, and in China in particular.¹ Inferring from the dispersion of firm-level marginal revenue products, Hsieh and Klenow (2009) find that the aggregate TFP loss in China due to resource misallocation is of a magnitude from 30 to 50 percent. Brandt et al. (2013) obtain a similar magnitude of loss using sector-province-level data across China. Song and Wu (2017) estimate that capital misallocation alone may reduce aggregate TFP in China by 20 percent even in later 2000s.

The qualitative significance and quantitative importance of capital misallocation raise two pertinent research questions. First, what are the underlying factors that cause the misallocation? And second, through what mechanisms do these factors operate? Two natural candidates have attracted increasing interest in the recent literature: capital market imperfections due to financial frictions and non-market distortions induced by government policies.²

It is obviously difficult to make a clean distinction between financial frictions and policy distortions. They are not necessarily very different in conceptual terms, and they may also overlap with a number of other frictions and distortions that are very similar. Therefore in this paper we narrow the definition of “financial frictions” strictly to those factors due to imperfect information or imperfect enforcement in the capital market that would cause capital misallocation even in those developed economies. We ask to what extent such factors contribute to the observed capital misallocation. This implies that all those non-typical financial frictions are labelled as policy distortions in a very broad sense.³ To open the black-box of the policy distortions, we then test some popular hypotheses on the possible driving forces lying behind.

¹Banerjee and Benjamin (2010) offer an excellent summary on the evidences of capital misallocation that appear in various forms. Brandt et al. (2013) provide direct evidences of capital misallocation across time, space and sectors in China.

²Some other possible explanations, which are assumed away in this paper, include lack of insurance, local externalities, and failure of patience or rationality. See Banerjee and Duffalo (2005) for a further discussion.

³For example, the standard financial frictions literature typically assume that profit maximization is the only objective when banks make lending decisions, which is not necessarily the case in China. Similar to Ho et al. (2015), such factors are also considered as a form of policy distortions in this paper.

A stylized fact on Chinese economy is that the average marginal revenue product of capital (MRPK) differs significantly across firms with different ownership (Dollar and Wei, 2007; Song et al., 2012; Brandt et al., 2013, among many others). This distinct phenomenon has often been taken as a direct evidence of policy distortions in capital allocation. After all, ownership should not matter for MRPK in a world without policy distortions, had ownership been orthogonal to other firm characteristics that may affect MRPK. However, as a less developed economy, China also has a less developed capital market with a lagged legal, auditing and contracting environment. If firms with different ownership do systematically differ in other characteristics, such as age and size, and if such characteristics do affect MRPK because of financial frictions, even in the absence of policy distortions, these firms could still have different MRPK under an imperfect capital market. Meanwhile, the effect of policy distortions on capital misallocation could be exacerbated or mitigated by the presence of financial frictions, if those firm characteristics through which financial frictions affect MRPK are themselves affected by policy distortions. This implies that the observed MRPK dispersion across firm ownership could be the consequence of both policy distortions and financial frictions.

The unique institutional feature on firm ownership and MRPK dispersion in China inspires us to design the following identification strategy. Imagine an investment promoting program which offers favorable treatment to some firms. The treatment status of a firm depends on its ownership. The exact treatment may take various forms, for example, an investment tax credit, or a special bank loan with low interest rate. The effect of the treatment is to lower the generalized user cost of capital, or the mirror image of the MRPK of those treated firms. Firms differ not only in their treatment status but also in a set of firm characteristics, known as covariates in an evaluation problem, through which financial frictions operate to affect their MRPK. The average treatment effect of the program on MRPK dispersion can then be decomposed into the average treatment effect on the treated (ATT) and the selection bias (SB). The ATT is the difference between the actual MRPK of those treated and the counterfactual MRPK of those treated had they not received the treatment, which identifies the effect of policy distortions on the average MRPK dispersion across ownership. The SB is the MRPK difference between the treated and the untreated in the absence of treatment, which captures the effect of financial frictions on the average MRPK dispersion across ownership.

Estimating how much the observed capital misallocation can be accounted by financial frictions is of particular interest. Financial frictions may reduce TFP through two channels – preventing entry of productive firms and misallocating capital among existing firms. Although there is a general agreement on the importance of the extensive margin, whether financial

frictions would cause large TFP loss on the intensive margin remains unsettled. On one hand, there is a large literature, such as Buera and Shin (2013) and Caselli and Gennaioli (2012), that simulates substantial TFP loss from various models of financial frictions. On the other hand, Midrigan and Xu (2014) find that a collateral constraint model consistent with Korean plant-level data only implies a fairly small loss (5 to 10 percent), where the key mechanism that undoes the capital misallocation is self-financing. Using firm-specific borrowing costs for U.S. manufacturing firms directly from the interest rate spreads on their outstanding publicly-traded debt, Gilchrist et al. (2013) also find a very modest loss (up to 3.5 percent).

More recently, the literature has pointed out some potential reasons that may drive the wide range of the effects. The reasons include the concavity of the revenue function (Banerjee and Moll, 2010); the microfoundations in modelling financial frictions (Moll et al., 2014); the persistence of the productivity shocks (Buera and Shin, 2011; Moll, 2014); and whether the effect is on transition dynamics or steady state (Jeong and Townsend, 2007; Buera and Shin, 2013; Moll, 2014). All these findings suggest that in disciplining the effect of financial frictions on aggregate TFP using micro-level data, the combination of a structural model and a non-parametric estimation approach might have its unique value. A structural model reveals the mechanisms that generate capital misallocation, while a non-parametric estimation avoids the potential parametric misspecification.

In this paper, we consider a structural model with both policy distortions and financial frictions. To nest those microfoundations that have been the most common building blocks of the recent literature on financial frictions and aggregate TFP, we allow for two types of highly synthesized reduced-form financial constraints. The aggregate TFP loss in our model economy depends on the dispersion of the firm-specific MRPK, which is determined by some joint distribution of a set of parameters. These parameters govern the magnitude of firm-specific policy distortions and financial frictions, and characterize the states of firm productivity and internal funds. We then conduct propensity score matching based on a set of covariates that are suggested by the model through which financial frictions may affect MRPK, even in the absence of policy distortions. These covariates are exactly the same as those that appear in the vast theoretical and empirical literature on financial frictions. However, by matching firms that have different treatment status but are otherwise similar in terms of these covariates, we do not have to take a stand on the functional relations among these observed covariates and MRPK; neither do we need to specify the exact causal direction between the treatment status and the observed covariates.

We use a detailed firm-level panel data from China's Annual Industrial Survey to obtain

point effect estimates on the ATT and the SB across different firm ownership. For example, not surprisingly, a state-owned firm on average has an MRPK 42 percent lower than that of a domestic private-owned firm, where policy distortions and financial frictions lower its MRPK by 22 and 20 percent, respectively. More interestingly, the average MRPK of a foreign-owned firm is 2 percent lower than that of a domestic private-owned firm. But without policy distortions, its MRPK would be 20 percent higher than that of a domestic private-owned firm due to financial frictions. This suggests that foreign-owned firms in fact receive similar level of favorable policy distortions as state-owned firms.

Although such estimates are interesting in their own right, what truly helps to answer our research questions is a by-product of the matching procedure – a counterfactual MRPK of those treated firms had they not received the treatment. Using this information, we calculate the aggregate TFP losses in a hypothetical economy without policy distortions, which turn out to vary from 7.3 to 9.4 percent over year 2000 to 2007. Thus our estimates on the effect of financial frictions on aggregate TFP loss are in line with Midrigan and Xu (2014). In contrast, the annual average aggregate TFP loss in the actual economy reaches 27.5 percent. This implies that 70 percent of the aggregate TFP loss can be attributed to policy distortions. We also find that the policy distortions have reduced the average MRPK of China by 15.5 percent, which provides one possible explanation to China’s unusually high investment rate.

This paper also complements a large literature on policy distortions and aggregate TFP. Restuccia and Rogerson (2008) offer a seminal framework to quantify the impact of distortions on aggregate TFP. Hsieh and Kelow (2009) provide an innovative approach to indirectly measure the size of distortions from micro-level data. However, the policy distortions in both papers are only modeled in an abstract and generic way. To offer specific policy implications, it is important to identify specific institutional factors that have distorted capital allocation.

Using matched samples made of firms with balanced covariates, we then evaluate some popular hypotheses on why there are policy distortions in China after all. These hypotheses include that the investment promoting program favors firms (i) contributing more tax revenue, (ii) exporting, (iii) belonging to upstream industries, (iv) having a lower beta and (v) being politically connected with the Communist Party. We find that hypothesis (i) is always rejected; (ii), (iii), and (v) are always confirmed; while (iv) is verified only in earlier years.

The rest of the paper develops as follows. Section 2 outlines a simple model with both policy distortions and financial frictions. Section 3 presents the distribution of MRPK, ownership and firm characteristics and how they are correlated with each other. Section 4 discusses our identification strategy. Empirical findings are reported in Section 5. Section 6 concludes.

2 Model

This section presents a theoretical framework to illustrate how policy distortions and financial frictions may cause capital misallocation. To highlight the implications in a highly heuristic and intuitive way, we start with a static model and leave the dynamic settings to Appendix A. The focus of our analyses is on the transition dynamics and on the intensive margin.⁴ We consider a very general setting. First, financial frictions operate through the channel of financial constraint as usual; however, the frictions are allowed to be firm-specific. Second, policy distortions may affect both the desired capital stock regardless whether the firms are financially constrained or not; and the financial constraint when the firms do raise capital from the external capital market. We show that in this simple model economy, the aggregate TFP loss arising from capital misallocation depends on the joint distribution of a set of parameters, which will be quantified by our empirical exercises.

2.1 Common Assumptions

The firm i receives a stochastic investment opportunity denoted by Z_i . It employs capital K_i and labor L_i to produce heterogeneous products, and competes in the Dixit-Stiglitz type of monopolistic competition environment. This leads to a revenue function

$$R_i = Z_i^{\eta_i} \left(K_i^{\alpha_i} L_i^{1-\alpha_i} \right)^{1-\eta_i},$$

where η_i is the inverse of the demand elasticity and α_i is the capital-output elasticity. Denote w_i as the wage rate. Notice that to account for the potential frictions/distortions in the product market, technology adoption and labor market, the model has allowed the η_i , α_i and w_i all to be firm-specific.⁵

For a given capital stock K_i , the firm chooses variable inputs L_i to maximize its instantaneous gross profits

$$\pi_i = \max_{L_i} \{ R_i - w_i L_i \}.$$

⁴The literature has consensus on the importance of financial frictions on capital misallocation on the extensive margin; and the unimportance of financial frictions on capital misallocation on the intensive margin at the steady state. Whether financial frictions cause large capital misallocation on the intensive margin during transition dynamics is still unclear.

⁵Here we have considered a very general scenario where η_i , α_i and w_i could all be firm-specific. It turns out that, in the solved out model, the firm-specific wage rate w_i does not affect the marginal or average revenue product of capital since it affects both the revenue and the capital in the same way. The firm-specific demand elasticity η_i and output elasticity α_i will cause a difference between the marginal and the average revenue product of capital. Section 3.2.1 discusses our underlying assumptions and empirical strategies to infer marginal revenue product of capital from the average revenue product of capital with firm-specific η_i and α_i .

The solved-out profit function is given by

$$\pi_i = c_i Z_i^{\gamma_i} K_i^{1-\gamma_i}, \quad (1)$$

where

$$\gamma_i \equiv \frac{\eta_i}{\eta_i + \alpha_i(1 - \eta_i)},$$

and

$$c_i = [\eta_i + \alpha_i(1 - \eta_i)] \left[\frac{(1 - \alpha_i)(1 - \eta_i)}{w_i} \right]^{\frac{(1 - \alpha_i)(1 - \eta_i)}{\eta_i + \alpha_i(1 - \eta_i)}}.$$

The first-order condition for optimal choice of labor yields

$$\frac{w_i L_i}{R_i} = (1 - \alpha_i)(1 - \eta_i).$$

It implies that the gross profit is always a constant share of the sales revenue in this model,

$$\frac{\pi_i}{R_i} = \eta_i + \alpha_i(1 - \eta_i). \quad (2)$$

To make the capital investment, firm i effectively pays a firm-specific after-tax capital goods price

$$P_i^K = P^K (1 + \tau_i) = 1 + \tau_i,$$

where P^K is the average capital goods price of the economy and is normalized to unity. τ_i denotes the firm-specific rate of investment tax credit. For example, if $\tau_i = -0.1$, firm i faces favorable distortions and receives a 10 percent subsidy from the government for its investment expenditure.

Besides the investment opportunity, firm i also has an amount W_i of internal funds available for investment. Consider the interesting case when W_i is less than the desired capital stock \tilde{K}_i , where \tilde{K}_i is defined as $\pi_K(Z_i, \tilde{K}_i) = (1 + \tau_i)$. This implies an amount $(K_i - W_i)$ has to be raised externally, via new issues of debt, equity or some other financial claims, where $W_i \leq K_i \leq \tilde{K}_i$ and K_i solves out the optimal investment problem specified below.

2.2 Financial Constraint

There is a wide variety of approaches in modeling financial frictions.⁶ Since the interest of the paper is to quantify the overall effect of various forms of financial frictions on capital misallocation, we consider two highly synthesized reduced-form models according to their nature on

⁶Stein (2003) and Sannikov (2012) provide useful surveys for the microfoundations of financial frictions and their implications to corporate finance. Brunnermeier et al., (2012) survey the macroeconomic implications of financial frictions.

the constraint – a cost constrained model and a quantity constrained model. These models are by no means to exhaust all possible mechanisms of financial frictions. Nevertheless, they do encompass those microfoundations that have been the most common building blocks of the recent literature on financial frictions and aggregate TFP.

2.2.1 A Cost Constrained Model

In a typical cost constrained model, there is a deadweight cost associated with using external financing. This makes issues of financial claims unattractive at some point, although the amount of new issues is effectively not limited. Assume that the cost function of external financing takes the form of $\theta_i \Lambda(K_i, W_i)$, where $\Lambda_K > 0$, $\Lambda_{KK} > 0$, $\Lambda_W < 0$ and $\Lambda_{KW} < 0$. Stein (2003) demonstrates that this simple reduced-form cost constraint model can be mapped precisely into a variant of the Townsend (1979) costly state verification model; and a re-parameterized Myers and Majluf (1984) adverse selection model can lead to essentially the same reduced form. Asymmetric information, and in particular costly state verification, has been widely applied to a large group of macro literature on financial frictions.⁷

The costly external financing model implies the following optimization problem

$$\max_{K_i} V_i = \pi(Z_i, K_i) - (1 + \tau_i) K_i - \theta_i \Lambda(K_i, W_i),$$

whose first-order condition is given by

$$\pi_K(Z_i, K_i) = (1 + \tau_i) + \theta_i \lambda(K_i, W_i), \quad (3)$$

where $\theta_i \lambda(K_i, W_i) \equiv \theta_i \Lambda_K(K_i, W_i) > 0$ is the marginal cost of external financing, with $\lambda_K > 0$ and $\lambda_W < 0$.

