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

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Abstract

Factor market wedges lead to severe resource misallocation in the Chinese R&D sector and considerable welfare loss. Private firms in China have worse factor market access than state-owned firms. This disadvantage reduces private innovators' profits when they compete with state-owned incumbents. Thus, the wedge distorts incentives to invest in R&D, lowers aggregate innovation, and leads to slower productivity growth. I develop and structurally estimate an endogenous growth model with a factor market wedge to capture this effect. 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. Distortions to R&D incentives are the primary cause of misallocation in the R&D sector. These distortions are quantitatively important in explaining the welfare loss.

Keywords: Innovation; Market competition; Resource misallocation

JEL Codes: O30, O38, O43

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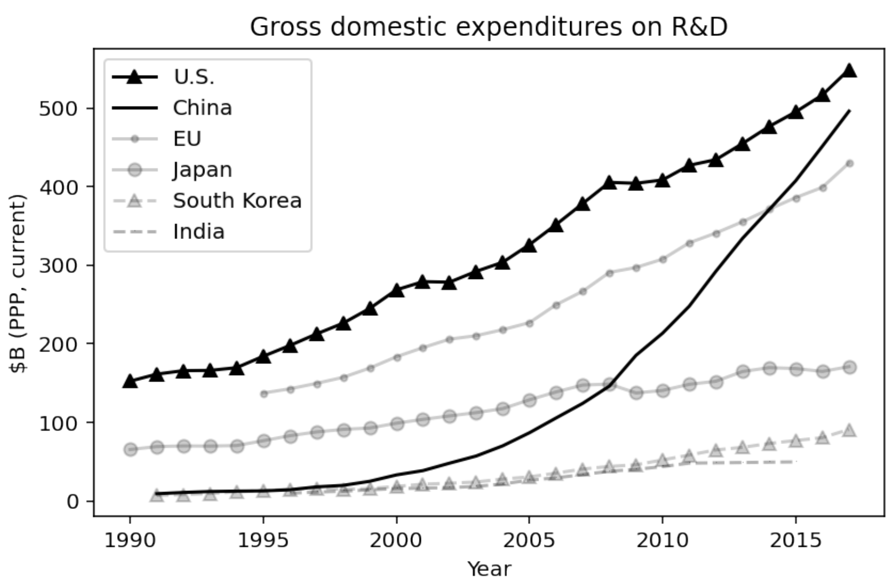
1 Introduction

China has shown real potential in overtaking the United States in key sectors via innovation. As illustrated in Figure 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 is resource misallocated in the Chinese R&D sector? What are the productivity and welfare consequences of this misallocation?

Figure 1: R&D Expenditures in China, U.S., and Other Countries



Source: Science and Engineering Indicators, NSF (2020)

In this paper, I document a severe resource misallocation within the Chinese R&D sector, which results in considerable welfare loss. The loss arises from the combination of two factors. First, state-owned firms are inefficient innovators: For a given amount of R&D inputs, private firms can produce more innovations than state-owned firms. Second, 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. As a result, state-owned firms have a higher return to R&D. Conversely, disadvantaged private firms has a lower return to R&D. This distortion incentivizes inefficient state-owned firms to innovate more at the expense of more efficient private firms. Together, these two forces lead to 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 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: State-owned firms have a higher return to R&D due to their better access to the factor market. This advantage incentivizes them to invest more intensively in R&D, shifting resources from private firms to state-owned firms.

I structurally estimate this model using Chinese firm-level data between 1998 and 2007. 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. 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, which translates into a 23% welfare loss.

[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

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 the 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.

Importantly, 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. 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

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, it is difficult for China to surpass the United States in sectors that require significant innovation outputs.

This paper documents 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. Consequently, the wedge in the factor market leads to a wedge in returns to R&D, 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 ineffi-

below the required threshold for the state-owned 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).

ciencies 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 the 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 showing how misallocation in the R&D sector could be an important mechanism leading to the low 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.

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.

2.1 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 publicly, where stock prices are used to evaluate their performances.

State-owned firms are actively competing with private firms in many industries. Figure C.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.

[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.

2.2 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 C.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 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 3.

2.3 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 C.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).

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.

3.1 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:

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

subject to the budge constraint

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

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

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

$$\frac{\dot{C}}{C} = \frac{r-\rho}{\theta}. \tag{2}$$

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

$$C(t) = Y(t), \tag{3}$$

$$L_{\mathcal{P}} + L_{\mathcal{R}} = L = 1. \tag{4}$$

3.2 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:

$$Y(t) = \exp\left\{\int_0^1 \ln y_i(t) di\right\}. \tag{5}$$

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

$$y_i(t) = \frac{Y(t)}{p_i(t)}. \tag{6}$$

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

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

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 Section 2.2.[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

$$mc_f(\tau, a, t) = \begin{cases} \frac{w(t)(1+\tau)}{a} & f \text{ is a private firm} \\ \frac{w(t)}{a} & f \text{ is a state-owned firm} \end{cases}, \tag{7}$$

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

$$\begin{aligned} L_{\mathcal{P}}(t) = \int_0^1 l_{Li}(t)di = \int_0^1 \frac{y_i(t)}{a_{Li}(t)}di = \int_0^1 \frac{Y(t)}{a_{Li}(t)p_i(t)}di = \int_0^1 \frac{Y(t)}{w(t)(1+\tau_{Fi}(t))\Delta a_i(t)}di \\ = \frac{Y(t)}{w(t)} \int_0^1 (1+\tau_{Fi}(t))^{-1} \Delta a_i(t)^{-1} di. \end{aligned} \tag{8}$$

Equation (8) and (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 out-

[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 B, I show that this model can be easily extended to include these potential differences. These extensions do not change the predictions of the model.

put is

$$Y(t) = A(t)\mathcal{M}(t)L_{\mathcal{P}}(t). \tag{9}$$

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

$$g_Y = g_A + \underbrace{g_{\mathcal{M}} + g_{L_{\mathcal{P}}}}_{=0}. \tag{10}$$

Appendix A.3 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 the 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]

3.3 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

[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 3.3 discusses this possibility in detail.

