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Yikai Zhao and Jun Nagayasu

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Center for Data Science and Service Research
Graduate School of Economic and Management
Tohoku University
27-1 Kawauchi, Aobaku
Sendai 980-8576, JAPAN

Privatization's Influence on Agglomeration and Selection Effects: Evidence from China's Manufacturing Industry

Yikai Zhao* Jun Nagayasu†

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Abstract

We study the impact of state-owned enterprises' (SOE) privatization on how firm productivity responds to agglomeration and selection effects, and investigate whether and how policymakers can utilize agglomeration and selection to benefit from privatization. As SOEs enjoy privileged treatment because of their government ties, we argue that the agglomeration advantages of SOEs are rooted in their connection with local governments who regulate them, who share local information with surrounding SOEs, such as labor markets, resources, and tacit knowledge. Overall, we attempt to answer the following questions: 1) Will the SOEs' reform negatively (positively) influence enterprises' agglomeration (selection) effects? 2) To what extent is this influence affected by the local government? 3) Is this adverse or favorable impact heterogeneous?

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

*Corresponding author, Tohoku University, Graduate School of Economics and Management, 27-1 Kawauchi, Aoba-Ku, Sendai-city, Miyagi 980-8576 JAPAN; Tel: +81 22 795 6265; Fax: +81 22 795 6270; Email: zhao.yikai.p7@dc.tohoku.ac.jp.

†Tohoku University, Graduate School of Economics and Management, 27-1 Kawauchi, Aoba-Ku, Sendai-city, Miyagi 980-8576 JAPAN; Tel: +81 22 795 6265; Fax: +81 22 795 6270; Email: jun.nagayasu.d8@tohoku.ac.jp.

1 Introduction

More than 100 countries have initiated extensive privatization programs since early 1980 (Megginson and Netter, 2001). Among them, China's privatization is characterized by cautiousness and gradualism but stands out due to its sheer scale and extent (Svejnar, 2002; Kikeri and Nellis, 2004). Large-scale privatization occurred in the country in the late 1990s. From 1995 to 2005, nearly 100,000 firms (two-thirds of China's state-owned enterprises (SOE)) with 11.4 trillion RMB worth of assets were privatized (Gan, 2009). From 2009 to 2015, China has constantly been among the top privatizers, being the second-largest privatizer in 2009, and the largest in 2013 and 2014 (Estrin and Pelletier, 2018). Importantly, these privatized firms are a growing presence in international trade and investment. Considering its scale, extent, and impact, the Chinese experiences can provide valuable insights into privatization design.

Most studies find a positive relationship between privatization and firm productivity (Brown et al., 2006); however, privatized SOEs rarely catch up with private firms (Boardman et al., 2016; Harrison et al., 2019). Minimizing the negative effect of possible shocks in the early stage of the privatization process and quickly reaping the outcomes of reforms are vital considerations for the government while implementing reform policies. In this context, agglomeration economies and market selection may offer vital information. Specifically, with urbanization, large cities have economically outperformed small cities due to agglomeration advantages (Zhao et al., 2003; Syverson, 2004). Then, privatizing SOEs in densely-populated cities can help in reducing the vulnerability in the early stages of reform since these SOEs can benefit more from positive externalities through sharing, matching, and learning from surrounding private firms; according to Marshall (2009) and Jacobs (2016), these are the three fundamental channels of agglomeration. Moreover, fierce market competition in urban areas motivates firms to raise productivity and eliminates low-quality firms (redistributing resources); thus, the surviving privatized SOEs are likely to be better.

To fully utilize the reform, policymakers can prioritize SOEs in urban cities where enhanced agglomeration and selection effects can be leveraged by the post-privatization SOEs. Here, we explore the impact of SOEs' privatization by studying how firm productivity responds to agglomeration and selection effects. We ask: Will the SOEs' reform negatively (positively) influence the enterprise's agglomeration (selection) effect? To what extent is this influence affected by the local government? Is this adverse or favorable impact heterogeneous? To address these questions, we estimate the differentials of agglomeration and selection effects between large and small cities for privatized SOEs by employing a quantile specification proposed by Combes et al. (2012) and using 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 SOEs' reform. For this, referring to Boardman et al. (2016), we construct five comparable groups as contrasts to demonstrate the unique behavior of privatized SOEs, i.e., *Always-SOEs*, *Always-COEs*, *Always-POEs*, *SPs*, and *CPs*.[1]

In addition to accounting for the agglomeration and selection effects during privatization, our study has another advantage in that it considers having local information as an influencing factor. We take inspiration from the seminal work of Huang et al. (2017), which is based on the conjectures of Hayek (1945) and Aghion and Tirole (1997). That is, one way to efficiently improve SOEs' performance is to utilize local information by enhancing their interaction with the government. We argue that this interaction is the primary source for SOEs to obtain agglomeration advantages. As SOEs' managers are usually appointed by the government, this gives SOEs more privileges in obtaining resources, industry licensing, and bank credits (Faccio, 2010). That is, most advantages of SOEs come from the political connections; thus, the agglomeration gains of SOEs likewise stem primarily from the government's information sharing, matching, and learning regarding resources, financing, taxation, and labor pool. Importantly, these gains usually diminish with increasing geographic distance from the government. Huang et al. (2017) note that closer physical distance between an SOE and the government/regulators which oversee it (hereinafter, "distance from oversight government"; meanwhile, the governments overseeing the respective jurisdiction are referred to as "oversight governments") can assure the availability of local information. Correspondingly, we use the physical distance to separate our sample into sub-groups (i.e., *C-Group* and *F-Group* as introduced in Section 3.3), and estimate the agglomeration and selection effects of each group.

Overall, while this study extends previous empirical work using a similar quantile approach (Arimoto et al., 2014; Accetturo et al., 2018; Ding and Niu, 2019; Adachi et al., 2021), it makes three main contributions. First, we focus on 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 impact of privatization in the short term. In contrast, the gradually increasing agglomeration that benefits only productive reformed SOEs has a positive impact. This empirical evidence enriches the existing research on agglomeration effects and partially explains why privatized firms have difficulties in improving productivity in the short term. Second, we collect night-light satellite data and use them to proxy city density, which differs from Ding and Niu (2019) who use population or population density. As indicated by Duranton and Puga (2020), night-light data can measure crowding more directly. Third, based on the oversight agency conjecture proposed by Hayek (1945) that governments have the motivation to decentralize distant SOEs, our study indicates that SOEs with fewer ex-ante government connections suffer less from the loss of agglomeration effects during the transition period; moreover, high-quality post-privatized SOEs can respond quickly to agglomeration effects. In short, SOEs with weaker government ties and higher productivity are most valuable for privatization.

[1] *SOE*, *COE*, and *POE* are the abbreviations for state-, collective-, and private-owned enterprises, respectively. The prefix *Always-* denotes firms where ownership does not change during the sample period. *SPs* are firms where ownership changes from state-owned to private-owned. Finally, *CPs* are firms where ownership changes from collective-owned to private-owned. Section 3.2 elaborates the definition of each group.

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

2 Literature Review

2.1 Agglomeration and Selection Effects

Large cities attract many firms despite high factor prices. These firms are more productive than their counterparts in small cities (Puga, 2010) and tend to innovate more significantly than those in rural regions (Naz et al., 2015). Seminal research (Marshall, 2009; Jacobs, 2016) on this area argues that one major cause are agglomeration advantages; urban areas are the outcome of a trade-off between increasing returns and costs of urban congestion.[2] Agglomeration can be of two types: localization economies and urbanization economics. The former refers to the Marshallian externalities arising from a concentration of firms in the same industry (Marshall, 2009). In contrast, the latter arises from an increase in city size that enables cross-fertilization of ideas among diverse economic activities (Jacobs, 2016).

Apart from the improvement in enterprises, the excellent performance of metropolises can be explained by the disappearance of inferior enterprises. Correspondingly, clustering weak firms that are not expelled may hinder the positive externalities from agglomeration due to a crowded market. Most of this evidence is presented by the inverted U-shaped productivity-to-agglomeration curve (Lin et al., 2011; Martin et al., 2011; Hu et al., 2015). This mechanism is named the selection effect, which contributes to the urban area by forcing firms at the tail to withdraw from the market. It serves to eliminate firms with low efficiency, thereby promoting urban productivity (Melitz, 2003; Melitz and Ottaviano, 2008; Combes et al., 2012).[3] This effect also hinders less productive firms from entering large markets. Moreover, the selection process, because of tough competition and the insolvency regime, can benefit society by reducing resource misallocation. Lam et al. (2017) noted that approximately 30% of "zombie" firms in China continuously survive despite low productivity and losses, crowding out private investment and hindering the market competition.[4] The harm caused

[2] Natural endowment is out of our discussion since man-made agglomeration (i.e., second nature) grants policymakers more space and possibility to promote the local economy. Further, with the evolution of society, the importance of natural resources has gradually weakened and can be ignored (Roos, 2005; Chasco et al., 2012); in addition, most of the agglomeration in China's manufacturing industry is the result of social outcomes and has little to do with natural endowments (Wen, 2004; Ge, 2009).