The firm-specific cost parameter θ_i measures the degree of financial frictions facing firm i . For example, all else being equal, an older and larger firm has a smaller θ_i , which captures the empirical regularity that older and larger firms pay a lower cost in issuing financial claims. Meanwhile, θ_i may also depend on the extent of policy distortions operating on firm i . For example, all else being equal, some institutional arrangements grant a policy favored firm a lower cost to access the capital market. Without loss of generality, denote $\theta_i = \theta(\theta_i^f, \theta_i^p)$, where θ_i^f and θ_i^p represent those firm-specific factors operating through financial frictions and policy distortions, respectively, in determining the cost of external financing facing firm i .

⁷For example, Bernanke and Gertler (1989), Castro et al. (2009), Greenwood et al. (2010), Greenwood et al. (2013) and Cole et al. (2015).

2.2.2 A Quantity Constrained Model

In a typical quantity constrained model, firms issue financial claims at the market-prevailing rate of return, but the amount of new issues is limited to a certain point. Assume the quantity constraint takes the form of $K_i - W_i \leq (1 - \phi_i) K_i$, where $0 \leq \phi_i \leq 1$. As surveyed in Brunnermeier et al. (2012), this simple collateral constraint is consistent with the limited pledgeability assumption as in Hart and Moore (1994). In the extreme case where $\phi_i = 1$, firm i faces a credit rationing as in Stiglitz and Weiss (1981). Most of the existing macro literature on financial frictions has either explicitly or implicitly adopted this form of financial constraint.⁸

The optimization problem of the firm is now

$$\max_{K_i} V_i = \pi(Z_i, K_i) - (1 + \tau_i) K_i,$$

subject to the quantity constraint

$$K_i - W_i \leq (1 - \phi_i) K_i.$$

Define $\mu(Z_i, W_i) > 0$, the Lagrangian multiplier associated with the quantity constraint, where $\mu_Z > 0$ and $\mu_W < 0$. The first-order condition for the optimal capital investment is given by

$$\pi_K(Z_i, K_i) = (1 + \tau_i) + \phi_i \mu(Z_i, W_i). \quad (4)$$

The microfoundations of the quantity constrained model imply that the firm-specific constraint parameter ϕ_i is a natural function of the pledgeability of the firm's assets or the volatility level of the firm's revenue. At the same time, a firm with favorable policy distortions may also face a smaller ϕ_i , for example, when the political connection serves as an additional implicit collateral. ϕ_i can therefore be written as $\phi_i = \phi(\phi_i^f, \phi_i^p)$, where ϕ_i^f and ϕ_i^p represent those firm-specific factors operating through financial frictions and policy distortions, respectively, in determining the quantity constraint facing firm i .

2.3 Capital Misallocation and Aggregate TFP

To highlight the sources of capital misallocation, we rewrite the equations (3) and (4) as follows:

$$\begin{aligned} MRPK_i &\equiv \pi_K(Z_i, K_i) = (1 + \tau_i) + \theta_i \lambda(K_i, W_i) \equiv UC_i \\ MRPK_i &\equiv \pi_K(Z_i, K_i) = (1 + \tau_i) + \phi_i \mu(Z_i, W_i) \equiv UC_i \end{aligned}$$

⁸Leading examples include Kiyotaki and Moore (1997), Banerjee and Duflo (2005), Jeong and Townsend (2007), Buera et al. (2011), Buera and Shin (2013), Caselli and Gennaioli (2013), Midrigan and Xu (2014) and Moll (2014).

where the left hand side of the equations are the MRPK of firm i , and the left hand side are its generalized user cost of capital. Thus despite different forms of financial constraint, these two types of model essentially deliver the same implications on capital misallocation: a firm's optimal investment will always equalize its MRPK with its generalized user cost of capital, while the latter depends on both the policy distortions $(\tau_i, \theta_i^p, \phi_i^p)$ and the financial frictions (θ_i^f, ϕ_i^f) facing the firm, and the state of productivity and internal funds with the firm (Z_i, W_i) .

Under the first-best allocation, there would be neither frictions nor distortions so that $\tau_i = \theta_i = \phi_i = 0$. Optimal investment guarantees equalized MRPK across all firms given that $MRPK_i = 1$, the normalized capital goods price, for each firm i .

In contrast, in the presence of financial frictions and policy distortions, the actual allocation depends on the firm-specific generalized user cost of capital, which is determined by some joint distribution $G(\tau_i, \theta_i^p, \phi_i^p, \theta_i^f, \phi_i^f, Z_i, W_i)$. With a large number of firms, the aggregate TFP loss can be approximated as proportional to the variance of the logarithm of the $MRPK_i$, which is a function of G in our model economy:

$$\Delta \log TFP = \frac{1}{2} \frac{\alpha(1-\eta)(1-(1-\alpha)(1-\eta))}{\eta} Var(\log MRPK_i),$$

where η and α are respectively, the average values of the inverse of the demand elasticity and the capital-output elasticity.

3 Data

This section presents the distribution and correlation of the MRPK, firm ownership and a set of firm characteristics in the data. The MRPK is the ultimate variable of our interest. We provide strong evidence on why firm ownership in China can be taken as the treatment status of an investment promoting program. We also discuss the rationale in choosing a set of firm characteristics through which financial frictions may affect MRPK. All together, they motivate the identification strategy discussed in Section 4.

3.1 China's Industrial Survey

Our empirical exercises are based on a detailed firm-level panel data. It comes from the China's Industrial Survey conducted by the National Bureau of Statistics on a yearly base. The survey includes all industrial firms that are identified as state-owned or as non-state-owned firms with sales revenue above RMB 5 million. These firms account for about 90 percent of the total

industrial output in China.⁹

The survey contains basic firm identify information, such as industry, location and birth year, and values of input and output, based on which Hsieh and Klenow (2009) and Song and Wu (2017) quantify the resource misallocation and the aggregate TFP loss in China. In addition, the survey also reports detailed information from the income statement and the balance sheet. Such information allows us to construct a set of key variables which will serve our identification strategy and shed light on policy distortions.

Given that the interest of this paper is on the intensive margin, and that some firm-specific characteristics have to be estimated from a relatively long time-series, we only focus on those existing and ongoing firms. This yields a sample covering 12829 firms and spanning from year 1998 to 2007. Although our identification *per se* is from the cross-sectional variation, using a balanced panel will allow us to explore how the effects of financial frictions and policy distortions have been evolving over time. Appendix E also further explores the panel structure of the data to test the validity of the identification conditions.

3.2 MRPK

3.2.1 Controlling for Other Frictions or Distortions

Although the dispersion of MRPK is a sufficient statistic for the capital misallocation in our model economy, there is a practical difficulty in bringing the model to the data – we don't observe the MRPK directly from the data. The literature has often utilized the revenue-to-capital ratio or the average marginal revenue product of capital (ARPK), which is directly observed from the data, as a proxy for MRPK. In our model, for any firm i and year t , the linear relationship between MRPK and ARPK can be established as:

$$MRPK_{i,t} \equiv \frac{\partial R_{i,t}}{\partial K_{i,t}} = \alpha_i (1 - \eta_i) \frac{R_{i,t}}{K_{i,t}} \equiv \alpha_i (1 - \eta_i) ARPK_{i,t}. \quad (5)$$

Equation (5) highlights the fact that ARPK will be a valid proxy for MRPK in inferring aggregate TFP loss only if $\alpha_i (1 - \eta_i)$ is common across firms, which may not be true in general due to the firm-specific α_i and η_i . For example, some firms might be more capital intensive due to frictions/distortions in technology adoption; other firms might have more market power due to product market frictions/distortions. To rule out these alternative frictions/distortions, we adopt the following strategy.

⁹Brandt et al. (2012) provide an excellent description on the survey and implement a series of consistency checks between the firm-level data and the aggregated industry-level data reported in China Statistic Yearbooks. We implement the same procedure as in Song and Wu (2015) to clean the data and construct the variables.

Taking log on both sides of equations (2) and (5), and applying a first-order Taylor expansion for $\log \alpha_i (1 - \eta_i)$ around $\log (\eta_i + \alpha_i (1 - \eta_i))$, we derive an approximation for $\log MRPK_{i,t}$,

$$\log MRPK_{i,t} \simeq \log ARPK_{i,t} + \log \frac{\pi_{i,t}}{R_{i,t}} - \eta_i \frac{R_{i,t}}{\pi_{i,t}}.$$

We then obtain an estimate for $\log MRPK_{i,t}$ as the residual from the following regression:

$$\log ARPK_{i,t} = a_0 + a_1 \cdot \log \frac{\pi_{i,t}}{R_{i,t}} + a_2 \cdot \frac{R_{i,t}}{\pi_{i,t}} + a_3 \cdot CIC4d_{i,t} + a_4 \cdot PROVINCE_{i,t} + \xi_{i,t}, \quad (6)$$

where $\log ARPK_{i,t}$ is the logarithm of revenue-to-capital ratio; $\log \frac{\pi_{i,t}}{R_{i,t}}$ is the logarithm of profit-to-revenue ratio; $\frac{R_{i,t}}{\pi_{i,t}}$ is the inverse of profit-to-revenue ratio; and $CIC4d_{i,t}$ and $PROVINCE_{i,t}$ include the four-digit industry dummies and province dummies, respectively. There are two implicit assumptions for the residual from equation (6) to be a good proxy for $\log MRPK_{i,t}$. First, firms within narrowly defined industries (there are 490 four-digit industry dummies) and provinces (there are 30 province dummies) share the same production technology so that $a_3 \cdot CIC4d_{i,t} + a_4 \cdot PROVINCE_{i,t}$ controls for firm-specific capital-output elasticity α_i . Within these narrowly defined industries and provinces $a_1 \cdot \log \frac{\pi_{i,t}}{R_{i,t}} + a_2 \cdot \frac{R_{i,t}}{\pi_{i,t}}$ controls for firm-specific inverse of demand elasticity η_i . Second, with a relatively short panel, it is not possible to infer a firm-specific η_i from equation (6) using heterogeneous panel techniques. Thus we do not impose any restrictions on a_1 and let a_2 to capture the average effect of η_i .

Under these two assumptions, there are two advantages with this measure of $\log MRPK_{i,t}$. First, it has properly controlled for heterogeneities in production technology and market power more than most of the works in the literature. Hence it only reflects the firm-specific user cost of capital, a quantity of our true interest. Second, as the residual from a regression, it naturally has a zero sample average. Hence the value itself provides an intuitive economic implication. For example, if $\log MRPK_{i,t} = -0.25$, the MRPK of firm i in year t is 25% lower than the average MRPK in the economy of that year. One potential downside of this measure, of course, is the functional form assumption imposed in the model. If one believes that the misspecification could be a more severe concern than heterogeneity, he may prefer using $\log ARPK_{i,t}$ to $\log MRPK_{i,t}$. In Appendix D, one of our empirical exercises also employs $\log ARPK_{i,t}$ as the outcome variable as a robustness check. We find stronger average effects for both policy distortions and financial frictions, but the relative importance is very similar to the benchmark case in using $\log MRPK_{i,t}$.

3.2.2 Empirical Distribution of MRPK

Row (3) of Table 1 reports the variance of $\log MRPK_{i,t}$ over our sample period. As expected, one salient feature of this data is the large dispersion in $\log MRPK_{i,t}$. If $\alpha = 1/3$ and $\eta = 0.15$, standard values imposed by the literature, such as Midrigan and Xu (2014) and Gilchrist et al. (2013), with an average variance of $\log MRPK_{i,t}$ around 0.71 across years, the aggregate TFP loss in China is about 29 percent due to capital misallocation. Furthermore, although the dispersion gradually declines over time from 1998 to 2003, it has been rather persistent since 2004. Explaining what has been causing such large and persistent capital misallocation is the ultimate goal of this paper.

<Insert Table 1 here>

As a comparison, row (1) and (2) in Table 1 also presents the variance of $\log ARPK_{i,t}$ calculated using all the firms from the industrial survey and firms from our balanced panel only. Thus the difference between row (2) and (3) highlights the existence and importance of firm-specific production technology and market power. Had we not controlled for such heterogeneities, we would overestimate the aggregate TFP loss by 13 percent, a point emphasized in Song and Wu (2017). The difference between row (1) and (2) indicates that in addition to the intensive margin, there is also a substantial aggregate productivity loss via the extensive margin, a consensus of the recent misallocation literature.

3.3 Ownership

3.3.1 Ownership as a Proxy for Policy Distortions

We refer those non-market factors that are induced by rules, regulations and institutions and will cause a dispersion in MRPK as policy distortions, which are captured by firm-specific parameters $(\tau_i, \theta_i^p, \phi_i^p)$ in our model. Of course, there are so many factors which one might reasonably imagine to fall into this category that it is nearly infeasible to quantify the importance for each of them. However, one well-known institutional feature in China is that most of such factors may work through firm ownership. For example, compared with other ownership type firms, a state-owned firm may receive low interest rate loans from the state-owned banking system and have easier access to the highly-regulated stock market. A firm whose contributed capital comes from outside mainland China may enjoy special investment tax breaks and subsidies when it brings in foreign direct investment. Inspired by the indirect approach as discussed in Restuccia and Rogerson (2013), we thus take ownership as a proxy

for the bundle of policy distortions and ask to what extent firm ownership can explain capital misallocation in China.

3.3.2 Definition of Ownership

This strategy implies the importance of a reliable definition for firm ownership. The China's Industrial Survey provides firm ownership with two different sources. First, the basic firm identity section records the ownership type according to registration. Second, the balance sheet breaks down a firm's total contributed capital into shares from different owner's types (state, collective, domestic private individual, investors from Hong Kong, Macau and Taiwan, foreign investors and legal person). Cross checking using both sources indicates that the actual ownership does not always correspond to the registered ownership. For example, some firms that registered as collective-owned are effectively wholly owned by domestic private individuals. There are also some firms that are registered as Hong Kong, Macau and Taiwan or foreign-owned, but more than 50 percent of their contributed capital in effect comes from domestic private individuals. A similar pattern of inconsistency is also found in Dollar and Wei (2007). For these reasons we define ownership of a firm according to its owner's type for the majority contributed capital. Results in which ownership is defined according to registration are reported as a robustness check in Appendix D.

By this criterion, there are six mutually exclusive ownership groups, namely state-owned firms (SOEs), collective-owned firms (COEs), domestic private-owned firms (DPEs), Hongkong, Macau and Taiwan-owned firms (HMTs) and foreign-owned firms (FIEs), if share of contributed capital from the corresponding owner's type is larger than 50 percent, together with mixed ownership (MIXs), if none of the owners contributes more than 50 percent of capital.

<Insert Table 2.1 here>

Table 2.1 displays the proportion of firms under each ownership group over our sample period. On one hand, the proportion of HMTs and FIEs are relatively stable. On the other hand, consistent with the national-scale privatization from late 1990s to early 2000s, the proportion of SOEs and COEs has been sharply declining over time while more and more firms become DPEs and MIXs.

3.3.3 Ownership and MRPK

Table 2.2 shows the results for a regression of $\log MRPK_{i,t}$ over ownership dummies, where DPE is taken as the baseline group. Consistent with the literature, such as Dollar and Wei

(2007) and Brandt et al. (2013), firms in China with different ownership are found to have significantly different level of $\log MRPK_{i,t}$. Recall that the MRPK is a mirror image of the user cost of capital. The regression thus suggests that all else being equal, a SOE on average has a user cost of capital 45.5% lower than a DPE, while the user cost of capital for HMTs, FIEs, COEs and MIXs are in the middle of the rank with an increasing magnitude.

<Insert Table 2.2 here>

The significant role of ownership has been often taken as a direct evidence of policy distortions, for example Liu and Siu (2012). After all, ownership of a firm shouldn't matter in a world without policy distortions, had firms with different ownership been completely comparable in other characteristics. However, firms with different ownership do differ in other characteristics, through which financial frictions may lead to different MRPK even in the absence of policy distortions.

3.4 Firm Characteristics

3.4.1 Measures on Financial Frictions

We refer those market forces that are driven by the capital market imperfections and will cause a dispersion in MRPK even in the absence of policy distortions as financial frictions. Our theoretical framework predicts heterogenous MRPK due to firm-specific parameters on financial constraint (θ_i^f, ϕ_i^f) and state variables (Z_i, W_i) .

An important theme of corporate finance is to examine how various frictions in raising external capital can generate financial constraints for firms. The vast majority of the empirical literature is explicitly or implicitly based on the cost constrained model. This literature has been prolific in developing possible measures on the severity of financial constraints. They include investment-cash flow sensitivities, the Kaplan and Zingales index of constraints, the Whited and Wu index of constraints, and a variety of different sorting criteria based on firm characteristics, such as payout ratio, leverage, financial slack, and bond rating.

To address the considerable debate with respect to the relative merits of each approach, Hadlock and Pierce (2010) provide an evaluation on some most commonly used measures in the literature. Their findings either cast doubt or offer mixed evidences on the validity of such measures due to the endogeneity problem. Instead, they find firm size and age, two relatively exogenous firm characteristics, are particularly useful and robust predictors of financial constraint levels, and therefore recommend a measure solely on firm size and age. Following their suggestions, we use firm age, according to the number of years since birth, and firm size,

according to number of employees, as proxies for θ_i^f . Using an alternative measure of firm size which is based on total assets delivers very similar results. See Appendix D.

Another strand of the empirical literature that is consistent with the quantity constrained model focuses on the assets pledgeability, such as Benmelech et al. (2005), Gan (2007) and Almeida and Campello (2010). This literature finds that firms with more pledgeable assets have higher collateral value and face less severe constraint, where pledgeable assets are those assets that are more redeployable and have higher market values on liquidation. We follow Berger et al. (1996) to construct a firm-specific measure on assets pledgeability, which is cash holdings + $0.715 \times$ receivables + $0.547 \times$ inventory + $0.535 \times$ physical capital, scaled by total assets. An alternative measure of pledgeability is the ratio of tangible assets to total assets. Appendix D shows that using such measure produces almost the same results.

To nest the economic rationale of credit rationing, we also include a firm-specific measure on the volatility level of the firm’s revenue. Stiglitz and Weiss (1981) show that if there are multiple observationally distinguishable firms, those firms with high volatility are more likely to be ‘red lined’. Appendix B explains how we may back out such measure using the standard deviation of within-group real revenue growth rate. Thus the pledgeability of assets and the volatility of revenue are employed as proxies for ϕ_i^f .

The proxies for the two state variables are more straightforward. Following the empirical literature on corporate finance, we use the real revenue growth rate to proxy the investment opportunity Z_i and the difference between total assets and total liabilities scaled by total assets to proxy the net worth W_i . A common alternative measure of net worth in the literature is cash flow to capital stock ratio. A robustness check is implemented in Appendix D and generates almost the same results.

To sum, we come up with a set of firm characteristics through which financial frictions may affect MRPK. They include firm age, size, pledgeability, volatility, revenue growth and net worth. While we cannot prove that this set of characteristics is complete or exclusive in measuring the importance of financial frictions, it has many advantages, including its intuitive appeal, its solid theoretical foundations, and its consistency with the extensive empirical evidences. In Appendix D we deduct some of the characteristics and add additional characteristic to check the robustness of our findings in using this particular set of variables.

3.4.2 Ownership and Firm Characteristics

Table 2.3 presents the mean value for these firm characteristics for the whole sample and by ownership groups. On average, firms in our sample are 17.4 years old and have 419 employees.

However, there is a considerable heterogeneity across different ownership in terms of age and size. While domestic firms are nearly 20 years or even older, HMTs and FIEs are only about 10 years old. SOEs, HMTs and FIEs are of a size of more than 500 employees on average while COEs and DPEs have less than 300 employees. With respect to revenue volatility and asset pledgeability, the difference across ownership groups is much less obvious. On average the standard deviation of within-group real revenue growth rate is 0.257 and the pledgeability is 0.62. The growth rate and net worth also witness substantial heterogeneities across ownership. As a whole the real revenue of these firms grows at 8 percent annually, but the growth rate varies from 9.7 percent for DEPs to 5.6 percent for HMTs. The mean value of net worth is around 43 percent. HMTs and FIEs have a net worth more than 50 percent, while this ratio is below 40 percent for the domestic firms.

<Insert Table 2.3 here>

A simple comparative static analysis for equations (3) and (4) predicts on how each of these firm characteristics may affect the financial constraint and hence the MRPK. All else being equal, a firm, such as DPE, that is young, small, with high volatility and low pledgeability, grows fast and has low net worth tends to face more severer financial constraint and have a higher level of MRPK. And a firm, such as SOE, with opposite characteristics will face less severer financial constraint and have a lower level of MRPK. The systematic correlation between ownership and firm characteristics highlighted in Table 2.3 implies that the differences in MRPK across ownership should not be taken solely as a result of policy distortions. On the one hand, if such firm characteristics are exogenous to policy distortions, financial frictions may cause a dispersion in MRPK even in the absence of policy distortions. On the other hand, if such firm characteristics are themselves affected by policy distortions, the effect of policy distortions may be exacerbated or mitigated by the presence of financial frictions.

4 Identification

4.1 The Evaluation Problem

Given that ownership appears in categorical form, and the firm characteristics are correlated with both MRPK and ownership, the methodology of program evaluation provides a natural setup to design the identification. To employ this methodology, we first structure the observational data as if they have arisen from a particular policy intervention. The policy promotes investment by offering favorable treatment to those firms that satisfy certain criteria. The exact criteria are not specified here but will be investigated in Section 5. However, the strong

association between ownership and MRPK found in Table 2.2 suggests that ownership can be taken as a useful proxy for the treatment status. Given that the DPEs have the highest MRPK, we take them as the control group, which does not receive any favorable treatment from the intervention. SOEs, COEs, HMTs, FIEs and MIXs are taken as the multiple treatment groups, which receive favorable treatment with different levels of strength. Appendix D shows that using alternative choices on the control and treatment groups delivers almost the same results.

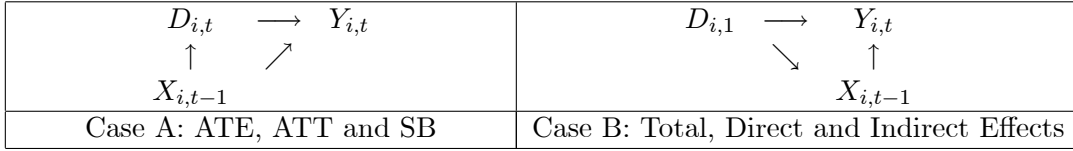
Let $D_{i,t}$ denote the observed treatment status, where $D_{i,t} = 0$ if firm i in year t is untreated (ownership = DPE) and 1 if treated (ownership = other types). Define $Y_{i,t}^1$ and $Y_{i,t}^0$ as the potential treated and untreated outcome, which in our application, correspond to the potential log $MRPK_{i,t}$ if firm i in year t receives or does not receive the treatment. The observed outcome is thus $Y_{i,t} \equiv D_{i,t}Y_{i,t}^1 + (1 - D_{i,t})Y_{i,t}^0$. Finally, label $X_{i,t}$ as the set of observed firm characteristics, or the covariates in the terminology of program evaluation. In the following, subscript i, t is often omitted to simplify presentation.

4.2 Two Possible Causal Chains

Following Lee (2005), Figure 1 illustrates two possible causal chains between D , X and Y , where each arrow means ‘causing’ or ‘affecting’. In case A, the set of pre-treatment firm characteristics X is a ‘common factor’ for D and Y . On the one hand, X affects Y due to financial frictions. On the other hand, X may simultaneously affect the treatment status D . For example, it is well-known that the reform of the state-owned enterprises from late 1990s to early 2000s has followed a strategy called ‘grasp the Large, and let go of the small’ (Hsieh and Song, 2014). This implies that the single most important determinant for the treatment status could be firm size, one of the covariates in X . If the arrow between D and Y were removed, there would be no causal effect from D to Y . However, Y could still be different across the control and treatment groups, if X are unbalanced between the two groups. To estimate the causal effect from D to Y , we have to control for X .

In case B, D affects Y both directly as well as indirectly through X . For example, a favorable policy intervention in the form of an investment tax credit directly reduces the user cost of capital or Y . With a lower user cost of capital, the desired capital stock of those treated firms increases. This implies all else being equal treated firms will on average have larger firm size. But firm size is one of the covariates in X , which will also affect Y through the channel of financial frictions. Since X itself is the outcome of D , controlling for X will show the net effect of D on Y .

Figure 1. Possible Causal Chains between D , X and Y



A familiar analogy to case A is the evaluation on a job training program, such as in Dehejia and Wahba (1999).¹⁰ To employ this evaluation framework, we conceptualize our data as if in every year t , firm i is selected into either the control or the treatment group $D_{i,t}$ according to $X_{i,t-1}$, its pre-treatment characteristics in year $t - 1$. And those who are allocated into the treatment group receives a favorable policy treatment in year t . In this case, the effect of policy distortions and financial frictions on the average MRPK dispersion across firm ownership can be transformed into the average treatment effect on the treated and the selection bias, respectively.

The causal chain in case B is similar to the one used for analyzing gender wage gap, such as in Nopo (2008).¹¹ To use this setup, we restrict our sample to those firms with constant ownership throughout our sample period so that the observed firm characteristics $X_{i,t-1}$ will be the consequence rather than the cause for treatment status $D_{i,1}$. In this case, the total effect of the policy intervention on $Y_{i,t}$ can be decomposed into a direct effect and an indirect effect, which correspond to the effects of policy distortions and financial frictions on the average MRPK dispersion across firm ownership, respectively. Since the two causal chains share the same identification conditions and estimation approach, we take case A as the benchmark and present case B as an alternative design in Appendix E.

4.3 ATT and Selection Bias

Estimating the effect of policy distortions on capital misallocation is now transformed into evaluating the effectiveness of this policy intervention. We ask ‘on average how much has the MRPK of those firms receiving the favorable treatment been reduced compared to what their MRPK would have been without receiving the treatment’. The answer is the so-called average treatment effect on the treated,

$$ATT \equiv E(Y^1 - Y^0 | D = 1).$$

¹⁰The fact that the average post-training earnings of the treated are lower than the controls does not necessarily imply the ineffectiveness of a job training program. This is because those with poorer labor market characteristics are more likely to choose to join the training program. Even in the absence of the training, they would have lower earnings than those who don’t receive the training, due to their differences in the labor market characteristics.

¹¹The fact that women are paid substantially lower wages than men may be the result of wage discrimination in the labour market. However, part of this wage gap may be also due to differences in education, experience and other skills, whose distribution differs between men and women.

The fundamental problem of causal inference arises because $E(Y^0|D = 1)$, the average counterfactual MRPK for those treated, is not observed. Instead, we observe a corresponding quantity for the untreated $E(Y^0|D = 0)$. The regression in Table 3, which compares the difference in the observed MRPK between those treated and untreated, effectively computes the average treatment effect,

$$ATE \equiv E(Y^1|D = 1) - E(Y^0|D = 0).$$

The ATE and ATT are in general not equal to each other due to the presence of selection bias,

$$ATE = ATT + SB,$$

where the selection bias is the difference between the average counterfactual MRPK of those firms who receive the treatment and the average observed MRPK of those who don't, had there been no policy intervention at all,

$$SB \equiv E(Y^0|D = 1) - E(Y^0|D = 0).$$

In the context of our application, selection bias arises because X , the firm characteristics of the treated and untreated are different. Therefore even in the absence of policy intervention, the average MRPK of those treated and untreated could have been different, due to the effect of financial frictions. This implies that by design the selection bias captures the effect of financial frictions on the average MRPK dispersion across firm ownership.

4.4 Propensity Score Matching

We adopt the propensity score matching, a widely used method for causal inference in observational studies, to estimate the quantities of our interest. Matching has been a popular method in labor, health and development economics. It also started to appear in many other areas of economics, such as international economics (Chang and Lee, 2011), monetary economics (Angrist and Kuersteiner, 2011) and financial economics (Campello et al., 2010). The basic idea in our application is to impute the missing counterfactual MRPK for those firms who are treated by finding other firms in the data whose covariates are similar but who are untreated. In other words, those untreated firms serve as the ‘matchers’ to those treated firms but with similar covariates. Then the observed difference in average MRPK between those matched firms gives the ATT. Appendix C presents this idea formally under the assumption of conditional independence and common support.