[10] Equation (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.

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 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

$$G_k(x, m, t) = m \frac{(1 + \tau_k) w(t)}{\phi_k} x^{\zeta},\ k \in \{P, S\}. \tag{11}$$

Notice that firms face the same factor market friction in both the production sector (Equation (7)) and the R&D sectors (Equation (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

[11] Section 5.4 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.

[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 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.

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 2.3, 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.

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

$$
\begin{aligned}
rV_P(n, \{\mu_i\}) = \dot{V}_P(n, \{\mu_i\}) + \sum_{i=1}^{n} \Big\{ \underbrace{\pi(\mu_i)}_{\text{flow profit}} + \underbrace{z[V_P(n-1, \{\mu_j\}_{j\neq i}) - V_P(n, \{\mu_i\})]}_{\text{business stolen by other's innovation}} \Big\} \\
+ \max_x \left\{ \underbrace{\sum_{i=1}^{n} x[\mathbb{E}_{\tilde{\mu}} V_P(n+1, \{\mu_i\} \cup \{\tilde{\mu}\}) - V_P(n, \{\mu_i\})]}_{\text{successful innovation}} - \underbrace{n\frac{(1+\tau)w}{\phi_P} x^{\zeta}}_{\text{innovation cost}} \right\},
\end{aligned} \tag{12}
$$

where $\{\mu_i\}, i = 1, ..., n$ are the markups the firm charges in each of its market, and z is the (endogenous) total innovation rate.

The value function (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

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

solve the following problem:

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

$$
+ \max_x \left\{ \sum_{i=1}^{m} x[\mathbb{E}_{\tilde{\mu}} V_S(n+1,m+1,\{\mu_i\} \cup \{\tilde{\mu}\}) - V_S(n,m,\{\mu_i\})] - m\frac{w}{\phi_S} x^{\zeta} \right\} \tag{13}
$$

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

The extra term

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

in (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 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. *Denote m the number of intermediate products in which firm k is the technology leader, then the value function (12) and (13) can be written as*

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

[14] The indicator function $\mathbb{1}\left[1+\tau > \lambda, \text{tech. leading}\right]$ 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.

where v_P, v_S are solutions to the problems

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

$\tilde{\pi}(\mu) = (1-\mu^{-1})$, 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 market leader even when a private firm acquires better technology through innovation. This is captured by the extra term $z_{P,x}\mathbb{1}\left[1+\tau > \lambda; \text{tech. leading}\right] v_S\left(\frac{\lambda}{1+\tau}\right)$.

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 $\mathbb{1}\left[\text{tech. leading}\right]$.

With the help of Lemma 1, I now calculate the optimal research intensity.

Proposition 1. *The optimal research intensity, x_k^* are given by*

$$x_k^* = \left(\frac{\phi_k \mathbb{E}_{\tilde{\mu}} v_k(\tilde{\mu})}{\zeta(1+\tau_k)\omega} \right)^{1/(\zeta-1)}. \tag{14}$$

Proof. See Appendix A.2 □

Proposition 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.

3.5 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 the entry barriers. 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

$$\max_x \left\{ x\mathbb{E}_{\tilde{\mu}}[pv_S(\tilde{\mu}) + (1-p)v_P(\tilde{\mu})] - \frac{(1+\tau)\omega}{\phi_\epsilon} x^\zeta \right\}. \tag{15}$$

Problem (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).

3.6 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 (7). Therefore, the markup can be pinned down my 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. Therefore, 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 (7) implies

$$\mu_{PP} = \mu_{SS} = \lambda, \quad \mu_{PS} = \frac{\lambda}{1+\tau}, \quad \mu_{SP} = \lambda(1+\tau). \tag{16}$$

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

$$\mu_{PPP} = \lambda, \mu_{PPS} = \frac{\lambda^2}{1+\tau}, \mu_{PS} = \frac{1+\tau}{\lambda}, \mu_{SPP} = \lambda(1+\tau), \mu_{SPS} = \lambda^2, \mu_{SS} = \lambda. \tag{17}$$

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

$$\begin{aligned}
\dot{S}_{PP} &= \underbrace{((S_{PP}+S_{PS})x_P + (1-p)x_\epsilon)(S_{PP}+S_{PS})}_{PP-\text{match created}} \quad - \quad \underbrace{zS_{PP}}_{PP-\text{match destroyed}} \\
\dot{S}_{PS} &= ((S_{SP}+S_{SS})x_P + (1-p)x_\epsilon)(S_{SP}+S_{SS}) - zS_{PS} \\
\dot{S}_{SP} &= ((S_{PP}+S_{PS})x_S + px_\epsilon)(S_{PP}+S_{PS}) - zS_{SP} \\
\dot{S}_{SS} &= ((S_{SP}+S_{SS})x_S + px_\epsilon)(S_{SP}+S_{SS}) - zS_{SP}.
\end{aligned} \tag{18}$$

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

The intuition behind equation (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.

