DSSR

Discussion Paper No. 137

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October, 2023

Data Science and Service Research
Discussion Paper

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Agglomeration and Selection Effects in Privatized-SOEs: The Role of SOE Reforms*

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October 25, 2023

Abstract

While privatizing state-owned enterprises (SOE) has been a global trend, its success as an economic policy remains controversial. Focusing on agglomeration and selection effects in firms with different types of ownership, we examine the impact of SOE privatization on firm productivity and how these effects alter during the SOE privatization process. We first show that both Always-private-owned enterprises, or *Always-POEs*, and *Always-SOEs* benefit from marked agglomeration effects, highlighting the extensive influence of urban concentration. However, the positive selection effects are present only among *Always-POEs*; privatized firms only marginally benefited from selection effects after SOE privatization. Moreover, while proximity to the government may be advantageous for improving productivity during their state-owned tenure, it can become an inhibitor after privatization.

Keywords: Agglomeration Effect, Selection Effect, Productivity, Privatization, Government Ties
JEL Classification: D24, O18, O47, P25

*An earlier version of this paper was circulated under the title ''Privatization's Influence on Agglomeration and Selection Effects: Evidence from China's Manufacturing Industry" (July 2022)

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1 Introduction

Privatizing public enterprises has been a global trend. While China's approach, marked by its caution and gradualism, stands out due to its magnitude and scope (Estrin and Pelletier, 2018), evidence suggests that privatized state-owned enterprises (SOEs) rarely catch up with private firms (Boardman et al., 2016). Therefore, minimizing the negative effect of possible shocks in the early stages of the privatization process and quickly reaping the outcomes of reforms are vital considerations for the government in implementing reforms. This study emphasizes that agglomeration economies and market selection can help address the challenges faced by privatized SOEs.[1] Specifically, we are motivated by the following three questions: 1) Are there agglomeration and selection effects among SOEs and private enterprises? 2) Does the SOE reform influence the enterprise's agglomeration and selection effect? 3) To what extent is this influence affected by the local government?

To address the first and second questions, we estimate the differentials in agglomeration and selection effects between large and small cities for privatized SOEs using a quantile specification proposed by Combes et al. (2012) and micro-data on Chinese manufacturing firms. An appropriate benchmark is required to validate our results to control the disturbance from changes in regulatory conditions, and other factors that impact agglomeration and selection effects during the SOEs' reform. For this, we follow Boardman et al. (2016) to demonstrate the unique behavior of privatized SOEs by constructing five comparable firm groups by ownership type: *Always-SOEs*, *Always-COEs*, *Always-POEs*, *SPs*, and *CPs*. *COE* and *POE* are the abbreviations for collective- and private-owned enterprises, respectively. The prefix *Always-* denotes firms whose ownership does not change during the sample period. *SPs* are firms where ownership changes from state- to private-owned. *CPs* are firms where ownership changes from

[1] Studies (Syverson, 2004; Marshall, 2009) demonstrate that firms in large cities consistently outperform those in smaller cities, which can be attributed to the inherent advantages of agglomeration. This urban-centric advantage suggests that privatizing SOEs in densely populated urban areas can be a strategic move to counteract potential vulnerabilities, especially during the initial phases of privatization, by tapping into positive externalities. Furthermore, the intense market competition in urban areas can push firms to enhance productivity and eliminate underperforming entities, ensuring that the remaining privatized SOEs are likely to improve overall productivity.

collective to private ownership.[2]

The third question arises from the notable change in the relationship between SOEs and the government before and after privatization. In the pre-privatization phase, the government's role in appointing SOE managers provides these enterprises with preferential access to resources, industry licenses, and bank credit (Faccio, 2010). However, this privilege often dissipates after privatization. Hayek (1945), Aghion and Tirole (1997), and Huang et al. (2017) advocated bolstering SOEs' interactions with the government, leveraging local information to drive performance improvements. Echoing this sentiment, we posit that the tight relationship between SOEs and the government becomes a linchpin for them to obtain agglomeration benefits while simultaneously sidestepping market-driven selection pressures. Interestingly, these benefits are absorbed with increased geographic separation from the government. Huang et al. (2017) underscored that proximity to the oversight government is crucial to ensure the ready availability of local insights. Similarly, Duchin et al. (2020) used the geographic distance between collective firms and local governments to explore the role of government involvement since the distance is largely exogenous due to the adjustment costs associated with relocating the firms. Building on this premise, we use the physical distance to classify our sample into distinct sub-groups, and our subsequent analyses quantify each subgroup's agglomeration and selection impacts.

We make four contributions by extending previous empirical works using a similar quantile approach (Arimoto et al., 2014; Accetturo et al., 2018; Ding and Niu, 2019; Adachi et al., 2021). First, we focus on Chinese SOEs and compare their agglomeration and selection effects with those of firms with different ownership types. This differs from studies (Ding and Niu, 2019), which investigated the heterogeneity among different industries. Second, while research focuses on the static nature of these effects (see Section 2), we study the role played by agglomeration and selection effects during the ownership transition period. The salient drop in general agglomeration benefits from pre- to post-privatized SOEs implies an adverse

[2]Section 3.2 elaborates the definition of each group.

impact of privatization in the short term. In contrast, the gradually increasing agglomeration, which only benefits productive reformed SOEs, has a positive impact. This empirical evidence enriches existing research on agglomeration effects and partially explains why privatized firms struggle to improve productivity in the short term. Third, we use nightlight satellite data to proxy city density, which differs from Ding and Niu (2019), who used population or population density. As indicated by Duranton and Puga (2020), nightlight data can measure crowding more directly. Finally, based on the oversight agency conjecture (Hayek, 1945) that governments have the motivation to decentralize distant SOEs, we study if SOEs with fewer ex-ante government connections suffer less from the loss of agglomeration effects during the transition period.

The remainder of this article is organized as follows. Section 2 reviews the literature on industrial agglomeration and selection effects. Section 3 describes our data. The theoretical model and empirical results of the various specifications for pre- and post-privatization for different groups are explained and discussed in Section 4. Section 5 conducts robustness checks. Finally, Section 6 presents the conclusions of this study.

2 Literature Review and Hypothesis Development

2.1 Agglomeration and Selection Effects

Large cities consistently attract more firms, and exhibit higher productivity and innovation than their smaller counterparts (Puga, 2010; Naz et al., 2015). A key reason is the advantages of aggregation, which encapsulates the trade-offs between increasing returns and costs of urban congestion (Marshall, 2009). Urban productivity also increases due to the selection effect. This mechanism removes inefficient "zombie" firms from the market, thereby enhancing overall productivity (Melitz, 2003; Melitz and Ottaviano, 2008; Combes et al., 2012). Besides their dwindling productivity, these firms occupy crucial market spaces, often thwarting private investments and genuine competition (Lam et al., 2017).

Agglomeration and selection operate through distinct channels while helping elevate average productivity. Agglomeration promotes productivity through shared resources, optimized matches, and knowledge dissemination; meanwhile, the selection process realigns market resources, ensuring dominant roles for efficient firms, fostering competitive dynamism, and contributing to aggregate productivity (Melitz, 2003; Melitz and Ottaviano, 2008). Moreover, Combes et al. (2012) argued that the synergy of agglomeration and selection manifests itself in a unique productivity distribution in larger cities: while agglomeration influences the mean and upper parts of this distribution, selection targets its bottom rungs, ensuring that urban productivity remains dynamic and efficient.

Several studies compare the magnitude of agglomeration advantages and selection gains. Some find that firm selection outweighs agglomeration in the Chilean food industry (Saito and Gopinath, 2009) and Japanese silk-reeling industry (Arimoto et al., 2014). In contrast, others find that productivity improvement is primarily due to agglomeration. Combes et al. (2012) developed a theoretical model and used a quantile regression to estimate the differentials in agglomeration and selection effects between large and small cities. Using data from French industries, the authors found that the selection process could not explain spatial productivity differences. Applying a similar model to Italian manufacturing firms, Accetturo et al. (2018) showed that while agglomeration effects play a significant role, the importance of the selection effect also increases in several sectors. Ding and Niu (2019) used the same method to examine China's manufacturing and construction industries, and reported strong evidence for the agglomeration effect, while the selection effect contributed less to productivity.

On SOEs, some researchers emphasized the growth-driving role of state capitalism, such as balancing social stability and economic performance (Bai et al., 2006). Meanwhile, others criticized their inefficiencies arising from policy burdens, agency problems, and monopolistic privileges (Xu et al., 2005; Liu and Zhang, 2018; Zhang et al., 2020). These arguments suggest that SOEs can enjoy agglomeration effects, given that their close ties with the state could attract resources, talent, and knowledge concentration. However, state protection can hinder the natural evolution of market forces. Instead of fostering a competitive environment where the most efficient thrive, these conditions may preserve and even protect many inefficient "zombie" firms, allowing them to linger despite their non-competitive performance (Chang et al., 2021). Thus, we propose the following hypotheses on the first question:

Hypothesis 1: *Both Always-POEs and Always-SOEs enjoy significant agglomeration effects.*

Hypothesis 2: *Always-POEs enjoy significantly positive selection effects, while Always-SOEs do not.*

2.2 Privatization and Firm Productivity in China

China initiated SOE privatization in the mid-1990s, although economic reforms started in 1979 (Bai et al., 2006). SOEs mainly rely on central and local governments. A hallmark of privatized SOEs is their diminished political ties, which is crucial in societies with frail institutional structures (Huang et al., 2019). Studies on government ties indicate that SOE managers maintain stronger governmental connections than their non-SOE counterparts (Li et al., 2011). Through an extensive meta-analysis, Luo et al. (2012) found that government relationships are more vital for SOEs. These ties provide SOEs with financial benefits, improved regulatory understanding, richer information, and specialized protection (Guo and Miller, 2010; Luo et al., 2012). These benefits shape the agglomeration effect. A key component of this effect is knowledge spillover, especially tacit knowledge (Howells, 2002). Therefore, the proximity of SOEs to local governments fosters rapid information exchange. Moreover, Huang et al. (2017) highlighted a distance-decay effect: SOEs distant from government centers tend to be more decentralized and face financial constraints.

Furthermore, firms with different types of ownership generally may not experience information exchange and technological diffusion (Zhu et al., 2019). Cognitive proximity and technological relatedness can explain this because SOEs and non-SOEs are subject to various operating codes and confront distinct threats and opportunities (Peng et al., 2004; Liao, 2015). Therefore, one may reasonably assume that after privatization, SOEs enjoy fewer agglomeration benefits from local governments. Meanwhile, Zhu et al. (2020) suggested that compared to *Always-SOEs*, reformed SOEs benefit more from knowledge spillovers from non-SOEs. This beneficial effect amplifies year by year after SOEs successfully transition and redefine their identities. Such knowledge spillovers can be a critical component of agglomeration effects, as they can foster innovation and improve business processes and overall productivity. However, realizing these benefits and the resultant growth in agglomeration effects for privatized SOEs heavily depends on the ability of their workforce to adapt and efficiently incorporate this new knowledge. Thus, the magnitude of the agglomeration effect observed after privatization is intrinsically tied to the efficiency and adaptability of SOEs' employees. Accordingly, we propose the following hypotheses to explore our second and third questions regarding agglomeration effects:

Hypothesis 3: *SOEs' reform negatively influences the agglomeration effect.*

Hypothesis 4: *The post-privatization change in the agglomeration effect is associated with the firm's relationship with the government.*

Compared with the agglomeration effect, the evolving selection effect for privatized SOEs is complex. While they might face selection stress as they assimilate into the private sector, the immediate implications for them may be obscure. Oi (2005) indicated that certain privatized firms are restricted from declaring bankruptcy. Boubakri et al. (2008) observed that privatized SOEs receive preferential treatment compared to native private firms. This suggests that the influence of the selection effect might differ between privatized SOEs and completely private enterprises. Given this background, we propose the following hypotheses to answer the second and third questions regarding selection effects:

Hypothesis 5: *SOEs' reform improves selection effects.*

Hypothesis 6: *The post-privatization change in the selection effects is associated with the firm's relationship with the government.*

3 Data

3.1 Firm Data

Our estimation of total factor productivity (TFP) extensively uses data from Chinese firms from 1998 to 2007. While three industries (mining, manufacturing, and public utilities) are included in the data set, we study only manufacturing firms because most sampled firms belong to this industry; moreover, the production behaviors of mining and public utilities differ. The Annual Survey of Industrial Firms Database (ASIF), maintained by the National Bureau of Statistics (NBS), covers all SOEs and non-SOEs with sales exceeding RMB 5 million in mainland China.[3] This data set has detailed information on firm balance sheets, income statements, and basic information, such as ownership, established time, and registration address.[4] After matching firms each year following the method proposed by Brandt et al. (2012), cleaning data, and extracting our basic sample according to Section 3.2, we obtain unbalanced panel data with 461,642 firms from 1998 to 2007 (1,653,782 observations in total) covering 28 two-digit manufacturing industries across 31 provinces and 287 prefecture-level cities. (Section 6 details how we obtain the basic sample, Figure B.1 displays the distribution of firms with dif-

[3] In the ASIF, a firm is defined as a legal unit. It means that a qualified subsidiary can be considered as another company and counted separately in the database. Fortunately, according to the Census, most sampled companies (96.6% in 2007) do not have subsidiaries (Brandt et al., 2014). Therefore, we can justifiably assume that an observation is a unique single-plant firm. In 2011, the designated size for non-state firms changed from RMB 5 million to 20 million.