4.5 Matching Versus Regression

Consider a straightforward regression analysis that regresses the MRPK on ownership dummy and firm characteristics, for example, $Y_i = \alpha_0 + \alpha_1 D_i + \alpha_2 X_i + \varepsilon_i$. Matching makes the same main identification assumption, i.e. conditional independence, as OLS on the usual exogeneity assumption $\varepsilon_i \perp D_i | X_i$. However, propensity score matching has three obvious advantages compared with OLS, which are particularly important in our application.

First, the additional common support condition focuses on comparison of comparable firms. Our empirical exercises do find the non-overlapping problem in the data, which would be masked by a regression analysis. Second, by conditioning on X , we do not need to model the structural relationship between X and Y and avoid the potential misspecification bias that may arise in a parametric approach. Finally, matching allows for the effects of policy intervention to be heterogeneous across firms and over years conditional on characteristics X in arbitrary ways.

5 Results

5.1 Implementation of Propensity Score Matching

To explain how we implement the propensity score matching approach to obtain the estimates reported in Table 4, we use DPE as the control group, SOE as the treatment group and year 2000 as an illustration. Results for other ownership types and other years are available upon request.

Since the true propensity score is unknown, the first step is to estimate it using a Probit model. The choice of the functional form in the Probit model makes the propensity score matching semi-parametric. Table 3.1 reports the regression results. All else being equal, a firm that is larger, older, with lower growth rate and higher net worth is more likely to be an SOE. We experiment with alternative functional forms by adding higher order terms and interaction terms of the covariates. The resulting propensity score and the estimated ATT are essentially the same.

<Insert Table 3.1 here>

In the second step, we use kernel as the matching algorithm to match the untreated firms to treated firms using the estimated propensity scores and impose the common support restriction. Table 3.2 summarizes the firms off and on support. In year 2000, there are 2,558 DPEs and 1,667 SOEs with non-missing score. Since the score for 19 SOEs is higher than the maximum or lower than the minimum propensity score of the DPEs, we discard these 19 observations.

<Insert Table 3.2 here>

The third step is to check whether the matching has built a good control group. A necessary condition of conditional independence requires that after matching the mean values of the covariates should not be significantly different across the control and treatment groups. Table 3.3 reports the mean values of the six covariates before and after the matching and the corresponding bias reduction. According to the test statistics of the biases, before matching the mean value of each covariate is significantly different across the DPEs and the SOEs. However, after matching on average the treated and untreated firms are no longer significantly different in any of these covariates.

<Insert Table 3.3 here>

Finally, we calculate the ATE and the ATT, key estimates of our interest. Table 3.4 presents the results. Before matching, the average MRPK of the SOEs is 47.0 percent lower than that of the DPEs. After matching, the difference is narrowed down to 19.2 percent but remains to be statistically significant.

<Insert Table 3.4 here>

The difference between the ATE and ATT gives the effect of SB, which means the MRPK of the SOEs would be 27.8 percent lower than DPEs even in the absence of policy distortions. Consistent with the predictions of the financing constraint model in Section 2, and as revealed in Table 3.3, this is because SOEs are on average older and larger (lower θ_i^f), and having a lower volatility (lower ϕ_i^f), a lower growth rate (lower Z_i) and a higher net worth (higher W_i).

5.2 Point Estimates for ATT and SB

Table 4 summarizes the yearly point estimates for the ATT and the SB from year 2000 to 2007.¹² The effects listed under columns SOE, COE, HMT, FIE and MIX are obtained by using DPE as the control group and each corresponding ownership as the treatment group, respectively. The combined effects where all other ownership types are taken together as the treatment group are listed in the last column.

<Insert Table 4 here>

¹²Our sample period spans from 1998 to 2007. Calculating revenue growth rate sacrifices one year of observations and using lagged values to measure pre-treatment firm characteristics sacrifices another.

Not surprisingly, the ATEs are negative across all the columns. This implies that on average all the non-DPEs have a lower MRPK than that of DPEs, a pattern that we have seen in Table 2.3 but is once again confirmed under the common support restriction. Recall that the ATE can be decomposed into the ATT and the SB, which capture the effects of policy distortions and financial frictions. Interestingly, the decomposed effects are very heterogeneous across different columns. When SOE is taken as the treatment group, $ATT = -0.22$ and $SB = -0.20$ averaging across the 8 years. This means even in the absence of policy distortions, financial frictions will cause the MRPK of the SOEs to be 20 percent lower than that of the DPEs, due to the advantageous firm characteristics of SOEs. The policy distortions cause the MRPK of the SOEs to be 32 percent further lower than that of the DPEs, so that the observed MRPK differences between SOEs and DPEs are enlarged to 42 percent. Although we don't detect significant ATT in the case when COE is taken as the treatment group, we do obtain negative and significant SB. In other words, within the domestic firms, policy distortions are not fully responsible for the observed MRPK dispersion, because the capital market also fails to allocate capital to the first-best due to the presence of financial frictions.

The patterns of the estimates are strikingly different when the treatment groups are HMT, FIE and MIX. Take the column of HMT as an example. Averaging across the 8 years, we estimate that $ATE = -0.06$, $ATT = -0.24$ and $SB = 0.18$. This implies that had there been no policy distortions, the MRPK of HMTs would have been 18 percent higher than that of DPEs due to the differences in their firm characteristics through which financial frictions operate. However, since HMTs receive a large favorable policy intervention which dominates the effect of financial frictions, the observed MRPK of HMTs turns out to be 6 percent lower than that of DPEs. The opposite signs between the ATT and the SB are also found when the treatment groups are FIE and MIX.

The negative ATE when HMT and FIE are taken as the treatment groups implies that DPEs do face higher user cost of capital, which is consistent with the typical findings of the corporate finance literature on Chinese firms. However, it is indeed one of the contributions of this paper to disentangle financial frictions from policy distortions, the two fundamental causes of capital misallocation. The large and negative ATT when HMT and FIE are taken as the treatment groups indicate that these two type of firms receive strong favorable policy distortions. This interesting finding is consistent with the external evidences that investment from HMT and FIE is categorized as FDI. Under the regional GDP yardstick competition, local Chinese governments may use taxes and subsidies as effective tools in attracting FDI (Xu, 2011).

The large and positive SB when HMT and FIE are taken as the treatment groups indicate that these two type of firms would be more financially constrained than DPE if there had been no policy distortions. This new finding is internally consistent with the firm characteristics listed in Table 2.3. First, HMT and FIE are the youngest among all type of firms. This implies that they face the highest cost of external finance according to the costly-state-verification rationale. Second, HMT and FIE have accumulated highest net worth among all type of firms. Notice that different from other firm characteristics, which are exogenous to a large extent, net worth is an endogenous state variable, which depends on firm’s optimal consumption-investment decision. According to equation (A.1), if a firm faces persistently higher cost of external finance, it would be optimal for the firm to accumulate more internal funds as a self-financing device to undo the constraints, a mechanism highlighted in Midrigan and Xu (2014) and Moll (2014).

Recall that in our model economy, policy and market are two alternative mechanisms of capital allocation. Comparison of the ATT across different groups indicates that the policy has a clear preference in allocating capital, with an ascending order from DPEs to COEs, MIXs, FIEs, HMTs and SOEs. However, comparison of the SB implies that the capital market alone would treat these firms very differently. If the capital market were the only mechanism in allocating capital, for the given firm characteristics, it would charge a user cost of capital in a descending order from FIEs, to HMTs, MIXs, DPEs, COEs and SOEs.

5.3 Financial Frictions and Aggregate TFP Loss

The point estimates in Table 4 illustrate the effects of policy distortions and financial frictions in explaining the observed differences in the first moment of MRPK across different ownership groups. To seek for the contribution of policy distortions and financial frictions in generating capital misallocation and causing aggregate TFP loss, we need to look at the second moment of MRPK across the whole sample. Row (4) of Table 1 lists the variance of $\log MRPK_{i,t}$ for the factual economy, calculated for all the firms that are on the common support, i.e. $Var(Y_{i,t})$. The differences between row (3) and (4) highlight the importance of comparing only comparable firms. Since it is not possible to find the counterfactuals for some extreme firms in the treatment groups, we rule out these firms in calculating the variance.

Row (5) of Table 1 lists the variance of $\log MRPK_{i,t}$ for the hypothetical economy, in which there is no policy distortion in year t , i.e. $Var(Y_{i,t}^0)$. For those firms that are in the control group, the counterfactual and factual MRPKs are the same; for those firms that are in the treatment groups, we impute their missing counterfactual MRPK using the factual

MRPK of those matched controls, a by-product of the propensity score matching procedure. Row (5) thus tells how large the variance of $\log MRPK_{i,t}$ would be, had there been no policy distortions. Notice that in this hypothetical economy, capital market is the only mechanism in allocating capital. Therefore if there is no model misspecification and no measurement error in data, row (5) gives the effect of financial frictions on capital misallocation. The differences between row (4) and (5) then yield the additional capital misallocation as a consequence of policy distortions, which is documented in row (6).

Averaging across years, the variance of $\log MRPK_{i,t}$ in row (4), (5) and (6) is 0.672, 0.203 and 0.470, respectively. This implies on average about 70 percent of the capital misallocation is due to policy distortions. In our hypothetical economy without policy distortions, financial frictions alone would predict a variance of $\log MRPK_{i,t}$ of 0.203. This implies an aggregate TFP loss of 8.3 percent, under values of α and η standard in the literature. Thus although the aggregate TFP loss in China is substantial, on the order of 27.5 percent, policy distortions are the major contributor to the large efficiency loss.

5.4 An Explanation to China's Unusually High Investment Rate

The counterfactual MRPK generated from the propensity score matching also allows us to calculate the average MRPK of this economy, had there been no policy distortions, i.e. $E(Y_{i,t}^0)$. These mean values are reported in row (8) of Table 1. As a comparison, row (7) gives the mean values of the factual MRPK in this economy, i.e. $E(Y_{i,t})$. Recall that these logarithm MRPKs are backed out as the residual of a regression. Therefore they are normalized to zero by definition. The slight difference between the values in row (7) and zero reflects the restriction of common support. The difference between row (7) and row (8) then tells the effect of policy distortions on the average MRPK, which is documented in row (9). Interestingly though not surprisingly, the values in row (9) are all negative and are averaged to -0.091 . This implies that the policy distortions have reduced the average MRPK of this economy by 9.1 percent.

Recall that MRPK is simply the mirror image of the generalized user cost of capital, as a consequence of firm's optimal investment-financing decision. With various policy distortions, those firms receive favorable treatment respond to a lower than otherwise user cost of capital and over-invest compared with the second-best benchmark – where there is still imperfect information or imperfect enforcement but no policy distortion. China has long been criticized for having an unusually high investment rate.¹³ This paper therefore suggests that policy distortions could be one of the possible explanations.

¹³The aggregate investment to GDP ratio in China is about 45 percent during our sample period, while the world average is only about 22 percent (World Economic Outlook Database, IMF).

5.5 Factors Underlying Policy Distortions

Our identification strategy so far has taken ownership as a proxy for the bundle of policy distortions. Using this proxy, we find that the majority of the aggregate TFP loss in China can be attributed to policy distortions. To offer specific suggestions on how to improve capital allocative efficiency, it is important to unblock those specific factors that are proxied by ownership and have caused substantial aggregate efficiency loss.¹⁴

5.5.1 Hypotheses

We consider several popular hypotheses on why the Chinese government have introduced various rules, regulations and institutions that favor certain firms. From the public finance perspective, the first possible reason for a government to favor a firm is that the firm contributes a large tax revenue.

Second, a government may also distort capital allocation in order to pursue specific industrial policies. For example, China is well known to adopt an export-led growth strategy from the ever beginning of the ‘reform and opening’ policy (Lin, 2012). More recently, China is suggested to practice a form of state capitalism in a vertical industrial structure: SOEs are explicitly or implicitly allowed to monopolize key industries in the upstream, whereas the downstream industries are largely open to private competition (Li et al., 2014). Under these two hypotheses, firms that are exporting and are in the upstream industries may expect to receive favorable policy distortions.

Third, the well-known trade-off between growth and stability facing the government has often been taken as an argument to justify policy distortions. To minimize social unease and reduce resistance to reform, the government may have a strong political motivation to maintain employment stability. For example, to avoid laying off workers or shutting down factories during an economic downturn, the government usually asked the state-owned banks to bail out loss-making SOEs which created a problem known as the ‘soft-budget constraint’ (Qian and Roland, 1998; Brandt and Zhu, 2001). Under this rationale, we may regard the government as a risk-averse social planner who optimally allocates capital according to the capital asset pricing model. If so, firms that are counter-cyclic have a smaller beta and only need to offer a lower required rate of return on capital.

Finally, different from all the above hypotheses which assume a benevolent government, an alternative hypothesis is that the government prefers firms with a political connection. For

¹⁴We recognize that such policy distortions may reflect certain objectives beyond the static allocative efficiency, as we discuss in this section. To the extent that such objectives are present, our results can be interpreted as measuring the cost of pursuing them in terms of allocative efficiency.

example, Party membership has been found to help private entrepreneurs to obtain loans from banks or other state institutions (Li et al. 2008; Guo et al. 2014). Firms with government-appointed or government-connected chief executive officers are found to face much less severe financial constraints (Fan et al. 2007; Cull et al. 2015). Since there is no information regarding the entrepreneur or chief executive officer in our dataset, we use whether the firm has a labor union as an alternative measure of political connection. Different from the labor unions in most western countries, which help workers to collectively bargain higher wages and better working conditions with the firms, a labor union in China passes on the ideology of the Communist Party to the workers and watch out whether the firm is politically correct or at least consistent with the Communist Party.

5.5.2 Empirical Findings

To test these interesting hypotheses, the following regression is implemented using the restricted sample made of matched firms only,

$$\begin{aligned} \Delta_{i,t} = & b_0 + b_1 \cdot \text{net tax}_{i,t} + b_2 \cdot \text{EXPORT}_{i,t} + b_3 \cdot \text{UPSTREAM}_{i,t} \\ & b_4 \cdot \text{beta}_i + b_5 \cdot \text{LABORUNION}_i + \varsigma_{i,t}. \end{aligned} \tag{7}$$

In equation (7), the dependant variable is $\Delta_{i,t} \equiv \left(Y_{i,t}^1 | D_{i,t} = 1 \right) - \left(Y_{i,t}^0 | D_{i,t} = 1 \right)$, the difference between the actual MRPK of firm i in year t and its counterfactual MRPK had firm i not received the favorable treatment in year t . The independent variables include the six factors inferred from the popular hypotheses. By testing whether the strength of the firm-specific treatment can be explained by the variation in those firm-specific factors of our interest, equation (7) thus provides a device to explore the fundamental motivation underlying the policy distortions.