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

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

$$\begin{aligned}
\dot{S}_{PPP} &= (S_{PPP} + S_{PPS})(S_{PP}x_P + (1-p)x_\epsilon) - zS_{PPP} \\
\dot{S}_{PPS} &= S_{PS}(S_{PP}x_P + (1-p)x_\epsilon) - zS_{PPP} \\
\dot{S}_{PS} &= (S_{SPS} + S_{SS} + S_{SPP})(S_{PP}x_P + (1-p)x_\epsilon) - zS_{PS} \\
\dot{S}_{SPP} &= (S_{PPP} + S_{PPS})((S_{SP} + S_{SS})x_S + px_\epsilon) - zS_{SPP} \\
\dot{S}_{SPS} &= S_{PS}((S_{SP} + S_{SS})x_S + px_\epsilon) - zS_{SPS} \\
\dot{S}_{SS} &= ((S_{SP} + S_{SS})x_S + px_\epsilon)(S_{SP} + S_{SS}) - zS_{SP}.
\end{aligned} \tag{19}$$

There are two differences between (18) and (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 (19) has the same intuition as in (18).

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

Proposition 2. *There exists unique BGP where*

1. *firms choose innovation intensity optimally according to (14)*
2. *entrants choose innovation intensity optimally according to (15)*
3. *the household maximizes utility according to (1)*
4. *the goods market and labor market clear as per (3) and (4)*
5. *the markup distribution is stationary, i.e.* $\dot{\mathbf{S}} = 0$

Proof. See Lentz and Mortensen (2008) and Appendix A.4 □

Finally, Proposition 3 summarizes the growth rate along the BGP of this economy.

Proposition 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, x_ϵ^* is given by (15), and F_k is the number of type k firms that are actively engaging in R&D activities:

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

Proof. See Appendix A.5. □

Proposition 3 states that the total innovation output equals to the sum of incumbent firms and entrants' innovation output.

3.7 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.

[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.

The introduction of τ leads to misallocation of labor within the R&D sector. Proposition 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 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.

3.8 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*

[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).

economy. The consumption-equivalence change, γ, is given by

$$U(\gamma C_S, g_S) = U(C_{LF}, g_{LF}), \tag{20}$$

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) 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). $\gamma > 1$ implies the household in the state capitalism economy has a lower life-time utility level.

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.6, 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.

4 Quantitative Exercise

I now structurally estimate this model using Chinese firm-level data. This section describes the data (Section 4.1), the mapping between my model and the data (Section 4.2), and the estimation procedure (Section 4.3). The next section reports the results from this exercise.

[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.

4.1 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.

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.

[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: 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 reports the summary statistics and the moments from ASIE data. Three observations 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. Finally, 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 4.2 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 productivity (TFP) growth than private firms. These statistics hint at the relative inefficiency of state-owned R&D.

4.2 Calibration

I need to calibrate 9 parameters in the model: the discount rate and the elasticity of intertemporal substitution (ρ, θ), 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 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, total R&D 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

Table 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

firms/entrants relative to the private firms. Section 5.4 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 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

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

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 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. On expectation, this effect depends on the equilibrium firm type distribution.

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

$$\ln TFPR_{ficrt} = \beta_1 \cdot age_{ficrt} + \beta_2 \cdot age^2_{ficrt} + \gamma_{icrt} + u_{ficrt}, \tag{21}$$

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 (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.

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 5.4 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 inflating 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.

4.3 Estimation Procedure

To calibrate moments in Panel (c) of Table 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.

[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 given this distribution. In each iteration, it updates F using the law of motion (18) or (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.

5 Results

This section reports the results of my quantitative exercise. Section 5.1 presents the parameter estimates of the baseline model. Section 5.2 discusses the growth and welfare implications of the factor market wedge. I also investigate the quantitative importance of the dynamic verses static distortions. Finally, I show distortions to R&D incentives via competition is necessary to generate the welfare loss. Section 5.3 shows the fit of the model. Section 5.4 consists of various robustness and sensitivity tests. Finally, Section 5.5 estimates two extensions of the model. I show these extensions lead to similar results as the baseline model.

5.1 Parameter Estimates

Table 3 reports the parameter estimates using the baseline model and procedure described in Section 4.3.

Table 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)

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.

5.2 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 4 reports the endogenous innovation intensities and welfare implications from the calibrated model. Consistent with Proposition 1 and the estimates reported in Table 3, panel (a) of Table 4 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 4 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 4 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 4: 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 the laissez-faire economy	
g_Y	loss in growth rate (95% CI)	(0.7, 1.5)
γ	cons. equiv. change (95% CI)	(115.9%, 136.8%)

Panel (a) reports the values of endogenous variables from the estimated baseline model (Table 3). Standard errors in panel (a) are calculated from running the estimation procedure on 500 bootstrapped samples. Panel (b) reports the 95% confidence interval of welfare loss when compared the baseline model with a *laissez-faire* economy in which both types of firms are subjected to τ. The confidence intervals in panel (b) are also calculating using the 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 according to

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

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.[23]

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

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

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 5 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).[24]

[23]Results from this decomposition exercise does not change if I measure use consumption-equivalent 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 $\frac{A_{LF}\mathcal{M}_{LF}-A_S\mathcal{M}_S}{A_{LF}\mathcal{M}_{LF}}$ 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 $\frac{A_{LF}\mathcal{M}_{LF}-A_S\mathcal{M}_S}{A_{LF}\mathcal{M}_{LF}}$ lead to similar results.

[24]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

Table 5: Static and Dynamic Loss

	growth loss	welfare loss
total loss (γ)	(0.7, 1.5)	(17%, 34%)
dynamic loss ($\gamma^{dynamics}$)	(0.7, 1.5)	(14%, 32%)
static loss $\left(\frac{A_{LF}\mathcal{M}_{LF}-A_S\mathcal{M}_S}{A_{LF}\mathcal{M}_{LF}}\right)$	(0.0, 0.0)	(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 4. "total loss" replicates the total growth and welfare losses from Table 4. "dynamic loss" reports loss from R&D misallocation. "static loss" reports loss from production misallocation.

Production and R&D Wedges 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 4. I then construct economies in which 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

limited heterogeneity results in a smaller estimate of the static inefficiency in my model.

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.[25] 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.

Results in Table 6 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

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

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

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.

Table 6: Production and R&D wedges

economy	growth loss	welfare loss
baseline	(0.7, 1.5)	(17%, 34%)
production wedge only	(0.3, 0.6)	(6%, 10%)
R&D wedge only	(0.0, 0.0)	(0%, 1%)
interaction effect	(0.3, 0.9)	(10%, 23%)

This table reports the 95% confidence interval of growth and welfare loss. The loss are calculated based on the baseline estimates reported in Table 4. "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.

5.3 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 7 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.[26] Nevertheless, the model successfully

[26]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).

reproduces the active business dynamism among Chinese manufacturing firms through the large employment share among entrants and high exit rates for incumbent firms.

Table 7: 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.

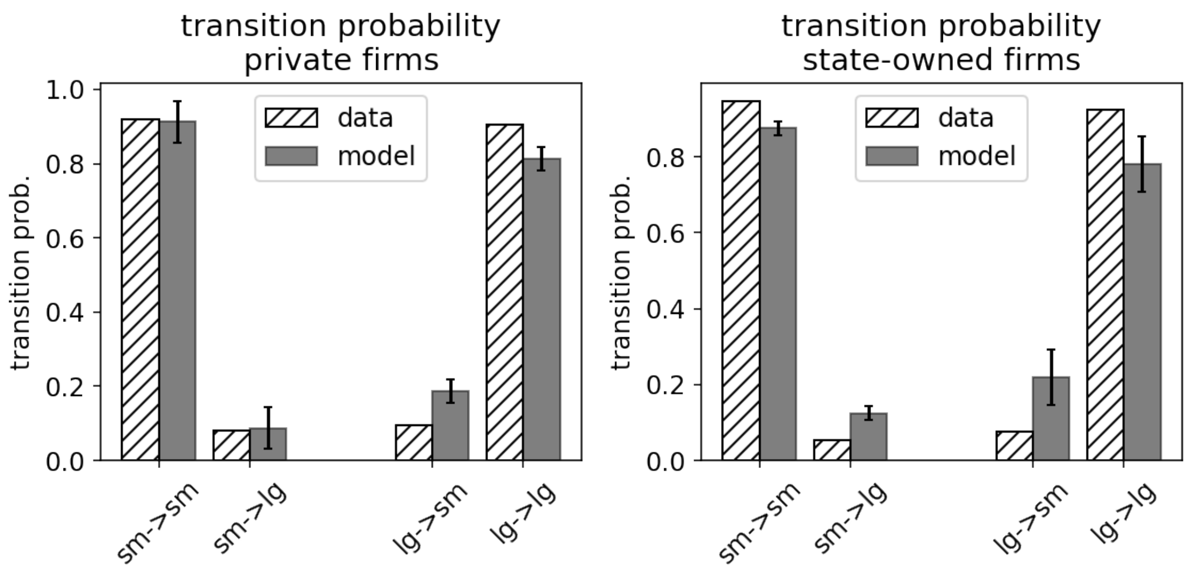
Non-targeted Moments I take advantage of the panel dimension of ASIE, and use various non-targeted moments to assess the model's ability to replicate the observed firm dynamics. Overall speaking, my baseline model successfully replicates the observed patterns in the Chinese firm-level data without explicitly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

Figure 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 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.

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 3 reports the results from

Figure 2: Transition Probability for State-owned and Private Firms



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 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 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 7. 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.

Figure 3: Survival Probability for 1999 and 2002 Entering Cohorts

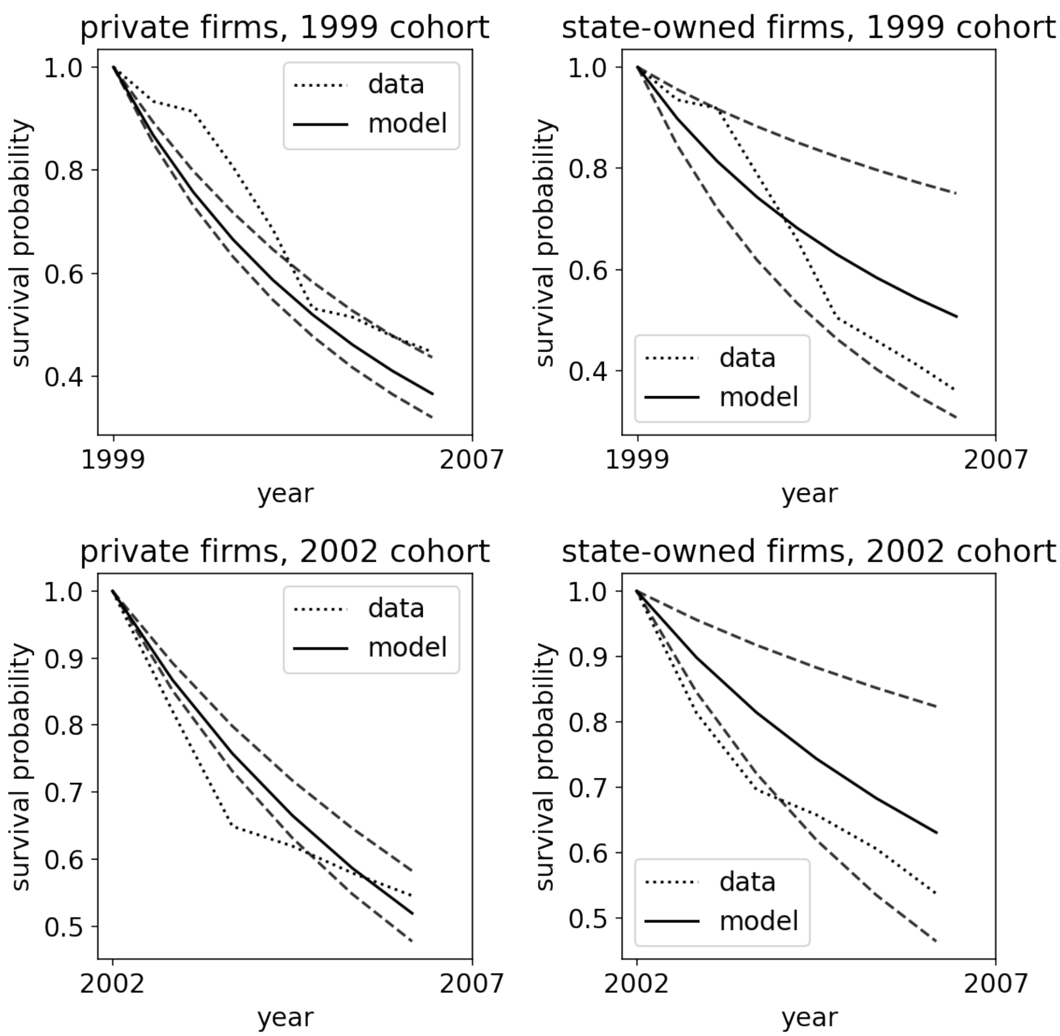
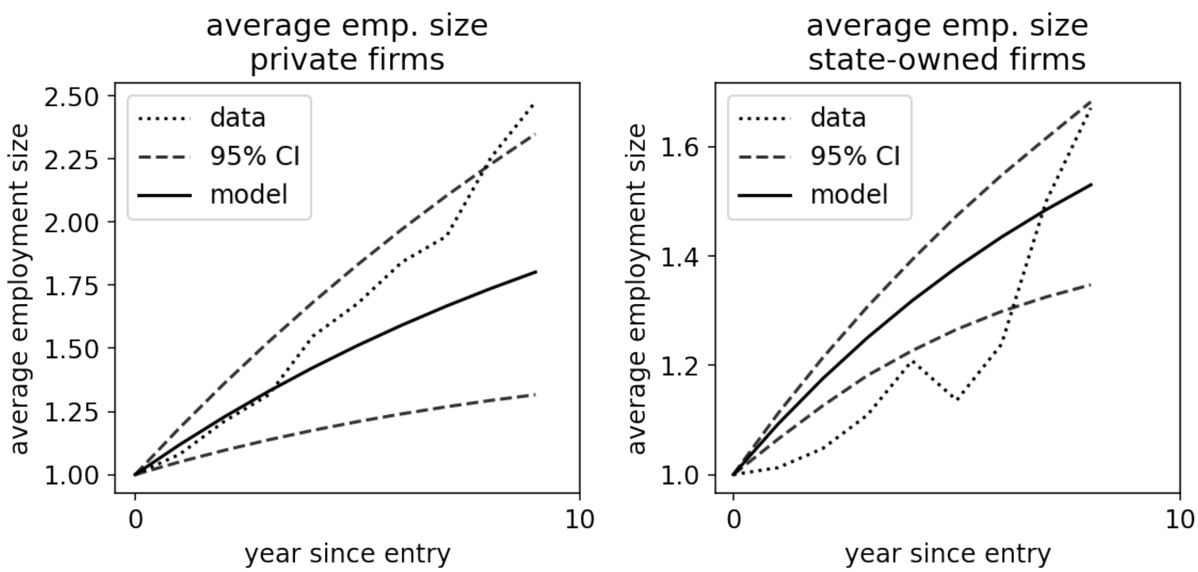


Figure 4: Employment Growth for Continuing Firms



5.4 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 8 reports the results of fitting the model with alternative TFP measure. Panel (a) of the table replicates the baseline estimates reported in Table 4. 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 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)	(0.7, 1.5)	(113%, 137%)
panel (b) using Olley and Pakes (1996)						
1	0.28 (0.04)	0.63 (0.10)	1.17 (0.02)	1.23 (0.03)	(0.6, 1.8)	(110%, 138%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4. Panel (b) reports the parameter estimates and welfare using Olley and Pakes (1996) method to calculate TFP growth. Bootstrapped standard errors 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.

[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.

Panel (b) of Table 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.

Table 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)	(0.7, 1.5)	(113%, 137%)
			panel (b) innovating subsample			
1	0.17 (0.02)	0.45 (0.05)	1.13 (0.01)	1.25 (0.04)	(0.7, 1.7)	(127%, 148%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4. Panel (b) reports the parameters and welfare estimated from a subsample of self-reported innovating firms. Bootstrapped standard errors 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 2.

Table 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.

Table 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)	(0.7, 1.5)	(113%, 137%)
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)	(0.5, 1.5)	(107%, 123%)
panel (c) lower IES ($\theta = 3$)						
1	0.30 (0.06)	0.69 (0.12)	1.16 (0.02)	1.22 (0.04)	(0.3, 1.3)	(107%, 122%)
panel (d) larger curvature ($\zeta = 2$)						
1	0.23 (0.06)	0.53 (0.09)	1.13 (0.01)	1.22 (0.05)	(1.0, 1.7)	(125%, 144%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4. 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 are reported in parentheses.

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 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 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)	(0.7, 1.5)	(113%, 137%)
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)	(1.3, 1.5)	(130%, 134%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4. Panel (b) reports the parameters and welfare estimated using the alternative normalization $\lambda = 1.132$. Bootstrapped standard errors are reported in parentheses.

Sensitivity to τ Section 4.2 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 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. 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 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

[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).

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 5 as the target moment for estimating the private market friction τ. Table 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.

[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.

Figure 5: log TFPR differences between private and other types of firms

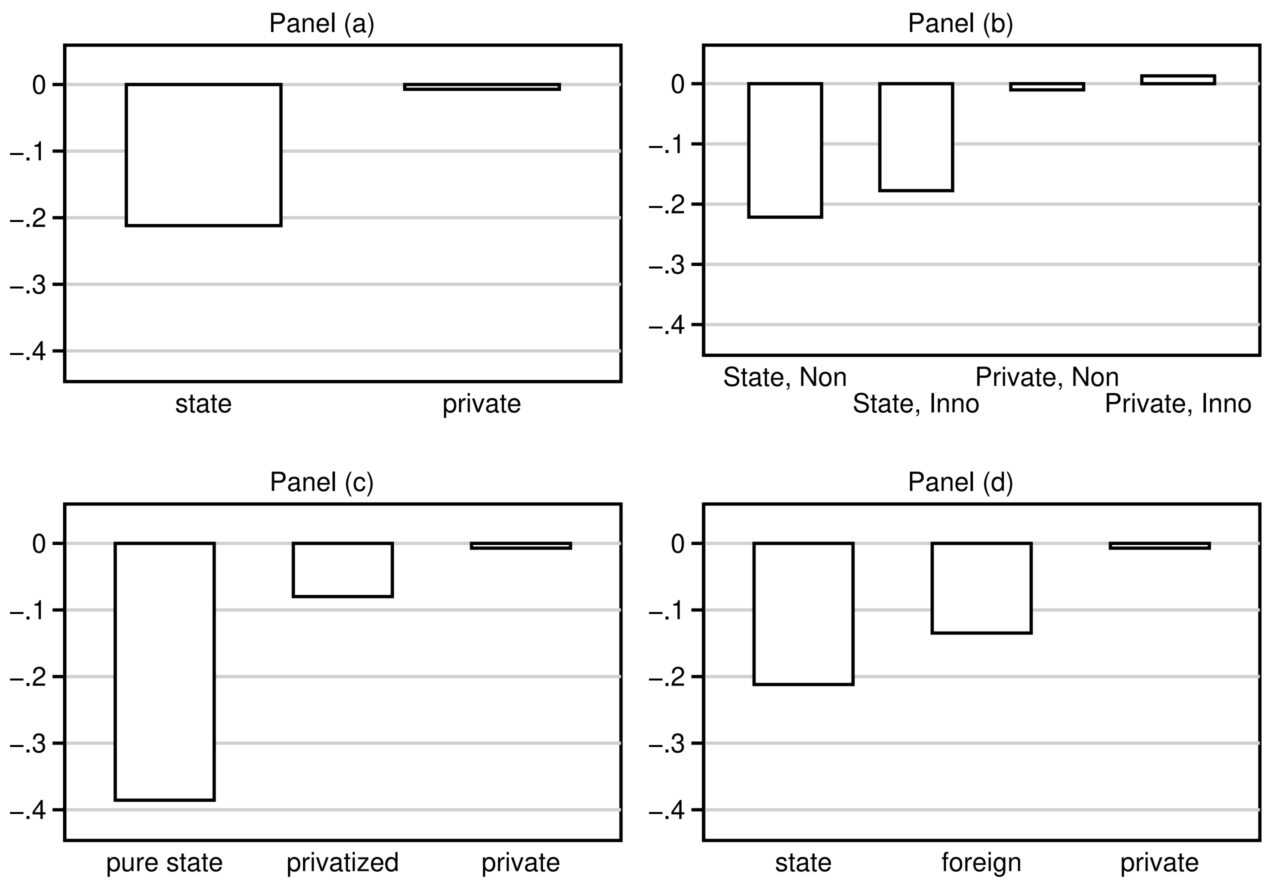


Table 12: Sensitivity to the Calibrated Factor Market Wedge

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)	(0.7, 1.5)	(113%, 137%)
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)	(0.2, 0.4)	(105%, 110%)
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)	(0.3, 0.5)	(107%, 113%)
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)	(0.2, 0.3)	(105%, 108%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4. 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 are reported in parentheses.

5.5 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] 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

[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.

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 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.

Table 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	(0.7, 1.5)	(113%, 137%)
panel (b) extension: exogenous destruction								
1	0.40 (0.07)	0.43 (0.02)	1.15 (0.01)	1.22 (0.03)	1%	8%	(1.8, 2.5)	(144%, 165%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4. Panel (b) estimates the extended model with exogenous destruction. Bootstrapped standard errors are reported in parentheses.

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. Since the state-owned firms are more efficient in innovation, 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, resulting in 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-owned-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 14 reports the results from this exercise.

Table 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)	(0.7, 1.5)	(113%, 137%)
			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)	(0.7, 1.3)	(117%, 134%)

Panel (a) replicates the results from the baseline model in Table 3 and Table 4 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 are reported in parentheses.

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.

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 3.8 and Appendix A.6 discuss the theoretical possibility that such privilege can be conductive to growth. Specifically, state-owned firms' privileged factor market access can be thought as a subsidy that incentivizes them to innovate more. Since there is under-investment in R&D, this subsidy may increase total innovation, thus improve welfare. 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 4. 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 6 and 7 plot the results from such exercises.

Figure 6: Productivity Loss under Counterfactual ϕ_S

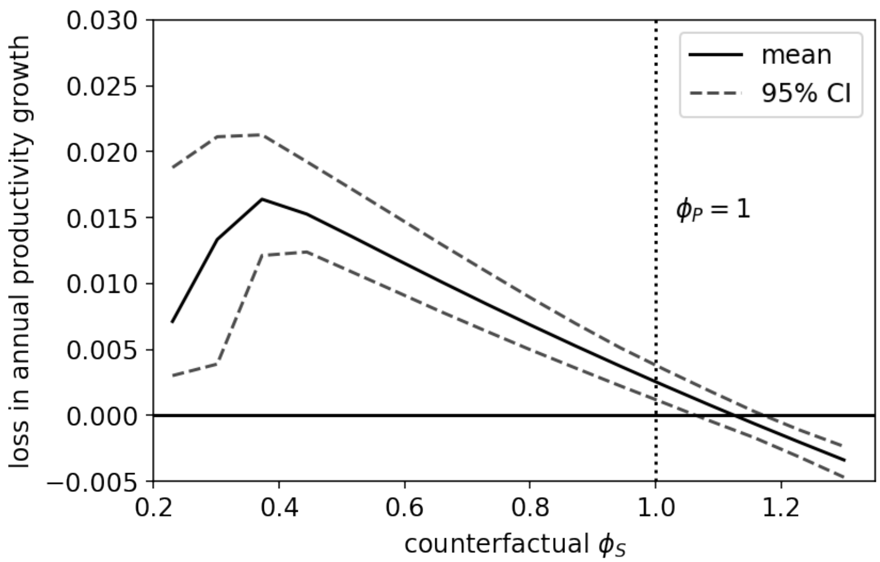
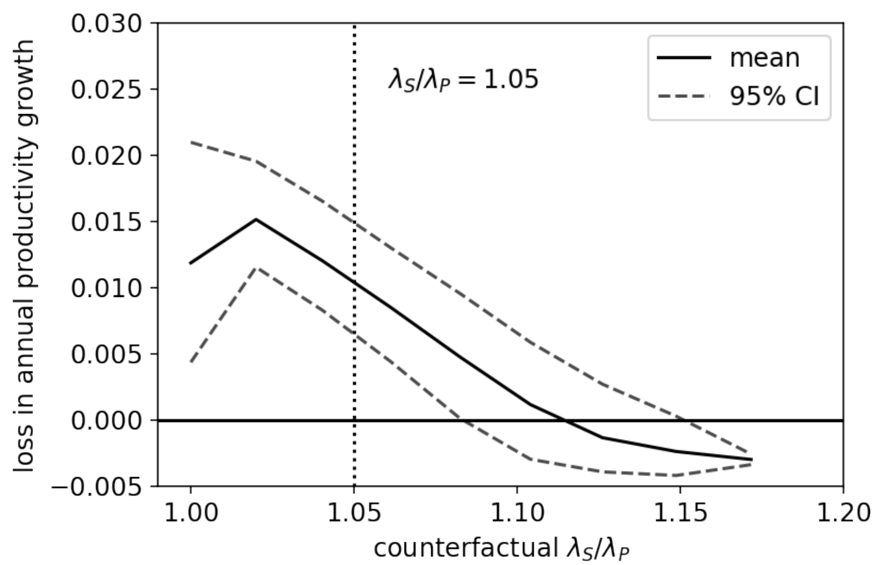


Figure 6 plots the growth loss from state-owned privilege against the counterfactual level of state-owned innovative capacity ϕ_S. There is an inverted-U relationship between ϕ_S and the growth loss. The loss first increases as ϕ_S increases from 0.2 to around 0.6, and then decreases as ϕ_S increases 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. 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.

Figure 7: Productivity Loss under Counterfactual λ_S



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 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 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.

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.

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Appendix

A Proof of Results in the Main Text

A.1 Proof to Lemma 1

Start with the value function (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.

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

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

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

Finally, the cost function, $G_P(x, n)$, is also linear in its last argument, n, as suggested by Equation (11). Together, I have

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

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

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

Similarly, for the value function of state-owned firms (13), conjecture $V_S(n, m, \{\mu_i\}) = Y \sum_i v_S(\mu_i)$. Note that

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

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

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

Move v_k in Equation (A.4) and (A.6) to the left gives the equations in Lemma 1. This concludes the proof for Lemma 1.

A.2 Proof to Proposition 1

Lemma 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.

A.3 $\mathcal{M}(t)$ and $L_{\mathcal{P}}(t)$ are constant on BGP

Recall that

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

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.

A.4 Proof to Proposition 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).

A.5 Proof to Proposition 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 3.

For the second part of Proposition 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 3.6, 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 3.

A.6 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 lassiez-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 life-time 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 (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.

B 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 3.

B.1 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

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

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

$$\begin{cases} \mu_{PP} = \mu_{SS} = \lambda, \mu_{PS} = \lambda\frac{1-\tau_y}{1+\tau}, \mu_{SP} = \lambda\frac{1+\tau}{1-\tau_y}; & \text{if } 1+\tau < \lambda \\ \mu_{PPP} = \lambda, \mu_{PPS} = \frac{\lambda^2}{(1+\tau)/(1-\tau_y)}, \mu_{PS} = \frac{(1+\tau)/(1-\tau_y)}{\lambda}, \mu_{SPP} = \lambda\frac{1+\tau}{1-\tau_y}, \mu_{SPS} = \lambda^2, \mu_{SS} = \lambda; & \text{o/w} \end{cases}.$$

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 (16) and (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.

B.2 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:

$$y_{f,i}(t) = a_{f,i}(t)\theta_f l_{f,i}(t), \tag{B.2}$$

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

$$mc_{f,i}(\tau, \theta_f, a, t) = \begin{cases} \frac{w(t)(1+\tau)}{a\theta_P} & f \text{ is a private firm} \\ \frac{w(t)}{a\theta_S} & f \text{ is a state-owned firm} \end{cases}. \tag{B.3}$$

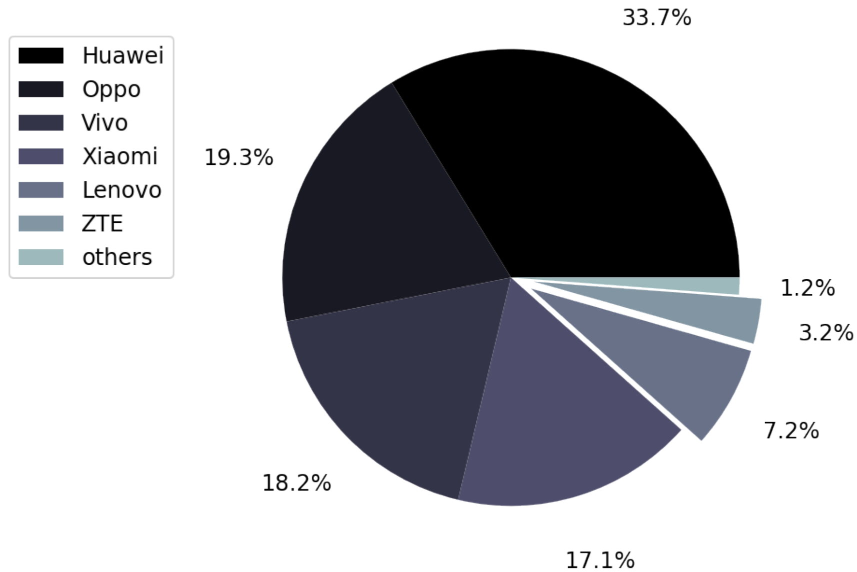
In this setting, the markups μ_{jkl} are given by

$$\begin{cases} \mu_{PP} = \mu_{SS} = \lambda, \mu_{PS} = \frac{\lambda}{(1+\tau)(\theta_S/\theta_P)}, \mu_{SP} = \lambda(1+\tau)\frac{\theta_S}{\theta_P}; & \text{if } \lambda > 1+\tau \\ \mu_{PPP} = \lambda, \mu_{PPS} = \frac{\lambda^2}{(1+\tau)(\theta_S/\theta_P)}, \mu_{PS} = \frac{(1+\tau)(\theta_S/\theta_P)}{\lambda}, \mu_{SPP} = \lambda(1+\tau)\frac{\theta_S}{\theta_P}, \mu_{SPS} = \lambda^2, \mu_{SS} = \lambda; & \text{o/w} \end{cases}.$$

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 (16) and (17). Again, instead of being the factor market wedge, the estimates $\hat{\check{\tau}}$ is the processing efficiency adjusted market friction.

C Additional Figures and Tables

Figure C.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 C.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 emp.	0.044***			0.492***
	(0.00)			(0.00)
log va		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 C.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 va	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