[3] Competition can also cause firms to initiate or continue their business in other cities (Gaubert, 2018), or spend considerable investments in upgrading equipment to increase productivity (Jiang et al., 2015); however, this is not within this study's scope.

[4] According to Lam et al. (2017), "zombies" are firms incurring persistent losses, with estimated interest payment

by zombie firms is even more severe because they worsen over-capacity by crowding out healthy firms and stalling technological diffusion in the proximity (Shen and Chen, 2017; Andrews et al., 2017). Waiting for these firms to mature seems too costly; instead, market selection helps clear away the zombie firms. This also limits productivity loss by reducing entry barriers in product markets, thus generating significant gains (Andrews et al., 2017). Hence, when the agglomeration expansion fails to deal with market congestion generated by zombie firms, examining the effect of the current selection process on local economic production efficiency is worthwhile.

Overall, results of agglomeration can be similar to that caused by selection, for example, average productivity improvement. Nevertheless, their mechanisms differ. On the one hand, we can roughly distinguish three fundamental channels through which agglomeration works: sharing, matching, and learning (Duranton and Puga, 2004); or labor, supplier, and knowledge spillovers (Marshall, 2009); or goods, people, and ideas (Ellison et al., 2010). On the other hand, the selection process can cause more efficient firms to be selected for a broader market, whereas less efficient firms serve the local market only. Intuitively, more trade increases average profits per firm, attracting more entrepreneurs to establish firms with certain fixed costs and employ workers, which increases wages in equilibrium. Consequently, the cut-off productivity level increases. The least productive firms no longer make profits in the new trade equilibrium, and therefore, exit; only firms with productivity above the cut-off can enter the markets. Even if there are no newly-established firms, incumbent firms can expand their production or reduce prices to seize market share, thereby strengthening competition. With the reallocation of market resources toward more efficient firms, the selection process contributes to an aggregate productivity gain (Melitz, 2003; Melitz and Ottaviano, 2008).

Therefore, we extrapolate that both agglomeration and selection contribute to the efficiency of urban cities, but act on different positions of the productivity distribution. A framework developed by Combes et al. (2012) distinguishes between agglomeration and selection, and explains why average productivity is higher in larger cities. Specifically, the agglomeration effect works at the mean value (the whole group of firms) or the right-hand tail (prominent firms), while the selection effect works via shrinking the left tail (inferior firms) of the productivity distribution. In other words, large cities differ from small ones by right-shifting, dilating, and left truncating the distribution of firm productivity.

The magnitude of agglomeration advantages and selection gains has been compared in several studies. Firm selection has outweighed agglomeration in the food industry in Chile (Saito and Gopinath, 2009) and the Japanese silk-reeling industry (Arimoto et al., 2014). In contrast, others find that the up-growing productivity is primarily due to agglomeration. Combes et al. (2012) developed a theoretical model and used the quantile regression to estimate the differentials of 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 simi-

costs below market lending rates.

lar model to Italian manufacturing firms, Accetturo et al. (2018) showed that agglomeration effects play a significant role, but there is also a substantial increase in the importance of the selection effect within several sectors. Ding and Niu (2019) and Zhang et al. (2020a) use the same method for examining China's manufacturing and construction industries, respectively. There is strong evidence for the agglomeration effect, while the selection effect contributes less to productivity.

2.2 Privatization and Firm Productivity in China

China's SOE reform has been a gradual and selective process. Privatization started in the mid-1990s, 15 years after the announcement of economic reforms in 1979 (Bai et al., 2006). Nevertheless, some scholars have advocated the role of state capitalism, underscoring that the remaining SOEs are the largest firms driving China's growth (Szamosszegi and Kyle, 2011; Hsieh and Song, 2015). However, SOEs are believed to be generally less efficient than private firms due to policy burdens, agency problems, and privileged licenses.[5] Bai et al. (2000) and Bai et al. (2006) provided a multitask theory of SOEs' reform; this can explain the fact that even in the process of gradually privatizing SOEs, China still emphasizes the importance of state capitalism. These authors suggested that because the Chinese SOEs have a crucial role in ensuring social stability, the government is cautious about reconstructing them. Even so, this stability is at the expense of firm performance, which thus motivates the government to consider reforming SOEs.

Most studies agree that privatization in China has improved the performance of SOEs. Researchers find different channels of SOE reforms. Bai et al. (2009) showed that the layoff of surplus labor is constrained even after privatization; however, privatized SOEs improve labor productivity by increasing sales. Meanwhile, the authors indicated that reducing managerial expenses to sales contributes the most to profit margins. Similarly, Sun and Tong (2003) reported that employee productivity has improved up to three years after privatization. The authors note that after privatization, improving firms' internal corporate governance can benefit their efficiency. Chen et al. (2021) also found productivity improvements after privatization, which helped reduce bureaucratic noise (less interference from governments enables them to make better decisions and implement better schemes) while denying the channels of downsizing or innovation. Su and He (2012) underlined lesser political influence and government administrative interference; the authors demonstrated the external market's positive impact during privatization, such as market competition.

Undoubtedly, the most notable feature of privatized SOEs is the reduced political connection (Huang et al., 2019), which is especially valuable in a transitional society with weak institutional

[5] Policy burdens tend to instruct SOEs to serve specific political goals, such as hiring more employees to promote social stability (Wen, 2020); a government-oriented executive evaluation mechanism is another policy burden among SOEs (Liu and Zhang, 2018), which can induce executives to abandon innovative investment projects that have higher risks but can be more profitable (Gao et al., 2018). SOEs suffer from severe agency problems, such as satisfying the managerial pursuit of personal benefits at the firm's expense due to the lack of adequate incentives and supervision for managers (Xu et al., 2005). Lastly, the administrative monopoly creates barriers through licenses, which reduces competitors, resulting in the low productivity and efficiency of SOEs (Zhang et al., 2020b).

arrangements (Nee, 1992). In the *guanxi* research, Li et al. (2011) analyzed 250 Chinese firms and noted that managers employed by SOEs possess more governmental tie channels than non-SOEs. Using a meta-analytic framework with a sample of 20,212 organizations, Luo et al. (2012) demonstrated that government ties are more critical to SOEs than non-SOEs. Apart from bank credits and better access to factor and product markets, the advantages of political connection subsume a sounder understanding of regulations and policies, more information, and special protection (Guo and Miller, 2010; Luo et al., 2012). These advantages, caused by close ties with the government instead of the spillovers from non-SOEs, can be generalized as the agglomeration effect. One source of agglomeration economies is knowledge spillover, specifically the tacit knowledge (Howells, 2002). That is, the potential for knowledge spillover between the regulators and SOEs may be a strong motivation for agglomeration since SOEs can exchange information quickly through the local government due to their close ties. Lower transaction and communication costs can be other reasons for SOEs being located in the proximity of the local government. Huang et al. (2017) noted that due to the distance–decay effect, when the distance to the government in the jurisdiction is farther, the SOE is more likely to be decentralized. The increased possibility of decentralization implies that the government lacks information exchange with distant SOEs, weakening the agglomeration effect of these SOEs.

SOEs primarily rely on the central and local governments. Firms with different ownership types may not usually have information exchange and technological diffusion (Zhu et al., 2019). Cognitive proximity and technological relatedness can explain this finding because SOEs and non-SOEs are subject to various operation codes, and confront distinct threats and opportunities (Peng et al., 2004; Liao, 2015). Therefore, it is sensible to posit that after privatization, SOEs may enjoy fewer agglomeration benefits from clustering around local governments with other SOEs. Notwithstanding this, using firm-level data, Zhu et al. (2020) implied that compared with *Always-SOEs*, reformed SOEs experience more knowledge spillovers from non-SOEs, and this effect strengthens year by year as they successfully change their identity. In this case, the final change in the agglomeration effect for privatized SOEs depends on which impact is more significant. For example, since privatized SOEs are part of the private sector, they may suffer from selection stress; however, this may not be clear in the short run. Based on the interview with factory directors and their accountants over five years, Oi (2005) found that some privatized firms that have stopped production are denied the option of declaring bankruptcy. Similarly, Boubakri et al. (2008) and Harrison et al. (2019) discovered that the government tends to offer privileged treatments to privatized SOEs compared to private firms which were never state-owned. Hence, the selection effect may not have the same impact on privatized SOEs as private firms.