Here net tax is the difference between tax and subsidies, as a share of revenue. EXPORT, UPSTREAM, and LABORUNION are dummy variables which take value 1 if firm i in year t is an exporter, belongs to the upstream industries, and has a labor union in the firm, respectively. beta measures the risk of firm i , inferred from the covariance between the revenue growth rate of firm i and the aggregate revenue growth rate over our sample period. Appendix B provides further details on how we define and calculate beta.

<Insert Table 5 here>.

Table 5 summarizes our empirical findings for equation (7). First, net tax turns out to have a positive sign. The direct interpretation is that the actual MRPK of those firms who

contribute high tax revenue is in fact higher than their counterfactual MRPK. This denies the first hypothesis that firms receive favorable policy distortions in capital because they contribute more tax revenue. Instead, it suggests that those firms who have received favorable policy distortions in capital also receive favorable tax treatment, such as tax breaks or direct subsidies. Second, the estimates for the three dummy variables all turn out to be negative and are all statistically significant. Averaging across the years, all else being equal, a firm that is an exporter, belongs to the upstream industries, and has a labor union has an MRPK 14.0 percent, 2.6 percent, and 14.9 percent respectively, lower than otherwise. Finally, beta is the only variable whose estimates change the signs from significantly positive to insignificantly negative over our sample period. A positive coefficient on beta is consistent with the capital asset pricing model thus verifies the motivation of policy distortions as a trade-off between risk and return. The fact that beta becomes irrelevant since 2005 seems to indicate that employment stability is no longer a major concern of the government in more recent years. The same pattern is highlighted in Hsieh and Song (2014) from a different set of evidences.

Three conclusions can be draw from our empirical exercises. First, favorable policy distortions in capital go hand-in-hand with favorable tax treatment. Second, pursuing an export-led growth strategy and practicing state capitalism are two important factors that drive policy distortions. Political connection with the Communist Party is another reason for firms to receive favorable treatment. Finally, the concern on the trade-off between return and risk also leads to policy distortions but is only relevant in early years.

6 Conclusion

Market and policy are two most important mechanisms in allocating resources. Capital market has been known as an imperfect market due to various financial frictions for a long time. From an investment model with a very general specification on financial frictions and using a non-parametric estimation approach, we find the aggregate TFP loss caused by financial frictions is up to 9.4 percent in China. This magnitude itself is by no means trivial. However, it is much smaller than the actual capital misallocation observed in China, where policy has been playing a much bigger role in allocating capital.

This motivates us to investigate the specific factors that lie behind policy distortions. Our findings indicate that in addition to political connection, the policy distortions could be the consequence of undertaking specific development strategies, and balancing some important trade-offs facing a government in the process of economic development. Although it is hard to know the exact objective function of a benevolent government, the substantial efficiency loss

caused by such distortions calls a serious re-evaluation of the rules, regulations and institutions in pursuing those non-efficiency objectives.

7 Appendix

7.1 Appendix A. Dynamic Models

Following the setup as in Midrigan and Xu (2014) and Moll (2014), each firm i is owned by entrepreneur i , who maximizes his life-time utility

$$E_0 \sum_{t=0}^{\infty} \beta^t u(C_{i,t}),$$

where β is his discount factor; $C_{i,t}$ is his consumption; $u' > 0$ and $u'' < 0$. At each point in time t , an investment opportunity represented by a stochastic productivity parameter $Z_{i,t}$ arrives for firm i . The firm employs capital $K_{i,t}$ and labor $L_{i,t}$ to produce revenue $R_{i,t} = Z_{i,t}^{\eta_i} (K_{i,t}^{\alpha_i} L_{i,t}^{1-\alpha_i})^{1-\eta_i}$ and generate instantaneous gross profits $\pi_{i,t} = Z_{i,t}^{\gamma_i} K_{i,t}^{1-\gamma_i}$. Besides the investment opportunity, entrepreneur i also has an amount $W_{i,t}$ of internal funds available for investment.

Capital in this economy is accumulated by an intermediary, who rents it out to firms. To make the capital investment, entrepreneur i effectively pays a firm-specific after-tax rental price

$$P_{i,t}^K = (1 + \tau_i)(r_t + \delta),$$

where r_t is the interest rate and δ is the depreciation rate of capital. τ_i denotes the firm-specific rate of investment tax credit.

The optimization problem of entrepreneur i can be represented by the Bellman equation

$$V(Z_{i,t}, W_{i,t}) = \max_{W_{i,t+1}, K_{i,t}} u(C_{i,t}) + \beta E(V(Z_{i,t+1}, W_{i,t+1})),$$

The intertemporal budget constraint in a cost constrained model is

$$W_{i,t+1} = \pi(Z_{i,t}, K_{i,t}) - (1 + \tau_i)(r_t + \delta)K_{i,t} - \theta_i \Lambda(K_{i,t}, W_{i,t}) + (1 + r_t)W_{i,t} - C_{i,t}.$$

The optimal accumulation of internal funds leads to the Euler equation

$$u'(C_{i,t}) = \beta E(u'(C_{i,t+1})(1 + r_{t+1} - \theta_i \Lambda_W(K_{i,t+1}, W_{i,t+1}))).$$

The optimal capital investment $K_{i,t}$ is governed by the first-order condition

$$\pi_K(Z_i, K_{i,t}) = (1 + \tau_i)(r_t + \delta) + \theta_i \lambda(K_{i,t}, W_{i,t}), \quad (\text{A.1})$$

where $\theta_i \lambda(K_{i,t}, W_{i,t}) \equiv \theta_i \Lambda_K(K_{i,t}, W_{i,t}) > 0$ is the marginal cost of external financing, with $\lambda_K > 0$ and $\lambda_W < 0$.

The intertemporal budget constraint in a quantity constrained model is

$$W_{i,t+1} = \pi(Z_{i,t}, K_{i,t}) - (1 + \tau_i)(r_t + \delta)K_{i,t} + (1 + r_t)W_{i,t} - C_{i,t},$$

together with the borrowing constraint

$$K_{i,t} - W_{i,t} \leq (1 - \phi_i)K_{i,t}.$$

The optimal consumption path can be characterized by the Euler equation

$$u'(C_{i,t}) = \beta E(u'(C_{i,t+1})(1 + r_{t+1} + \mu(Z_{i,t+1}, W_{i,t+1}))).$$

The first-order condition for the optimal capital investment is given by

$$\pi_K(Z_i, K_{i,t}) = (1 + \tau_i)(r_t + \delta) + \phi_i \mu(Z_{i,t}, W_{i,t}), \quad (\text{A.2})$$

where $\mu(Z_{i,t}, W_{i,t}) > 0$ is the Lagrangian multiplier associated with the quantity constraint, with $\mu_Z > 0$ and $\mu_W < 0$.

We rewrite the equations (A.1) and (A.2) as follows:

$$\begin{aligned} MRPK_{i,t} &\equiv \pi_K(Z_{i,t}, K_{i,t}) = (1 + \tau_i)(r_t + \delta) + \theta_i \lambda(K_{i,t}, W_{i,t}) \equiv UC_{i,t} \\ MRPK_{i,t} &\equiv \pi_K(Z_{i,t}, K_{i,t}) = (1 + \tau_i)(r_t + \delta) + \phi_i \mu(Z_{i,t}, W_{i,t}) \equiv UC_{i,t} \end{aligned}$$

which deliver the same implications on capital misallocation as in equations (3) and (4), despite in a dynamic setting.

7.2 Appendix B. Recover Firm-Specific Volatility and Risk

7.2.1 Firm-Specific Volatility

Assume the productivity $Z_{i,t}$ is governed by the following process,

$$\begin{aligned} \log Z_{i,t} &= \mu t + z_{i,t} \\ z_{i,t} &= z_{i,t-1} + e_{i,t} \end{aligned}$$

where μ is a trend growth rate and $e_{i,t}$ is the productivity shock that firm i receives in year t . Firm-specific volatility implies that the variance of the productivity shocks is firm-specific,

$$e_{i,t} \stackrel{i.i.d.}{\sim} N(0, \sigma_i^2),$$

where σ_i follows a certain distribution D so that

$$\sigma_i \stackrel{i.i.d.}{\sim} D(\mu_\sigma, \sigma_\sigma^2).$$

Although the productivity shocks are unobservable, the observable revenue growth rates capture the useful information on productivity shocks. Bloom (2009) shows that even if there is investment friction, in the long-run, both revenue and capital grow at the rate of μ on average, essentially because the gap between frictionless and friction capital stock is bounded. This implies

$$\begin{aligned} \Delta \log R_{i,t} &= \Delta \log Z_{i,t} \\ &= (\mu t + z_{i,t}) - (\mu(t-1) + z_{i,t-1}) \\ &= \mu + z_{i,t} - z_{i,t-1} \\ &= \mu + e_{i,t}. \end{aligned}$$

Therefore using our balanced panel data, the level of volatility of firm i can be obtained by calculating the standard deviation of the within-group revenue growth rate for firm i across the years,

$$\begin{aligned} volatility_i &\equiv wsd(\Delta \log R_{i,t}) \\ &= wsd(\mu + e_{i,t}) \\ &= wsd(e_{i,t}) \\ &= \sigma_i. \end{aligned}$$

7.2.2 Firm-Specific Risk

Define the gross rate of return from investing in firm i in year t as

$$1 + r_{i,t} = \frac{V_{i,t+1} + \pi_{i,t+1}}{V_{i,t}}.$$

According to the consumption-capital asset pricing model, the expected rate of return $E[r_{i,t}]$ must satisfy

$$E[r_{i,t}] - r^f = \beta_i (E[r_{m,t}] - r^f),$$

where r^f is the rate of return on risk free asset, $r_{m,t}$ is the rate of return on the market, and β_i is defined as

$$\beta_i = \frac{cov[r_{i,t}, r_{m,t}]}{var[r_{m,t}]}.$$

Empirically if we have expected market rate of return, the riskless rate and the expected rate of return on each firm, we will be able to estimate β_i for each firm. However, by definition, such estimation requires information on firm value and expected firm value, which are not available in our data since most firms are not publicly traded.

To use information available in China's Annual Survey of Industry, we generalize the specification for $Z_{i,t}$ as follows,

$$\begin{aligned}\log Z_{i,t} &= \mu t + z_{i,t} \\ z_{i,t} &= z_{i,t-1} + \lambda_i e_t + e_{i,t},\end{aligned}$$

where e_t is an aggregate productivity shock that is common to all the firms; $-1 < \lambda_i < 1$ is a firm-specific factor loading; and $e_{i,t}$ is an idiosyncratic productivity shock. In this case, the revenue growth rate can be represented as

$$\Delta \log R_{i,t} = \mu + \lambda_i e_t + e_{i,t}.$$

Therefore one feasible strategy is to proxy β_i using the covariance between the revenue growth rate of firm i and the aggregate revenue growth rate, or

$$\beta_i = \frac{\text{cov} [\Delta \log R_{i,t}, \Delta \log R_t]}{\text{var} [\Delta \log R_t]}$$

where

$$\Delta \log R_t = \frac{1}{N} \sum_{i=1}^N \Delta \log R_{i,t} = \mu + e_t \frac{1}{N} \sum_{i=1}^N \lambda_i = \mu + \bar{\lambda} e_t$$

The rationale is that a pro-cyclical firm ($\lambda_i > 0$) is a risky firm, so it has a positive beta and must pay a higher rate of return; in contrast, a counter-cyclical firm ($\lambda_i < 0$) can hedge against low consumption, so it has a negative beta and consumers will require a lower rate of return.

7.3 Appendix C. Identification Assumptions

Formally, under the assumption of **conditional independence**,

$$Y^0 \perp D | X \tag{C.1}$$

and **common support**,

$$0 < \Pr(D = 1 | X) < 1 \text{ for all } X, \tag{C.2}$$

we have

$$\begin{aligned}E(Y | D = 1, X) - E(Y | D = 0, X) &= E(Y^1 | D = 1, X) - E(Y^0 | D = 0, X) \\ &= E(Y^1 | D = 1, X) - E(Y^0 | D = 1, X) \\ &= E(Y^1 - Y^0 | D = 1, X).\end{aligned}$$

Once this X -conditional effect is found, X can be integrated out to yield the ATT,

$$E_S(Y^1 - Y^0|D = 1) = \frac{\int_S E(Y^1 - Y^0|D = 1, X) dF(X|D = 1)}{\int_S dF(X|D = 1)}$$

where S is a subset of the support of X given $D = 1$ and $F(X|D = 1)$ is the distribution of $X|D = 1$.

The conditional independence assumption implies that

$$E(Y^0|D = 0, X) = E(Y^0|D = 1, X)$$

a key step in deriving the matching estimator for the ATT. Intuitively, it says conditional on observed characteristics X , the MRPK of those untreated is on average the same as the MRPK of those treated would have been if they had not received the treatment. This assumption is also known as ‘selection on observables’, which means the only source of selection bias is via the observed covariates so that the selection into treatment is random once X is controlled for. This identifying condition is actually equivalent to the condition in parametric regression approaches that the treatment dummy be uncorrelated with the error term of the regression. Under this condition, the MRPK of those untreated whose X are similar to those treated can be taken as the missing counterfactual MRPK of the treated.

The common support assumption says the probability of receiving treatment conditional on each possible value of X is strictly within the unit interval. This condition ensures that there is sufficient overlap in the characteristics of the treated and the untreated so that it is possible to find adequate matches.

Matching that is conditioning on all relevant covariates is limited in the case of a high dimensional vector X . Thus we apply the propensity score matching proposed by Rosenbaum and Rubin (1983) in our empirical exercises. Define the propensity score $P(X) = \Pr(D = 1|X)$, the probability of being treated given observed characteristics X . Rosenbaum and Rubin (1983) demonstrate that (C.1) and (C.2) together imply that $Y^0 \perp D|P(X)$, so that matching can be performed on $P(X)$ alone to reduce the curse of dimensionality.

7.4 Appendix D. Robustness Checks

A series of matching exercises are employed to check whether the findings in Table 4 are robust. First, we use $\log ARPK_{i,t}$ instead of the backed out $\log MRPK_{i,t}$ as a measure of the marginal revenue product of capital. As illustrated by Table D.1, when $\log ARPK_{i,t}$ is the outcome variable, we estimate both stronger ATE and ATT. But both the relative importance of policy distortions and financial frictions, and the over-time pattern of the effects are very similar to the benchmark case in using $\log MRPK_{i,t}$ as the outcome variable.

<Insert Table D.1 here>

The second set of the checks is to use alternative measures of firm characteristics. Tables D.2, D.3 and D.4 respectively report the effects when firm size is measured using logarithm of total assets, when pledgeability is measured using tangible assets as a share of total assets and when net worth is measured using cash flow to capital stock ratio. The results are found to be very similar to those in Table 4, both across columns and over years.

<Insert Table D.2 to Table D.4 here>

The multiple categories of ownership in the Chinese manufacturing also allow us to check the robustness of the findings using alternative control groups and multiple ordered treatment groups. Table D.5 presents the effects when SOE is taken as the control group. Both the ATE and the SB are positive across each column of the table. This implies that first, on average SOEs have a lower MRPK among all type of firms; and second, part of the differences in the average MRPK can be explained by the advantageous firm characteristics of SOEs relative to other ownership types. The sign of the ATT are different across columns. When COE, DPE and MIX are taken as the treatment groups, the ATTs are positive and large, indicating the unfavorable treatment these type of firms have received due to policy distortions. In contrast, the ATTs when HMT and FIE are taken as the treatment are not substantially different from zero. These findings are completely consistent with what we have seen from Table 4. Table D.6 presents the effects when MIX is taken as the control group. Once again, the negative ATTs when SOE, HMT and FIE are taken as the treatment and the positive SBs when HMT and FIE are taken as the treatment are consistent with those findings from Table 4.

<Insert Table D.5 to Table D.6 here>

The fourth robustness check is to define ownership by registration and keep all other aspects as the same as in Table 4. The fact that some *de facto* DPEs are registered as COEs, HMTs and FIEs is an implicit sign of favorable policy distortions receiving by COEs, HMTs and FIEs relative to DPEs. Therefore when COEs, HMTs and FIEs are the treatment groups, we would expect stronger ATTs in Table 4, where we define ownership according to contributed capital, than in Table D.7, where we define ownership by registration. And this is indeed the pattern we observe by comparing the results in both tables.

<Insert Table D.7 here>

The fifth set of robustness check is to add and deduct several variables in the benchmark set of covariates to test whether the six observed characteristics are "exhaustive" in determining the MRPK through which financial frictions operate. In particular, Table D.8 reports the results after deducting growth rate and net worth from the set of covariates; Table D.9 presents the results after deducting volatility and pledgeability; while Table D.10 summarizes the results by adding debt-to-assets ratio as an additional variable into the set of covariates. Taking Table 4 as the benchmark, it turns out that there are slight changes in the magnitude of the effects in Table D.8; very little change in Table D.9 and virtually no change in Table D.10. This implies that first, our set of covariates are quite exhaustive so that even the debt-to-assets ratio, a very common measure of financial status does not provide additional information. Second, among the six observed characteristics we considered, size and age are the most important financial characteristics. Omitting the state variables – growth rate and net worth – will affect the results to some extent. But volatility and pledgeability play a much smaller role, at least in our sample. This is consistent with the fact in Table 2.3 that firms with different ownership do not seem to show substantial differences in volatility and pledgeability.

<Insert Table D.8 to Table D.10 here>

7.5 Appendix E. Utilization of the Panel Structure

The panel structure of the dataset also allows us to conduct a set of interesting exercises. First, Table E.1 decomposes the total effect of the policy intervention as a direct effect and an indirect effect, using a sub-sample made of firms that have the constant ownership over the ten years. Here the indirect effect is the average difference in MRPK that can be explained by the average differences in covariates across the treatment and control groups, which captures the effect of financial frictions on average MRPK dispersion across ownership. The direct effect is the average difference in MRPK had firms in the treatment and control groups share the same covariates on average, which captures the effect of policy distortions on average MRPK dispersion across ownership.

Similar patterns are found in Table E.1 and Table 4 in terms of the sign of the effects. But the magnitudes of the direct effect from Table E.1 are larger than the corresponding ATT from Table 4. This suggests the effects of policy distortions are even stronger among firms with constant ownership. This also suggests that the *de nova* DPEs face more unfavorable policy distortions than those DPEs switched from other ownerships in later years, an implication consistent with the finding from Table 4 that all non-DPEs have received favorable policy distortions relative to DPEs.

More interestingly, the magnitudes of the indirect effect from Table E.1 are also larger than the corresponding SB from Table 4. Recall that the SB and the indirect effect capture the effect of financial frictions in case A and case B, respectively. The difference lies in that in case A the covariates $X_{i,t-1}$ are exogenous or predetermined to the policy intervention in year t ; in case B, the covariates $X_{i,t-1}$ are themselves affected by the policy intervention from year 1 to year $t - 1$. Thus, a stronger effect of financial frictions found in case B suggests that the effect of policy distortions is exacerbated by the presence of financial frictions.

<Insert Table E.1 here>

Second, since most of the ownership type variation happens when a SOE was privatized as a DPE, we further restrict our exercises to *de nova* DPEs, *de nova* SOEs, and those DPEs that were privatized from SOEs. Though ownership switching is likely related to some unobserved shocks, it is one way to check against any permanent heterogeneity, such as entrepreneur’s ability and managerial practice, that may confound our earlier ATT estimates. Table E.2 presents the estimates when *de nova* SOEs are taken as the control group while SOEs-switched-DPEs and *de nova* DPEs are taken as the treatment groups, respectively. Table E.3 provides the results when we reverse the exercises. That is to take *de nova* DPEs as the control group and take the SOEs-switched-DPEs and *de nova* SOEs as the treatment groups, respectively. In both cases, the magnitudes for ATT are smaller for those ownership switching firms than for those firms that have been DPEs or SOEs for ten years. This pattern is consistent with our earlier findings that SOEs do receive favorable policy distortions. And it further indicates the persistency of such distortions.

<Insert Table E.2 and E.3 here>

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Table 1

Variance of logarithm average and marginal revenue products of capital and aggregate TFP losses

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Avg.	TFP loss
(1) Var(arpk)	2.250	2.374	2.168	1.913	1.800	1.566	1.303	1.227	1.186	1.111	1.690	0.692
(2) Var(arpk)	1.164	1.104	1.060	1.038	1.009	0.991	0.970	0.989	1.008	1.018	1.035	0.424
(3) Var(mrpk)	0.783	0.732	0.693	0.688	0.680	0.673	0.683	0.688	0.714	0.739	0.707	0.289
(4) Var(mrpk)	N.A.	N.A.	0.672	0.672	0.672	0.656	0.656	0.672	0.689	0.723	0.672	0.275
(5) Var(c_mrpk)	N.A.	N.A.	0.168	0.176	0.194	0.194	0.212	0.221	0.221	0.230	0.203	0.083
(6) Var(mrpk)-Var(c_mrpk)	N.A.	N.A.	0.504	0.496	0.479	0.463	0.445	0.452	0.468	0.492	0.470	0.192
(7) E(mrpk)	N.A.	N.A.	0.009	0.012	0.014	0.012	0.012	0.007	0.015	0.014	0.012	
(8) E(c_mrpk)	N.A.	N.A.	0.097	0.114	0.108	0.095	0.094	0.115	0.097	0.107	0.103	
(9) E(mrpk) - E(c_mrpk)	N.A.	N.A.	-0.088	-0.102	-0.094	-0.083	-0.082	-0.108	-0.082	-0.093	-0.091	

Notes:

Row (1): variance of logARPK for all firms in China's Annual Survey of Industry

Row (2): variance of logARPK for firms in the balanced panel

Row (3): variance of normalized logMRPK for firms in the balanced panel

Row (4): variance of normalized logMRPK for firms in the balanced panel and on common support

Row (5): variance of counterfactual normalized logMRPK for firms in the balanced panel, on common support and in absence of policy distortions

Row (6): difference between row (4) and (5)

Row (7): mean of normalized logMRPK for firms in the balanced panel and on the common support

Row (8): mean of counterfactual normalized logMRPK for firms in the balanced panel, on common support and in absence of policy distortions

Row (9): difference between row (7) and (8)

Avg. is the value of variance or mean averaged across years.

TFP Loss is the average aggregate TFP loss calculated by assuming $\alpha = 1/3$ and $\eta = 0.15$.

Table 2.1

Proportion of firms under each ownership group (%)

	SOE	COE	DPE	HMT	FIE	MIX
1998	18.2	21.0	16.0	14.9	13.0	17.0
1999	17.1	19.1	17.4	15.8	12.4	17.3
2000	15.3	17.9	20.4	15.5	12.3	18.7
2001	13.8	15.8	23.5	16.4	12.0	18.1
2002	13.1	14.2	25.7	15.8	12.6	18.7
2003	12.3	12.0	27.4	16.2	12.4	19.8
2004	10.6	11.3	28.3	15.7	12.8	21.3
2005	9.7	9.5	29.4	15.9	12.8	22.7
2006	8.9	9.2	29.6	16.1	12.6	23.6
2007	8.2	9.1	29.5	16.1	12.8	24.3

Notes: SOE, COE, DPE, HMT, FIE and MIX means a firm is state-owned, collective-owned, domestic private-owned, Hong Kong, Macau and Taiwan-owned, foreign-owned, and mixed-owned, respectively.

Table 2.2

Log(MRPK) and ownership dummies

	Coefficient	Robust standard error
SOE	-0.455	0.008
COE	-0.028	0.008
HMT	-0.098	0.007
FIE	-0.055	0.008
MIX	-0.017	0.007

Notes: Dependent variable is log(MRPK). Baseline group is DPE.

Table 2.3

Mean value of firm characteristics by ownership group

	Age	Size	Volatility	Pledge	Growth	Net worth
SOE	29	554	0.250	0.612	0.061	0.387
COE	19	292	0.255	0.625	0.084	0.392
DPE	18	279	0.256	0.614	0.097	0.389
HMT	11	557	0.268	0.621	0.056	0.509
FIE	10	546	0.250	0.623	0.077	0.522
MIX	18	408	0.260	0.621	0.087	0.423
Average	17	419	0.257	0.619	0.080	0.431

Notes: Age: number of years since birth; Size: number of employees; Volatility: standard deviation of within-group real revenue growth rate; Pledge: assets pledgeability defined following Berger et al. (1996); Growth: real revenue growth rate; Net worth: (total assets - total liabilities)/total assets.

Table 3.1

Results for probit regression

Treat	Coeff.	Std. Err.	z	p> z
Age1999	0.036	0.002	23.06	0.000
Size1999	0.672	0.051	13.06	0.000
Volatility1999	0.500	0.217	2.30	0.021
Pledge1999	0.143	0.222	0.64	0.520
Growth1999	-0.361	0.068	-5.28	0.000
Networth1999	0.578	0.096	6.03	0.000
Constant	-1.511	0.163	-9.26	0.000

Notes: Dependent variable: D = 1 (0) if ownership = SOE (DPE) in year 2000

Table 3.2

Summary for number of firms off and on support

Treatment assignment	Common support		Total
	Off Support	On Support	
Untreated	0	2,558	2,558
Treated	19	1,648	1,667
Total	19	4,206	4,225

Table 3.3

Mean values of the covariates before and after the matching

Variable	Sample	Mean		% Bias	% Bias reduction	t-test	
		Treated	Control			t	p> t
Age1999	Unmatched	25.381	13.514	90.3		29.61	0.000
	Matched	25.226	25.368	-1.1	98.8	-0.27	0.785
Size1999	Unmatched	0.637	0.237	49.5		17.39	0.000
	Matched	0.553	0.533	2.5	94.9	0.82	0.411
Volatitlity1999	Unmatched	0.239	0.257	-18.6		-5.91	0.000
	Matched	0.240	0.243	-3.2	82.6	-0.90	0.366
Pledge1999	Unmatched	0.610	0.616	-6.9		-2.19	0.029
	Matched	0.610	0.607	3.7	46.0	1.05	0.292
Growth1999	Unmatched	0.099	0.170	-24.3		-7.62	0.000
	Matched	0.100	0.098	0.6	97.5	0.18	0.855
Networth1999	Unmatched	0.391	0.371	9.5		3.03	0.002
	Matched	0.391	0.381	4.8	49.2	1.40	0.163

Table 3.4

Results for the ATE and the ATT

Variable	Sample	Treated	Controls	Difference	Std. Err.	T-stat
mrpk2000	Unmatched	-0.362	0.107	-0.470	0.025	-18.80
	ATT	-0.357	-0.165	-0.192	0.034	-5.56

Table 4

Summary of the yearly point estimates for the ATE, ATT and the SB

	SOE			COE			HMT			FIE			MIX			COMBINE			Std(logMRPK)	
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	Unmatched	Matched
2000	-0.47	-0.19	-0.28	<i>-0.04</i>	<i>0.02</i>	-0.06	-0.11	-0.24	0.12	-0.06	-0.22	0.16	<i>-0.01</i>	<i>-0.02</i>	0.01	-0.13	-0.11	-0.02	0.82	0.41
2001	-0.43	-0.22	-0.21	<i>-0.02</i>	<i>0.01</i>	-0.03	-0.08	-0.25	0.18	<i>-0.03</i>	-0.22	0.20	<i>-0.04</i>	-0.05	0.02	-0.11	-0.14	0.03	0.82	0.42
2002	-0.39	-0.21	-0.18	<i>0.00</i>	<i>0.04</i>	-0.03	-0.06	-0.26	0.20	<i>-0.02</i>	-0.23	0.21	<i>0.00</i>	<i>-0.03</i>	0.03	-0.08	-0.13	0.05	0.82	0.44
2003	-0.43	-0.27	-0.16	<i>0.02</i>	<i>0.04</i>	-0.02	<i>-0.02</i>	-0.22	0.20	<i>0.02</i>	-0.18	0.21	<i>0.03</i>	<i>0.00</i>	0.03	-0.06	-0.12	0.06	0.81	0.44
2004	-0.43	-0.23	-0.20	<i>0.00</i>	<i>0.02</i>	-0.02	-0.05	-0.23	0.18	<i>0.03</i>	-0.17	0.20	<i>0.00</i>	<i>-0.02</i>	0.02	-0.06	-0.12	0.05	0.81	0.46
2005	-0.43	-0.25	-0.18	<i>-0.04</i>	<i>-0.02</i>	-0.02	-0.05	-0.25	0.19	<i>-0.03</i>	-0.25	0.22	<i>-0.02</i>	-0.05	0.03	-0.08	-0.16	0.07	0.82	0.47
2006	-0.40	-0.21	-0.19	<i>-0.04</i>	<i>-0.04</i>	0.00	-0.05	-0.20	0.15	<i>0.00</i>	-0.18	0.17	<i>-0.01</i>	<i>-0.03</i>	0.02	-0.07	-0.12	0.05	0.83	0.47
2007	-0.37	-0.20	-0.17	<i>-0.01</i>	<i>0.01</i>	-0.02	-0.06	-0.24	0.18	<i>-0.03</i>	-0.25	0.21	<i>0.00</i>	<i>-0.03</i>	0.03	-0.06	-0.13	0.07	0.85	0.48
Avg.	-0.42	-0.22	-0.20	-0.02	0.01	-0.03	-0.06	-0.24	0.18	-0.02	-0.21	0.20	-0.01	-0.03	0.02	-0.08	-0.13	0.05	0.82	0.45

Notes:

Control group is DPE.

Treatment group is SOE, COE, HMT, FIE and MIX, respectively.

COMBINE is the combined effect of the five evaluations using different treatment groups.

ATE: average treatment effect

ATT: average treatment effect on the treated

SB: selection bias, which is calculated as the difference between ATE and ATT

Average is the value of estimates averaged across years.

Estimates in *Italic* are not statistically different from zero at 5% significance level.

All other estimates for ATE and ATT are statistically different from zero at 5% significance level.

Table 5

Test on possible factors underlying policy distortions

	2000	2001	2002	2003	2004	2005	2006	2007	Average
Net tax/sale	0.155	0.170	0.145	0.145	0.154	0.157	0.147	0.145	0.152
EXPORT	-0.137	-0.147	-0.180	-0.149	-0.141	-0.127	-0.110	-0.132	-0.140
UPSTREAM	-0.034	-0.023	-0.013	-0.021	-0.039	-0.014	-0.038	-0.028	-0.026
Beta	0.030	0.016	0.005	0.027	0.017	<i>-0.001</i>	<i>-0.013</i>	<i>-0.026</i>	<i>0.007</i>
LABORUNION	-0.126	-0.173	-0.173	-0.180	-0.125	-0.122	-0.147	-0.148	-0.149

Notes:

Dependent variable is the difference between factual and counterfactual log(MRPK) of those treated firms.

Net tax is (tax-subsidies)/revenue.

EXPORT = 1 if a firm is an exporter.

UPSTREAM = 1 if a firm belongs to the upstream industries.

Beta is risk of a firm proxied by the cyclicity of its revenue growth.

LABORUNION = 1 if a firm has a labor union.

Average is the value of estimates averaged across years.

Estimates in *Italic* are not statistically different from zero at 5% significance level.

All other estimates are statistically different from zero at 5% significance level.

Table D Robustness checks for the yearly point estimates for the ATE, ATT and the SB**Table D.1**

When log(ARPK) is the outcome variable

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-1.05	-0.55	-0.51	-0.21	-0.10	-0.11	-0.13	-0.31	0.19	-0.22	-0.44	0.22	-0.23	-0.23	0.00	-0.35	-0.31	-0.05
2001	-0.99	-0.58	-0.40	-0.21	-0.14	-0.07	-0.10	-0.36	0.25	-0.19	-0.46	0.27	-0.24	-0.25	0.02	-0.32	-0.34	0.02
2002	-0.90	-0.57	-0.33	-0.16	-0.11	-0.05	-0.10	-0.40	0.30	-0.17	-0.47	0.29	-0.18	-0.22	0.04	-0.28	-0.34	0.06
2003	-0.90	-0.61	-0.29	-0.13	-0.10	-0.03	-0.04	-0.33	0.29	-0.10	-0.39	0.28	-0.14	-0.17	0.03	-0.23	-0.30	0.07
2004	-0.83	-0.52	-0.31	-0.09	-0.06	-0.03	-0.04	-0.31	0.27	-0.05	-0.33	0.29	-0.12	-0.16	0.04	-0.18	-0.26	0.08
2005	-0.82	-0.54	-0.27	-0.17	-0.14	-0.03	-0.05	-0.31	0.26	-0.09	-0.37	0.28	-0.16	-0.21	0.04	-0.21	-0.29	0.09
2006	-0.78	-0.51	-0.27	-0.14	-0.13	-0.01	-0.05	-0.28	0.22	-0.08	-0.32	0.24	-0.13	-0.16	0.03	-0.18	-0.25	0.08
2007	-0.71	-0.47	-0.25	-0.07	-0.05	-0.02	-0.06	-0.31	0.25	-0.07	-0.35	0.28	-0.10	-0.14	0.04	-0.14	-0.24	0.09
Avg.	-0.87	-0.54	-0.33	-0.15	-0.10	-0.04	-0.07	-0.32	0.25	-0.12	-0.39	0.27	-0.16	-0.19	0.03	-0.24	-0.29	0.05

Table D.2

When firm size is measured using logarithm of total assets

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.47	-0.16	-0.31	-0.04	0.03	-0.07	-0.11	-0.15	0.04	-0.06	-0.10	0.04	-0.01	0.03	-0.04	-0.13	-0.06	-0.07
2001	-0.43	-0.17	-0.26	-0.02	0.01	-0.04	-0.08	-0.18	0.10	-0.03	-0.12	0.09	-0.04	-0.01	-0.03	-0.11	-0.08	-0.02
2002	-0.39	-0.16	-0.23	0.00	0.04	-0.03	-0.06	-0.18	0.12	-0.02	-0.13	0.11	0.00	0.01	-0.01	-0.08	-0.08	0.00
2003	-0.43	-0.25	-0.18	0.02	0.04	-0.02	-0.02	-0.15	0.13	0.02	-0.09	0.11	0.03	0.04	-0.01	-0.06	-0.07	0.02
2004	-0.43	-0.24	-0.19	0.00	0.01	-0.01	-0.05	-0.18	0.14	0.03	-0.08	0.11	0.00	0.01	-0.01	-0.06	-0.08	0.02
2005	-0.43	-0.25	-0.17	-0.04	-0.03	-0.01	-0.05	-0.21	0.15	-0.03	-0.18	0.16	-0.02	-0.04	0.01	-0.08	-0.13	0.05
2006	-0.40	-0.21	-0.19	-0.04	-0.05	0.00	-0.05	-0.16	0.11	0.00	-0.10	0.10	-0.01	-0.02	0.01	-0.07	-0.09	0.03
2007	-0.37	-0.19	-0.17	-0.01	0.01	-0.02	-0.06	-0.22	0.16	-0.03	-0.20	0.17	0.00	-0.02	0.02	-0.06	-0.12	0.06
Avg.	-0.42	-0.20	-0.21	-0.02	0.01	-0.02	-0.06	-0.18	0.12	-0.02	-0.13	0.11	-0.01	0.00	-0.01	-0.08	-0.09	0.01

Table D.3

When pledgeability is measured using tangible assets as a share of total assets

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.47	-0.20	-0.28	-0.04	0.05	-0.09	-0.12	-0.25	0.13	-0.06	-0.24	0.18	-0.02	-0.02	0.00	-0.13	-0.11	-0.02
2001	-0.43	-0.21	-0.22	-0.02	0.03	-0.05	-0.08	-0.26	0.17	-0.04	-0.21	0.17	-0.04	-0.05	0.01	-0.11	-0.13	0.02
2002	-0.40	-0.19	-0.20	0.00	0.05	-0.05	-0.07	-0.25	0.18	-0.03	-0.21	0.18	-0.01	-0.02	0.01	-0.09	-0.12	0.03
2003	-0.44	-0.26	-0.19	0.01	0.04	-0.03	-0.03	-0.21	0.18	0.01	-0.19	0.19	0.02	0.01	0.01	-0.07	-0.11	0.05
2004	-0.43	-0.22	-0.20	0.00	0.02	-0.03	-0.05	-0.21	0.16	0.03	-0.16	0.19	0.00	-0.01	0.02	-0.06	-0.10	0.04
2005	-0.43	-0.24	-0.19	-0.04	-0.03	-0.01	-0.06	-0.25	0.18	-0.04	-0.25	0.21	-0.03	-0.05	0.03	-0.09	-0.15	0.07
2006	-0.40	-0.20	-0.21	-0.05	-0.06	0.01	-0.07	-0.20	0.13	-0.01	-0.17	0.15	-0.02	-0.03	0.01	-0.08	-0.12	0.04
2007	-0.38	-0.19	-0.19	-0.02	0.01	-0.02	-0.08	-0.25	0.17	-0.05	-0.24	0.18	-0.02	-0.03	0.01	-0.07	-0.13	0.06
Avg.	-0.42	-0.21	-0.21	-0.02	0.01	-0.03	-0.07	-0.23	0.16	-0.03	-0.21	0.18	-0.01	-0.03	0.01	-0.09	-0.12	0.04

Table D.4

When net worth is measured using cash flow to capital stock ratio

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.47	-0.14	-0.33	-0.04	0.02	-0.06	-0.14	-0.21	0.08	-0.08	-0.22	0.14	-0.01	-0.02	0.01	-0.14	-0.10	-0.04
2001	-0.44	-0.18	-0.27	-0.04	-0.01	-0.03	-0.09	-0.19	0.09	-0.06	-0.24	0.18	-0.04	-0.06	0.01	-0.12	-0.12	0.00
2002	-0.42	-0.16	-0.26	-0.01	0.03	-0.04	-0.08	-0.19	0.12	-0.06	-0.23	0.18	-0.01	-0.02	0.01	-0.10	-0.11	0.01
2003	-0.43	-0.18	-0.25	0.00	0.02	-0.02	-0.03	-0.17	0.13	-0.02	-0.21	0.18	0.02	-0.01	0.03	-0.07	-0.10	0.03
2004	-0.43	-0.13	-0.31	-0.03	-0.02	-0.01	-0.06	-0.18	0.12	-0.03	-0.21	0.18	0.00	-0.03	0.03	-0.09	-0.11	0.02
2005	-0.43	-0.13	-0.30	-0.08	-0.04	-0.03	-0.06	-0.18	0.12	-0.07	-0.25	0.18	-0.03	-0.06	0.03	-0.10	-0.13	0.03
2006	-0.41	-0.10	-0.31	-0.08	-0.06	-0.02	-0.08	-0.17	0.09	-0.05	-0.21	0.15	-0.02	-0.03	0.01	-0.09	-0.11	0.01
2007	-0.39	-0.07	-0.32	-0.05	-0.01	-0.03	-0.06	-0.17	0.11	-0.06	-0.23	0.17	-0.01	-0.01	0.00	-0.07	-0.10	0.02
Avg.	-0.43	-0.14	-0.29	-0.04	-0.01	-0.03	-0.08	-0.18	0.11	-0.05	-0.23	0.17	-0.01	-0.03	0.02	-0.10	-0.11	0.01

Table D.5

When SOE is the control group

	COE			DPE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	0.43	0.24	0.19	0.47	0.18	0.29	0.35	-0.05	0.40	0.41	-0.01	0.42	0.46	0.19	0.27	0.43	0.13	0.30
2001	0.40	0.24	0.17	0.43	0.20	0.23	0.35	-0.07	0.42	0.40	-0.04	0.43	0.39	0.15	0.24	0.40	0.11	0.28
2002	0.40	0.25	0.14	0.39	0.18	0.21	0.34	-0.04	0.38	0.37	0.02	0.36	0.39	0.17	0.22	0.38	0.13	0.25
2003	0.45	0.29	0.16	0.43	0.23	0.20	0.41	0.04	0.37	0.45	0.10	0.35	0.46	0.25	0.21	0.44	0.19	0.25
2004	0.43	0.26	0.17	0.43	0.24	0.19	0.38	0.03	0.35	0.46	0.10	0.36	0.43	0.22	0.22	0.43	0.18	0.25
2005	0.39	0.23	0.15	0.43	0.22	0.21	0.38	-0.08	0.45	0.40	-0.04	0.44	0.40	0.16	0.25	0.41	0.12	0.29
2006	0.35	0.17	0.19	0.40	0.20	0.20	0.35	0.03	0.31	0.39	0.11	0.28	0.39	0.16	0.22	0.38	0.15	0.24
2007	0.36	0.22	0.14	0.37	0.20	0.16	0.31	0.00	0.30	0.33	0.03	0.30	0.36	0.17	0.19	0.35	0.14	0.21
Avg.	0.40	0.24	0.16	0.42	0.21	0.21	0.36	-0.02	0.38	0.40	0.03	0.37	0.41	0.18	0.23	0.40	0.14	0.26

Table D.6

When MIX is the control group

	SOE			COE			DPE			HMT			FIE			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.46	-0.14	-0.31	-0.03	0.04	-0.06	0.01	0.00	0.01	-0.10	-0.22	0.12	-0.05	-0.20	0.15	-0.11	-0.09	-0.02
2001	-0.39	-0.12	-0.27	0.01	0.05	-0.04	0.04	0.03	0.01	-0.04	-0.19	0.15	0.01	-0.16	0.17	-0.05	-0.06	0.01
2002	-0.39	-0.14	-0.25	0.01	0.05	-0.04	0.00	-0.01	0.01	-0.06	-0.19	0.14	-0.02	-0.15	0.13	-0.07	-0.07	0.00
2003	-0.46	-0.25	-0.21	-0.01	0.02	-0.03	-0.03	-0.03	0.00	-0.05	-0.20	0.15	-0.01	-0.17	0.16	-0.09	-0.11	0.02
2004	-0.43	-0.22	-0.21	-0.01	0.02	-0.03	0.00	0.00	0.00	-0.05	-0.19	0.14	0.03	-0.11	0.14	-0.06	-0.08	0.02
2005	-0.40	-0.22	-0.19	-0.02	0.00	-0.02	0.02	0.03	-0.01	-0.03	-0.15	0.12	0.00	-0.15	0.15	-0.04	-0.07	0.02
2006	-0.39	-0.16	-0.23	-0.03	-0.02	-0.01	0.01	0.03	-0.02	-0.04	-0.17	0.13	0.01	-0.15	0.15	-0.05	-0.07	0.02
2007	-0.36	-0.15	-0.21	0.00	0.04	-0.04	0.00	0.01	-0.01	-0.06	-0.20	0.14	-0.03	-0.18	0.15	-0.05	-0.08	0.03
Avg.	-0.41	-0.18	-0.24	-0.01	0.03	-0.03	0.01	0.01	0.00	-0.05	-0.19	0.14	-0.01	-0.16	0.15	-0.06	-0.08	0.01

Table D.7

When ownership is defined by business registration type

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.65	-0.26	-0.40	-0.09	0.04	-0.13	-0.19	-0.24	0.05	-0.10	-0.18	0.07	-0.23	-0.06	-0.17	-0.23	-0.13	-0.10
2001	-0.60	-0.25	-0.35	-0.08	0.02	-0.10	-0.15	-0.25	0.10	-0.10	-0.22	0.12	-0.24	-0.09	-0.14	-0.21	-0.16	-0.05
2002	-0.57	-0.18	-0.39	-0.02	0.06	-0.08	-0.11	-0.25	0.13	-0.07	-0.22	0.15	-0.20	-0.05	-0.15	-0.17	-0.13	-0.04
2003	-0.59	-0.27	-0.32	-0.02	0.04	-0.06	-0.12	-0.24	0.13	-0.05	-0.20	0.15	-0.22	-0.09	-0.13	-0.17	-0.16	-0.02
2004	-0.56	-0.32	-0.24	-0.03	0.02	-0.05	-0.09	-0.23	0.14	-0.03	-0.19	0.16	-0.18	-0.09	-0.09	-0.15	-0.16	0.01
2005	-0.58	-0.35	-0.23	-0.05	-0.03	-0.01	-0.09	-0.23	0.13	-0.08	-0.25	0.17	-0.21	-0.13	-0.08	-0.17	-0.19	0.02
2006	-0.49	-0.22	-0.27	-0.03	-0.03	-0.01	-0.10	-0.23	0.13	-0.05	-0.21	0.16	-0.19	-0.12	-0.07	-0.15	-0.17	0.02
2007	-0.50	-0.27	-0.23	-0.03	-0.01	-0.01	-0.12	-0.27	0.15	-0.09	-0.27	0.18	-0.21	-0.14	-0.08	-0.17	-0.20	0.03
Avg.	-0.57	-0.27	-0.30	-0.04	0.01	-0.06	-0.12	-0.24	0.12	-0.07	-0.22	0.14	-0.21	-0.09	-0.11	-0.18	-0.16	-0.01

Table D.8

When growth rate and net worth is deducted from the covariates set

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.48	-0.23	-0.25	-0.05	<i>0.00</i>	-0.05	-0.13	-0.29	0.17	-0.07	-0.24	0.17	<i>-0.02</i>	<i>-0.04</i>	0.02	-0.14	-0.15	0.01
2001	-0.46	-0.26	-0.19	<i>-0.04</i>	<i>-0.02</i>	-0.02	-0.10	-0.27	0.17	<i>-0.04</i>	-0.23	0.19	<i>-0.04</i>	-0.07	0.03	-0.12	-0.16	0.04
2002	-0.42	-0.24	-0.17	<i>-0.01</i>	<i>0.02</i>	-0.03	-0.08	-0.27	0.20	<i>-0.03</i>	-0.24	0.21	<i>-0.01</i>	<i>-0.04</i>	0.03	-0.10	-0.15	0.05
2003	-0.45	-0.30	-0.15	<i>0.00</i>	<i>0.01</i>	-0.01	<i>-0.04</i>	-0.23	0.19	<i>0.00</i>	-0.20	0.20	<i>0.03</i>	<i>-0.01</i>	0.04	-0.07	-0.14	0.06
2004	-0.44	-0.25	-0.19	<i>-0.03</i>	<i>-0.02</i>	-0.01	-0.07	-0.27	0.19	<i>0.01</i>	-0.21	0.22	<i>0.00</i>	<i>-0.04</i>	0.04	-0.08	-0.15	0.07
2005	-0.44	-0.26	-0.18	-0.06	<i>-0.04</i>	-0.02	-0.07	-0.25	0.18	<i>-0.04</i>	-0.24	0.20	<i>-0.01</i>	<i>-0.04</i>	0.03	-0.09	-0.16	0.06
2006	-0.43	-0.26	-0.16	-0.06	<i>-0.05</i>	-0.01	-0.07	-0.25	0.18	<i>-0.04</i>	-0.24	0.20	<i>-0.02</i>	-0.05	0.03	-0.09	-0.16	0.07
2007	-0.42	-0.27	-0.15	<i>-0.03</i>	<i>-0.03</i>	0.00	-0.07	-0.27	0.20	-0.06	-0.28	0.22	<i>-0.02</i>	-0.05	0.03	-0.08	-0.17	0.08
Avg.	-0.44	-0.26	-0.18	-0.03	-0.02	-0.02	-0.08	-0.26	0.18	-0.03	-0.24	0.20	-0.01	-0.04	0.03	-0.10	-0.15	0.06

Table D.9

When volatility and pledgeability is deducted from the covariates set

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.47	-0.19	-0.28	<i>-0.04</i>	<i>0.04</i>	-0.07	-0.11	-0.26	0.14	-0.06	-0.24	0.18	<i>-0.01</i>	<i>-0.02</i>	0.01	-0.13	-0.12	-0.01
2001	-0.43	-0.22	-0.21	<i>-0.02</i>	<i>0.02</i>	-0.04	-0.08	-0.26	0.18	<i>-0.03</i>	-0.22	0.19	<i>-0.04</i>	-0.05	0.01	-0.11	-0.13	0.03
2002	-0.39	-0.20	-0.19	<i>0.00</i>	<i>0.04</i>	-0.04	-0.06	-0.25	0.19	<i>-0.02</i>	-0.22	0.20	<i>0.00</i>	<i>-0.02</i>	0.02	-0.08	-0.12	0.04
2003	-0.43	-0.26	-0.17	<i>0.02</i>	<i>0.05</i>	-0.03	<i>-0.02</i>	-0.20	0.18	<i>0.02</i>	-0.18	0.20	<i>0.03</i>	<i>0.01</i>	0.02	-0.06	-0.11	0.05
2004	-0.43	-0.23	-0.20	<i>0.00</i>	<i>0.02</i>	-0.02	-0.05	-0.22	0.17	<i>0.03</i>	-0.15	0.18	<i>0.00</i>	<i>-0.01</i>	0.02	-0.06	-0.11	0.05
2005	-0.43	-0.24	-0.19	<i>-0.04</i>	<i>-0.02</i>	-0.02	-0.05	-0.23	0.18	<i>-0.03</i>	-0.23	0.21	<i>-0.02</i>	-0.05	0.03	-0.08	-0.15	0.06
2006	-0.40	-0.20	-0.20	<i>-0.04</i>	<i>-0.04</i>	-0.01	-0.05	-0.19	0.14	<i>0.00</i>	-0.15	0.14	<i>-0.01</i>	<i>-0.02</i>	0.01	-0.07	-0.10	0.04
2007	-0.37	-0.18	-0.19	<i>-0.01</i>	<i>0.01</i>	-0.02	-0.06	-0.22	0.16	<i>-0.03</i>	-0.22	0.18	<i>0.00</i>	<i>-0.02</i>	0.02	-0.06	-0.12	0.06
Avg.	-0.42	-0.21	-0.20	-0.02	0.02	-0.03	-0.06	-0.23	0.17	-0.02	-0.20	0.19	-0.01	-0.02	0.02	-0.08	-0.12	0.04

Table D.10

When debt-to-assets ratio is added into the covariates set

	SOE			COE			HMT			FIE			MIX			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.47	-0.19	-0.28	<i>-0.04</i>	<i>0.02</i>	-0.06	-0.11	-0.24	0.12	-0.06	-0.22	0.16	<i>-0.01</i>	<i>-0.02</i>	0.01	-0.13	-0.11	-0.02
2001	-0.43	-0.22	-0.21	<i>-0.02</i>	<i>0.01</i>	-0.03	-0.08	-0.25	0.18	<i>-0.03</i>	-0.22	0.20	<i>-0.04</i>	-0.05	0.02	-0.11	-0.14	0.03
2002	-0.39	-0.21	-0.18	<i>0.00</i>	<i>0.04</i>	-0.03	-0.06	-0.26	0.20	<i>-0.02</i>	-0.23	0.21	<i>0.00</i>	<i>-0.03</i>	0.03	-0.08	-0.13	0.05
2003	-0.43	-0.27	-0.16	<i>0.02</i>	<i>0.04</i>	-0.02	<i>-0.02</i>	-0.22	0.20	<i>0.02</i>	-0.18	0.21	<i>0.03</i>	<i>0.00</i>	0.03	-0.06	-0.12	0.06
2004	-0.43	-0.23	-0.20	<i>0.00</i>	<i>0.02</i>	-0.02	-0.05	-0.23	0.18	<i>0.03</i>	-0.17	0.20	<i>0.00</i>	<i>-0.02</i>	0.02	-0.06	-0.12	0.05
2005	-0.43	-0.25	-0.18	<i>-0.04</i>	<i>-0.02</i>	-0.02	-0.05	-0.25	0.19	<i>-0.03</i>	-0.25	0.22	<i>-0.02</i>	-0.05	0.03	-0.08	-0.16	0.07
2006	-0.40	-0.21	-0.19	<i>-0.04</i>	<i>-0.04</i>	0.00	-0.05	-0.20	0.15	<i>0.00</i>	-0.18	0.17	<i>-0.01</i>	<i>-0.03</i>	0.02	-0.07	-0.12	0.05
2007	-0.37	-0.20	-0.17	<i>-0.01</i>	<i>0.01</i>	-0.02	-0.06	-0.24	0.18	<i>-0.03</i>	-0.25	0.21	<i>0.00</i>	<i>-0.03</i>	0.03	-0.06	-0.13	0.07
Avg.	-0.42	-0.22	-0.20	-0.02	0.01	-0.03	-0.06	-0.24	0.18	-0.02	-0.21	0.20	-0.01	-0.03	0.02	-0.08	-0.13	0.05

Notes:

Benchmark results are reported in Table 4.

Estimates in Italic are not statistically different from zero at 5% significance level.

All other estimates for ATE and ATT are statistically different from zero at 5% significance level.

Table E Utilization of the panel structure to estimate the ATE, ATT and the SB**Table E.1**When *de novo* DPE is the control group, *de novo* SOE, COE, HMT, FIE and MIX is the treatment group

	SOE10			COE10			HMT10			FIE10			MIX10			COMBINE		
	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB	ATE	ATT	SB
2000	-0.57	-0.23	-0.34	-0.13	<i>0.01</i>	-0.14	-0.13	-0.26	0.13	<i>-0.02</i>	-0.18	0.16	<i>-0.06</i>	<i>-0.09</i>	0.03	-0.18	-0.17	-0.01
2001	-0.54	-0.24	-0.30	<i>-0.10</i>	<i>0.00</i>	-0.09	-0.12	-0.25	0.13	<i>-0.04</i>	-0.17	0.13	<i>-0.07</i>	<i>-0.10</i>	0.03	-0.17	-0.17	0.00
2002	-0.53	-0.30	-0.23	<i>-0.06</i>	<i>-0.02</i>	-0.04	<i>-0.06</i>	-0.20	0.14	<i>-0.03</i>	-0.19	0.16	<i>-0.04</i>	<i>-0.10</i>	0.05	-0.14	-0.18	0.04
2003	-0.53	-0.29	-0.24	<i>-0.07</i>	<i>0.02</i>	-0.08	<i>-0.06</i>	-0.22	0.16	<i>0.02</i>	-0.17	0.20	<i>0.00</i>	<i>-0.02</i>	0.02	-0.13	-0.17	0.04
2004	-0.55	-0.32	-0.23	<i>-0.09</i>	<i>-0.01</i>	-0.07	-0.11	-0.25	0.14	<i>-0.01</i>	-0.19	0.19	<i>-0.02</i>	<i>-0.04</i>	0.01	-0.15	-0.19	0.04
2005	-0.57	-0.40	-0.17	<i>-0.05</i>	<i>0.00</i>	-0.05	-0.13	-0.29	0.16	<i>-0.07</i>	-0.31	0.23	<i>-0.06</i>	<i>-0.10</i>	0.04	-0.18	-0.26	0.08
2006	-0.49	-0.29	-0.21	<i>-0.07</i>	<i>-0.04</i>	-0.03	-0.10	-0.27	0.17	<i>-0.04</i>	-0.25	0.22	<i>-0.09</i>	<i>-0.12</i>	0.02	-0.15	-0.22	0.07
2007	-0.51	-0.30	-0.21	-0.12	<i>-0.04</i>	-0.08	-0.17	-0.33	0.16	-0.12	-0.32	0.20	<i>-0.04</i>	<i>-0.09</i>	0.05	-0.20	-0.26	0.06
Avg.	-0.54	-0.29	-0.24	-0.08	-0.01	-0.07	-0.11	-0.26	0.15	-0.04	-0.22	0.19	-0.05	-0.08	0.03	-0.16	-0.20	0.04

Table E.2

When SOE10 is the control group

	SOE-switched-DPE			DPE10		
	ATE	ATT	SB	ATE	ATT	SB
2000	0.18	0.13	0.05	0.57	0.20	0.37
2001	0.18	0.14	0.05	0.54	0.21	0.33
2002	0.20	0.12	0.08	0.53	0.17	0.36
2003	0.21	0.17	0.04	0.53	0.16	0.36
2004	0.20	0.16	0.05	0.55	0.21	0.34
2005	0.17	0.13	0.03	0.57	0.21	0.35
2006	0.11	<i>0.07</i>	0.04	0.49	0.18	0.32
2007	<i>0.07</i>	<i>0.02</i>	0.04	0.51	0.20	0.30
Avg.	0.16	0.12	0.05	0.54	0.19	0.34

Table E.3

When DPE10 is the control group

	SOE-switched-DPE			SOE10		
	ATE	ATT	SB	ATE	ATT	SB
2000	-0.39	<i>-0.11</i>	-0.28	-0.57	-0.23	-0.34
2001	-0.36	<i>-0.11</i>	-0.25	-0.54	-0.24	-0.30
2002	-0.33	<i>-0.08</i>	-0.25	-0.53	-0.30	-0.23
2003	-0.32	<i>-0.10</i>	-0.21	-0.53	-0.29	-0.24
2004	-0.35	-0.13	-0.22	-0.55	-0.32	-0.23
2005	-0.40	-0.25	-0.15	-0.57	-0.40	-0.17
2006	-0.38	-0.17	-0.21	-0.49	-0.29	-0.21
2007	-0.44	-0.22	-0.22	-0.51	-0.30	-0.21
Avg.	-0.37	-0.15	-0.22	-0.54	-0.29	-0.24

Notes:

Benchmark results are reported in Table 4.

Estimates in *italic* are not statistically different from zero at 5% significance level.

All other estimates for ATE and ATT are statistically different from zero at 5% significance level.