Reviving Small-Scale Reservations: Evidence from the Korean Ready-Mixed Concrete Industry*

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Abstract

Korea revived its small-scale industry (SSI) reservation policy in the early 2010s to protect small businesses and promote their competitiveness. But there has been ongoing debate about whether this size-contingent entry regulation causes allocative inefficiency. This paper examines the effects of SSI reservation on both small plants' performances and allocative efficiency in the Korean ready-mixed concrete industry. By exploiting exogenous variation in preexisting large plants across geographically independent markets, we find that the SSI policy increases average productivity of small plants in the affected market, but decreases competition and thus weakens the market selection process among those plants. Our findings suggest that the revived SSI policy may result in allocative inefficiency for the reserved industries.

***JEL* codes**: L11, L53, L61

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1 Introduction

The government can mandate that certain goods and services be produced exclusively by small businesses, through regulation of the entry of large firms in those markets. Such small-scale industry (SSI) reservation is one of the most restrictive size-dependent policies, because a typical policy imposes additional costs on large firms rather than merely limiting their entry.[1] Historically, only a small number of developing countries (e.g., India) adopted the SSI policy, and it has largely disappeared in recent decades (Garcia-Santana and Pijoan-Mas, 2014; Martin *et al.*, 2017). For example, the Korean government abolished the SSI policy during the mid-2000s, on the advice of the World Trade Organization (WTO). But Korea revived its SSI reservation in 2012; though ostensibly a form of industry-level voluntary agreement, in practice it has been effectively equivalent to a legal policy.[2]

The rationale behind this entry barrier is that protecting small firms from the competitive pressure created by large rivals can improve small firms' competitiveness. Opponents of the policy argue that shielding small firms from competition may generate allocative inefficiency in the reserved industry. While some studies of Korea's revived SSI policy have examined this debate, they have failed to provide evidence for the *causal* effect of the rule (Bihn and Woo, 2014; Lee, 2015). For example, because SSI reservations for most goods and services were implemented at the same time, it is difficult to find variation in the timing of reservation across industries, and thus its effects. Hence, this paper tackles these two claims by choosing an industry with exogenous geographic variations in the implementation of the SSI reservation.

Specifically, we investigate the effect of Korea's revived SSI policy on productivity gains of small firms and allocative inefficiency at the industry level. To exploit exogenous geographic variations in the policy, we focus on the ready-mixed concrete (hereafter "concrete") industry, which was newly reserved for SSI in 2012.[3] A concrete manufacturer operates in a local geographic market due to the high transportation costs of concrete (Syverson, 2004).[4] This feature presumably creates

[1] For example, under the US Affordable Care Act, firms with more than 50 employees became subject to tax penalties for failure to offer health care insurance to their employees, which increases labor costs significantly for those above the threshold. Additionally, see Garica *et al.* (2016) for welfare costs of size-dependent labor regulation in France.

[2] The industry coverage of the former reservation policy was confined to manufacturing industries, but the revived policy has recently expanded to service industries.

[3] The institution of SSI policy in 2012 was far from expected, as both the government and ruling party were conservative and market-oriented.

[4] Concrete is manufactured in a batching plant and must be delivered to a construction site by concrete mixer trucks before it hardens. The whole process of mixing, delivering, and discharging concrete must be completed in 90 minutes at most. In fact, mixing and discharging take about one hour and so the maximum allowable delivery time is about

divergent competitive environments containing plants operated by small firms (hereafter "small plants") during the regulation period, depending upon the presence of preexisting plants operated by large firms (hereafter "large plants") in their local markets.[5] Specifically, the implementation of SSI imposes significant restrictions on large firms' business activities (not only as related to constructing new plants but also to expanding capacity) and thus eventually drives them out of the market. Consequently, small plants in the local markets that had preexisting large plants make the most of the reduced competitive pressure, whereas those in markets without such previous larger competitors receive little benefit from the SSI reservation policy.

However, the reservation policy is not necessarily favorable to small incumbents alone, because small new *entrants* can enjoy all policy-related benefits as well. Furthermore, if the reservation policy provokes allocative inefficiency, this could arise from underperforming small incumbents, small entrants, or both. Thus, by using panel data on all concrete plants from 2009 to 2014, we estimate the impact of SSI reservation through the differences-in-differences (DID) specification not only for incumbents but for all firms, including both incumbents and entrants.

We summarize our findings as follows: First, small plants in counties with preexisting large plants have on average higher productivity than those in control counties. Although the treatment counties had more small entrants than the control counties during the post-treatment period of 2012-2014, there was no significant difference in performance between small incumbents and entrants in the treatment group. That is, the entry effect was not sufficiently large to offset the benefits of limiting competition from large plants. Thus, protected small (incumbent) plants obtain productivity gains, thereby implying achievement of the regulatory goal.

Second, in order to examine the effect of SSI policy on allocative efficiency caused by reduced competition, we compare productivity dispersion among small plants in the treatment and control counties. For example, if the SSI policy reduces competitive pressure, market selection effect weakens, and productivity levels in the treatment county will be more widely distributed than those in the control. Our results show that the SSI regulation causes a larger dispersion in productivity in the treatment county compared to the control group, and this increased dispersion is driven by weakened market selection. This pattern is especially strong among small incumbents, and suggests that SSI may incur allocative inefficiency in the concrete industry.

30 minutes. This time constraint determines the tight geographic boundaries of players in the concrete market. See Syverson (2008) for more details about the concrete industry.

[5] To define local markets, we use two geographic definitions: administrative district (county) and distance (30-minute driving radius). Our results are robust to both definitions.

To conclude, Korea's revived SSI policy raised the productivity of small plants in the concrete industry, suggesting achievement of the regulation's primary goal. Nonetheless, the policy promotes the side effect of weakened selection, which in turn impedes market efficiency. Therefore, implementation of SSI regulation in general may result in poor long-term economic performance for the reserved industry.

There is a growing body of research on size-dependent regulatory policy. Findings to date suggest the policy fails to improve employment in the reserved industry, lowers productivity by reducing technology adoption, and distorts the size distribution of establishments (Guner *et al.*, 2008; Gourio and Roys, 2014; Garicano *et al.*, 2016; Martin *et al.*, 2017). However, most studies have examined the impact of such regulation at the *aggregate* level, so the specific mechanism driving inefficiency at the individual industry level has remained unknown. Therefore, this paper contributes to the literature by providing empirical evidence that SSI policy helps underperforming small plants survive while also reducing market efficiency.

Our study is related broadly to research on entry regulation and allocative inefficiency.[6] Theory suggests that entry regulation reduces competition and thus expands productivity dispersion (Balnchard and Giavazzi, 2003; Holmes and Schmitz, 2010; Poschke, 2010). Schivardi and Viviano (2011) provided evidence that low-productive incumbents associated with entry barriers induce such elevation of dispersion in the retail trade.[7] Our findings confirm that decreased competition due to the reservation policy induces weaker market selection, resulting in industry-wide allocative inefficiency.

The remainder of this paper is organized as follows. Section 2 provides a brief review of Korea's SSI reservation policy and concrete industry. Section 3 describes our data set and key variables. Section 4 presents our empirical specification and results, and Section 5 presents robustness checks for the results. Section 6 concludes.

[6] Moreover, some studies show that misallocation across plants is a key determinant of cross-county productivity differences (Hsieh and Klenow, 2008; Alfaro *et al.*, 2009).

[7] On the other hand, Nishiwaki and Kwon (2013) found that inefficient divestment patterns of Japanese cement plants may cause industry-wide allocative inefficiency.

2 Background

2.1 The Small-Scale Industry Reservation Policy

SSI policy is, in general, adopted to protect small businesses in the reserved industry. But the regulation's ultimate goals may differ by country. For instance, India aimed such legislation at improving employment, with the belief that labor-intensive small firms can create more jobs than capital-intensive large firms (Martin *et al.*, 2017). Korea, in contrast, intended for SSI policy to correct the imbalance between small and large firms and, eventually, to enhance the competitiveness of small firms.

Korea first implemented the reservation policy in 1979, for 23 product categories. Since the 1960s, the Korean economy had grown quickly through export-oriented industrialization; but rapid growth generated side effects. Specifically, large firms exercised their monopolistic power and squeezed domestic suppliers to reduce costs, which limited the competitiveness of their smaller rivals. To resolve these social issues, the Korean government implemented and reinforced the reservation policy until 1989, increasing the total number of reserved products to 237. But in the 1990s, the WTO advised repeal of SSI policy, leading to debate about the regulation's effectiveness. Therefore, to meet internal and external demands, the Korean government gradually eliminated products from the reservation list, removing the last 18 in 2006.

Since the reservation period ended, however, there have been continuing concerns about the widening productivity gap between small and large firms. As such, in 2012 Korea's reservation policy was revived as a form of voluntary agreement between small and large firms. The Korea Commission for Corporate Partnership (KCCP) sets guidelines regarding entry and expansion. These guidelines form the basis for the revived SSI policy, but in practice the policy acts to regulate large firms stringently, because the KCCP can request the Small and Medium Business Administration (SMBA) to judge whether large firms fail to comply with the agreements. The non-compliance penalty includes fine or imprisonment. Moreover, the political and public pressures imposed on large firms in this context operate as a binding force on them.

Similar to traditional SSI policies, Korea's revived policy imposes restrictions on large firms' market entry and capacity expansion, but has two distinct features relative to the earlier regulations. First, *service* industries can be reserved in the revived SSI policy. Of 73 total reserved industries, there were 54 manufacturing (e.g., insulated wires and cables, plastic bags, tofu) and 19 service or retail industries (e.g., bookstore, bakery, auto repair services) as of 2017. Second, the reservation period under the current policy is limited to 6 years, while the former policy stipulated no limit.

In late 2011, the concrete industry was reserved as a SSI for the 3-year agreement period from January 1, 2012, to December 31, 2014. According to the guidelines applied to the concrete industry, large firms could neither build new plants nor expand existing capacity. However, small firms were not affected directly by the guidelines. After implementation of the SSI reservation, large firms experienced decreased relative share in both the number of plants and product outputs. The revived SSI policy shifted these from larger concrete firms to their smaller rivals. Specifically, the number of plants owned by large firms accounted for on average 18.3% of the industry before the regulation period (i.e., 2009-2011), but only 15.3% post-SSI (i.e., 2012-2014); large firms' market share decreased from 31% to 24% across these two periods.[8]

2.2 Korean Concrete Industry

In Korea's concrete industry, the criterion to separate large and small firms was determined through mutual agreement among firms. As a result, 11 businesses were designated large firms: Tongyang Inc., Rexcon, Sampyo, Sungshin Cement, Ssangyong Remicon, Asia Cement, Aju, Eugene, Halla Encom, Hanil Industrial Co., and Hanil Cement.[9] This set of designated large firms did not change during our sample period of 2009-2014. These firms owned five or more plants, while approximately 90% of firms in Korea's concrete industry are single-plant small firms. Also, plants operated by the large firms had 1.5 times more capacity on average than those of small firms.

Concrete consists of cementitious materials, water, aggregate, and sand or crushed stone that are mixed and blended in a batcher plant and delivered to construction sites in fluid form. Concrete is highly perishable because consumers must receive the product before it hardens. According to the Korea Ready-Mixed Concrete Industry Association (KRMCIA), the process of concrete mixing, delivery, and discharging should be completed in no more than 90 minutes; this time constraint defines the market's geographic boundaries. As a result, the concrete industry consists of numerous geographically independent markets, conducive for investigating SSI policy effects through exogenous geographic variation.

Physical homogeneity is another key feature of concrete products. Although concrete can be

[8] In contrast, the deregulation of compulsory licensing in India induces reallocation of market share toward a small number of large firms (Alfaro and Chari, 2014).

[9] Out of 11 large firms in the Korean concrete industry, only Rexcon was a subsidiary of one of the 30 major Korean companies (i.e., chaebols). It was owned by Doosan Engineering & Construction, but had only five plants and very small market share compared to other large firms.

differentiated along non-spatial dimensions such as compressive strength and cure time, the overall degree of product differentiation is far lower than that of other manufacturing products. The advantage of analyzing homogeneous goods such as concrete and sugar is that the physical quantity of production at the plant can be measured directly, contrary to the conventional measurement method of deflating the nominal amount of production by the price index. However, the appropriate plant-level price index is not usually observable for economists, and the plant-level price can be substituted with the industry price, which can create bias in measuring the true quantity of production and level of productivity at the plant (Foster *et al.*, 2008). Thus the physical uniformity of concrete enables us to measure true quantity and productivity at the plant level.

3 Data

We created our main data set from the *2009-2014 Ready-Mixed Concrete Almanacs* published by the KRMCIA.[10] The almanacs contain detailed plant-level information on all individual firms in the Korean concrete industry, including names of plants and their managing firms, address, monthly production volume (in cubic meters), hourly production capacity volume (in cubic meters per hour), volume of cement storage silos (in tons), and date of initial operation.

To examine changes in competitive environment and allocative efficiency during the reservation period from 2012 to 2014, we first divide the plants into treatment and control groups on the basis of institutional county. As discussed in the previous section, the concrete industry comprises geographically independent sub-markets due to its high transportation costs and constraints. More specifically, the maximum allowable time for delivery itself is only about 30 minutes, which, in turn, determines the ideal delivery distance (Syverson, 2004). A typical Korean county could be covered in about 30 minutes of driving: on average, an area with a 15-kilometer radius. Collard-Wexler (2013) also used a county as a separate market in the U.S. Therefore, we use county borders as the primary criteria for market definition.[11] In the robustness section, we examine alternative definitions for geographic markets.

[10] Even at the research data center, Statistics Korea does not allow access to county-level information (only province-level data accessible) for concrete plants in the *Annual Survey of Manufacturers*. Therefore, we cannot use it for our analysis. The *Almanacs* published by KRMCIA do not provide information about numbers of workers, preventing us from constructing total factor productivity measures.

[11] In previous literature, a Si/Gun/Gu has been regarded as a county equivalent to that in the U.S. (Baek and Park, 2015; Cho *et al.*, 2015).

Because the SSI reservation policy was implemented for 11 large Korean concrete firms, the competition environment each plant in our study faced should be influenced by whether it was located in the same county as large regulated plants. The SSI reservation policy imposed limitations on large firms' business activities such as capacity expansion and new plant construction, yielding a more favorable competitive environment for small local rivals. However, small plants that did not compete with large firms in their local markets experienced no changes in their competitive environment during the reservation period.

Next, we defined the plants located in counties with and without preexisting large plants in 2012 as the treatment and control groups, respectively. For example, in 2012, 192 of 252 counties in Korea had at least one concrete plant: 84 of these fell into our treatment group category; 108 into the control group.[12] For all small plants, we assign 2,105 plant-year observations to the treatment group and 2,338 to the control group; for small incumbents (i.e., those having entered in 2011 and earlier), 1,927 to the treatment group and 2,212 to the control group.

We use capital productivity as the productivity measure, because the concrete industry is highly capital-intensive, particularly in Korea. According to Korea's *Economic Census*, labor costs in the concrete industry account for approximately 6% of the total value of production and 18% of the value-added. Thus, the level of productivity depends mainly on how efficiently capital stocks (e.g., batching plant, cement storage silos, concrete mixer trucks) are utilized in responding to shifting demand for concrete products.[13] We derive the (capital) productivity as follows: We first compute a plant's annual production volume by summing its monthly production volumes by year. We also convert a plant's hourly production volume into an annual one, following the KRMCIA's report that plants' annual operating hours are 2,000.[14] Then we divide the annual production volume by the sum of annual capacities of all batching plants and multiply it by 100 to create a productivity measure with a range between 0 and 100 (%).

To control for changes in construction demand which, in turn, reflect those in demand for concrete, we use the county-level variables, lagged by one year. The county-level demand control variables are as follows: population growth rate (%), population age 40 years and older (% of

[12] Due to entry and/or exit, there was a very slight change in counties with at least one concrete plant. But the total numbers were quite stable: 192 counties in 2012-2014, and 191 in 2009-2011.

[13] Because concrete products are not storable as inventory, plants have an incentive to maintain overcapacity in anticipation of high demand.

[14] For entrants, we adjust annual operating hours in the entry year based on actual operating months. For instance, if a plant entered in September 2012, its operating months in 2012 were only four (from September to December) and hence the annual operating hours were downward-adjusted to 666.7 ($= 2000 \div (4 \div 12)$).

total), crude marriage rate (the number of marriages per 1,000 people in the population), per-capita gross regional domestic product in 1 million KRW, construction employment growth rate (%), and rate of change in land price (%).[15] Those variables are constructed from various sources such as administrative resident registration data, *Population Trend Survey*, *Census of Establishments*, and *Land Price Statistics*.

[Insert Table 1 about here]

Table 1 presents descriptive statistics for plant-level productivity, county-level dispersion in productivities, and lagged county-level demand controls. As seen in Panel A, the average productivity of small plants (22.9%) is lower than that of all plants including large ones (24.0%). The productivity of small incumbents (23.2%) is weakly higher than that of small plants including small entrants, suggesting that small plants with lower average efficiency might enter the market. In Panel B, we compare three dispersion measures of productivity between all plants and small plants: (i) standard deviation, (ii) interdecile range (i.e., difference between 90$^{\text{th}}$ and 10$^{\text{th}}$ percentiles), and (iii) interquartile range (i.e., difference between top and bottom quartiles). To compute the dispersions, we exclude counties with fewer than four small plants.[16] The standard deviation of productivity of small plants is close to that of all plants including large ones. This is also true for both the interdecile and interquartile ranges. This suggests that the productivity dispersion reflects mainly the productivity gap among small plants, rather than the gap between small and large plants.

[Insert Figure 1 and Table 2 about here]

Figure 1 illustrates the productivity gains SSI reservation facilitated for small plants. In particular, as presented in Table 2B, we find that the mean difference between the treatment and control groups in county-level annual mean productivity of all small plants was 1.8%p before reservation, and this gap became wider (i.e., 3.8%p) post-reservation. That is, our DID estimate suggests that the net increase in productivity was 2.0%p if there were preexisting large plants in the market, and implies that the SSI reservation policy may improve the performance of small plants. However, Table 2A shows that the improvement in productivity of all plants including large ones in

[15] According to the *2012 Statistics of House Ownership*, over 80% of houses in Korea were owned by people ages 40 and above.

[16] Because the standard deviation, our main measure of dispersion, is sensitive to outliers, we exclude plants with productivities either less than two standard deviations below the mean or greater than two standard deviations above the mean.

the treatment group is not statistically significant. Consistently, as seen in Figure 1, the average productivity of large plants decreased slightly in the treatment group during the reservation period. Thus the reservation policy improved the productivity of small plants in the treatment group, but did not increase the concrete industry's overall productivity.

Table 2D shows that the dispersion of productivity increases due to reservation. The mean difference between the treatment and control groups in county-level standard deviations of small plants was minimal (approximately 0.1%p) before reservation, but the gap increases to 1.0%p post-reservation. Thus, the DID estimate is about 1.1%p. The results in Table 2C are also similar when large plants are included. The findings suggest that reservation widens productivity dispersion, particularly for small plants in the treatment market. In the next section, we provide more accurate results of the DID regression, with the control variables for construction demand and plant and year effects.