[4] Table B.1 compares our original data set with that of Brandt et al. (2014). As the database has been reviewed several times (mainly to remove duplicate reports), the original data used here slightly differ from these authors' but are still very close to the statistics summarized in the Statistical Yearbook. The database has been updated until 2013 from 1998; however, the data after 2007 are generally considered debatable due to the small number of variables and large discrepancy with the Statistical Yearbook contents. Therefore, we only consider the period from 1998 to 2007.

ferent ownership every year, and Figure B.2 demonstrates the trends of employment, capital and value-added.)[5]

3.2 State-Owned and Private Firms

Many studies (Brandt et al., 2017; Khandelwal et al., 2013) find that Chinese SOEs have distinct operational characteristics that cannot be ignored. First, the production function and growth trajectory of SOEs differ from those of private firms. Second, because China is implementing large-scale SOE reforms during the sample period, the type of firm ownership is an important factor.

The ASIF reports the officially registered company structure but does not properly reflect the type of owner controlling the firm. This is because firms rarely modify their registration status even if the controlling shareholder changes (Dougherty et al., 2007). Instead, we examine the structure of the shareholding by capital share to understand the *de facto* firm owner. Following Dougherty et al. (2007), we define a firm as an SOE when it directly reports that it is held by the state. Among non-SOEs, COEs are those with a collective capital share greater than 50%, while the remainder are POEs.[6] Finally, we divide the firms into five categories based on changes in ultimate control. In line with Boardman et al. (2016), we extract groups of *Always-POEs*, *Always-SOEs*, and *Always-COEs*; these firms have no changes in ultimate control during our sample period. *SPs* refer to privatized firms that have changed from SOEs to POEs, while *CPs* are those that have transition from COEs to POEs. Overall, we focus

[5]China has four *de facto* tiers of local governance: provinces, prefecture-level cities, county-level cities, and townships. This article focuses on the second tier but includes four municipalities from the first tier (but without being broken into sub-areas): Beijing, Shanghai, Tianjin, and Chongqing. Henceforth, we collectively refer to them as "prefecture-level" cities.

[6]Private firms can be controlled by private companies (non-state legal persons), individuals, non-mainland agents, or other shareholders, depending on which capital exceeds 50%. 50% is a common threshold to distinguish controlling ownership, as seen in other studies (Liao et al., 2014). Unlike simply dividing firms into SOEs and non-SOEs, we also distinguish COEs. This is because compared with SOEs, COEs are viewed as a competitive organizational form with remarkable performance under China's partial reform; however, they still suffer from policy burdens and agency problems as local governments oversee them. However, many COEs transitioned from collective ownership to private ownership during the SOE reform period (Xia et al., 2009).

on firms whose ultimate control has never changed and those privatized only once; importantly, we exclude firms whose ownership has changed multiple times or those that have been nationalized.

3.3 The Distance from the Oversight Government

We regard SOEs' decentralization as losing agglomeration advantages because they can no longer leverage local information. Huang et al. (2017) used the physical distance between SOEs and the corresponding oversight governments to proxy the availability of local information exchange. This was based on Hayek (1945), who argued that one way to improve SOE performance is by taking advantage of local information when the government urges them to improve efficiency. Intuitively, firms may be able to access more local information when they are closer to local governments. This points to more relation-based government ties, strengthening the agglomeration advantages from the interaction between SOEs and government officials, and the inextricable connection among SOEs through the relationship with the government.

Thus, following Huang et al. (2017), we consider three levels of affiliation: central, provincial, and municipal governments. Using Google Maps API, we obtain each government's geolocation (WGS84). For the central level, we use the location of the China State Council. For others, we use the location of the People's governments of provinces and cities. We classify firms at each level from the smallest to the largest based on distance and compare the top 50% and bottom 50% (top-1/2 versus bottom-1/2), and top and bottom third (top-1/3 versus bottom-1/3). The geographically close and distant groups are denoted as C- and F-Groups, respectively.

3.4 Market Size

Market size is essential to measure the effects of agglomeration and selection in our setting. Two questions arise regarding this issue: the choice of the index (e.g., population, employment, or nightlight data) and spatial unit (e.g., provinces or cities). Agglomeration always occurs on a local scale. Therefore, we take the prefecture-level city as the spatial unit in our benchmark model.[7] Regarding the first question, instead of using population or employment data that are popularly used in previous studies (Ding and Niu, 2019), we employ nighttime light data to measure the market size; these data have been demonstrated to reflect and project the trajectory of urban development directly (Ma et al., 2012; Duranton and Puga, 2020). Chan (2007) stated that in many Chinese statistical publications, the the National Bureau of Statistics' (NBS) definition of urban areas — an average population density of at least 1,500 per sq km or contiguity of the built-up area — can be an appropriate criterion to reflect the *de facto* population density. This is because the population of a city administrative unit (*shi*) includes both an urbanized core and extensive rural areas (which are primarily agricultural areas and sometimes quite broad). Thus, using city (*shi*) population or population density is not ideal for the size or urbanization of the market. Meanwhile, the *hukou* system in China does not count workers who migrate from rural areas to urban centers. Therefore, using the *hukou* population of urban areas (labeled as *chengzhen renkou*) may underestimate the actual population. According to Chan (2007), approximately 150 million people in Chinese cities belong to this category in 2005. Therefore, remotely sensed nightlight datasets are more appropriate for measuring the market size. We use employment data as a proxy for urban population.[8]

[7] Provinces with low average population density also have densely-populated capital cities. Therefore, we use prefecture-level city data. Intuitively, the city boundaries may inhibit the impact of agglomeration caused by mutual interaction even within a province. As Puga (2010) noted, the agglomeration effect generally operates within restricted spatial boundaries. The indicators we use to classify cities are at the prefecture level, different from Ding and Niu (2019), who used local data. Hence, our results may differ, especially when identifying dilation effects.

[8] DMSP-OLS nighttime lights nighttime data are downloaded from `https://ngdc.noaa.gov/eog/download.html`. To verify the reliability of light brightness, we also use other measures of city size: the number of employees in the secondary industry (employment density) and population (population density) in urban areas (*shi xia qu*). These data are collected from city statistics yearbooks (Table A.1 presents the five main and last

3.5 Total Factor Productivity Estimation

Based on the standard Cobb–Douglas production function for firm i at time t, TFP can be estimated using: $\ln \mathrm{TFP}_{it} = \ln(\text{value-added})_{it} - \beta_{k,s}\ln(\text{Capital})_{it} - \beta_{l,s}\ln(\text{Labor})_{it}$. The coefficients are estimated by Equation (1) as follows:

$$\ln \mathrm{Y}_{isct} = \beta_{0,s} + \beta_{k,s}\ln X_{1,isct} + \beta_{l,s}\ln X_{2,isct} + \gamma_s + \theta_c + \mu_t + \varepsilon_{isct} \tag{1}$$

where Y, X_1, and X_2 stand for industrial value-added, capital, and labor, respectively. s and c denote industry and city, respectively. γ_s, θ_c, and μ_t represent industry, city, and time effects, respectively. We calculate TFP for firms by the Olley-Pakes (OP) method on an industry-by-industry basis (Olley and Pakes, 1992). Table 1 presents the descriptive statistics for the key variables by subgroups.

[TABLE 1 about here.]

4 Methodology

4.1 Agglomeration, Selection, and Dilation Effects

Based on the firm data and estimated TFP, we investigate the discrepancies between firms in large and small cities by identifying agglomeration, dilation, and selection effects; these effects can improve productivity through various channels (Combes et al., 2012).[9]

Agglomeration effect (A_i): Each worker is more productive in large cities by interacting with each other, represented as $A_i = ln[a(N_i + \delta \sum_{i \neq i} N_j)]$, where δ is a decay parameter and N_i is the size of city i.[10]

cities according to different criteria).

[9]STATA codes are based on Kondo (2017), who also elaborated on the correctness of the estimation process.

[10]$\delta \in [0,1]$ $\delta = 0$ means that workers in city i can only interact with people in the same place. $\delta = 1$ means that workers enjoy interactions with workers from everywhere with the same intensity; in this case, the dilation or agglomeration effects between cities do not differ: $D_i = D_j$, $A_i = A_j$

Dilation effect (D_i): Workers are more productive when they work for a more efficient firm, expressed as $D_i = ln[d(N_i + \delta \sum_{i \neq i} N_j)]$. Then, $\phi_i(h) = A_i - D_i ln(h)$ where h stands for labor requirement per output (or marginal cost); a higher h means lower productivity ϕ_i. This effect suggests that the benefits of agglomeration are also related to individual productivity and not just to city size.

Selection effect (S_i): This effect is estimated as the probability that a firm will exit the local market. It is represented as $S_i = 1 - G(\bar{h}_i)$,[11] where $G(.)$ is the cumulative density function (CDF) from which a firm randomly draws its h and is assumed to be the same across cities; and $\bar{h}$ is the price threshold such that only firms with $h \leq \bar{h}$ can sell their products.[12] We can easily understand that a lower $\bar{h_i}$ (higher ϕ_i) leads to a higher S_i. Entry barriers keep potential entrants out of the market due to high sunk costs or productivity pressures.

Then, the CDF of the city i can be written as a function of the CDF ($\tilde{F}(.)$) without A_i, D_i, or S_i:

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - A_i}{D_i}\right) - S_i}{1 - S_i}\right\} \tag{2}$$

This equation cannot be estimated because the underlying distribution $\tilde{F}(.)$ is unknown. Nevertheless, Combes et al. (2012) showed that by comparing the distribution of log productivity across two cities of different sizes i and j, $\tilde{F}(.)$ can be eliminated. That is:

$$D \equiv \frac{D_i}{D_j}, \quad A \equiv A_i - DA_j, \quad S \equiv \frac{S_i - S_j}{1 - S_j} \tag{3}$$

Then, Equation (2) can be arranged as follows:

[11] Low-efficiency firms may also relocate to smaller cities; however, we do not consider these dynamic sorting effects. We analyzed the sample and found that only 2% (10326/513500) of the companies have changed their locations (prefecture-level city level) during 1998–2007.

[12] $\bar{h}$ is the function of $\frac{N_i}{4\gamma} \int_0^{\bar{h}_i} \left(\bar{h}_i - h\right)^2 g(h)dh + \sum_{j \neq i} \frac{N_j}{4\gamma} \int_0^{\bar{h}_j/\tau} \left(\bar{h}_j - \tau h\right)^2 g(h)dh = s$. This means that city size, marginal distribution ($g(.)$), sunk entry cost s, and degree of product differentiation parameter γ influence $\bar{h}$, and thus, the selection effect. If selling in other cities has no additional cost ($\tau = 1$), then the selection density does not differ: $S_i = S_j$.

$$F_i(\phi) = \max\left\{0, \frac{F_j\left(\frac{\phi - A}{D}\right) - S}{1 - S}\right\} \quad if \quad S_i > S_j \tag{4}$$

$$F_j(\phi) = \max\left\{0, \frac{F_i(D\phi + A) - \frac{-S}{1-S}}{1 - \frac{-S}{1-S}}\right\} \quad if \quad S_i < S_j \tag{5}$$

Finally, we rewrite these two equations in quantiles and estimate the following function:

$$\lambda_i\left(r_S(u)\right) = D\lambda_j\left(S + (1-S)r_S(u)\right) + A \quad \text{for} \quad u \in [0,1] \tag{6}$$

where $\lambda_i(u) \equiv F_i^{-1}(u)$ is the uth quantile of F_i and $r_S(u) = \max\left(0, \frac{-S}{1-S}\right) + \left[1 - \max\left(0, \frac{-S}{1-S}\right)\right] u$. Using this method, we can obtain the relative shift parameter A, relative dilation parameter D, and relative truncation parameter S. Returning to Equation (3), the hypothesis of no agglomeration, dilation, or selection effect between two cities can be denoted as follows:

$$H_0 : A = 0, \quad D = 1, \quad S = 0 \tag{7}$$

Figure 1 displays the simulated CDF of productivity between large and small cities with specific A, D, and S. In summary, densely populated cities have a dual impact on enterprises. First, the agglomeration effects enhance productivity. This enhancement can be further dissected into two distinct facets: a universal increase in TFP across all firms, quantified as A, and an additional increase in TFP specifically observed among higher performing companies, denoted by D. Concurrently, a selection mechanism exists in which productivity is left truncated due to the market's natural inclination to phase out less efficient firms.

[FIGURE 1 about here.]

4.2 Empirical Results

4.2.1 Agglomeration and Selection Effects under Different Ownership

Estimates of agglomeration (A and D) and selection effects (S) using light brightness for grouping cities are reported in Table 2. Note that R^2 often exceeds 0.90, indicating that these effects can explain most of the productivity divergence between large and small cities. Moreover, agglomeration positively affects productivity for all firms controlled by various types of ownership. Based on bootstrapped standard errors, estimates of A differ significantly from zero, validating **Hypothesis 1** that both *Always-POEs* and *Always-SOEs* enjoy significant agglomeration effects. Furthermore, we observe different trajectories of productivity on agglomeration effects over time (column (1) in Table 2). Specifically, A gradually declines in *Always-POEs* and drops slightly among *Always-SOEs*, while *Always-COEs* still enjoy more agglomeration effects over time.

Meanwhile, due to an insignificant S at most times, no evidence of stronger firm selection is detected for *Always-COEs* in larger cities. Conversely, *Always-SOEs* unsurprisingly have negative values of S, corresponding instead to greater truncation in less dense areas. With the government's extensive support, SOEs are less likely to exit the local market, even on the verge of a breakdown. Better access to credit markets may explain why growing firms, such as Chinese SOEs with low productivity, survive (Hu et al., 2015). Typically, urban cities tend to have the ability to provide more bank credit.

Nevertheless, we find evidence of fierce selection in larger cities for *Always-POEs*, where S is always positive and statistically significant. This result is similar to Arimoto et al. (2014), who investigated the Japanese silk-reeling industry, Accetturo et al. (2018), who controlled for market access, and Ding and Niu (2019), who examined Chinese manufacturing industries and found that 15 out of 29 industries exhibit a significant S using provincial population density as the standard. Thus, without considering the selection effect, productivity gains from agglomeration advantages may be overestimated. Still, the effect of selection on productivity is much less than the agglomeration effect. As Brandt et al. (2012) reckoned, although the Chinese market exhibits market selection, limited efficiency-enhancing input re-allocations may curtail this function. In general, Table 2 supports **Hypothesis 2** that *Always-POEs* have statistically significant selection effects; however, positive selection effects are not found among *Always-SOEs*.

[TABLE 2 about here.]

4.2.2 Post-privatization: TFP

Before investigating the extent to which privatization impacts productivity through agglomeration and selection effects, we first check changes in TFP before and after privatization. Figure 2 displays the productivity trends of different groups. The left graph shows that at the point of privatization, $t = 0$, the TFP of the SOEs undergoing privatization substantially increases. The post-privatization trajectory is also positive, exhibiting a consistent increase in their productivity. When juxtaposed with the *Always-SOEs* group from the right graph, the privatized SOEs exhibit a considerably larger increase in TFP. The productivity trend for COEs during their privatization phase remains relatively stable. Unlike SOEs, privatized COEs do not experience a similar boost in productivity during or after privatization. In particular, even with the observed surge in TFP for privatized SOEs, their average TFP, when compared to the right graph, remains below that of *Always-POEs*.

In other words, at least in the short term, the TFP of recently privatized enterprises does not seem to match up to entities that have always operated in the private sector. This suggests that while privatization can be beneficial for productivity growth, privatized SOEs have a period of adjustment and transition before they can reach the productivity benchmarks set by their always-private counterparts. Considering these findings, to further investigate the agglomeration and selection effects during SEO privatization, we estimate the values of A, D and S for privatized SOEs.

[FIGURE 2 about here.]

4.2.3 Post-privatization: Agglomeration Effect

Table 3 reports A, D, and S before and after privatization (Panel A), and according to the distance from the corresponding oversight government (Panel B, top-1/2 versus bottom-1/2). In Table A.2, we demonstrate results grouped by top versus bottom one-third of the distance from the corresponding oversight governments. The agglomeration effects A and D with confidence intervals (CI) are plotted in Figure 3 and Figure 4, respectively. Here, $t = 0$ stands for the year when a SOE changed its ultimate control from state to private ownership, while $t = -1$ is one year before the reform and $t = +1$ is one year after.

[FIGURE 3 about here.]

[FIGURE 4 about here.]

[TABLE 3 about here.]

In column (1) of Table 3, the estimates of A are always significantly positive before the SOE reform. However, A drops after $t = 0$ and starts becoming insignificant two years after privatization. This shows that productivity improvements in all firms due to agglomeration advantages gradually fade away once SOEs are privatized. For example, according to Panel A, in the year preceding privatization ($t = -1$), the value of A is 0.181. In the year following privatization ($t = +1$), A decreases to 0.090. This indicates that if a firm moved to a denser area before its privatization, its TFP would increase by 19.8% ($e^{0.181} - 1 = 0.198$).[13] Yet, when the same firm moves to a denser area after privatization, its TFP would only increase by 9.4% ($e^{0.090} - 1 = 0.094$), exhibiting a difference of 10%. In particular, this decline is even

[13] Following Combes et al. (2012), we have $\phi_i(h) = A_i - D_i \ln(h)$ and $A = A_i - DA_j = \phi_i(h) - D_i ln(h) - \phi_j(h) + D_j ln(h)$. If $D = \frac{D_i}{D_j} = 1$, then $A = \phi_i(h) - \phi_j(h)$, where $\phi_i(h)$ refers to $\ln \mathrm{TFP}_i$. Thus, we rewrite this equation as $e^A - 1 = (\frac{TFP_i}{TFP_j} - 1)$. This implies an increase in mean TFP if a firm relocates from a small city to a large city due to a general agglomeration effect A.

more pronounced for firms near the local government (C-Group), exceeding 20%. In contrast, for those in the F-Group, the drop is approximately 6%.

According to Siegel (2007), political networks burdened companies after a change in the political regime in Korea because the way they accessed information and resources in the past was outdated in the new environment. Song et al. (2022) likewise demonstrated that during China's transition, firms' close ties with the pre-reform institutions impeded new activities as firms' operations were constrained by the connections established in the past and employees continued following old business norms. As the environment evolves, privatized SOEs might find that these historical ties, rather than providing them with leverage, often act as shackles. Their organizational structures, corporate cultures, operational models, and decision-making processes are formulated during their time as SOEs. This makes them considerably different from emerging private companies. Furthermore, the close ties maintained by privatized SOEs with previous institutional systems often make their integration with the private sector challenging. This assertion is supported by the fact that C-Group firms' A becomes insignificant earlier (since $t = +1$) than that of F-Group firms (since $t = +3$).

Then, why does the average productivity of private firms substantially increase after privatization? We hypothesize that this could be attributed to the driving force behind the increase in the productivity of high-quality enterprises with fewer government connections (**Hypothesis 3**). Comparing column (2) of C-Group with that of F-Group in Panels B of Table 3, D is insignificantly less than one pre-privatization but substantially rises above one for post-privatized SOEs located far from their oversight governments. A value of D above one demonstrates that more productive firms benefit more from being in denser areas, while D smaller than one indicates that more productive firms benefit less from being in denser areas. Figure 3 and Figure 4 complement this finding, and show a steady increasing D starting from $t = 0$. This holds significantly only for post-privatized SOEs, which are far from the oversight government. For post-privatized SOEs close to the oversight government, except for estimates at $t = +1$, the estimates of D are insignificantly above one. Briefly, according to columns (1) and (2) in Table 3, after transitioning to a private firm, the agglomeration benefits that come from a shift to the right of the productivity distribution (represented by A) decline, while the agglomeration benefits of dilation (represented by D) increase. That is, only pre-privatized SOEs with high quality (e.g., hiring efficient workers) can improve productivity through the agglomeration effect after the reform; this is especially true for F-Group firms. These discoveries support **Hypothesis 3** and **Hypothesis 4**.

Next, we ask whether agglomeration effects (or, more generally, productive advantages) shared by post-privatized SOEs weaken after they lose the privileged treatment. Specifically, we weigh the gain (due to dilation D) and loss (due to shift A) of the agglomeration economies at different quantiles of the logarithmic productivity distribution. Figure 5 depicts $\ln \mathrm{TFP}$ differences in the 25th, 50th, and 75th quantiles between large and small cities. The sample is grouped by the distance from the corresponding oversight government, where thick arrows represent C-groups (top half) and thin arrows represent F-groups (bottom half). The direction of each arrow is from small to large cities.

[FIGURE 5 about here.]

We have two observations. First, productivity increases substantially when SOEs are privatized ($t = 0$). However, thereafter, the 25th and 50th percentiles of the $\ln \mathrm{TFP}$ distribution of these privatized SOEs do not exhibit a trend of substantial productivity increases; only distant firms in the 75th percentile productivity group show a steady increase (as shown by F-Group *p=75* in Figure 5). Second, the size of productivity increases firm relocation from small to large cities, as a response to agglomeration benefits, differs between large and small cities. After privatization, the difference in production efficiency between large and small cities narrows significantly, as shown by the most paired-coordinate plots in Figure 3. Thus, the scale effect of large cities is not efficient or accretive for mediocre privatized SOEs.[14] Nonetheless,

[14]Here, mediocre firms are those with productivity below the 50th percentile.

the advantages of agglomeration effects still exist for more efficient and distant firms (F-Group *p=75*), especially between the $[t=-3]$ and $[t=+3]$ windows. Regarding the agglomeration effect, most SOEs instantly lose this advantage after privatization, which may further affect productivity growth. Instead, high-productivity SOEs with weak government relations maintain or even enhance the agglomeration benefit. However, this effect does not last long and disappears four years after SOE reform (as shown by F-Group *p=75*). However, the outstanding privatized SOEs (such as firms in the 95th percentile) that are far from the oversight government demonstrate a lasting agglomeration effect, which is accompanied by a steady increase in efficiency (see F-Group *p=95* in Figure 6). This discovery is interesting because privatized SOEs absorb the advantages of large cities through the agglomeration effect, which implies a relatively straightforward possibility of improving firm productivity.

[FIGURE 6 about here.]

4.2.4 Post-privatization: Selection Effects

Column (3) reports the estimates of the selection effects S. Unlike the agglomeration effect shown by A and D, the values of S are insignificant and negligible in all periods. This suggests that privatization does not significantly improve the selection process. However, by linking column (3) of *Always-SOEs* in Table 2 to column (3) in Table 3, S among *Always-SOEs* is significantly negative but insignificant among SOEs soon to be privatized. This suggests that governments in large cities tend to protect SOEs on the brink of bankruptcy. Conversely, as reported in Panel A, the pre-privatization values of S are often negative; meanwhile, S has positive values after privatization. Residual government connections within newly privatized SOEs may also explain the poor performance (Boubakri et al., 2008). Harrison et al. (2019) discovered that privatized SOEs are still favored for low-interest loans and government subsidies relative to *Always-POEs* in China. This favoritism for resources means that privatized SOEs continue to operate even if their performance is not outstanding. Thus, without creating a competitive market environment, privatizing SOEs may have little effect on their productivity (Konings et al., 2005).

However, regarding the negative to positive change in *S*, as shown in Panel A of Table 3, we optimistically expect that privatization can help improve firm efficiency in large cities if the government can also change their behavior (e.g., less credit); however, this may take longer. Unlike *Always-POEs*, *SPs* barely have significantly negative selection effects. The positive *S* (although statistically insignificant) partially indicates that SOE reform contributes to market selection. Thus, even though we cannot strongly support **Hypotheses 5 and 6** statistically, the improved competitive market for privatized SOEs remains noteworthy.

4.2.5 Summary of Findings

Without finding a similar pattern among *CPs* as reported in Table A.3, we see a characteristic unique to *CPs*. Our results shed light on several key hypotheses. Evidently, both *Always-POEs* and *Always-SOEs* experience considerable agglomeration effects, suggesting a wide-reaching impact of urban concentration. Furthermore, *Always-POEs* display significant selection effects, while *Always-SOEs* do not.

Interestingly, while SOE reform adversely influences agglomeration effects, this negative trend can be offset by the quality of the firm (e.g., the efficiency of a firm's employees). This is because high-efficiency privatized SOEs are often better equipped to adapt to market changes and face external challenges. Consequently, they are more likely to attract a wider network of partners, suppliers, and clients, thus amplifying the effects of agglomeration. This finding is consistent with previous studies. Combes et al. (2012) found that workers are more productive in a more efficient firm, which is the origin of the dilation effect. Zhu et al. (2020) found that privatized SOEs can benefit from increased knowledge spillover effects through interactions with the private sector, hinting at the ability to learn from private firms. Furthermore, Chong et al. (2011) underscored the adverse outcomes of pre-privatization retrenchment initiatives and emphasized that skill-biased retrenchment strategies stand out as the only approaches correlated with elevated privatization valuations. Therefore, this also supports our finding and highlights the beneficial influence of the dilation effect on privatized SOEs that boast a high-efficiency workforce.