To the best of our knowledge, no study has explored the agglomeration and selection effects during the period of SOEs' privatization. It may take several years to fully reap the benefits of privatization (Chen et al., 2021). By examining the role of agglomeration and selection effects during privatization, our study sheds light on the methods to speed up the realization of benefits; that is, catching up with the private firms that were never state-owned. Given this background, we propose the following hypotheses to answer our questions:

Hypothesis 1a: *Always-POEs enjoy agglomeration and selection effects, but their agglomeration effect is smaller than that of Always-SOEs.*

Hypothesis 1b: *Always-SOEs enjoy an agglomeration effect; meanwhile, Always-SOEs in proximity to their regulating local governments have a more considerable agglomeration effect.*

Hypothesis 2a: *Post-privatization, SOE-to-POEs (SPs) enjoy a smaller (or more significant) agglomeration effect than pre-privatization; in addition, the change experienced by privatized SOEs closer to and farther from their regulating local governments differ.*

Hypothesis 2b: *After privatization, SPs experience an improved selection effect, which is not detected for pre-privatized SOEs.*

Although our interest is in the changes in the impact of agglomeration and selection effects on firm productivity before and after SOEs' reform, and the role of government connections, **Hypotheses 1a** and **1b** are still necessary conditions before evaluating **Hypotheses 2a** and **2b**. Considering that the goal of privatizing SOEs is to make them improve their performance by bringing more private capital, we can see whether privatization helps SOEs in catching up with the private sector by comparing them with *Always-POEs*. Meanwhile, the predecessors of privatized SOEs are state-owned enterprises, which allows us to accurately understand the influence of government connections on the agglomeration effect of SOEs and then reasonably predict the outcomes after losing government support.

3 Data

3.1 Firm Data

Our total factor productivity (TFP) estimation extensively uses Chinese firm-level data. While three industries (mining, manufacturing, and public utilities) are included in the data set, we only use manufacturing because most sampled firms belong to this industry; moreover, the production behaviors of mining and public utilities are disparate. 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 5 million RMB in mainland China.[6] [7] Furthermore, the dataset has detailed in-

[6] 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 in the database. Fortunately, according to the Census, the vast majority of these companies (96.6% in 2007) do not have subsidiaries (Brandt et al., 2014). Therefore, we can justifiably suppose that an observation is a unique single-plant firm.

[7] In 2011, the designated size for non-state firms changed from 5 million to 20 million RMB.

formation on firms' balance sheets and income statements, as well as basic information, such as ownership, established time, and registration address.[8] [9] 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 (Appendix B details how we obtain the basic sample, Figure B.1 displays the distribution of firms with different ownership per year, and Figure B.2 demonstrates the trends of employment, capital and value-added.)[10]

3.2 State-Owned and Private Firms

Many studies (Brandt et al., 2017; Khandelwal et al., 2013) find that Chinese SOEs have distinct operation features that cannot be ignored; that is, SOEs' production function and growth trajectory differ from those of private firms. Moreover, because China is implementing large-scale SOE reforms during the sample period, it is necessary to consider the type of ownership.

ASIF reports the official registered enterprise structure but does not rightly reflect the type of owner controlling firms. This is because firms rarely modify their registration status even if the controlling shareholder changes (Dougherty et al., 2007). Instead, we examine the shareholding structure by capital share to understand the *de facto* owner of a firm. Following Dougherty et al. (2007), we define a firm as an SOE when it directly reports that it is state held. Amongst non-state-held firms, collective-owned enterprises (COEs) are those with a collective capital share greater than 50%, while the remainder are the private-owned enterprises (POEs).[11] [12] Furthermore, we divide firms into five categories corresponding to 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

[8]Table B.1 compares our original dataset 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 are slightly different from these authors but are still very close to the statistics summarized in the Statistical Yearbook.

[9]The database has been updated till 2013 from 1998; however, the data after 2007 are generally considered debatable due to the small number of variables and the large discrepancy with the Statistical Yearbook contents. Therefore, we only consider the period from 1998 to 2007.

[10]According to Kamal-Chaoui et al. (2009), China has four *de facto* tiers of local governance: provinces, prefecture-level cities, county-level cities, and townships. This article is based 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.

[11]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, which can be seen in other studies (Liao et al., 2014).

[12]Unlike simply dividing firms into SOEs and non-SOEs, we also distinguish COEs because compared with SOEs, COEs are viewed as a competitive organizational form with remarkable performance under China's partial reform; however, they still have to suffer from policy burdens and agency problems as local governments oversee them. Nevertheless, many COEs have also transitioned from collective ownership to private ownership during the SOE reform period (Xia et al., 2009).

from being SOEs to POEs, while *CPs* are those that transition from COEs to POEs. Overall, we focus on firms that have never changed ultimate control and those privatized only once, but exclude firms whose ownership has changed multiple times or those which have been nationalized.

3.3 Distance From Oversight Government

Here, we regard the SOEs' decentralization as a loss of agglomeration advantages as 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 the assertion of Hayek (1945) 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 in proximity. This points to more relation-based government ties, which strengthens 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 affiliations: central, provincial, and municipal. Using Google Maps API, we obtain each government's geo-location (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 rank firms at each level from the smallest to largest based on distance, and compare the top 50% and bottom 50% (top-1/2 versus bottom-1/2), and the top third and bottom third (top-1/3 versus bottom-1/3). The geographically close group is denoted as *C-Group* and the distant one as *F-Group*.

3.4 Market Size

Market size is essential to measure agglomeration and selection effects in our setting. Two questions arise regarding this issue: 1) the choice of the index (e.g., population or light-night data) and 2) spatial unit (e.g., provinces or cities). Agglomeration always occurs on a local scale. Hence, we take the prefecture-level city as the spatial unit in our benchmark model.[13] Regarding the first question, instead of using population, we employ nighttime lights 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 National Bureau of Statistics' definition (NBS-defined) 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

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

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 are quite broad). Thus, using city (*shi*) population or population density is not an ideal measure for the market size or urbanization. Meanwhile, the *hukou* system in China does not count workers who migrate from rural areas to urban cores. Hence, the *hukou* population of the urban areas (labeled as *chengzhen renkou*) may underestimate the actual population. According to Chan (2007), approximately 150 million people in Chinese cities belonged to this category in 2005. Therefore, remotely sensed nighttime lights datasets are more reasonable for measuring the market size and have been tested for robustness. In addition, we use employment data as a proxy for urban population.[14] [15]

3.5 TFP Estimation

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

$$\ln \mathrm{Y}_{isct} = \beta_0 + \beta_k \ln X_{1,isct} + \beta_l \ln X_{2,isct} + \gamma_s + \theta_c + \mu_t + \varepsilon_{isct} \tag{1}$$

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. When the ordinary least squares (OLS) method is applied to estimate firm-level TFP, unavoidable measurement technical problems emerge. The most noticeable one is the simultaneity of production decision-making. To ensure the reliability of the results, we conduct a group-by-group regression (using the ultimate control as grouped in Section 3.2) based on the Olley-Pakes (OP) method (Olley and Pakes, 1992). In Section 5, we use labor productivity and productivity estimated by the OLS method to check the robustness.

Next, following Combes et al. (2012), we calculate the average productivity to reduce noise. Moreover, as our interest is whether ownership (ultimate controller) affects agglomeration and selection effects, we consider the manufacturing industry as a whole. However, the productivity of different 2-digit industries is not comparable (Van Beveren, 2012), as well as the industrial structure of each city. Before computing average TFP, expressed as Equation (2), across years 1998 to 2007, we standardize productivity by industry to reduce the variability caused by different industries. Fur-

[14] DMSP-OLS nighttime lights nighttime data are downloaded from `https://ngdc.noaa.gov/eog/download.html`.

[15] To verify the reliability of the light brightness, we also used other measures of city size: the number of employees in the secondary industry (employment density) and population (population density) in the urban areas (*shi xia qu*). These data are collected from the city statistic yearbooks (Table A.1 presents the top five and last but five cities by different criteria).

ther, the cities are grouped into *large city* and *small city* by median values of light brightness in 2003, as discussed in Section 3.4.[16]

$$\ln \mathrm{TFP}_{ic} = \frac{1}{(T-t+1)} \sum_{t}^{T} (\ln \mathrm{TFP}_{isct}) \quad (2)$$

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 diverse channels (Combes et al., 2012).[17]

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.[18]

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), and higher h means lower productivity ϕ_i. This effect hints that agglomeration benefits are also related to individual productivity and not just to city size.

Selection effect (S_i): This effect is estimated as the probability of a firm exiting from the local market. It is represented as $S_i = 1 - G(\bar{h}_i)$,[19] 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.[20] We can easily understand that lower $\bar{h}_i$ (higher ϕ_i) leads to higher S_i. Entry barriers keep potential entrants out of the market because of high sunk costs or productivity pressures.

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

[16] For sample period analysis, t starts from 1998 and ends at 2007. However, for a certain period of time, say the, three-year average for 1998–2000 in Table 1, t starts from 1998 and ends at 2000.

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

[18] $\delta \in [0,1]$ $\delta = 0$ means that workers in city i can only interact with people in the same place. $\delta = 1$ means that workers enjoy interactions with the same intensity with workers from everywhere; in this case, there are no difference in dilation or agglomeration effects among cities: $D_i = D_j, A_i = A_j$

[19] 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.

[20] $\bar{h}$ 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. Accetturo et al. (2011) also extended this equation into various s_i and found no changes in the results. Specifically, if there is no additional cost when they sell in other cities ($\tau = 1$), then there are no differences in selection density: $S_i = S_j$.

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - A_i}{D_i}\right) - S_i}{1 - S_i}\right\} \tag{3}$$

This is impossible to estimate because of the lack of the exact underlying distribution $\tilde{F}(.)$. 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:

$$D \equiv \frac{D_i}{D_j}, \quad A \equiv A_i - DA_j, \quad S \equiv \frac{S_i - S_j}{1 - S_j} \tag{4}$$

Then, Equation (3) can be arranged as follows:

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

$$F_j(\phi) = \max\left\{0, \frac{F_i(D\phi + A) - \frac{-S}{1-S}}{1 - \frac{-S}{1-S}}\right\} \quad if \quad S_i < S_j \tag{6}$$

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

$$\lambda_i\left(r_S(u)\right) = D\lambda_j\left(S + (1 - S)r_S(u)\right) + A \quad \text{for} \quad u \in [0,1] \tag{7}$$

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 the relative truncation parameter S. Back to the Equation (4), the hypothesis of no agglomeration, dilation, or selection effect between two cities can be denoted as follows:

$$H_0 : A = 0, \quad D = 1, \quad S = 0 \tag{8}$$

Figure 1 displays the CDF of the productivity between large and small cities with a certain A, D, and S. Here, the selection effect is the result after comparison. If there is no trade cost (i.e., $\tau = 1$, see footnote 20), S will be 0. This is seemingly contrary to the finding in Syverson (2004) that the reduction in transportation costs will enhance the competition via selection. This may be because what Syverson (2004) described is an absolute raise (or S_i instead of S). If two cities are compared, there is probably no difference ($S = 0$).

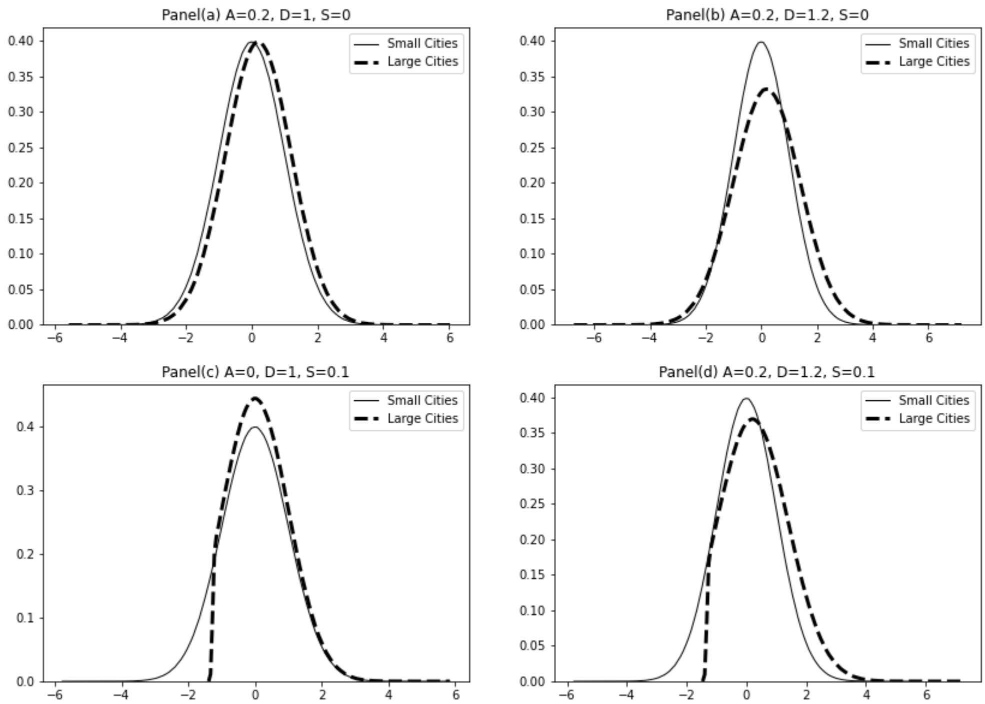

FIGURE 1. MONTE CARLO SIMULATIONS, DISTRIBUTIONS IN LARGE AND SMALL CITIES

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 $\ln \mathrm{TFP}$ distributions in large cities and small cities.

4.2 Empirical Results

4.2.1 Agglomeration and Selection Effects of Different Ownership

Estimates of A, D and S using light brightness as a criterion to group cities are reported in Table 1 and Table 2. Note that R^2 are often above 0.90, indicating that the agglomeration (A and D) and selection effects (S) can explain the majority of divergence in productivity between large and small cities. Moreover, we find positive agglomeration effects on productivity for all firms controlled by various ownership types. Based on bootstrapped standard errors, estimates of A differ significantly from zero. Further, generally, there are different trajectories of productivity on agglomeration effects over time (column (1) in Table 1). The agglomeration effect from shifting gradually fades away among the private sector and benefits toward SOEs slightly drop, while collective firms still enjoy more and more agglomeration effects.

Meanwhile, owing to an insignificant $\hat{S}$ at most times, no evidence of stronger firm selection in larger cities is detected among *Always-COEs*. In contrast, SOEs unsurprisingly have negative values of S, corresponding instead to greater truncation in less dense areas. SOEs with the government's extensive support are less likely to exit the local market, even on the verge of a break-down. Better access to credit markets may explain the fact that growing firms, such as Chinese SOEs, with low productivity, survive (Hu et al., 2015). Nevertheless, urban cities tend to have the ability to provide more bank credit.

We find evidence of fierce selection in larger cities for *Always-POEs*, where $\hat{S}$ is always positive and statistically significant.[21] Thus, without considering the selection effect, productivity gains from agglomeration advantages may be overestimated. Even so, the selection effect on productivity is far less than the agglomeration effect. As Brandt et al. (2012) reckoned, there is market selection in the Chinese market; however, limited efficiency-enhancing input re-allocations may curtail this function. Overall, Table 1 supports **Hypothesis 1a** that *Always-POEs* have statistically significant agglomeration and selection effects, though the agglomeration effect for this group is smaller than that for *Always-SOEs*.

Table 2, where firms are divided by the distance from their overseeing government, provides more information about the sources of SOEs' agglomeration effects. As specified by Huang et al. (2017), a longer distance implies fewer direct observations of firm-specific information as well as fewer interaction activities. Moreover, stimulated by the tax sharing system and the lack of enough POEs, supporting SOEs in the jurisdiction is the main way for the local government to obtain tax revenues.[22] The agglomeration effect ($\hat{A}$) shows that the 95% confidence interval (CI)

[21] 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 a couple of Chinese manufacturing industries. Notably, Ding and Niu (2019) used the provincial population density as the standard and found that 15 out of 29 industries exhibit a significant S regardless of enterprise ownership.

[22] As an important fiscal reform, the 1994 tax reform replaced the previous fiscal contracting system with a tax sharing system (the previous one was a tax contracting system): central, local, and shared taxes. This tax system drives local

of *Always-SOEs* classified to C-Group is $[0.1754, 0.2619]$, while that of being classified to F-Group is $[0.0817, 0.1416]$ (column (1), Panel A). These two CIs significantly differ. This is more obvious in Panel B ($[0.1957, 0.2755]$ for *Always-SOEs* of C-Group and $[0.0651, 0.1508]$ for *Always-SOEs* of F-Group). Furthermore, in Panel B, the selection effect for SOEs close to the government is significantly negative, but is insignificant for distant SOEs. We attribute the pronounced discrepancy to the agglomeration advantages from political ties intensified by proximity. As the government is always located in the center of an urban city, one may question whether this discrepancy simply comes from economic agglomeration. This concern is reinforced because while we use the light brightness of a city to proxy the density, the density is not evenly distributed within a city. Then, firms classified in the same density tier may have higher economies of scale because they are closer to the city center. Nevertheless, if this reason holds, all firms close to the local government should exhibit a significantly larger $\hat{A}$ or $\hat{D}$ value. Especially for *Always-POEs*, the $\hat{S}$ should be larger as well due to tougher competition (e.g., high land costs). However, we see no difference between C- and F-Groups for *Always-POEs* and *Always-COEs*. Therefore, we argue that *Always-SOEs* that are closer to their overseeing regulator enjoy more agglomeration advantages through their interaction with the government. Table 2 also demonstrates that **Hypothesis 1b** is supported.

4.2.2 After Privatization

Now, we investigate the extent to which privatization impacts productivity through agglomeration and selection effects. Private ownership is believed to be necessary for improving firm efficiency (Xu and Wang, 1999). Table 3 reports A, D, and S before and after privatization by distance from the corresponding oversight government (Panel A shows top versus bottom half, while Panel B shows top versus Bottom one-third). Their agglomeration effects A and D with CI are plotted in Figure 2 and Figure 3, respectively. Here, $t = 0$ stands for the year when an SOE changed its ultimate control from state- to private-owned, while $t = -1$ is one year before the reform and $t = +1$ is one year after.

In column (1) of Table 3, the estimates of A are always significantly positive before the SOE reform, except in one case ($t = -4$ in F-Group (bottom-1/3)). We find the largest value $\hat{A} = 0.249$ at $t <= -5$ and the smallest value $\hat{A} = 0.215$ at $t = -2$ in Panel A for pre-privatized SOEs in proximity to the local government. This implies an approximately 30% productivity increase if they move to a denser area.[23] For those located far from the oversight government, the increase is almost halved to nearly 15 percent with $\hat{A}$ around between 0.193 ($t <= -5$) to 0.122 ($t = -2$). These results are

governments to generate revenues within their jurisdictions efficiently and transparently (Park et al., 2006; Shen et al., 2012).

[23] 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 re-write 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.

TABLE 1. 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 2. MEAN ESTIMATION RESULTS FOR DIFFERENT ULTIMATE CONTROL FIRMS BY DISTANCE FROM OVERSIGHT GOVERNMENT, 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: top-1/2 vs. bottom-1/2									
Always-SOEs:									
C-Group	0.219***	[0.1754,0.2619]	1.050***	[1.0118,1.0891]	-0.013***	[-0.0184,-0.0087]	0.976	17,698	6,045
F-Group	0.112***	[0.0817,0.1416]	1.038***	[1.0130,1.0633]	-0.010***	[-0.0146,-0.0063]	0.948	16,564	7,330
Always-COEs:									
C-Group	0.124***	[0.0878,0.1596]	1.003	[0.9719,1.0342]	0.001	[-0.0054,0.0066]	0.973	12,880	2,381
F-Group	0.143***	[0.0947,0.1906]	0.951	[0.9012,1.0003]	-0.005	[-0.0148,0.0041]	0.937	12,945	2,466
Always-POEs:									
C-Group	0.153***	[0.1395,0.1660]	1.004	[0.9938,1.0151]	0.002	[-0.0007,0.0039]	0.979	148,992	23,494
F-Group	0.157***	[0.1474,0.1657]	0.978***	[0.9687,0.9874]	0.000	[-0.0018,0.0013]	0.990	149,001	23,651
Panel B: top-1/3 vs. bottom-1/3									
Always-SOEs:									
C-Group	0.236***	[0.1957,0.2755]	1.049***	[1.0087,1.0883]	-0.015***	[-0.0214,-0.0085]	0.981	11,809	3,852
F-Group	0.108***	[0.0651,0.1508]	1.085***	[1.0510,1.1193]	-0.002	[-0.0066,0.0032]	0.960	10,959	5,131
Always-COEs:									
C-Group	0.141***	[0.0921,0.1901]	1.004	[0.9570,1.0518]	-0.002	[-0.0101,0.0062]	0.972	8,509	1,511
F-Group	0.186***	[0.1311,0.2415]	0.920***	[0.8826,0.9568]	-0.010*	[-0.0194,-0.0023]	0.960	8,707	1,721
Always-POEs:									
C-Group	0.148***	[0.1359,0.1607]	0.993	[0.9792,1.0071]	0.001	[-0.0011,0.0040]	0.980	99,248	15,585
F-Group	0.159***	[0.1437,0.1751]	0.966***	[0.9541,0.9783]	0.000	[-0.0029,0.0026]	0.991	99,404	15,853

Notes: The prefix *Always-* denotes firms without changing ultimate control during the sample period as Section 3.2; Firms are ranked from nearest to farthest by distance from the corresponding oversight government in Section 3.3, and thus, *top-1/2* (*top-1/3*) are the nearest 50% (33%) firms, while *bottom-1/2* (*bottom-1/3*) are the farthest 50% (33%) firms. The null hypothesis H_0 is $A = 0$, $D = 1$, $S = 0$; Bootstrap replication (50); 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

consistent with the findings for *Always-SOEs* discussed in Section 4.2.1: productivity rises in denser areas relative to less dense areas because of agglomeration; being proximate to the government additionally intensifies this effect. Furthermore, we find a conspicuous drop in the value of A after $t = 0$, A starts to become insignificant for both C-Group and F-Group firms in the next few years. That is, the productivity improvements in all firms due to agglomeration advantages gradually fade away once SOEs are privatized. According to Siegel (2007), political networks burdened firms after a change in 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 period, 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. Rather, there is little evidence about considerable laid-off staff after SOEs' reform (Omran, 2004; Bai et al., 2009) (demonstrated in Figure B.2 as employment scarcely changes around $t = 0$). SOEs with close ties before the reform would have likely maintained the old way of acquiring information and resources even after the privatization. Thus, the fall in the agglomeration effect of post-privatization SOEs is understandable.

By contrast, comparing column (2) of C-Group with that of F-Group in Panels A and B (Table 3), D is insignificantly less than one pre-privatization but becomes above one significantly 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 2 and Figure 3 complement this finding, and show a steady increasing tendency of $\hat{D}$ starting from $t = 0$ This holds significantly only for post-privatized SOEs far from the oversight government. For post-privatized SOEs close to the oversight government, except for estimates at $t = +1$, D estimates are insignificantly above one. Briefly, according to columns (1) and (2) in Table 3, after transitioning to a private firm, agglomeration benefits that come from the rightward shift of the productivity distribution (represented by $\hat{A}$) decline, while agglomeration benefits stemming from dilation (represented by $\hat{D}$) increases. 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.

Next, we ask whether agglomeration economies (or, more generally, productive advantages) shared by post-privatized SOEs are weakened after they lose the privileged treatment. Specifically, we weigh the gain (due to dilation $\hat{D}$) and loss (due to shift $\hat{A}$) from agglomeration economies at different quantiles of the log productivity distribution. Figure 4 depicts $\ln \text{TFP}$ differences at 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 stand for C-Groups (top half) and thin arrows for F-Groups (bottom half). The direction of each arrow is from small to large cities.

We see two facts. First, productivity increases substantially when SOEs are privatized ($t = 0$).

However, after this jump in productivity at $t = 0$, the 25th and 50th percentiles of the $\ln$ TFP distribution of these privatized SOEs do not exhibit a gratifying high-speed increase movement; rather, only distant firms at the 75th percentile productivity show a steady increase (as shown by F-Group *p=75* in Figure 4). Second, we observe discrepancies between large and small cities regarding the size of productivity increases if a firm relocates from small to large cities as a response to agglomeration benefits. After privatization, the difference in production efficiency between large and small cities narrows significantly, as shown by the most paired-coordinate plots in Figure 2. This indicates that the scale effect brought by large cities is not efficiency accretive for mediocre privatized SOEs.[24] Nonetheless, the advantages of agglomeration effects still exist for more efficient and distant firms (F-Group *p=75*), specially between the $[t = -3]$ and $[t = +3]$ windows. From the agglomeration effect perspective, most SOEs have instantly lost this advantage after privatization, which may further affect productivity growth. Instead, high-quality SOEs with weak government relations can maintain or even enhance the agglomeration benefit. This does not last for a long time and recedes four years after SOEs' reform (as shown by F-Group *p=75* in Figure 2). Nevertheless, outstanding privatized SOEs (such as firms at the 95th percentile) which are distant 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 5). This discovery is of interest because privatized SOEs absorb the advantages of large cities through the agglomeration effect, implying the possibility of improving firm productivity in a relatively straightforward way.

Column (3) reports the estimates of selection effects S. Unlike the agglomeration effect shown by $\hat{A}$ and $\hat{D}$, the values of S are insignificant and negligible in all periods. This suggests that privatization fails to enhance the selection process significantly. However, the sign of $\hat{S}$ changes from negative to positive in some cases. Moreover, by linking column (3) of *Always-SOEs* in Table 1 to column (3) in Table 3, notice that $\hat{S}$ among *Always-SOEs* is significantly negative but insignificant among soon-to-be-privatized SOEs. This suggests that governments in large cities tend to protect SOEs on the brink of bankruptcy while selectively privatizing enterprises that they are not willing to support. For example, strategically important enterprises are all backed by state capital (Huang et al., 2017). By contrast, as reported in Panel B, the pre-privatization values of S are often negative; meanwhile, after privatization, $\hat{S}$ has some positive values. For F-Group, this change is quite noticeable. Before the privatization reform, $\hat{S}$ values are negative, except for the third year; after the privatization, $\hat{S}$ values exceed zero. These results provide reliable evidence, regardless of SOEs' reform, that denser and less dense areas show no significant differences in the truncation of the distribution of firm productivity. Market selection appears to have a similar intensity across cities in mainland China, irrespective of the market size. Moreover, residual government connections within newly privatized SOEs may likewise explain the poor performance (Boubakri et al., 2008). Harrison et al. (2019) discovered that privatized SOEs are still favored by low-interest loans and government

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

subsidies relative to *Always-POEs* in China. This favoritism from the government regarding resources means that privatized SOEs continue to operate even if their performance is not outstanding. Thus, privatizing SOEs without creating a competitive market environment may have little effect on their productivity (Konings et al., 2005). Nevertheless, regarding the negative-to-positive change of $\hat{S}$ in F-Group firms, we optimistically expect that privatization can contribute to improving the efficiency of firms 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 significant selection effects; however, the positive $\hat{S}$ partially indicates that SOEs' reform contributes to market selection. Thus, **Hypothesis 2b** is still supported.

Moreover, *SPs* generally exhibit a smaller agglomeration effect after privatization and this decrease varies with the distance from the oversight governments. Furthermore, firms distant from the government and hiring employees with higher efficiency respond better to the agglomeration effect after privatization. After privatization, they can enjoy more agglomeration advantages and gradually increase their productivity even in the short term. Even so, the changing value of $\hat{S}$ from negative to positive implies a gradual improvement in the market exit mechanism. Conclusively, without finding a similar pattern among *CPs* as reported in Table 4, this feature is unique to *SPs*. It shows that: 1) *Always-SOEs* in proximity to oversight governments have a more substantial agglomeration effect; 2) after privatization, middle *SPs* have a smaller agglomeration effect than before; 3) the decreased contribution from the agglomeration of privatized SOEs farther from oversight governments is less than those who are closer; 4) Outstanding SOEs that employ highly productive employees and are distant from oversight governments can enhance agglomeration benefits after privatization, and show steady productivity growth.

5 Robustness

Our primary variables are the division of the ownership and productivity of firms.[25] Here, we use productivity and labor productivity (industrial value-add divided by employment) for testing 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 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

[25]There may be endogeneity concerns due to the government's preference for the privatization of high-efficiency firms or loss-making firms. However, the dilation effect (denoted as D in Equation (8)) already addresses this issue. Specifically, the agglomeration effect consists of two parts: the increase in the average agglomeration effect (denoted as A Equation (8)) of SOEs after privatization, and the benefits that only high-quality SOEs can obtain (marked as D Equation (8)).

TABLE 3. ESTIMATION RESULTS OF SPS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 (1/3) VS. BOTTOM-1/2 (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 A: 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
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 privatizes from a 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* (*top-1/3*) are the nearest 50% (33%) firms denoted by prefix *C-*, while *bottom-1/2* (*bottom-1/3*) are the farthest 50% (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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

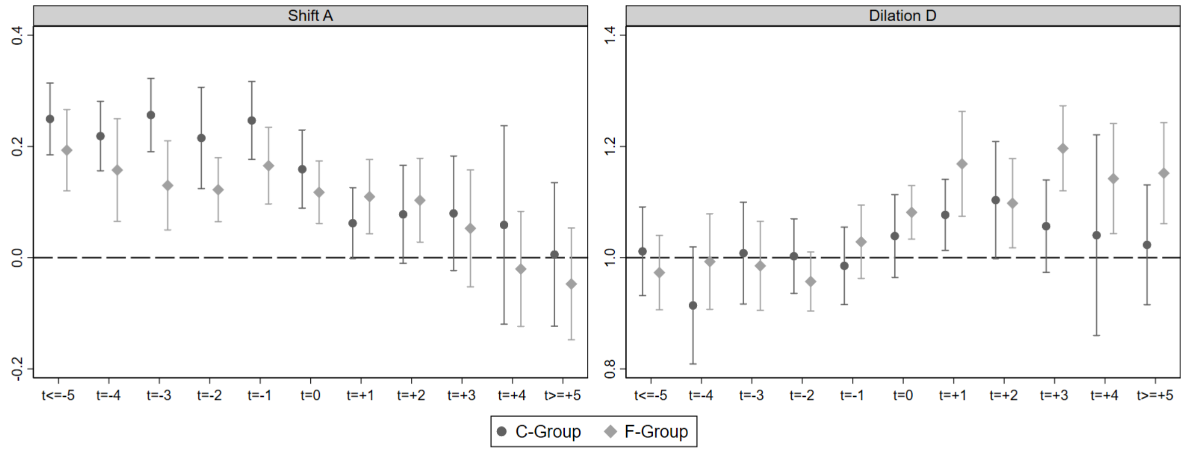

FIGURE 2. PARAMETERS OF SPS AGGLOMERATION EFFECTS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

Notes: *SPs* are firms change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm privatizes from a 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 $A = 0$, $D = 1$; Bootstrap replication (50); Estimated values with 95% confidence intervals are plotted.

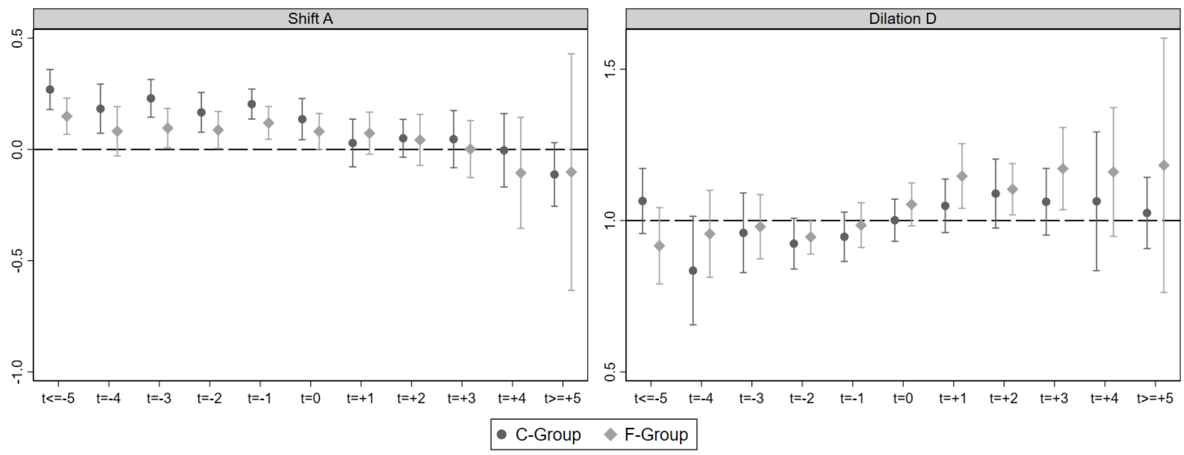

FIGURE 3. PARAMETERS OF SPS AGGLOMERATION EFFECTS BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/3 VS. BOTTOM-1/3, CITIES ARE GROUPED BY MEDIAN VALUE OF LIGHT BRIGHTNESS

Notes: *SPs* are firms change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm privatizes from a 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-1/3* 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.

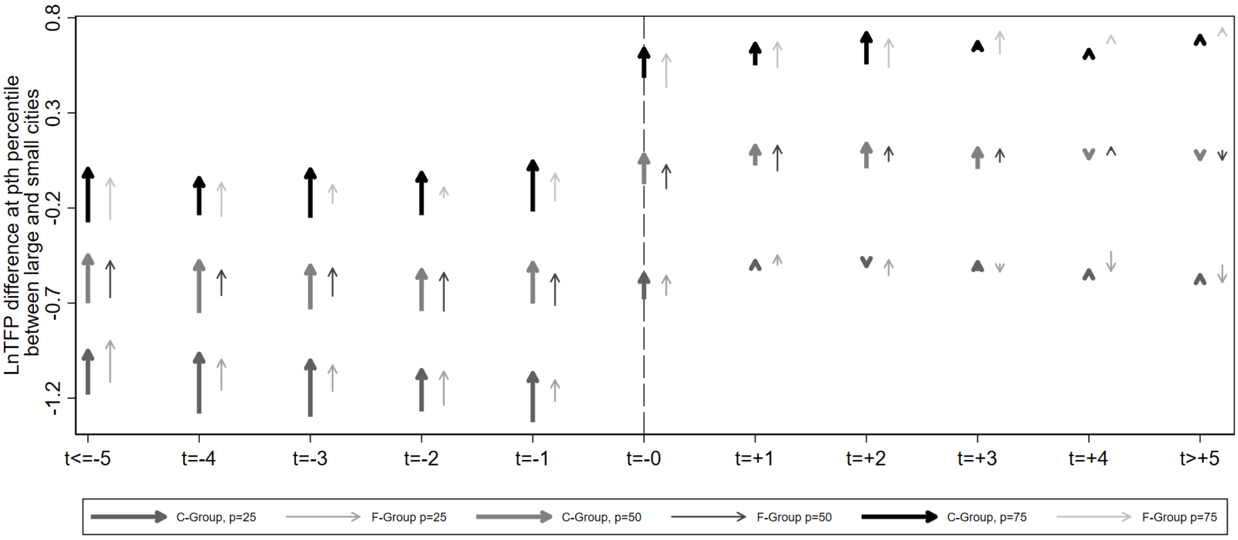

FIGURE 4. PRODUCTIVITY DIFFERENCE OF SPS AT 25TH, 50TH AND 75TH PERCENTILE BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2

Notes: *SPs* are firms change their ownership from state-owned to private-owned, as Section 3.2; 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-* (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.

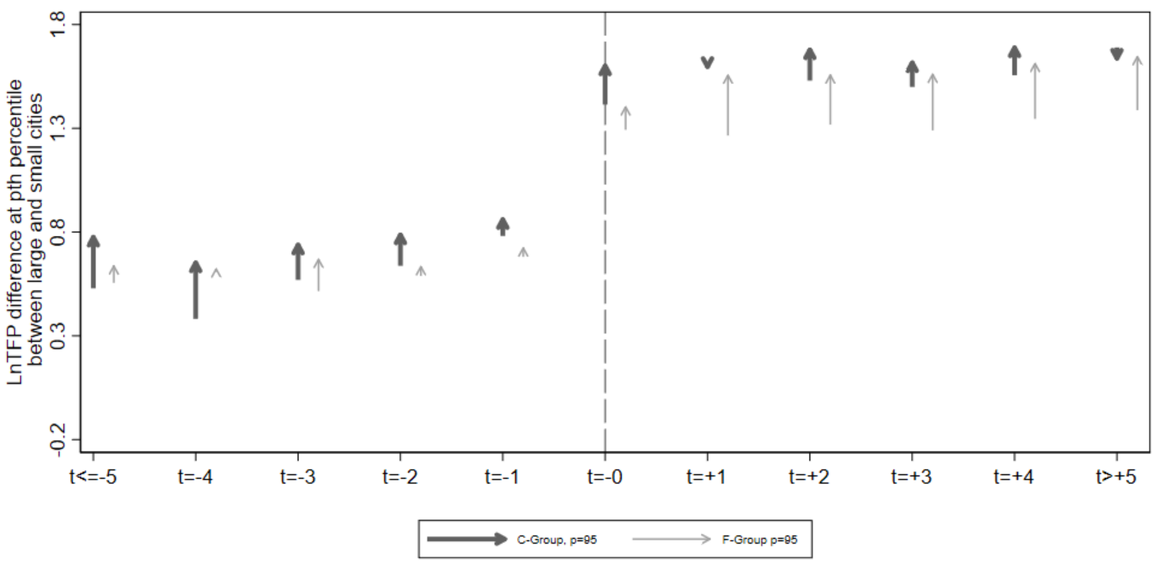

FIGURE 5. PRODUCTIVITY DIFFERENCE OF SPS AT 95TH PERCENTILE BY DISTANCE FROM OVERSIGHT GOVERNMENT, TOP-1/2 VS. BOTTOM-1/2

Notes: *SPs* are firms change their ownership from state-owned to private-owned, as Section 3.2; 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-* (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.

TABLE 4. 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 change their ownership from collective-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm privatizes from a 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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 5 uses different firm productivity estimation methods, while Table 6 uses another firm ownership classification. These tables show that our results continue to hold and suggest that the market competition and withdrawal mechanisms have gradually improved after the SOE reform.

6 Conclusion

Employing a large firm-level dataset and following the generalized firm selection model (Melitz, 2003; Melitz and Ottaviano, 2008), we examine the impact of SOEs' privatization on Chinese firms' productivity in response to agglomeration and selection effects. We use extensive manufacturing firm data with a quantile specification (Combes et al., 2012). This specification allows us to estimate a relative change in shift (*A*, agglomeration benefits shared by all firms), dilation (*D*, productivity benefits shared by top firms), and left truncation (*S*, selection that eliminates the least productive firms) in the productivity distribution between small and large cities. We find that agglomeration explains a large part of productivity differentials across cities in China's manufacturing industry for each ownership type, in line with most of the literature that uses the same measures (Combes et al., 2012; Arimoto et al., 2014; Ding and Niu, 2019; Zhang et al., 2020a). We also find a statistically significant selection effect among *Always-POEs*, which is a specific result relative to Ding and Niu (2019) and Zhang et al. (2020a). We attribute this to the classification of the sample by firm ownership. In the five sub-samples (*Always-SOEs*, *Always-COEs*, *Always-POEs*, *SPs*, and *CPs*), only *Always-POEs* display a significantly positive selection effect while the selection effects of the other groups are insignificant (or even negative).

We also find that *Always-SOEs* enjoy a statistically significant agglomeration effect which is greater than that for *Always-POEs*. This differs from research (Hu et al., 2015) which argues that private enterprises benefit the most from agglomeration. A possible reason is that these studies do not consider the agglomeration enjoyed by SOEs as the government supports them by sharing local information, such as tacit knowledge, labor markets, and resources. Intimate ties with the government characterize SOEs; we assume that the agglomeration effect of SOEs will increase with access to more local information. Following Huang et al. (2017), we use the geographic distance between firms and their corresponding oversight governments to proxy the capability to access local knowledge such that firms far from the oversight governments have less interaction with the government and less information sharing, and thus, hinting at a lower level of agglomeration advantages. In contrast, firms close to the oversight government enjoy more agglomeration gains.

Regarding the selection effects, we only detect a statistically significant but minor selection effect among *Always-POEs*. Moreover, we fail to find a significant selection effect after SOEs are privatized. Residual government ties that provide preferential credit policies may explain the disparity in

TABLE 5. 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 A: LnTFP, OLS method									
C-Group (top-1/2)									
t<=-5	0.281***	[0.2124,0.3505]	1.034	[0.9557,1.1128]	-0.001	[-0.0140,0.0128]	0.966	2,326	787
t=-4	0.347***	[0.2760,0.4175]	0.877*	[0.8096,0.9435]	-0.013	[-0.0273,0.0005]	0.980	1,409	530
t=-3	0.322***	[0.2403,0.4040]	1.016	[0.9359,1.0953]	-0.006	[-0.0252,0.0133]	0.980	1,931	710
t=-2	0.314***	[0.2209,0.4066]	0.963	[0.8900,1.0360]	-0.014*	[-0.0255,-0.0021]	0.986	2,628	971
t=-1	0.309***	[0.2404,0.3780]	0.976	[0.9004,1.0519]	-0.011	[-0.0246,0.0036]	0.981	3,267	1,182
t=0	0.201***	[0.1281,0.2737]	1.065*	[1.0107,1.1193]	-0.003	[-0.0116,0.0065]	0.986	3,592	1,300
t=+1	0.107**	[0.0278,0.1862]	1.061	[0.9645,1.1567]	-0.002	[-0.0174,0.0129]	0.877	2,634	963
t=+2	0.092*	[0.0021,0.1813]	1.149*	[1.0495,1.2495]	0.012	[-0.0011,0.0249]	0.912	2,095	795
t=+3	0.101*	[0.0002,0.2014]	1.090*	[1.0108,1.1692]	-0.012	[-0.0250,0.0008]	0.909	1,752	622
t=+4	0.054	[-0.1023,0.2099]	1.108	[0.9339,1.2821]	0.002	[-0.0475,0.0511]	0.673	1,221	444
t>=+5	0.039	[-0.1110,0.1896]	1.036	[0.9423,1.1293]	0.001	[-0.0642,0.0653]	0.533	1,858	622
F-Group (bottom-1/2)									
t<=-5	0.255***	[0.1671,0.3422]	1.035	[0.9412,1.1295]	0.011	[-0.0141,0.0370]	0.967	1,708	797
t=-4	0.204***	[0.1248,0.2827]	1.017	[0.9034,1.1314]	-0.001	[-0.0272,0.0256]	0.961	1,084	535
t=-3	0.174***	[0.1002,0.2484]	1.018	[0.9382,1.0985]	0.005	[-0.0172,0.0271]	0.892	1,546	737
t=-2	0.178***	[0.0952,0.2614]	0.998	[0.9091,1.0878]	0.001	[-0.0240,0.0253]	0.933	2,146	1,005
t=-1	0.161***	[0.1024,0.2205]	1.082*	[1.0122,1.1524]	-0.002	[-0.0144,0.0111]	0.973	2,783	1,220
t=0	0.158***	[0.0957,0.2203]	1.080*	[1.0283,1.1311]	0.000	[-0.0090,0.0084]	0.973	2,983	1,343
t=+1	0.160***	[0.0937,0.2268]	1.171**	[1.0743,1.2684]	0.001	[-0.0116,0.0138]	0.971	2,171	1,012
t=+2	0.139***	[0.0570,0.2211]	1.118*	[1.0383,1.1973]	-0.002	[-0.0225,0.0176]	0.932	1,746	821
t=+3	0.097	[-0.0126,0.2072]	1.184**	[1.1115,1.2557]	0.001	[-0.0190,0.0215]	0.960	1,434	678
t=+4	0.007	[-0.1357,0.1492]	1.159**	[1.0061,1.3112]	0.001	[-0.0362,0.0385]	0.857	975	483
t>=+5	-0.026	[-0.9574,0.9061]	1.183	[0.6363,1.7304]	0.003	[-0.3039,0.3103]	0.835	1,675	677
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 change their ownership from state-owned to private-owned, as Section 3.2; $t = 0$ denotes the year when a firm privatizes from a 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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 6. 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)		**(2)**		**(3)**		**(4)**	**(5)**	**(6)**
	Agglomeration Effects				**Selection Effects**			**Obs.**	
	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 transition from *H-SOEs* to *Non-SOEs* as discussed in Section 5; $t = 0$ denotes the year when a firm privatizes from a 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; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the selection effect of *Always-POEs* and *SPs* (Boubakri et al., 2008; Harrison et al., 2019). However, the negative-to-positive change of $\hat{S}$ suggests that privatization can improve firm efficiency in large cities through tougher competition; however, this can take longer, and require a well-established firm exit and resource reallocation mechanism.

Finally, based on the above methodology and results, we show that **Hypotheses 1a**, **2a**, **1b**, and **2b** are supported: First, the SOE reforms negatively influences the agglomeration effect for mediocre privatized SOEs, but positively improves the selection effect. Second, weakened government ties after SOEs' reform account for the drop in agglomeration advantages, and the more or less improved market selection of post-privatized SOEs. Finally, privatization can reinforce the agglomeration advantages for SOEs with high ex-ante productivity and less close ties to the government.

In summary, to smoothly transition and catch up with the productivity levels of private firms sooner, the government can utilize the agglomeration and selection effects of the urban areas by prioritizing the privatization of SOEs that are efficient and not closely linked to the government. After privatization, SOEs may lose privileged treatment and face the dilemma of sharply reduced agglomeration benefits, such as productivity improvements generated by labor market matching, resource sharing, and knowledge spillovers. To allow privatized SOEs to maintain their original agglomeration advantages and consistently increase productivity, the government should reduce political ties with pre-privatized SOEs, prompting them to adapt to a market that is characterized by both cooperation and competition with private firms. The government should also privatize high-quality SOEs with efficient employees or managers so that these firms can better leverage the post-privatization agglomeration benefits. Meanwhile, the government should reduce the preferential credit support for SOEs that have already been privatized, allowing market competition-induced selection effects to play out. That is, constructing a competitive market environment is necessary for improving firm productivity.

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Appendix A Table

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

Appendix B Data Cleaning Process

The firm linkages over time are made using the methods by Brandt et al. (2012, 2014) and Brandt et al. (2017), who made do-files available online, including programs of matching firms over years and tables of industrial concordance codes.[26] 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 assets, fixed assets, or net fixed assets larger than total assets;
6. Make 4-digit industrial numerical codes uniform across the entire period following the practice introduced by Brandt et al. (2014). And also update the renamed or merged city to the latest city name.[27]
7. Firms that changed their locations are deleted.[28]
8. Observations without population data, another critical variable collected from city statistical yearbooks, are deleted.
9. According to the method of distinguishing the firm ownership instructed in Section 3.2, we exclude firms that have changed their ownership many times and have been nationalized.

we finally obtain an unbalanced panel data with 461,642 (specifically, there are 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.[29]

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

[27]During 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.

[28]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 place to reopen.

[29]*SCs* are those change from SOEs to COEs, but we do not analysis this group firms due to few 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)

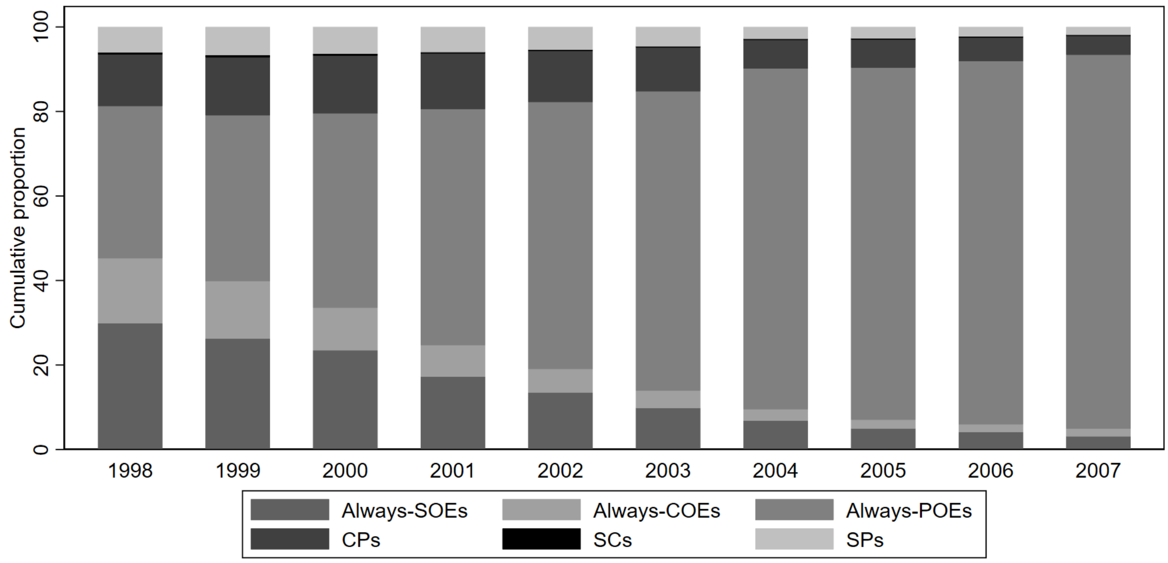

FIGURE B.1. PERCENTAGE OF FIRM WITH DIFFERENT ULTIMATE OWNERSHIP PER YEAR

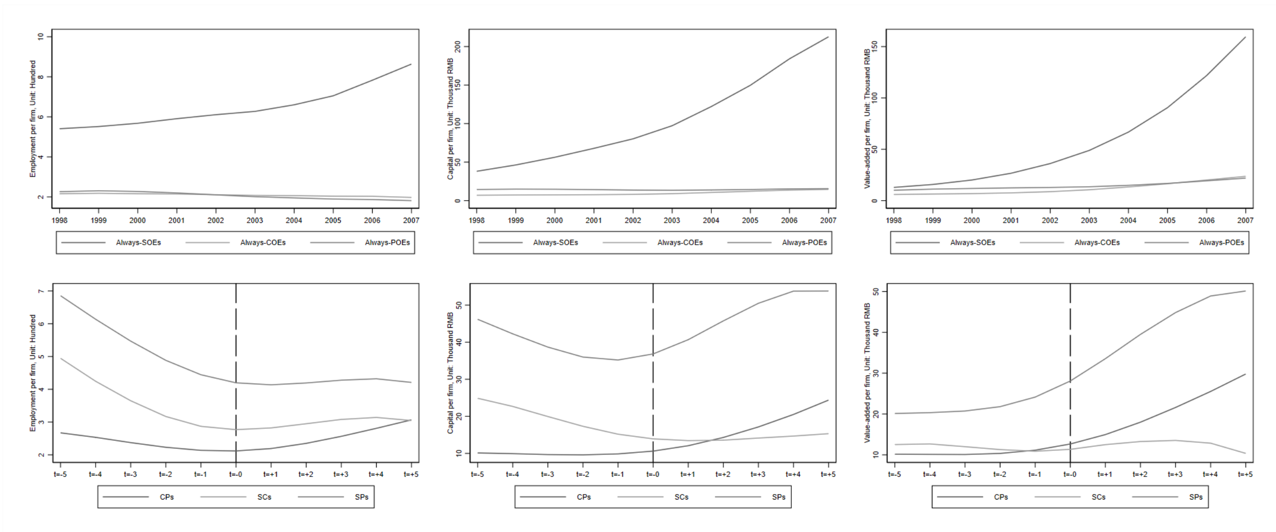

FIGURE B.2. AVERAGE FIRM PERFORMANCE GROUPED BY ULTIMATE OWNERSHIP

Appendix C OP Method

We start with the production function:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} \tag{C.9}$$

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 natural logs of Equation (C.9) results in a linear production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \varepsilon_{it} \tag{C.10}$$

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

Olley and Pakes (1992) assumes 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):

$$\omega_{it} = h_t\left(k_{it}, i_{it}\right) \tag{C.11}$$

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

$$y_{it} = \beta_l l_{it} + \beta_0 + \beta_k k_{it} + h_t\left(k_{it}, i_{it}\right) + u_{it} \tag{C.12}$$

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

$$\varphi\left(i_{it}, k_{it}\right) = \beta_0 + \beta_k k_{it} + h_t\left(i_{it}, k_{it}\right) \tag{C.13}$$

$$y_{it} = \beta_l l_{it} + \varphi\left(i_{it}, k_{it}\right) + u_{it} \tag{C.14}$$

Through the estimation of Eq.(C.14), an unbiased labor coefficient can be obtained. Then, the estimated coefficient is used to fit the polynomial term ($\varphi\left(i_{it}, k_{it}\right)$) formed by investment and capital stock:

$$\begin{aligned} & y_{it+1} - \beta_l l_{it+1} \\ &= \beta_0 + \beta_k k_{it+1} + g\left(\phi_{it}, \beta_k k_{it}\right) + \xi_{it+1} + u_{it+1}^q \end{aligned} \tag{C.15}$$

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