4 Estimation Results

4.1 Main Results

We first examine the impact of SSI reservation policy on plants' productivity by estimating the following equation:

$$productivity_{ijt} = \beta_0 + \beta_1 policy_{jt} + X'_{j,t-1}\gamma + \mu_i + \delta_t + \varepsilon_{ijt}, \tag{1}$$

where $productivity_{ijt}$ is the productivity of plant i in county j in year t. $policy_{jt}$ is a dummy variable that takes a value of 1 when county j includes a preexisting large plant in at least one year in the pre-reservation period of 2009-2011, and year t falls within the reservation period of 2012-2014. That is, the coefficient β_1 estimates the *mean* effect of SSI reservation policy on plant productivity. $X_{j,t-1}$ includes the lagged county-level demand control variables such as the population growth rate, population age 40 and above, crude marriage rate, per-capita gross regional domestic product in 1 million KRW, and construction employment growth rate. μ_i is the plant fixed effects that capture the time-invariant heterogeneity, and δ_t is the year fixed effects. ε_{ijt} is the clustered standard errors at the county level.

[Insert Table 3 about here]

Table 3 presents the estimates of equation (1).[17] Columns (1)-(2) show the results for all plants in 2009-2014, and columns (3)-(4) those for small plants during the same period. Columns (1) and (3) contain the policy variable only; we additionally include county-level demand control variables in columns (2) and (4). In all columns we include both the plant and year fixed effects.

We find that the estimates for the policy effect on all plants are not significant in columns (1)-(2), while those for the effect on small plants are positive and statistically significant at the 5% level in columns (3)-(4). The reservation policy improves performance of small treatment plants by 2.5%p more *on average*, compared to those in the control group, but this impact does not extend to the entire concrete industry, as shown in columns (1) and (2). The finding suggests that the productivity gain of small plants in the treatment group is offset by the productivity loss observed in large plants (as seen in Figure 1). These results are similar to the DID estimates presented in Table 2, and are stable regardless of inclusion of demand control variables. Therefore, the reservation policy is beneficial for small plants, but fails to elevate industry-wide productivity. Among the lagged demand control variables included in columns (2) and (4), only the impact of the construction employment growth rate in a county is positive and statistically significant at the 5% level. That is, not the demographic characteristics but actual construction demand in a local market is critical in enhancing productivity in the concrete industry (Syverson, 2004; Collard-Wexler, 2013). More specifically, plant productivity rises around 0.01 to 0.02%p with the 1%p increase in a county's construction employment growth rate.

Next, we explore the reservation policy effect on county-level productivity dispersion, by estimating the following equation:

$$dispersion_{jt} = \beta_0 + \beta_1 policy_{jt} + X'_{j,t-1}\gamma + \mu_j + \delta_t + \varepsilon_{jt}, \tag{2}$$

where $dispersion_{jt}$ is the standard deviation of the productivities among plants located in county j in year t, and μ_j and δ_t are the county and year fixed effects, respectively. ε_{jt} represents clustered standard errors at the county level. The control variables and coefficients are the same as those in equation (1). Thus, the coefficient β_1 estimates the *dispersion* effect of reservation policy on plant productivity.

[Insert Table 4 about here]

[17] Clustering at the plant level generates qualitatively identical results.

Table 4 provides the estimation results for equation (2). As before, columns (1)-(2) present the results for all plants, and columns (3)-(4) those for small plants. In Table 4, we find that the local market affected by the policy has a more dispersed productivity distribution than its unaffected counterpart, across all columns (1)-(4). For example, in columns (1)-(2), due to the reservation policy, the county-level standard deviation of all plants in the treatment group increases by about 1.4 to 1.5%p more than that in the control group. Moreover, such impact is similar to that on small plants only (about 1.4%p) in columns (3)-(4). This suggests that the dispersion effect of the reservation policy is attributable mainly to the increased productivity dispersion among small treatment plants, rather than that between small and large plants. All individual effects of the lagged demand control variables are non-significant, and their joint effect is also not significant (the F-statistics for column (2) and (4) are 0.77 and 0.81, respectively).

The findings from Tables 3 and 4 suggest that the distribution of small treatment plants shifts to the right and becomes more spread out after reservation, relative to that of control plants. Several explanations can account for this observation. First, the reservation policy benefits small plants in general, shifting the productivity distribution to the right. Second, if the reservation policy helps more of the less productive small plants survive, this reduces selection-driven left-truncation of such plants, leading to a more dispersed productivity distribution. Third, if more productive small plants have large benefits from the reservation policy, they become even more productive, further dilating the productivity distribution in the treatment county as well as shifting it to the right.

Therefore, to identify whether the increased productivity dispersion observed is associated with weakened market selection (not with heterogeneous productivity effects), it is crucial to decompose the policy-driven distributional change into three cases: truncation, shift, and dilation, as illustrated in Figure 2. Such changes are driven by weaker selection for Figure 2A, right shift for Figure 2B, and right shift with positive dilation for Figure 2C. As described in the figures, weaker selection increases the dispersion, and the shift with a positive dilation also extends the dispersion, but a simple right shift does not modify the dispersion. Thus, a larger standard deviation due to the reservation found in this study may come from (i) weaker selection and/or (ii) shift with positive dilation.

[Insert Figure 2 about here]

In general, one of three methods can be used to check the validity of weaker selection as an explanation: (i) exit regression, (ii) truncation cut-off regression, and (iii) structural estimation of the distributional changes. Unfortunately, because of the limited number of observations for exiting plants during the three-year reservation period, we cannot secure a valid estimate for the exit regression. Also, the cut-off regression cannot be freed from the impact of a shift with a positive dilation. Thus to confirm whether the wider dispersion observed in our reserved industry results from weaker selection, we use the structural estimation method that compares two distributions, as discussed further in Section 4.2 below.

4.2 Analysis of Distributional Changes

In this subsection, we use structural estimation to examine whether weaker selection occurs due to the reservation. We follow the basic method introduced in Combes *et al.* (2012) to identify three factors (i.e., truncation related to selection, shift, and dilation) that drive changes between two productivity distributions. But we modify slightly their method to compare four distributions together, because our analysis is based on a DID structure.

[Insert Figure 3 about here]

Before proceeding to the technical elements, we first compare productivity distributions in the control and treatment groups before and after implementation of SSI reservation policy. The graphs in Figures 3A(a) and 3A(b) describe the distributions of all plants located in the control and treatment counties (i.e., those without and with preexisting large plants, respectively), before (dashed) and after (solid) the reservation policy was introduced in 2012. The graphs in Figures 3B(a) and 3B(b) describe the productivity distributions of small plants in the same way as those in Figures 3A(a) and 3A(b) do. First, the productivity distribution of the control group in Figure 3A(a) (the same as for Figure 3B(a)) does not seem to shift, whereas that of the treatment group in Figures 3A(b) and 3B(b) appears to have shifted to the right (relative to the control group). A right shift is more evident for small plants in the treatment group in Figure 3B(b), which is consistent with the significant positive productivity effect of the reservation policy for small plants shown in Table 3. If the reservation policy weakens left truncation due to decreased competition, the slope of the distribution becomes flatter, especially for the left side of the distribution. Relative to the control distribution, the slope of the treatment distribution seems weakly flatter, and the treatment distribution becomes more dispersed. But we still cannot exclude other possibilities. For example, if benefits of reservation policy are concentrated on low- and medium-productivity plants rather than high-productivity plants, leading to a shift with a negative dilation, this also reduces the productivity dispersion among small plants. Thus, we must more carefully investigate whether the increased productivity dispersion after implementation of the reservation policy reflects weakened market selection.

We briefly explain our estimation strategy.[18] First, following Combes *et al.* (2012), we define the relationship between two distributions. We denote the cumulative density function of productivity for group i as $F_i(\phi)$, where ϕ is the productivity. And we denote the measure of the strength of selection in group i by s_i; that of shift with a positive dilation in group i by d_i; and that of right shift in group i by a_i. It is noteworthy that s_i is the proportion of the left-truncating area due to selection. Compared to the underlying cumulative density function of productivity $\tilde{F}(\phi)$ without any changes, $F_i(\phi)$ can be written by:

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - a_i}{d_i}\right) - s_i}{1 - s_i}\right\}. \tag{3}$$

In equation (3), we cannot directly evaluate s_i, d_i, and a_i from the data, because the underlying cumulative density function cannot be identified. Instead, for two cumulative density functions of productivity, both of which come from the same underlying distribution of $\tilde{F}(\phi)$, we can estimate relative distributional changes. The three relative strengths can be defined by:

$$S_{1,2} \equiv \frac{s_1 - s_2}{1 - s_2}, \quad D_{1,2} \equiv \frac{d_1}{d_2}, \quad A_{1,2} \equiv a_1 - D_{1,2} a_2, \tag{4}$$

where, for group 1 compared to group 2, $S_{1,2}$ is the relative strength of stronger selection; $D_{1,2}$ is that of shift with positive dilation; and $A_{1,2}$ is that of right shift. The relationship between F_1 and F_2 depends upon the three parameters in equation (4):

$$\begin{aligned}
&\text{(i)}\ \ S_{1,2} > 0: \quad F_1(\phi) = \max\left\{0, \frac{F_2\left(\frac{\phi - A_{1,2}}{D_{1,2}}\right) - S_{1,2}}{1 - S_{1,2}}\right\}, \\
&\text{(ii)}\ \ S_{1,2} < 0: \quad F_2(\phi) = \max\left\{0, \frac{F_1\left(\frac{D_{1,2}\phi + A_{1,2}}{D_{1,2}}\right) - \frac{-S_{1,2}}{1 - S_{1,2}}}{1 - \frac{-S_{1,2}}{1 - S_{1,2}}}\right\}.
\end{aligned} \tag{5}$$

As explained in Appendix A, we can derive the moment conditions from equation (5) using a

[18] See Appendix A for the full explanation.

quantile specification in Combes *et al.* (2012), Gobillon and Roux (2010), and Carrasco and Florens (2000), and thus estimate $S_{1,2}$ (as well as $D_{1,2}$ and $A_{1,2}$). However, to evaluate the relative selection strength among four distributions under our DID structure, we consider one additional step.

We denote the measure of the strength of selection in the control group before reservation by s_{CB}, the same measure in the control group after reservation by s_{CA}, that in the treatment group before reservation by s_{TB}, and that in the treatment group after reservation by s_{TA}. Then, our treatment effect on selection can be written by $s_{TA} - s_{TB} - s_{CA} + s_{CB}$. Because we can only estimate the relative strength, we rewrite the treatment effect on selection as follows:

$$\begin{aligned} s_{TA} - s_{TB} - s_{CA} + s_{CB} &= (s_{TA} - s_{CB}) - (s_{TB} - s_{CB}) - (s_{CA} - s_{CB}) \\ &= (1 - s_{CB}) \left(\frac{s_{TA} - s_{CB}}{1 - s_{CB}} - \frac{s_{TB} - s_{CB}}{1 - s_{CB}} - \frac{s_{CA} - s_{CB}}{1 - s_{CB}} \right) \\ &= (1 - s_{CB}) \left(S_{TA,CB} - S_{TB,CB} - S_{CA,CB} \right). \end{aligned} \tag{6}$$

In equation (6), we cannot identify $(1 - s_{CB})$, but estimate $S_{TA,CB}$, $S_{TB,CB}$, and $S_{CA,CB}$ from the data. Nonetheless, we can check whether selection becomes stronger or weaker by evaluating $(S_{TA,CB} - S_{TB,CB} - S_{CA,CB})$, because s_{CB} is the share of the left-truncating area due to selection, which is less than 1, and thus $(1 - s_{CB})$ is always positive. Therefore, we define $(S_{TA,CB} - S_{TB,CB} - S_{CA,CB})$ by selection criteria:

$$\text{Selection Criteria} \equiv S_{TA,CB} - S_{TB,CB} - S_{CA,CB}. \tag{7}$$

Using equation (5), we derive the relationship between F_{TA} and F_{CB}, that between F_{TB} and F_{CB}, and that between F_{CA} and F_{CB}, based on which we construct the moment conditions and estimate all nine parameters, as well as selection criteria.

[Insert Table 5 about here]

Table 5 presents the estimate results for the three relative selection parameters of $S_{TA,CB}$, $S_{TB,CB}$, and $S_{CA,CB}$, and for the selection criteria.[19] Column (1) shows the result for all plants, and column (2) that for small plants. In column (1), we find that the estimates for $S_{TA,CB}$, $S_{TB,CB}$, and the selection criteria are negative and statistically significant at the 1% or 5% levels, while that

[19] See Appendix Table A2 for the full results of all nine parameter estimates.

for $S_{CA,CB}$ is positive and statistically significant at the 1% level. Compared to the control group before reservation, selection is weaker in the treatment group regardless of the introduction of reservation, but becomes stronger in the control group during the reservation period (capturing a common time effect). Thus, combining these three relationships, we can conclude that the increased dispersion among all plants observed in Table 4 is evidence for weaker selection. In column (2) of small pants, all three parameter estimates are positive and statistically significant at the 1% level. However, because the relative selection strength in the control group post-reservation is the largest compared to the control group pre-reservation, the combining effect under the DID structure implies that increased dispersion among small plants also emerges from weaker selection. Therefore, results of structural estimation of distribution changes confirm that the increased productivity dispersion among small plants due to the reservation policy is based on weakened market selection in the concrete industry.

[Insert Figure 4 about here]

4.3 Incumbents and Entrants

In this subsection, we reexamine the impacts of reservation by focusing on incumbent plants. During our research period, only a handful of small plants exited the market, but a considerable number of such players entered. As described in Figure 4, the number of small plants gradually increased in both the control and treatment counties after introduction of reservation (i.e., between 2012 and 2014), but the entry of small plants has rapidly risen in the treatment county since the reservation policy introduced in 2012. To check whether the increased dispersion is driven by entrants with low productivity rather than by weaker selection for incumbent plants, we use the sample of incumbents excluding new entrants. In fact, approximately 91% of small plants as of 2014 were incumbents that began to operate before 2012. Moreover, because the goal of the reservation policy was to protect small incumbents rather than new entrants, we investigate the policy's effect on these targeted plants.

[Insert Tables 6 and 7 about here]

Tables 6 and 7 present the estimates of equations (1) and (2), respectively, excluding new entrants. In Table 6, we find that the estimation results without new entrants are almost equivalent to those with them in Table 3. Reservation enhances the productivity levels of small treatment incumbent plants by 2.5%p more *on average*, compared to those in the control group, but the impact on all incumbent plants including large ones is not significant. Moreover, in Table 7, the productivity distribution of incumbents in the treated markets spreads out more than that of those in control markets, which is also similar to the results in Table 4. Specifically, due to reservation, the county-level standard deviation of incumbent plants (regardless of the inclusion of large plants) in the treatment group increases by about 1.6%p more than that of the control plants. This confirms that the reservation policy weakens competition among small incumbents, resulting in more dispersed productivity among them. Therefore, the findings presented in Tables 6 and 7 imply that the reservation impacts found in Section 4.1 are related deeply to incumbent plants. Small incumbents not only receive the benefit from the reservation policy but also generate allocative inefficiency.

5 Robustness

To assess the robustness of our findings, we examine various issues related to alternative definition of geographic markets, pre-announcement effects, alternative measures of productivity dispersion, and alternative demand controls. A wide range of robustness tests produce qualitatively similar results: that is, our pattern of findings for the SSI reservation policy's impact under these tests remains largely identical to that in the tables presented earlier.

5.1 Robustness Checks for Plant-Level Productivities

In this subsection, we perform several robustness checks regarding the average productivity effect of the reservation policy. First, we use distance criteria as an alternative market definition to confirm the validity of our main results for county-based markets. In Korea, a 30-minute driving distance (i.e., maximum feasible distance for delivering concrete) is approximately 7.5 kilometers in urban areas and 15 kilometers in rural areas (Jeon and Whang, 2010). Because plants are, in general, located in suburban or rural areas, a distance of about 15 kilometers is likely appropriate to define a local market. To check the robustness of our results to this market definition, we use 15 and 20 kilometers as threshold values for market radius and estimate the following equation:

$$productivity_{ijt} = \beta_0 + \beta_1 policy_{it} + X'_{j,t-1}\gamma + \mu_i + \delta_t + \varepsilon_{ijt}, \tag{8}$$

where $policy_{it}$ is a dummy variable that takes the value of 1 whenever at least one preexisting large firm is located within a specific distance from plant i, and year t falls within the SSI reservation period of 2012-2014. Technically, the closest distance from a large plant to any large ones is 0, so we focus only on small plants in this robustness check. Thus, the coefficient β_1 estimates the *mean* effect of SSI reservation policy on small plants. The other variables and coefficients are the same as those in equation (1).

[Insert Table 8 about here]

Table 8 presents the results under these alternative market-distance criteria. Panels A and B use 15 and 20 kilometers, respectively, as threshold values of distance for market definitions. The samples in columns (1)-(2) include small plants; those in columns (3)-(4) contain small incumbents (i.e., those having entered in 2011 or earlier). In all columns of both panels, the estimated policy impact on small plants is positive and statistically significant at the 1% level, and ranges from 3.5 to 3.7%p. Those impacts are qualitatively the same as those under the county criteria we used for our main analyses. Therefore, the results are not sensitive to choice of market definition.

Second, we return to the original market definition and examine the pre-announcement effect. In late 2011, it was announced officially that the concrete industry would be a reserved industry starting in 2012; but there had been an expectation of this news since early 2011. Thus we can reasonably hypothesize that firms would have reacted *prior to* the actual policy implementation. In other words, the productivity levels of small plants might have been affected before implementation. To analyze the pre-announcement effect of the SSI reservation, we exclude the plant-year observations in 2011 and re-estimate equation (1).

[Insert Table 9 about here]

Panel A in Table 9 presents the results excluding 2011. We find once again that only small treatment plants receive the benefits of reservation. Specifically, in columns (3)-(4), the estimated policy impacts (about 2.7%) are marginally stronger than those in Table 3. That is, there might be a pre-announcement effect one year ahead of the SSI reservation, but this lead effect is weak, implying that the pre-announcement effect in our model is associated with a small amount of anticipation rather than endogeneity (Malani and Reif, 2015).

Last, we consider another variable to capture shifts in demand for concrete. Specifically, after replacing the construction employment growth rate with the rate of change in land price in a county, we re-estimate equation (1). Panel B in Table 9 summarizes the results. Because the unconditional estimates are not affected by an alternative demand control variable, we do not report them. Similar to Table 3, column (2) presents the conditional effect on all plants, and column (4) that on small plants. The pattern of estimated policy impacts is very similar to that found previously. That is, use of a different construction-related demand variable does not influence the results qualitatively.

5.2 Robustness Checks for County-Level Dispersion in Productivity Level

In this subsection, we conduct robustness checks for county-level dispersion in productivity level. First, we use two alternative measures for productivity dispersion. Table 10 presents the estimated policy impact on the interdecile range in productivity levels in Panel A and that on the interquartile range in Panel B. In both panels, columns (1)-(4) present the summarized results as in Table 4.

[Insert Table 10 about here]

In both panels, all estimates are positive and statistically significant at the 5% level. For example, the conditional effects on all plants regarding the interdecile and interquartile ranges are about 3.3%p and 2.3%p, respectively, whereas those on small plants for the same ranges are about 3.6%p and 1.9%p, respectively. Thus, just as in Table 4, a local market affected by the SSI policy exhibits more dispersed productivity distribution than its counterpart.

[Insert Table 11 about here]

Next, we examine the pre-announcement effect on dispersion, by again using the standard deviation as a dispersion measure. Panel A in Table 11 summarizes the estimation results of equation (2) excluding 2011. The estimated policy impact (1.5 to 1.7%p) is only slightly larger than that in Table 4. Thus, a pre-announcement effect one year ahead of the SSI reservation was found, but only a limited one. Finally, we exploit the rate of change in land price instead of the growth rate of construction employment in Table 4, and re-estimate equation (2). Panel B in Table 11 summarizes the results in a similar way to that of Panel B in Table 9. The estimated policy impact is robust regardless of the choice of a construction-related demand variable. In sum, our results for dispersion are also robust.

6 Conclusions

In this paper, we examined the impact of SSI policy on small plants' performance, as well as on allocative inefficiency in the concrete industry. We summarize our main findings as follows: First, small plants in treatment counties (those affected by SSI) with preexisting large plants have higher productivity gains on average than those in control counties. Second, SSI regulation causes a larger productivity dispersion in treatment counties compared to the control group, and this increased dispersion is driven by weakened market selection. The findings suggest that SSI may incur allocative inefficiency in the concrete industry.

The revived SSI policy in Korea increased productivity levels of small plants in the concrete industry, suggesting achievement of the regulation's primary goal. Nonetheless, the policy provokes side effects of weakened selection, which in turn impedes market efficiency. Therefore, implementation of SSI regulation may result in poor economic performance for the reserved industry in the long run.

Our study contributes to the literature by identifying the causal effect of SSI policy using exogenous variation in preexisting conditions across local markets. Our findings also have policy implications, because the Korean government is expanding the reservation policy's industry coverage, suggesting the need for more accurate analysis of its effects. Nonetheless, results from the concrete industry may have only limited application to other reserved markets, due to its highly capital-intensive nature. Thus it may be necessary to examine other labor-intensive or technology-intensive industries to draw more general conclusions regarding the short- and long-run effects of SSI policy.

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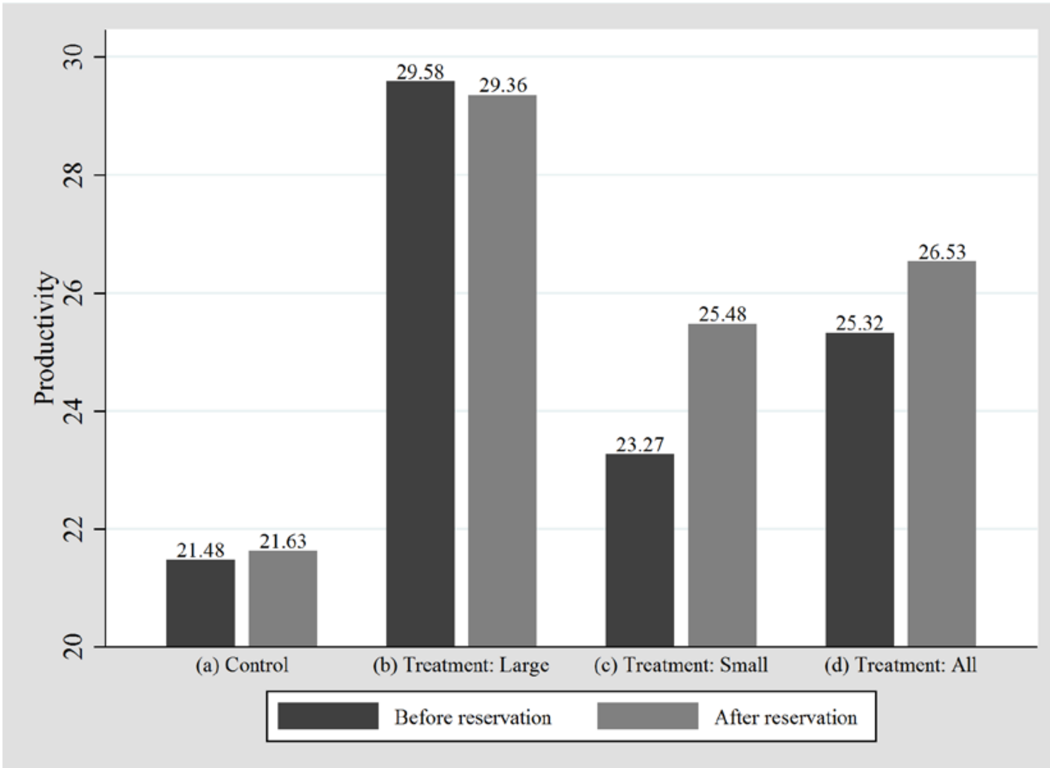
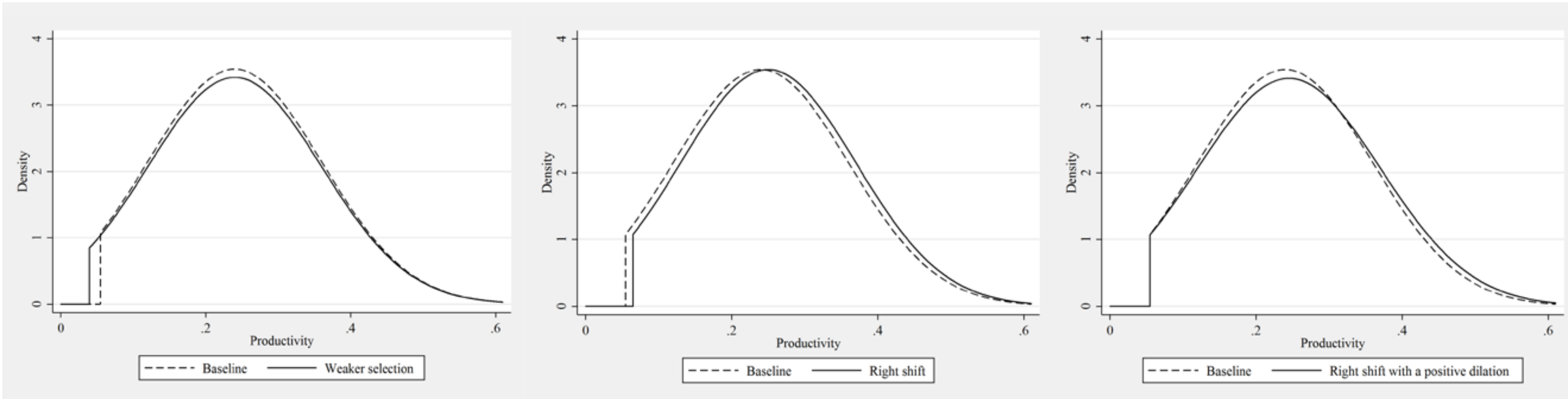
Figure 1. Mean Productivity Levels



Note: The bar graph describes the mean productivities of plants located in the treatment and control counties (i.e., those with and without preexisting large plants, respectively), before and after the SSI reservation policy was introduced in 2012.

Figure 2. Three Illustrations of Distributional Changes

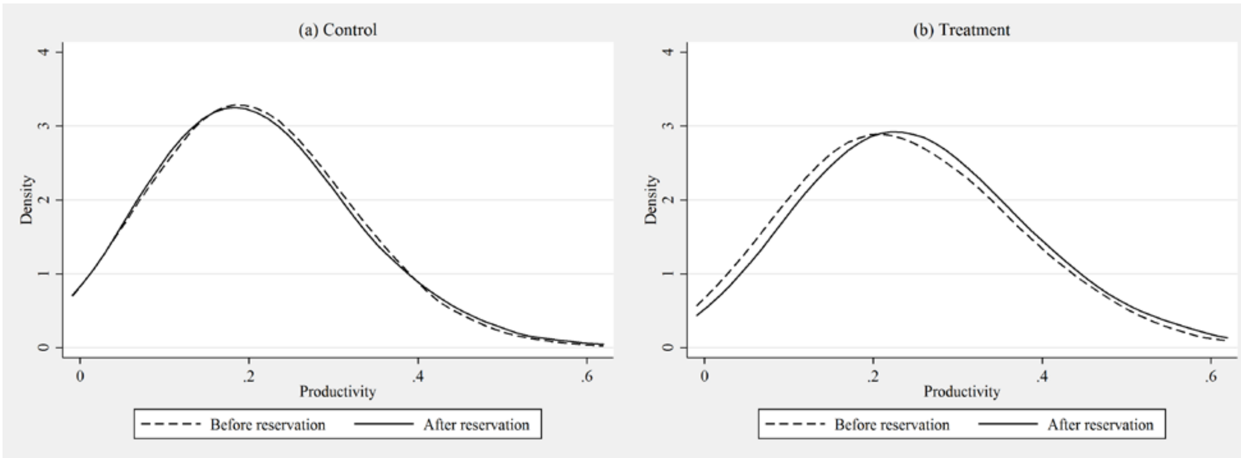
2A. Weaker selection only 2B. Right shift only 2C. Right shift with a positive dilation only



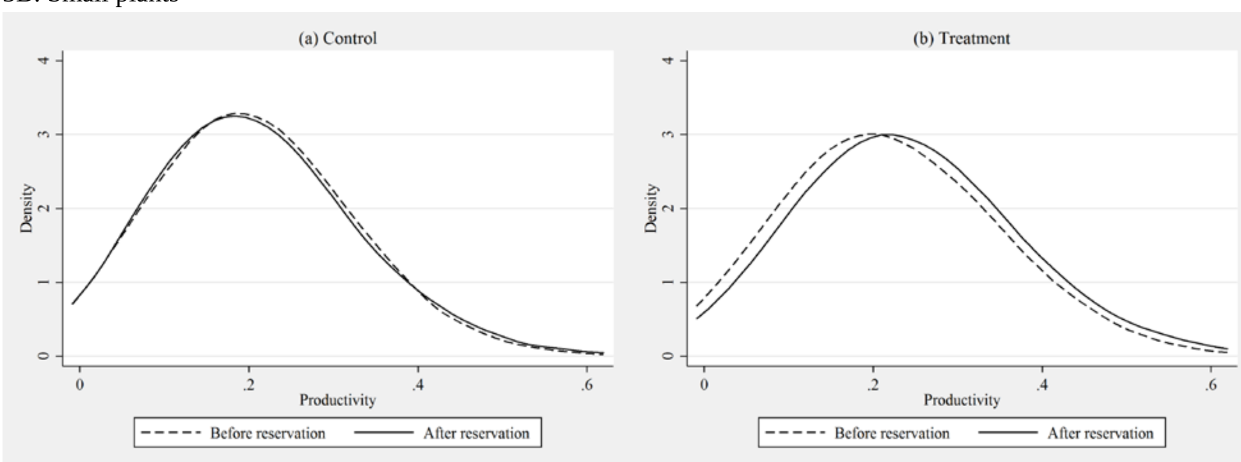
Note: The dashed lines are the baseline distributions before reservation; the solid lines are the distributions with changes after that.

Figure 3. Productivity Distributions

3A. All plants

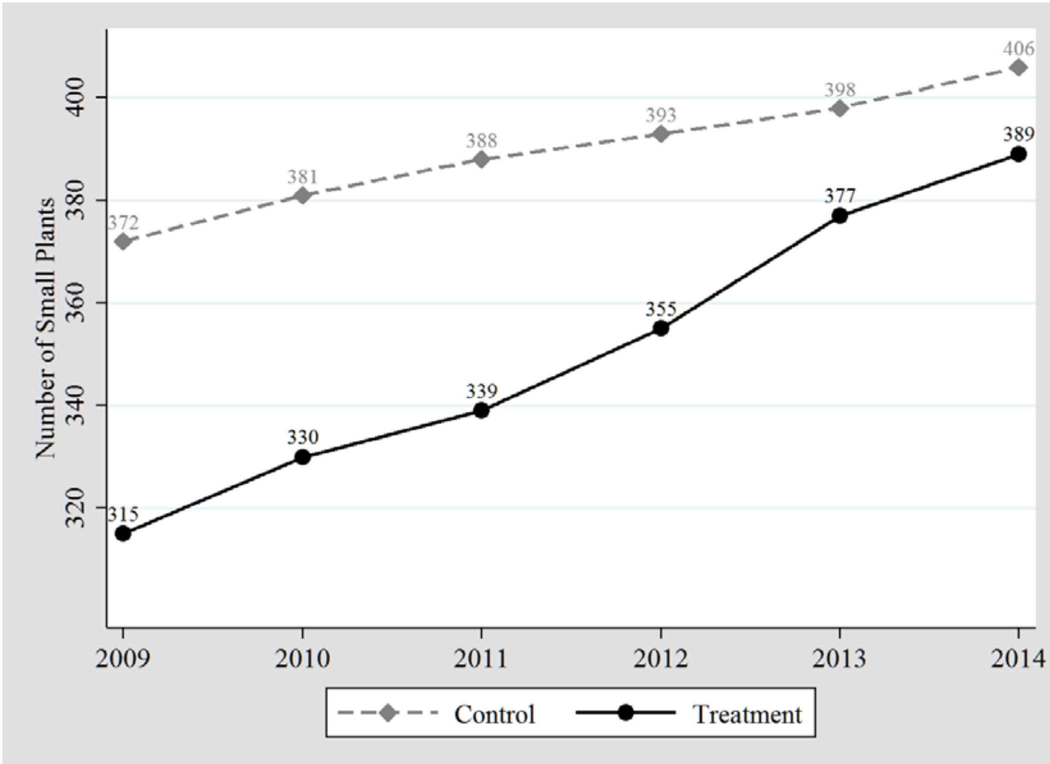


3B. Small plants



Note: The graphs in Figures 3A(a) and 3A(b) describe the productivity distributions of all plants located in the control and treatment counties (i.e., those without and with preexisting large plants, respectively), before the SSI reservation policy was introduced in 2012 (dashed) and after that (solid). The graphs in Figures 3B(a) and 3B(b) describe the productivity distributions of small plants in the same way as those in Figures 3A(a) and 3A(b).

Figure 4. Trends in Number of Small Plants



Note: The diamond and bullet points represent the numbers of small plants in the control and treatment groups, respectively, in each year.

Table 1. Descriptive Statistics

	Mean	Median	S.D.	P25	P75	Obs.
A. Plant-level productivity (%)						
All plants	24.022	22.076	12.728	14.745	31.083	5,337
Small plants	22.924	21.266	12.018	14.173	29.627	4,443
Incumbents	24.356	22.383	12.703	15.113	31.435	5,014
Small incumbents	23.242	21.534	11.983	14.494	30.043	4,139
B. County-level productivity dispersion						
Standard deviation						
All plants	7.337	7.264	3.067	5.029	9.329	523
Small plants	7.287	7.037	3.168	4.964	9.410	523
Incumbents	7.139	7.034	3.175	4.778	9.381	523
Small incumbents	7.082	6.882	3.285	4.710	9.523	523
Interdecile range						
All plants	18.945	18.727	8.380	12.603	24.665	523
Small plants	18.534	18.267	8.481	12.176	24.065	523
Interquartile range						
All plants	9.754	8.655	5.374	5.567	13.194	523
Small plants	9.406	8.518	5.199	5.534	12.611	523
C. Lagged county-level demand control variables						
Population growth rate (%)	0.469	0.097	2.349	-0.689	1.124	1,149
Population age 40 and above (% of total)	52.609	51.458	8.656	45.406	60.189	1,149
Crude marriage rate	5.589	5.534	1.173	4.637	6.414	1,149
Per-capita gross regional domestic product (1 million KRW)	25.926	22.163	15.837	16.986	28.388	1,149
Construction employment growth rate (%)	4.985	3.518	22.705	-7.396	16.498	1,149
Rate of change in land price (%)	0.792	0.794	0.990	0.248	1.244	1149

Note: Each panel uses the pooled sample in 2009-2014. Small incumbents are small plants that entered in 2011 and earlier. In Panel B, counties with fewer than 4 small plants are excluded. The crude marriage rate is the number of marriages per 1,000 people in the population.

Table 2. Differences-in-Differences Estimates

A. Means of Plant-Level Productivity of All Plants

	(1) Control	(2) Treatment	*(2) – (1)*
(α) Before reservation	21.480	25.324	*3.845*
(β) After reservation	21.628	26.533	*4.904*
(β) – (α)	*0.149*	*1.208*	*1.059* *(0.984)*

B. Means of Plant-Level Productivity of Small Plants

	(1) Control	(2) Treatment	*(2) – (1)*
(α) Before reservation	21.480	23.268	*1.7887*
(β) After reservation	21.628	25.478	*3.849*
(β) – (α)	*0.149*	*2.209*	*2.061*** *(0.942)*

C. County-Level Dispersion in Productivity of All Plants

	(1) Control	(2) Treatment	*(2) – (1)*
(α) Before reservation	7.447	7.405	*-0.041*
(β) After reservation	6.705	7.815	*1.110*
(β) – (α)	*-0.742*	*0.409*	*1.151*** *(0.518)*

D. County-Level Dispersion in Productivity of Small Plants

	(1) Control	(2) Treatment	*(2) – (1)*
(α) Before reservation	7.447	7.324	*-0.123*
(β) After reservation	6.705	7.697	*0.992*
(β) – (α)	*-0.742*	*0.373*	*1.114*** *(0.538)*

Note: Panels A and C (B and D) describe the means and standard deviations, respectively, of the plant-level productivity of all plants (small plants) located in the treatment and control counties (i.e., those with and without preexisting large plants, respectively), before and after the SSI reservation policy was introduced in 2012. The number in the bottom right cell is a differences-in-differences estimate. Numbers in parentheses are county-clustered standard errors. ** indicates significance at the 5% level.

Table 3. Reservation Impacts on Plant-Level Productivity

	Dependent Variable: Productivity			
	All Plants		Small Plants	
	(1)	(2)	(3)	(4)
Policy	1.148	1.246	2.470**	2.496**
	(1.125)	(1.148)	(1.057)	(1.078)
Demand controls				
Population growth rate		0.043		0.109
		(0.259)		(0.237)
Population age 40 and above (% of total)		0.791		0.752
		(0.682)		(0.585)
Crude marriage rate		-0.875		-0.494
		(0.724)		(0.620)
Log of per-capita gross regional domestic product		-0.024		1.889
		(2.889)		(2.912)
Construction employment growth rate		0.015**		0.014**
		(0.007)		(0.006)
Demand controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,337	5,337	4,443	4,443
Adj. *R*-squared	0.694	0.696	0.691	0.693

Note: The samples in columns (1)-(2) include all plants in 2009-2014; those in columns (3)-(4) contain small plants during the same period. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All demand control variables are lagged by one year. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 4. Reservation Impacts on County-Level Dispersions in Productivities

	Dependent Variable: Standard Deviation of Productivity			
	All Plants		Small Plants	
	(1)	(2)	(3)	(4)
Policy	1.439**	1.482**	1.385**	1.429**
	(0.560)	(0.578)	(0.582)	(0.605)
Demand controls				
Population growth rate		-0.045		-0.046
		(0.105)		(0.123)
Population age 40 and above (% of total)		0.501		0.462
		(0.371)		(0.391)
Crude marriage rate		0.114		0.127
		(0.294)		(0.318)
Log of per-capita gross regional domestic product		-1.635		-1.868
		(1.910)		(1.868)
Construction employment growth rate		0.002		0.001
		(0.005)		(0.005)
Demand controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	523	523	523	523
Adj. R-squared	0.502	0.504	0.480	0.481

Note: The sample in each column includes counties with at least 4 small plants in 2009-2014. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All demand control variables are lagged by one year. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 5. Selection Criteria

	(1) All Plants	(2) Small Plants
$S_{TA,CB}$	-0.007**	0.003***
	(0.003)	(0.001)
$S_{TB,CB}$	-0.008***	0.008***
	(0.003)	(4×10^{-4})
$S_{CA,CB}$	0.023***	0.052***
	(0.005)	(0.001)
Selection criteria	-0.021***	-0.058***
	(0.008)	(0.001)
Observations	5,337	4,443

Note: The selection criteria is $S_{TA,CB} - S_{TB,CB} - S_{CA,CB}$. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 6. Reservation Impacts on Incumbents' Plant-Level Productivity

	Dependent Variable: Productivity			
	Incumbents		Small Incumbents	
	(1)	(2)	(3)	(4)
Policy	1.170	1.287	2.480**	2.525**
	(1.103)	(1.126)	(1.037)	(1.057)
Demand controls				
Population growth rate		0.053		0.111
		(0.256)		(0.235)
Population age 40 and above (% of total)		0.810		0.789
		(0.678)		(0.588)
Crude marriage rate		-0.858		-0.458
		(0.727)		(0.625)
Log of per-capita gross regional domestic product		-0.561		1.190
		(2.861)		(2.867)
Construction employment growth rate		0.015**		0.015**
		(0.006)		(0.006)
Demand controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,014	5,014	4,139	4,139
Adj. R-squared	0.697	0.699	0.693	0.695

Note: The samples in columns (1)-(2) include all incumbents in 2009-2014; those in columns (3)-(4) contain small incumbents during the same period. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All demand control variables are lagged by one year. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 7. Reservation Impacts on County-Level Dispersions in Incumbents' Productivity

	Dependent Variable: Standard Deviation of Productivity			
	Incumbents		Small Incumbents	
	(1)	(2)	(3)	(4)
Policy	1.567**	1.629**	1.580**	1.635**
	(0.611)	(0.622)	(0.626)	(0.644)
Demand controls				
Population growth rate		-0.014		-0.019
		(0.105)		(0.119)
Population age 40 and above (% of total)		0.521		0.404
		(0.393)		(0.392)
Crude marriage rate		0.055		0.089
		(0.302)		(0.317)
Log of per-capita gross regional domestic product		-1.639		-1.849
		(2.023)		(1.953)
Construction employment growth rate		0.001		-0.001
		(0.005)		(0.006)
Demand controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	523	523	523	523
Adj. R-squared	0.500	0.502	0.486	0.485

Note: The sample in each column includes counties with at least 4 small plants in 2009-2014. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All demand control variables are lagged by one year. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 8. Robustness Checks with Alternative Market Definitions

	Dependent Variable: Productivity			
	Small Plants		Small Incumbents	
	(1)	(2)	(3)	(4)
	A. Threshold Value: 15 kilometers			
Policy	3.523***	3.566***	3.582***	3.632***
	(0.989)	(1.006)	(0.954)	(0.969)
Observations	4,443	4,443	4,139	4,139
Adj. *R*-squared	0.694	0.696	0.697	0.699
	B. Threshold Value: 20 kilometers			
Policy	3.567***	3.594***	3.649***	3.690***
	(1.082)	(1.100)	(1.038)	(1.055)
Observations	4,443	4,443	4,139	4,139
Adj. *R*-squared	0.694	0.696	0.697	0.699
Demand controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Panels A and B use 15 and 20 kilometers, respectively, as threshold values of distances for market definitions. The samples in columns (1)-(2) include small plants in 2009-2014; those in columns (3)-(4) contain small incumbents (i.e., those having entered in 2011 and earlier) during the same period. The variable Policy is a dummy variable that takes a value of 1 if at least one preexisting large firm is located within a specific distance from a small plant and the year falls within the reservation period of 2012-2014. All regressions include the same control variables as in Table 3. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 9. Other Robustness Checks for Plant-Level Productivity

	Dependent Variable: Productivity			
	All Plants		Small Plants	
	(1)	(2)	(3)	(4)
	A. Pre-announcement Effect			
Policy	1.076	1.136	2.692**	2.662**
	(1.347)	(1.404)	(1.236)	(1.279)
Observations	4,460	4,460	3,716	3,716
Adj. *R*-squared	0.678	0.680	0.676	0.678
	B. Alternative Demand Control			
Policy		1.427		2.602**
		(1.105)		(1.055)
Observations		5,337		4,443
Adj. *R*-squared		0.700		0.695
Demand controls	No	Yes	No	Yes
Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Each panel has one distinction relative to the specification used in Table 3. In panel A, the sample excludes observations in 2011, to test a pre-announcement effect. In panel B, the rate of change in land price is alternatively exploited to capture potential impact from the construction sector. The samples in columns (1)-(2) include all plants; those in columns (3)-(4) contain all small plants. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All regressions include the same control variables as in Table 3. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 10. Robustness Checks with Alternative Dispersion Measures

	All Plants		Small Plants	
	(1)	(2)	(3)	(4)
	A. Dependent Variable: Interdecile Range of Productivity			
Policy	3.222**	3.316**	3.467**	3.601**
	(1.519)	(1.572)	(1.510)	(1.551)
Observations	523	523	523	523
Adj. *R*-squared	0.544	0.546	0.522	0.523
	B. Dependent Variable: Interquartile Range of Productivities			
Policy	2.217**	2.264**	1.843*	1.886*
	(0.921)	(0.910)	(0.965)	(0.990)
Observations	523	523	523	523
Adj. *R*-squared	0.513	0.521	0.451	0.458
Demand controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: For the dependent variable, panel A uses the interdecile range (difference between the 90^{th} and 10^{th} percentiles) and panel B the interquartile range. The sample in each column includes the counties with at least 4 small plants in 2009-2014. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All regressions include the same control variables as in Table 4. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Table 11. Other Robustness Checks for Productivity Dispersion

	Dependent Variable: Standard Deviation of Productivity			
	All Plants		Small Plants	
	(1)	(2)	(3)	(4)
	A. Pre-announcement Effect			
Policy	1.583**	1.686**	1.501**	1.612**
	(0.665)	(0.689)	(0.720)	(0.751)
Observations	436	436	436	436
Adj. *R*-squared	0.510	0.512	0.491	0.492
	B. Alternative Demand Control			
Policy		1.506***		1.469**
		(0.569)		(0.591)
Observations		523		523
Adj. *R*-squared		0.504		0.483
Demand controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Each panel has one distinction relative to the specification used in Table 4. In panel A, the sample excludes observations in 2011, to test a pre-announcement effect. In panel B, the rate of change in land price is alternatively exploited to capture potential impact from the construction sector. The sample in each column includes counties with at least 4 small plants in 2009-2014. The variable Policy is a dummy variable that takes a value of 1 if a plant is located in a county with preexisting large plants and the year falls within the reservation period of 2012-2014. All regressions include the same control variables as in Table 4. Numbers in parentheses are county-clustered standard errors. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Appendix A. Estimation Strategy for Productivity Distribution

This appendix provides details of our estimation strategy for productivity distribution. We reiterate the notations regarding functions as well as functional changes introduced in Section 4.2. The cumulative density function of productivity for group i, $F_i(\phi)$, can be written by:

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}\left(\frac{\phi - a_i}{d_i}\right) - s_i}{1 - s_i}\right\}, \tag{A1}$$

where ϕ is the productivity and $\tilde{F}(\phi)$ is the underlying cumulative density function of productivity. s_i, d_i, and a_i are the measure of the strength of selection in group i, that of shift dilation, and that of right shift, respectively. Consider a pair of cumulative density functions of productivity (groups 1 and 2) where both come from the same underlying distribution $\tilde{F}(\phi)$. As explained in Section 4.2, we cannot separately identify s_1, s_2, d_1, d_2, a_1, and a_2 from the data, but estimate the statements about the relative strengths for a stronger selection ($S_{1,2}$), shift with dilation ($D_{1,2}$), and right shift ($A_{1,2}$). Following Combes *et al*. (2012), we define the three relative strengths by:

$$S_{1,2} \equiv \frac{s_1 - s_2}{1 - s_2}, \qquad D_{1,2} \equiv \frac{d_1}{d_2}, \qquad A_{1,2} \equiv a_1 - D_{1,2}a_2. \tag{A2}$$

As derived in Combes *et al*. (2012), if $S_{1,2} > 0$ (i.e., $s_1 > s_2$), F_1 can be obtained by left-truncating a share of $S_{1,2}$, dilating F_2 by $D_{1,2}$, and shifting it by $A_{1,2}$ of its values:

$$F_1(\phi) = \max\left\{0, \frac{F_2\left(\frac{\phi - A_{1,2}}{D_{1,2}}\right) - S_{1,2}}{1 - S_{1,2}}\right\}. \tag{A3}$$

On the other hand, if $S_{1,2} < 0$ (i.e., $s_1 < s_2$), F_2 can be obtained by left-truncating a share of $\frac{-S_{1,2}}{1-S_{1,2}}$, dilating F_1 by $\frac{1}{D_{1,2}}$, and shifting it by $-\frac{A_{1,2}}{D_{1,2}}$ of its values:

$$F_2(\phi) = \max\left\{0, \frac{F_1(D_{1,2}\phi + A_{1,2}) - \frac{-S_{1,2}}{1-S_{1,2}}}{1 - \frac{-S_{1,2}}{1-S_{1,2}}}\right\}. \tag{A4}$$

To derive the estimable equations, we follow a series of transformations introduced in Combes *et al*. (2012). First, assuming that $\tilde{F}$, F_1, and F_2 are invertible, we define $\lambda_i(u) \equiv F_i^{-1}(u)$ so as to denote the u-th quantile of F_i, $i = 1, 2$. If $S_{1,2} > 0$, (A3) can be rewritten by:

$$\lambda_1(u) = D_{1,2}\lambda_2\big(S_{1,2} + (1 - S_{1,2})u\big) + A_{1,2} \quad \text{for } u \in [0, 1]. \tag{A5}$$

If $S_{1,2} < 0$, (A4) can be rewritten by:

$$\lambda_2(u) = \frac{1}{D_{1,2}}\lambda_1\left(\frac{u - S_{1,2}}{1 - S_{1,2}}\right) - \frac{A_{1,2}}{D_{1,2}} \quad \text{for } u \in [0, 1]. \tag{A6}$$

As we make u converge to $S + (1 - S)u$, (A6) changes to:

$$\lambda_2\big(S_{1,2} + (1 - S_{1,2})u\big) = \frac{1}{D_{1,2}}\lambda_1(u) - \frac{A_{1,2}}{D_{1,2}} \quad \text{for } u \in \left[\frac{-S_{1,2}}{1 - S_{1,2}}, 1\right]. \tag{A7}$$

Combining equations (A5) and (A7), we have:

$$\lambda_1(u) = D_{1,2}\lambda_2\big(S_{1,2} + (1 - S_{1,2})u\big) + A_{1,2} \quad \text{for } u \in \left[\max\left(0, \frac{-S_{1,2}}{1 - S_{1,2}}\right), 1\right]. \tag{A8}$$

To make the set of u not influenced by $S_{1,2}$, we change u converging to $r_s(u)$, where $r_s(u) = \max\left(0, \frac{-S_{1,2}}{1-S_{1,2}}\right) + \left[1 - \max\left(0, \frac{-S_{1,2}}{1-S_{1,2}}\right)\right]u$. Then, equation (A8) is transformed to the estimable form as:

$$\lambda_1\big(r_s(u)\big) = D_{1,2}\lambda_2\left(S_{1,2} + (1 - S_{1,2})r_s(u)\right) + A_{1,2} \quad \text{for } u \in [0, 1]. \tag{A9}$$

Table A1. Functional Changes in the DID Setting

	(1) Control group	(2) Treatment group	*(2) – (1)*
(α) Before reservation	s_{CB} d_{CB} a_{CB}	s_{TB} d_{TB} a_{TB}	$s_{TB}-s_{CB}$ $d_{TB}-d_{CB}$ $a_{TB}-a_{CB}$
(β) After reservation	s_{CA} d_{CA} a_{CA}	s_{TA} d_{TA} a_{TA}	$s_{TA}-s_{CA}$ $d_{TA}-d_{CA}$ $a_{TA}-a_{CA}$
(β) – (α)	$s_{CA}-s_{CB}$ $d_{CA}-d_{CB}$ $a_{CA}-a_{CB}$	$s_{TA}-s_{TB}$ $d_{TA}-d_{TB}$ $a_{TA}-a_{TB}$	$s_{TA}-s_{TB}-s_{CA}+s_{CB}$ $d_{TA}-d_{TB}-d_{CA}+d_{CB}$ $a_{TA}-a_{TB}-a_{CA}+a_{CB}$

Then, we convert (A9) to the empirical moment condition with the finite number of observations of F_1 and F_2 as follows (Combes *et al.*, 2012; Gobillon and Roux, 2010; Carrasco and Florens, 2000):

$$\widehat{m}_{1,2}^{\theta}(u)=\lambda_1\big(r_s(u)\big)-D_{1,2}\lambda_2\left(S_{1,2}+\big(1-S_{1,2}\big)r_s(u)\right)-A_{1,2}\quad \text{for } u\in[0,1], \tag{A10}$$

where $\theta=\big(A_{1,2},D_{1,2},S_{1,2}\big)$. For a more robust estimation, we also consider the reverse comparison of (A10) as follows:

$$\widetilde{m}_{1,2}^{\theta}(u)=\lambda_2\big(\tilde{r}_s(u)\big)-\frac{1}{D_{1,2}}\lambda_1\left(\frac{\tilde{r}_s(u)-S_{1,2}}{1-S_{1,2}}\right)+\frac{A_{1,2}}{D_{1,2}}\quad \text{for } u\in[0,1], \tag{A11}$$

The estimator is finally derived by:

$$\hat{\theta}=\text{argmin}_{\theta}\,M(\theta)=\int_0^1\left[\widehat{m}_{1,2}^{\theta}(u)\right]^2du+\int_0^1\left[\widetilde{m}_{1,2}^{\theta}(u)\right]^2du. \tag{A12}$$

To apply the above method to our DID structure, we consider four groups as follows: the control group before reservation (CB), control group after reservation (CA), treatment group before reservation (TB), and treatment group after reservation (TA). Then, our treatment effect on each category of functional changes can be written as presented in Table A1, and then they can be converted to the statements with the relative strength compared to group CB as follows:

Selection: $$s_{TA} - s_{TB} - s_{CA} + s_{CB} = (1 - s_{CB})\left(S_{TA,CB} - S_{TB,CB} - S_{CA,CB}\right) \quad \text{(A13a)}$$

Dilation: $$d_{TA} - d_{TB} - d_{CA} + d_{CB} = d_{CB}\left(D_{TA,CB} - D_{TB,CB} - D_{CA,CB} + 1\right) \quad \text{(A13b)}$$

Right shift: $$\begin{aligned} & a_{TA} - a_{TB} - a_{CA} + a_{CB} \\ & = A_{TA,CB} - A_{TB,CB} - A_{CA,CB} + \left(D_{TA,CB} - D_{TB,CB} - D_{CA,CB} + 1\right)a_{CB} \end{aligned} \quad \text{(A13c)}$$

First, in equation (A13a), we cannot identify $(1 - s_{CB})$ but estimate $S_{TA,CB}$, $S_{TB,CB}$, and $S_{CA,CB}$ from the data. Nevertheless, we can check whether a selection becomes stronger or weaker by evaluating $\left(S_{TA,CB} - S_{TB,CB} - S_{CA,CB}\right)$, because s_{CB} is the share of the left-truncating area due to the selection which is less than 1 and thus $(1 - s_{CB})$ is always positive. Therefore, we define $\left(S_{TA,CB} - S_{TB,CB} - S_{CA,CB}\right)$ by selection criteria. Similarly, in equation (A13b), d_{CB} is not identifiable but has a positive value by definition, so that we can check whether dilation is positive or negative by evaluating $\left(D_{TA,CB} - D_{TB,CB} - D_{CA,CB} + 1\right)$. However, in equation (A13c), although we can partially identify $A_{TA,CB} - A_{TB,CB} - A_{CA,CB}$ and $\left(D_{TA,CB} - D_{TB,CB} - D_{CA,CB} + 1\right)$, the inclusion of a_{CB} prevents us from estimating the whole statement regarding the right shift.

Finally, to address the functional changes in four distributions, we convert (A12) into (A13) and estimate it:

$$\begin{aligned} \hat{\theta} = \text{argmin}_\theta\, M(\theta) = & \int_0^1 \left[\widehat{m}^{\theta}_{TA,CB}(u)\right]^2 du + \int_0^1 \left[\widetilde{m}^{\theta}_{TA,CB}(u)\right]^2 du \\ & + \int_0^1 \left[\widehat{m}^{\theta}_{TB,CB}(u)\right]^2 du + \int_0^1 \left[\widetilde{m}^{\theta}_{TB,CB}(u)\right]^2 du \\ & + \int_0^1 \left[\widehat{m}^{\theta}_{CA,CB}(u)\right]^2 du + \int_0^1 \left[\widetilde{m}^{\theta}_{CA,CB}(u)\right]^2 du. \end{aligned} \quad \text{(A13)}$$

Table A2 presents the estimation results for equation (A13) and provides all nine parameter estimates as well as selection criteria. Column (1) shows the result for all plants; column (2) shows that for small plants. As explained in Section 4.2., from the estimates for $S_{TA,CB}$, $S_{TB,CB}$, $S_{CA,CB}$, and selection criteria, we find weaker selection. In addition, in the case of the dilation, $(D_{TA,CB} - D_{TB,CB} - D_{CA,CB} + 1)$ is negatively estimated in both columns, which implies a right shift with a negative dilation.

Table A2. Parameter Estimations

	(1) All Plants	(2) Small Plants
$S_{TA,CB}$	-0.007**	0.003***
	(0.003)	(0.001)
$S_{TB,CB}$	-0.008***	0.008***
	(0.003)	(4×10^{-4})
$S_{CA,CB}$	0.023***	0.052***
	(0.005)	(0.001)
$D_{TA,CB}$	0.958***	0.911***
	(0.007)	(0.001)
$D_{TB,CB}$	1.005	1.075***
	(0.009)	(3×10^{-4})
$D_{CA,CB}$	0.991	0.996***
	0.008	(0.001)
$A_{TA,CB}$	-2×10^{-4}	0.014***
	(0.002)	(0.001)
$A_{TB,CB}$	0.025***	0.017***
	(0.006)	(0.001)
$A_{CA,CB}$	-1×10^{-4}	-0.004***
	(0.004)	(0.001)
Selection criteria	-0.021***	-0.058***
	(0.008)	(0.001)
Observations	5,337	4,443

Note: The selection criteria is $S_{TA,CB} - S_{TB,CB} - S_{CA,CB}$. * indicates significance at the 10% level; ** at the 5% level; and *** at the 1% level.