Another significant observation is the clear correlation between changes in agglomeration effects after SOE privatization and firm ties to the government. Specifically, if privatized SOEs are located closer to the local government, their post-privatization agglomeration benefits diminish more significantly. Thus, while proximity to governmental entities may be beneficial during their state-owned phase due to preferential treatment or easier access to resources, it becomes a liability after privatization. Close physical and operational proximity could expose these firms to bureaucratic inefficiencies, policy volatilities, or other challenges that dilute the advantages typically associated with economic clustering.

Lastly, contrary to our initial expectations, the results do not significantly corroborate the hypothesis that SOE reforms positively affect selection effects, nor do they provide a link between changes in selection effects after SOE privatization and the firm's governmental ties.

5 Robustness checks

Our primary variables are the division of ownership and firm productivity.[15] Here, we use productivity and labor productivity (industrial value-add divided by employment) to test the robustness of our results. Following Liao et al. (2014), we distinguish firm ownership by the ratio of state-owned equity to total equity. Firms are assigned by their state ownership into four groups: *Non-SOEs*, *L-SOEs*, *M-SOEs*, and *H-SOEs*. *Non-SOEs* include firms without any state-owned equity. The rest are ranked ascendingly by low, medium, and high firm ownership

[15] There may be endogeneity concerns due to the government's preference for the privatization of high-efficiency or loss-making firms. However, the dilation effect (D in Equation (7)) already addresses this issue. Specifically, the agglomeration effect consists of two parts: the increase in the average agglomeration effect (A Equation (7)) of SOEs after privatization and benefits that only high-quality SOEs can obtain (D Equation (7)).

as *L-SOEs*, *M-SOEs*, and *H-SOEs*, respectively. Privatization is equivalent to selling state-owned equity; that is, the transition from *H-SOEs* to *Non-SOEs* directly (only one change). Firms that have undergone multiple transitions are not included in the robustness test because the preceding section (Section 4.2) only incorporates firms that have been privatized once. Table 4 uses a different firm productivity estimation method, and Table 5 uses another firm ownership classification. These tables show that our results hold, and suggest that market competition and withdrawal mechanisms have gradually improved after the SOE reform.

[TABLE 4 about here.]

[TABLE 5 about here.]

6 Conclusion

Employing a large firm-level dataset and the generalized firm selection model (Melitz, 2003; Melitz and Ottaviano, 2008), we examine the impact of SOE privatization on Chinese firms' productivity through two transmission channels: agglomeration and selection effects and report significant heterogeneities in productivity changes by ownership type. Using extensive data from manufacturing firms with a quantile specification (Combes et al., 2012), we establish that agglomeration explains a large part of the productivity differences between cities in China's manufacturing industry for each type of ownership. In contrast, a statistically significant selection effect is present only among *Always-POEs*. The remaining sub-samples (*Always-SOEs*, *Always-COEs*, *Always-POEs*, *SPs*, and *CPs*) exhibit insignificant (or even negative) selection effects.

In addition, the transformative journey of SOE reforms is focused on agglomeration effects. High-quality firms, especially those endowed with efficient and competent human capital, demonstrate remarkable resilience after privatization. Their TFP withstands the adverse consequences of reforms and even increases. This underscores the crucial role of workforce efficiency in harnessing and increasing the benefits of agglomeration, regardless of ownership transitions. However, the picture becomes more complex when we consider the geographical proximity to government centers. Privatized SOEs closer to these centers, regardless of firm quality, face a paradoxical challenge. Although such proximity may have been a boon during their state-owned tenure, offering them preferential treatment and resource access, it is a double-edged sword after privatization. For instance, these firms might grapple with bureaucratic entanglements and policy volatility, eroding some of their post-privatization TFP gains.

Intriguingly, our data do not offer a conclusive endorsement of the assumptions that SOE reforms unequivocally amplify selection effects or that these effects' post-reform trajectory is significantly influenced by firm proximity to the government. This may be one reason for the limited evidence supporting privatization. One possible explanation for the limited evidence might be the temporal nature of market competition: the formation and maturation of a more competitive market might be much longer than our study period. Nonetheless, despite the absence of stark significance, subtle indications point towards improved selection effects. This suggests that while the changes might be incremental now, more pronounced changes may be observed in the long run.

Given our findings, the government may consider reassessing its associations with pre-privatized SOEs. This may help privatized SOEs maintain their inherent agglomeration advantages and embark on sustained productivity improvement. Encouraging such enterprises to navigate a market characterized by cooperation and competition could be beneficial. Furthermore, giving precedence to SOEs which demonstrate efficiency and have minimal government dependencies may be beneficial. This can position them better to take advantage of privatization. Moreover, our data point towards the possible merits of nurturing a market environment rich in genuine competition. A reflective approach might involve credit support policies for privatized SOEs, ensuring that the policies are balanced and fair. Such refinements could pave the way for more discernible selection effects driven by market competition, potentially boosting firm productivity.

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Figures

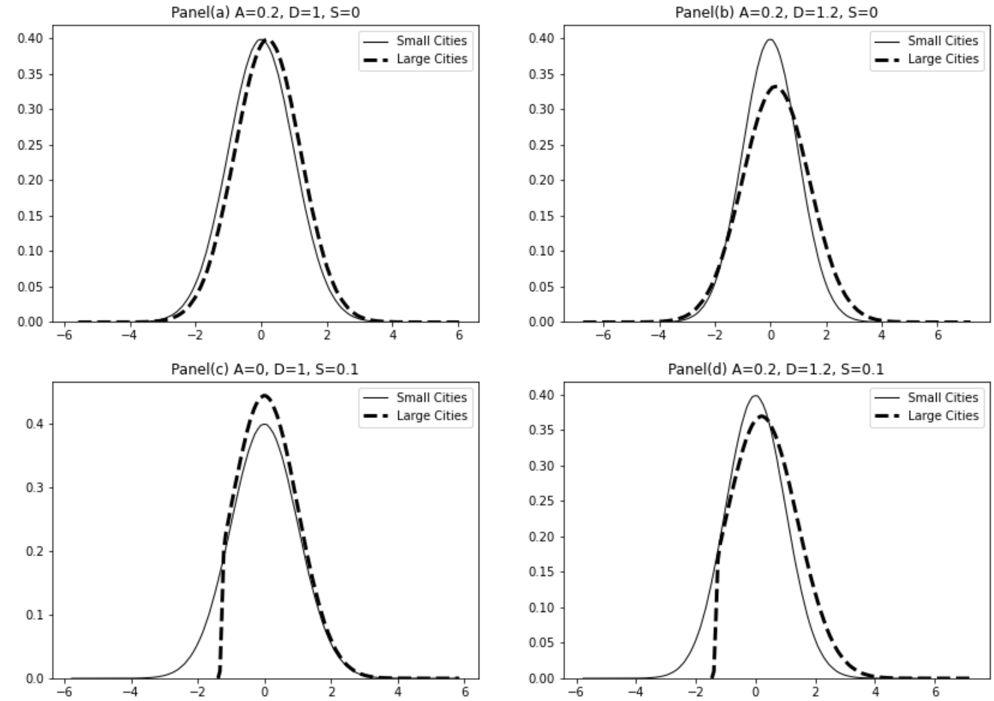

FIGURE 1. MONTE CARLO SIMULATIONS, DISTRIBUTIONS IN LARGE AND SMALL CITIES

Notes: Created by the authors. In panel (a), $A_i = 0, A_j = 0.2$, $D_i = D_j = 1$, $S_i = S_j = 0$ and thus $A = 0.2, D = 1, S = 0$, it corresponds to the differences in agglomeration that are required to move the entire (only right-shift); in panel (b), $A_i = 0, A_j = 0.2$, $D_i = 1, D_j = 1.2$, $S_i = S_j = 0$, it additionally dilates the distribution by stretching out the productivity especially at the right-side tail (right-shift and dilation); in panel (c), $A_i = A_j = 0$, $D_i = D_j = 1$, $S_i = 0, S_j = 0.1$, it corresponds to the differences in selection required to left truncate the productivity by taking probability away from the left of the distribution (left-truncation); the panel (d) identifies right-shift, dilation and left-truncation by visual comparison of two distributions of $\ln$TFP distributions in large cities and small cities.

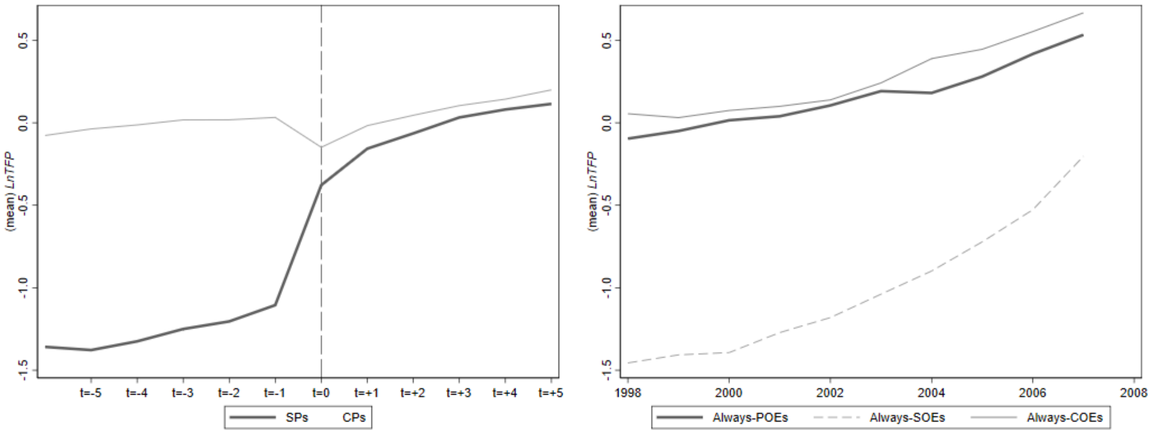

FIGURE 2. TREND IN AVERAGE *LnTFP* BY DIFFERENT GROUPS

Notes: This figure consists of two side-by-side graphs, both showing the group average *LnTFP* on the y-axis; The left graph represents the trend around the time of privatization of SOEs or COEs; The x-axis uses a relative time scale, with $t = 0$ denoting the year of privatization, $t = +1$ indicating one year post-privatization; The x-axis of the right graph is the actual years. The groups (*SPs*, *CPs*, *Always-POEs*, *Always-SOEs* and *Always-COEs* are described in Section 3.2.

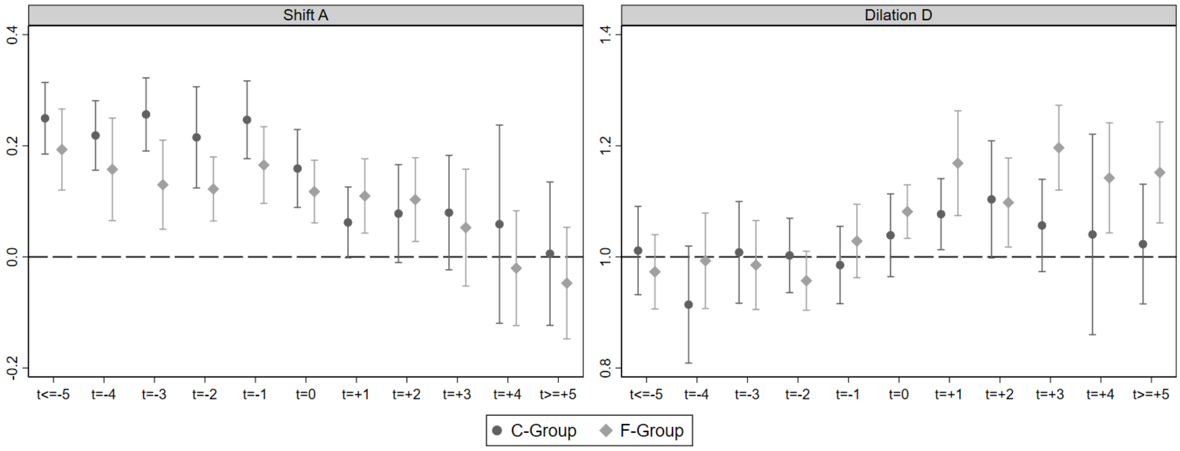

FIGURE 3. PARAMETERS OF SPS AGGLOMERATION EFFECTS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

Notes: *SPs* are firms that change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C-*, while *bottom-1/2* are the farthest 50% firms denoted by prefix *F-*; The null hypothesis H_0 is $A = 0$, $D = 1$; Bootstrap replication (50); Estimated values with 95% confidence intervals are plotted.

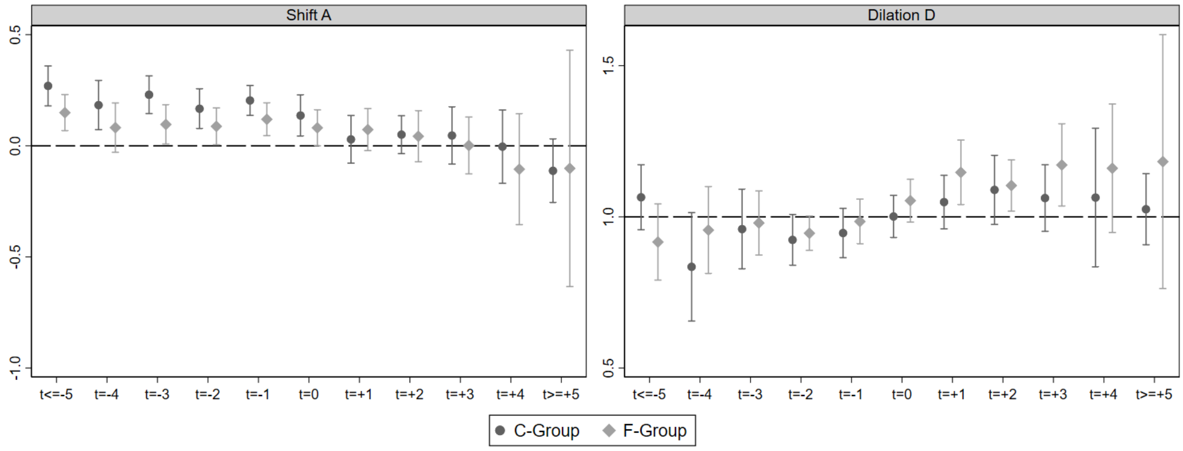

FIGURE 4. PARAMETERS OF SPS AGGLOMERATION EFFECTS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/3 VS. BOTTOM-1/3, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

Notes: *SPs* are firms that change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/3* are the nearest 33% firms denoted by prefix *C-*, while *bottom-1/3* are the farthest 33% firms denoted by prefix *F-*; The null hypothesis H_0 is $A = 0$, $D = 1$; Bootstrap replication (50); Estimated values with 95% confidence intervals are plotted.

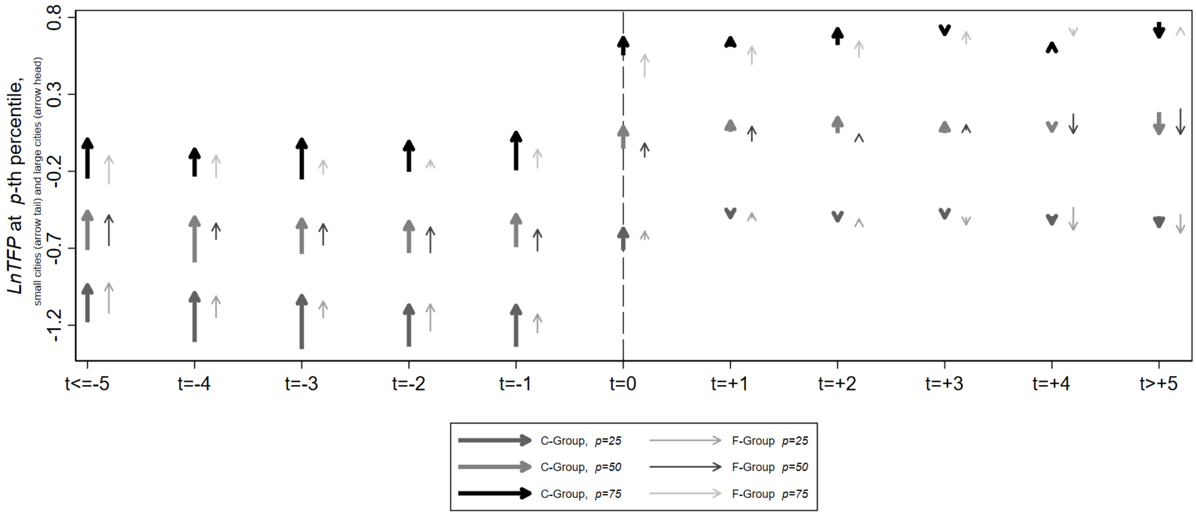

FIGURE 5. Productivity Difference of SPs at 25th, 50th and 75th Percentile by Distance From Oversight Government, top-1/2 vs. bottom-1/2

Notes: *SPs* are firms that change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government as described in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C-* (deep color), while *bottom-1/2* are the farthest 50% firms denoted by prefix *F-* (light color); The paired-coordinate arrows point from small cities to large cities; The y-axis is $lnTFP$ at different percentiles. The length of each arrow is explained by the combined effects of agglomeration and selection. Within the context of our study, an observed increase in the length of the arrow implies an increase in these effects.

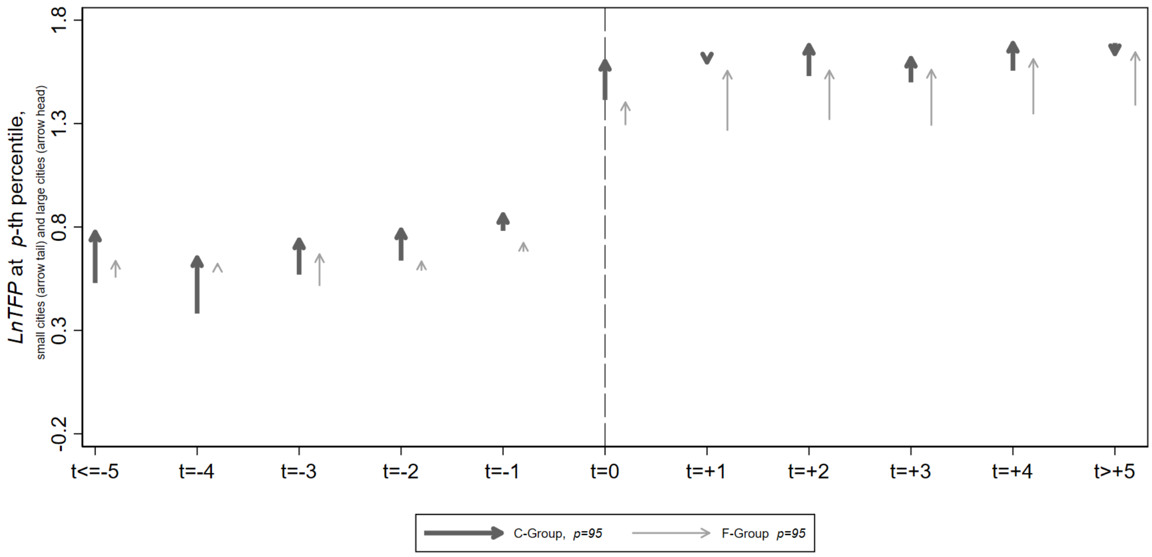

FIGURE 6. PRODUCTIVITY DIFFERENCE OF SPS AT 95*th* PERCENTILE BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2

Notes: *SPs* are firms change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government as described in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C-* (deep color), while *bottom-1/2* are the farthest 50% firms denoted by prefix *F-* (light color); The paired-coordinate arrows point from small cities to large cities. The y-axis is $lnTFP$ at different percentiles. The length of each arrow is explained by the combined effects of agglomeration and selection. Within the context of our study, an observed increase in the length of the arrow implies an increase in these effects.

Tables

TABLE 1. DESCRIPTIVE STATISTICS OF KEY VARIABLES

Groups		LnTFP	LnAsset	LnLabor	LnOutput	LnCapital	Obs.	Percentage
Always-SOEs	Mean	-1.058	9.790	4.980	8.760	3.905	164,487	9.95%
	Std	0.986	1.857	1.453	2.349	2.062		
Always-COEs	Mean	0.303	9.279	4.701	9.549	3.246	81,818	4.95%
	Std	0.888	1.176	1.046	1.194	1.396		
Always-POEs	Mean	0.072	9.553	4.616	9.979	3.493	1,200,095	72.57%
	Std	0.876	1.255	1.024	1.175	1.475		
CPs	Mean	0.312	9.622	4.872	10.049	3.618	144,184	8.72%
	Std	0.839	1.215	1.003	1.186	1.414		
SPs	Mean	-0.263	10.410	5.392	10.180	4.489	63,198	3.82%
	Std	0.946	1.419	1.158	1.519	1.650		
Top-1/2 vs. bottom-1/2	Small Cities						266,442	16.11%
	Big Cities						1,387,340	83.89%
Top-1/3 vs. bottom-1/3	Small Cities						120,314	7.28%
	Big Cities						1,249,737	75.57%

Notes: Always-SOEs, Always-COEs, Always-POEs, CPs, and SPs are defined in Section 3.2; Cities are divided by the median value of light brightness to *top-1/2* (*top-1/3*) and *bottom-1/2* (*bottom-1/3*).

TABLE 2. INTER-TEMPORAL ESTIMATION RESULTS FOR DIFFERENT ULTIMATE CONTROL FIRMS, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

	(1) Agglomeration Effects		(2)		(3) Selection Effects		(4)	(5) Obs.	(6)
	A		**D**		**S**		R^2	**Big City**	**Small City**
Always-SOEs									
1998-2000	0.143***	[0.1142,0.1730]	1.010	[0.9844,1.0352]	-0.014***	[-0.0186,-0.0098]	0.950	27,619	11,455
1999-2001	0.162***	[0.1325,0.1920]	1.046***	[1.0218,1.0702]	-0.012***	[-0.0164,-0.0068]	0.938	24,553	10,053
2000-2002	0.168***	[0.1336,0.2028]	1.073***	[1.0418,1.1046]	-0.009**	[-0.0150,-0.0036]	0.924	21,837	8,300
2001-2003	0.176***	[0.1418,0.2107]	1.062***	[1.0262,1.0983]	-0.013***	[-0.0197,-0.0071]	0.925	17,173	6,129
2002-2004	0.182***	[0.1473,0.2182]	1.066***	[1.0343,1.0970]	-0.013***	[-0.0176,-0.0085]	0.943	17,664	5,768
2003-2005	0.196***	[0.1513,0.2409]	1.082***	[1.0478,1.1153]	-0.013***	[-0.0179,-0.0074]	0.948	15,298	4,596
2004-2006	0.164***	[0.1107,0.2181]	1.069***	[1.0236,1.1144]	-0.014**	[-0.0227,-0.0043]	0.926	12,940	3,484
2005-2007	0.135***	[0.0731,0.1979]	1.082***	[1.0378,1.1261]	-0.030***	[-0.0398,-0.0199]	0.976	10,196	2,576
Always-COEs									
1998-2000	0.125***	[0.0977,0.1541]	0.960***	[0.9347,0.9856]	0.001	[-0.0044,0.0062]	0.981	18,105	3,577
1999-2001	0.166***	[0.1308,0.2025]	0.985	[0.9441,1.0278]	-0.012**	[-0.0196,-0.0042]	0.964	15,728	2,778
2000-2002	0.135***	[0.0914,0.1798]	1.056***	[1.0152,1.0975]	-0.004	[-0.0119,0.0041]	0.981	12,170	2,249
2001-2003	0.182***	[0.1277,0.2377]	1.019	[0.9618,1.0768]	-0.005	[-0.0148,0.0046]	0.970	9,149	1,675
2002-2004	0.140***	[0.0823,0.1990]	1.092***	[1.0439,1.1409]	0.003	[-0.0043,0.0104]	0.982	9,370	1,572
2003-2005	0.234***	[0.1641,0.3053]	1.065***	[1.0087,1.1213]	0.009	[-0.0020,0.0195]	0.963	8,106	1,244
2004-2006	0.181***	[0.1084,0.2546]	1.116***	[1.0517,1.1805]	-0.002	[-0.0123,0.0078]	0.960	6,498	847
2005-2007	0.180***	[0.1252,0.2362]	1.101***	[1.0430,1.1604]	-0.002	[-0.0158,0.0122]	0.968	5,603	870
Always-POEs									
1998-2000	0.130***	[0.1109,0.1504]	0.984	[0.9609,1.0080]	0.006**	[0.0015,0.0107]	0.949	55,581	7,208
1999-2001	0.124***	[0.1015,0.1478]	1.012	[0.9872,1.0368]	0.009***	[0.0049,0.0147]	0.951	72,327	9,666
2000-2002	0.132***	[0.1187,0.1465]	1.000	[0.9852,1.0156]	0.003*	[0.0002,0.0068]	0.946	85,717	11,715
2001-2003	0.153***	[0.1394,0.1684]	1.017***	[1.0004,1.0348]	0.008***	[0.0050,0.0113]	0.965	102,966	14,884
2002-2004	0.094***	[0.0835,0.1058]	1.031***	[1.0190,1.0430]	0.005***	[0.0021,0.0081]	0.931	176,519	22,260
2003-2005	0.102***	[0.0902,0.1150]	1.016***	[1.0052,1.0281]	0.003**	[0.0014,0.0057]	0.930	193,043	26,598
2004-2006	0.079***	[0.0686,0.0909]	1.017***	[1.0089,1.0267]	0.002*	[0.0001,0.0050]	0.875	214,605	30,966
2005-2007	0.034***	[0.0232,0.0454]	1.027***	[1.0184,1.0368]	0.003***	[0.0014,0.0057]	0.613	235,966	38,033

Notes: The prefix *Always-* denotes firms without changing ultimate control during the sample period as Section 3.2; The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 3. ESTIMATION RESULTS OF SPS BY DISTANCE FROM OVERSIGHT GOVERNMENT, ALL SAMPLE AND TOP-1/2 VS. BOTTOM-1/2, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

	(1) Agglomeration Effects		(2)		(3) Selection Effects		(4)	(5) Obs.	(6)
	A		**D**		**S**		R^2	**Big City**	**Small City**
Panel A: all sample									
t<=-5	0.228***	[0.1728,0.2825]	1.029	[0.9779,1.0796]	-0.001	[-0.0140,0.0123]	0.874	4,034	1,584
t=-4	0.178***	[0.1120,0.2435]	0.998	[0.9182,1.0782]	-0.011	[-0.0317,0.0093]	0.925	2,493	1,065
t=-3	0.182***	[0.1301,0.2334]	1.003	[0.9391,1.0664]	-0.001	[-0.0268,0.0241]	0.929	3,477	1,447
t=-2	0.153***	[0.0807,0.2245]	1.011	[0.9771,1.0457]	-0.029	[-0.0635,0.0064]	0.923	4,774	1,976
t=-1	0.181***	[0.1034,0.2579]	1.012	[0.9751,1.0483]	-0.007	[-0.0181,0.0038]	0.924	6,050	2,402
t=0	0.120***	[0.0976,0.1433]	1.036***	[1.0156,1.0573]	0.008	[-0.0029,0.0198]	0.918	6,575	2,643
t=+1	0.090***	[0.0486,0.1306]	1.029*	[1.0075,1.0606]	0.012	[-0.0055,0.0291]	0.913	4,805	1,975
t=+2	0.088***	[0.0382,0.1374]	1.027**	[1.0027,1.0510]	0.010	[-0.0074,0.0264]	0.889	3,841	1,616
t=+3	0.066	[-0.0134,0.1451]	1.069**	[1.0118,1.1259]	0.020	[-0.0316,0.0726]	0.901	3,186	1,300
t=+4	0.011	[-0.0786,0.1013]	1.048	[0.9163,1.1804]	0.000	[-0.1257,0.1252]	0.806	2,196	927
t>=+5	0.013	[-0.2570,0.2840]	1.053	[0.8669,1.2395]	0.007	[-0.1204,0.1348]	0.902	3,533	1,299
Panel B: top-1/2 vs. bottom-1/2									
C-Group (top-1/2)									
t<=-5	0.249***	[0.1850,0.3140]	1.011	[0.9318,1.0910]	-0.003	[-0.0156,0.0104]	0.966	2,326	787
t=-4	0.219***	[0.1561,0.2811]	0.914	[0.8089,1.0195]	-0.004	[-0.0390,0.0309]	0.968	1,409	530
t=-3	0.256***	[0.1906,0.3224]	1.008	[0.9166,1.0997]	-0.002	[-0.0194,0.0146]	0.955	1,931	710
t=-2	0.215***	[0.1241,0.3063]	1.003	[0.9356,1.0697]	-0.003	[-0.0143,0.0085]	0.978	2,628	971
t=-1	0.247***	[0.1767,0.3168]	0.985	[0.9157,1.0550]	-0.009	[-0.0189,0.0017]	0.970	3,267	1,182
t=0	0.159***	[0.0890,0.2292]	1.039	[0.9643,1.1133]	-0.008	[-0.0206,0.0040]	0.958	3,592	1,300
t=+1	0.062	[-0.0016,0.1257]	1.077***	[1.0131,1.1409]	-0.003	[-0.0117,0.0063]	0.842	2,634	963
t=+2	0.078	[-0.0102,0.1660]	1.104	[0.9982,1.2088]	0.001	[-0.0134,0.0162]	0.857	2,095	795
t=+3	0.080	[-0.0232,0.1827]	1.057	[0.9735,1.1397]	-0.015	[-0.0302,0.0000]	0.846	1,752	622
t=+4	0.059	[-0.1195,0.2373]	1.040	[0.8600,1.2208]	-0.014	[-0.0641,0.0371]	0.721	1,221	444
t>=+5	0.006	[-0.1233,0.1348]	1.023	[0.9153,1.1308]	-0.004	[-0.0710,0.0634]	0.474	1,858	622
F-Group (bottom-1/2)									
t<=-5	0.193***	[0.1202,0.2663]	0.973	[0.9062,1.0401]	0.001	[-0.0200,0.0225]	0.979	1,708	797
t=-4	0.158***	[0.0653,0.2499]	0.993	[0.9070,1.0789]	-0.004	[-0.0212,0.0126]	0.965	1,084	535
t=-3	0.130**	[0.0497,0.2100]	0.985	[0.9053,1.0654]	0.003	[-0.0122,0.0173]	0.924	1,546	737
t=-2	0.122***	[0.0646,0.1799]	0.957	[0.9040,1.0103]	0.000	[-0.0116,0.0107]	0.890	2,146	1,005
t=-1	0.165***	[0.0964,0.2344]	1.029	[0.9625,1.0946]	-0.004	[-0.0161,0.0084]	0.964	2,783	1,220
t=0	0.118***	[0.0613,0.1739]	1.082***	[1.0334,1.1297]	0.001	[-0.0089,0.0112]	0.949	2,983	1,343
t=+1	0.110**	[0.0429,0.1766]	1.169***	[1.0743,1.2630]	0.002	[-0.0128,0.0177]	0.938	2,171	1,012
t=+2	0.103**	[0.0278,0.1785]	1.098***	[1.0177,1.1781]	-0.002	[-0.0188,0.0138]	0.911	1,746	821
t=+3	0.053	[-0.0525,0.1579]	1.197***	[1.1202,1.2729]	0.003	[-0.0140,0.0207]	0.937	1,434	678
t=+4	-0.020	[-0.1237,0.0830]	1.142***	[1.0432,1.2412]	0.003	[-0.0165,0.0221]	0.823	975	483
t>=+5	-0.047	[-0.1477,0.0534]	1.152***	[1.0611,1.2428]	0.003	[-0.0160,0.0211]	0.836	1,675	677

Notes: *SPs* are firms change their ownership from stated-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C*-, while *bottom-1/2* are the farthest 50% firms denoted by prefix *F*-; The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 4. ESTIMATION RESULTS OF SPS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS, PRODUCTIVITY ARE ESTIMATED BY OLS METHOD AND LABOR PRODUCTIVITY

	(1) Agglomeration Effects		(2)		(3) Selection Effects		(4)	(5) Obs.	(6)
	A		D		S		R^2	Big City	Small City
Panel B: LnTFP, Labor Productivity									
C-Group (top-1/2)									
t<=-5	0.312***	[0.2329,0.3903]	1.081***	[1.0083,1.1528]	0.000	[-0.0119,0.0120]	0.983	2,326	787
t=-4	0.299***	[0.2017,0.3954]	0.922	[0.7973,1.0464]	0.001	[-0.0473,0.0498]	0.984	1,409	530
t=-3	0.336***	[0.2565,0.4163]	1.058	[0.9816,1.1354]	-0.001	[-0.0152,0.0122]	0.990	1,931	710
t=-2	0.304***	[0.2391,0.3682]	1.055	[0.9891,1.1210]	0.004	[-0.0077,0.0150]	0.984	2,628	971
t=-1	0.340***	[0.2745,0.4046]	1.009	[0.9324,1.0856]	-0.010	[-0.0229,0.0021]	0.986	3,267	1,182
t=0	0.221***	[0.1639,0.2772]	1.073**	[1.0172,1.1292]	0.000	[-0.0087,0.0083]	0.982	3,592	1,300
t=+1	0.120**	[0.0481,0.1918]	1.047	[0.9874,1.1072]	-0.003	[-0.0144,0.0078]	0.957	2,634	963
t=+2	0.133**	[0.0494,0.2156]	1.106**	[1.0391,1.1730]	-0.001	[-0.0115,0.0102]	0.950	2,095	795
t=+3	0.093*	[0.0112,0.1746]	1.04	[0.9472,1.1319]	-0.011	[-0.0375,0.0152]	0.635	1,752	622
t=+4	0.098	[-0.0096,0.2053]	1.108	[0.9700,1.2451]	0.001	[-0.0307,0.0332]	0.759	1,221	444
t>=+5	0.022	[-0.0727,0.1174]	1.038	[0.9519,1.1232]	-0.002	[-0.0246,0.0213]	0.317	1,858	622
F-Group (bottom-1/2)									
t<=-5	0.278***	[0.2032,0.3521]	1.027	[0.9535,1.1011]	0.004	[-0.0129,0.0210]	0.958	1,708	797
t=-4	0.205***	[0.1158,0.2938]	1.057	[0.9439,1.1709]	0.001	[-0.0324,0.0350]	0.918	1,084	535
t=-3	0.174***	[0.1021,0.2459]	1.049	[0.9335,1.1650]	0.010	[-0.0132,0.0340]	0.878	1,546	737
t=-2	0.199***	[0.1274,0.2701]	1.005	[0.9528,1.0571]	-0.002	[-0.0144,0.0113]	0.922	2,146	1,005
t=-1	0.201***	[0.1418,0.2596]	1.067**	[1.0101,1.1244]	0.001	[-0.0107,0.0136]	0.977	2,783	1,220
t=0	0.145***	[0.0702,0.2199]	1.093**	[1.0424,1.1427]	0.003	[-0.0069,0.0132]	0.960	2,983	1,343
t=+1	0.142***	[0.0754,0.2079]	1.179***	[1.1034,1.2549]	0.002	[-0.0098,0.0147]	0.958	2,171	1,012
t=+2	0.113*	[0.0135,0.2121]	1.105**	[1.0375,1.1721]	-0.001	[-0.0136,0.0113]	0.956	1,746	821
t=+3	0.087	[-0.0125,0.1864]	1.149*	[1.0415,1.2572]	-0.001	[-0.0287,0.0274]	0.871	1,434	678
t=+4	0.002	[-0.1072,0.1111]	1.126***	[1.0126,1.2398]	0.002	[-0.0151,0.0186]	0.862	975	483
t>=+5	-0.01	[-0.1001,0.0809]	1.153***	[1.0656,1.2401]	0.005	[-0.0085,0.0188]	0.838	1,675	677

Notes: *SPs* are firms that change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C-*, while *bottom-1/2* are the farthest 50% firms denoted by prefix *F-*; The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 5. ESTIMATION RESULTS SNONS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

	(1) Agglomeration Effects		(2)		(3) Selection Effects		(4)	(5) Obs.	(6)
	A		D		S		R^2	Big City	Small City
C-Group (top-1/2)									
t<=-5	0.991**	[0.2388,1.7427]	0.481*	[0.0818,0.8802]	-1.014	[-2.1164,0.0885]	0.932	748	182
t=-4	0.422	[-0.0393,0.8833]	0.860	[0.5016,1.2176]	-0.031	[-0.6569,0.5957]	0.970	541	162
t=-3	0.452***	[0.3308,0.5723]	1.016	[0.8913,1.1403]	-0.013	[-0.0469,0.0212]	0.988	882	274
t=-2	0.451***	[0.3030,0.5997]	1.120**	[1.0167,1.2228]	-0.016	[-0.0396,0.0084]	0.960	1,707	525
t=-1	0.371***	[0.2828,0.4596]	1.002	[0.9373,1.0672]	0.002	[-0.0129,0.0160]	0.994	3,225	917
t=0	0.264***	[0.1860,0.3417]	1.044	[0.9747,1.1138]	-0.017*	[-0.0307,-0.0028]	0.970	3,584	1,049
t=+1	0.115*	[0.0195,0.2113]	1.142**	[1.0323,1.2518]	0.014*	[0.0005,0.0276]	0.947	2,366	659
t=+2	0.152**	[0.0492,0.2555]	1.149**	[1.0138,1.2843]	0.008	[-0.0128,0.0298]	0.906	1,831	506
t=+3	0.155	[-0.0025,0.3117]	1.099	[0.9624,1.2363]	-0.004	[-0.0438,0.0365]	0.853	1,402	381
t=+4	0.011	[-0.1437,0.1659]	1.141*	[1.0032,1.2795]	-0.002	[-0.0298,0.0261]	0.879	1,081	298
t>=+5	0.047	[-0.0752,0.1685]	1.058	[0.9468,1.1701]	-0.015	[-0.0338,0.0042]	0.819	2,055	520
F-Group (bottom-1/2)									
t<=-5	0.191	[-0.1828,0.5647]	1.323***	[1.0078,1.6376]	0.045	[-0.0871,0.1778]	0.923	367	151
t=-4	0.398	[-0.2512,1.0470]	1.167	[0.4987,1.8360]	-0.017	[-0.7279,0.6937]	0.945	327	135
t=-3	0.482***	[0.3345,0.6287]	1.181	[0.9932,1.3684]	-0.001	[-0.0609,0.0588]	0.969	630	235
t=-2	0.328***	[0.1961,0.4603]	1.077	[0.9068,1.2478]	0.003	[-0.0562,0.0622]	0.951	1,381	503
t=-1	0.261***	[0.1824,0.3395]	1.05	[0.9640,1.1362]	-0.002	[-0.0168,0.0127]	0.944	2,661	928
t=0	0.131***	[0.0583,0.2044]	1.106**	[1.0182,1.1935]	0.015	[-0.0047,0.0339]	0.897	2,984	1,056
t=+1	0.122*	[0.0212,0.2221]	1.232*	[1.0844,1.3791]	0.012	[-0.0072,0.0312]	0.938	1,881	670
t=+2	0.120*	[0.0108,0.2284]	1.188**	[1.0804,1.2961]	0.008	[-0.0099,0.0250]	0.914	1,463	501
t=+3	0.096	[-0.0348,0.2261]	1.214**	[1.0563,1.3718]	0.014	[-0.0100,0.0383]	0.945	1,126	369
t=+4	0.028	[-0.1429,0.1991]	1.188**	[1.0220,1.3548]	0.005	[-0.0439,0.0545]	0.870	892	308
t>=+5	-0.027	[-0.1354,0.0809]	1.158***	[1.0540,1.2620]	0.018	[-0.0038,0.0399]	0.752	1,829	520

Notes: *SnonS* are firms that transform from *H-SOEs* to *Non-SOEs* as discussed in Section 5; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C-*, while *bottom-1/2* are the farthest 50% firms denoted by prefix *F-*; The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appedix

Rank	Province	City	Employment (secondary industry)	Employment Density	Population *(hukou)*	Population Density	Light
Sort by employment of the secondary industry in the urban areas							
1	Tibet	Lasa	**695**	13	181,991	3,321	8,545
2	Yunan	Lincang	**1,600**	42	288,307	7,500	6,913
3	Gansu	Longnan	**2,600**	397	559,049	85,351	2,964
4	Yunan	Lijiang	**3,100**	102	153,023	5,057	6,016
5	Qinghai	Haidong	**3,100**	389	416,148	52,214	5,749
283	Shandong	Guangzhou	**763,900**	1,256	5,882,553	9,676	231,834
284	Helongjiang	Harbin	**913,500**	3,021	4,754,753	15,723	110,809
285	Tianjin	Tianjin	**928,400**	1,905	7,912,385	16,232	276,413
286	Shanghai	Shanghai	**1,434,800**	2,611	13,091,515	23,821	364,622
287	Beijing	Beijing	**1,651,700**	1,400	11,453,643	9,706	383,236
Sort by employment density of the secondary industry in the urban areas							
1	Tibet	Lasa	695	**13**	181,991	3,321	8,545
2	Yunnan	Lincang	1,600	**42**	288,307	7,500	6,913
3	Inner Mongolia	Ulanqab	6,700	**60**	298,887	2,681	16,048
4	Inner Mongolia	Hulunbuir	10,400	**66**	263,005	1,662	36,640
5	Yunnan	Lijiang	3,100	**102**	153,023	5,057	6,016
283	Sichuan	Panzhihua	141,500	**3,369**	664,700	15,826	16,847
284	Jiangxi	Xinyu	125,100	**3,475**	821,919	22,831	8,301
285	Henan	Pingdingshan	188,000	**3,547**	1,104,000	20,830	41,156
286	Fujian	Putian	125,600	**3,873**	2,016,300	62,174	33,335
287	Henan	Puyang	152,600	**4,348**	516,600	14,718	37,515
Sort by population (hukou) in the urban areas							
1	Yunan	Lijiang	3,100	102	**153,023**	5,057	6,016
2	Tibet	Lasa	695	13	**181,991**	3,321	8,545
3	Helongjiang	Heihe	9,200	497	**191,440**	10,348	15,207
4	Gansu	Jinchang	42,000	1,712	**198,401**	8,088	7,241
5	Jiangxi	Yintan	5,400	284	**201,787**	10,620	7,049
283	Tianjin	Tianjin	928,400	1,905	**7,912,385**	16,232	276,413
284	Hubei	Wuhan	621,800	2,824	**8,282,137**	37,608	105,769
285	Beijing	Beijing	1,651,700	1,400	**11,453,643**	9,706	383,236
286	Shanghai	Shanghai	1,434,800	2,611	**13,091,515**	23,821	364,622
287	Chongqing	Chongqing	677,400	1,293	**15,260,234**	29,139	113,443
Sort by population density (hukou) in the urban areas							
1	Inner Mongolia	Hulunbuir	10,400	66	263,005	**1,662**	36,640
2	Guangdong	Zhaoqing	52,800	271	477,428	**2,453**	37,040
3	Inner Mongolia	Ordos	25,900	284	243,429	**2,669**	35,097
4	Inner Mongolia	Ulanqab	6,700	60	298,887	**2,681**	16,048
5	Guangdong	Shenzhen	576,600	809	2,168,453	**3,041**	176,437
283	Guangxi	Laibin	12,700	698	1,023,100	**56,214**	7,364
284	Fujian	Putian	125,600	3,873	2,016,300	**62,174**	33,335
285	Guizhou	Bijie	12,700	605	1,415,638	**67,411**	6,633
286	Sichuan	Bazhong	22,700	1,437	1,332,929	**84,363**	2,524
287	Gansu	Longnan	2,600	397	559,049	**85,351**	2,964
Sort by light brightness							
1	Sichuan	Yaan	20,100	1,267	350,987	22,116	**2,431**
2	Sichuan	Bazhong	22,700	1,437	1,332,929	84,363	**2,524**
3	Gansu	Longnan	2,600	397	559,049	85,351	**2,964**
4	Shaanxi	Shangluo	5,400	470	552,900	48,078	**3,418**
5	Hunan	Zhangjiajie	5,300	277	497,957	26,071	**3,998**
283	Jiangsu	Suzhou	249,600	1,675	2,940,849	19,737	**226,203**
284	Guangdong	Guangdong	763,900	1,256	5,882,553	9,676	**231,834**
285	Tianjin	Tianjin	928,400	1,905	7,912,385	16,232	**276,413**
286	Shanghai	Shanghai	1,434,800	2,611	13,091,515	23,821	**364,622**
287	Beijing	Beijing	1,651,700	1,400	11,453,643	9,706	**383,236**

TABLE A.1. CITY RANKS ACCORDING TO DIFFERENT CRITERIA

TABLE A.2. ESTIMATION RESULTS OF SPS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/3 VS. BOTTOM-1/3, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

	(1) Agglomeration Effects		(2)		(3) Selection Effects		(4)	(5) Obs.	(6)
	A		**D**		**S**		R^2	**Big City**	**Small City**
Panel B: top-1/3 vs. bottom-1/3									
C-Group (top-1/3)									
t<=-5	0.269***	[0.1795,0.3593]	1.065	[0.9571,1.1720]	0.013	[-0.0059,0.0317]	0.979	1,696	538
t=-4	0.183**	[0.0724,0.2938]	0.835	[0.6552,1.0139]	-0.009	[-0.0648,0.0462]	0.960	1,035	350
t=-3	0.230***	[0.1451,0.3146]	0.959	[0.8279,1.0911]	-0.005	[-0.0277,0.0186]	0.928	1,381	477
t=-2	0.167***	[0.0776,0.2562]	0.924	[0.8398,1.0075]	-0.010	[-0.0243,0.0038]	0.960	1,839	637
t=-1	0.204***	[0.1368,0.2713]	0.946	[0.8648,1.0279]	-0.012	[-0.0270,0.0035]	0.961	2,291	779
t=0	0.136**	[0.0438,0.2290]	1.001	[0.9315,1.0708]	-0.007	[-0.0189,0.0051]	0.913	2,526	865
t=+1	0.029	[-0.0784,0.1363]	1.049	[0.9603,1.1371]	-0.007	[-0.0288,0.0156]	0.806	1,855	629
t=+2	0.050	[-0.0351,0.1356]	1.089	[0.9750,1.2030]	0.006	[-0.0145,0.0264]	0.851	1,486	520
t=+3	0.046	[-0.0822,0.1750]	1.062	[0.9519,1.1721]	-0.015	[-0.0325,0.0021]	0.814	1,257	408
t=+4	-0.004	[-0.1688,0.1609]	1.064	[0.8346,1.2928]	-0.003	[-0.0524,0.0467]	0.467	860	296
t>=+5	-0.112	[-0.2553,0.0307]	1.025	[0.9073,1.1426]	0.002	[-0.0316,0.0357]	0.812	1,257	432
F-Group (bottom-1/3)									
t<=-5	0.149***	[0.0679,0.2303]	0.917	[0.7907,1.0428]	-0.012	[-0.0438,0.0199]	0.967	1,178	570
t=-4	0.082	[-0.0292,0.1926]	0.956	[0.8125,1.0997]	-0.010	[-0.0913,0.0718]	0.796	750	380
t=-3	0.096*	[0.0079,0.1847]	0.980	[0.8736,1.0855]	0.003	[-0.0158,0.0211]	0.821	1,079	528
t=-2	0.088*	[0.0047,0.1704]	0.946	[0.8891,1.0025]	-0.004	[-0.0208,0.0128]	0.823	1,454	701
t=-1	0.119**	[0.0455,0.1931]	0.985	[0.9107,1.0586]	-0.005	[-0.0245,0.0136]	0.933	1,848	846
t=0	0.081*	[0.0001,0.1616]	1.053	[0.9824,1.1243]	0.000	[-0.0133,0.0142]	0.877	1,985	931
t=+1	0.073	[-0.0217,0.1674]	1.147***	[1.0403,1.2539]	0.005	[-0.0153,0.0246]	0.892	1,428	699
t=+2	0.043	[-0.0721,0.1578]	1.104***	[1.0187,1.1883]	0.001	[-0.0178,0.0194]	0.847	1,152	572
t=+3	0.001	[-0.1265,0.1295]	1.171***	[1.0356,1.3074]	0.013	[-0.0229,0.0489]	0.876	942	462
t=+4	-0.105	[-0.3549,0.1444]	1.161	[0.9480,1.3731]	0.016	[-0.0505,0.0825]	0.740	631	323
t>=+5	-0.102	[-0.6336,0.4301]	1.183	[0.7627,1.6023]	0.004	[-0.1874,0.1955]	0.821	1,078	449

Notes: *SPs* are firms change their ownership from stated-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year before the privatization while $t = +1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/3* are the nearest 33% firms denoted by prefix *C*-, while *bottom-1/3* are the farthest 33% firms denoted by prefix *F*-; The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE A.3. ESTIMATION RESULTS OF CPS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

	(1) **Agglomeration Effects**		**(2)**		**(3)** **Selection Effects**		**(4)**	**(5)** **Obs.**	**(6)**
	A		**D**		**S**		R^2	**Big City**	**Small City**
C-Group (top-1/2)									
t<=-5	0.042	[-0.0549,0.1380]	1.144***	[1.0184,1.2689]	0.015	[-0.0022,0.0330]	0.960	2,802	418
t=-4	0.140	[-0.0733,0.3524]	1.074	[0.8810,1.2680]	-0.013	[-0.1085,0.0831]	0.974	2,150	334
t=-3	0.154***	[0.0761,0.2316]	1.06	[0.9726,1.1466]	0.010	[-0.0076,0.0278]	0.969	3,365	549
t=-2	0.097*	[0.0179,0.1763]	1.011	[0.9205,1.1011]	-0.003	[-0.0196,0.0134]	0.851	5,621	851
t=-1	0.106***	[0.0440,0.1681]	1.048	[0.9927,1.1030]	0.010	[-0.0000,0.0201]	0.934	9,457	1,455
t=0	0.086**	[0.0319,0.1402]	1.063*	[1.0122,1.1136]	0.002	[-0.0087,0.0122]	0.906	9,944	1,509
t=+1	0.117***	[0.0640,0.1706]	1.058*	[1.0031,1.1127]	0.001	[-0.0084,0.0099]	0.916	7,353	1,082
t=+2	0.141***	[0.0646,0.2169]	1.027	[0.9546,1.1001]	-0.012	[-0.0259,0.0024]	0.944	5,863	844
t=+3	0.158	[-0.0481,0.3638]	1.006	[0.8506,1.1609]	-0.012	[-0.0913,0.0673]	0.885	4,515	635
t=+4	0.109*	[0.0247,0.1932]	1.061	[0.9813,1.1406]	-0.001	[-0.0177,0.0155]	0.865	3,492	476
t>=+5	-0.014	[-0.0906,0.0625]	1.050	[0.9947,1.1051]	0.008	[-0.0053,0.0212]	0.611	6,259	857
F-Group (bottom-1/2)									
t<=-5	0.050	[-0.0397,0.1392]	1.157**	[1.0699,1.2446]	0.012	[-0.0049,0.0292]	0.911	2,586	485
t=-4	0.136*	[0.0089,0.2637]	1.02	[0.9074,1.1334]	0.005	[-0.0222,0.0323]	0.951	2,160	341
t=-3	0.152*	[0.0226,0.2815]	1.031	[0.9322,1.1304]	0.004	[-0.0261,0.0350]	0.959	3,507	545
t=-2	0.128**	[0.0484,0.2084]	1.014	[0.9328,1.0954]	0.012	[-0.0013,0.0244]	0.955	5,864	891
t=-1	0.184***	[0.1343,0.2342]	0.994	[0.9358,1.0516]	-0.002	[-0.0120,0.0084]	0.984	10,156	1,617
t=0	0.092***	[0.0471,0.1359]	1.045**	[1.0011,1.0892]	-0.001	[-0.0083,0.0065]	0.943	10,580	1,684
t=+1	0.105**	[0.0270,0.1821]	1.01	[0.9404,1.0800]	-0.011	[-0.0335,0.0109]	0.871	7,879	1,222
t=+2	0.039	[-0.1444,0.2219]	1.074	[0.9301,1.2171]	0.010	[-0.0546,0.0746]	0.603	6,368	958
t=+3	0.075	[-0.0243,0.1739]	1.063	[0.9746,1.1512]	0.003	[-0.0254,0.0321]	0.747	4,831	719
t=+4	0.036	[-0.5926,0.6651]	1.108*	[0.6922,1.5242]	-0.002	[-0.2117,0.2078]	0.781	3,691	547
t>=+5	-0.015	[-0.1215,0.0909]	1.181*	[1.0821,1.2809]	0.029	[-0.0002,0.0588]	0.787	6,833	889

Notes: *CPs* are firms that change their ownership from collective-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm is privatized from an SOE to a POE, and $t = -1$ is one year prior to the privatization while $t+1$ one year after, and so forth; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/2* are the nearest 50% firms denoted by prefix *C-*, while *bottom-1/2* are the farthest 50% firms denoted by prefix *F-*; The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Data Cleaning Process

The firm linkages over time are made using the methods of Brandt et al. (2012, 2014) and Brandt et al. (2017), who provided do-files online, including programs for matching firms over years and tables of industrial concordance codes.[16] After matching firms, we follow standard procedures documented in the previous literature to clean the data (Wei and Liu, 2006; Brandt et al., 2012, 2014; Yang, 2018):

1. Only keep the manufacturing industry;
2. Exclude the tobacco industry;
3. Use observations with positive industrial value-added, intermediate inputs, and net fixed assets;
4. Keep observations with no less than eight employees;
5. Drop observations not under accounting principles: liquid, fixed, or net fixed assets larger than total assets;
6. Make 4-digit industrial numerical codes uniform across the entire period following Brandt et al. (2014). Further, update the renamed or merged city to the latest city name.[17]
7. Firms that changed their locations are deleted.[18]
8. Observations without population data, another critical variable collected from city statistical yearbooks, are deleted.
9. According to the method for distinguishing the ownership of the firm instructed in Section 3.2, we exclude firms that have changed ownership many times and have been nationalized.

we finally obtain unbalanced panel data with 461,642 (specifically, 50,041 *Always-SOEs*, 30,854 *Always-COEs*, 347,056 *Always-POEs*, 23,717 *CPs*, 756 *SCs*, and 9,218 *SPs*) unique firms from 1998 to 2007 (totally 1,653,782 observations) covering 28 two-digit manufacturing industries across 31 provinces and 287 prefecture-level cities.[19]

[16]Online website:`https://feb.kuleuven.be/public/u0044468//CHINA/appendix/`, accessed March 13th, 2021.

[17]During the analysis period from 2000 to 2007, industrial standard classification for national economic activities was revised in 2002 from GB/T 4754—1994 to GB/T 4754—2002, where some 4-digit industries were merged while others were divided.

[18]Firms whose addresses have changed accounted for only 0.16% of the whole sample. Hence, we can assume that the firm does not have the possibility of relocation; it can only go bankrupt and cannot change its official location.

[19]*SCs* are those who changed from SOEs to COEs; however, we do not analyze this group's firms due to limited observations.

Year	Number of firms			Sales			Output			Value added			Employment			Net value of fixed assets			Export		
	Brandt et al. (2014)	Dataset	Diff.	Brandt et al. (2014)	Dataset	Diff.	Brandt et al. (2014)	Dataset	Diff.	Brandt et al. (2014)	Dataset	Diff.	Brandt et al. (2014)	Dataset	Diff.	Brandt et al. (2014)	Dataset	Diff.	Brandt et al. (2014)	Dataset	Diff.
1998	165,118	165,116	2	6.41	6.41	0.00	6.77	6.77	0.00	1.94	1.94	0.00	56.44	56.44	0.00	4.41	4.41	0.00	1.08	1.08	0.00
1999	162,033	162,033	0	6.99	6.99	0.00	7.27	7.27	0.00	2.16	2.16	0.00	58.05	58.05	0.00	4.73	4.73	0.00	1.16	1.15	0.01
2000	162,833	162,885	-52	8.42	8.42	0.00	8.57	8.57	0.00	2.54	2.54	0.00	53.68	53.68	0.00	5.81	5.18	0.63	1.46	1.46	0.00
2001	169,030	171,256	-2226	9.24	9.37	-0.13	9.41	9.54	-0.13	2.79	2.83	-0.04	52.97	54.41	-1.44	5.45	5.54	-0.09	1.61	1.62	-0.01
2002	181,557	181,557	0	10.95	10.95	0.00	11.08	11.08	0.00	3.30	3.30	0.00	55.21	55.21	0.00	5.95	5.95	0.00	2.01	2.01	0.00
2003	196,222	196,222	0	14.32	14.32	0.00	14.23	14.23	0.00	4.20	4.20	0.00	57.49	57.49	0.00	6.61	6.61	0.00	2.69	2.69	0.00
2004	279,092	274,886	4206	20.43	19.88	0.55	20.16	20.10	0.06	6.62	5.67	0.95	66.27	66.26	0.01	7.97	7.96	0.01	4.05	4.05	0.00
2005	271,835	270,043	1792	24.69	24.82	-0.13	25.16	24.99	0.17	7.22	7.14	0.08	68.96	69.09	-0.13	8.95	10.53	-1.58	4.77	4.77	0.00
2006	301,961	301,961	0	31.36	31.42	-0.06	31.66	31.66	0.00	9.11	9.11	0.00	73.58	73.58	0.00	10.58	10.58	0.00	6.05	6.05	0.00
2007	336,768	336,768	0	39.97	40.06	-0.09	40.52	40.51	0.01	11.70	11.70	0.00	78.75	79.27	-0.52	12.34	12.34	0.00	7.34	7.34	0.00

TABLE B.1. ORIGINAL DATA VS. TABLE.4 IN BRANDT ET AL. (2014)

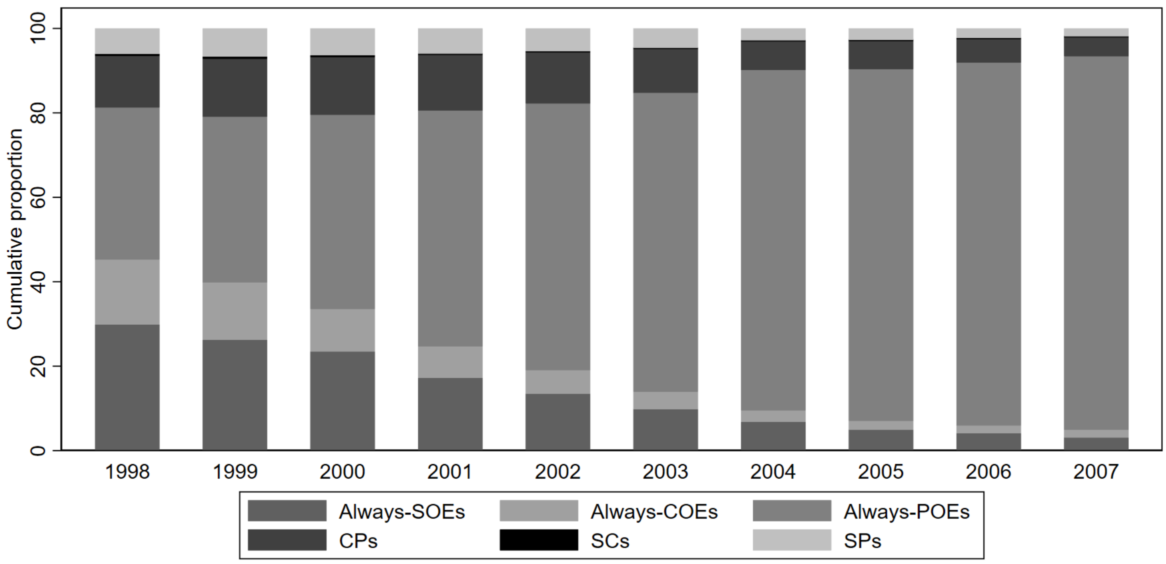

FIGURE B.1. PERCENTAGE OF FIRM WITH DIFFERENT ULTIMATE OWNERSHIP PER YEAR

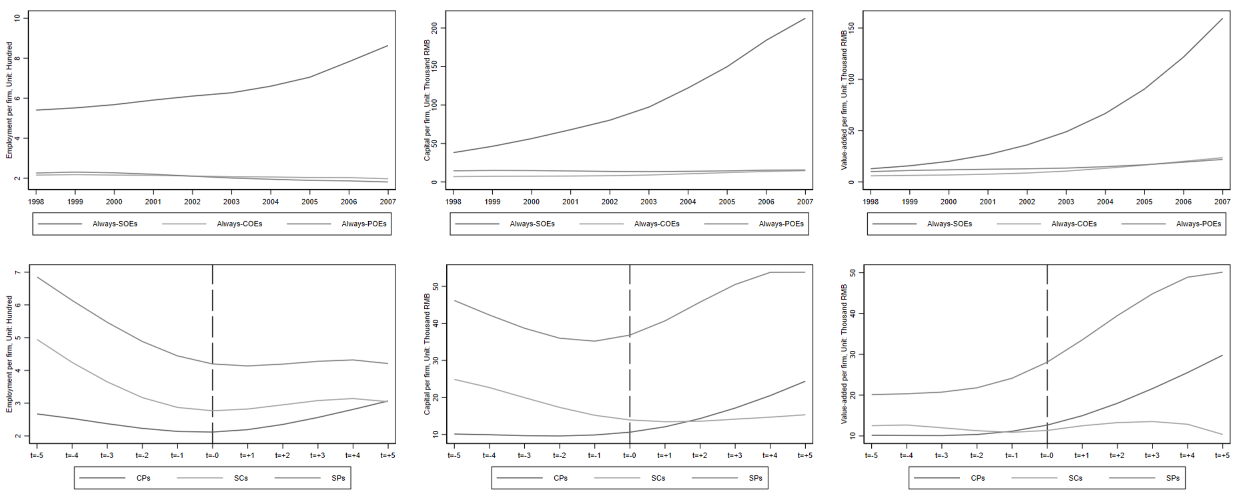

FIGURE B.2. AVERAGE FIRM PERFORMANCE GROUPED BY ULTIMATE OWNERSHIP

OP Method

We start with the production function:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} \tag{.8}$$

where Y_{it} stands for value-added; the revenue production function looks like: $Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m}$, where Y_{it} is gross output. Taking the natural logarithm of Equation (.8) results in a linear production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \varepsilon_{it} \tag{.9}$$

and ε_{it} includes two parts $\omega_{it} + u_{it}$, where ω_{it} represents firm-level productivity and u_{it} is i.i.d. A direct estimation using OLS will cause endogeneity problems and selection bias, and lead to biased productivity results.

Olley and Pakes (1992) assumed that investment decisions at the firm level can be shown to depend on capital ($I_{it} = K_{it+1} - (1-\delta)K_{it}$) and productivity (higher expectation, higher investment decision):

$$\omega_{it} = h_t(k_{it}, i_{it}) \tag{.10}$$

Since this is a monotonically increasing function, it can be written as $h_t(.) = i_t^{-1}(.)$:

$$y_{it} = \beta_l l_{it} + \beta_0 + \beta_k k_{it} + h_t(k_{it}, i_{it}) + u_{it} \tag{.11}$$

The first term on the right side of the equation represents the contribution of labor. The latter term represents the contribution of capital and can be further written as:

$$\varphi(i_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + h_t(i_{it}, k_{it}) \tag{.12}$$

$$y_{it} = \beta_l l_{it} + \varphi(i_{it}, k_{it}) + u_{it} \tag{.13}$$

An unbiased labor coefficient can be obtained by estimating Eq.(.13). Then, the estimated coefficient is used to fit the polynomial term ($\varphi(i_{it}, k_{it})$) formed by investment and capital stock:

$$\begin{aligned} & y_{it+1} - \beta_l l_{it+1} \\ & \quad = \beta_0 + \beta_k k_{it+1} + g(\phi_{it}, \beta_k k_{it}) + \xi_{it+1} + u_{it+1}^{q} \end{aligned} \tag{.14}$$

The second stage of the estimation includes the estimation of high-order polynomials. The current and lag periods of the capital stock exist simultaneously, which needs to be completed by the nonlinear least square method.