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Agglomeration or Selection?
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Abstract

Plants in clusters are often more productive than those located in non-clusters. This has been explained by agglomeration effects that improve productivity of all plants in a region. However, recent theoretical development of trade and spatial economic theories with heterogeneous firms has shed light on another channel of productivity improvement in clusters, “plant-selection effects." This paper uses plant-level data on the Japanese silk reeling industry from 1909 to 1916 to distinguish between these two effects based on a nested model of firm-selection and agglomeration. We identify the plant-selection effect by using the fact that the two effects have different implications on the distribution of plant-level productivity. Major findings are as follows. First, we confirmed that plants in clusters were indeed more productive. Second, at the same time, the widths of distribution of plant productivity in clusters were narrower and more severely truncated than those in non-clusters. Finally, productivity distribution did not shift rightwards in clusters. Our findings imply that the plant-selection effect was the source of the higher plant-level productivity in silk-reeling clusters in this period.

Key words: Agglomeration; Plant-selection; Heterogenous firms; Economic geography

JEL classification: L10; O18; R12

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1 Introduction

Plants in industrial clusters are often more productive than those located in non-clusters. Indeed, positive association between plant density and productivity has been empirically confirmed in the literature. For example, Ciccone and Hall (1996) reveals that labor density has a positive effect on regional productivity in the U.S. Henderson (2003) used plant-level micro datasets and found positive scale externalities from other plants.

Higher productivity of plants in industrial clusters has long been explained by *agglomeration effects* as typified by Marshallian externalities: transferring knowledge and innovative ideas by densely agglomerated workers, alleviating matching by thick labor markets, or by reducing transaction costs by densely agglomerated firms. These Marshallian externalities are effects that directly improve plant-level productivities.

On the other hand, recent theoretical development of spatial economics with heterogeneous firms has shed light on another channel of productivity improvement. That is, in clusters, intensification of competition shakes out less productive plants, and consequently only relatively productive plants can be observed. Thus, clusters improve average regional productivity, even though they do not actually improve productivity of each plant. This effect, referred to as *plant-selection*, was proposed in the pioneering work in the field of international trade by Melitz (2003).[1]

The purpose of this paper is empirically identifying agglomeration effects and plant-selection effects in industrial clusters. To do this, we focus on a specific industry in specific time and space: the Japanese silk-reeling industry in the period from 1909 to 1916. Focusing on the Japanese silk-reeling industry in this period has a number of attractive features. First, there existed clusters: Japanese silk reeling industry formed some huge clusters in the central region of Japan, especially in Nagano, Gifu, and Yamanashi Prefectures. Second, besides plants in the clusters, there were numerous silk-reeling plants around Japan. [2] Hence, we can utilize regional variations in the empirical analysis. Third is the characteristics of the products, "raw-silk". Most of the plants in the industry produced the single products, raw-silk which is horizontally differentiated and produced by similar equipment. That is, plants both in clusters and non-clusters produced same product by using similar equipment. Moreover, production process of silk-reeling in this period was not so complicated, which allows us to estimate plant-level productivities accurately.[3] Thus, we can compare the productivities across plants in clusters and non-clusters accurately.

In order to distinguish between agglomeration and plant-selection effect, we rely on a theoretical model developed by Combes et al. (2009) which nests firm-selection and agglomeration effects. The model enabled us to derive implications of these two effects on the distribution of plant-level productivies in a given region. Intuitively, the agglomeration effect will shift the distribution to the right by improving productivity of all the plants in the region but keeping the shape of the distribution unchanged. On the other hand, plant-selection effect will drive the less productive plants out of the market and thus the distribution will be truncated at the lower tail. Therefore, it is possible to identify the two effects by comparing the characteristics of the distribution of plant productivity between clusters and non-clusters.

[1]Melitz (2003) introduced heterogeneous firms in Krugman's (1980) international trade model, and Melitz and Ottaviano (2008) showed that only higher productive firms operate in large market because of the tough competitions. Behrens et al. (2009) generalized those type of selection models by means of multi-regions and variable demand elasticity, then, they estimated model parameters and conducted counterfactual simulations. Baldwin and Okubo (2006) applied Melitz's (2003) model into new economic geography model (Baldwin et al., 2003; Fujita et al., 1999), and showed spatial selection and sorting in the spatial equilibrium.

[2]There existed over 2800 plants in Japan at those periods.

[3]Syverson (2004) focused on ready-mixed concrete industry which has similar product characteristics on the product differentiation and technology.

For a robustness check, we examine the timing when the two effects avail. If agglomeration effect is in place, then we would observe a higher productivity growth in clusters after the entry of the plants. On the other hand, selection effect can avail before the operation of the plants. By comparing productivity growth-rate and productivities of the younger plants across clusters and non-clusters, we distinguish those effects in more detail.

Our empirical findings are as follows. First, plants in clusters had indeed relatively higher productivity. Second, the width of the distribution of plant-level productivities in clusters was narrower and more severely truncated at the lower tail than non-clusters. Third, plant-level productivity distribution in clusters did not shift rightwards. Fourth, productivity growth after start-up in clusters was not observed. Fifth, productivity distribution of younger plants was also more severely truncated in clusters. These results suggest that, plant-selection effect rather than agglomeration effect improved average productivity in clusters.

This paper relates to the strand of literature which tries to identify productivity improvement effects of clusters. First, Syverson (2004) examines the role of demand density on the plant-selection by focusing on ready-mixed concrete industry. While Syverson (2004) focuses only on the role of plant-selection, this paper distinguishes between agglomeration effects and plant-selection effects. Second, Combes et al. (2009) distinguish agglomeration effects from selection effects. For this purpose, they extend the model presented in Melitz and Ottaviano (2008) by introducing the form of Fujita and Ogawa (1982) and Lucas and Rossi-Hansberg (2002) agglomeration economies, and built a model that includes both selection and agglomeration effects. They then structurally parameterized the strength of selection and agglomeration, and estimated the strength of these two effects using the two digit industry level data. In contrast to their approach, we focus on a specific sector (silk-reeling industry) rather than all of manufacturing sectors, so that we can control for sector-specific factors such as condition of competition, form of production functions, or conditions of consumers.

The rest of this paper is organized as follows. The next section provides a theoretical explanation of industrial clusters and plant-level productivities, and proposes an idea for identifying the agglomeration and selection effects. Section 3 overviews the Japanese silk-reeling industry in this period from 1909 to 1916. Section 4 provides our main results on identification of the plant-selection effect. Section 5 discusses its robustness by focusing on the timing of the cluster effects. Section 6 concludes.

2 Overview of Japanese silk-reeling industry

The silk-reeling industry was one of the major industries in pre-war Japan. For example in 1909, it employed 24.5% of the total factory workers, and its product, raw silk, occupied 30.1% of the total export (Ministry of International Trade and Industry 1962; Toyo Keiizai Shinposha 1927). A distinctive feature of the silk-reeling industry was that it was composed of numerous small and medium-sized plants. In 1909, there were more than 2,800 silk-reeling plants in Japan. These plants formed several clusters, of which Nagano, Gunma and Gifu in the central region of Japan were the largest. Indeed, 28.3% of the silk reeling plants were located in these three prefectures in 1909. At the same time, it is notable that while there were large clusters of silk reeling plants, silk-reeling plants operated in other areas, i.e. non-clustering areas, as well. Figure 1 is the map of Japan, indicating the density of silk-reeling plants in 1909.

= Figure 1 =

Dark colored areas refer to the prefectures where silk-reeling plants were densely located.

In early twentieth century Japan, there were two types of silk-reeling plants, namely traditional hand-reeling (*zaguri*) plants and machine-reeling (*kikai*) plants. Hand-reeling and machine-reeling were fundamentally different technologies, and the production with the latter technology was becoming dominant , this paper mainly focuses on the machine-reeling plants. A typical process of machine-reeling was as follows[4]: A silk-reeling plant purchased dried cocoons from sericulture peasants. Dried cocoons were boiled to unwind the cocoon filament. Then, from a group of boiled cocoons, unwound filaments were taken and bundled to be reeled onto small moving reels which were powered by water, steam, electric, or gas. In this production process of raw silk, young female workers played a central role. The raw silk reeled on small reels was re-reeled onto large reels to make standard sized hanks and was shipped to raw silk markets. The largest raw-silk market in Japan was at Yokohama Port, the gateway to export, where Japanese merchants (urikomi-sho) and foreign merchants traded each other (Yamaguchi 1966, pp.3-24) .

Urikomi-sho played not only a commercial role, but it also played an essential role in financing silk-reeling plants, together with regional banks. In sending raw silk to urikomi-sho in Yokohama a silk-reeling plant drew a documentary bill on that urikomi-sho, and discounted the bill at a neighboring regional bank to have credit. In addition, before producing raw silk, a silk-reeling plant drew a draft on urikomi-sho to discount it at a regional bank. The latter practice was for raising fund to purchase cocoons from peasants in cash (Yamaguchi 1966, p.26-29; Ishii 1972, pp.118-125).

The largest silk-reeling cluster was located in Suwa district in Nagano Prefecture. The formation of cluster in Suwa seems to rest on several comparative advantages in silk-reeling. First, as Suwa is mountainous district with cold weather, it was not suitable for rice cultivation and sericulture was wide spread instead. On the other hand, cold weather was good for storing cocoons. Also, they could utilize plenty of water of the Suwa Lake and the Tenryu River, whose quality is suitable for silk-reeking (Hirano Village Office 1932, p.555). Those conditions facilitated entry into machine-reeling silk market in this area.

Besides these natural conditions, agglomeration of silk-reeling plants itself had a positive effect on entry and growth. In agglomerated areas, plants organized associations which cooperatively re-reeled raw silk. Through participating in these associations, plants had easier access to transaction with urikomi-sho and their credit (Yamaguchi 1966, p.10; Ishii 1972, p.199; Nakabayashi 2003, p.164). Furthermore, agglomeration attracted branches of banks. For example, in Suwa district, Daikyujugo Bank established a branch in 1879, which was the first bank branch in the district. Along with the development of silk-reeling industry in Suwa district, Dai Juyon Bank, Saku Bank and Daijukyu Bank established branches in 1879, 1881 and 1881, respectively, which, in turn, made it easier for silk-reeling plants to have access to credit (Hirano Village Office 1932, p.540). Such access to credit would reduce operation cost, and improve plant-level productivities.

Therefore the above discussions indicate that the silk-reeling clusters were able to provide effects which reduces both barriers to entry and operation costs after the start-up.

3 Theoretical model and empirical strategy

How do industrial clusters improve plants' productivity? This section discusses the channels of productivity improvement in clusters, and proposes an idea for identifying agglomeration effects and selection effects.

[4]This overview of the process is based on Duran (1913)

3.1 General framework of the model

Agglomeration effects have been considered to be the effects that concentration of plants makes them more productive through transferring knowledge and innovative ideas by densely agglomerated workers, alleviating matching by thick labor markets, and reducing transaction costs by densely agglomerated firms. These agglomeration effects are considered to offer the benefits in general to all of the plants that are located in the cluster. On the other hand, selection effects are the effects in clusters, intensification of competition shakes out less productive plants, and consequently only relatively productive plants can be observed.

To distinguish these two effects, Combes et al. (2009) developed a model which includes both agglomeration and selection effects. They combined a generalized model of Melitz and Ottaviano (2008)[5] with agglomeration economieses of Fujita and Ogawa (1982); Lucas and Rossi-Hansberg (2002) type. Modifying and applying the model of Combes et al. (2009), we describe the theoretical background of the productivity improvement effects in silk-reeling clusters in Japan.

First, we introduce the general framework of the model. A consumer's utility is given as follows,

$$u = q^0 + \alpha \int_{i\in\Omega} q^i di - \frac{1}{2}\gamma \int_{i\in\Omega} (q^i)^2 di - \frac{1}{2}\eta \left(\int_{i\in\Omega} q^i di \right)^2, \tag{1}$$

where q^i denotes the consumption of variety i of a set Ω of differentiated varieties of raw silk, and q^0 denotes the consumption of a homogeneous composite good other than the raw silk.[6] