Essays in Development Economics and Political Economy

by

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Abstract

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Recent studies have listed resource misallocation as one of the key reasons of cross-country income gaps. This dissertation uses China as an example and asks whether political distortions can be a source of resource misallocation, and if so, what are the cost of those political distortions. Chapter 1 asks whether Chinese state-owned firms' preferential access to credit have any impact on the aggregate R&D activities. I find that the difference in access to credit creates a wedge in the factor market, which leads to considerable welfare loss by misallocating R&D inputs across Chinese firms. Specifically, worse access to credit market creates severe disadvantages to private innovators when they compete with state-owned incumbents. Such disadvantages distorts private innovators' incentives to invest in R&D. As a result, the wedge in access to credit between state-owned and private firms lowers aggregate innovation, leading to slower productivity growth. I develop and structurally estimate an endogenous growth model with a factor market wedge to capture this effect. I show that removing the wedge increases annual productivity growth by 1.2 percentage points and total welfare by 23%. Compared with the static loss from cross-sectional markup dispersion, the dynamic loss from misallocation in the R&D sector accounts for 90% of the total welfare loss. Compared with other mechanisms that lead to welfare loss, distortions to R&D incentives are the primary cause of misallocation in the R&D sector. These distortions are also quantitatively important in explaining the welfare loss.

State-owned firms enjoying preferential access to credit serves as an important foundation of my analysis in Chapter 1. Chapter 2 investigates this empirical relationship in depth by providing causal evidence on the wedge in access to credit between state-owned and private firms. Specifically, I estimate the effect of the 2004 Chinese banking reform on allocation of credits. Before the reform, connections to the government give unproductive state-owned firms preferential access to credit from state-owned banks. The banking reform changes the incentive structure of the banks, making them profit-oriented and thus limits the role government connections play in loan allocation. Using exogenous variations in the numbers of state-owned firms resulting from a high-profile national defense project, I find that the banking reform improves allocative efficiency more in cities with more state-owned firms.

This improvement is driven by extending credit access to more productive private firms who lack access to credit prior to the reform. With the newly acquired credit, they invest more and grow faster. A back-of-the-envelope calculation shows that the banking reform leads to 4% gain in sectoral TFP among the most affected cities.

Chapter 3 switches gear and asks whether constraints and incentives of authoritarian regimes can lead to resource misallocation. To this end, I exploit the spatial discontinuity at the boundaries of *Soviet Zones* that separated regions controlled by the Chinese Communist Party (CCP) and the rivaling *Kuomintang* during the First Chinese Civil War. I find that counties controlled by the CCP in the past receive 20% more targeted fiscal transfers from the central government today. Since Soviet Zone boundaries are determined by uncertain results of military operations, I can attribute the difference in fiscal support from the central government to differences in counties' Soviet Zone status. I argue that supporting Communist-controlled counties helps the CCP to maintain its political legitimacy as the ruling party of China, while supporting *Kuomintang*-controlled counties do not. Therefore, favoritism towards Soviet Zones originates from constraints and incentives the CCP faces. Finally, I document the cost associated with such favoritism. Despite receiving extra resources from the central government, favored counties do not exhibit faster economic growth. The lackluster outcome is driven by misallocation of local fiscal resources: local government in the favored counties have higher per-capita administrative expenditures and have more people on government payrolls. On the other hand, they do not spend more to support infrastructure, education, or agriculture. My results suggest that political favoritism can be an important source of resource misallocation.

To my family

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Chapter 1

Resource Misallocation in the R&D Sector: Evidence from China

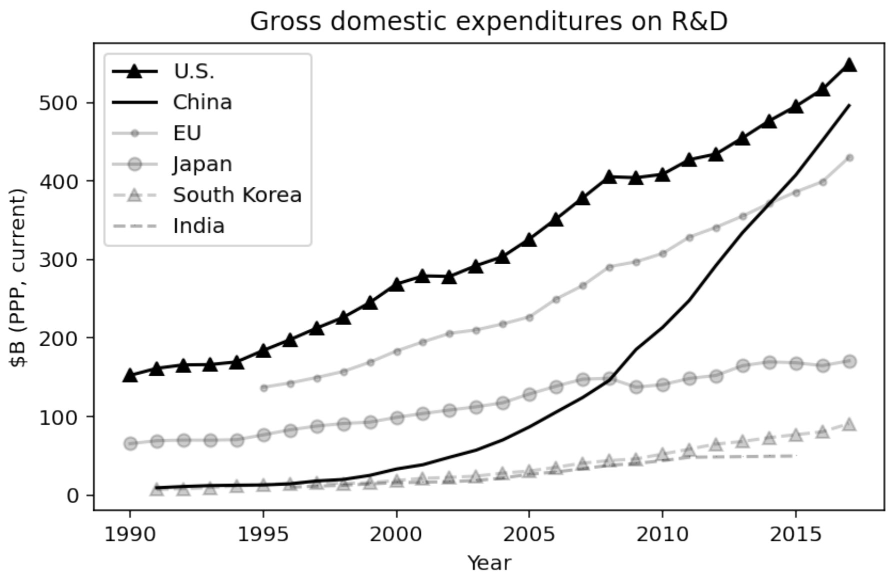
1.1 Introduction

China has shown real potential in overtaking the United States in key sectors via innovation. As illustrated in Figure 1.1, China's total R&D expenditure has increased fifteen-fold between 2000 and 2017. If the current trend continues, China will surpass the United States by 2023 and become the country that spends the most on R&D. Nevertheless, innovation output depends not only on the total R&D expenditure but also on the allocation of R&D inputs. There is a great deal of evidence suggesting misallocation exists in the Chinese R&D sector, especially between state-owned and private firms (Zhang, Zhang, and Zhao, 2003; Wei, Xie, and Zhang, 2017). The remarkable increase in R&D expenditure in China may proven ineffective should the additional inputs be misallocated. This paper asks two questions regarding this misallocation: To what extent are resources misallocated in the Chinese R&D sector? What are the productivity and welfare consequences of this misallocation?

In this paper, I document a severe resource misallocation within the Chinese R&D sector, which results in considerable welfare loss. The losses arise from the heterogeneous factor market access: state-owned firms have better factor market access due to their connections to the government. This advantage provides state-owned innovators an edge when competing with private incumbents, giving them a higher return to R&D than private firms. As a result, such heterogeneous factor market access incentivizes state-owned firms to innovate more at the expense of private firms. Furthermore, state-owned firms are inefficient innovators: For a given amount of R&D inputs, private firms can produce more innovations than state-owned firms. Together, the wedge results in inefficient state-owned firms crowding out efficient private firms in the R&D sector, exacerbating the misallocation in the R&D sector.

To formalize this intuition, I develop a quality ladder model with heterogeneous firms. My model extends the framework in Klette and Kortum (2004) to incorporate a factor market wedge. In the model, firms' R&D investments produce innovations. A successful innovation

Figure 1.1: R&D Expenditures in China, U.S., and Other Countries



Source: Science and Engineering Indicators, NSF (2020)

enables the innovator to leapfrog the incumbent firm in productivity. The return to R&D depends on the product market competition between the innovator and the incumbent. Having a lower input price increases the innovator's profit, resulting in a higher return to R&D. Conversely, firms with worse factor market access have lower returns to R&D. As a result, the factor market wedge distorts the incentive to innovate, which leads to resource misallocation.

There are two types of firms in the model, state-owned and private firms, which differ in two aspects. First, they have different innovative capacities, which determine how efficient they are in producing innovations. Second, institutionalized connections to the government allow state-owned firms to avoid market frictions, granting them better factor market access.[1] The factor market wedge is critical in determining the allocation of resources in the R&D sector: inefficient state-owned firms innovates more as they have better factor market access, resulting in lower growth rate of the economy.

I structurally estimate this model using Chinese firm-level data between 1998 and 2007. I find that private firms in China are about 2–3 times more efficient in innovating than state-owned firms. However, they face a 20% higher price in the factor market. As a result, private firms innovate less than state-owned firms despite their higher innovative capacity.

[1]For evidence on state-owned firms' better factor market access, see Poncet, Steingress, and Vandenbussche 2010; Chen, Liu, and Su 2013; Hale and Long 2012; Agarwal, Milner, and Riaño 2014; Cull, Li, Sun, and Xu 2015

This distortion leads to substantial loss in growth and welfare. I compare the estimated economy to a *laissez-faire* economy where there is no differential factor market access across firms. I find that the annual productivity growth rate is 5.0% in the *laissez-faire* economy versus 3.8% in the estimated economy. In other words, the factor market wedge leads to 1.2 percentage points slower productivity growth. By comparing the steady state of the estimated and the *laissez-faire* economy, I find that the wedge creates 23% welfare loss.

In the model, the factor market wedge leads to a static and a dynamic welfare loss. Statically, the factor market wedge generates resource misallocation in the production sector, which lowers the productivity level. Dynamically, it also creates resource misallocation in the R&D sector, which lowers productivity growth. I find that 90% of the welfare loss comes from the dynamic channel, whereas the static channel accounts for only 10%. This result implies that resource misallocation in the R&D sector plays an important role in determining the overall welfare effect from the factor market wedge.

The factor market wedge distorts firms' innovation decisions in two ways. First, private firms face a higher R&D input price because of the wedge. Therefore, the factor market wedge directly depresses private innovation. Second, the wedge leads to a higher production input price for private innovators compared to the state-owned incumbents they compete with. This disadvantage lowers the profit private innovators make, and thus decreases private firms' return to R&D. Therefore, the factor market wedge indirectly depresses private innovation. I find that the direct effect alone creates very little distortion. Whereas the indirect effect accounts for almost all distortions to firms' R&D decisions. This result suggests that distorting incentives to R&D is the primary mechanism through which the factor market wedge generates misallocation in China's R&D sector.

To be clear, the factor market wedge is not inherently inefficient in my model; instead, it may increase productivity growth and welfare. In a decentralized equilibrium, firms under-invest in R&D because they do not internalize its full social returns (Lentz and Mortensen, 2016; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018). Better factor market access enjoyed by state-owned firms is equivalent to a subsidy. Although not a first best policy, this subsidy may address the issue of under-investment in R&D by incentivizing state-owned firms to innovate more. I investigate this possibility by examining the conditions under which state-owned firms' privileged factor market access leads to faster economic growth. Unsurprisingly, the estimated parameters do not meet those conditions. For such privilege to increase welfare, state-owned firms need to be 5 times more efficient in producing innovation than my estimate. Alternatively, state-owned firms' innovations need to generate 12% higher productivity gain. The 12% threshold I find is more than double the size of the most optimistic estimate documented in the literature.[2]

[2]Reduced-form studies using various measures of innovation quality find mixed evidence on the relative quality of state-owned and private innovations. Boeing (2016); Fang, Lerner, and Wu (2017); Wei, Xie, and Zhang (2017); Cheng, Fan, Hoshi, and Hu (2019) report that state-owned innovations receive fewer citations and lead to smaller total-factor productivity (TFP) growth. On the other hand, Fang, He, and Li (2020) indicate that state-owned firms have a 2–5% higher TFP-patent elasticity. Nevertheless, the 5% upper end of the estimate reported in Fang, He, and Li (2020) is well below the required threshold for the state-owned

My findings indicate that distortions such as factor market wedges can lead to dynamic inefficiency. In countries with large R&D expenditures such as China, the dynamic welfare loss can be an order of magnitude larger than the static loss. My findings have two broad implications. First, factor market wedges may be responsible for slow economic growth in less developed countries. Second, the political economy between firms and the government can be a crucial source of distortion that leads to slow economic growth. With the substantial factor market wedge found in this paper and in the literature, it is difficult for China to surpass the United States in sectors that require significant innovation outputs.

This paper contributes to four strands of literature. First, I document a novel and important channel through which factor market wedges distort firms' R&D investment decisions. In my model, the competition between innovators and incumbents is a key determinant of returns to R&D. Heterogeneous factor market access tilts this competition in favor of some firms over others, resulting in resource misallocation in the R&D sector. Using Chinese manufacturing firm data, I demonstrate that distortions to R&D incentives are quantitatively important. These results complement the literature on the sources and consequences of distortions in innovation and firm dynamics.[3]

Second, this paper speaks to a growing literature on how resource misallocation affects productivity growth (Da-Rocha, Restuccia, and Tavares, 2019; König, Song, Storesletten, and Zilibotti, 2020). While earlier studies emphasize the role of R&D by incumbent firms, I focus on creative destruction where entrants contribute significantly to the total innovation. In a similar manner, Aghion, Bergeaud, and Van Reenen (2019) study the effect of size-dependent taxes on creative destruction. They find a moderate loss from size-dependent policies in France. By focusing on a more salient distortion in China, I find a much larger cost of resource misallocation through creative destruction.

Third, this paper considers an indirect channel through which connections to the government generate inefficiency. In the model, connections to the government do not incur any cost directly; rather, they reduce market frictions for connected firms. Nevertheless, I demonstrate that these connections lead to a quantitatively important distortion to R&D incentives of unconnected firms that are competing with connected firms. This disincentivization effect discourages unconnected firms from investing in R&D. My results complement the existing research on the direct inefficiencies that state ownership generates (Song, Storesletten, and Zilibotti, 2011; Li, Liu, and Wang, 2015; Wang, 2020; Chen, Igami, Sawada, and Xiao, 2020).

Finally, I contribute to the literature on low return to Chinese R&D investment. Previous research suggests that the low return could be due to relabeling R&D expenditures (Chen, Liu, Suárez Serrato, and Xu, 2018; König, Song, Storesletten, and Zilibotti, 2020), or misdirection of state subsidies (Jia and Ma, 2017; Wei, Xie, and Zhang, 2017; Fang, Lerner, and Wu, 2017; Cheng, Fan, Hoshi, and Hu, 2019). My results complement this literature by

privilege to be welfare-enhancing.

[3]These sources include size-based policies (Hsieh and Klenow, 2014; Aghion, Bergeaud, and Van Reenen, 2019), financial market imperfection (Gorodnichenko and Schnitzer, 2013; Varela, 2018; Vereshchagina, 2018), firms' heterogeneous innovative capacities (Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018), and firms' heterogeneous processing efficiency (Aghion, Bergeaud, Boppart, Klenow, and Li, 2019).

showing how misallocation in the R&D sector could be an important mechanism leading to low aggregate return to innovation in China.

The paper that most closely relates to mine is König, Song, Storesletten, and Zilibotti (2020) (KSSZ hereafter). KSSZ also study how market wedges affect innovation decisions in China. There are two main differences between our papers. First, KSSZ abstract from competitions between entrants and incumbents, focusing instead on incumbent firms' R&D investment. In contrast, I focus on creative destruction, in which incumbents *and* entrants compete on the product market. By doing so, my model captures a quantitatively important disincentive effect on private innovation from their worse factor market access. Second, firm ownership and connections to the government are the sole source of the market wedge in this paper. In contrast, KSSZ do not take any stand on the sources of the wedge; in fact, in their research, the wedge may or may not relate to firm ownership and connections to the government. Despite the narrower focus of this paper, I find similar magnitudes for the cost of resource misallocation as in KSSZ. The productivity gain from equalizing factor market access across firm ownership in my model (1.2 percentage points) is comparable to the gain from halving the wedges in KSSZ (1.3 percentage points). This comparison suggests that state ownership has first-order effects on the cost of misallocation in China's R&D sector.

1.2 State Ownership and Factor Market Access

This section presents the institutional background in China. I first discuss the differences between state-owned and private firms. I then describe the institutionalized connections between the government and state-owned firms, and how these connections affect firms' access to the factor market. Finally, I examine the inefficiencies that make Chinese state-owned firms unproductive innovators.

Chinese State-owned Firms

State-owned firms in China are different from public firms in other countries. Particularly in their objective functions. Rather than maximizing welfare, Chinese state-owned firms are profit maximizers with the government being a major shareholder. Two observations corroborate this distinction. First, Chinese state-owned firms operate like private firms. They face constraints and market pressures just like their private counterparts. Second, many Chinese state-owned firms compete directly with private firms.

The profit-maximizing objective results from a series of reforms aimed at introducing modern corporate governance mechanisms to state-owned firms. First, the management agency of state-owned firms explicitly states that profit maximization is the goal for these firms (State-owned Assets Supervision and Administration Commission, 2003). Second, the government exercises its ownership right over state-owned firms through modern corporate governance mechanisms (e.g., personnel appointment or shareholder activism). It is rare to see the government using executive orders and place explicit administrative goals to those state-owned firms.[4] Moreover, many state-owned firms are traded on public stock exchanges, where stock prices are used to evaluate their performances.

State-owned firms are actively competing with private firms in many industries. Figure A.1 shows an example of the competition between state-owned and private firms in the Chinese smartphone market. Despite having many private producers, two state-owned firms, ZTE and Lenovo, combine to more than 10% of the market share in 2018. In other cases, existing state-owned firms expand from their uncontested core businesses to more competitive markets. A notable example of such expansion is the China Oil and Foodstuffs Corporation (COFCO). COFCO operates mainly in the agricultural goods import/export sector. It has expanded into real estate, food processing, and online grocery delivery, all of which have large numbers of private competitors. Additionally, there are also new state-owned firms being set up directly in highly competitive sectors like the computer chip manufacturing sector (e.g., Semiconductor Manufacturing International Corporation, SMIC). With their heavy presences in those competitive sector, it is difficult to conclude that the state-owned firms are public good providers who maximize social welfare.

State-owned Firms and Factor Market Access

Like many developing countries, China lacks well-functioning market institutions. Several rounds of World Bank enterprise surveys find private firms have difficulties in accessing external finance (The World Bank, 2005, 2012; Claessens and Tzioumis, 2006). These difficulties may result from informational and contractual frictions. For example, Feenstra, Li, and Yu (2014) show the non-observability of firm output creates credit constraints. Chen (2019) finds the lack of pledgeability for intangible assets restricts private firms' access to credit. These market frictions are non-trivial: Lack of external credits significantly hinders private firms' ability to innovate and adopt technology (Agarwal, Milner, and Riaño, 2014), which leads to slower employment growth (Ayyagari, Demirgüç-Kunt, and Maksimovic, 2010).

State-owned firms do not face these problems to the same extent as their private competitors. State-owned firms' better access to credit stem from their institutionalized connections to the government, who facilitates transactions between state-owned firms and state-owned financial institutions. Such state-owned privilege is also well documented in the literature: Cull and Xu (2003) find state ownership is associated with better access to loans from state-owned banks; Cull, Xu, and Zhu (2009) and Cull, Li, Sun, and Xu (2015) show state-owned firms rely less on internal cash flows and costly trade credits as their primary source of funds. Consistent with this literature, I show in Table A.2 that in my sample of manufacturing firms, state-owned firms have higher leverages, are more likely to have any type of credit, and face lower interest rates than private firms.

Similar to Akcigit, Baslandze, and Lotti (2020), I consider state-owned firms' connections as ways to circumvent market frictions. As a result, these connections do not generate any

[4] In practice, the state assets management commission does not directly hold stocks of state-owned firms; instead, it uses tools like cross-holding to control state-owned firms indirectly. This practice makes using direct executive orders more difficult.

inefficiency directly; instead, they hinder economic growth by redirecting resources towards inefficient state-owned firms by distorting the competition between state-owned and private firms, as I will show in Section 1.3.

Inefficiency in State-owned Firms

State-owned firms play an important role in the rapid expansion of the Chinese R&D sector: Between 2001 and 2007, state-owned firms contribute to 25–35% of the total R&D spending in China. Moreover, super-stars state-owned firms like ZTE are among firms that file and own the most patents by the U.S. standard.[5] In Table A.1, I show that conditional on size, state-owned firms invest more intensively in R&D and are more likely to innovate than private firms.

Despite their extensive engagement in the R&D activities, state-owned firms are inefficient innovators. First, the agency problem between the government owner and firm managers leads to widespread presence of poor managerial practices and misalignment in incentives among state-owned firms. Those inefficiencies limit state-owned firms' ability to screen R&D projects (Huang and Xu, 1998; Qian and Xu, 1998; Zhang, Zhang, and Zhao, 2003). Second, readily accessible external credit can also be a factor that leads to inefficiency in R&D (Almeida, Hsu, and Li, 2013; Almeida, Hsu, Li, and Tseng, 2017). With better access to credit, state-owned firms have less incentives to focus on the cost effectiveness of their R&D investment. Ultimately, state-owned firms are inefficient innovators who have low returns to R&D (Boeing, 2016; Wei, Xie, and Zhang, 2017).

1.3 Model

This section extends the quality ladder model from Klette and Kortum (2004) to incorporate state-owned and private firms. Connections to the government provide state-owned firms access the factor market without friction. In contrast, private firms face frictions in accessing the factor market. I show this difference leads to a wedge in return to R&D between state-owned and private firms, which affects the growth rate and welfare in the economy.

Preference

The economy is inhabited by an infinitely-living representative household, who supplies $L = 1$ unit of labor inelastically in each period (i.e., there is no population growth). The household chooses consumption $C(t)$ to maximize its life-time utility:

$$\max_{C(t)} U = \int_{t=0}^{\infty} \exp\{-\rho t\} \frac{C(t)^{1-\theta} - 1}{1-\theta} dt \tag{1.1}$$

[5] ZTE owns over 150,000 patents. (source: https://patents.google.com/?assignee=zte&oq=zte).

subject to the budge constraint

$$\dot{A}(t) = rA(t) + w(t) + \pi(t) + T(t) - C(t),$$

where $A(t), w(t), \pi(t), T(t), r$ are household savings, wage rate, profit from owning private firms, government transfer, and the interest rate at time t. Solution to the household problem leads to the standard Euler equation

$$\frac{\dot{C}}{C} = \frac{r-\rho}{\theta}. \tag{1.2}$$

Let $Y(t)$ be the total output at time t, and $L_{\mathcal{P}}, L_{\mathcal{R}}$ the labor employed in the production and the R&D sector, the goods and labor market clearing conditions imply

$$C(t) = Y(t), \tag{1.3}$$

$$L_{\mathcal{P}} + L_{\mathcal{R}} = L = 1. \tag{1.4}$$

Production

The economy consists of a perfectly competitive final good sector and a continuum of intermediate goods sectors of measure 1. The final good is produced by combining all intermediate goods in a Cobb-Douglas fashion:

$$Y(t) = \exp\left\{\int_0^1 \ln y_i(t)di\right\}. \tag{1.5}$$

Using the final good as the numeraire, the demand for intermediate good i is

$$y_i(t) = \frac{Y(t)}{p_i(t)}. \tag{1.6}$$

The intermediate goods are produced by multi-product firms using a linear production function with a single factor ("labor"):[6]

$$y_{f,i}(t) = a_{f,i}(t)l_{f,i}(t),$$

where $y_{f,i}(t), a_{f,i}(t)$ and $l_{f,i}(t)$ denote the output, productivity and labor hired by firm f in producing i at time t.

There are two types of firms in the economy: State-owned firms (S) and private firms (P). They differ in two aspects. First, Connections to the government provide state-owned firms access to the labor market at the prevailing wage $w(t)$. On the other hand, private firms have to pay extra τ percent of the wage in order to overcome market frictions discussed in

[6] Although the factor is called labor, one should consider it as a composition factor that includes labor, capital, and material inputs.

Section 1.2.[7] The wedge is non-stochastic: It does not change over time. Second, state-owned and private firms may have different innovative capacities (to be defined later).[8]

Let $\tau > 0$ be the reduced-form representation of the factor market wedge. The marginal costs of producing an intermediate good is given by

$$mc_f(\tau, a, t) = \begin{cases} \frac{w(t)(1+\tau)}{a} & f \text{ is a private firm} \\ \frac{w(t)}{a} & f \text{ is a state-owned firm} \end{cases}, \tag{1.7}$$

which is a function of both the productivity of the firm, a, and the market friction it faces, τ.

Firms producing the same intermediate good engage in Bertrand competition. Only the firm with the lowest marginal cost ("market leader", L) can produce. The market leader will price at the second lowest marginal cost ("market follower", F). Let $a_{Li}(t), l_{Li}(t)$ to be the productivity, production labor of the market leader in market i at time t, $\tau_{Fi}(t)$ to be the factor market wedge the market follower in i at time t faces, and $\Delta a_i(t) = \frac{a_{Li}(t)}{a_{Fi}(t)}$ to be the productivity gap between L and F in market i, the total production workers in the intermediate goods sector is

$$\begin{aligned} L_{\mathcal{P}}(t) &= \int_0^1 l_{Li}(t)di = \int_0^1 \frac{y_i(t)}{a_{Li}(t)}di = \int_0^1 \frac{Y(t)}{a_{Li}(t)p_i(t)}di = \int_0^1 \frac{Y(t)}{w(t)(1+\tau_{Fi}(t))\Delta a_i(t)}di \\ &= \frac{Y(t)}{w(t)} \int_0^1 (1+\tau_{Fi}(t))^{-1}\Delta a_i(t)^{-1}di. \end{aligned} \tag{1.8}$$

Equation (1.8) and (1.5) give the expression for equilibrium wage

$$w(t) = \exp\left\{\int_0^1 \ln a_{Li}(t)di\right\} \exp\left\{\int_0^1 \ln[(1+\tau_{Fi}(t))^{-1}\Delta a_i(t)^{-1}]di\right\}.$$

Denote $A(t) = \exp\left\{\int_0^1 \ln a_{Li}(t)di\right\}$ and $\mathcal{M}(t) = \frac{\exp\left\{\int_0^1 \ln[(1+\tau_{Fi}(t))^{-1}\Delta a_i(t)^{-1}]di\right\}}{\int_0^1 (1+\tau_{Fi}(t))^{-1}\Delta a_i(t)^{-1}di}$, the aggregate output is

$$Y(t) = A(t)\mathcal{M}(t)L_{\mathcal{P}}(t). \tag{1.9}$$

That is, the total output at time t is determined by the productivity index, $A(t)$, the markup dispersion, $\mathcal{M}(t)$, and the total labor used in production, $L_{\mathcal{P}}(t)$. Furthermore, the output

[7] The factor market wedge can be micro-founded by a capacity-constrained government providing a costly market smoothing tool for firms by taxing the household in a lump-sum fashion. Since the government is fiscally constrained, it can only provide this tool to state-owned firms, who are connected, but not for private firms who are not connected.

[8] There are other potential differences between state-owned and private firms. In Appendix A.2, I show that this model can be easily extended to include these potential differences. These extensions do not change the predictions of the model.

growth is the sum of the growth of all three components:

$$g_Y = g_A + \underbrace{g_{\mathcal{M}} + g_{L_{\mathcal{P}}}}_{=0}. \tag{1.10}$$

Appendix A.1 shows $\mathcal{M}(t)$ and $L_{\mathcal{P}}(t)$ are constant on the balanced growth path. Therefore $g_{\mathcal{M}} = g_{L_{\mathcal{P}}} = 0$. The output growth is determined solely by productivity growth.

The factor market wedge τ affects both the level and growth rate of the output. First, since only private firms face τ, a mixture of state-owned and private producers leads to cross-sectional markup dispersion. $\mathcal{M}(t)$ summarizes this dispersion. Since $\mathcal{M}(t) < 1$ for all $\tau > 0$, a positive τ leads to a lower output level.[9] Second, as I will show in the rest of this section, τ encourages state-owned firms to innovate while discouraging private firms from innovating. Therefore, τ affects resource allocation within the R&D sector. Since R&D is the only source of productivity growth, τ affects the growth rate of the economy as well. Depending on how firms respond to τ, its impact on the growth rate can be either positive or negative.[10]

Innovation

The growth implications of the factor market wedge depends on the underlying evolution of productivity. Productivity improves as firms innovate. Firms choose the level of R&D investment by hiring researchers from the labor market to generate innovations. The return to R&D investment depends not only on how much an innovation improves productivity, but also the competition between the innovator and the incumbent.

Innovations take the form of creative destruction: Upon success, the innovating firm acquires a new technology that improves upon the best available technology of a randomly selected intermediate good $i \in [0, 1]$. Mathematically, the innovator becomes the technology leader in producing i with $a_{f,i}(t+) = \lambda \max_{f'} a_{f',i}(t)$ for some $\lambda > 1$. $t+$ denotes the moment after t. The incumbent market leader f' becomes the technology follower after the innovation. From a social planner's point of view, innovations from state-owned and private firms are perfect substitutes. They increase the productivity by the same amount λ.[11]

R&D is undirected: Firms cannot control in which market their innovations occur. Since firms can be leaders in at most countable number of markets, and there is a continuum of intermediate goods, the probability of a technology leader extending its lead by innovating

[9] τ can also lead to a lower productivity level $A(t)$. This happens when the market leader does not have the best technology. If some market leaders have worse technology than the market follower, the productivity and the total output level will be lower. This inefficiency happens when private firms' productivity advantage cannot overcome their disadvantage in the factor market. Section 1.3 discusses this possibility in detail.

[10] Equation (1.8) suggests that τ also affects the allocation of labor between the production and the R&D sector. However, the direction of this effect is unclear. τ can either increase or decrease the total labor hired in the R&D sector. In my data, this effect is quantitatively small.

[11] Section 1.5 introduces an extension allowing state-owned firms' innovations to be more effective than those from private firms. The main results do not change with this extension added to the model.

into its own product is 0. Hence, the productivity gap between a technology leader and a follower is always λ.

In the absence of τ, technology leaders will always have the lowest marginal costs, making them also the market leaders. This statement is not necessarily true when a factor market wedge presents. In particular, when $1+\tau > \lambda$, a technologically following state-owned firm can still have a lower marginal cost than a technologically leading private firm. In this case, better integration to the factor market fully offsets state-owned firms' technological disadvantage, allowing them to be market leaders despite having unproductive technology.[12]

Firms produce innovations by combining researchers, l, with their existing knowledge capital, m, according to the production function $X_k = (\phi_k l)^{1/\zeta} m^{1-1/\zeta}, k \in \{P, S\}$. X_k is the Poisson arrival rate of an innovation, and $1/\zeta$ is the innovation-R&D elasticity. Denote $x = X/m$ as the innovative intensity, the R&D cost function for type k firms is

$$G_k(x, m, t) = m \frac{(1+\tau_k) w(t)}{\phi_k} x^{\zeta}, \ k \in \{P, S\}. \tag{1.11}$$

Notice that firms face the same factor market friction in both the production sector (Equation (1.7)) and the R&D sectors (Equation (1.11)). This feature highlights that production and innovation use the same factor. Since production workers and researchers are from the same labor market, firms should face the same frictions when hiring in either sector.

Following Klette and Kortum (2004), I measure knowledge capital in a firm by the number of the cutting edge technologies it owns. Since private firms can produce in a market only when they have the best technology, their knowledge capital equals to the number of markets they lead. On the other hand, state-owned firms can be the market leader without having the cutting edge technology when $1+\tau > \lambda$. The amount of knowledge capital they own can be lower than the number of markets they lead in this case.

Another important heterogeneity across state-owned and private firms is their innovative capacities, ϕ_k. ϕ_k determines how efficient type k firms are in producing innovations from researchers. Despite the discussion in Section 1.2, I do not make any *ex ante* restriction on which type of firms has a higher innovative capacity; instead, I will estimate innovative capacities from the data.

Value Functions

This section describes the optimization problems firms solve.

Private Firms The household owns private firms. Any profits they make are distributed back to the household. A private firm producing n products chooses the level of innovation

[12] To simplify the analysis, I assume $1+\tau < \lambda^2$, so that the difference in factor market access is not too extreme. As shown in Section 1.5, $\lambda < 1+\tau < \lambda^2$ is the empirically relevant case. All results presented in the paper hold with minimal modification if I drop this assumption.

intensity, x, to solve the following optimization problem:[13]

$$rV_P(n,\{\mu_i\}) = \dot{V}_P(n,\{\mu_i\}) + \sum_{i=1}^{n}\Big\{ \underbrace{\pi(\mu_i)}_{\text{flow profit}} + \underbrace{z[V_P(n-1,\{\mu_j\}_{j\neq i}) - V_P(n,\{\mu_i\})]}_{\text{business stolen by other's innovation}} \Big\}$$
$$+ \max_x \left\{ \underbrace{\sum_{i=1}^{n} x[\mathbb{E}_{\tilde{\mu}} V_P(n+1,\{\mu_i\}\cup\{\tilde{\mu}\}) - V_P(n,\{\mu_i\})]}_{\text{successful innovation}} - n\underbrace{\frac{(1+\tau)w}{\phi_P}x^{\zeta}}_{\text{innovation cost}} \right\}, \tag{1.12}$$

where n and $\{\mu_i\}$ are the number of markets owned by the state-owned firm and the markup in each market z_k are the (endogenous) total innovation rate by type k firms, and $m \le n$ is the number of markets in which the state-owned firm is both the technology and the market leader.

The value function (1.12) consists of three parts. First, the capital gain, $\dot{V}_P$. Second, the flow profit, $\sum_i \pi(\mu_i)$. Third, any change to the product portfolio of the firm. The change can be either the firm loses a market to another firm or gains a market via a successful innovation. When choosing the level of innovation intensity, the firm takes as given the aggregate innovation intensity chosen by other firms.

State-owned Firms the government owns state-owned firms. It distributes any profit from the state-owned firms back to the household in the form of government transfers. State-owned firms solve the following problem:

$$rV_S(n,m,\{\mu_i\}) = \dot{V}_S(n,m,\{\mu_i\})$$
$$+ \sum_{i=1}^{n} \left\{ \begin{array}{l} \pi(\mu_i) + z_S[V_S(n-1,m-1,\{\mu_j\}_{j\neq i}) - V_S(n,m,\{\mu_i\})] \\ +z_P \left[\begin{array}{l} \mathbf{1}\,[1+\tau>\lambda, \text{tech. leading}] \times \\ (V_S(n,m-1,\{\mu_j\}_{j\neq i}\cup\{\hat{\mu}\}) - V_S(n,m,\{\mu_i\})) \\ +(1-\mathbf{1}\,[1+\tau>\lambda, \text{tech. leading}])\times \\ (V_S(n-1,m-1,\{\mu_j\}_{j\neq i}) - V_S(n,m,\{\mu_i\})) \end{array} \right] \end{array} \right\},$$
$$+ \max_x \left\{ \sum_{i=1}^{m} x[\mathbb{E}_{\tilde{\mu}} V_S(n+1,m+1,\{\mu_i\}\cup\{\tilde{\mu}\}) - V_S(n,m,\{\mu_i\})] - m\frac{w}{\phi_S}x^{\zeta} \right\} \tag{1.13}$$

where z_k are the (endogenous) total innovation rate by type k firms, and $m \le n$ is the number of markets in which the state-owned firm is both the technology and the market leader.

The extra term

$$z_P \left[\begin{array}{l} \mathbf{1}\,[1+\tau>\lambda, \text{tech. leading}]\,(V_S(n,m-1,\{\mu_j\}_{j\neq i}\cup\{\hat{\mu}\}) - V_S(n,m,\{\mu_i\})) \\ +(1-\mathbf{1}\,[1+\tau>\lambda, \text{tech. leading}])(V_S(n-1,m-1,\{\mu_j\}_{j\neq i}) - V_S(n,m,\{\mu_i\})) \end{array} \right]$$

[13] I suppress the time variable in those value functions for cleanness.

in (1.13) captures the possibility that a state-owned firm remains the market leader despite a private innovator acquires a better technology through innovation.[14] In this case, although the private innovator cannot take over the market, it can put a downward price pressure on the state-owned incumbent, who can only charge a lower markup, $\hat{\mu}$. Otherwise, state-owned firms' value function is identical to that of private firms up to markups $\{\mu_i\}$ and the innovation cost function G_S.

Lemma 1.1 demonstrates that the value functions are additively separable in intermediate markets i. Consequently, an n-product firm behave in the same way as n 1-product firms of the same ownership type. This result allows me to focus on the values of intermediate markets, instead of multi-product firms.

Lemma 1.1. *Denote m the number of intermediate products in which firm k is the technology leader, then the value function (1.12) and (1.13) can be written as*

$$V_k(n, \{\mu_i\}) = Y(t) \sum_{i}^{n} v_k(\mu_i), k \in \{P, S\},$$

where v_P, v_S are solutions to the problems

$$\begin{aligned} v_P(\mu) &= \frac{\tilde{\pi}(\mu) + \Xi_P}{r+z}, \\ v_S(\mu) &= \frac{\tilde{\pi}(\mu) + z_P \mathbf{1}\left[1+\tau > \lambda; \textit{tech. leading}\right] v_S\left(\frac{\lambda}{1+\tau}\right) + \mathbf{1}\left[\textit{tech. leading}\right] \Xi_S}{r+z}, \end{aligned}$$

$\tilde{\pi}(\mu) = (1 - \mu^{-1})$, r is the interest rate, g_Y is the growth rate of Y, and

$$\Xi_k = \max_x \left\{ x \mathbb{E}_{\tilde{\mu}} v_k(\tilde{\mu}) - \frac{(1+\tau_k)\omega x^{\zeta}}{\phi_k} \right\}$$

is the option value of being the technology leader in a market with normalized wage $\omega = w/Y$.

Proof. See Appendix A.1 □

The value of producing an intermediate good consists of two parts: The flow profit from producing the goods, $\tilde{\pi}(\mu)$, and the option value Ξ where the knowledge capital in market i could help the firm innovating into another market. The value is discounted by both the interest rate and the possibility of being replaced by other firms.

As discussed above, when $1 + \tau > \lambda$, state-owned firms can be market leaders without having the best technology. There are two implications: First, a state-owned firm can remain as a market leader even when a private firm acquires better technology through innovation. This is captured by the extra term $z_{P,x}\mathbf{1}\left[1+\tau > \lambda; \text{tech. leading}\right] v_S\left(\frac{\lambda}{1+\tau}\right)$.

[14] The indicator function $\mathbf{1}\left[1+\tau > \lambda, \text{tech. leading}\right]$ shows that this happens when $1+\tau > \lambda$ and the state-owned firm was the technology leader in the market before the private innovator enters.

Second, state-owned firms do not have any knowledge capital in technologically following market even when they are market leaders. In this case, they cannot innovate. Therefore, the option value of research is non-zero only when state-owned market leaders have technology advantages over market followers. This is captured by the indicator function $\mathbf{1}$ [tech. leading].

With the help of Lemma 1.1, I now calculate the optimal research intensity.

Proposition 1.1. *The optimal research intensity, x_k^* are given by*

$$x_k^* = \left(\frac{\phi_k \mathbb{E}_{\tilde{\mu}} v_k(\tilde{\mu})}{\zeta(1+\tau_k)\omega} \right)^{1/(\zeta-1)}. \tag{1.14}$$

Proof. See Appendix A.1 □

Proposition 1.1 summarizes how the factor market wedge affects the optimal innovation intensity. The wedge τ distorts R&D decisions in two ways. First, innovation requires firms hiring researchers from the labor market. The wedge τ affects directly the cost of inputs in the R&D sector and distorts the research intensity chosen by firms. Private firms face higher friction τ, which increases the cost of R&D activities. Hence they will innovate less. Second, τ affects the return to innovation through changes in the *firm composition*. Lower private R&D intensity lead to fewer innovations and a smaller market share for private firms in equilibrium. Thus, the remaining private firms will more likely to compete with state-owned firms when they innovate, which further lowers their expected return to R&D investments. Thus, this general equilibrium effect also disincentivizes private firms from innovating.

Entry

A unit mass of potential entrants has access to the same innovation production function with innovative capacity ϕ_ϵ. Potential entrants also face the wedge τ, which captures entry barriers they face. After a successful innovation, a fraction p of the entrants exogenously acquire state ownership and become state-owned firms. The remaining entrants become private firms. Entrants engage in Bertrand competition with incumbents on the intermediate good market after their ownership types realize.

The entrants solve the following optimization problem

$$\max_x \left\{ x\mathbb{E}_{\tilde{\mu}}[pv_S(\tilde{\mu}) + (1-p)v_P(\tilde{\mu})] - \frac{(1+\tau)\omega}{\phi_\epsilon} x^\zeta \right\}. \tag{1.15}$$

Problem (1.15) determines entrants' innovation intensity, x_ϵ^*. I focus on the empirically relevant case in which $x_\epsilon^* > 0$, i.e., there are positive entry into the economy (see, e.g., Brandt, Van Biesebroeck, and Zhang 2012).

Balanced Growth Path

I focus on a balanced growth path (BGP) where the markup distribution is stationary over time.

The markup in market i at time t is given by $\mu_i(t) = \frac{mc_{Fi}(t)}{mc_{Li}(t)}$, where the marginal costs are given by Equation (1.7). Therefore, the markup can be pinned down by the match of the types between the market leader and the follower. When $1+\tau \leq \lambda$, market leaders are always technology leaders, and the market followers are always technology followers. Therefore, the markup can be pinned down by the match between the technology leader and follower. There are 4 possible matches among 2 types, so the markup can only take 4 different values. Let μ_{jk} be the markup in a market where the technology leader is type j, and the follower is type k, equation (1.7) implies

$$\mu_{PP} = \mu_{SS} = \lambda, \quad \mu_{PS} = \frac{\lambda}{1+\tau}, \quad \mu_{SP} = \lambda(1+\tau). \tag{1.16}$$

When $1+\tau > \lambda$, markup depends on more than the technology leader and follower match. Specifically, a private technology follower may not be the market follower, since a state-owned firm with the third-best technology will have a lower marginal cost than the private technology follower. In this case, I need to track firms ranked third in the productivity ladder.[15] As a result, there are six matches. Denote μ_{jkl} to be the markup the market leader charge in a market where j is the technology leader, k is the technology follower, and l is the firm with third-best technology, then

$$\mu_{PPP} = \lambda, \mu_{PPS} = \frac{\lambda^2}{1+\tau}, \mu_{PS} = \frac{1+\tau}{\lambda}, \mu_{SPP} = \lambda(1+\tau), \mu_{SPS} = \lambda^2, \mu_{SS} = \lambda. \tag{1.17}$$

Since markups are determined by the matches of market leaders' and followers' types, the stationarity condition for the markup distribution requires the share of each match to be constant. When $1+\tau \leq \lambda$, denote S_{jk} the number of intermediate product market with a technologically leading type j firm and a following type k firm. Since there is a measure of 1 intermediate market in total, S_{jk} is also the share of jk match. The law of motion for S_{jk} is given by

$$\begin{aligned}
\dot{S}_{PP} &= \underbrace{((S_{PP}+S_{PS})x_P + (1-p)x_\epsilon)(S_{PP}+S_{PS})}_{PP-\text{match created}} \quad - \quad \underbrace{zS_{PP}}_{PP-\text{match destroyed}} \\
\dot{S}_{PS} &= ((S_{SP}+S_{SS})x_P + (1-p)x_\epsilon)(S_{SP}+S_{SS}) - zS_{PS} \\
\dot{S}_{SP} &= ((S_{PP}+S_{PS})x_S + px_\epsilon)(S_{PP}+S_{PS}) - zS_{SP} \\
\dot{S}_{SS} &= ((S_{SP}+S_{SS})x_S + px_\epsilon)(S_{SP}+S_{SS}) - zS_{SP}.
\end{aligned} \tag{1.18}$$

A stationary markup distribution requires $\dot{\mathbf{S}} = 0$.

[15] With the assumption $1+\tau < \lambda^2$, I do not need to go down the list to firms with the forth-best technology.

The intuition behind equation (1.18) is simple: Changes in the jk match share is the difference between all new jk match created, which happens when a j type firms innovate into a market controlled by a k incumbent, and all destruction of the existing jk match, which happens when any firms innovating into a jk market.

Similarly, when $1+\tau > \lambda$, the law of motion for markup distribution is given by

$$\begin{aligned}
\dot{S}_{PPP} &= (S_{PPP} + S_{PPS})(S_{PP}x_P + (1-p)x_\epsilon) - zS_{PPP} \\
\dot{S}_{PPS} &= S_{PS}(S_{PP}x_P + (1-p)x_\epsilon) - zS_{PPP} \\
\dot{S}_{PS} &= (S_{SPS} + S_{SS} + S_{SPP})(S_{PP}x_P + (1-p)x_\epsilon) - zS_{PS} \\
\dot{S}_{SPP} &= (S_{PPP} + S_{PPS})((S_{SP} + S_{SS})x_S + px_\epsilon) - zS_{SPP} \\
\dot{S}_{SPS} &= S_{PS}((S_{SP} + S_{SS})x_S + px_\epsilon) - zS_{SPS} \\
\dot{S}_{SS} &= ((S_{SP} + S_{SS})x_S + px_\epsilon)(S_{SP} + S_{SS}) - zS_{SP}.
\end{aligned} \tag{1.19}$$

There are two differences between (1.18) and (1.19): first, in an economy with $1+\tau > \lambda$, some state-owned firms do not invest in R&D at all since they do not have the required knowledge capital. Second, the transition matrix between different matches is different because of more matching types. Otherwise, the law of motion (1.19) has the same intuition as in (1.18).

Given this stationarity condition, I can now define the BGP.

Proposition 1.2. *There exists unique BGP where*

1. *firms choose innovation intensity optimally according to (1.14)*
2. *entrants choose innovation intensity optimally according to (1.15)*
3. *the household maximizes utility according to (1.1)*
4. *the goods market and labor market clear as per (1.3) and (1.4)*
5. *the markup distribution is stationary, i.e.* $\dot{\mathbf{S}} = 0$

Proof. See Lentz and Mortensen (2008) and Appendix A.1 □

Finally, Proposition 1.3 summarizes the growth rate along the BGP of this economy.

Proposition 1.3. 1. *Let z be the endogenous rate of total innovation, then*

$$g_Y = g_A = z \ln \lambda.$$

2. *On BGP, z is given by*

$$z = F_P x_P^* + F_S x_S^* + x_\epsilon^*,$$

where x_P^*, x_S^* are given in Proposition 1.1, x_ϵ^* is given by (1.15), and F_k is the number of type k firms that are actively engaging in R&D activities:

$$F_P = \begin{cases} S_{PP} + S_{PS} & \text{if } 1+\tau \leq \lambda \\ S_{PPP} + S_{PPS} & \text{if } 1+\tau > \lambda \end{cases}; \quad F_S = \begin{cases} S_{SP} + S_{SS} & \text{if } 1+\tau \leq \lambda \\ S_{SPP} + S_{SPS} + S_{SS} & \text{if } 1+\tau > \lambda \end{cases}.$$

Proof. See Appendix A.1. □

Proposition 1.3 states that the total innovation output equals to the sum of incumbent firms and entrants' innovation output.

Distortions and Market Failures

This section summarizes both static and dynamic distortions in my model.

Static Distortions I focus first on static distortions of τ, defined as its effects on the productivity level. The aggregate output is given by

$$Y = A\mathcal{M}L_{\mathcal{P}}$$

with $A = \exp\left\{\int_0^1 \ln a_i di\right\}$, $\mathcal{M} = \frac{\exp\left\{\int_0^1 \ln[(1+\tau_{Fi})^{-1}\Delta a_{it}^{-1}]di\right\}}{\int_0^1 (1+\tau_{Fi})^{-1}\Delta a_{it}^{-1} di}$, and $L_{\mathcal{P}} = \frac{1}{\omega}\int_0^1 \ln(1+\tau_{Fi})^{-1}\Delta a_i^{-1} di$. The factor market wedge τ lowers the level of productivity in two ways. First, it generates markup dispersion, $\mathcal{M} < 1$. Second, in the case of $1+\tau > \lambda$, some technologically following state-owned firms will be producing. Both effects lower the dispersion-adjusted productivity, $A\mathcal{M}$.

Dynamic Distortions Dynamic distortions are distortions to the growth rate of the economy. There are two dynamic distortions in this economy: The first one results from the positive externality of R&D investment, which does not depend on τ. The second one is τ specific.

In the absence of τ, there is insufficient R&D investment due to incomplete appropriation of the social benefit from R&D. This is because firms do not internalize the value of future innovations that build on their R&D outputs[16]. In other words, τ creates a wedge between the marginal social benefit and marginal social cost of R&D investment. It creates misallocation of labor between the production and the R&D sector.

The introduction of τ leads to misallocation of labor within the R&D sector. Proposition 1.1 shows that a positive τ creates a wedge in the marginal return to R&D between state-owned and private firms. Since the R&D cost function is convex, total innovation output is higher if marginal returns are equalized across firms. Therefore, the wedge leads to

[16]There is also a business stealing effect that encourages too much R&D investment for firms to steal other firms' business. In empirically relevant cases, the incomplete appropriation effect dominates. Hence there is underinvestment in R&D activities.

lower aggregate innovation. The extent to which R&D labor is misallocated depends on the relative innovative capacities between state-owned and private firms. A positive τ encourages state-owned firms to invest more in R&D, while decreases private firms' engagement in R&D. Therefore, the dynamic distortion from τ is large if state-owned firms are less efficient in innovating, since inefficient firms innovate more, while more efficient firms innovate less. Conversely, the magnitude of dynamic distortion would be smaller if state-owned firms are more efficient in innovating.

In this model, connections to the government serve only to reduce market frictions state-owned firms face. They do not impose any direct cost on any firm. Yet, these connections can still generate inefficiency by misallocating resources across connected and unconnected firms. This result suggests that even corruption thought to alleviate regulatory burdens ("greasing the wheel") can lead to welfare loss.

Welfare

This section discusses how I measure the welfare implication of the factor market wedge.

I compare the welfare between two economies: a *state capitalism* economy in which only private firms are subjected to market frictions, and a *laissez-faire* economy in which both types of firms are subjected to frictions. The main difference between the state capitalism and the *laissez-faire* economies is the return to R&D investment across firms of different ownership. In the *laissez-faire* economy, state-owned and private firms have the same factor market access and return to R&D. Consequently, the marginal return to innovation across different types of firms is equalized in the *laissez-faire* economy.[17]

To compare welfare, I calculate the consumption-equivalent change. Denote C_S, g_S to be the initial consumption level and the equilibrium growth rate under the state capitalism economy, and C_{LF}, g_{LF} to be the initial consumption level and the equilibrium growth rate under the *laissez-faire* economy. The consumption-equivalence change, γ, is given by

$$U(\gamma C_S, g_S) = U(C_{LF}, g_{LF}), \tag{1.20}$$

where $U(C_0, g) = \frac{1}{1-\theta}\left[\frac{C_0^{1-\theta}}{\rho-(1-\theta)g} - \frac{1}{\rho}\right]$ is the life-time utility of household (1.1) on the balanced growth path (C_0, g). The consumption-equivalence change, γ is the net present value difference of the consumption flows implied by (C_{LF}, g_{LF}) and (C_S, g_S), properly discounted using the utility function (1.1). $\gamma > 1$ implies the household in the state capitalism economy has a lower life-time utility level.

[17] Alternatively, I can compare the state capitalism economy to a frictionless economy in which there is no friction to state-owned and private firms. The welfare implication calculated using the frictionless economy is the same as the *laissez-faire* economy. This is because the wage in my model is a free variable that ensures market clear in equilibrium. The decentralized equilibrium in a frictionless economy is equivalent to the decentralized equilibrium in a *laissez-faire* economy with $w_{frictionless} = w_{laissez-faire} - \tau$. I focus on the *laissez-faire* economy as my counterfactual since it is interpretation is clearer (removing the state-owned privilege).

To be clear, the *laissez-faire* economy is not socially optimal. Incomplete appropriation of the social benefits of innovation still exists when there is no heterogeneous factor market access. Compared with the first-best equilibrium, firms still under-invest in R&D.[18] In Appendix A.1, I show that the decentralized equilibrium in *laissez-faire* economy results in lower welfare when comparing to the social planner's solution.

The *laissez-faire* economy's suboptimality implies that the factor market wedge does not always lead to welfare loss. In the model, state-owned firms' better factor market access is isomorphic to a government subsidy on their labor usage. The subsidy may address the under-investment in R&D by increasing state-owned firms' returns to R&D and lower their costs, incentivizing them to innovate more. However, it also discourages innovations from private firms who are disadvantaged by the subsidy. In addition, the subsidy generates a wedge in the R&D returns, which leads to resource misallocation. In the end, the overall welfare effect of τ depends on the parameters in the model.

1.4 Quantitative Exercise

I now structurally estimate this model using Chinese firm-level data. This section describes the data (Section 1.4), the mapping between my model and the data (Section 1.4), and the estimation procedure (Section 1.4). The next section reports the results from this exercise.

Data

The dataset I use is the Annual Survey for Industrial Enterprises (ASIE) between 1998 and 2007, compiled by the Chinese National Bureau of Statistics. ASIE contains information on balance sheets and income statements for all state-owned firms, and firms with other ownership whose annual sales is above 5 million RMB ($\sim$ 700k USD). Despite this left censoring, ASIE is the most comprehensive firm-level dataset in China, covering over 90% of the total industrial output.

ASIE is particularly suitable for estimating the dynamic effect of factor market wedges. First, the total R&D expenditure in China increased over seven-fold from 1998 to 2007, making this period the fastest growing episode in China (National Science Foundation, 2020). Second, ASIE tracks firms over time. Its panel structure allows me to examine whether the model can capture firm dynamics. Third, Hsieh and Song (2015) find that registered ownership types misclassify many state-owned firms as private due to share cross-holding. ASIE reports not only the registration types, but also the capital structure of the firm. This information allows me to identify state-owned firms using more accurate *de facto* ownership.

[18] Furthermore, under-investment in R&D exists even if I removed the factor market wedge for both state-owned and private firms. This is because changes in equilibrium wage can offset any effect from a uniform factor market wedge. As a result, the decentralized equilibrium in a frictionless economy will be the same as the decentralized equilibrium in a *laissez-faire* economy.

The procedure for identifying firm ownership takes two steps. In the first step, I determine the ownership of firms for each year I observe them. A firm is state-owned in a year if its largest shareholder reported in that year is the state (i.e., the central or local government). On the other hand, a firm is private in a given year only if it reports no state or foreign capital in that year. The second step determines the ownership at the firm level. A firm is private if it is private for all years I observe them. A firm is state-owned if it is state-owned at any point during its life span.[19]

To construct the final dataset, I keep only the identified state-owned and private firms in the dataset. I follow Cai and Liu (2009) and Nie, Jiang, and Yang (2012) to drop firms reporting abnormal values.[20] I end up with 367,000 unique firms and around 1.4 million firm-year observations. To calculate moments for calibration, I derive moments that do not depend on firm ownership by taking the average across all firms. For ownership-specific moments, I take the average across firms with the same ownership. Following the standard practice in using the ASIE dataset, I winsorize the top and bottom 1% of the data to exclude extreme values when calculating moments.

Table 1.1 reports the summary statistics and the moments from ASIE data. Three features stand out. First, there is active entry and exit of firms. The number of firms increases from around 50,000 in 1998 to over 267,000 in 2007. On average, entrants account for almost 13% of total employment. In addition, both private and state-owned firms have high exit probabilities (10% and 11%, respectively). Consistent with Brandt, Van Biesebroeck, and Zhang (2012), these figures suggest creative destruction is an important aspect of the firm dynamics among Chinese manufacturing firms. Using a model of creative destruction allows me to explicitly capture this feature, which is missing in similar studies (e.g., Chen 2019; König, Song, Storesletten, and Zilibotti 2020).

Second, the average revenue total-factor productivity (TFPR) in private firms is higher than that in state-owned firms. This difference reflects state-owned firms having better access to factor markets (Hsieh and Klenow, 2009; Cull, Xu, and Zhu, 2009; Cull, Li, Sun, and Xu, 2015). I return to the measure and interpretation of the TFPR difference in Section 1.4 for more discussion.

Third, similar to Boeing (2016), Wei, Xie, and Zhang (2017) and others, I also find state-owned firms have lower returns to R&D. In my data, state-owned firms are more likely to report R&D engagement, and conditional on engaging in R&D activities, they report higher spending in R&D. Nevertheless, state-owned firms have slower total-factor produc-

[19] According to this classification strategy, privatized firms are classified as state-owned. Privatized firms are firms that started as state-owned firms. Over time, they are sold to private parties (often in the form of management buyout). These firms may maintain their connections to state-owned financial institutions after privatization. As a result, they could continue enjoy better access to credit than true private firms. According to the model, privatized firms with better factor market access should be grouped with state-owned firms, rather than private firms.

[20] Specifically, I drop observations with missing values in equity structure, sales, employment, total output, and asset. I also drop observations reporting lower total assets than fixed or intangible assets. Finally, I drop observations reporting negative total equity.

Table 1.1: Summary Statistics

variable	mean (s.d.)	variable	mean (s.d)
	panel a: sample statistics		
total no. firms	367,730	no. firms in 1998	51,710
% state	15.17	no. firms in 2007	267,337
% reported R&D activity (private)	.065 (.247)	% reported R&D activity (state)	.117 (.322)
avg. log R&D exp. (private)*	.445 (1.56)	avg. log R&D exp. (state)*	1.14 (2.58)
obs. per firm	3.91 (2.45)		
N. obs	1,437,576		
	panel b: data moments		
entrants' emp. share	.1251 (.0014)	log TFPR(P) − log TFPR(S)	.2073 (.0047)
% state entry	.1515 (.0013)		
TFP growth (LP)	.0375 (.0002)		
TFP growth (private, LP)	.0412 (.0002)	TFP growth (state, LP)	.0160 (.0006)
exit (private)	.1011 (.0003)	exit (state)	.1109 (.0005)

Source: Annual Survey of Industrial Enterprises, 1998 - 2007
Note: firm level TFP are calculated following Levinsohn and Petrin (2003) with Ackerberg, Caves, and Frazer (2015) correction. Standard errors in panel (b) are calculated by bootstrapping the sample 500 times
*: data only available for 2001, 2005, 2006 and 2007

Table 1.2: Calibration of Model Parameters

Parameter	Description	Source/Moments
	panel a: calibrate from other studies	
$\theta = 2$	intertemporal elasticity of substitution	Havranek et al. (2015)
$\rho = 0.02$	discount factor, $\approx 97\%$ annual discount rate	Akcigit and Kerr (2018); Acemoglu et al. (2018)
$\zeta = 1.77$	Innovation elasticity	Chen et al. (2020)
	panel b: calibrate from data moment	
p	% entrant is state	entrant composition
	panel c: jointly estimate from data moment	
ϕ_P	private innovative capacity	normalization
ϕ_S	state innovative capacity	state/private TFP growth and state/private exit rate
ϕ_ϵ	entrant innovative capacity	entrant employment shares
λ	innovation step size	aggregate TFP growth
τ	factor market wedge	private-state log TFPR ratio

tivity (TFP) growth than private firms. These statistics hint at the relative inefficiency of state-owned R&D.

Calibration

I need to calibrate 9 parameters in the model: the discount rate (θ) and the elasticity of intertemporal substitution (ρ), the curvature in the R&D cost function (ζ), the entrant composition (p), the innovative capacities for private, state-owned, and entering firms ($\phi_P, \phi_S, \phi_\epsilon$), the size of innovation improvement (λ), and the factor market frictions (τ). Table 1.2 summarizes my calibration strategy for these parameters.

I calibrate these parameters using three strategies. First, I calibrate parameters governing the utility function and the curvature of the R&D cost function externally. Havranek, Horvath, Irsova, and Rusnak (2015) provide a meta-study on the elasticity of intertemporal substitution in China. They report an average estimate of around 0.5 in China, which translates to $\theta = 2$ in the model. I set the discount factor ρ to 0.02, which corresponds to a 97% annual discount rate. These values of θ and ρ are also used in Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018).

I calibrate the curvature of the R&D cost function ζ based on the estimate of cost elasticity for innovation ($\frac{\Delta R\&D}{\Delta cost}$) reported in Chen, Liu, Suárez Serrato, and Xu (2018).

Chen, Liu, Suárez Serrato, and Xu (2018) obtain a cost elasticity estimate of 1.3 via a change in the Chinese tax code in 2008. In my model, the total R&D expenditure for type k firms is given by

$$\text{R\&D} = m[(1+\tau)w]^{-1/(\zeta-1)} \left(\frac{\phi_k}{Y}\right)^{1/(\zeta-1)} \left(\frac{\mathbb{E}v_k}{1+\tau_k}\right)^{\zeta/(\zeta-1)}.$$

This implies a cost elasticity of $\frac{1}{\zeta-1}$. Therefore, an elasticity of 1.3 corresponds to $\zeta = 1.77$.

Second, I calibrate the entrant composition, p, to match directly to the entrant composition observed in the data. Consistent with Hsieh and Song (2015), entrants are mostly private firms during my sample period. However, there are also new state-owned firms entering the market.

Third, I estimate the rest of the parameters using simulated method of moments. These parameters include the innovative capacities $(\phi_P, \phi_S, \phi_\epsilon)$, the innovation step size λ, and the factor market wedge τ. I use 7 moments to pin down these parameters: the average TFP growth of state-owned, private, and all firms; the exit rate of state-owned and private firms; the entrant employment shares, and the log TFPR ratio between the private and state-owned firms. I normalize the private innovative capacity, ϕ_P to 1, so ϕ_S, ϕ_ϵ are innovative capacities of state-owned firms/entrants relative to the private firms. Section 1.5 shows that my results do not depend on this normalization.

Although these parameters are jointly estimated from the data moment, there is a clear mapping between the moments and the parameters they identify. The innovation step size λ is pinned down by the aggregate TFP growth rate using Proposition 1.3. Entrants' innovative capacity is pinned down by entrants' share of employment in the economy. State-owned firms' innovative capacity is pinned down by the relative TFP growth rate between state-owned and private firms, as well as their exit rates.

Finally, the factor market wedge τ is pinned down by the log TFPR difference between private and state-owned firms. In the model, the TFPR of firm f is given by

$$TFPR_f = \frac{\sum_{i\in f} p_i y_i}{w \sum_{i\in f}(\underbrace{(1+\tau_{Fi})^{-1}\Delta a_i^{-1}}_{prod\ labor} + \underbrace{(x_{fi}^*)^\zeta/\phi_f}_{R\&D\ labor})}.$$

State-owned and private firms have different levels of TFPR in the model due to the difference in their wedge. In particular, τ affects the sizes of both the production unit and the R&D unit in a firm. Proposition 1.1 shows a positive τ shrinks the size of R&D units for private firms and increases the size for state-owned firms. The effect of τ on the production unit depends on the types of market followers.

To calculate the log TFPR differences between state-owned and private firms in the data, I first calculate TFPR for each firm in each year in my sample following Hsieh and Klenow (2009). I then residualize the TFPR with the regression

$$\ln TFPR_{ficrt} = \beta_1 \cdot age_{ficrt} + \beta_2 \cdot age^2_{ficrt} + \gamma_{icrt} + u_{ficrt}, \tag{1.21}$$

where the subscripts denote firm f in (four-digit) industry i, located in city c at time t. r represents whether the firm is part of any "research park" programs that provide tax incentives and financial access to firms (Tian and Xu, 2018). I also include a second degree polynomial of firm age to take out potential life-cycle effect documented in Peters (forthcoming). By taking the residualized TFPR measure, u_{ficrt}, from regression (1.21), I compare only firms at the same stage of the life-cycle, operating in the same industry and city, observed in the same year, and subject to the same tax incentives. After obtain residualized TFPR, $\hat{u}_{ficrt}$, I aggregate this measure to the ownership level. The estimated log TFPR difference between state-owned and private firms is reported in Table 1.1.

In order to infer the factor market wedge using the residualized log TFPR difference, I assume that the only *systematic* difference between state-owned and private firms is their access to the factor market conditional on fixed effects and the life cycle effect. In other words, there cannot be any systematic difference between state-owned and private firms in their realizations of idiosyncratic demand shocks, adjustment costs, factor utilization and quality after conditioning on controls. Matching only the mean difference in TFPR across firm types alleviates some concerns. Since this measure aggregates many firms across long period of times, it is unlikely that these transitory firm-specific factors are driving the difference. Section 1.5 provides additional justification and robustness test for the identification of τ.

I do not target R&D expenditure or patent-related moments. There are several reasons for this decision. First, ASIE only reports R&D expenditure for selected years. Using R&D expenditure will reduce the size of my sample, especially for earlier years. Second, Chen, Liu, Suárez Serrato, and Xu (2018) and König, Song, Storesletten, and Zilibotti (2020) have documented widespread practices of misreport inflated R&D expenditure among Chinese firms. Consequently, I cannot reliably calibrate parameters using moments involving R&D expenditure.

Measuring R&D intensity using patenting activities also has its issues. First, patents only capture a small share of R&D outcome. For example, there are more firms introducing new products than firms filing for patents in the ASIE data. Second, there is insufficient intellectual property right (IPR) protection in China (Hu and Jefferson, 2009; Fang, Lerner, and Wu, 2017). Chinese firms may strategically choose not to patent their R&D outcomes to avoid exposing them to potential competitors. Moreover, there could be systematic differences in the levels of IPR protection for state-owned and private firms (Massey, 2006; Fang, Lerner, and Wu, 2017). Thus, firms with different ownership could have different incentives to patent. As a result, calibrations based on patenting activities will underestimate private firms' R&D activity.

Estimation Procedure

To calibrate moments in Panel (c) of Table 1.2, I first start with a parameter configuration $\vartheta = (\phi_S, \phi_\epsilon, \lambda, \tau)$ and solve the model for the optimal innovation intensity and the markup distribution, x_k^*, S^*.[21] Then I simulate 50,000 firms for approximately 40 years to obtain the equilibrium firm distribution.[22] I calculate the moments from the simulated firms, $\hat{\mathbf{m}}(\vartheta)$, and compare it to the observed moments $\mathbf{m}$. I solve for the parameter configuration that minimizes the GMM objective function

$$\vartheta^* = \arg\min_{\vartheta} \hat{\mathbf{e}}(\vartheta)' W \hat{\mathbf{e}}(\vartheta),$$

where $\hat{\mathbf{e}}(\vartheta) = (e_0, ...e_n)$, with $e_i = \frac{\hat{m}_i(\vartheta) - m_i}{m_i}$. I assign the aggregate TFP growth rate a weight of 3 in W to make sure the estimated model matches this moment. All other moments in $\mathbf{e}$ have unit weight.

To acquire standard errors for the parameters, I perform the estimation procedures on 500 bootstrapped samples then calculate standard errors from the corresponding distribution of the parameters. I stratify by firm ownership and 2-digit industry when constructing bootstrapped samples. Resampling is conducted at the firm level: if a firm is drawn, I keep all years in which the firm is observed.

1.5 Results

This section reports the results of my quantitative exercise. Section 1.5 and 1.5 present the parameter estimates and the fit of the baseline model. Section 1.5 discusses the growth and welfare implications of the factor market wedge. I find that distortions to R&D incentives via competition is necessary to generate the welfare loss. Furthermore, welfare loss from the dynamic distortion is an order of magnitude larger than the static distortion. Section 1.5 consists of various robustness and sensitivity tests. Finally, Section 1.5 estimates two extensions of the model. I show these extensions lead to similar results as the baseline model.

Parameter Estimates

Table 1.3 reports the parameter estimates using the baseline model and procedure described in Section 1.4.

[21] I follow Lentz and Mortensen (2008) and use a fixed point solver for this system. The solver starts with an initial firm type match distribution, F, and solves for x_k^* according to Proposition 1.1 given this distribution. In each iteration, it updates F using the law of motion (1.18) or (1.19) and x_k^*. The process continues until F converges. The algorithm is efficient. Solving for the equilibrium on a modern desktop with an 8-core CPU takes less than 10 seconds.

[22] I simulate 4000 periods. In my model, one period is one week.

Table 1.3: Parameter Estimates, Baseline Model

Variable	Description	Value
ϕ_P	private innovative capacity	1 (normalized)
ϕ_S	state innovative capacity	0.28 (0.050)
ϕ_ϵ	entrant innovative capacity	0.65 (0.116)
λ	innovation step size	1.15 (0.014)
$1+\tau$	factor market wedge	1.20 (0.028)

Note: This table reports parameter estimates from the baseline model. Standard errors reported in parentheses are calculated by running the estimation procedure on 500 bootstrapped samples.

The estimates from the baseline model are consistent with the literature on Chinese manufacturing firms. First, there is an enormous difference in the innovative capacity between state-owned and private firms: The estimated private innovative capacity is 3 times higher than the state-owned innovative capacity. This result echoes with previous reduced-form findings on low return to R&D investments among Chinese state-owned firms (Boeing, 2016; Jia and Ma, 2017; Wei, Xie, and Zhang, 2017).

Second, Chinese entrants are efficient innovators. Chinese entrants' innovative capacity is around 65% of the innovative capacity of private incumbents. This result is driven by entrants' large employment share observed in the data. Moreover, entrants contribute to approximately 45% of the innovation output and productivity growth. This number is consistent with Brandt, Van Biesebroeck, and Zhang (2012), who find entering firms account for 41–72% of the total productivity growth in China.

Third, there is a large factor market wedge between private and state-owned firms. Private firms need to pay a 20% higher factor price to overcome market frictions. This estimate suggests that private firms face a severe disadvantage when competing with state-owned firms. Furthermore, the estimated productivity improvement from innovation, λ, is lower than the gross factor market wedge. This implies state-owned firms with inefficient technology can outcompete private firms with higher productivity by merely having better factor market access. This finding is also consistent with narratives of state-owned privileges in the late 1990s and early 2000s China.

Goodness of Fit

This section discusses the fit of my model. I present evidence suggesting that the model successfully captures key patterns of Chinese firm dynamics in my data.

Targeted Moments Table 1.4 reports targeted moments both in the data and calculated from the model. The model fits the data well, except for a slightly underestimation of the TFP growth rate of private firms. This is because all productivity improvements in the model come from creative destruction. There are likely other types of innovation that are not captured by the model, which lead to faster productivity growth in private firms.[23] Nevertheless, the model successfully reproduces the active business dynamism among Chinese manufacturing firms through the large employment share among entrants and high exit rates for incumbent firms.

Table 1.4: Targeted Data and Model Moments

variable	data	model
entrants' employment share	0.13	0.08 (0.017)
log private/state TFPR ratio	0.21	0.20 (0.014)
TFP growth	0.04	0.03 (0.005)
TFP growth, private	0.04	0.02 (0.003)
exit rate, private	0.10	0.13 (0.020)
TFP growth, state	0.02	0.02 (0.003)
exit rate, state	0.11	0.10 (0.020)

Note: This table reports targeted moments from the data and the baseline model. Bootstrapped standard error for model moments are reported in parentheses.

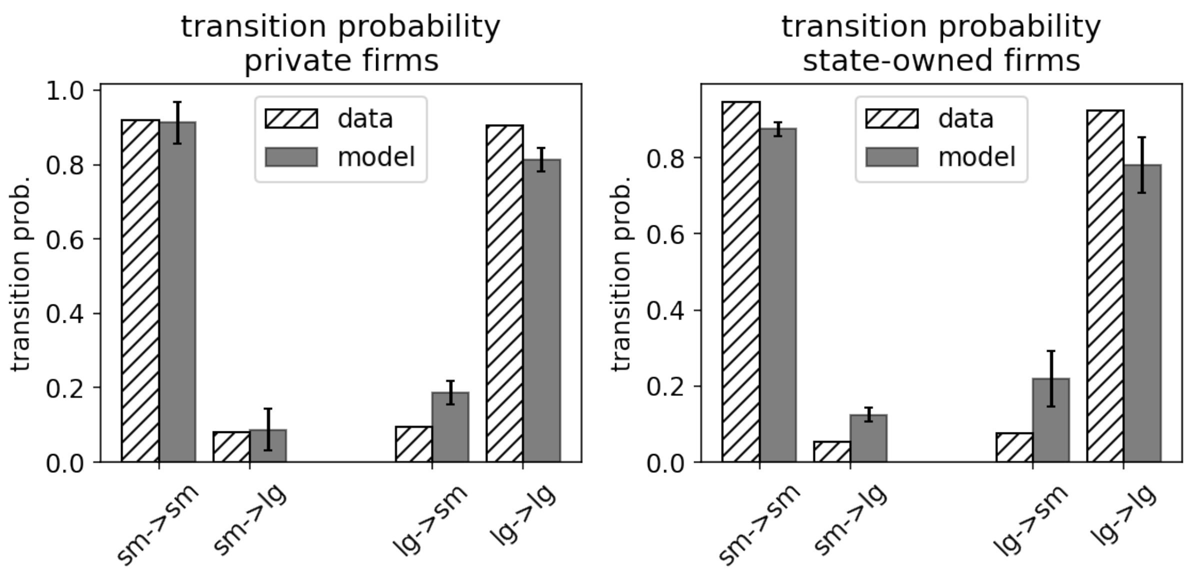
Non-targeted Moments I take advantage of the panel dimension of ASIE, and use various non-targeted moments to assess the model's ability to replicate the observed firm dynamics. Overall speaking, my baseline model successfully replicates the observed patterns in the Chinese firm-level data without explicitly targeting them.

Figure 1.2 plots the transition probabilities between large and small for state-owned and private firms. A firm is large if its employment is above vth percentile among its corresponding ownership type. I calibrate v by matching the firm size distribution in the model and in the data. In this exercise, I define a firm being large if it produces in 2 or more markets. This correspond to firms with employment levels above 40–50th percentile. I then follow the continuing firms and plot their probability of moving across this threshold in consecutive years, both in data and in the model.

Although I do not explicitly target the transition probabilities, Figure 1.2 shows that the model does a good job matching the transition probabilities for both types of firms. Both in my model and in the data, small firms are likely to stay small, and big firms are likely to remain big.

[23]Examples of different types of innovations include incumbents innovate to extend the technology lead they have (Peters, forthcoming), and firms innovate to develop a new variety (Garcia-Macia, Hsieh, and Klenow, 2019).

Figure 1.2: Transition Probability for State-owned and Private Firms



This figure plots transition probabilities for private and state-owned firms. The left panel plots the probabilities of a.) small private firms remain small; b.) small private firms grow and become large; c.) large private firms shrink and become small; and d.) large private firms remain large, first the observed probability in data and then the inferred probability from the model. 95% confidence interval calculated using the bootstrapped sample is also included for inferred probabilities. The right panel plots similar version for state-owned firms.

Second, I follow each entrant cohort in my data and plot their survival probabilities. I compare the observed survival probabilities with the model counterparts. Figure 1.3 reports the results from this exercise for the 1999 and 2002 cohorts. For private firms, the model implied survival probabilities track closely observed survival probabilities. Although the estimates have wider confidence intervals for state-owned firms, the mean survival probabilities implied by the model again follow closely to the observed survival probabilities.

Finally, I calculate the employment growth over the life cycle for state-owned and private firms. Figure 1.4 plots the results of this exercise. I normalize the employment at entry to 1 and report the mean employment of continuing firms relative to the mean entry size. Figure 1.4 shows that my model slightly underestimates the employment growth of private firms. This underestimation is likely driven by the underestimation of the private TFP growth reported in Table 1.4. As a low private TFP growth rate implies a low research intensity, hence a lower probability of expansion and slower employment growth. On the other hand, the fit of the employment growth of state-owned firms is better.

Welfare Implications

This section discusses first the growth and welfare implications from the factor market wedge. I then present two decompositions to study the channels through which the factor market wedge affects welfare. There are 3 takeaways from these exercises. The factor market wedge leads to significant growth and welfare loss. The majority of this loss comes from misallocation in the R&D sector. Distorting R&D incentives is a key mechanism through which the wedge lowers welfare.

Growth and Welfare Losses Table 1.5 reports the endogenous innovation intensities and welfare implications from the calibrated model. Consistent with Proposition 1.1 and the estimates reported in Table 1.3, panel (a) of Table 1.5 shows that more efficient private firms choose a lower level of innovation intensity in equilibrium because of their worse factor market access. This leads to large growth and welfare loss. Panel (b) of Table 1.5 reports these loss. Compared with the *laissez-faire* economy where state-owned firms lose their privilege and face the same factor market frictions, the annual productivity growth rate is 1.2 percentage points lower. This represents a 32% decrease in the annual productivity growth (from 5.0% to 3.8%). This loss is large even at the low end of the 95% confidence interval (0.7 percentage points). It can be as high as 1.6 percentage points at the high end of the 95% confidence interval.

This massive loss in productivity growth leads to considerable welfare loss. With an intertemporal elasticity of substitution of 0.5 and an annual discount rate of 97%, the factor market wedge leads to a 23% lower welfare when compared to the *laissez-faire* economy. There is still a 16% welfare loss at the low end of the 95% confidence interval. The cost can go as high as 37% at the high end of the confidence interval.

To put the estimated growth and welfare loss in perspective, I compare the welfare loss reported in Table 1.5 to the results from König, Song, Storesletten, and Zilibotti (2020) (KSSZ). KSSZ estimate a similar model in which market wedge affects returns to R&D. In their quantitative exercise, KSSZ find that halving the dispersion leads to a 1.3 percentage points increase in annual productivity growth rate. My results imply that state ownership alone can generate the same magnitude of loss in productivity growth. This comparison suggests that state ownership plays a significant role in misallocating resources in China's R&D sector.

In the rest of this section, I decompose the welfare effect in different ways to investigate the mechanisms through which the factor market wedge lowers welfare.

Table 1.5: The Baseline Economy

Variable	Description	Value
	panel (a): Endogenous Variables	
x_P	private innovation intensity	0.12 (0.015)
x_S	state innovation intensity	0.16 (0.012)
x_ϵ	entrant innovation intensity	0.11 (0.019)
	panel (b): Welfare Loss Compared to Laissez-faire	
g_Y	loss in growth rate (95% CI)	1.2 (0.7, 1.5)
γ	cons. equiv. change (95% CI)	1.23 (1.16, 1.37)

Note: Panel (a) reports the values of endogenous variables from the estimated baseline model (Table 1.3). Panel (b) reports the mean and the 95% confidence interval of welfare loss when compared the baseline model with a *laissez-faire* economy. The standard errors and the confidence intervals are calculated from running the estimation procedure on 500 bootstrapped samples.

Static and Dynamic Welfare Losses The factor market wedge leads to two distortions: a static distortion from misallocation in the production sector, and a dynamic distortion from misallocation in the R&D sector. I calculate the welfare loss due to each of these distortions. I find that the dynamic loss is an order of magnitude larger than the static loss.

The static loss is caused by misallocation in production labor. There are two components to this loss: the cross sectional markup dispersion and inefficient production from technologically following state-owned firms. The dispersion-adjusted productivity, $A\mathcal{M}$ captures both components. Hence, I calculate the static distortion using the ratio of $A\mathcal{M}$ in the state capitalism and the *laissez-faire* economy, i.e.

$$\text{static loss} = \frac{A_{LF}\mathcal{M}_{LF}}{A_S\mathcal{M}_S},$$

where A_{LF} and $\mathcal{M}_{LF}$ are the initial productivity index and markup dispersion in the *laissez-faire* economy, and A_S, $\mathcal{M}_S$ are the corresponding subjects in the state capitalism economy. I normalize $a_i = 1$ for all i in the *laissez-faire* economy. So $A_{LF} = \exp(\int_i \ln a_i di) = 1$, and $A_S = \exp(S_{PS}\ln(1/\lambda))$, where S_{PS} is the mass of markets produced by technology following state-owned firms.[24]

The dynamic loss is defined as the consumption-equivalent change from growth rate $\gamma^{dynamic}$ as

$$U(\gamma^{dynamic}C_{LF}, g_S) = U(C_{LF}, g_{LF}).$$

[24]Results from this decomposition exercise does not change if I measure use consumption-equivalent

The difference between γ and $\gamma^{dynamic}$ is that $\gamma^{dynamic}$ captures only the welfare effect from different growth rates between the state capitalism and the *laissez-faire* economy.

Table 1.6: Static and Dynamic Loss

	growth loss (95% CI)	welfare loss (95% CI)
total loss (γ)	1.2 (0.7, 1.5)	23% (16%, 34%)
dynamic loss ($\gamma^{dynamics}$)	1.2 (0.7, 1.5)	22% (14%, 32%)
static loss $\left(\frac{A_{LF}\mathcal{M}_{LF}}{A_S\mathcal{M}_S}\right)$	0.0 (0.0, 0.0)	3% (2%, 4%)

This table reports the 95% confidence interval of growth and welfare losses. The losses are calculated based on the baseline estimates reported in Table 1.5. "total loss" replicates the total growth and welfare losses from Table 1.5. "dynamic loss" reports loss from R&D misallocation. "static loss" reports loss from production misallocation.

Table 1.6 reports the static and dynamic loss using the baseline parameter estimates. The result shows that the static distortions account for only a small fraction of the total welfare loss. The majority of the welfare loss comes from the dynamic distortions (i.e., a lower productivity growth rate in the state capitalism economy).[25]

Production and R&D Wedges In the baseline model, firms hire production workers and researchers from the same factor market. Consequently, they face the same factor market friction in the production and the R&D sector. In this section, I decompose the growth and welfare loss caused by factor market wedges in the production and the R&D sector. The wedge in the R&D factor market alone generates little distortion. Almost all distortions come from the wedge in the production market and the interaction between the two wedges. This result suggests that R&D subsidies cannot fully address resource misallocation in the R&D sector.

To separate the distortions from the production and the R&D wedge, I start with my baseline parameter estimates reported in Table 1.5. I then construct economies in which

change γ^{static} from static distortions

$$U(\gamma^{static}C_S, g_{LF}) = U(C_{LF}, g_{LF}).$$

The difference between γ^{static} and my measure $\frac{A_{LF}\mathcal{M}_{LF}}{A_S\mathcal{M}_S}$ is γ^{static} includes the effect of τ on allocation of labor between the production and the R&D sector. Empirically, this effect is quantitatively small: τ distorts mainly resource allocation within the R&D sector across firms, but not allocation between the production and the R&D sector. Therefore, using γ^{static} and $\frac{A_{LF}\mathcal{M}_{LF}}{A_S\mathcal{M}_S}$ lead to similar results.

[25] The static inefficiency reported here is much smaller than Hsieh and Klenow (2009). Difference in the degree of heterogeneity in the market wedge between our models can be the reason behind this discrepancy. Hsieh and Klenow (2009) allow market wedges to vary across individual firms, whereas I only allow them to vary across ownership. This limited heterogeneity results in a smaller estimate of the static inefficiency in my model.

there is only the production (or R&D) wedge. That is, connections to the government help state-owned firms only when hiring production workers (researchers). To assess the welfare effect of individual wedges, I calculate the growth and welfare of those economies by comparing them against the corresponding *laissez-faire* economies.

In the model, both the production and the R&D wedges distort firms' R&D decisions. However, they work through different channels. Recall that the optimal innovation intensity for type k firms is given by

$$x_k^* = \left(\frac{\phi_k \mathbb{E}_{\tilde{\mu}}[v_k(\tilde{\mu})|\tau_k^{prod}]}{\zeta(1+\tau_k^{R\&D})\omega} \right)^{1/(\zeta-1)}.$$

The R&D wedge affects the optimal innovation intensity directly by affecting the price of researchers. On the other hand, The production wedge τ_k^{prod} affects only the expected gain $\mathbb{E}_{\tilde{\mu}}[v_k(\tilde{\mu})|\tau_k^{prod}]$. Thus, the production wedge distorts R&D investment decisions through only an indirect effect.[26] The two wedges can reinforce each other, generating an interaction effect. Together, these changes in the optimal innovation intensity lead to distortions to the equilibrium firm composition, which impacts the growth rate and welfare.

The magnitudes of the welfare losses from the production and R&D wedges depend on their impacts on equilibrium firm composition. With $1+\tau > \lambda$ in my baseline estimates, the production wedge should generate a larger loss. Because private innovators cannot produce in state-owned markets when $1+\tau > \lambda$, the production wedge drastically lowers the expected return to R&D for private firms, and thus their incentives to invest in R&D. On the other hand, private firms' higher innovative capacity can partially offset their disadvantage in hiring researchers. Therefore, the R&D wedge should have a smaller effect on firm composition, which results in a smaller welfare loss.

[26] To see this more clearly, note the first order condition for firms' optimal choice is

$$\underbrace{\mathbb{E}_{\tilde{\mu}}[v_k(\tilde{\mu})|\tau_k^{prod}]}_{\text{marginal return}} = \underbrace{\zeta \frac{(1+\tau_k^{R\&D})\omega}{\phi_k} x^{\zeta-1}}_{\text{marginal cost}}.$$

Table 1.7: Production and R&D wedges

economy	growth loss (95% CI)	welfare loss (95% CI)
baseline	1.2 (0.7, 1.5)	23% (16%, 34%)
production wedge only	0.5 (0.3, 0.6)	8% (6%, 10%)
R&D wedge only	0.0 (0.0, 0.0)	1% (0%, 1%)
interaction effect	0.7 (0.3, 0.9)	13% (10%, 23%)

Note: This table reports the point estimates and the 95% confidence interval of growth and welfare loss. The loss are calculated based on the baseline estimates reported in Table 1.5. "baseline" denotes a state capitalism economy in which private firms face both the production and the R&D wedges. "production wedge only" denotes a state capitalism economy in which private firms face only the production wedge. "R&D wedge only" denotes a state capitalism economy in which private firms face only the R&D wedge. "interaction effect" denotes the growth and welfare effect that are not accounted for in neither production wedge only nor R&D wedge only economy.

Results in Table 1.7 confirm this intuition: the welfare loss from the factor market wedge comes almost entirely from the production wedge and the interaction effect. The R&D wedge alone causes at most 1% welfare loss. This result indicates that distorting the incentives to R&D is a key ingredient in generating growth and welfare loss in my model. Static market wedges like output subsidy or preferential credit market access distort competitions between innovators and incumbents. Such distortion leads to misallocation in the R&D sector, resulting in slower productivity growth and lower welfare.

This decomposition exercise implies that R&D subsidies alone are not enough to address the misallocation issue. Although private R&D subsidies lower the direct cost to invest in R&D, it does not address the issue of low returns to R&D private firms face. Since the difference in the direct cost of R&D (and the interaction effect) only accounts for 2/3 of the growth and welfare loss, R&D subsidies addressing the R&D cost wedge cannot fully correct resource misallocation in R&D.

Robustness and Sensitivity

I show my baseline estimates are robust to various checks. In particular, the estimated growth and welfare loss remain large for a wide range of alternative calibrations.

Alternative TFP Measures Table 1.8 reports the results of fitting the model with alternative TFP measure. Panel (a) of the table replicates the baseline estimates reported in Table 1.5. Panel (b) reports the estimates when targeting TFP growth rates using methods developed in Olley and Pakes (1996). Estimates from this alternative measure of TFP are very close to my baseline results, with slightly wider confidence intervals on growth and welfare loss.

Table 1.8: Alternative Productivity Measure

ϕ_P	ϕ_S	ϕ_ϵ	λ	$1+\tau$	g_Y	γ
panel (a) baseline model (Levinsohn and Petrin 2003)						
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.20 (0.03)	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) using Olley and Pakes (1996)						
1	0.28 (0.04)	0.63 (0.10)	1.17 (0.02)	1.23 (0.03)	1.1 (0.6, 1.8)	1.22 (1.10, 1.38)

Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5. Panel (b) reports the parameter estimates and welfare using Olley and Pakes (1996) method to calculate TFP growth. Bootstrapped standard errors and confidence intervals are reported in parentheses.

Innovating Subsample Despite the surge in R&D expenditure during my sample period, imitation and technological adoption are important sources of TFP growth in China (Agarwal, Milner, and Riaño, 2014; König, Song, Storesletten, and Zilibotti, 2020). Since there is no technological adoption decision in my model, investment in learning and adopting existing technology show up as R&D investment. The estimated private/state-owned innovative capacity gap may reflect not the difference in innovative capacities, but the difference in their choices between innovation or imitation. In particular, a large ϕ_P could be driven by private firms choosing more imitation, rather than them being more efficient in R&D.

To address this issue, I estimate the model on a subsample of self-reporting innovators.[27] The subsample consists of firms that have reported at least one innovation during my sample period. Panel (b) of Table 1.9 reports the results from fitting the model to this subsample. Compared with the baseline results replicated in panel (a), there is a wider gap between the state-owned and private firms' innovative capacities: The innovative capacity in state-owned firms is only one-fifth of that in private firms. As a result, the estimated growth and welfare loss from the factor market wedge are larger. This exercise implies that imitation is not likely the driving factor behind the baseline results.

[27]In the ASIE, firms self-report whether they have successfully produced any innovation or not. Allocation of R&D subsidy and other incentives do not depend on this information. Thus, there is no incentive for firms to misreport. This contrasts to the self-reported R&D expenditure data, which can be used to determine the eligibility of R&D subsidy.

Table 1.9: Innovation Firm Only

ϕ_P	ϕ_S	ϕ_ϵ	λ	$1+\tau$	g_Y	γ
panel (a) baseline model						
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.20 (0.03)	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) innovating subsample						
1	0.17 (0.02)	0.45 (0.05)	1.13 (0.01)	1.25 (0.04)	1.3 (0.7, 1.7)	1.37 (1.27, 1.48)

Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5. Panel (b) reports the parameters and welfare estimated from a subsample of self-reported innovating firms. Bootstrapped standard errors and confidence intervals are reported in parentheses.

Sensitivity to Calibrated Parameters In this section, I explore alternative values of externally calibrated parameters, θ, ρ, ζ. I show that my findings do not depend on the particular parameter values I pick in Table 1.2.

Table 1.10 reports the results using alternative calibrations. Panel (a) replicates the baseline estimates, where $\theta = 2$, $\rho = 0.02$ and $\zeta = 1.77$. Panel (b) reports the results with a higher discount factor, $\rho = 0.05$. This value of ρ translates into an annual discount rate of 95%. With higher discount factor, the household values the future less. Therefore, the growth rate matters less to the welfare. In this case, the estimated welfare loss is smaller relative to the baseline model.

Panel (c) reports parameter estimates and welfare consequences with lower intertemporal elasticity of substitution. The intuition in panel (c) is similar to that in panel (b). With a lower intertemporal elasticity of substitution, current and future consumption are less substitutable. Again, the growth rate matters less to the welfare. The estimates reported in panel (c) are almost identical to those reported in panel (b).

Finally, panel (d) reports the estimates with $\zeta = 2$, calibrated using the R&D cost elasticity in the U.S. (Hall and Ziedonis, 2001; Blundell, Griffith, and Windmeijer, 2002). A larger ζ gives the knowledge capital a higher weight in the innovation production function. Thus, it favors larger firms. Because state-owned firms are more likely to survive and expand, they benefit more from a larger ζ. As a result, setting ζ to 2 leads to more state-owned firms in equilibrium and larger growth and welfare loss.

Alternative Normalization In the baseline model, I normalize the private innovative capacity to 1. In this section, I demonstrate that my results do not depend on this normalization. In particular, I normalize the innovation step size, λ, to 1.132 as reported in Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018). Table 1.11 reports the results from this exercise. The private-state innovative capacity gap, ϕ_P/ϕ_S, is similar to that in the baseline model. So does the estimated factor market wedge τ. Consequently, the growth and welfare loss found in the model with alternative normalization are similar to those in the baseline model.

Table 1.10: Sensitivity to Externally Calibrated Parameters

ϕ_P	ϕ_S	ϕ_ϵ	λ	$1+\tau$	g_Y	γ
panel (a) baseline model ($\rho = 0.02, \theta = 2, \zeta = 1.77$)						
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.20 (0.03)	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) high discount rate ($\rho = 0.05$)						
1	0.24 (0.03)	0.67 (0.08)	1.15 (0.01)	1.26 (0.02)	0.9 (0.5, 1.5)	1.14 (1.07, 1.23)
panel (c) lower IES ($\theta = 3$)						
1	0.30 (0.06)	0.69 (0.12)	1.16 (0.02)	1.22 (0.04)	0.8 (0.3, 1.3)	1.12 (1.07, 1.22)
panel (d) larger curvature ($\zeta = 2$)						
1	0.23 (0.06)	0.53 (0.09)	1.13 (0.01)	1.22 (0.05)	1.3 (1.0, 1.7)	1.31 (1.25, 1.44)

Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5. Panel (b) reports the parameters and welfare estimated using $\rho = 0.05$. Panel (c) reports the parameters and welfare estimated using $\theta = 3$. Panel (d) reports the parameters and welfare estimated using $\zeta = 2$. Bootstrapped standard errors and confidence intervals are reported in parentheses.

Sensitivity to τ Section 1.4 mentioned that the identification of τ hinges on the assumption that the log TFPR difference between state-owned and private firms is driven entirely by the difference in their factor market access. I will overestimate τ if other differences between state-owned and private firms also contribute to the log TFPR difference.[28] In this section, I recalibrate the model using log TFPR differences between private and more comparable firms. I find that the estimated growth and welfare loss remain large with conservatively estimated τ.

Figure 1.5 plots various log TFPR differences between private firms and other types of firms. Panel (a) plots the log TFPR for private and state-owned firms reported in Table 1.1. In panel (b), I limit the comparison between state-owned and private firms to the subsample of self-reported innovators. I show that the unproductive "zombie" state-owned firms do not drive the mean difference in log TFPR between private and state-owned firms; instead, the difference remains stable even among state-owned and private firms who actively engage in R&D.

Second, I compare the mean log TFPR difference between private and privatized firms in panel (c). Privatized firms are state-owned firms that are either sold to private parties

[28]One candidate that could lead to TFPR difference is different objective functions between state-owned and private firms. Even though it is contradictory to the explicit goal set by the State Asset Management Commission (State-owned Assets Supervision and Administration Commission, 2003), the government may still put political pressures to state-owned firms and ask them to consider other objectives (Bai, Lu, and Tao, 2006).

or introduced significant private equity. In those firms, private parties are making production and innovation decisions, as the government is only a minor shareholder. However, the presence of state ownership, albeit minor, could still grant these firms access to loans from state-owned banks, a privilege that private firms do not have. Thus, the difference in mean log TFPR between private and privatized firms, as shown in panel (c), could provide information on the true difference in factor market access between private and state-owned firms.[29]

In panel (d), I compare the average log TFPR between foreign and private firms. On the one hand, foreign firms are not credit-constrained due to their foreign investor and their connections to foreign financial institutions. On the other hand, foreign firms do not report to the government, nor do they have any alternative objective as the state-owned firms may have. Thus, the log TFPR gap between foreign and private firms should reflect the difference in their relative factor market access. If foreign and state-owned firms have similar factor market access, the mean TFPR difference between foreign and private firms is informative to the true difference in factor market access between state-owned and private firms.

I use the mean log TFPR differences in Figure 1.5 as the target moment for estimating the private market friction τ. Table 1.12 reports the results from these exercises. In panel (b), I assume only half of the observed log TFPR difference between state-owned and private firms is due to heterogeneous factor market access. In panel (c) and (d), I assume log TFPR differences between private and privatized/foreign firms give the true difference in factor market access. Since the log TFPR difference is the identifying moment for τ, the estimate of τ is sensitive to using different log TFPR gaps. A smaller log TFPR difference implies a smaller gap in factor market access and a smaller τ. However, the magnitudes of other parameter estimates are insensitive to alternative log TFPR gaps, as the moments I use to calibrate these parameters do not change. The welfare and growth loss depend positively on the estimated size of τ: a smaller estimated τ leads to smaller welfare and growth loss. Nevertheless, there is still a 0.3 percentage points annual growth loss with the most conservative target for τ, which translates into a sizable 7% welfare loss.

Extensions

This section considers two extensions to the baseline model and reports the results from estimating the extended models. The welfare consequences of the factor market wedge do not change in those extended models.

State Sector Reform The first extension considers the state-owned firm reform in the late 1990s and early 2000s. The reform closed down many unprofitable state-owned firms.[30]

[29] The privatized-private TFPR gap likely underestimates the actual difference in factor market access, since some privatized firms have entirely cut off their connections to the government. Thus, they lose their access to cheap credits and become true private firms.

[30] As another part of the reform, many state-owned firms that did not close down was privatized. I cover the privatization campaign in the baseline model by classifying privatized firms as state-owned.

Table 1.11: Alternative Normalization

ϕ_P	ϕ_S	ϕ_ϵ	λ	$1+\tau$	g_Y	γ
panel (a) baseline model (normalizing $\phi_P = 1$)						
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.20 (0.03)	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) alternative normalization (normalizing $\lambda = 1.132$)						
1.42 (0.02)	0.38 (0.01)	1.10 (0.00)	1.132	1.21 (0.01)	1.4 (1.3, 1.5)	1.32 (1.30, 1.34)

Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5. Panel (b) reports the parameters and welfare estimated using the alternative normalization $\lambda = 1.132$. Bootstrapped standard errors and confidence intervals are reported in parentheses.

Table 1.12: Sensitivity to the Calibrated Factor Market Wedge

ϕ_P	ϕ_S	ϕ_ϵ	λ	$1+\tau$	g_Y	γ
panel (a) baseline ($\Delta TFPR = 0.2$)						
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.20 (0.03)	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) halve TFPR ratio ($\Delta TFPR = 0.1$)						
1	0.31 (0.06)	0.57 (0.15)	1.10 (0.01)	1.12 (0.02)	0.3 (0.2, 0.4)	1.07 (1.05, 1.10)
panel (c) use private-foreign TFPR ratio ($\Delta TFPR = 0.13$)						
1	0.38 (0.05)	0.74 (0.06)	1.11 (0.01)	1.13 (0.02)	0.4 (0.3, 0.5)	1.12 (1.07, 1.13)
panel (d) use private-privatized TFPR ratio ($\Delta TFPR = 0.07$)						
1	0.44 (0.05)	0.70 (0.11)	1.10 (0.01)	1.10 (0.03)	0.3 (0.2, 0.3)	1.07 (1.05, 1.08)

Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5. Panel (b), (c), and (d) report the parameters and welfare estimated using the alternative target moments for τ. In panel (b), I estimate the model with only half of the observed log TFPR difference between state-owned and private firms. Panel (c) uses the observed log TFPR difference between foreign and private firms. Panel (d) estimates the model using the observed log TFPR difference between privatized and private firms. Bootstrapped standard errors and confidence intervals are reported in parentheses.

To model this, I allow exogenous destruction of firms. In this extension, a firm can lose a market either because another firm acquires a better technology through R&D (creative destruction); or an exogenous close-down event occurs (exogenous destruction). In the case of exogenous destruction, the market follower becomes the new market leader. To simplify the model, I abstract from the potential negative selection of such event (Hsieh and Klenow, 2009; Chen, Igami, Sawada, and Xiao, 2020) and assume the probability of exogenous destruction is the same within ownership type. Since private firms are not directly affected by this reform, I also allow private and state-owned firms to have different exogenous destruction probabilities.

Table 1.13 summarizes the results from estimating the extended model. Consistent with the history of the reform, the probability of exogenous exit is much higher for state-owned firms than private firms. State-owned firms have an 8% probability of exit due to exogenous close-down events, whereas private firms only face a 1% chance of exit exogenously. The estimates of productivity improvement (λ) and the factor market wedge (τ) are similar to those in the baseline model.

Interestingly, I find a smaller innovative capacity gap between state-owned and private firms when allowing exogenous exit. The new estimate finds state-owned innovative capacity at about 40% of that of private firms. Intuitively, with a higher probability of being exogenously shut down, state-owned firms have to be more efficient and produce more innovation to grow at the same rate as before.

Despite the narrower gap in innovative capacity, the factor market wedge results in *larger* growth and welfare loss: there is 2.2 percentage points loss in annual productivity growth and a 57% welfare loss. Changes in equilibrium firm composition causes these larger effects. On the one hand, state-owned firms are more efficient in innovation relative to my baseline model, they will innovate more intensively. Higher state-owned innovation intensity leads to a larger state-owned market share in equilibrium. With more state-owned firms in equilibrium, private firms are more likely to innovate into a state-owned market, which yields low returns. Thus, the disincentivization effect is stronger in this extension. On the other hand, state-owned firms are still less innovative than private firms. A stronger disincentivization effect will therefore result in more resource misallocation in the R&D sector, and larger welfare loss.

The Entrepreneurial State In the baseline model, Innovations from state-owned and private firms are perfect substitutes. Regardless of who innovate, the productivity of an intermediate good is always improved by λ. However, state-owned innovations may improve productivity more. This possibility is consistent with the "entrepreneurial state" argument: state-owned firms engage in high-risk, high-reward innovations, whereas private firms are conservative and only engage in incremental innovations. As a result, state-owned firms may produce fewer innovations per R&D dollar, but their innovations generate larger productivity gains (Mazzucato, 2013). In this case, the estimated state-private gap in the innovative capacities reflects their difference in innovation strategies, rather than their difference in efficiencies. This section extends the model by relaxing the perfect substitution assumption and allowing state-owned and private innovations to generate different productivity improvements.

Despite the theoretical soundness of the entrepreneurial state argument, the empirical literature finds mixed evidence regarding the relative productivity gains from state-owned and private innovations. Using patent citation counts and TFP growth as measures of innovation quality, the majority of existing studies find private innovations are better (Boeing, 2016; Fang, Lerner, and Wu, 2017; Wei, Xie, and Zhang, 2017; Cheng, Fan, Hoshi, and Hu, 2019). On the other hand, Fang, He, and Li (2020) find state-owned firms have a 2–5% higher productivity-patent elasticity, implying state-owned innovations improve productivity by 2–5% more than private innovations.

In this extension, I allow the productivity improvement to differ between state-owned and private firms. Let λ_S and λ_P to be the productivity improvements from state-owned and private innovations, respectively. I set the ratio λ_S/λ_P to 1.05 using the upper bound of the estimate reported in Fang, He, and Li (2020) and recalibrate the model. Table 1.14 reports the results from this exercise.

Compared with the baseline model, the state entrepreneur model reports a larger innovative capacity gap between state-owned and private firms. The estimated state-owned innovative capacity is now only 20% of the private firms' capacity. Otherwise, the two models return similar parameter estimates. Furthermore, this extension delivers similar growth and welfare loss as the baseline model. To understand this, recall that state-owned firms' TFP growth rate observed in the data pins down their innovative capacity. In this extension, every state-owned innovation increases productivity by more. To match the low productivity growth observed in the data, state-owned firms would need to produce fewer innovations, meaning that state-owned firms should have a lower innovative capacity. Without changing the data moment that pins down innovative capacities, the magnitudes of estimated growth and welfare loss will not change.

Table 1.13: Allowing Exogenous Destruction

ϕ_P	ϕ_S	ϕ_ϵ	λ	$1+\tau$	ψ_P	ψ_S	g_Y	γ
panel (a) baseline								
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.20 (0.03)	0	0	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) extension: exogenous destruction								
1	0.40 (0.07)	0.43 (0.02)	1.15 (0.01)	1.22 (0.03)	1%	8%	2.2 (1.8, 2.5)	1.56 (1.44, 1.65)

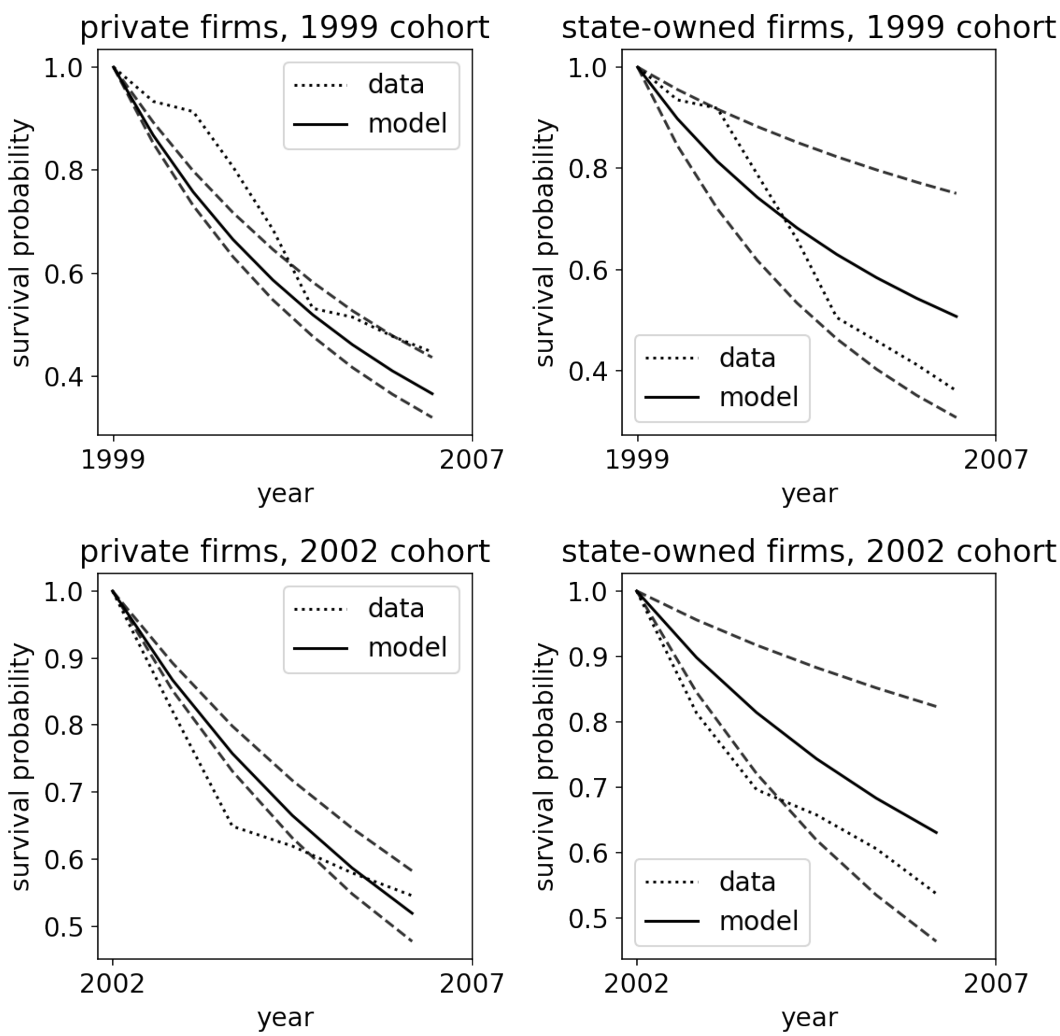
Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5. Panel (b) estimates the extended model with exogenous destruction. Bootstrapped standard errors and confidence intervals are reported in parentheses.

Table 1.14: Entrepreneurial State Model

ϕ_P	ϕ_S	ϕ_ϵ	λ_P	λ_S	$1+\tau$	g_Y	γ
panel (a) baseline ($\lambda_S = \lambda_P$)							
1	0.29 (0.05)	0.64 (0.11)	1.15 (0.01)	1.15 (0.01)	1.20 (0.03)	1.2 (0.7, 1.5)	1.23 (1.13, 1.37)
panel (b) extension: entrepreneurial state ($\lambda_S/\lambda_P = 1.05$)							
1	0.19 (0.02)	0.60 (0.12)	1.14 (0.01)	1.20 (0.01)	1.24 (0.03)	1.0 (0.7, 1.3)	1.23 (1.17, 1.34)

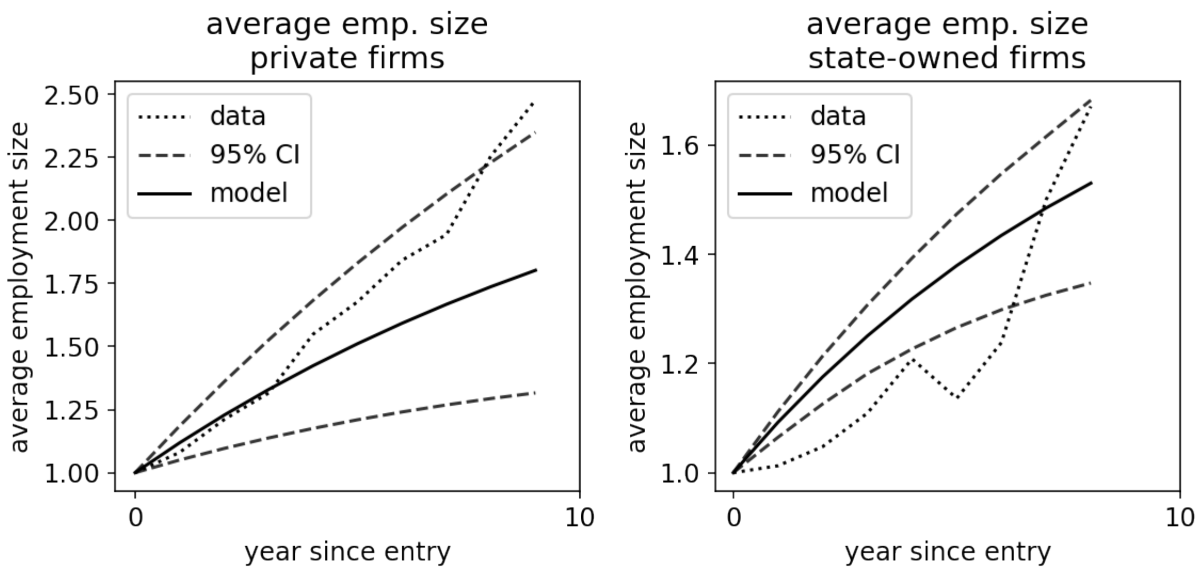
Note: Panel (a) replicates the results from the baseline model in Table 1.3 and Table 1.5 in which $\lambda_S = \lambda_P$. Panel (b) reports the results from the entrepreneurial state extension of the model. I calibrate λ_S/λ_P to 1.05 according to Fang, He, and Li (2020). Bootstrapped standard errors and confidence intervals are reported in parentheses.

Figure 1.3: Survival Probability for 1999 and 2002 Entering Cohorts



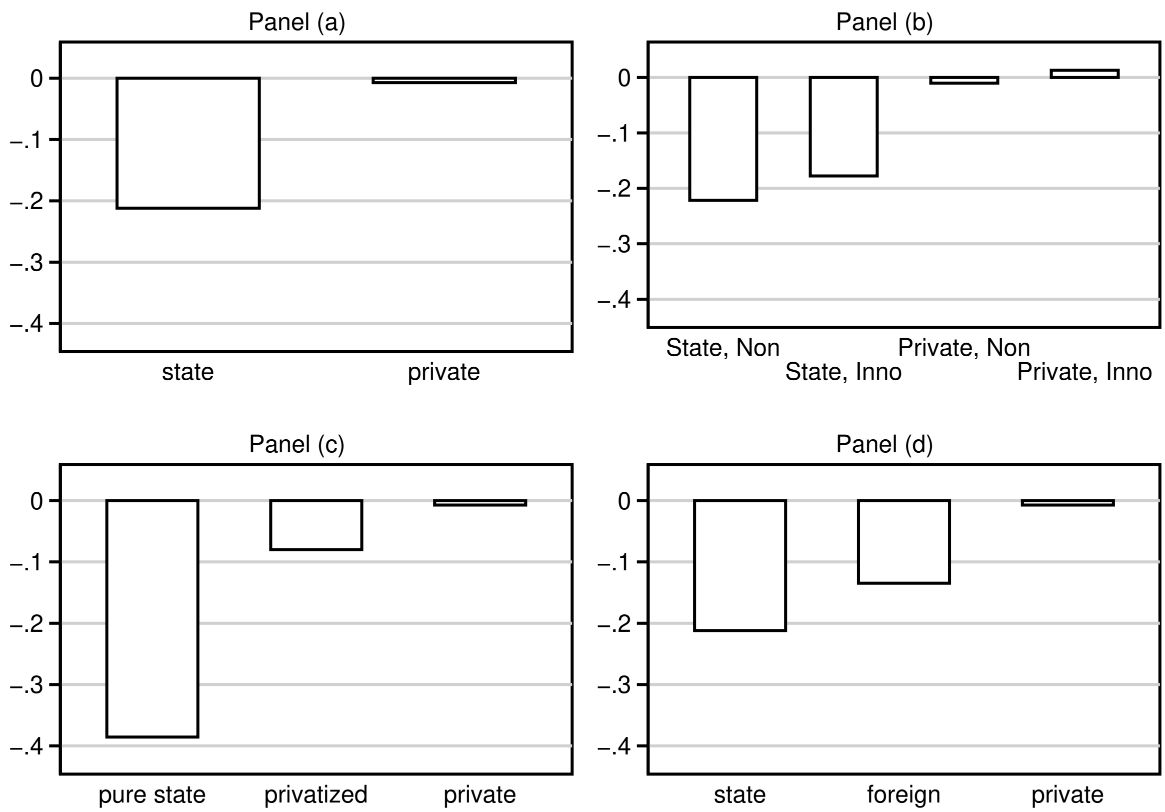
This figure plots survival probabilities for private and state-owned firms in two cohorts. The top panel plots survival probabilities for firms entering in 1999, and the bottom panel plots survival probabilities for firms entering in 2002. The dotted line represents observed survival probability, and the solid line represents inferred survival probability from the model. The corresponding 95% confidence interval calculated using the bootstrapped sample is also included for inferred probabilities.

Figure 1.4: Employment Growth for Continuing Firms



This figure plots employment growth, measured using the average of current-year employment relative to employment at entry year, for private and state-owned firms conditional on survival. The left panel plots employment growth for private firms, and the right panel plots employment growth for state-owned firms. The dotted line represents observed average employment growth, and the solid line represents inferred employment growth from the model. The corresponding 95% confidence interval calculated using the bootstrapped sample is also included for inferred probabilities.

Figure 1.5: log TFPR differences between private and other types of firms



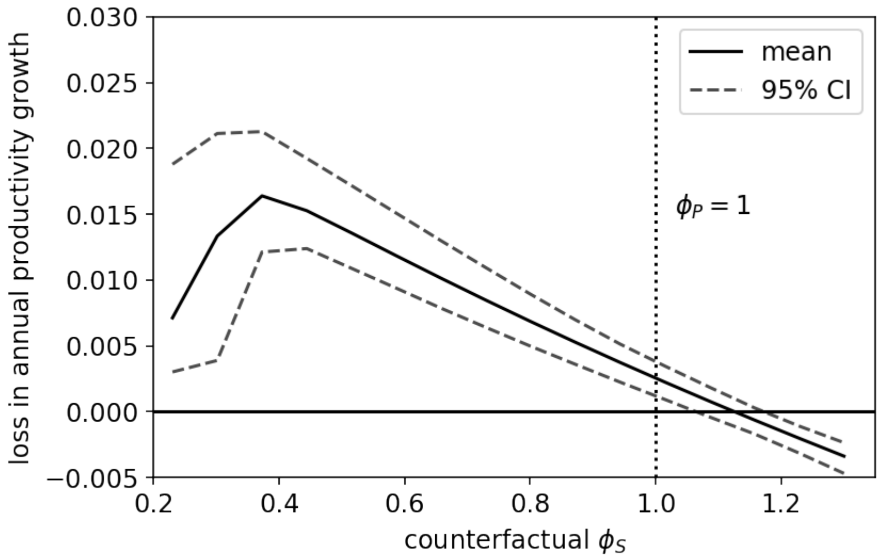
This figure plots the mean TFPR differences between various types of firms. Panel (a) plots the differences between state-owned and private firms. Panel (b) separates innovative and non-innovative firms among state-owned and private firms, where innovativeness is defined by whether the firm has introduced any new products at all. Panel (c) separates state-owned firms into "pure state-owned firms", defined as state-owned firms who did not have private equity owner(s) in all observed years, and "privatized firms", defined as state-owned firms who introduced private equity owner(s) for at least one year. Panel (d) introduces a new category called "foreign firms", defined as firms with foreign or Hong Kong, Macao, Taiwan equity owner(s).

1.6 Can State-owned Privilege be Growth-enhancing?

Thus far, I demonstrate that granting state-owned firms privileged factor market access failed to increase aggregate innovation output. Nevertheless, Section 1.3 and Appendix A.1 discuss the theoretical possibility that such privilege can be conductive to growth: the *laissez-faire* economy produces a below-optimal level of innovation, and state-owned firms' privileged factor market access can be thought as a subsidy that incentivizes them to innovate more, hence correcting the inefficiency in *laissez-faire* economy. In this final exercise, I examine the conditions under which state-owned firms' privilege is growth-enhancing.

To conduct the counterfactual analysis, I start with my baseline parameter estimates reported in Table 1.5. I then change the state-owned innovative capacity, ϕ_S, and the state-owned innovative quality, λ_S, to create counterfactual state capitalism economies. I calculate the annual productivity growth loss in the counterfactual state capitalism economy by comparing its growth rate to the equilibrium growth rate in the corresponding *laissez-faire* economy with new values for ϕ_S or λ_S. Privileged state-owned factor market access becomes growth-enhancing when the growth loss becomes negative. Figure 1.6 and 1.7 plot the results from such exercises.

Figure 1.6: Productivity Loss under Counterfactual ϕ_S



This figure plots the loss in productivity growth due to heterogeneous factor market access under counterfactual level of state-owned firm innovative capacity, ϕ_S. The vertical dotted line represents the (normalized) innovative capacity of private firms (ϕ_P). The figure reports the average loss inferred from the model in solid line, and the 95% confidence interval in dash line, both calculated using the bootstrapped sample.

Figure 1.6 plots the growth loss from state-owned privilege against the counterfactual level of state-owned innovative capacity ϕ_S. There is an inverted-U relationship between ϕ_S and the growth loss. The loss first increases as ϕ_S increases from 0.2 to around 0.6, and then decreases as ϕ_S increases further. Finally, when ϕ_S reaches 1.2, the growth loss turns negative, meaning that the state-owned privilege leads to a growth gain.

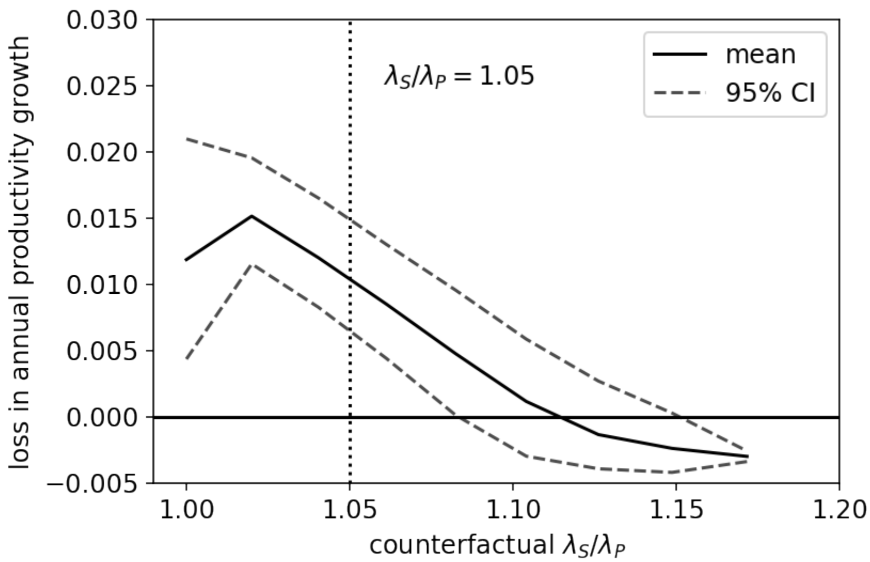
The inverted-U relationship is driven by a general equilibrium effect of changing firm composition. Intuitively, when ϕ_S increases from a very low level, state-owned firms increase innovation intensity according to Proposition 1.1. Higher state-owned innovation intensity gives them a larger market share in equilibrium. More state-owned firms on the market means a stronger disincentivization effect for private firms, who now face a lower expected return to R&D due to a higher probability of having to compete with a state-owned incumbent. Thus, private R&D investments are further depressed, which leads to more growth loss. This growth loss eventually comes down as state-owned firms are more and more efficient, and the loss in private innovations is offset by the increase in state-owned innovations. When state-owned firms become 20% more innovative than private firms, the additional state innovations fully compensate for the loss in private innovations, and state-owned privilege becomes growth-enhancing.

The fact that state-owned privilege can be justified only when $\phi_S > \phi_P$ highlights the misallocative nature of heterogeneous factor market access. Differential factor market access leads to a wedge in return to R&D investment. With convex cost function, this wedge induces privileged state-owned firms to innovate at a higher marginal cost than unprivileged private firms. Supporting state-owned firms leads to growth and welfare losses even if they are as innovative as those unprivileged firms (i.e., $\phi_S = \phi_P$).

Figure 1.7 plots the loss in productivity growth against the relative quality of state innovation λ_S/λ_P. There is a similar inverted-U relationship between the loss and λ_S/λ_P, where the magnitude of resource misallocation in the R&D sector increases first before coming down. Figure 1.7 shows that the state-owned privilege is growth-enhancing only when state innovations produce 12% higher productivity gains. Again, the 12% requirement is way beyond the most optimistic estimate (5% as reported by Fang, He, and Li 2020).

Despite the theoretical possibility, results in this section imply that state-owned privilege is unlikely to be justifiable from an economic standpoint. The conditions under which state-owned privilege becomes growth-enhancing are much more demanding than the estimates from data: it requires state-owned firms to be 20% more innovative, or produce 12% higher quality innovation than private firms. Whereas state-owned firms are less than half as innovative and their innovations produce at most 5% more productivity growth.

Figure 1.7: Productivity Loss under Counterfactual λ_S



This figure plots the loss in productivity growth due to heterogeneous factor market access under counterfactual level of the relative step size between state-owned and private firms, λ_S/λ_P. The vertical dotted line represents the calibrated relative step size from Fang, He, and Li (2020). The figure reports the average loss inferred from the model in solid line, and the 95% confidence interval in dash line, both calculated using the bootstrapped sample.

1.7 Conclusion

This paper finds that the factor market wedge leads to resource misallocation in not only the production sector, but also the R&D sector. Specifically, it creates a wedge in expected returns to R&D, which distorts firms' innovation incentives. I formalize this intuition in an endogenous growth model and estimate it using Chinese manufacturing firm data. In China, connections to the government provide inefficient state-owned firms better factor market access. With this privilege, state-owned firms have higher expected returns to R&D, which incentivizes them to engage in R&D activities more intensively at the expense of private innovation. This causes considerable growth and welfare loss: compared with a *laissez-faire* economy, annual productivity growth rate is 1.2 percentage points lower, which translates to 23% welfare loss. Given the large efficiency loss I find, it is difficult for China to surpass the United States in innovation without addressing distorted incentives the factor market wedge creates.

In theory, state-owned firms' better factor market access reduce market frictions they face, which could leads to a better economic performance. Nevertheless, this "greasing the wheel" argument fails to consider the general equilibrium effect from market competitions. By greasing the wheels of inefficient firms, efficient firms get crowded out. Applying this idea to the Chinese R&D sector, I calculate the conditions for which the state-owned privilege is growth-enhancing. Unsurprisingly, the estimated innovativeness of state-owned firms does not meet those conditions. These counterfactual analyses suggest that it is difficult to justify state-owned privilege even if it does not directly incur any cost to other firms.

To be clear, the findings of this paper do not dispute the potential positive effects of R&D subsidies and tax incentives; instead, it shows potential pitfalls of such policies. In particular, subsidized firms could crowd out unsubsidized competitors. Identifying efficient recipients is crucial in determining the effectiveness of such subsidies. On the one hand, if inefficient but politically connected firms are the beneficiaries, it is unlikely that these subsidies lead to a higher growth rate. On the other hand, if efficient firms are targeted, there is potential for the subsidies to improve welfare.

Chapter 2

Political Connections, Financial Frictions, and Allocative Efficiency

2.1 Introduction

Misallocation occurs when resources flow to less productive firms. Political connections arising from state-ownership are important causes of resource misallocation observed in the Chinese manufacturing sector (Hsieh and Klenow, 2009; Wu, 2018). Researchers have long suspected that limiting the role of political connections in allocating resources contributes to China's growth miracle during the last few decades. However, providing a well-identified answer to this conjecture faces two challenges. First, it is difficult to find a natural experiment that generates random variations in the degree of political connectedness across different geographic units. This makes it difficult to identify the effect of political connections in creating resource misallocation. Second, it is even harder to pinpoint how do political connections lead to resource misallocation. This makes it difficult for policymakers to implement reforms that improve allocative efficiency.

This paper makes progress in addressing both challenges. First, I combine two policies to causally evaluate both the impact of political connections on allocative efficiency and the improvement from limiting such connections. Second, the policies I focus on allow me to understand the mechanisms through which political connections distort resource allocation. I find politically connected firms have better access to external credits like bank loans at the cost of politically unconnected firms. This leads to inefficient allocation of credit. Limiting such differential access to bank loans accounts for over 60% of the total improvement of allocative efficiency in cities where political unconnected firms having the most difficulty in getting external finance. This translate into a 4% increase in the sectoral aggregate total factor productivity (TFP) among the affected cities according to a back-of-the-envelope calculation.

The combination of two policy shocks allows me to identify and estimate the effect of political connections on allocative efficiency. The first shock is the restructuring of the state-owned banks staring from 2004, which I call the banking reform. Through listing state-owned banks on major stock exchanges, the reform subjects the loan performance of those banks to the scrutiny of the capital market, I argue that such scrutiny changes the incentives for the banks to prioritize potential borrowers' qualities over their political connectedness , thus improves the allocative efficiency of credit and capital. The second policy shock is a high-profile national defense industrialization project called the Third Front (TF) project. The TF project placed politically connected state-owned firms across cities in Western China based on national defense requirements, generating variations in the number of politically connected firms that is orthogonal to the local economic conditions and potential. This provides exogenous variations in the composition of firms that are politically connected across Chinese cities.

With the help of these two shocks, the impact of limiting political connection induced credit market inequality can be identified by the heterogeneity in the effect of the banking reform across cities with different exposure to the TF project. In particular, the banking reform should improve allocative efficiency more in cities with more exposures to the TF project, where there are more politically connected firms and thus have more room to improve. Indeed, I find cities received more TF investment benefit more from the banking reform. Despite them having less efficient credit allocation before the reform, the banking reform helps those cities to close around 70% of the gap in allocative efficiency when compared with cities received less TF investment.

The nature of the banking reform allows me to study the exact channel(s) through which political connections matter. Since the reform applies solely on the bank side, it does *not* change the direct relationship between the government and firms with or without connections. Therefore, the improvement I observe is driven by limiting financial privileges of the political connections and extending access to external credits to unconnected firms. Firm-level analyses support this explanation. I find that the reform improves access to credit for politically unconnected firms who are credit rationed or constrained before the reform, while some politically connected firms lost their preferential credit access after the reform. Unconnected firms who gain access to credit after the reform grow faster and are more likely to become exporters. In addition to improvements in the intensive margin, I also find an effect on the extensive margin: there are more entrants in cities where the banking reform creates a better improvement in allocative efficiency.

Finally, I discuss whether mechanisms other than changing banks' lending criteria and priority can be responsible for my results. Note that a necessary condition for generating the observed pattern in the data requires changes in the marginal borrower from the politically connected firms to politically unconnected firms. I show that neither a credit expansion, nor the concurrent privatization campaign alone can derive the pattern I documented above. Therefore, I conclude that it is the changes in the bank's lending practice that lead to the improvement of allocative efficiency.

Despite the positive and economically meaningful effect I find in this paper, the banking reform alone cannot fully correct the damage of political connection on allocative efficiency. For example, firms can use their political power to increase profitability by lobbying the regulatory agencies. In this case, unconnected firms still have worse access to credit as they are not as profitable as otherwise identical politically connected firms, which makes them more attractive than unconnected firms for profit-oriented banks. As a result, the banking reform failed to remove financial inequality between politically connected and unconnected firms completely. Therefore, the effect I find is relatively small compared to papers documenting the total gain from removing resource misallocation (e.g., Hsieh and Klenow 2009).

This paper contributes to several strands of literature. First, I combine the indirect method pioneered by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), which use dispersion in the marginal products across firms to infer the degree of resource misallocation, and the direct method like those in Banerjee, Breza, Townsend, and Vera-Cossio (2019); Bau and Matray (2020) that aims at identifying the root cause of misallocation using quasi experiments. I find a direct link between changes in the indirect measures of allocative efficiency and improvements in credit allocation at the firm level. This new evidence demonstrate the validity and usefulness of the indirect measures of allocative efficiency in a within country setting.

Second, this paper adds to the literature documenting various types of cost from political connections (Fisman, 2001; Johnson and Mitton, 2003; Fisman and Wang, 2015). I demonstrate that political connections have an *opportunity cost* beyond the direct cost documented in the literature. Specifically, unproductive yet politically connected firms can deplete scarce resources like capital that could be better employed by more productive unconnected firms. In the case of China, where political connections are closely linked to the state ownership, I find private firms' ability of getting external credit across Chinese cities negatively relates to the number of state-owned firms in those cities, suggesting politically connected firms crowd out unconnected firms on the capital market. Misallocation caused by political connections is costly: I find a 4% improvement in sectoral TFP in cities where political connection creates more distortions to credit allocation.

Third, my results also speak to the literature of soft budget constraint in the banking sector (Berglöf and Roland, 1997). Chinese state-owned banks have soft budget constraint and are guaranteed government bailout when facing financial distress. I show empirically that soft budget constraint in the banking sector leads to severe misallocation and inefficiency in the border economy, hindering economic development. Consequently, hardening the budget constraint of the banks has the additional benefit of improving allocative efficiency elsewhere in the economy.

I start by introducing the relevant institutional background of the Third Front project and the banking reform in Section 2.2. Section 2.3 discusses my empirical strategy based on the two policies shocks, as well as the data that allow me to measure them. Section 2.4 presents the main results. Section 2.5 discusses alternative mechanisms and why them cannot drive my results. Finally, Section 2.6 concludes.

2.2 Institutional Background

This section discusses the institutional settings for the two policy shocks that are relevant to my identification strategy. Section 2.2 introduces the Third Front (TF) project. The TF project is a national defense investment project in the 1960s and 1970s. It placed large manufacture firms based on criteria orthogonal to idiosyncratic shocks in the local economic conditions and potential. Section 2.2 argues that firms crated by the TF project are politically connected, who enjoy many privileges and perks that politically unconnected private firms do not. As a result, an unintended consequence of the TF project is that it generates random variations in the number of politically connected firms across cities it targets. This variation serves as the basis of my identification strategy. Finally, Section 2.2 introduces the 2004 banking reform, which limits politically connected firms' preferential access to bank loans. Combining these two policy shocks, the impact of limiting political connections on allocative efficiency can be identified using the heterogeneous treatment effect of the 2004 banking reform across cities with high or low number of politically connected firms.

The Third Front (TF) Project

The main source of the exogenous variation I exploit comes from the TF project. The TF project is a national defense construction plan aiming at creating a new industrial cluster in the heartland of China. The main purpose of the TF project is to prepare for potential conflicts between China and the United States and the Soviet Union.[1] In this section, I will focus only on its site selection criteria of placing new plants, which, as I will argue below, generates variations in the number of politically connected state-owned firms across cities that do not correlate with local economic conditions. This exogenous variation forms the basis of my identification strategy.

The TF project was China's response to deterioration of international relations in the 1960s. On the one hand, continuous boarder conflicts with the Soviet Union showed signs of intensification and escalation. A potential China-Soviet war will put China's northeastern industrial cluster directly under threat. On the other hand, Despite little active engagement, the Communist China was still in the middle of a civil war with the *Kuomintang* (Nationalist Party) in Taiwan who were backed by the United States. Therefore, the coastal regions were also at a high risk of being attacked. Since the northeastern and the coastal regions account for more than 90% of the manufacturing output in China at the time, China's enemy could paralyze its production of military equipment and severely damage its war potential. To alleviate this concern, Mao and other Chinese Communist Party leaders decided to build a new industrial base in China's heartland outside of the strike range of potential enemies from the east and the north[2]. They believed that this new industrial base can produce

[1]See Naughton (1988) for an excellent overview of the TF project and its impact.

[2]The name "Third Front" comes from the notion that the new base will be far away from direct confrontation on the front line ("First Front"), and air strikes to the supporting regions behind the front line

necessary manufacturing goods and military equipment in the event of destruction of the coastal and/or northeastern industrial clusters, and thus is essential to maintain China's war potential. Panel A of Figure 2.1 highlights the region considered by the TF project.

The site selection criterion is crucial in fulfilling the objective of the TF project. The official slogan of the TF project is "dispersed, hidden, close to the mountain", as new plants and factories must survive strategic bombing or even nuclear strikes. Panel B in Figure 2.1 overlays a digital elevation map of China and the TF region. It shows that region targeted by the TF project are located mostly in the regions with high elevation, which is consistent with the slogan. Moreover, instead of placing new plants at economic and population centers, they were placed in the mountainous part with rugged terrains. A prime example of the site selection criterion is the Panzhihua Iron and Steel Company, located in Panzhihua City, Sichuan. Before this investment, Panzhihua City was a rural village with only subsistence farming. In fact, the name of the Steel Company (and later the city) was taken from the name of a local wildflower that grown at the site of the planned Steel plant.

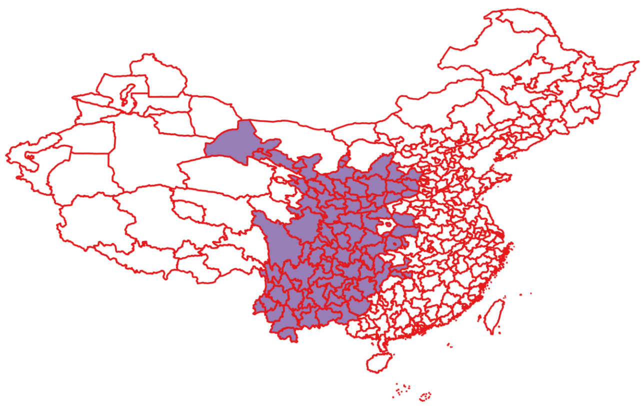
For plants that were placed to existing cities, they were rarely placed near the population center. Rather, they were placed in the surrounding areas of the existing city center. As an example, Figure 2.2 plots the locations of plants from Shaanxi Airplane Manufacturing Corporation (formally *012-base*), an airplane design and manufacturing plant. It shows that those plants was placed in a few dozens of locations scattered in mountains around Hanzhong Shi, Shaanxi. Different workshops of the plant was connected with each other using narrow gauge railroads to transfer staffs and intermediate products. *012-base* is not an isolated example. Until today, many Western Chinese cities in the TF region have a second urban cluster developed from the TF firms they received that are separated from the original city center. Together, these examples show that TF firms are placed in locations that are safer and more difficult to access, rather than economically important or promising.

The geopolitical tension that led to the inception of the TF project eased in the early to mid 1970s with the unexpected visit of President Nixon and the beginning of Chinese-American Rapprochement. The TF project and its objective of creating a separate and safe industrial cluster became increasing unnecessary. While existing unfinished projects continue to receive funding, the new TF plant construction stopped in the mid-1970s. Existing plants that were focused on military products were repurposed to produce civilian goods. Although the *Central Committee of the Third Front Construction* ("the TF Committee"), the organization in charge of overseeing the TF project, has never officially declared the conclusion of the TF project, China shifted industrial investment back to the coastal area after the economic reform in the manufacturing sector started in the mid-1980s, *de facto* ended the TF project.

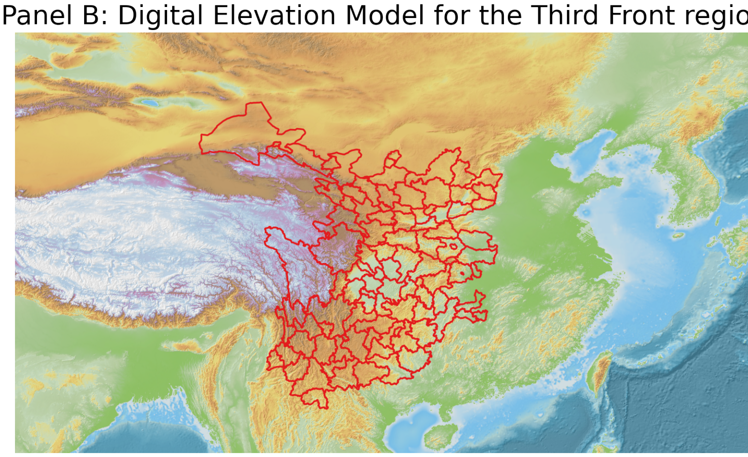
("Second Front"), and thus is safe.

Figure 2.1: The Third Front Region

Panel A: The Third Front Region



Panel B: Digital Elevation Model for the Third Front region



This figure plots the administrative boundary of Chinese cities on the top panel, and a digital elevation map of China on the bottom panel. On the top panel, cities that are considered by the TF project are highlighted in blue. On the bottom panel, the boundaries of cities that are considered by the TF project are highlighted in red. Elevation of the city is color-coded in this panel. The higher the elevation, the darker the color. The list of cities that are considered by the TF project are collected from Naughton (1988) and Fan and Zou (2021).

Figure 2.2: Plant Distribution Map of *012-base*

Souce: Beijing Air and Space Museum
Note: This figure plots location of the Shaanxi Airplane Manufacturing Corporation (*012-base*). A green dot represents a completed plant, a gray dot represents a canceled plant. The number associated with each dot represents the code name of each plant.

TF Firms and Political Connections

There are several differences between the firms created by the TF and the private firms located in the TF cities. First, due to the way and the historic context of when and how these firms are setup, TF firms are all state-owned firms controlled by the government, whereas private firms are, by definition, owned by private parties and not by government agencies. Like other state-owned firms, TF firms can use their political connections to get refinance and bailout when they face financial distress, while private firms lack such connection and will have to close down if they face similar situations. Second, there are severe incentive problems in state-owned firms due to potential government bailout (Li and Liang, 1998; Kornai, Maskin, and Roland, 2003). Since the managers and workers will not suffer the consequences of failing, they have little incentives to innovate and improve. Thus, state-owned firms are often inefficient and unproductive. (Chen, Igami, Sawada, and Xiao, 2020)

The TF project ended before private entrepreneurs were allowed to enter the manufacturing sector, therefore, TF firms are all owned by the state and operated by the government appointed managers, party representatives, and officials. Furthermore, like all other major projects and movements during the Maoist China, the planning and implementation of the TF project followed a top-down approach, with the TF Committee in charge of approving construction plans for all TF firms. Once the plant construction finishes, the government decides the type of product it needs to produce, assigns the production quota it needs to meet, and any adjustment in capital or employment size of the firm. The ending of the TF project does not change the status of the TF firms: since there is no change in the ownership status of the TF firms, they remained controlled by and connecting to the government.

Being connected to the government offers many perks and privileges to TF firms. In particular, they have better access to bank credits due to the facilitation of the government between the firms who demand credits and the bank who offers them. As I will argue in Section 2.2, the government can also interfere with banks' credit allocation process directly before the banking reform, therefore, the privileged access to bank credits is particularly pronounced. Furthermore, state-owned firms also face fewer regulations and/or less strict enforcement of the same regulations (Fisman and Wang, 2015). Their connections to the government also shield them from bureaucratic harassment (The World Bank, 2005). Finally, state-owned firms operating in "key industries" are also protected from private competitions by deliberately introduced entry barriers (Li, Liu, and Wang, 2015).

Despite these perks and privileges, TF firms are inefficient and unproductive. First and specifically to the TF firms, due to their national defense purpose, TF firms were designed to produce either industrial or military equipment. The technology they had was not suitable for meeting civilian demands. In fact, many of TF firms had a difficult time to pivot towards civilian production after the TF project ended (Naughton, 1988).

Second, like other state-owned firms who expect (and receive) help from the government when facing financial distress, TF firms face little risks of closing down.[3] The expectation of being bailed out by the government provides little incentives for managers and workers in the state-owned firms to focus on profitability and innovation, including engaging in cost-reducing and productivity-enhancing activities (Qian and Xu, 1998; Huang and Xu, 1998; Kornai, Maskin, and Roland, 2003). The expectation of bailout is particularly damaging for TF firms, as they need to exert more efforts to transition from military-oriented to civil-oriented production. In fact, a job at a state-owned firm is often referred as an "iron bowl", meaning that one can never lose the job like a bowl made from iron cannot be broken. As a result, many TF firms failed to improve their profitability and productivity even after multiple rounds of bailouts (Li and Liang, 1998).

The Banking Reform

The other main policy shock I exploit is the restructuring of major state-owned banks starting in 2004. I argue that the reform fundamentally changed how these banks allocate loans: first, the reform *de facto* separates local bank branches from local governments, so that the local government can no longer direct loans towards unproductive state-owned firms for political purposes. Second, the reform takes all major state-owned banks to the

[3] Of course, this is no longer true since the privatization campaign started in the late 1990s. I discuss how privatization campaign affects my results in Section 2.5.

capital market by listing them on stock exchanges. The scrutiny from the capital market changes the incentives of the banks, who become much more performance-oriented when making loan decisions. Ultimately, this reform limits the extent to which unproductive yet politically connected state-owned firms having preferential access to the bank credit, while extending the credit access to more productive yet politically unconnected private firms.

The banking reform aimed at addressing the cumulative nonperforming loans to unproductive state-owned firms. After the market reform in the late 1980s, state-owned firms with misaligned incentives for workers and managers had a difficult time competing with more efficient private firms. Renewing loans from state-owned banks was one of the only lifelines for many unproductive state-owned firms. These banks agreed to making nonperforming loans to state-owned firms continuously before the reform for two reasons: first, local governments value low unemployment rates, and state-owned firms were the main (if not the only) employers in the manufacturing sector at the time. Letting them go bankruptcy can create social turmoils, hurting the political career of the local officials. To avoid such political disaster, local governments often pressure local bank branches to offer loans to state-owned firms as they have the ability to interfere with allocation of bank loans. Although state-owned commercial banks was *de jure* independent entities separated from the government in the *Commercial Bank Act* in 1994, local governments still a large influence over allocation of credits and loans from those banks. Such influence is a legacy from the planned economy and early years of the market liberalization reform, when state-owned banks were specialized in different areas (e.g., commerce, construction, international trade, etc.), and local governments were in charge of determining which projects should be funded by which bank.

Second, the banks and their loan officers do not have incentive to scrutinize loan applications backed by the local government before the reform, as they do not bear the responsibility of nonperforming loans. State-owned banks are fully insured by the central government for any potential loss they may have.[4] As a result, the banks do not have incentive to refuse direction from local governments to lend to politically connected state-owned firms.

This is no longer the case after the banking reform. The reform restructures state-owned banks by listing them on the stock exchanges. From the banks' perspective, exposing to the capital market puts pressure to the profitability of the loans, incentivizes them to lend according to firms' performances and their ability to repay the loan, not their political connectedness. In 2004, China Construction Bank became the first major state-owned bank finishing Initiate Public Offering (IPO) and listed on the Hong Kong Stock Exchange. By 2010, after the IPO of China Agricultural Bank in both the Hong Kong and Shanghai Stock Exchanges, all major state-owned banks in China are listed publicly.

[4] For example, the central government set up 4 asset management companies to purchase CNY 1.4 trillions nonperforming loans from major state-owned banks, effectively bailing them out. Nevertheless, the bailout had proven to be ineffective, as the banks continued to grant loans to inefficient state-owned firms. At the end of 2002, 3 years after the bailout, major state-owned banks had again accumulated CNY 1.7 trillions nonperforming loans, with over 26% of the loans are nonperforming. I will discuss the implication of this bailout in Section 2.5.

The reform is considered successful: the share of nonperforming loans of the major state-owned banks decreased from over 26% in 2003 to less than 1.6% in 2017. Furthermore, all major state-owned banks become profitable after their IPO. In fact, these state-owned banks are among the firms with the highest profits listed in Shanghai and Shenzhen stock exchanges (Li, 2008).

The specificity of the reform (i.e., it addresses only the banking sector) allows me to evaluate how politically connections affect allocative efficiency through distorting access to formal bank credits. The banking reform did not eliminate or change other perks politically connected firms enjoy. For example, connected firms are still more likely to receive direct subsidy from government (Wei, Xie, and Zhang, 2017); The government can still bailout failing politically connected firms through other means like granting them government contracts (Qian and Roland, 1998; Kornai, Maskin, and Roland, 2003).

Nevertheless, having access to low cost loans from the bank remains an quantitatively important perks of political connections (Cull and Xu, 2000, 2003; Cull, Li, Sun, and Xu, 2015). A large literature has documented that differential access to the financial market can be a major obstacle to economic growth. By exploiting the heterogeneous effect of the banking reform across cities with different level of TF investments, I can identify the effect of limiting politically connected firms' preferential access to the bank loan on allocative efficiency of the local economy in the context of China.

The specificity of the banking reform inevitably limits its scope and the potential effect, as connected firms can use their political power to regain preferential access to credit. Li, Liu, and Wang (2015) shows that many politically connected firms operate in industries with high entry barriers created by the government. This protection gives them more market power and higher profitability than otherwise identical unconnected firms, making connected firms more attractive to the banks even after the reform.

Together, the TF project and the banking reform provide an unique opportunity for me to understand whether political connections hinders efficient allocation of bank credits, and whether changing banks' lending criteria and priority can limits the damage political connections create in credit allocation. I discuss the data and empirical strategy I use to identify the causal impact of the banking reform on allocative efficiency in the next section.

2.3 Empirical Strategy and Data

This section describes the research design and the data used to identify the effect of the banking reform on allocative efficiency. I first discuss an empirical strategy stemming from the TF project and the banking reform. The key to identification is the exogeneity of the variation in the number of politically connected firms generated by the TF project, and the timing of the banking reform. With those exogeneity conditions, the impact of removing political connections in credit allocation process can be identified by the heterogeneous treatment effect of the banking reform across cities with more or less exposures to the TF project. I then examine the data requirement of my empirical strategy. I show that by combining two sets of firm-level surveys, I can measure the exposure to the TF project on each cities in the region targeted by the TF project, as well as the allocative efficiency in those cities before and after the banking reform.

Empirical Strategy

This section discusses the specification and the underlying identification assumptions in my research design.

To identify the impact of removing preferential credit access from politically connected firms on allocative efficiency, I use the exposure to the TF project as treatment variable, and the timing of banking reform in a difference-in-difference (DiD) framework. Specifically, cities with more exposure to the TF project are assigned to the treatment group, and cities with less exposure to the TF project are assigned to the control group. The treatment occurs in 2004, when the first major state-owned bank finished its IPO. The baseline specification is given by

$$y_{ict} = \delta_{ic} + \delta_t + \beta \; treat_c \times post_t + \varepsilon_{ict}, \tag{2.1}$$

where the subscripts c, t denotes city and year. Depending on the level of analysis, the subscript i could mean either firm or industry. $treat_c$ is either a continuous treatment variable of the TF exposure city i received, or a binary variable that takes value 1 if city i's TF investment is above median value ("treated cities") and 0 otherwise ("control cities"). $post_t$ is a dummy variable that equals to 1 if $t > 2004$. δ_{ic}, δ_t are entity and time fixed effect, respectively. β in regression (2.1) is the main parameter of interest. It captures the differences in the changes in the dependent variable y_{ict} due to the banking reform across the treated and the control cities. Finally, since the treatment (the TF project) occurs at the city level, I cluster the standard error at the city level.

To analyze the effect of the banking reform on allocative efficiency, I estimate a version of regression (2.1) with y_{ict} being the log TFPR dispersion in the industry i at city c, year t. I expect the reform improves allocative efficiency more in the treated cities, as there are more politically connected firms, and the unconnected private firms can benefit more from a reform that limits the role of political connections in allocating credits. Furthermore, to estimate who gets credit after the banking reform, I estimate another version of regression (2.1) at the firm-level with y_{ict} being firm-level characteristics like their access to credit, size, output, and productivity. I hypothesize that the banking reform incentivizes the bank to lend more to the more productive yet politically unconnected private firms, resulting in them becoming more leveraged and faster-growing after the reform. Similarly, I hypothesize that this effect should be stronger in the treated cities with more TF firm presents.

The underlying identification strategy in regression (2.1) is similar to a DiD design, where the treatment is defined by the exposure to the TF project, and the treatment happens after the banking reform. In this case, the underlying identification assumption is that the idiosyncratic shock, ε_{ict} follows the same trend in the control and treated cities in the absence of treatment.

I argue that the parallel trend assumption is satisfied in my setup. If both *treat* and *post* are independent to the error term ε_{ict} conditional on the fixed effects, the parallel trend assumption will automatically satisfied. This is likely to be true. For the exposure to the TF project (*treat*), as I argued in Section 2.2 that conditional on the geographic feature of the locality (absorbed by the entity fixed effect δ_{ic}), exposure to the TF project should not be correlated with the economic conditions and potential, thus *treat* should not be correlated with ε_{ict}.

Following the discussion in Section 2.2, the timing of the banking reform (*post*) is also likely exogenous for two reasons. First, the banking reform aims at addressing the huge nonperforming loan in the state-owned banks nationally. It is thus unlikely that the Chinese government implemented the banking reform having its potential consequence on regional allocative efficiency in mind. Second, while the TF project represents a large fraction of China's total industrial investment between late 1960s and early 1970s, the newly built TF plants account only a small share of GDP nationwide. Therefore, the design and implementation of the banking reform should not correlate to the economic conditions and potentials of the cities affected by the TF project, let along differently across cities with different exposure to the TF project.

Data

Two measures are required to identify the effect of the banking reform. First, I need to measure the level of exposure to the TF project at the city level. The 1985 Large and Medium Industrial Firm Survey, which contains information on total TF investment in each cities, provides this information. Second, I need to measure allocative efficiency of cities affected by the TF project before and after the banking reform. The Annual Survey of Industrial Enterprises between 1998 and 2007 allows me to extract those information.

To measure the level of exposure to the TF project, I use the 1985 Industrial Firm Survey. The 1985 Industrial Firm Survey is the first survey with firm-level information available after the TF project. The survey includes address, employment, output, the book value of capital, and the establish time for a list of medium and large industrial firms. Since I know the time period and region targeted by the TF project, I can use their addresses and establish time to identify firms placed by the TF project (i.e., the TF firms). I then aggregate the total employment, output and capital of all TF firms for each cities located in the TF region to construct a measure of their exposures to the TF project.

According to the site selection criteria of TF firms discussed in Section 2.2, the placements of TF firms should not be correlated to economic condition and potential given on geographic characteristics (absorbed by the city fixed effect). Therefore, my measure of TF exposure offers exogenous variations in the number of political connected firms across cities: cities with larger TF exposure have more politically connected firms for reasons unrelated to economic conditions.

The 1985 survey is better in identifying TF firms for two reasons. First, although more recent firm surveys have more detailed balance sheet information, these information are not essential for calculating the exposure to the TF project. Second, reforms in the manufacturing sector did not start until 1984. Therefore, the majority of the TF firms were kept in 1984 with little change to their sizes and employment levels (Naughton, 1988; Fan and Zou, 2021). After 1998 when more recent surveys become available, firms have already exposed to the market and are able to adjust their employment or asset holdings, making those recent surveys a poor measure of the true exposure to the TF project. This difference makes the 1985 survey a more accurate measures of cities' exposure to the TF project.[5]

I use 3 variables to measure cities' exposure to the TF project: the log total output, employment, total book value of the capital in 1984 for all TF firms in the cities that are considered for TF projects. Table 2.1 reports these measures as well as the number of TF firms across cities located in the TF regions.[6] Panel A of Table 2.1 provides summary statistics of my measures of the TF exposure. There are significant variations in all three measures, indicating that there are large differences in the TF exposure across cities. Furthermore, Panel B of Table 2.1 shows that the correlations among different TF exposure measures are above 0.95. Consequently, all my results are robust to using different measures of exposures to the TF project.

To measure allocative efficiency, I use the Annual Survey of Industrial Enterprises (ASIE) from 1998 to 2007. The survey includes the universe of state-owned firms, and private firms with more than CNY 5,000,000 ($ 625,000) in annual sales. The survey covers over 90% of the manufacturing output in China and it is widely used in studying resource misallocation in China (e.g., Hsieh and Klenow 2009; Song and Wu 2015; Wu 2018). The survey provides information on firms' value added, sales, employment, intermediate good input, and capital stocks, which can be used to calculate allocative efficiency. I follow the standard procedures documented in Cai and Liu (2009) to exclude abnormal observations, including those with missing values in equity structure, sales, employment, total output, and asset. I also drop observations reporting lower total assets than fixed or intangible assets. Finally, I drop observations reporting negative total equity.

Following Hsieh and Klenow (2009), I use dispersion in the revenue total factor productivity (TFPR) to measure allocative efficiency. Specifically, denote $P_{si}, Y_{si}, K_{si}, L_{si}$ the price, output, capital stock and labor of firm i in industry s, α_s the labor share in industry s, and w the prevailing wage rate in the economy, the TFPR can be calculated as

$$TFPR_{si} = \frac{P_{si}Y_{si}}{K_{si}^{1-\alpha_s}(wL_{si})^{\alpha_s}}. \tag{2.2}$$

I obtain information on $P_{si}Y_{si}, wL_{si}$ directly from the ASIE dataset. The capital stock, K_{si}, is calculated following the method documented in Brandt, Van Biesebroeck, and Zhang (2012). The sectoral level labor share, α_s, is calculated using the NBER-CES Manufacturing Industry

[5] Furthermore, many TF firms are already shut down by the government in 1998 due to the privatization campaign.

[6] Technically speaking, I look at exposure to the TF project in each "prefecture", which includes urban districts and the surrounding rural areas.

Table 2.1: Exposure to the TF project

Panel A: exposure to the TF project

	p10	p25	p50	p75	p90	mean	std. error	N. city
log Total TF firms' Assets	6.78	9.12	10.28	11.17	11.70	9.40	2.9	91
log Total TF firms' Output	6.36	8.46	9.78	10.61	11.10	8.92	2.77	91
log Total TF firms' Employment	6.16	7.81	9.31	10.26	10.67	8.57	2.66	91
log Total Number of TF firms	1	2	6	13	21	8.76	8.89	91

Panel B: correlation matrix of various measures

log Total TF firms' Assets	1.0			
log Total TF firms' Output	0.98	1.0		
log Total TF firms' Employment	0.97	0.97	1.0	
log Total Number of TF firms	0.52	0.53	0.57	1.0

Source: 1985 Industrial Firm Survey. Only cities considered by the TF project are included.
Note: each observation is a city considered by the TF project whose boundary is defined in 1985. A firm is considered a TF firm if it started operating between 1964 and 1972. The variables are constructed by aggregating total assets, outputs, employments, and the number of TF firms in each city that are considered by the TF project.

Database for the corresponding industry in China. Since I calculate TFPR dispersion within each industry-cells, my results are robust to using different estimates of α_s.

Efficient allocation of capital requires equalization of TFPR across firms within each industry: If two firms have different TFPR, the economy can attain higher total output by moving resources from firms with low TFPR to firms with high TFPR. Therefore, dispersion in the TFPR can be a measure of allocative efficiency. Panel A of Table 2.2 presents summary statistics of the TFPR dispersion, measured by the standard deviation and the interquartile range of log TFPR, for each industry-city cell inside the TF region. I also separately report these measures for cities below and above the median TF exposure.

Previous studies have pointed out several issues with using TFPR dispersion as a measure of the allocative efficiency. First, there are measurement issues regarding the firm level TFPR. Measurement errors in either the input (K_{si}, wL_{si}) or the value added $(P_{si}Y_{si})$ will lead to dispersion in TFPR when there is no misallocation (White, Reiter, and Petrin, 2018; Bils, Klenow, and Ruane, 2020). Moreover, dispersion in TFPR may reflect idiosyncratic demand shocks at the firm-level as oppose to market frictions (Haltiwanger, 2016). Finally, investment is costly and time-consuming. Firms may deviate from the optimal size because of the lumpiness of the investment (Bartelsman, Haltiwanger, and Scarpetta, 2013; Asker, Collard-Wexler, and De Loecker, 2014). In this case, TFPR dispersion may reflect simply firms making investment in different time.[7]

I argue that my results are not driven by measurement errors. Notice that my empirical strategy is based on comparing the *changes* in the TFPR dispersion across different cities. As long as measurement errors are not correlated with my measure of TF exposure and the timing of the banking reform conditional on the fixed effects, β in regression (2.1) can identify the true treatment effect. Indeed, given the discussions in Section 2.2 and Section 2.3, any measurement error should not affect the identification of β: First, Exposures to the TF project is pre-determined and thus should not be correlated with issues like contemporary idiosyncratic demand shocks that introduce measurement errors in TFPR. Second, given the fact that the banking reform is designed to target a national level issue, it is unlikely that its timing correlates with idiosyncratic factors affecting measurement errors in TFPR dispersion.

Second, even without any measurement issue, TFPR dispersion measures allocative efficiency only under strong structure assumptions. For example, Haltiwanger (2016) shows that an efficient allocation leads to equalization of TFPR across firms only if firms face a unit price elasticity with respect to their quantity-based total factor productivity (TFPQ).[8]

[7]Although David and Venkateswaran (2019) argues that non-convex adjustment cost explains very little dispersion in the value-added-to-capital ratio among Chinese manufacturing firms.

[8]Specifically, eq. (2.2) can be rewrite as

$$TFPR_{si} = P_{si} \cdot TFPQ_{si},$$

where $TFPQ_{si} = \frac{Y_{si}}{K_{si}^{1-\alpha_s}(wL_{si})^{\alpha_s}}$. Dispersion in $TFPR_{si}$ can be interpret as misallocation only if any changes in $TFPQ_{si}$ can be perfectly offset by the changes in P_{si} in the absence of any misallocation.

This strong structural assumption may not hold in my data. To address this issue, I follow Gilchrist, Sim, and Zakrajšek (2013) and use the dispersion of interest rate across firms as an alternative measure of allocative efficiency. Since I observe the total liability and the interest payment firms made in my dataset, I can calculate a gross interest rate each firm faces in my dataset. The gross interest rate is a measure that does not depend on the underlying production function and idiosyncratic demand shocks. Furthermore, having bank loan with discounted interest rate is a well-documented privileges for the politically connected state-owned firms (e.g., Cull, Li, Sun, and Xu 2015). As a result, using the standard deviation of interest rate can serve as an alternative measure of allocative efficiency.

Using dispersion of interest rate as a measure of allocative efficiency has its own issues. In particular, interest rate could be different for reasons unrelated to the political privileges of the state-owned firms. For example, larger firms could get lower interest rate because they have more collateral. To address this issue, I residualize the interest rate by running the following regression

$$interest\ rate_i = \iota + \kappa' X_i + \widehat{interest\ rate}_i,$$

where X_i is a vector of firm-level controls including firm size, age, total fixed assets and the debt-to-asset ratio (total liability over total assets). I then use the standard deviation of the residualized interest rate $\widehat{interest\ rate}_i$ as a measure of credit allocative efficiency. In addition, I also group firms to industry-year cells when calculating the standard deviation to absorb possible industry and year differences in the interest rate firms face. Panel A of Table 2.2 shows that the dispersion of the residualized gross interest rate displays similar pattern as measures of TFPR dispersion.

Note that I do *not* require the residualized interest rate to be exactly equalized across firms in the absence of misallocation. Rather, I assume factors other than market friction that lead to dispersion of residualized interest rate do not correlate with cities' exposures to the TF project and the timing of the banking reform. Again, exogeneity of exposures to the TF project and the timing of the banking reform ensure that this assumption is satisfied.

The ASIE dataset also contains information on firms' balance sheets like output, value added, total employment, total debts and assets, and the industry the company operates in, as well as the political connectedness of the firm (measured by firm ownership). Panel B of Table 2.2 presents summary statistics of these firm characteristics, also separately for cities below and above the median TF investments. Consistent with the finding of Fan and Zou (2021), firms in cities received more TF investment are larger and more likely to be in the same industry targeted by the TF project. Cities received more TF investment also have *lower* shares of state-owned firms. These statistics suggest that the TF project may generate local spillover to private firms. Furthermore, compared to state-owned firms, private firms have lower debt-to-asset ratio. They are also less likely to have bank loans. When they do, these private firms face higher interest rate. Finally, private firms have higher TFPR than their state-owned counterparts. These patterns are consistent with the narrative that private firms have more difficulties in getting loans and thus are more credit rationed/constrained.

Table 2.2: Summary Statistics

						above median		below median		
	p25	p50	p75	mean	std. error	mean	std. err.	mean	std. err.	N
Panel A: measures of allocative efficiency										
s.d. log TFPR	0.58	0.84	1.11	0.89	0.50	0.92	0.50	0.84	0.52	12,658
i.q.r log TFPR	0.71	1.07	1.52	0.21	0.80	1.23	0.79	1.18	0.83	12,658
s.d. interest rate	.013	.022	.033	.028	.025	.029	.025	.027	.026	12,470
Panel B: firm characteristics										
log output	4.36	5.13	6.06	5.21	1.50	5.27	1.48	5.01	1.52	162,359
log value added	3.08	3.93	4.90	3.98	1.57	4.03	1.56	3.80	1.58	158,497
employment	65	136	300	367.8	1235.9	384.8	1281.1	315	1084.6	165,353
TF industry	0	0	1	0.424	0.494	0.50	0.50	0.17	0.38	165,369
state-owned	0	0	0	0.19	0.40	0.18	0.38	0.23	0.42	165,369
has loan	0	1	1	0.72	0.45	0.70	0.45	0.74	0.44	165,369
private only	0	1	1	0.70	0.45	0.68	0.45	0.76	0.42	102,208
interest rate	0.004	0.016	0.037	0.027	0.040	0.027	0.040	0.028	0.041	153,342
private only	0.003	0.020	0.040	0.030	0.043	0.029	0.43	0.030	0.44	117,070
debt/asset	0.42	0.63	0.83	0.64	0.39	0.64	0.38	0.67	0.41	163,814
private only	0.39	0.55	0.75	0.59	0.31	0.58	0.31	0.62	0.32	102,208
log TFPR	-1.08	-0.38	0.36	-0.37	1.20	-0.35	1.20	-0.44	1.21	160,672
private only	-0.82	-0.19	0.50	-0.14	1.08	-0.13	1.08	-0.16	1.08	102,208

Source: ASIE 1998 - 2007, I only include the cities considered by the TF project, or firms located in those cities.
Note: The unit of observation in Panel A is a city-industry-year cell. The dispersion measures are calculated for each city, industry and year cell, and reported in each row. The unit of observation in Panel B is a firm-year cell. log output, value added, employment, state ownership, the industry the firm is operating in, and whether it has loan are directly observed from the ASIE dataset. The interest rate is calculated by dividing the firm's interest payment to its total liability. Debt-to-asset ratio is calculated by dividing the firm's total liability to its total asset. The TFPR is calculated using the formula given in the text.

Finally, private firms located in the cities received more TF investments are having more difficulties in accessing external funding than private firms located in the cities received fewer TF investments, suggesting that they face even more severe disadvantages in getting outside finance.

Finally, I need to match my measure of TF exposure and my measure of allocative efficiency. To this end, I assign each firm I observed in the ASIE dataset to its corresponding 1985 industry-city cell in order to match to its TF exposure measure I calculated using the 1985 survey dataset. There are two issues associated with this assignment. First, the 1985 Industry Survey contains only the 1985 version of the two-digit industry classification, whereas the ASIE surveys use an updated version of the four-digit classification system. I manually map all forty 1985 industry codes to the new industry classification system used in later surveys. Appendix B.2 reports this mapping. Second, the administrative boundaries of cities changed over the year. I follow the complete list of those boundary changes published by the Ministry of Civil Affairs to map ASIE firms from the city of their reported address to the corresponding 1985 cities.[9]

2.4 Results

This section presents results. First, cities received more TF investments have worse credit allocation before the reform. Second, cities received more TF investment benefits more from the banking reform. Third, this improvement in allocative efficiency is driven by unconnected private firms having better access to credit after the reform. Supports in the form of external credits allow them to invest more and grow faster. I draw two conclusions from these results. First political connections lead to less efficient credit allocation before the reform. Second, the banking reform changes the lending criteria and priority of the banks, which limits the role political connections play, and allow previously credit constrained private firms to have better access to credit, boosting their growth.

Results on Allocative Efficiency

This section presents the effect of the banking reform on allocative efficiency at the city level. I find the banking reform improves allocative efficiency more in treated cities. I interpret this result as evidence supporting the hypothesis that the banking reform limits the role political connections play in credit allocation by making banks' lending criteria performance oriented.

Table 2.3 reports results from running regression (2.1) with standard deviation of log TFPR being the dependent variable. Column 1 of Table 2.3 reports the baseline result without any fixed effect. The signs of coefficients are expected: first, the point estimate for variable *treat* is positive and statistically significant, suggesting allocation of credit is less

[9] The data on the administrative boundary changes is available at http://www.mca.gov.cn/article/sj/xzqh/2020/.

efficient in treated cities, who received more unproductive and politically connected state-owned firms. Second, the overall allocative efficient improved after the banking reform in both the treated and the control cities, as the point estimate for variable *post* is negative and statistically significant. Third, the improve is much larger in the treated cities than in the control cities: the point estimate for the interaction term $treat \times post$ is negative and statistically significant at 1% level.

The differential effect of the banking reform I find in Table 2.3 is economically meaningful. First, a back-of-the-envelope calculation suggests that the banking reform closes 70% of the gap in the dispersion of log TFPR between the treated and the control cities. Second, the banking reform leads to 4% gains in the sectoral TFP in the treated cities, which is 3.5% higher than that in the control cities. To calculate this number, I use the structure model in Hsieh and Klenow (2009) and write the sectoral TFP as

$$\log TFP = \frac{1}{\sigma - 1} \log \left(\sum_i TFP_i^{\sigma-1} \right) - \frac{\sigma}{2} var(\log TFPR_i), \tag{2.3}$$

where σ denotes elasticity of substitution between products produced by different firms operating in the same industry. Calibrating σ to 5 and notice that the total reduction in the standard deviation in log TFPR in the treated cities is 0.125 (=0.048+0.077) and that in the control cities is 0.048.

Column 1 has a potential endogeneity issue: geographic conditions are important determinants of both the local economic potential and the placements of TF plants. Thus, the variable *treated city* may be correlated to factors other than exposure to the TF project which could affect local TFPR dispersion. Column 2 and 3 in Table 2.3 address this issue by including fixed effects in regression (2.1). Column 2 includes the year and city fixed effects, where I calculate the average change in the TFPR dispersion within the same city before and after the banking reform and compare them across the treated and control cities. By including the city fixed effect, I am able to control time invariant factors like geographic conditions. This helps me to pin down the causal channel through which the banking reform affects allocative efficiency (i.e., by changing lending criteria and priority). The point estimate of the interaction term in column 2 remains highly significant. Furthermore, there is little change in the magnitude of the coefficient: if anything, the point estimate of the interaction term become larger after controlling for fixed effects.

Column 3 takes a step forward by controlling for the city-by-industry fixed effect. In this case, I calculate the average change in the TFPR dispersion within the same industry in each city and compare the changes between treated and control cities. This allows me to control for time invariant, industry-specific impact from local geographic conditions. Again, including city-by-industry fixed effect does not change my results: the point estimate of the interaction term is still negative and highly statistical significant with a similar magnitude.

Column 1 - 3 consider only the heterogeneity across cities received above or below median TF investment, defined using the *treat* variable. To fully utilize the heterogeneity generated by the TF project, I replace the binary treatment variable with the log amount of TF

Table 2.3: log TFPR dispersion across TF cities, before and after the banking reform

	standard deviation of log TFPR				
	(1)	(2)	(3)	(4)	(5)
treated city	0.095***				
	(0.03)				
post	-0.048*				
	(0.03)				
treated city × post	-0.077**	-0.082**	-0.089**		
	(0.03)	(0.03)	(0.03)		
TF investment × post				-0.017**	-0.015*
				(0.01)	(0.01)
Constant	0.833***	0.911***	0.914***	0.949***	0.946***
	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)
mean dvar.	0.894	0.894	0.895	0.894	0.895
Year FE		X	X	X	X
City FE		X		X	
CityXInd FE			X		X
N. Obs	12658	12654	12495	12654	12495

Source: ASIE 1998 - 2007. Only cities considered by the TF project are included.
Note: Each observation is a industry-city-year cell. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *TF investment* is a continuous variable that equals to the log value of the total TF firm assets in a city reported in the 1985 Industry Survey. The dependent variables in all columns are the standard deviation of the log TFPR. Column 2 and 4 include year and city fixed effects. Column 3 and 5 include year and industry-city fixed effects. Standard errors are clustered at the city level.

investment each city received, which is a continuous measure of the exposure to the TF project. Column 4 and 5 in Table 2.3 report the results from using the new measure. The point estimate of the interaction term in column 4 remains statistically significant, implying that the improvement from the banking reform is still significantly larger (at 5% level) in cities exposed more to the TF project. The coefficient is also economically meaningful: a simple back-of-the-envelope calculation shows that moving from the 25th percentile in the exposure to the TF project to the 75th percentile means doubling the effect of the banking reform in terms of improving allocative efficiency (0.017×2.7 vs. 0.048).

Column 5 again uses the city-by-industry fixed effect to control for time-invariant intra-city, inter-industrial variations that could be correlated with exposure to the TF project or the timing of the banking reform. The magnitude of the point estimates reported in column

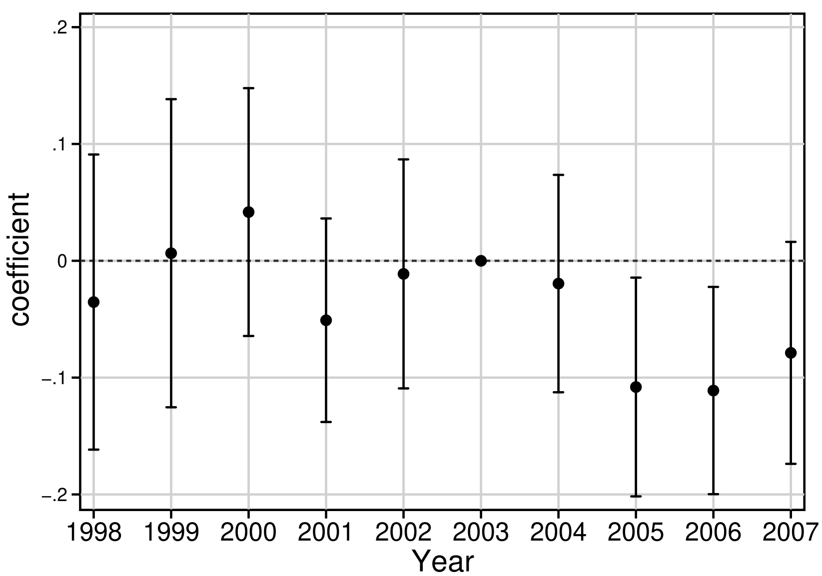
5 is consistent with that in column 4. However, the interaction term is only significant at 10% level, as I am slightly under-powered by trying to detect a smaller treatment effect from incremental changes in the exposure to the TF project.

ASIE surveys provide a long enough panel for me to test for the parallel trend assumption directly. To this end, I run a version of regression (2.1) with a full set of interaction term between year dummies and the (binary) treatment status for each city:

$$y_{ict} = \delta_{ic} + \sum_{s} \mathbf{1}(t = s) + \sum_{s} \beta_s \, treat_c \times \mathbf{1}(t = s) + \varepsilon_{ict}, \tag{2.4}$$

where β_s denotes the difference in the effect of the banking reform between cities with above or below median TF exposure in year s relative to the effect at year 2003. Figure 2.3 plots β_s with 95% confidence interval from running regression (2.4) with standard deviation of log TFPR as the dependent variable. Furthermore, Figure B.1, B.2, and B.3 in the Appendix report similar patterns using alternative measures of allocative efficiency. I conclude from these figures that allocative efficiency in different cities did not evolve differently before 2005, the second year after the banking reform. Therefore, the parallel assumption is satisfied.

Figure 2.3: Treatment Effect of the Banking Reform, Separate by Year



This figure plots the coefficient β_s from regression (2.4). The dependent variable is the standard deviation of log TFPR. Year and industry-city fixed effects are included in the regression. Standard error is clustered at the city level. All coefficients plotted here are relative to year 2003, which is the year before the banking reform. The vertical bar in the figure represents 95% confidence interval.

Table 2.4 reports results from estimating regression (2.1) using interquartile range of log TFPR as dependent variable. These results are consistent with those reported in Table 2.3.

Column 1 in Table 2.4 shows that the treated cities have larger interquartile range than control cities; the interquartile range decreases after the banking reform for all cities; and the gap in the interquartile range between treated and control cities shrinks after the banking reform. Column 2 and 3 include the year, city and/or industry-city fixed effects. The interaction terms in these columns remain statistically significant. Furthermore the magnitude of the point estimates do not change compared to that reported in column 1. Column 4 and 5 replace the binary treatment status with the continuous TF exposure measure using the log of total TF investment. The results are again consistent with using standard deviation of log TFPR as reported in Table 2.3.

Table 2.4: log TFPR dispersion across TF cities, before and after the banking reform

	Interquantile range of log TFPR				
	(1)	(2)	(3)	(4)	(5)
treated city	0.095**				
	(0.05)				
post	-0.056*				
	(0.03)				
treated city × post	-0.123***	-0.117***	-0.122***		
	(0.04)	(0.04)	(0.05)		
TF investment × post				-0.024**	-0.020*
				(0.01)	(0.01)
Constant	1.159***	1.237***	1.239***	1.292***	1.278***
	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)
mean dvar.	1.212	1.212	1.213	1.212	1.213
Year FE		X	X	X	X
City FE		X		X	
CityXInd FE			X		X
N. Obs	12658	12654	12495	12654	12495

Source: ASIE 1998 - 2007. Only cities considered by the TF project are included.
Note: Each observation is a industry-city-year cell. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *TF investment* is a continuous variable that equals to the log value of the total TF firm assets in a city reported in the 1985 Industry Survey. The dependent variables in all columns are the interquartile range of log TFPR. Column 2 and 4 include year and city fixed effects. Column 3 and 5 include year and industry-city fixed effects. Standard errors are clustered at the city level.

As discussed in Section 2.3, using TFPR dispersion as a measure of allocative efficiency depends on strong structural assumptions. Without those assumptions, TFPR dispersion does not necessarily imply inefficient allocation of credit. Residualized interest rate provides an alternative measure of allocative efficiency without those assumptions. Table 2.5 reports results from running regression (2.1) using standard deviation of residualized interest rate as dependent variable. In addition, Table B.1 reports result from running regression (2.1) using interquartile range of residualized interest rate as dependent variable. Again, these results are highly consistent with that reported in Table 2.3 and 2.4. In all specifications, the point estimates of the interaction term between exposure to the TF project and the post reform indicator are all negative and statistically significant at 5% or 10% level.

Table 2.5: interest rate dispersion across TF cities, before and after the banking reform

	standard deviation of residualized interest rate				
	(1)	(2)	(3)	(4)	(5)
treated city	0.004				
	(0.00)				
post	-0.007***				
	(0.00)				
treated city × post	-0.006**	-0.005**	-0.004*		
	(0.00)	(0.00)	(0.00)		
TF investment × post				-0.001*	-0.001*
				(0.00)	(0.00)
Constant	0.024***	0.029***	0.029***	0.031***	0.031***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
mean dvar.	0.028	0.028	0.028	0.028	0.028
Year FE		X	X	X	X
City FE		X		X	
CityXInd FE			X		X
N. Obs	12470	12466	12298	12466	12298

Source: ASIE 1998 - 2007. Only cities considered by the TF project are included.
Note: Each observation is a industry-city-year cell. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *TF investment* is a continuous variable that equals to the log value of the total TF firm assets in a city reported in the 1985 Industry Survey. The dependent variables in all columns are the standard deviation of the residualized interest rate. Column 2 and 4 include year and city fixed effects. Column 3 and 5 include year and industry-city fixed effects. Standard errors are clustered at the city level.

In summary, this section shows that allocative efficiency improves more after the banking reform in cities with more exposure to the TF project using different measures, including the standard deviation and interquartile range of log TFPR and residualized interest rates.

This result is consistent with the interpretation that having more politically connected state-owned firms hinders credit allocation before the banking reform, and the reform improves credit allocation more in cities endowed with more state-owned firms. I argue that changes in the lending criteria and priority induced by the banking reform is responsible for such improvement. Consistent with this explanation, I will provide further evidence in the next section showing that the narrowing of the efficiency gap between the treated and the control cities is indeed driven by politically unconnected private firms getting more credit and growing faster.

Results on Firm Growth

The last section shows that allocative efficiency, measured by the dispersion of both TFPR and residualized interest rate, has improved more in treated cities after the banking reform. However, it remains an open question of how does the reform leads to such improvement. In this section, I show that such improvement is driven by changes in banks' lending practice induced by the reform. In particular, I find that it becomes easier for politically unconnected firms to obtain external funding after the reform. As a result, these firms invest more and become larger, which lowers their TFPR and thus leads to decrease of dispersion of TFPR across politically connected and unconnected firms.

Table 2.6 report results of the banking reform on firms' access to credit. Column 1 and 2 look at the extensive margin effect, measured by the percentage of firms having bank loans. The ASIE dataset includes only relatively large firms, many of those are already having access to bank loans before the reform. Nevertheless, I am still able to detect differential trends between the treated and the control cities after the banking reform. First, the point estimate of the interaction term between *treat* and *post* is *negative* and statistically significant, meaning that firms in the treated cities become *less* likely to have bank loan after the reform. A negative coefficient of the interaction term $treat \times post$ could suggest that banks are more skeptical in giving out loans to firms located in the treated city after the reform, possibly because those firms have worse credit history pre-reform. Column 4 takes a closer look at this result by separating the effect for private and state-owned firms. I find that the decrease in the loan access is completely driven by the state-owned firms in the treated cities. Whereas the net effect for private firms in the treated cities is 0, meaning that the probability of having bank loan does not become lower for private firms in the treated cities. Consistent with my hypothesis of changing lending criteria and lending policy, this result shows a clear change in access to finance between the political connected state-owned and unconnected private firm after the reform.

The remaining columns in Table 2.6 look at the intensive margin effect. Column 3 and 4 report results on the interest rate firms face. Relative to firms in the control cities, firms in the treated cities experience a larger drop in the interest rate they borrow at after the reform. This is shown by the negative and statistically significant point estimate of the interaction term between *treat* and *post*. Furthermore, column 2 shows that this interest rate drop is driven by politically unconnected firms: when looking separately between private and state-owned firms, only private firms experiences a drop in the interest rate after the reform. This finding is consistent with my hypothesis that the banking reform changes banks' lending criteria and priority, which benefits unconnected private firms more. Since private firms in the treated cities are more constrained, they benefit more so than their counterparts in the control cities.

Column 5 and 6 in Table 2.6 report results on another measure of the intensive margin effect using firms' debt-to-asset ratio. I find firms in the treated cities become more leveraged after the reform when compared to firms in the control cities, showing as the positive and statistical significant point estimate for the interaction term between *treat* and *post* in column 5. Column 6 again separates the effect for state-owned and private firms by including the triple interaction term. After such change, the interaction term *treat* $\times$ *post* is no longer statistical significant. This change suggests that the relative increase in the debt-to-asset ratio happens only among private firms in the treated cities.

Results presented in Table 2.6 implies that access to credit has improved more for politically unconnected private firms located in the cities received more TF investment. On the other hand, access to credit deteriorates, at least in the extensive margin, for politically connected state-owned firms in those cities. Does this improvement in access to credit translate into any gains in the firm outcome for those politically unconnected firms? Table 2.7 answers this question. Column 1 and 2 report the effect on log value added at the firm level. Column 1 shows that firms in the treated cities experience faster growth than those in the control cities. The point estimate of the interaction term between *treat* and *post* is positive and significant at 10% level. Column 2 further decomposes this increase in value added into the state-owned and private firms. I find that the increase is completely driven by private firms in the treated cities, shown by the positive and statistically significant point estimate of the triple interaction term. On the other hand, state-owned firms in the treated cities actually experience a *decrease* in their value added, as the point estimate of the interaction term between *treat* and *post* becomes negative and statistically significant at 5% level. I interpret this pattern as resources moving from state-owned firms to private firms after the reform.

Column 3 and 4 of Table 2.7 look at a different measure of firm growth, namely, the percentage of firms who are exporter. This variable provides a measure of the share of high quality firms, as exporting firms are not only larger than non-exporters, they also tend to have higher productivity. Column 3 shows that firms in the treated cities are more likely to start exporting after the banking reform. Being in the treated cities after the reform increases the probability of being an exporter by 4 percentage point more than firms in the control cities. Considering that there is only 15.2% of the firms that are exporters in the dataset, the magnitude of this effect is very large. The large point estimate could be driven partially by the selection before the banking reform: firms who enter the market before the banking reform in the treated cities may have higher productivity than those in the control cities, as they face more difficulty in getting bank credit and would not able to survive without those extra edge.

Column 4 of Table 2.7 breaks down this effect by ownership. I find not only private firms

Table 2.6: Access to Credit

	% have loan		interest rate		debt-to-asset ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
post × treated city	-0.026***	-0.043**	-0.004***	-0.001	0.020**	0.011
	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)	(0.02)
post × private		0.021		-0.001		0.014**
		(0.01)		(0.00)		(0.01)
treated city × private		-0.059***		0.008		0.001
		(0.01)		(0.01)		(0.02)
post × treated city × private		0.043**		-0.003***		0.027*
		(0.02)		(0.00)		(0.02)
Constant	0.728***	0.693***	0.028***	0.022***	0.636***	0.778***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)
mean dvar.	0.719	0.719	0.027	0.027	0.643	0.643
Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
N. Obs	165208	165208	153176	153280	163647	163647

Source: ASIE 1998 - 2007. Only firms located in the cities considered by the TF project are included.
Note: Observation is at the firm-year level. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *private* is an indicator function that equals to 1 for private firms, and 0 for state-owned firms. The dependent variables in column 1 and 2 are binary variables of whether a firm has bank loan or not. The dependent variables in column 3 and 4 are gross interest rate. The dependent variables in column 5 and 6 are the debt-to-asset ratio. Year and firm fixed effects are included in all columns. Standard errors are clustered at the industry by city level.

Table 2.7: Firm Growth

	log value added		% exporter		No. of Private Entrants		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treated city					5.041***		
					(1.56)		
post					8.905***		
					(1.81)		
treated city × post	0.073*	-0.109**	0.041***	0.026**	5.881***	5.346**	5.495***
	(0.04)	(0.05)	(0.01)	(0.01)	(1.60)	(2.37)	(2.18)
treated city × post × private		0.146***		0.024**			
		(0.04)		(0.01)			
Constant	4.015***	3.857***	0.102***	0.087***	3.021***	8.953***	8.994***
	(0.01)	(0.09)	(0.00)	(0.02)	(0.59)	(0.70)	(0.81)
mean dvar.	3.991	3.991	0.115	0.115	9.973	9.977	10.051
Year FE	X	X	X	X		X	X
City FE						X	
CityXInd FE							X
Firm FE	X	X	X	X			
N. Obs	151963	151963	159061	159061	17226	17220	17008

Source: ASIE 1998 - 2007. Only firms located in the cities considered by the TF project are included.

Column 1 - 4: Observation is at the firm-year level. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *private* is an indicator function that equals to 1 for private firms, and 0 for state-owned firms. The interaction terms *post* × *private* and *treated city* × *private* are omitted from the table. The dependent variables in column 1 and 2 are the log value added. The dependent variables in column 3 and 4 are binary variables of whether a firm is an exporter or not. Year and firm fixed effects are included in all columns. Standard errors are clustered at the industry by city level.

Column 5 - 7: Observation is at the industry-city-year level. *treated city*, *post* are defined as in column 1 - 4. The dependent variables in column 5 - 7 are the number of private entrants in each city. Column 6 includes year and city fixed effects. Column 7 includes year and industry-city fixed effects. Standard errors are clustered at the city level.

in the treated cities are more likely to become exporters, state-owned firms in the treated cities are also more likely to become exporters, suggesting some reallocation between state-owned firms. Nevertheless, the magnitude of the effect for private firms is twice in size as that for state-owned firms. Again, this is likely due to both the difference in selection before the banking reform, and the different treatment effect from the banking reform. Specifically, it is more difficult to enter and survive in the pre-reform market as a politically unconnected private firm compared to politically connected state-owned firms. Consequently, private firms may be of higher quality than state-owned firms. Furthermore, private firms benefit more from the banking reform, as shown in Table 2.6. The larger effect for private firms could also be driven by the fact that the improvement in acquiring credit is larger than the improvement enjoyed by a subset of state-owned firms who are productive.

So far, I have focused on the existing firms and the intensive margin of firm growth. Column 5 - 7 of Table 2.7 report growth on the extensive margin. In those columns, I focus again on the industry-city-year level data and use the total number of private entrants in those cells as the dependent variable. Column 5 presents the baseline result without any fixed effects. Consistent with Fan and Zou (2021), the treated cities have more private entrants, suggesting the TF project may generate local spillovers 30 years after it is implemented. Furthermore, there are more private entrants after the reform in both the treated and the control cities. This observation is also consistent with the gradualism experience of the reform in China: exposure to the market institutions increasing with time, thus there are more private entrants in the later years in my sample. Finally, compared to the control cities, the treated cities experienced faster increase in the number of private entrants after the reform. On average, each industry in the treated cities have almost 6 more private entrants per year when compared to the control cities. This result suggests that the banking reform not only benefits existing private firms, it also makes it easier for entrepreneurs without any political connection to enter the market.

Column 6 and 7 improves the result reported in column 5 by including various fixed effects. Column 6 includes city and year fixed effects. Column 7 includes industry-city and year fixed effects. The results with fixed effects are consistent with the baseline result reported in column 5, with little changes in the magnitude and statistical significance of the point estimates of the interaction term.

Finally, Table 2.8 connects the firm-level results reported in this section to the industry-city-level results reported in Section 2.4. Column 1 and 2 repeat the exercise of column 3 and 4 in Table 2.6, where I estimate regression 2.1 at the firm level with the interest rate being the dependent variable. The negative and statistically significant point estimate for the triple interaction term suggests that private firms enjoy a larger decrease in the interest rate they face after the reform. Since private firms face a higher interest rate to begin with, this decrease narrows the interest rate gap, resulting in smaller interest rate dispersion reported in Table 2.5.

Similarly, column 3 and 4 of Table 2.8 report the changes in log TFPR at the firm level before and after the banking reform. Similar to the interest rate patterns reported in the first two columns, the triple interaction term is negative and statistically significant, suggesting

Table 2.8: Changes in log TFPR and interest rate before and after the banking reform

	interest rate		log TFPR	
	(1)	(2)	(3)	(4)
treated city	0.001*		0.075	
	(0.00)		(0.05)	
post	-0.002**		0.134*	
	(0.00)		(0.04)	
private	0.010***		0.772***	
	(0.00)		(0.04)	
treated city × post	-0.004***	-0.001	-0.106**	-0.053
	(0.00)	(0.00)	(0.05)	(0.04)
treated city × private	0.002*	0.008	0.122	0.269
	(0.00)	(0.01)	(0.10)	(0.20)
post × private	0.001	-0.001	-0.218***	-0.178**
	(0.00)	(0.00)	(0.04)	(0.08)
treated city × post × private	-0.003***	-0.003***	-0.116***	-0.120***
	(0.00)	(0.00)	(0.05)	(0.04)
Constant	0.023***	0.022***	-0.563***	-0.389***
	(0.00)	(0.00)	(0.04)	(0.09)
mean dvar.	0.027	0.027	-0.371	-0.383
Year FE		X		X
Firm FE		X		X
N. Obs	153342	146646	160672	154186

Source: ASIE 1998 - 2007. Only firms located in the cities considered by the TF project are included.

Note: Observation is at the firm-year level. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *private* is an indicator function that equals to 1 for private firms, and 0 for state-owned firms. The dependent variables in column 1 and 2 are the interest rate. The dependent variables in column 3 and 4 are log TFPR. Column 2 and 4 include year and firm fixed effects. Standard errors are clustered at the industry by city level.

that private firms located in the treated cities experienced a larger decline in their TFPR after the reform. Such decrease in TFPR is likely be driven by the expansion of the firm and decreasing marginal return of capital, as shown by Table 2.7. This decrease closes the TFPR gap between the state-owned and private firms, which leads to the result reported in Table 2.3 and 2.4.

To summarize, consistent with my hypothesis that the banking reform improves allocative efficiency by allocating more credits to the constrained/rationed private firms, I find the banking reform lowers interest rate and increases the debt-to-asset ratio for private firms in the treated cities more when compared to either state-owned firms in the treated cities or private firms in the control cities. With improving access to finance, those firms expand more rapidly, shown by their higher growth in value-added and probability of becoming exporters. This also improves the efficiency of allocation of credit more in the treated cities, as shown by the larger improvements in various measures of allocative efficiency in those cities.

2.5 Alternative Mechanisms

I argue that results in Section 2.4 are driven by the banking reform changing the lending criteria and priority of state-owned banks. Nevertheless, alternative mechanisms like the privatization campaign and credit expansion associated with the banking reform may also be responsible for those results. In this section, I show that these alternative mechanisms alone cannot explain the pattern reported in Section 2.4.

Credit Expansion

Another important aspect of the banking reform is credit expansion. Banks who successfully IPO receive large capital injections from investors, allowing them to extend credits to previously underserved customers (in my case, the private firms). Despite this capital injection, I argue that credit expansion is not responsible for the improvement in allocative efficiency I observed.

Depending on who are on the margin to receive bank loans, a credit expansion may increase or decrease TFPR dispersion. Consider a credit expansion without changing the bank's loan allocation policy. On the one hand, if the marginal borrowers are still politically connected state-owned firms, the extra credit will be allocated to them instead of the credit constrained/rationed private firms. Having more credits from the bank further decreases the TFPR in state-owned firms, while the private firms who remain credit constrained/rationed still have a high TFPR due to lack of credit. Consequently, the TFPR dispersion will increase. On the other hand, if the marginal borrowers are politically unconnected private firms, a credit expansion can help private firms to expand and decrease their TFPR, therefore lower the TFPR dispersion after the reform.

It is difficult to separately identify the effect of a credit expansion and changes in the lending criteria and priority of the banks, as they happen simultaneously during the banking reform. Nevertheless, a different historic episode provides an ideal setting for estimating the effect of a credit expansion without change in banks' lending practice. The banking reform is not the first time the Chinese central government attempts to address the issue of non-performing loans among state-owned banks. In 1999, the Chinese government spend over CNY 1.4 trillions to purchase nonperforming loans from state-owned banks. The revenue from selling those assets allow banks to provide credits to the marginal borrowers. Nevertheless, this bailout from the government does not come with any requirement on changing the lending practice. Neither does it change the incentives of the local bank branches nor the relationship between local governments and these branches, which the banking reform did. The 1999 bailout thus allows me to separately evaluate the impact of a credit expansion without change in the banks' incentive.

I take advantage of the 1999 capital injection as a placebo test by estimating a modified version of regression (2.1)

$$y_{ict} = \delta_{ic} + \delta_t + \beta \; treat_c \times post \; placebo_t + \varepsilon_{ict}, \tag{2.5}$$

where $y_{ict}, \delta_{ic}, \delta_t$ and $treat_c$ are measures of allocative efficiency, industry-city and time fixed effects, and an indicator function that equals to 1 when city c receive above median TF investment. The new variable *post placebo*$_t$ equals to 1 after 1999 and 0 otherwise. In estimating regression (2.5), I also use only the data between 1998 and 2003, i.e., before the banking reform. A negative and statistically significant β in regression (2.5) would imply that the credit expansion associated with the banking reform is at least partially responsible for the my results.

Table 2.9 reports the results from estimating regression (2.5). These results are consistent with the case in which the marginal borrowers in 1999 are state owned firms. Column 1 offers three observations. First, treated cities have less efficient allocation of bank credits than control cities, as documented in earlier sections. Second, allocative efficiency *worsens* after the 1999 capital injection, as shown in the positive and statistically significant point estimates of the variable *post placebo*. Third, consistent with Table 2.3 and Figure 2.3, the point estimates of the interaction term is economically and statistically insignificant, suggesting that there is no differential trend in allocative efficiency between the treated and the control cities after the capital injection.

Column 2 and 3 of Table 2.9 improve column 1 by including fixed effects at various levels. Column 2 includes the city and the year fixed effects. Column 3 includes the industry-by-city and the year fixed effects. The point estimate of the interaction term is again very close to 0 and remains statistically insignificant. In column 4 and 5, I use alternative measures of allocative efficiency. Again, the interaction term is both economically and statistically insignificant.

Generate improvements in allocative efficiency requires the banks choosing private firms over state-owned firms when screening loan applications. Changing the marginal borrowers from state-owned to private firms is a necessary condition to generate results reported in Section 2.4. The placebo exercise in this section shows that a credit expansion without any

Table 2.9: Effect of 1999 Capital Injection on Allocative Efficiency

	s.d. log TFPR			i.q.r log TFPR	s.d. interest rate
	(1)	(2)	(3)	(4)	(5)
treated city	0.107**				
	(0.04)				
placebo post	0.073**				
	(0.03)				
treated city × placebo post	-0.014	-0.005	-0.002	-0.017	-0.001
	(0.04)	(0.05)	(0.05)	(0.07)	(0.00)
Constant	0.782***	0.897***	0.899***	1.238***	0.029***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.00)
mean dvar.	0.896	0.895	0.898	1.230	0.027
Year FE		X	X	X	X
City FE		X			
CityXInd FE			X	X	X
N. Obs	7160	7156	6951	6951	6857

Source: ASIE 1998 - 2003. Only cities considered by the TF project is included.
Note: Each observation is a industry-city-year cell. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities targeted by the TF project. *placebo post* is a binary variable that equals to 1 if the year of the observation is after 1999. The dependent variables in column 1, 2, and 3 are the standard deviation of log TFPR. The dependent variable in column 4 is the interquartile range of log TFPR. The dependent variable in column 5 is the standard deviation of residualized interest rate. Column 2 includes year and city fixed effects. Column 3, 4, and 5 includ year and industry-city fixed effects. Standard errors are clustered at the city level.

change in the lending criteria and priority did not generate the necessary change. With this evidence, I conclude that the credit expansion alone is not responsible for improving allocative efficiency after the banking reform.

It is possible that factors other than changes in the lending criteria and priority that are responsible for the changes in the marginal borrowers. Specifically, the privatization campaign which shuts down and privatizes many state-owned firms is a potential candidate for inducing such changes. The privatization campaign altered the firm composition significantly between 1999 and 2004: many state-owned firms who are marginal borrowers in 1999 may be shut down or privatized by the campaign. As a result, the banks allocate loans to private firms only because there are no more state-owned firms to lend to. If this is true, the improvement in the allocative efficiency has nothing to do with changing lending criteria and priority. In the next section, I show that the privatization campaign alone cannot generate the pattern reported in Section 2.4.

Privatization

The privatization campaign changes the landscape of Chinese manufacturing sector in the late 1990s and the early 2000s. The campaign consists of both shutting down and privatizing state-owned firms. Since TF firms are state-owned firms who are targeted by the campaign, the privatization campaign can affect cities with more TF exposures more because there are more state-owned firms in those cities. Nevertheless, I show that the privatization campaign along cannot derive my main results.

Besides changing the composition of marginal borrowers that I alluded to in the previous section, there are other ways in which the privatization campaign can generate the results reported in Section 2.4. First, shutting down state-owned firms can lead to improvement of allocative efficiency, as there is negative selection into privatize/shut down, where the state-owned firms being shut down have lower productivity (Chen, Igami, Sawada, and Xiao, 2020). Second, the privatization campaign may also give the appearance of improving access to credit to private firms: many state-owned firms become private after the campaign. Some privatized state-owned firms may retain their connection to the government while being classified as private firms. If those firms continue having better access to credit, private firms as a group may seem improvement in access to credit, while the true private firms without any connection still struggle to have external finance.

I argue that those concerns are not likely to be responsible for deriving my results. First, I classify privatized firms as state-owned firms in all my analysis. I classify a firm as private only if it is private for all the years I observe this firm. Since ASIE surveys contain the universe of state-owned firms, this classification strategy should not mischaracterize privatized state-owned firms as true private firms. With privatized firms grouped together with state-owned firms as being politically connected, I argue that classification errors in firm ownership should not be responsible for my results.

Second, the privatization campaign started in 1998, whereas the banking reform did not start until 2004. If the privatization campaign has differential impact on allocative efficiency across cities with different exposure to the TF project, β_s from regression 2.4 would be negative and statistically significant for years *before* 2004. However, there is no change in the allocative efficiency before the banking reform started, as shown in Figure 2.3.

Third, my result is robust if I control for time-varying privatization intensity in each industry-city cell. Denote $privatization\ intensity_{ict}$ the share of firms in industry i, city c that are privatized. Then $privatization\ intensity_{ict}$ provides a city-industry specific, time varying measure of the intensity of the privatization campaign. With this measure, I can estimate an augmented version of regression (2.1):

$$y_{ict} = \delta_{ic} + \delta_t + \beta\ treat_c \times post_t + privatization\ intensity_{ict} + \varepsilon_{ict}. \tag{2.6}$$

If the privatization campaign is an important mechanism that can explain the different evolution of allocative efficiency in cities with different exposures to the TF project, β in the augmented regression (2.6) should have a much smaller magnitude and statistically insignificant when compared to results estimated from the baseline specification (2.1).

Table 2.10: Changes in Allocative Efficiency, Controlling for Privatization

	s.d. log TFPR		i.q.r log TFPR		s.d. interest rate	
	(1)	(2)	(3)	(4)	(5)	(6)
treated city × post	-0.089**		-0.122***		-0.004*	
	(0.03)		(0.05)		(0.00)	
TF investment × post		-0.015*		-0.025**		-0.001*
		(0.01)		(0.01)		(0.00)
Privatization Intensity	-0.046	-0.043	0.049	0.053	-0.013***	-0.013***
	(0.06)	(0.06)	(0.10)	(0.10)	(0.00)	(0.00)
Constant	0.926***	0.957***	1.226***	1.264***	0.032***	0.034***
	(0.02)	(0.03)	(0.03)	(0.05)	(0.00)	(0.00)
mean dvar.	0.895	0.895	1.213	1.213	0.028	0.028
Year FE	X	X	X	X	X	X
CityXInd FE	X	X	X	X	X	X
N. Obs	12495	12495	12495	12495	12298	12298

Source: ASIE 1998 - 2007. Only cities considered by the TF project is included.
Note: Each observation is a industry-city-year cell. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities targeted by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *TF investment* is a continuous variable that equals to the log value of the total TF firm assets in a city reported in the 1985 Industry Survey. The dependent variables in column 1 and 2 are the standard deviation of log TFPR. The dependent variables in column 4, 5 are the interquartile range of log TFPR. The dependent variables in column 5, 6 are the standard deviation of residualized interest rate. All columns include year and industry-city fixed effects. Standard errors are clustered at the city level.

Table 2.10 reports the results from estimating (2.6). The heterogeneous effect of the banking reform remains consistent with my earlier findings. Column 1 and 2 report results from running regression (2.6) using the standard deviation of log TFPR to measure allocative efficiency. The privatization campaign seems to help in reducing TFPR dispersion. First, the point estimates of *privatization intensity* is negative, although it is statistically insignificant. Second, the magnitude of the point estimate of *privatization intensity* is somewhat economically meaningful: moving from the 25th percentile in the intensity of privatization to the 75th percentile reduces the standard deviation of log TFPR by around the same amount as the additional improvement of the banking reform in cities who receiving 1% more TF investment.[10]. However, controlling for the time-varying privatization intensity does not change the magnitude or the statistical significance of β. Both the magnitude and the statistical significance of the point estimate β are very similar to that reported in Table 2.3.

Column 3 and 4 report results from using the interquartile range of log TFPR as the dependent variable. Similar to column 1 and 2, the magnitude and the statistical significance of the interaction term are almost identical to results reported in Table 2.4. The point estimate of *privatization intensity* is again negative but statistically insignificant. Its magnitude is also comparable to the additional improvement from the banking reform in cities who received 1% more TF investment, as in the case of column 1 and 2.

Finally, column 5 and 6 use the standard error of interest rate as the dependent variable. In this case, the point estimates of *privatization intensity* is negative and statistically significant at 1% level. Its magnitude is also economically significant: moving from the 25th percentile to the 75th percentile in privatization intensity result in an improvement in allocative efficiency twice as much as the additional improvement from the banking reform in cities who received 1% more TF investment. Nevertheless, the magnitude and the statistical significance of the interaction term are almost identical to results reported in Table 2.5, suggesting that controlling for privatization intensity does not affect my estimate of the heterogeneous effect of the banking reform across TF cities.

In summary, Table 2.10 provides two main messages. First, consistent with results from Hsieh and Klenow (2009), there are evidence supporting the claim that privatization helps to improve allocative efficiency. However, privatization does not seem to be responsible for the differential trend in allocative efficiency between the treated and the control cities. After controlling for industry-city specific, time varying privatization intensity, the coefficient of my interaction term between the exposure to the TF project and the indicator of when the banking reform started remains statistically significant. The magnitudes of their point estimates also remain stable.

[10]The 25th percentile of intensity of privatization is 0.042, while the 75th percentile is 0.42.

2.6 Conclusion

Identifying the effect of systematically limiting political connections on credit allocation is difficult. With exogenous variation in the number of politically connected firms across cities generated by the TF project, this paper provides one of the first causal evidence on such effect by exploring the heterogeneous treatment effect of the restructure of Chinese state-owned banks in 2004.

My identification strategy hinges on two exogeneity conditions. First, the TF project places politically connected state-owned firms based on time-invariant factors that are specific to the cities within the TF region (e.g., the geographic condition), so that cities with more exposures to the TF project have more politically connected firms for reasons orthogonal to the idiosyncratic local economic conditions and potential. Second, the timing of the banking reform does not depend on the idiosyncratic shocks in cities inside the TF region. With these two conditions, the effect of limiting political connections on the banks' credit allocation can be identified using the interaction terms between cities' exposure to the TF project and an indicator of the banking reform.

I document two key findings from this exercise. First, the banking reform improves allocative efficiency more in cities received more TF investment. Second, this improvement is driven by private firms getting better access to bank loans after the banking reform. I find the banking reform closes 70% of the gap in the TFPR dispersion between cities with more or less exposure to the TF project. It also improves sectoral TFP by 4% among cities with more exposure to the TF project.

Consistent with the historic narrative, these findings provide evidence that the banking reform limits the role political connections play in the allocation of bank loans. Furthermore, I show that other mechanisms like the parallel privatization reform or credit expansion cannot generate similar patterns I observed, collaborating my conclusion that changing lending criteria and priority is responsible for the improvement of allocative efficiency I found in this paper.

Misallocation of credit is a common cause for low productivity in the developing world (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Politically connected firms who are not necessarily more productive having better access to external credits can be responsible for such misallocation. My findings demonstrate that market reform in the banking sector can be a powerful way of limiting the impact of political connections: when profitability becomes a major goal, banks will have incentive to scrutinize loan applications from politically connected firms, which not only improves the loan performance of the bank, but also improve the allocative efficiency in the border economy.

However, banking reforms alone cannot eliminate differential access to credit all together. It is possible to have a perfectly competitive banking sector on the one hand and still having a sizable misallocation on the other hand. This occurs when political connections improve firm profitability without changing their productivity. In reality, political connections often come with more market power, making equally productive connected firms earning higher markup and become more profitable. This limits the effectiveness of banking reforms in correcting misallocation of credit.

Chapter 3

Redistribution Policy in Authoritarian Regimes: Evidence from China

3.1 Introduction

Survival of an authoritarian regime often requires the ruling elites sharing rents with other interest groups (Acemoglu and Robinson, 2001; Albertus and Menaldo, 2012). China is no exception (He, Liu, Webster, and Wu, 2009; Wallace, 2014). An important determinant of rent-sharing plans concerns the political importance of potential recipients: political scientists have hypothesized that autocrats incline to share rents with politically powerful groups who have the ability to delegitimize or overthrow their rules (Ades and Glaeser, 1995; Henderson, 2003; Wallace, 2013). However, existing empirical evidences supporting those hypotheses are based on urban-rural comparisons in which the urban areas are considered politically powerful due to their lower costs in coordinating collection actions against the regime. However, many other differences between urban and rural areas could be responsible for the urban biasedness documented in the literature. Those confounding factors make linking redistribution priority and political power in authoritarian regimes difficult.

To causally investigate redistributive policies in authoritarian regimes, I exploit a natural experiment from the early 20th century China that generates variations in political power across neighboring Chinese counties using a spatial regression discontinuity design. Specifically, I compare the central government's fiscal transfers towards counties located in different sides of *Soviet Zone* boundaries. Soviet Zones are the regions occupied by the Chinese Communist Party (CCP) during the First Chinese Civil War between 1927 and 1937, where the CCP started the military campaign that eventually succeeded. Favoritism towards Soviet Zone counties may reinforce the legitimacy of the CCP rule: achieving continuous improvement in living standards in Soviet Zone counties helps to maintain the legitimacy of the CCP, as their success as the birthplace of the CCP can reaffirm its capability of delivering sustained economic growth.

My identification strategy boils down to compare counties across the Soviet Zone boundaries. I argue that this is a valid comparison for two reasons. First, the boundaries of Soviet Zones were determined by outcomes of military operations. The inherent randomness of those outcomes ensures that counties on either sides of the Soviet Zone boundaries are similar in geographic conditions. Such similarity in turns leads to resemblances in local economic structure. Second, before the economic reform, the CCP did not have the intention or the resource to favor Soviet Zone counties fiscally. As a result, counties just inside of the Soviet Zones are comparable to counties jut outside in both their geographic and socioeconomic conditions, with the exception that counties inside Soviet Zones are politically important given their status during the Chinese Civil War.

I argue that subsidizing Soviet Zones helps to maintain the legitimacy of CCP's proclaimed status as the ruling party of China. After the economic reform, the legitimacy of CCP's rule comes from its ability to promote economic development and maintain social stability (Laliberte and Lanteigne, 2007). Accomplishing economic success in the Soviet Zones helps CCP in achieving this goal in two ways. First, it demonstrates that the CCP is capable in improving living standard of ordinary Chinese citizens. Being the regions under the rule of the CCP for the longest time, the economic development of the Soviet Zones symbolizes the capability of the CCP in promoting economic growth. Second, increasing income inequality has became one of the major issues that lead to instability in China. Since Soviet Zones are among some of the least developed regions in China (Lewis and Xue, 2003), investing in Soviet Zones also signifies CCP's commitment to address inequality, hence maintaining political stability.

Using my spatial regression discontinuity design, I find Soviet Zone counties receive 20% more in fiscal transfers than neighboring non-Soviet Zone counties. A decomposition shows that the additional fiscal resources Soviet Zone counties received come from targeted transfers for which the central government has discretionary power. There is no difference in rule-based fiscal transfers towards Soviet Zone and non-Soviet Zone counties. In addition, I do not find difference in fiscal contribution to the central government between Soviet Zone and non-Soviet Zone counties either.

Despite the goal of boosting economic development in Soviet Zones with the targeted transfers, I do not find Soviet Zone counties experiencing faster economic growth. This negative result can be explained by local governments' expenditure patterns: there is no statistically significant difference in expenditures on infrastructure, education, and agriculture between Soviet Zone and nearby non-Soviet Zone counties. Instead, local government in Soviet Zone counties spend the extra resources they received from targeted transfers in administrative tasks and have more people on government payrolls.

The negative result on economic growth implies two types of resource misallocation. First, fiscal resources are misallocated within the Soviet Zone counties, where the local government spend more on non-productivity-enhancing categories like administration and personnel instead of the productivity-enhancing categories like infrastructure and education. Second, fiscal resources are also misallocated nationwide due to the favoritism towards Soviet Zone counties. For place-based redistribution like the targeted fiscal transfers towards Soviet Zones to be efficiency-enhancing, its local benefit must exceed the opportunity cost (Kline and Moretti, 2014). Since the opportunity cost of those transfers is positive, the result that Soviet Zone counties do not exhibit faster growth implies that such transfers generate inefficiency nationwide.

This paper contributes to three strands of literature. First, there is a growing literature on redistributive policies in authoritarian regimes. For instance, Gandhi and Przeworski (2006) argues that autocrats need to share rents with those who intend to rebel. Albertus and Kaplan (2013) examines data from Colombia and concludes redistributive policies were indeed used to disincentivize rebellions. Wallace (2013) argues that urban areas are politically more powerful and therefore in a better position in bargaining with the autocrat on splitting the rents. Along this line, Glaeser and Steinberg (2017) studies the relationship between urbanization and democratization. In the context of China, Wallace (2014) argues that the CCP improves the economic incentives in the rural China to counter formation of slums in cities that threatens the regime. This paper complements this literature by providing one of the first casual evidence on the relationship between redistribution and political importance in authoritarian regimes. The spatial regression discontinuity design allows me to compare fiscal transfers towards nearby regions whose only difference is their Pareto weights.

Second, this paper adds to the literature studying the means and consequences of CCP's governance in China. There is a growing literature documenting the mechanisms of how the CCP maintains control over China (Li, Roland, and Xie, 2018; Li, 2019; Wang, 2021). This paper contributes to this literature by focusing on a specific policy tool, namely the fiscal redistribution. I also document empirically incidences of the CCP using this tool to advance its political goals. Finally, my findings show potential efficiency loss associated with the use of redistribution policies.

Finally, this paper contributes to the literature on the source of misallocation in less developed countries (Guner, Ventura, and Xu, 2008; Song, Storesletten, and Zilibotti, 2011; Restuccia and Rogerson, 2017; Hsieh and Moretti, 2019). I show that political favoritism can be an important cause of misallocation. In particular, favoritism towards Soviet Zone counties not only failed to generate local economic benefits in those underdeveloped regions, it also implies fiscal resources are inefficiently allocated towards Soviet Zone counties.

The rest of the paper is organized as follows. Section 3.2 discusses the institutional context of Soviet Zones and the fiscal system in China. Section 3.3 presents the data and empirical strategy. Section 3.4 presents the main results. Section 3.5 concludes.

3.2 Background

This section contains a brief introduction of the history of Soviet Zones. I focus on two aspects. First, the determination of the Soviet Zone boundaries and how it provides the necessary exogeneity in my spatial regression discontinuity design. Second, why Soviet Zones are important politically to the central government, and how does the central government redistribute resources towards counties inside Soviet Zones.

Determination of the Soviet Zone Boundaries

Soviet Zones are territories controlled by the CCP during the First Chinese Civil War between 1927 and 1937. The CCP setup local governments and party branches, collected taxes, enlisted military personnels and built factories within the Soviet Zones. In this section, I argue that comparing fiscal transfers across the boundaries of Soviet Zones consists of a valid design to investigate aspects of redistributive policies in China.

Figure 3.1 plots the locations of Soviet Zone counties recorded in *The Organizational History of Chinese Communist Party*.[1] The locations of Soviet Zones are not randomly chosen: Mao Zedong, the military leader of the CCP, explicitly argued that the Communist Party "should start from remote areas where the *Kuomintang* does not have control over".[2] This strategy suggests that Soviet Zone counties are possibly different from the average Chinese county. In fact, Soviet Zone counties are poorer, less accessible and have worse infrastructure than the average Chinese county. Those undesirable characteristics were probably the reason why *Kuomintang* failed to establish a solid presence in those areas in the first place.

Nevertheless, it is likely that Soviet Zones and the area *next to* them have similar geographically and socioeconomically conditions for two reasons. First, the boundaries of Soviet Zones are determined by outcomes of a series of uncertain military operations. Such randomness ensures that counties on either sides of Soviet Zone boundaries are similar in terms of their time-invariant characteristics like geographic conditions. Second, the central government did not favor Soviet Zone counties fiscally until China was well into the process of economic reform. Consequently, the population size, industrial composition, local economic policy and other socioeconomic conditions are similar for counties across the Soviet Zone boundaries. Such similarity forms the foundation for me to identify whether being inside a Soviet Zone brings any rewards from the central government.

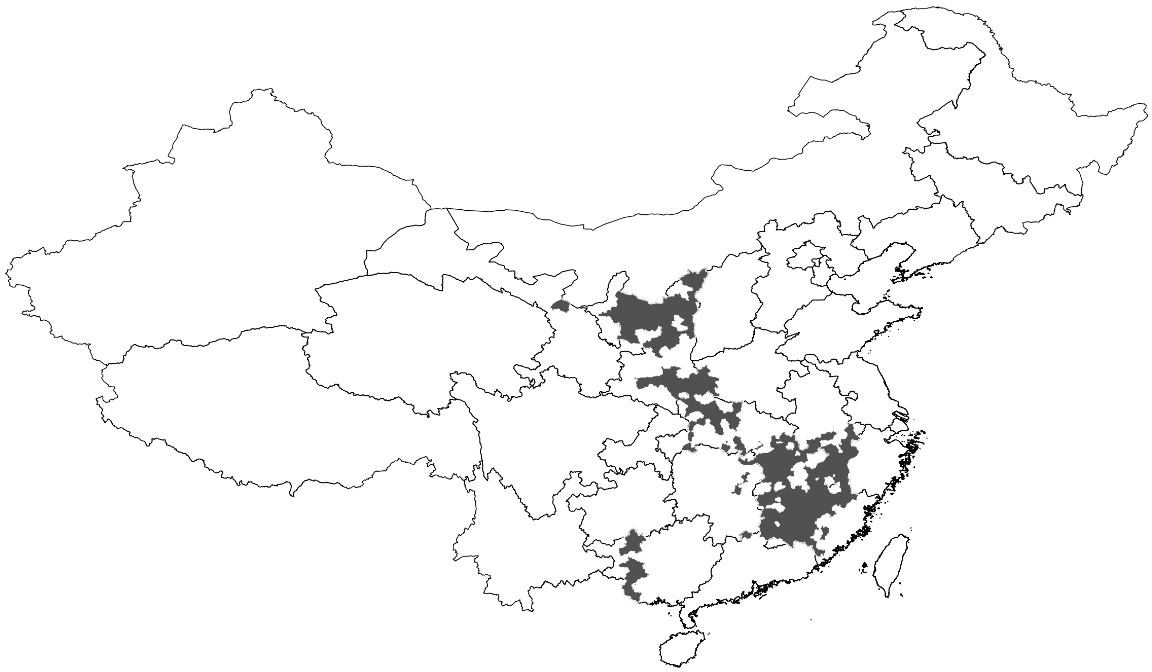
The randomness of the exact location of the Soviet Zone boundaries provides the main source of the exogeneity for my spatial regression discontinuity design. The boundaries of Soviet Zones depends on outcomes of military operations. By nature, those operations involve high degrees of uncertainty and randomness. As a result, Soviet Zone boundaries changed constantly during the Chinese Civil War. Some counties were part of the Soviet Zone at one point and were taken away by the *Kuomintang* army at another. For example, Figure 3.2 plots the territory of Central Soviet Zone in Jiangxi and Fujian Province in 1932, 1933 and 1935. It shows that the boundary for the Central Soviet Zone moved significantly outwards between 1932 and 1933 as a result of a series of successful military operations by the Communist army. However, the whole Soviet Zone was abandoned due to unsuccessful battles in the following year. Consequently, the whole region did not contain any Soviet Zone in 1935.[3]

[1] To be clear, those counties did not under the control of the CCP at all times during the First Chinese Civil War. I discuss the exact process of selecting Soviet Zone counties in Section 3.3.

[2] The Chinese Nationalist Party, the other contender in the Chinese Civil War.

[3] There were small groups of militia remained in the region engaging in guerrilla warfare. However, there is no longer any formal government structure last.

Figure 3.1: Locations of Soviet Zone Counties



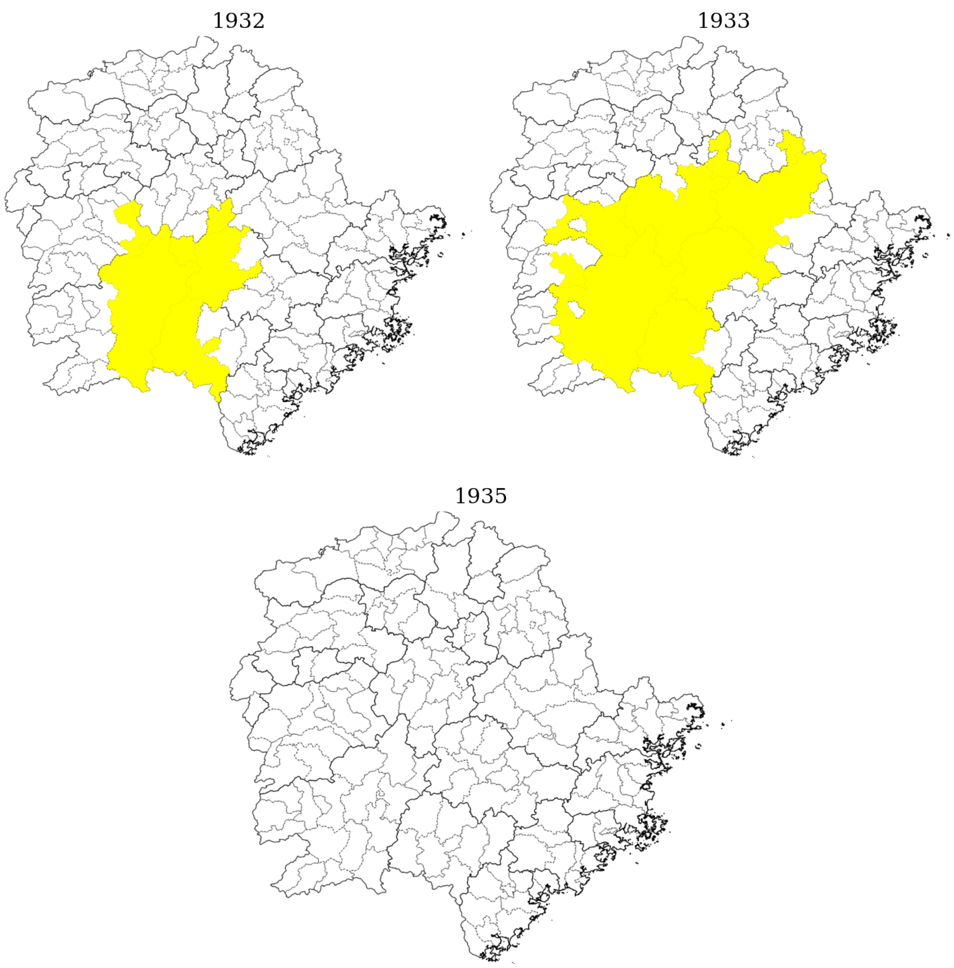
Source: *The Organizational History of Chinese Communist Party (Volume 2)*.
This figure plots all Soviet Zone counties controlled by the CCP between 1927 and 1937. Soviet Zone counties are plotted in gray. A county is identified as a Soviet Zone county if a Communist Party branch or a government branch established in that county for at least a full year. Note that not all gray areas are Soviet Zones *at the same time*: for example, the Shaanxi-Gansu-Ningxia Soviet Zones in the northwestern China did not exists before 1934.

The uncertainty originated from military operations places the Soviet Zone boundaries at arbitrary locations. I argue that this exogeneity makes the neighboring non-Soviet Zone counties a valid control group for the Soviet Zone counties. Time-invariant characteristics like topographical conditions, soil types, and climate of counties at both sides of the Soviet Zone boundaries should be very similar, as there is no reason to expect a discontinuous change in those characteristics right at the boundaries given their arbitrary locations.[4]

Second, there is a lack of intention from the central government to subsidize Soviet Zones fiscally until the 1990s. The lack of intention is signified by the low number of articles on Soviet Zones published by the *People's Daily*. *People's Daily* is the main media outlet of the

[4]Indeed, as I find in Table 3.1, the geographic difference between Soviet Zone counties and neighboring non-Soviet Zone counties is not statistically different.

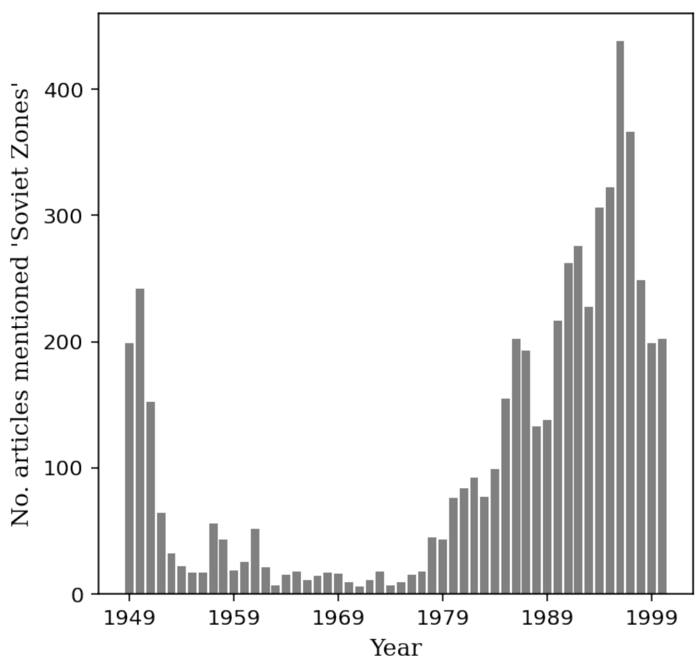
Figure 3.2: Changes in the Boundary of Central Soviet Zone, 1932 - 1935



Source: *The Organizational History of Chinese Communist Party (Volume 2).*
This figure plots the territory of Central Soviet Zone in 1932 (top-left), 1933 (top-right) and 1935 (bottom) in Jiangxi and Fujian Province. The highlighted region represents counties controlled by the CCP (and hence part of the Central Soviet Zone). In late 1934, Central Soviet Zone was abandoned due to the military pressure from the *Kuomintang* army. Only small squads of milita groups remained in the area after that.

CCP. Articles from the *People's Daily* are important indicators of the policy focus of the CCP. Thus, the number of articles on Soviet Zones serves as a measure of how important they are from the perspective of the central government. Figure 3.3 plots the number of articles reporting Soviet Zones published by the *People's Daily* between 1949 and 2000. Apart from a few years immediately after the victory of the Chinese Civil War in 1949, there is only a few *People's Daily* reports on Soviet Zones. This changed after 1978, when the economic reform started and Soviet Zones started to get traction from the central government. The number of articles peaked in the mid 1990s and declined afterwards, but the numbers of articles in the late 1990s and the early 2000s are still significantly higher than before 1978.

Figure 3.3: *People's Daily*'s Coverage of Soviet Zones



Source: Full text archive of the *People's Daily*, Central Committee of the Chinese Communist Party.
This figure plots the number of articles mentioning the word "Soviet Zones", "revolutionary base", or other related words published by the *People's Daily* newspaper from 1949 to 2001.

Changing policy priority in the 1950s is the main reason why Soviet Zones are neglected from the development plans. The majority of the Soviet Zone counties locate in the rural area due to the strategic choice made by Mao Zedong and other military leaders of the CCP. Focusing on the rural areas was also one of the main strategy the CCP employed during the Civil War. However, after winning the Civil War, the main goal of the CCP shifted to industrializing and modernizing the country. Soviet Zones were quickly left behind like other rural area in China.[5] Sheng (1993) argues that the industrialization during Mao Zedong's era is heavily subsidized by setting low procurement prices for agricultural goods produced in the rural areas, and levy tax on farmers. Consequently, the Soviet Zones, along with other rural China, paid the prices for the high growth rate in the manufacturing sector. This is also salient from the *Five-year Plans* initiated by the central government. *Five-year Plans* were the most important development projects in China. The *Plans* did not include any projects to develop rural economy during Mao's era. Neither did it mention Soviet Zones at all. The lack of support from the central government is also consistent with the urban biasedness in authoritarian regimes documented in the literature: rural areas have less political power than urban areas due to their inability to mobilize and potentially overthrown the regime, thus the lack of support (Wallace, 2013).

The negligence changed, at least partially, after the economic reform started in 1978. Soviet Zone counties become politically important compared to the neighboring non-Soviet Zone counties due to a change in the source of ruling legitimacy of the CCP. In the next section, I discuss the reason of such change and how the central government redistributes fiscal resources towards Soviet Zones.

Soviet Zones are Politically Important

This section discusses potential reasons of redistributing fiscal revenues towards the Soviet Zones. I also outlines the Chinese fiscal transfers system and the specific methods in which the central government redistributes resources towards the Soviet Zones.

Soviet Zones are among some of the least developed regions in China due to their rugged terrain, infertile soil and inaccessibility. The lagging performance of the Soviet Zones did not post any threat to the legitimacy of the regime in Mao's China: subpar economic performance and sluggish growth were justified by priority in issues regarding national security and ideological conformity to the communism, or even by Mao's personal charisma. The end of Mao's era led to a legitimacy crisis (Dickson, 2016). Since then, the CCP turned to a proclaimed eudaemonic legitimacy based on its ability to promote economic growth and maintain social stability (Chen, 1997; Lewis and Xue, 2003; Laliberte and Lanteigne, 2007). As a result, Soviet Zones become politically important for two reasons. First, as the regions under CCP's control for the longest time, continuous improvements in the living standards in the Soviet Zones certainly attest to the CCP's ability to promote economic development. Second, economic growth widens the inequality gap in China. This gap has become one of the key drivers of social unrest and political instability. Policies favoring Soviet Zones shows

[5] To be fair, there were large scale urbanization programs during Mao's era, for example, the *Third Front* project. However, the goal of those programs was never developing rural economy. Rather, they were military-oriented programs aiming to prepare China for the anticipated next world war. In addition, none of the Soviet Zones and their surrounding regions focused in this paper was included in those urbanization programs.

CCP's commitment in bridging the regional income gap in China, which helps to maintaining social stability.

The central government initiated various targeted transfer campaigns and fiscal aids towards Soviet Zones starting from the 1990s. Those programs are funded via targeted fiscal transfers. Targeted fiscal transfers are grants made to local government for specific projects/tasks like poverty reduction, promotion of education, or infrastructure construction. Unlike other transfers granted to local governments, the central government has considerable discretionary power over the recipient and the amount of targeted transfers. Conversely, other fiscal transfers are rule-based and more rigid in terms of the recipients and the amount transferred. For example, the central government is entitled to 75% of the VAT income. So the rest 25% are rebated to the local government in the form of proportional transfers. As a result, the amount Soviet Zone counties received from proportional transfers depends on the total amount of the VAT collected within the county administrative boundaries and not at the discretion of the central government.

There are two issues with the targeted fiscal transfers towards the Soviet Zones. First, the central government did not have the resources to fund Soviet Zones until the tax reform in 1994 (Wong, 2000). Before the reform, fiscal power is decentralized via contracts between the central and local governments, where the local governments are able to buyout the fiscal revenues in their jurisdictions and become residual claimants of those revenues. Those contracts limits the revenue of the central government and thus its ability to redistribute resources towards Soviet Zones. The 1994 tax reform is a directly response from the central government to address this issue (Knight and Shi, 1999; Wong, 2000). It centralizes the fiscal power and increases the central government's revenue significantly, making redistributing resources towards Soviet Zones possible.

Second, the fiscal resources local governments have are fungible. In theory, targeted transfer made towards Soviet Zone counties is meant to spend on specific projects in pre-defined categories like poverty alleviation, education, infrastructure, etc. Nevertheless, there is a lack of auditing process to make sure the money is indeed spent on specified categories. Moreover, targeted transfers can crowd out local government funding. For example, local governments can cut existing local poverty alleviation funds when receiving poverty alleviation transfers from the central government. Therefore, even though the targeted transfers are attached to specific projects, the local government can still substitute away those funding by cutting existing, non-targeted projects.

3.3 Empirical Method and Data

I compile data from three different sources to study redistribution policies towards the Soviet Zones. First, I draw data on local economic activities from the *Statistic Yearbook* published by the National Bureau of Statistics of China. Second, I extract data on fiscal revenue, expenditure and transfers is drawn from the *Annual Financial Statistics of Cities and Counties* published by the Ministry of Finance of China. Finally, I hand collect the list of counties that located in the Soviet Zones is taken from *The Organizational History of Chinese Communist Party* (volume 2), published by the *History of Chinese Communist Party Press*. I focus on the post tax reform period between 1994 to 2001 where the targeted transfer had started and when the fiscal data is available.

Determining the Soviet Zone status faces a main challenge. As the boundaries of the Soviet Zone were constantly changing during the Chinese Civil War, it is difficult to determine exactly which county is inside Soviet Zone and which is outside. To determine the Soviet Zone status, I record a county as being part of the Soviet Zones only if the *Organizational History* record shows a party branch or a government branch established in that county for at least a full year.[6] I also exclude all counties on the routes of the *Long March*, since the CCP had rarely stopped more than a month during the *Long March*, and the CCP branches established during Long March are mostly underground with very limited capacity and tasks.[7] Furthermore, I drop all counties that are classified as urban and focus on only the rural counties. Finally, I drop all autonomous regions, since they have different fiscal rules, including the transfer and contribution received from and made to the central government due to their autonomousity status. This left me with around 200 counties located inside 8 different Soviet Zones.

I employ a spatial regression discontinuity (RD) design to evaluate whether the central government favors Soviet Zone counties by granting them more fiscal transfers. To this end, I compare targeted fiscal transfers from the central government towards Soviet Zone counties (treated counties hereafter) with nearby non-Soviet Zone counties (control counties hereafter). To identify the control counties, I start with the list of treated counties and construct the corresponding control counties for each Soviet Zone county by looking at the counties that are 1.) not in the Soviet Zones, 2.) not classified as urban or autonomous region, 3.) belongs to the same prefecture as the Soviet Zone county,[8] and 4.) are within 75 km radius of the Soviet Zone county. I place each treated county and the corresponding control counties into a group. The counterfactural transfer for each treated county is then calculated based on average transfer the control counties belong to the same group receive. Figure 3.4 shows an example of the process of determining the control counties for a Danyang Shi, Hubei Province.

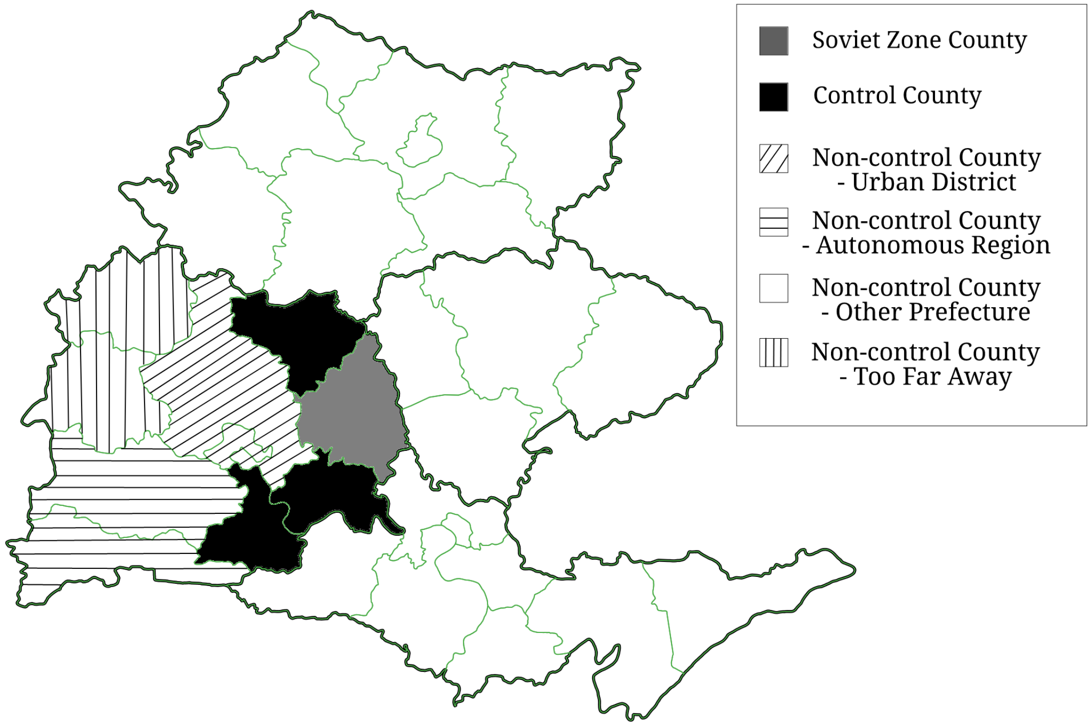
To causally identify the favoritism towards Soviet Zone counties using my spatial RD design, counties on either sides of the boundaries must be similar in all aspects except that counties on the Soviet Zones side were occupied by CCP during the Civil War. Given

[6]Having established party/government branch for a full year does *not* mean that the county is under complete control under the CCP. As The Communist Red Army often employ the feigned retreat tactics and give up territorial controls in exchange for better strategic positions. Mao Zedong has a famously quote summarizing this tactics: “defending territory at all cost means losing both the territory and the manpower”.

[7]The tasks those underground organizations undertook include mostly tending the wounded, military intelligence, and promoting communism in local communities. They were not backed by the military power by the CCP army, neither did they collect tax or provide essential public services.

[8]Prefecture is an administrative unit that between province and county. On average, a province contains 11 prefectures, and a prefecture contains 10 counties.

Figure 3.4: An Example of Constructing Control County for Dangyang Shi, Hubei Province



This figure shows the process of constructing the control group for Danyang Shi, Hubei Province. I divide the candidate counties into 5 categories. First, the control counties that satisfies all the criteria listed in the main text. Second, counties that are disqualified because they are urban districts. Third, counties that are disqualified because they are autonomous regions. Fourth, the counties that are disqualified because they are located in other prefectures. Fifth, counties under the same prefecture but still disqualified due to them being too far away from Danyang Shi.

this assumption, if the Soviet Zone counties receive more targeted transfer than otherwise comparable counties, I can conclude that the difference can be attributed to Soviet Zone of status these counties. I argue that this condition is likely holds. First, as discussed in Section 3.2, countries near Soviet Zone boundaries changed hands frequently between the CCP and the *Kuomintang*. The boundaries themselves are determined by results of battles whose outcomes are highly uncertain. Second, even thought the locations of Soviet Zones are deliberately chosen by the Communist Party leadership to avoid *Kuomintang* strongholds, the geographic conditions are similar for counties across the Soviet Zone boundaries due to their proximity. Third, before the 1994 tax reform, the central government either did not prioritize development of Soviet Zones counties or faced a severe budget constraint that makes redistributing resources towards those counties impossible. Fourth, I test directly an implication of this assumption. Specifically, I compare key variables for counties on different sides of the Soviet Zone boundaries in 1993, the year before the tax reform which boosts the fiscal revenue of the central government and enables redistribution towards Soviet Zone counties. Table 3.1 reports this comparison.

Table 3.1 shows that among the key geographic and socioeconomic variables, only one (log area of the county) is statistically different at 5% level. To account for the differences in the county size have on my results, I control for the log area in all my analysis below. On the other hand, there is no statistical difference between the treated and control counties in their accessibility and ruggedness of terrain, measured by the average and standard deviation of their elevations. This result is consistent with the geographic continuity discussed in Section 3.2. In addition, there is no statistical difference in the aggregate fiscal variables like total organic fiscal income, expenditure, and the government spending on different categories (e.g., on rural area, agriculture, and education).[9] Therefore, I conclude from Table 3.1 that there is no difference between the treated and control counties in important dimensions that may contaminate my results.

To implementing the spatial regression discontinuity design, I estimate the following model

$$y_{igt} = \beta SZ_{ig} + \gamma X_{igt} + \theta_g + \delta_t + \varepsilon_{igt} \tag{3.1}$$

where y_{igt} is various measures of different fiscal transfers county i in group g receive at year t. SZ_{ig} is an dummy variable that equals to 1 if county i in group g is located inside of a Soviet Zone, and equals to 0 otherwise. X_{igt} is additional (possibly time-varying) county characteristics (e.g., the size of the county, per-capita GDP). θ_g and δ_t are group and year fixed effects, respectively. By including these fixed effect, regression (3.1) only compares fiscal transfers granted towards Soviet Zones with non-Soviet Zone counties that belongs to the same group at the same year. If the central government redistributes fiscal revenues towards Soviet Zone counties, the estimate of β in regression 3.1 should be positive and statistically significant.

[9]Organic fiscal income/expenditure mean fiscal income and expenditure that are derived and spent locally without any redistribution from and to the center government.

Table 3.1: Balance Test

	(1) Control	(2) Treated	(3) (1) vs. (2), p-value
Log Industrial Output	9.055	8.880	0.560
	(0.088)	(0.079)	
Log Agricultural Output	6.940	6.661	0.227
	(0.057)	(0.111)	
Log Organic Fiscal Expenditure	1.747	1.827	0.962
	(0.115)	(0.056)	
Log Organic Fiscal Income	4.442	4.480	0.899
	(0.063)	(0.049)	
Log Admin. Expenditure	1.890	1.911	0.196
	(0.049)	(0.043)	
Log Targeted Transfer	4.505	4.467	0.515
	(0.066)	(0.048)	
Log Targeted Contribution	4.842	4.855	0.319
	(0.041)	(0.031)	
Log Edu. Expenditure	1.878	2.072	0.826
	(0.084)	(0.056)	
Log Gov't Payrolls	5.349	5.570	0.521
	(0.114)	(0.034)	
Log No. Towns	2.494	2.629	0.158
	(0.030)	(0.027)	
Log Area	-1.797	-1.521	0.034
	(0.065)	(0.033)	
Mean Elevation	618.055	543.549	0.749
	73.594	33.363	
Std. Dev. Elevation	185.863	178.295	0.432
	15.301	7.078	
N	144	225	

Source: Statistical Yearbook and Annual Financial Statistics of Cities and Counties, 1994.

Note: All variables are in per-capita log term except for Log No. Towns, Log Area, Mean Elevation, and Std. Err. Elevation. Organic fiscal expenditure/income are expenditure/revenue net of any transfers or contribution from and to the central government. Government payrolls stands for the total number of people whose salaries are paid by the local government. This includes any local government employees and people who work at the local branches of public institutions. Column 1 and 2 report the means and standard errors (in parentheses) of the variables indicated in each row in the control and treated counties, respectively. Column 3 reports the p-value of a test that the means for treated and control counties equals to each other. All tests include group fixed effect, standard errors are clustered at the group level.

3.4 Results

This section formally test whether Soviet Zone counties receive more fiscal transfer from the central government and whether such redistribution is effective. In Section 3.4, I find the central government actively redistribute resources towards Soviet Zone counties in the form of targeted fiscal transfers. Furthermore, Section 3.4 finds that such redistribution is ineffective: it does not increase local spending on agriculture or education. There is also no effect on the industrial and agricultural outputs. Nevertheless, Soviet Zone counties have higher administrative expenditures, and also have more per-capita government employees that are paid using fiscal resources. Consequently, Soviet Zone counties do not exhibit faster economic growth compared to nearby non-Soviet Zone counties.

Do Soviet Zone Counties Receive More Fiscal Transfer?

Table 3.2 presents the effect of Soviet Zone status on post-reform targeted fiscal transfer. The point estimates of the effect on log per-capita transfer received range from 0.2 to 0.23, suggesting counties on the Soviet Zone side receive around 20% (column 1) to 23% (column 3) more per-capita targeted transfers when compared with counties on the non-Soviet Zone side. This difference remains significant after controlling for county land area (column 2) and local socioeconomic variables (column 3). This further confirms that more transfers to the treated counties are not due to the differences in socioeconomic conditions between the them and the counties in the control group, but rather their Soviet Zone status.

Targeted transfers to local governments are only part of the fiscal redistribution the central government employs. There are other fiscal transfers from the central to local governments. These fiscal transfers are less arbitrary and more rule-based, Some of those transfers were legacies of pre-reform era, with the amount and recipient of the transfers determined as a collective bargaining outcome between the central and the provincial governments. Others are ruled-based split of the taxes collected by the local government (e.g., the VAT tax). As a result, I should not detect any difference in those rule-based transfers between counties on either sides of the Soviet Zones. Indeed, a difference in rule-based transfers would imply that there could be factors other than being just inside of the Soviet Zones behind the results reported in Table 3.2.

Table 3.3 tests whether those rule-based transfers differ between Soviet Zone and nearby non-Soviet Zone counties. In column 1, I show that there is no difference in the amount of proportional transfers received between Soviet Zone counties and the nearby non-Soviet Zone counties. Proportional transfers are rebates of tax revenues from the central government back to the local governments where the tax are collected. This transfer is mainly applied to the value-added tax. And the split of its revenue between the central and local governments are predetermined and uniform across all counties. Therefore, there should be no difference in the amount of per-capita proportional transfers received by Soviet Zone and non-Soviet Zone counties if there is no significant differences in their overall economic activities, which is consistent with the result reported in column 1.

Table 3.2: Targeted Transfers in Soviet and Non-Soviet Counties

	Log Targeted Transfers		
	(1)	(2)	(3)
Soviet Zones	0.195***	0.201***	0.228***
	(0.07)	(0.07)	(0.06)
Log Area		-0.230***	-0.221***
		(0.07)	(0.06)
Log Industrial Output			-0.079***
			(0.02)
Log Agricultural Output			0.034*
			(0.02)
Log Organic Fiscal Exp.			0.037**
			(0.02)
Constant	3.711***	3.291***	3.636***
	(0.04)	(0.12)	(0.21)
mean dvar.	3.713	3.710	3.699
Year FE	X	X	X
Group FE	X	X	X
N. Groups	236	235	235
N. Obs	3050	2983	2931

Source: Annual Financial Statistics of Cities and Counties, 1994 - 2001.

Note: Each observation is a county-year cell. *Soviet Zones* is a binary variable that equals to 1 if the county the observation belongs to is a Soviet Zone county. *Log Area* is the log of total area of the territory within the administrative boundary of the county. *Log Industry Output* is the log per-capita industrial output. *Log Agricultural Output* is the log per-capita agricultural output. *Log Organic Fiscal Exp.* is the log per-capita fiscal expenditure net of any contribution to the central government. The dependent variable in all columns is the log per-capita targeted transfers received. All columns include year and group fixed effects, where the group is defined in Section 3.3. Standard errors are clustered at the group level.

Table 3.3: Other Local Incomes in Soviet and Non-Soviet Counties

	Log Proportional Transfers	Log Pre-reform Transfers	Log Pre-reform Contribution	Log Targeted Contribution
	(1)	(2)	(4)	(5)
Soviet Zones	0.048	0.138	-0.150	-0.036
	(0.08)	(0.23)	(0.29)	(0.07)
Log Area	0.010	-0.633**	0.209	-0.052
	(0.09)	(0.24)	(0.38)	(0.09)
Constant	3.396***	0.658	2.388***	1.797***
	(0.16)	(0.43)	(0.74)	(0.16)
mean dvar.	3.409	1.858	1.943	1.859
Year FE	X	X	X	X
Group FE	X	X	X	X
N. Groups	235	148	158	235
N. Obs	2995	1066	1672	2735

Source: Annual Financial Statistics of Cities and Counties, 1994 - 2001

Note: Each observation is a county-year cell. *Soviet Zones* is a binary variable that equals to 1 if the county the observation belongs to is a Soviet Zone county. *Log Area* is the log of total area of the territory within the administrative boundary of the county. The dependent variables are the log per-capita proportional transfers in column 1, the log per-capita pre-reform transfers in column 2, the log per-capita per-reform contribution in column 3, and the log per-capita targeted contribution in column 4. All columns include year and group fixed effects, where the group is defined in Section 3.3. Standard errors are clustered at the group level.

Column 2 in Table 3.3 reports the result for pre-reform transfers. Pre-reform transfers are transfers before the 1994 tax reform. In order to convince local governments to accept the tax reform proposal, the central government pledged to continue any existing transfers the local government received from the central government. Given that there is no difference in fiscal support from the central government between Soviet Zone and non-Soviet Zone counties prior to the tax reform, I should not find them receiving different amount of the pre-reform transfers. Column 2 shows that although the point estimate for log per-capita pre-reform transfers is positive with moderate magnitude, it is not statistically significant.

Column 3 and 4 investigate the contributions rather than the transfer. Contributions are fiscal obligations local governments must pay to the central government. I focus on two types of such contributions: pre-reform contribution, which represents the contributions local government needs to made prior to the tax reform; and targeted contributions, which are contributions with specific purposes (national defense, public infrastructure investment, etc.). Column 3 and 4 show that Soviet Zone counties seem to make less contribution to the central government, nevertheless, these differences are not statistically significant.

In summary, Table 3.2 and 3.3 show that counties just inside of Soviet Zones receive more fiscal transfers when compared with nearby counties outside of the Soviet Zones. The additional fiscal transfers take the form of targeted transfers. I also provide two pieces of evidence arguing that additional targeted transfers Soviet Zone counties received are not derived by the differences in their socioeconomic conditions. First, I control for the industrial and agricultural output directly and show that the difference in the pre-capita targeted transfers do not change between Soviet Zone and non-Soviet Zone counties. Second, I investigate other rule-based fiscal transfers between the central and local governments. I find that there is no statistically significant difference between Soviet Zone and nearby non-Soviet Zone counties in the amount of those rule-based fiscal transfers.

I argue that the extra resources Soviet Zone counties receive is evidence of their political importance. Since the economic reform and the end of the Cold War, the CCP derives its legitimacy of ruling from its ability to deliver extraordinary economic growth. By being the regions under the control of the current region for the longest time, the economic success of Soviet Zone counties is therefore politically important and warrants extra resources.

An alternative rationale behind the favoritism towards Soviet Zones is that the central government may observe investment opportunities in Soviet Zone counties that I do not. As a result, they invest more in those counties using targeted transfers hoping to materialize such opportunities. However, I argue that this is not likely the case. Given the arbitrariness of the location of Soviet Zone boundaries, it is not likely that investment opportunities occurs consistently on one side of the boundaries but not the other for a sustained period of times. Furthermore, as I will discuss in the next section, targeted fiscal transfers towards Soviet Zone counties do not payoff: despite of the extra resources, I do not find Soviet Zone counties experience faster economic growth.

Where Do Soviet Zone Counties Spend The Additional Fiscal Income?

A crucial question regarding the overall welfare consequences of the fiscal transfers towards Soviet Zone counties is whether those transfers benefit the local economy, and if so, whether the local benefits outweighs global costs. I show in this section that the favoritism towards Soviet Zone does not even generate local benefits, let alone covering its opportunity cost. Specifically, I show that Soviet Zone counties do not produce more industrial or agricultural output than the neighboring non-Soviet Zone counties. To investigate potential reasons behind this lackluster performance, I examine further the local government expenditure patterns. I find local governments in Soviet Zone counties do not invest more in infrastructure, education or agriculture. Instead, they spend more in administration and have more people on the local government payrolls.[10]

[10] Local government payrolls include employees of the local government agencies and public institutions.

Table 3.4: Economic Consequences of Soviet Zone Favoritism

	Log Industry Output	Log Agriculture Output	Log GDP
	(1)	(2)	(3)
Soviet Zones	-0.074	-0.028	-0.080
	(0.07)	(0.05)	(0.05)
Log Area	0.008	-0.093*	-0.107**
	(0.08)	(0.05)	(0.05)
Constant	9.530***	7.302***	8.078***
	(0.15)	(0.09)	(0.10)
mean dvar.	9.472	7.436	8.203
Year FE	X	X	X
Group FE	X	X	X
N. Groups	235	235	235
N. Obs	3008	3015	3014

Source: Statistical Yearbook and Annual Financial Statistics of Cities and Counties, 1994 - 2001.

Note: Each observation is a county-year cell. *Soviet Zones* is a binary variable that equals to 1 if the county the observation belongs to is a Soviet Zone county. *Log Area* is the log of total area of the territory within the administrative boundary of the county. The dependent variables are log per-capita industrial, agricultural outputs in column 1 and 2, respectively, and log per-capital GDP in column 3. All columns include year and group fixed effects, where the group is defined in Section 3.3. Standard errors are clustered at the group level.

I start with analyzing the real outputs. Table 3.4 shows the results of log per-capita industrial and agricultural output. Column 1 compares the industrial output between Soviet Zone counties and the nearby non-Soviet Zone counties. The point estimate is negative and statistically insignificant. Column 2 reports the result for agricultural output. Similar to column 1, the point estimate for Soviet Zone is negative and statistically insignificant. These results suggest that the Soviet Zone counties do not experience faster economic growth than neighboring non-Soviet Zone counties, despite them receiving more targeted transfers from the central government. If anything, Soviet Zone counties show slightly worse economic performance in both agricultural and industrial sectors. Finally, column 3 reports the result for log per-capita GDP. Since the Chinese rural economy consists mostly of agricultural and industrial activities with little or no service at all, the result using log per-capita GDP is similar to that in column 1 and 2, where Soviet Zone counties have lower GDP per-capita than nearby non-Soviet Zone counties, although the difference is not statistically significant.

The negative results reported in Table 3.4 implies that redistribution towards Soviet Zone counties do not generate local benefits. The non-results suggests potentially resource misallocation in how local government allocates fiscal expenditures. Table 3.5 takes a closer look at the fiscal expenditures in Soviet Zone and Non-Soviet Zone counties. Column 1 and 2 focus on the infrastructure expenditures. An important component of the infrastructure expenditure is public goods like utilities and transportation. Column 1 suggests that Soviet Zone counties do not spend more on infrastructure than non-Soviet Zone counties. Column 2 adds the lagged per-capita GDP as an additional control to account for the overall local economic activities. Neither the statistical significance nor the magnitude of the point estimate of Soviet Zone status changed in column 2 when compared with that reported in column 1.

Column 3 and 4 of Table 3.5 focus on per-capita education expenditures. Education expenditures include mostly subsidies to schools and tuition fees for students living in the rural areas. Again, Soviet Zone counties do not disproportionally spend more on education than nearby non-Soviet Zone counties. This conclusion does not change if I control for the lagged per-capita GDP as a proxy to the overall local economic activities. In both cases, the point estimates for the Soviet Zone status are small and statistically insignificant.

Column 5 and 6 of Table 3.5 focus on agriculture expenditures, which contain subsidies to agricultural activities and poverty alleviation in the rural area. Similar to previous results, I find the Soviet Zone counties do not spend more money in this category either. Again, this result is robust to controlling for lagged per-capita GDP.

Despite the Soviet Zone counties do not spend more in productive and public service, they do have higher administrative expenditures. Column 7 and 8 of Table 3.5 report this result. Contrary to column 1 - 6, Soviet Zone counties exhibit 15% higher per-capita administrative expenditures. This magnitude is notably larger than that reported in previous columns. The point estimate of Soviet Zone status is also highly statistically significant. Column 8 repeat the exercise in column 7 with lagged per-capita GDP as an extra control. The magnitude and statistical significance of the point estimate for Soviet Zone status are exactly the same as that reported in column 7.

Finally, I also look at the total number of personnel included in the local government payrolls. Consistent with the result reported in column 7 and 8, column 9 and 10 of Table 3.5 shows that Soviet Zone counties have more people on the government payroll than nearby non-Soviet Zone counties. Column 9 shows that the local governments of Soviet Zone counties include 8% more personnel in their payrolls.[11] Controlling for lagged per-capita GDP does not change this result, as shown in column 10.

Together, results reported in Table 3.5 suggest that Soviet Zone counties spend their extra fiscal resources on a larger sized administration but not productivity-enhanced investments like infrastructure, agricultural investment, or education. This result provides an explanation on the lackluster performances in both industrial and agricultural sectors in those Soviet Zone counties reported in Table 3.4, where despite of receiving more fiscal transfers from the central government, Soviet Zone counties do not produce more industrial or agricultural goods than non-Soviet Zone counties. I argue that those results imply misallocation of resources within

[11] In the context of local government in China, those people could be government officials, employees of local branches of public institution, schools, government-owned public entertainment facilities (e.g., theaters, libraries), and the former employees who retire from the government and those organizations.

Table 3.5: Local Expenditures in Soviet and Non-Soviet Counties

	Log Infra. Exp.		Log Edu. Exp.		Log Agri. Exp.		Log Admin. Exp.		Log Gov. Payrolls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Soviet Zones	0.051	0.064	0.028	0.029	0.044	0.050	0.154***	0.154***	0.082**	0.082**
	(0.08)	(0.07)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Log Area	0.087	0.078	-0.124***	-0.120***	-0.115**	-0.104*	-0.228***	-0.218***	-0.169***	-0.166***
	(0.07)	(0.07)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
Log GDP_{-1}		0.024		0.048***		0.080***		0.078***		0.047***
		(0.05)		(0.01)		(0.02)		(0.01)		(0.01)
Constant	0.597***	0.448*	4.063***	3.868***	2.949***	2.629***	3.314***	3.007***	5.327***	5.134***
	(0.12)	(0.24)	(0.07)	(0.09)	(0.10)	(0.13)	(0.11)	(0.12)	(0.08)	(0.11)
mean dvar.	0.488	0.457	4.281	4.281	3.162	3.160	3.718	3.717	5.651	5.651
Year FE	X	X	X	X	X	X	X	X	X	X
Group FE	X	X	X	X	X	X	X	X	X	X
N. Groups	235	235	235	235	235	235	235	235	235	235
N. Obs	3017	2914	3009	2914	3008	2913	3009	2914	3367	3265

Source: Statistical Yearbook and Annual Financial Statistics of Cities and Counties, 1994 - 2001.

Note: Each observation is a county-year cell. *Soviet Zones* is a binary variable that equals to 1 if the county the observation belongs to is a Soviet Zone county. *Log Area* is the log of total area of the territory within the administrative boundary of the county. *Log* GDP_{-1} is the lagged log per-capita GDP. The dependent variables are the log per-capita infrastructure expenditures in column 1 and 2, the log per-capita education expenditures in column 3 and 4, the log per-capita agricultural and rural expenditures in column 5 and 6, the log per-capita administrative expenditures in column 7 and 8, and the log per-pcatia government personnel in column 9 and 10. All columns include year and group fixed effects, where the group is defined in Section 3.3. Standard errors are clustered at the group level.

the Soviet Zone counties. Furthermore, since the resources transferred into Soviet Zones are raised by the central government with non-zero cost, there is also an opportunity cost associated with the transfers. Therefore, the lackluster performance of Soviet Zone counties is at a cost of wasting investment opportunities elsewhere in China, suggesting a larger scale misallocation of resources nationwide.

3.5 Conclusion

Soviet Zones are the bases from which the CCP started the revolution that finally succeeded, I show counties just inside of the Soviet Zone boundaries receive 20% more fiscal transfers from the central government than neighboring counties outside of them. Since the Soviet Zone boundaries are determined by uncertain outcomes of military operations, I argue that such difference is not driven by any inherent difference of counties belong to different sides of the Soviet Zone boundaries. Therefore, I conclude that such differences result from the central governments' favoritism towards Soviet Zone counties.

I document two types of inefficiencies associated with this favoritism. First, fiscal resources are misallocated within the Soviet Zone counties. Despite receiving more resources from the central government, the local governments in Soviet Zone counties do not make more productivity-enhancing investments: I find no statistically significant differences in per-capita spending on infrastructure, education and agriculture between Soviet Zone counties and nearby non-Soviet Zone counties. Nevertheless, Soviet Zone counties have significantly higher administrative expenses, and have more people on government payrolls.

Second, the lackluster economic performance in Soviet Zone counties also implies resources are misallocated across Chinese counties. Favoritism towards Soviet Zones is a form of place-based redistribution. For those redistribution to be efficiency-enhancing, the local gain must outweighs the opportunity cost (Kline and Moretti, 2014). However, since fiscal transfers towards Soviet Zone counties failed to even generate local gain, it will not cover the opportunity cost of the fiscal resources transferred to Soviet Zone counties, resulting in spatial misallocation.

Bibliography

ACEMOGLU, D., U. AKCIGIT, H. ALP, N. BLOOM, AND W. KERR (2018): "Innovation, reallocation, and growth," *American Economic Review*, 108(11), 3450–91.

ACEMOGLU, D., AND J. ROBINSON (2001): "Inefficient Redistribution," *American Political Science Review*, 95(3), 649 – 61.

ACKERBERG, D. A., K. CAVES, AND G. FRAZER (2015): "Identification Properties of Recent Production Function Estimators," *Econometrica*, 83(6), 2411–2451.

ADES, A. F., AND E. L. GLAESER (1995): "Trade and circuses: explaining urban giants," *The Quarterly Journal of Economics*, 110(1), 195–227.

AGARWAL, N., C. MILNER, AND A. RIAÑO (2014): "Credit constraints and spillovers from foreign firms in China," *Journal of Banking & Finance*, 48(C), 261–275.

AGHION, P., A. BERGEAUD, T. BOPPART, P. J. KLENOW, AND H. LI (2019): "A Theory of Falling Growth and Rising Rents," NBER Working Papers 26448, National Bureau of Economic Research, Inc.

AGHION, P., A. BERGEAUD, AND J. VAN REENEN (2019): "The Impact of Regulation on Innovation," Discussion paper.

AKCIGIT, U., S. BASLANDZE, AND F. LOTTI (2020): "Connecting to Power: Political Connections, Innovation, and Firm Dynamics," FRB Atlanta Working Paper 2020-5, Federal Reserve Bank of Atlanta.

ALBERTUS, M., AND O. KAPLAN (2013): "Land Reform as a Counterinsurgency Policy," *Journal of Conflict Resolution*, 57(2), 198–231.

ALBERTUS, M., AND V. MENALDO (2012): "If You're Against Them You're With Us: The Effect of Expropriation on Autocratic Survival," *Comparative Political Studies*, 45(8), 973–1003.

ALMEIDA, H., P.-H. HSU, AND D. LI (2013): "Less is more: Financial constraints and innovative efficiency," *Available at SSRN 1831786*.

Almeida, H., P.-H. Hsu, D. Li, and K. Tseng (2017): "More cash, less innovation: The effect of the American Jobs Creation Act on patent value," *Journal of Financial and Quantitative Analysis*, pp. 1–28.

Asker, J., A. Collard-Wexler, and J. De Loecker (2014): "Dynamic Inputs and Resource (Mis)Allocation," *Journal of Political Economy*, 122(5), 1013–1063.

Ayyagari, M., A. Demirgüç-Kunt, and V. Maksimovic (2010): "Formal versus informal finance: Evidence from China," *The Review of Financial Studies*, 23(8), 3048–3097.

Bai, C.-E., J. Lu, and Z. Tao (2006): "The Multitask Theory of State Enterprise Reform: Empirical Evidence from China," *American Economic Review*, 96(2), 353–357.

Banerjee, A., E. Breza, R. Townsend, and D. Vera-Cossio (2019): "Access to Credit and Productivity," .

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013): "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, 103(1), 305–34.

Bau, N., and A. Matray (2020): "Misallocation and capital market integration: Evidence from India," Discussion paper, National Bureau of Economic Research.

Berglöf, E., and G. Roland (1997): "Soft budget constraints and credit crunches in financial transition," *European Economic Review*, 41(3), 807–817, Paper and Proceedings of the Eleventh Annual Congress of the European Economic Association.

Bils, M., P. J. Klenow, and C. Ruane (2020): "Misallocation or mismeasurement?," Discussion paper, National Bureau of Economic Research.

Blundell, R., R. Griffith, and F. Windmeijer (2002): "Individual effects and dynamics in count data models," *Journal of Econometrics*, 108(1), 113–131.

Boeing, P. (2016): "The allocation and effectiveness of China's R&D subsidies-Evidence from listed firms," *Research policy*, 45(9), 1774–1789.

Brandt, L., J. Van Biesebroeck, and Y. Zhang (2012): "Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing," *Journal of development economics*, 97(2), 339–351.

Cai, H., and Q. Liu (2009): "Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms," *The Economic Journal*, 119(537), 764–795.

Chen, F. (1997): "The dilemma of eudaemonic legitimacy in post-Mao China," *Polity*, 29(3), 421–439.

Chen, Y., M. Igami, M. Sawada, and M. Xiao (2020): "Privatization and Productivity in China," Discussion paper, SSRN.

Chen, Y., M. Liu, and J. Su (2013): "Greasing the wheels of bank lending: Evidence from private firms in China," *Journal of Banking & Finance*, 37(7), 2533–2545.

Chen, Z. (2019): "Finance, R&D Investment, and TFP Dynamics," Discussion paper, The Pennsylvania State University.

Chen, Z., Z. Liu, J. C. Suárez Serrato, and D. Y. Xu (2018): "Notching R&D investment with corporate income tax cuts in China," Discussion paper, National Bureau of Economic Research.

Cheng, H., H. Fan, T. Hoshi, and D. Hu (2019): "Do innovation subsidies make chinese firms more innovative? evidence from the china employer employee survey," Discussion paper, National Bureau of Economic Research.

Claessens, S., and K. Tzioumis (2006): "Measuring firms' access to finance," *World Bank*, pp. 1–25.

Cull, R., W. Li, B. Sun, and L. Xu (2015): "Government connections and financial constraints: Evidence from a large representative sample of Chinese firms," *Journal of Corporate Finance*, 32(C), 271–294.

Cull, R., and L. Xu (2000): "Bureaucrats, State Banks, and the Efficiency of Credit Allocation: The Experience of Chinese State-Owned Enterprises," *Journal of Comparative Economics*, 28, 1–31.

——— (2003): "Who gets credit? The behavior of bureaucrats and state banks in allocating credit to Chinese state-owned enterprises," *Journal of Development Economics*, 71(2), 533–559.

Cull, R., L. Xu, and T. Zhu (2009): "Formal finance and trade credit during China's transition," *Journal of Financial Intermediation*, 18(2), 173–192.

Da-Rocha, J.-M., D. Restuccia, and M. M. Tavares (2019): "Firing costs, misallocation, and aggregate productivity," *Journal of Economic Dynamics and Control*, 98, 60 – 81.

David, J. M., and V. Venkateswaran (2019): "The Sources of Capital Misallocation," *American Economic Review*, 109(7), 2531–67.

Dickson, B. (2016): *The dictator's dilemma: The Chinese Communist Party's strategy for survival*. Oxford University Press.

Fan, J., and B. Zou (2021): "Industrialization from Scratch: The'Third Front'and Local Economic Development in China's Hinterland," *Available at SSRN 2676645*.

Fang, J., H. He, and N. Li (2020): "China's rising IQ (Innovation Quotient) and growth: Firm-level evidence," *Journal of Development Economics*, p. 102561.

Fang, L. H., J. Lerner, and C. Wu (2017): "Intellectual property rights protection, ownership, and innovation: Evidence from China," *The Review of Financial Studies*, 30(7), 2446–2477.

Feenstra, R. C., Z. Li, and M. Yu (2014): "Exports and Credit Constraints under Incomplete Information: Theory and Evidence from China," *The Review of Economics and Statistics*, 96(4), 729–744.

Fisman, R. (2001): "Estimating the Value of Political Connections," *American Economic Review*, 91(4), 1095–1102.

Fisman, R., and Y. Wang (2015): "The Mortality Cost of Political Connections," *The Review of Economic Studies*, 82(4), 1346–1382.

Gandhi, J., and A. Przeworski (2006): "Cooperation, Cooptation, And Rebellion Under Dictatorships," *Economics and Politics*, 18(1), 1–26.

Garcia-Macia, D., C.-T. Hsieh, and P. J. Klenow (2019): "How destructive is innovation?," *Econometrica*, 87(5), 1507–1541.

Gilchrist, S., J. W. Sim, and E. Zakrajšek (2013): "Misallocation and financial market frictions: Some direct evidence from the dispersion in borrowing costs," *Review of Economic Dynamics*, 16(1), 159–176, Special issue: Misallocation and Productivity.

Glaeser, E. L., and B. M. Steinberg (2017): "Transforming cities: does urbanization promote democratic change?," *Regional Studies*, 51(1), 58–68.

Gorodnichenko, Y., and M. Schnitzer (2013): "Financial constraints and innovation: Why poor countries don't catch up," *Journal of the European Economic association*, 11(5), 1115–1152.

Guner, N., G. Ventura, and Y. Xu (2008): "Macroeconomic implications of size-dependent policies," *Review of Economic Dynamics*, 11(4), 721–744.

Hale, G., and C. Long (2012): "If You Try, You'll Get By: Chinese Private Firms' Efficiency Gains from Overcoming Financial Constraints," *The Evolving Role of China in the Global Economy*, p. 231.

Hall, B., and R. H. Ziedonis (2001): "The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995," *RAND Journal of Economics*, 32(1), 101–28.

Haltiwanger, J. (2016): "Firm dynamics and productivity: tFPQ, TFPR, and demand-side factors," *Economía*, 17(1), 3–26.

Havranek, T., R. Horvath, Z. Irsova, and M. Rusnak (2015): "Cross-country heterogeneity in intertemporal substitution," *Journal of International Economics*, 96(1), 100 – 118.

He, S., Y. Liu, C. Webster, and F. Wu (2009): "Property Rights Redistribution, Entitlement Failure and the Impoverishment of Landless Farmers in China," *Urban Studies*, 46(9), 1925–1949.

Henderson, V. (2003): "The urbanization process and economic growth: The so-what question," *Journal of Economic growth*, 8(1), 47–71.

Hsieh, C.-T., and P. J. Klenow (2009): "Misallocation and manufacturing TFP in China and India," *The Quarterly journal of economics*, 124(4), 1403–1448.

——— (2014): "The life cycle of plants in India and Mexico," *The Quarterly Journal of Economics*, 129(3), 1035–1084.

Hsieh, C.-T., and E. Moretti (2019): "Housing constraints and spatial misallocation," *American Economic Journal: Macroeconomics*, 11(2), 1–39.

Hsieh, C.-T., and Z. M. Song (2015): "Grasp the Large, Let Go of the Small:: The Transformation of the State Sector in China," *Brookings papers on economic activity*, (1), 3.

Hu, A. G., and G. Jefferson (2009): "A great wall of patents: What is behind China's recent patent explosion?," *Journal of Development Economics*, 90(1), 57–68.

Huang, H., and C. Xu (1998): "Soft budget constraint and the optimal choices of research and development projects financing," *Journal of Comparative Economics*, 26(1), 62–79.

Jia, J., and G. Ma (2017): "Do R&D tax incentives work? Firm-level evidence from China," *China Economic Review*, 46(C), 50–66.

Johnson, S., and T. Mitton (2003): "Cronyism and capital controls: evidence from Malaysia," *Journal of financial economics*, 67(2), 351–382.

Klette, T. J., and S. Kortum (2004): "Innovating firms and aggregate innovation," *Journal of political economy*, 112(5), 986–1018.

Kline, P., and E. Moretti (2014): "Local economic development, agglomeration economies, and the big push: 100 years of evidence from the Tennessee Valley Authority," *The Quarterly journal of economics*, 129(1), 275–331.

Knight, J., and L. Shi (1999): "Fiscal decentralization: incentives, redistribution and reform in China," *Oxford Development Studies*, 27(1), 5–32.

König, M., Z. M. Song, K. Storesletten, and F. Zilibotti (2020): "From imitation to innovation: Where is all that Chinese R&D going?," Discussion paper, National Bureau of Economic Research.

Kornai, J., E. Maskin, and G. Roland (2003): "Understanding the Soft Budget Constraint," *Journal of Economic Literature*, 41(4), 1095–1136.

Laliberte, A., and M. Lanteigne (2007): "The Issue of Challenges to the Legitimacy of CCP rule," The Chinese Party-State in the 21st Century: Adaptation and the Reinvention of Legitimacy, chap. 1, pp. 1–22. Taylor & Francis.

Lentz, R., and D. T. Mortensen (2008): "An empirical model of growth through product innovation," *Econometrica*, 76(6), 1317–1373.

——— (2016): "Optimal growth through product innovation," *Review of Economic Dynamics*, 19, 4–19.

Levinsohn, J., and A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70(2), 317–341.

Lewis, J. W., and L. Xue (2003): "Social Change and Political Reform in China: Meeting the Challenge of Success," *The China Quarterly*, 176, 926–942.

Li, D. D., and M. Liang (1998): "Causes of the Soft Budget Constraint: Evidence on Three Explanations," *Journal of Comparative Economics*, 26(1), 104–116.

Li, W. (2008): *Restructure of State-owned Commercial Banks*. Social Sciences Academic Press (China).

Li, W. (2019): "Rotation, Performance Rewards, and Property Rights," Discussion paper, Working paper.

Li, W., G. Roland, and Y. Xie (2018): "Crony capitalism, the party-state, and political boundaries of corruption," Discussion paper, Mimeo, UC Berkeley.

Li, X., X. Liu, and Y. Wang (2015): "A Model of China's State Capitalism," HKUST IEMS Working Paper Series 2015-12, HKUST Institute for Emerging Market Studies.

Massey, J. A. (2006): "The Emperor Is Far Away: China's Enforcement of Intellectual Property Rights Protection, 1986-2006," *Chicago Journal of International Law*, 7(1).

Mazzucato, M. (2013): *The Entrepreneurial State*. Anthem Press.

National Science Foundation (2020): "Science and Engineering Indicators," .

Naughton, B. (1988): "The Third Front: Defence Industrialization in the Chinese Interior," *The China Quarterly*, (115), 351–386.

Nie, H., T. Jiang, and R. Yang (2012): "A Review and Reflection on the Use and Abuse of Chinese Industrial Enterprises Database (In Chinese)," *World Economy*, 5.

Olley, G. S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1297.

Peters, M. (forthcoming): "Heterogeneous Markups, Growth and Endogenous Misallocation," *Econometrica*.

Poncet, S., W. Steingress, and H. Vandenbussche (2010): "Financial constraints in China: Firm-level evidence," *China Economic Review*, 21(3), 411–422.

Qian, Y., and G. Roland (1998): "Federalism and the Soft Budget Constraint," *The American Economic Review*, 88(5), 1143–1162.

Qian, Y., and C. Xu (1998): "Innovation and bureaucracy under soft and hard budget constraints," *The Review of Economic Studies*, 65(1), 151–164.

Restuccia, D., and R. Rogerson (2008): "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic dynamics*, 11(4), 707–720.

——— (2017): "The causes and costs of misallocation," *Journal of Economic Perspectives*, 31(3), 151–74.

Sheng, Y. (1993): "The Capital Sources Of China's Industrialization," *The Developing Economies*, 31(2), 173–205.

Song, Z., K. Storesletten, and F. Zilibotti (2011): "Growing like china," *American economic review*, 101(1), 196–233.

Song, Z., and G. L. Wu (2015): "Identifying capital misallocation," *Work. Pap., Univ. Chicago, Chicago*.

State-owned Assets Supervision and Administration Commission (2003): "Interim Measures for the Administration of State-owned Assets inEnterprises," .

The World Bank (2005): "Investment Climate Survey," .

——— (2012): "Enterprise Survey," .

Tian, X., and J. Xu (2018): "Do Place-Based Policies Promote Local Innovation and Entrepreneurial Finance?," *Available at SSRN 3118661*.

Varela, L. (2018): "Reallocation, competition, and productivity: evidence from a financial liberalization episode," *The Review of Economic Studies*, 85(2), 1279–1313.

Vereshchagina, G. (2018): "Financial constraints and economic development: the role of innovative investment," 2018 Meeting Papers 1107, Society for Economic Dynamics.

WALLACE, J. (2013): "Cities, Redistribution, and Authoritarian Regime Survival," *The Journal of Politics*, 75, 632–645.

——— (2014): *Cities and stability: Urbanization, redistribution, and regime survival in China*. Oxford University Press.

WANG, Y. (2020): "The Politico-Economic Dynamics of China's Growth," *Journal of the European Economic Association*, jvz080.

——— (2021): "The Politico-Economic Dynamics of China's Growth," *Journal of the European Economic Association*, 19(1), 305–346.

WEI, S.-J., Z. XIE, AND X. ZHANG (2017): "From" Made in China" to" Innovated in China": Necessity, prospect, and challenges," *Journal of Economic Perspectives*, 31(1), 49–70.

WHITE, T. K., J. P. REITER, AND A. PETRIN (2018): "Imputation in US manufacturing data and its implications for productivity dispersion," *Review of Economics and Statistics*, 100(3), 502–509.

WONG, C. P. (2000): "Central-local relations revisited the 1994 tax-sharing reform and public expenditure management in China," *China Perspectives*, pp. 52–63.

WU, G. L. (2018): "Capital misallocation in China: Financial frictions or policy distortions?," *Journal of Development Economics*, 130(C), 203–223.

ZHANG, A., Y. ZHANG, AND R. ZHAO (2003): "A study of the R&D efficiency and productivity of Chinese firms," *Journal of Comparative Economics*, 31(3), 444–464.

Appendix A

Appendices for Resource Misallocation in the R&D Sector: Evidence from China

A.1 Proof of Results in the Main Text

Proof to Lemma 1.1

Start with the value function (1.12). First note that neither the number of products (n) nor the markup (μ_i) is function of time, so $\dot{V}_P(n, \{\mu_i\}) = 0$. Conjecture the value function takes an additive form, $V_P = Y \sum_{i=1}^{n} v_P(\mu_i)$ for the total output Y and some function v_P. I now decompose each of the terms in the right hand side to find v_P.

The flow profit from producing intermediate good i, $\pi(\mu_i)$, can be written as

$$\begin{aligned}\pi(\mu_i) &= (p_i - mc_i)y_i = (p_i - mc_i)y_i = (p_i - mc_i)\frac{Y}{p_i} \\ &= \left(1 - \frac{mc_i}{p_i}\right)Y = \left(1 - \mu_i^{-1}\right)Y \\ &= \tilde{\pi}(\mu_i)Y, \end{aligned} \tag{A.1}$$

where μ_i is the markup firm charges in market i.

Moreover, note that $V_P(n-1, \{\mu_j\}_{j\neq i}) = Y \sum_{j\neq i} v_P(\mu_j)$, so the business stolen term can be express as a function of $v_P(\cdot)$, i.e.

$$\begin{aligned}
&\sum_i z[V_P(n-1,\{\mu_j\}_{j\neq i}) - V_P(n,\{\mu_i\})] \\
=&\sum_i z\left[\sum_{j\neq i} v_P(\mu_j) - \sum_j v_P(\mu_j)\right] \\
=&-zY\sum_i v_P(\mu_i). \qquad \text{(A.2)}
\end{aligned}$$

Similarly, the linearity of V_P in n allows me to exchange the expectation operator and the summation. Thus, the firm value from innovation is

$$\begin{aligned}
&\sum_{i=1}^n x[\mathbb{E}_{\tilde{\mu}} V_P(n+1,\{\mu_i\}\cup\{\tilde{\mu}\}) - V_P(n,\{\mu_i\})] \\
=&\sum_i x\{\mathbb{E}_{\tilde{\mu}}[Y\sum_j v_P(\mu_j) + v_P(\tilde{\mu})] - Y\sum_j v_P(\mu_j)\} \\
=&\sum_i xY\mathbb{E}_{\tilde{\mu}} v_P(\tilde{\mu}) \\
=&nY\mathbb{E}_{\tilde{\mu}} v_P(\tilde{\mu}). \qquad \text{(A.3)}
\end{aligned}$$

Finally, the cost function, $G_P(x,n)$, is also linear in its last argument, n, as suggested by Equation (1.11). Together, I have

$$\begin{aligned}
rV_P(n,\{\mu_i\}) =& \sum_{i=1}^n \left\{\pi(\mu_i) + z[V_P(n-1,\{\mu_j\}_{j\neq i}) - V_P(n,\{\mu_i\})]\right\} \\
&+ \max_x \left\{ \sum_{i=1}^n x[\mathbb{E}_{\tilde{\mu}} V_P(n+1,\{\mu_i\}\cup\{\tilde{\mu}\}) - V_P(n,\{\mu_i\})] - G_P(x,n) \right\} \\
=& Y\sum_i[\tilde{\pi}(\mu_i) - zv_P(\mu_i)] + nY\max_x\{x\mathbb{E}_{\tilde{\mu}} v_P(\tilde{\mu}) - \frac{(1+\tau)w}{\phi_P Y}x^\zeta\} \\
=& Y\sum_i\left\{\tilde{\pi}(\mu_i) - zv_P(\mu_i) + \max_x[x\mathbb{E}_{\tilde{\mu}} v_P(\tilde{\mu}) - \frac{(1+\tau)w}{\phi_P Y}x^\zeta]\right\}. \qquad \text{(A.4)}
\end{aligned}$$

Solve for $v_P(\cdot)$ from Equation (A.4) and the conjuncture $V_P(n,\{\mu_i\}) = Y\sum_i v_P(\mu_i)$, I have

$$rv_P(\mu_i) = \tilde{\pi}(\mu_i) - zv_P(\mu_i) + \max_x[x\mathbb{E}_{\tilde{\mu}} v_P(\tilde{\mu}) - \frac{(1+\tau)w}{\phi_P Y}x^\zeta]. \qquad \text{(A.5)}$$

Similarly, for the value function of state-owned firms (1.13), conjecture $V_S(n, m, \{\mu_i\}) = Y \sum_i v_S(\mu_i)$. Note that

$$z_S[V_S(n-1, m-1, \{\mu_j\}_{j\neq i}) - V_S(n, m, \{\mu_i\})] = -z_S Y \sum_i v_S(\mu_i),$$
$$\sum_i V_S(n, m-1, \{\mu_j\}_{j\neq i} \cup \{\hat{\mu}\}) - V_S(n, m, \{\mu_i\}) = Y \sum_i v_S(\hat{\mu}) - v_S(\mu_i),$$
$$\sum_i V_S(n-1, m-1, \{\mu_j\}_{j\neq i}) - V_S(n, m, \{\mu_i\}) = -Y \sum_i v_S(\mu_i),$$

which gives the following representation of $v_S(\cdot)$:

$$\begin{aligned} rv_S(\mu_i) =& \tilde{\pi}(\mu_i) + z_P \mathbf{1}\,[1+\tau > \lambda; \text{tech. leading}]\, v_S(\hat{\mu}) - z v_S(\mu_i) \\ & + \mathbf{1}\,[\text{tech. leading}] \max_x \left[x \mathbb{E}_{\tilde{\mu}} v_S(\tilde{\mu}) - \frac{w}{\phi_S Y} x^{\zeta} \right]. \end{aligned} \tag{A.6}$$

Move v_k in Equation (A.4) and (A.6) to the left gives the equations in Lemma 1.1. This concludes the proof for Lemma 1.1.

Proof to Proposition 1.1

Lemma 1.1 shows that the optimal R&D intensity, x_k depends only on the optional value of technology leadership, $\Xi_k = \max_x \left[x \mathbb{E}_{\tilde{\mu}} v_S(\tilde{\mu}) - \frac{(1+\tau_k)\omega}{\phi_k} x^{\zeta} \right]$. The first order condition gives

$$\mathbb{E}_{\tilde{\mu}} v_k(\tilde{\mu}) = \zeta \frac{(1+\tau_k)\omega}{\phi_k} x^{\zeta-1}.$$

Rearrange the first order condition gives Proposition 1.1.

$\mathcal{M}(t)$ and $L_{\mathcal{P}}(t)$ are constant on BGP

Recall that

$$\mathcal{M}(t) = \frac{\exp\left\{ \int_0^1 \ln[(1+\tau_{Fi}(t))^{-1} \Delta a_i(t)^{-1}] di \right\}}{\int_0^1 (1+\tau_i(t))^{-1} \Delta a_i(t)^{-1} di},$$
$$L_{\mathcal{P}}(t) = \frac{Y(t)}{w(t)} \int_0^1 (1+\tau_{Fi}(t))^{-1} \Delta a_i(t)^{-1} di.$$

It suffices to show the distribution of $(1+\tau_{Fi}(t))\Delta a_i(t)$ is constant on BGP.

First, a stationary markup distribution requires the market shares of state-owned and private firms to be constant. Otherwise, the type match between the market leader and follower cannot be constant, this contradicts with the stationarity condition $\dot{\mathbf{S}} = 0$. Recall that $\tau_{Fi}(t)$ is the factor market wedge market follower in product i faces. Therefore, a stationary distribution of the types of market leader implies a stationary distribution for $(1+\tau_{Fi}(t))$.

Second, markup is a function of technology gap Δa_i. A stationary markup distribution also implies the distribution of technology gap should also be stationary. A non-stationary technology gap distribution leads to a non-stationary markup distribution. Therefore, when $\dot{\mathbf{S}} = 0$, the distribution of Δa_i is stationary.

Given those stationarity conditions, we have

$$\int_0^1 g(1+\tau_{Fi}(t), \Delta a_i(t))di = \int g(1+\tau_{Fi}, \Delta a_i)dF(i)$$

for function $g(\cdot)$ and the stationary distribution of markup F. Note the right hand side of the last equation is not a function of time t, so

$$\mathcal{M}(t) = \frac{\exp\left\{\int \ln[(1+\tau_{Fi})^{-1}\Delta a_i^{-1}]dF(i)\right\}}{\int (1+\tau_{Fi})^{-1}\Delta a_i^{-1}dF(i)}$$

is constant. For $L_{\mathcal{P}}$, note that on BGP, $Y(t)$ and $w(t)$ grow at the same rate, so $Y(t)/w(t) = 1/\omega$ is a constant. Therefore,

$$L_{\mathcal{P}}(t) = \frac{1}{\omega}\int (1+\tau_{Fi})^{-1}\Delta a_i^{-1}dF(i)$$

is also a constant.

Proof to Proposition 1.2

The existence and uniqueness result follows directly from Lentz and Mortensen (2008). The only difference between my model and theirs is the factor market wedge τ, which is a fixed parameter in the model. However, since τ is fixed, it does not affect the existence and the uniqueness of the equilibrium as long as $x^*_\epsilon > 0$, as discussed in Appendix C of Lentz and Mortensen (2008).

Proof to Proposition 1.3

On the balance growth path, the only source of growth is the growth in the productivity index $\ln A(t) = \int_i \ln a_{Li}(t)di$. The changes in the productivity index for an infinitesimal time Δt is

$$\ln A(t+\Delta t) = \int_i \ln a_{Li}(t+\Delta t)di = \int_i [z\Delta t \ln \lambda a_{Li}(t) + (1-z\Delta t)a_{Li}(t)]di, \tag{A.7}$$

where the second equality follows the process of productivity improvement in the model: given the total creative destruction rate z, the total number of product lines experiencing an increase in productivity is $z\Delta t$. For each of these events, the productivity of the product line improves λ.

Equation (A.7) suggests that for small enough Δt, the growth rate of the productivity index is given by

$$\begin{aligned}\frac{\ln A(t+\Delta t)-\ln A(t)}{\Delta t} &= \frac{\int_i [z\Delta t \ln \lambda a_{Li}(t) + (1-z\Delta t)a_{Li}(t)]di - \int_i \ln a_{Li}(t)di}{\Delta t} \\ &= \frac{z\Delta t \int_i \ln \lambda a_{Li}(t) - \ln a_{Li}(t)di}{\Delta t} \\ &= z\int_i \ln \lambda di = z \ln \lambda,\end{aligned}$$

which concludes the first part of Proposition 1.3.

For the second part of Proposition 1.3, note that the total destruction in the economy, z, equals to the total innovation, $\int_i x_i^* di + x_\epsilon^*$. Denote F_k the number of k type firms that are actively engaging in R&D, then

$$z = \int_i x_i^* di + x_\epsilon^* = \int_{i\in S} x_S^* di + \int_{j\in P} x_P^* di + x_\epsilon^* = F_S x_S^* + F_P x_S^* + x_\epsilon^*.$$

Finally, since all firms do at least some R&D in the model whenever it is possible, F_k equals to the share of type k firms that are both technology and market leaders. However, some state-owned market leaders may not be leading in technology when the market friction is significantly large (i.e., $1+\tau > \lambda$). In these cases, they will not have the required knowledge capital to engage in R&D, and thus will not spend anything on R&D. Using the notations defined in Section 1.3, this happens with frequency S_{PS}. Therefore, F_k is given by

$$F_P = \begin{cases} S_{PP} + S_{PS} & \text{if } 1+\tau \le \lambda \\ S_{PPP} + S_{PPS} & \text{if } 1+\tau > \lambda \end{cases}; \qquad F_S = \begin{cases} S_{SP} + S_{SS} & \text{if } 1+\tau \le \lambda \\ S_{SPP} + S_{SPS} + S_{SS} & \text{if } 1+\tau > \lambda \end{cases}.$$

This concludes the proof to Proposition 1.3.

The Decentralized Equilibrium in the *Laissez-faire* Economy is Not Optimal

In this section, I calculate the first-best allocation using the baseline estimates and show that it leads to a higher growth and welfare than the decentralized equilibrium in the *laissez-faire* economy. Thus, the decentralizd equilibrium in the *laissez-faire* economy cannot be optimal.

Consider the social planner's problem

$$\begin{aligned}
\max_{x_P,x_S,x_\epsilon} U(C_0,g) &= \frac{1}{1-\theta}\left[\frac{C_0^{1-\theta}}{\rho-(1-\theta)g}-\frac{1}{\rho}\right] \\
s.t. \quad C_0 &= 1 - S_P\frac{x_P^\zeta}{\phi_P} - (1-S_P)\frac{x_S^\zeta}{\phi_S} - \frac{x_\epsilon^\zeta}{\phi_\epsilon} \\
g &= (S_P x_P + (1-S_P)x_S + x_\epsilon)\ln\lambda \\
S_P &= \frac{p x_\epsilon}{(S_P x_P + (1-S_P)x_S + x_\epsilon) - x_P},
\end{aligned} \tag{A.8}$$

where she chooses the innovation intensities for different types of firms to maximize the lifetime utility, subject to the resource (labor) constraint. S_P is the share of intermediate goods produced by private firms in equilibrium. S_P is determined by the evolution of productivity. Lentz and Mortensen (2008) shows that the equilibrium market share S_P given x_P, x_S, x_ϵ and the entrant composition p is

$$S_P = \frac{p x_\epsilon}{(S_P x_P + (1-S_P)x_S + x_\epsilon) - x_P}.$$

I first solve the social planner's problem (A.8) with the parameters $\rho, \theta, \zeta, p, \phi_P, \phi_S, \phi_\epsilon, \lambda$ estimated from my baseline model and obtain C^*, g^*. In the sprite of Equation (1.20), the welfare loss from the decentralized equilibrium in the *laissez-faire* economy can be summarized by the consumption-equivalent change γ^* in

$$U(\gamma^* C_{LF}, g_{LF}) = U(C^*, g^*).$$

The first-best allocation addresses under-investment in innovation by equalizing the social marginal benefit of R&D to the marginal cost of R&D. Because of the positive externality of R&D, the decentralized equilibrium failed to achieve this. Specifically, the first-best allocation achieves 31% higher welfare than the decentralized equilibrium. The social planner accomplishes this improvement by drastically increase the total researchers hired by private incumbents: the production sector in the first-best allocation is only 75% the size of the production sector in the decentralized equilibrium. Furthermore, private firms hire the majority of researchers. They innovate 10 times more intensively than state-owned firms. This reallocation of resources towards research units in private firms leads to a 9% annual productivity growth rate, almost double that in the decentralized equilibrium.

A.2 Additional Differences between State-owned and Private Firms

In this section, I discuss several potential differences between state-owned and private firms, and how they map to my model laid out in Section 1.3.

Product Market Subsidy

I model the state-owned privilege as their better access to factor market. However, it is also possible to allow state-owned firms to receive a subsidy from the government for each unit they produced. Denote τ_y the output subsidy, then the marginal costs of producing intermediate good i are

$$mc_{f,i}(\tau, \tau_y, a, t) = \begin{cases} \frac{w(t)(1+\tau)}{a} & f \text{ is a private firm} \\ \frac{w(t)(1-\tau_y)}{a} & f \text{ is a state-owned firm} \end{cases}. \tag{A.9}$$

In this setting, the markups μ_{jkl} are given by

$$\mu_{PP} = \mu_{SS} = \lambda, \mu_{PS} = \lambda \frac{1-\tau_y}{1+\tau}, \mu_{SP} = \lambda \frac{1+\tau}{1-\tau_y},$$

if $1 + \tau < \lambda$, and

$$\mu_{PPP} = \lambda, \mu_{PPS} = \frac{\lambda^2}{(1+\tau)/(1-\tau_y)}, \mu_{PS} = \frac{(1+\tau)/(1-\tau_y)}{\lambda},$$
$$\mu_{SPP} = \lambda \frac{1+\tau}{1-\tau_y}, \mu_{SPS} = \lambda^2, \mu_{SS} = \lambda$$

Otherwise.

Introducing product market friction/subsidy does not change my main results. To see this, denote $\tilde{\tau} = (\tau_y + \tau)/(1 - \tau_y)$ as the compound market friction, the markups given above reduce back to the baseline markups in Equation (1.16) and (1.17). The only difference in this extension will be the interpretation of $\hat{\tilde{\tau}}$. Instead of being the factor market wedge, $\hat{\tilde{\tau}}$ will be the estimated compound wedge.

Different Processing Efficiency between State-owned and Private firms

State-owned and private firms may differ in their processing efficiency due to the more severe misalignment of incentives between the shareholder (the state) and the firms. Therefore, in addition to being inefficient in innovation, state-owned firms may have lower efficiency in production conditional on the productivity level. Conversely, connections to the government can help state-owned firms to avoid bureaucratic hassle. Because state-owned firms face fewer red tapes, they may have higher processing efficiency conditional on the productivity level.

Following Aghion, Bergeaud, Boppart, Klenow, and Li (2019), I model the processing efficiency an extra term in the production function:

$$y_{f,i}(t) = a_{f,i}(t)\theta_f l_{f,i}(t), \tag{A.10}$$

where θ_f to be the processing efficiency for firm f. This new production function gives the following marginal costs:

$$mc_{f,i}(\tau,\theta_f,a,t) = \begin{cases} \frac{w(t)(1+\tau)}{a\theta_P} & f \text{ is a private firm} \\ \frac{w(t)}{a\theta_S} & f \text{ is a state-owned firm} \end{cases}. \tag{A.11}$$

In this setting, the markups μ_{jkl} are given by

$$\mu_{PP} = \mu_{SS} = \lambda, \mu_{PS} = \frac{\lambda}{(1+\tau)(\theta_S/\theta_P)}, \mu_{SP} = \lambda(1+\tau)\frac{\theta_S}{\theta_P},$$

if $\lambda > 1+\tau$, and

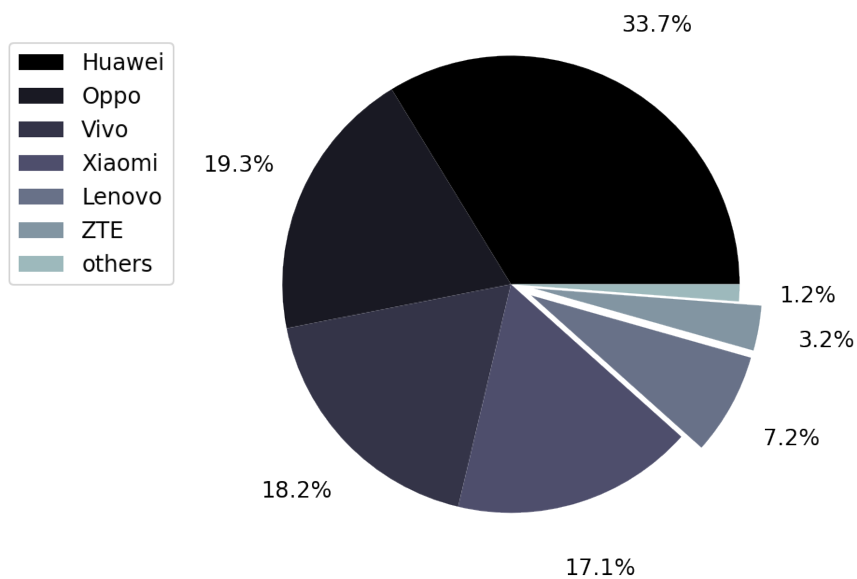
$$\mu_{PPP} = \lambda, \mu_{PPS} = \frac{\lambda^2}{(1+\tau)(\theta_S/\theta_P)}, \mu_{PS} = \frac{(1+\tau)(\theta_S/\theta_P)}{\lambda},$$
$$\mu_{SPP} = \lambda(1+\tau)\frac{\theta_S}{\theta_P}, \mu_{SPS} = \lambda^2, \mu_{SS} = \lambda,$$

Otherwise.

Similar to the extension with product market subsidies, introducing differential processing efficiency does not change my main results. Denote $\check{\tau} = \frac{(1+\tau)\theta_S - \theta_P}{\theta_P}$ as the processing efficiency adjusted market friction, the markups given above reduce back to the baseline markups in Equation (1.16) and (1.17). Again, instead of being the factor market wedge, the estimates $\hat{\check{\tau}}$ is the processing efficiency adjusted market friction.

A.3 Additional Figures and Tables

Figure A.1: Market Share of Domestic Smartphone Producer, 2018



Note: This pie chart plots the market shares for various domestic smartphone producers in 2018. The floating pies indicates market shares by state-owned firms (Lenove and ZTE). Data source: Sohu Technology

Table A.1: Innovation Intensity by Firm Ownership

	report innovation (1/0)		log R&D exp.	
	(1)	(2)	(3)	(4)
State	0.037***	0.057***	0.572***	0.379***
	(0.00)	(0.00)	(0.01)	(0.01)
log Employment	0.044***			0.492***
	(0.00)			(0.00)
log Value Added		0.029***	0.346***	
		(0.00)	(0.00)	
mean dvar.	0.072	0.072	0.522	0.523
FE	X	X	X	X
N. cells	187461	184099	96155	97446
N. obs	1242740	1220008	714032	724891

Data: ASIE 1998 - 2007
FE: 4-digit industry by city by “research park” program by year

Table A.2: Access to Credit by Firm Ownership

	interest rate		% have loan	leverage
	(1)	(2)	(3)	(4)
State	-0.019***	-0.011***	0.023***	0.033***
	(0.00)	(0.00)	(0.00)	(0.00)
log Value Added	0.003***	0.003***	0.059***	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.011***	0.006***	0.143***	0.607***
	(0.00)	(0.00)	(0.00)	(0.00)
mean dvar.	0.035	0.025	0.656	0.568
FE	X	X	X	X
N. Cells	180426	180470	184099	173701
N. Obs	1184824	1184810	1220008	1142810

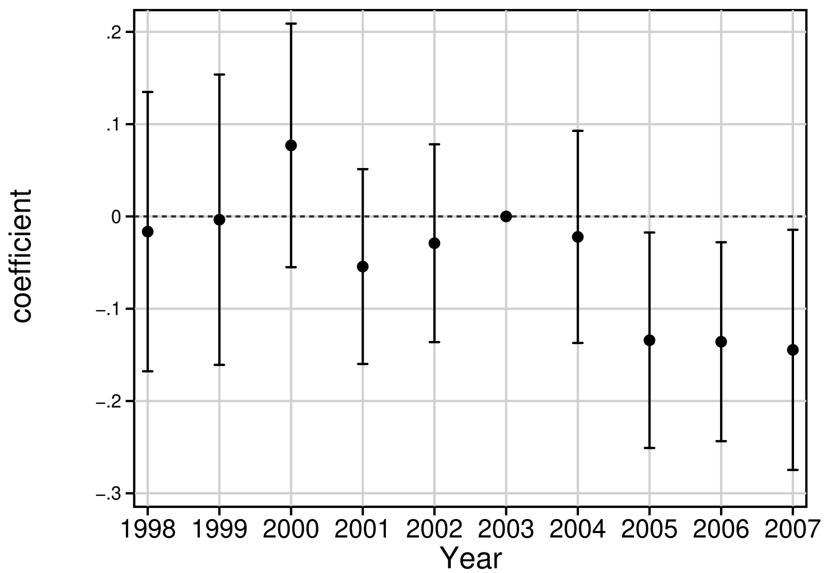
Data: ASIE 1998 - 2007
FE: 4-digit industry by city by “research park” program by year

Appendix B

Appendices for Political Connections, Financial Frictions, and Allocative Efficiency

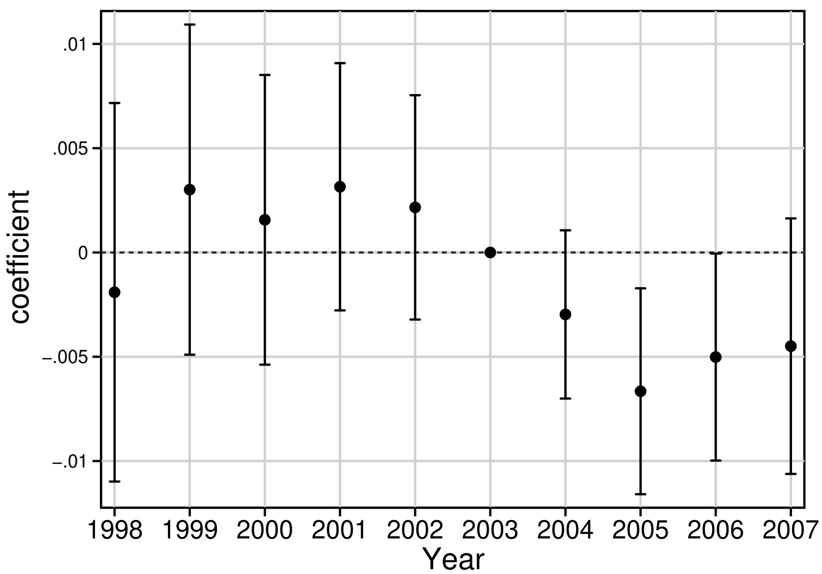
B.1 Additional Tables and Figures

Figure B.1: Treatment Effect of the Banking Reform on Interquartile Range of log TFPR



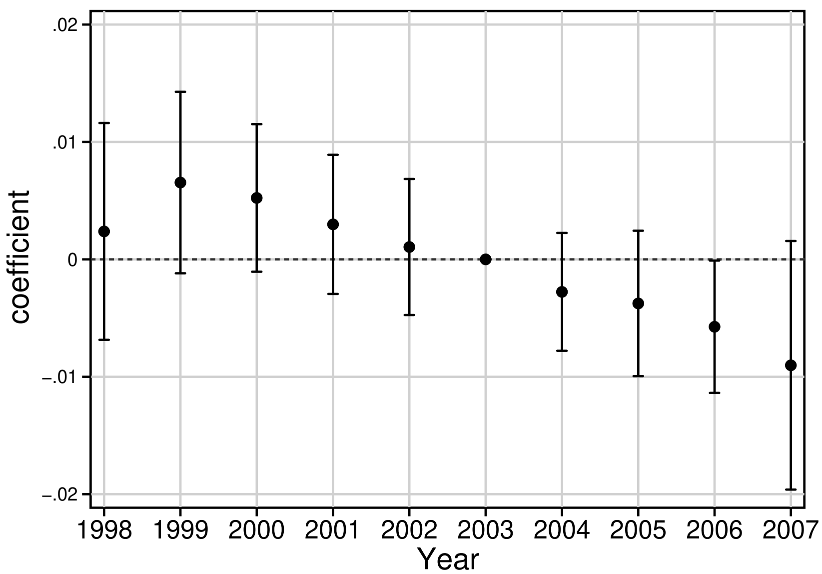
This figure plots the coefficient β_s from regression (2.4). The dependent variable is the interquartile range of log TFPR. Year and industry-city fixed effects are included in the regression. Standard error is clustered at the city level. All coefficients plotted here are relative to year 2003, which is the year before the banking reform. The vertical bar in the figure represents 95% confidence interval.

Figure B.2: Treatment Effect of the Banking Reform on Dispersion of Residualized Interest Rate



This figure plots the coefficient β_s from regression (2.4). The dependent variable is the standard deviation of residualized interest rate. Year and industry-city fixed effects are included in the regression. Standard error is clustered at the city level. All coefficients plotted here are relative to year 2003, which is the year before the banking reform. The vertical bar in the figure represents 95% confidence interval.

Figure B.3: Treatment Effect of the Banking Reform on Dispersion of Residualized Interest Rate



This figure plots the coefficient β_s from regression (2.4). The dependent variable is the interquartile range of the residualized interest rate. Year and industry-city fixed effects are included in the regression. Standard error is clustered at the city level. All coefficients plotted here are relative to year 2003, which is the year before the banking reform. The vertical bar in the figure represents 95% confidence interval.

Table B.1: TFPR dispersion across TF cities, before and after the banking reform

	Interquantile range of residualized interest rate				
	(1)	(2)	(3)	(4)	(5)
treated city	0.003				
	(0.00)				
post	-0.006**				
	(0.00)				
treated city × post	-0.008**	-0.007**	-0.005*		
	(0.00)	(0.00)	(0.00)		
TF investment × post				-0.001**	-0.001*
				(0.00)	(0.00)
Constant	0.032***	0.035***	0.035***	0.039***	0.038***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
mean dvar.	0.034	0.034	0.034	0.034	0.034
Year FE		X	X	X	X
City FE		X		X	
CityXInd FE			X		X
N. Obs	12635	12631	12472	12631	12472

Source: ASIE 1998 - 2007. Only cities considered by the TF project are included.
Note: Each observation is a industry-city-year cell. *treated city* is a binary variable that equals to 1 if the city the observation belongs to received above median TF investment across all cities considered by the TF project. *post* is a binary variable that equals to 1 if the year of the observation is after 2004. *TF investment* is a continuous variable that equals to the log value of the total TF firm assets in a city reported in the 1985 Industry Survey. The dependent variables in all columns are the interquartile range of the residualized interest rate. Column 2 and 4 include year and city fixed effects. Column 3 and 5 include year and industry-city fixed effects. Standard errors are clustered at the city level.

B.2 Industry Code Correspondence

Table B.2: Correspondence between 1985 and 2002 Industry Code

1985 Code	1985 Industry	2002 Code	2002 Industry
1	Coal Mining	06	Coal Mining
2	Petroleum and Natural Gas Mining	07	Petroleum and Natural Gas Mining
3	Ferrous Metal Mining	08	Ferrous Metal Mining
4	Non-ferrous Metal Mining	09	Non-ferrous Metal Mining
5	Non-metal Mining	10	Non-metal Mining
6	Salt Mining	103	Salt Mining
7	Logging and Transport of Timber/Bamboo	022	Logging and Transport of Timber/Bamboo
8	Production and Supply of Tap Water	46	Production and Supply of Tap Water
9	Food Manufacturing	131	Grain Milling
9	Food Manufacturing	133	Vegetable Oil Processing
9	Food Manufacturing	134	Sugar Processing
9	Food Manufacturing	135	Butchering and Meat Processing
9	Food Manufacturing	136	Sea Food Processing
9	Food Manufacturing	137	Fruit, Vegetable and Nuts Processing
9	Food Manufacturing	139	Other Food Processing
9	Food Manufacturing	14	Food Manufacturing
10	Beverage Manufacturing	15	Beverage Manufacturing
11	Tobacco Processing	16	Tobacco Processing
12	Feed Processing	132	Feed Processing
13	Textile	17	Textile
14	Sewing	18	Sewing
15	Leather and Furs Manufacturing	19	Leather and Furs Manufacturing
16	Timber and Bamboo Processing	20	Timber and Bamboo Processing
17	Furniture Manufacturing	21	Furniture Manufacturing
18	Papermaking	22	Papermaking
19	Printing	23	Printing
20	Cultural, Educational and Sports Goods	24	Cultural, Educational and Sports Goods
21	Craft and Art Productions	421	Craft and Art Productions

Table B.2: Correspondence between 1985 and 2002 Industry Code (continued)

1985 Code	1985 Industry	2002 Code	2002 Industry
21	Craft and Art Manufacturing	245	Entertainment Equipment Productions
22	Electricity, Steam and Hot Water	44	Electricity, Steam and Hot Water
23	Petroleum Processing	251	Petroleum Processing
24	Coking, Gas and Coal Processing	252	Coking
24	Coking, Gas and Coal Processing	45	Gas Production
24	Coking, Gas and Coal Processing	423	Coal Product Manufacturing
25	Chemical Industry	26	Chemical Industry
26	Pharmaceutical Industry	27	Pharmaceutical Industry
27	Chemical Fiber Industry	28	Chemical Fiber Industry
28	Rubber Manufacturing	29	Rubber Manufacturing
29	Plastic Manufacturing	30	Plastic Manufacturing
30	Construction Materials Processing	31	Construction Materials Processing
31	Ferrous Metals Processing	32	Ferrous Metals Processing
32	Non-ferrous Metals Processing	33	Non-ferrous Metals Processing
33	Metal Manufacturing	34	Metal Manufacturing
34	Machinery Manufacturing	35	General Machinery Manufacturing
34	Machinery Manufacturing	36	Dedicated Machinery Manufacturing
35	Transportation Equipment Manufacturing	37	Transportation Equipment Manufacturing
36	Electric Equipment Manufacturing	39	Electric Equipment Manufacturing
37	Telecom. Equipment Manufacturing	40	Telecom. Equipment Manufacturing
38	Instruments Manufacturing	41	Instruments Manufacturing
39	Other Manufacturing	422	Other Non-durable Goods Manufacturing
39	Other Manufacturing	429	Other Manufacturing
39	Other Manufacturing	43	Recycling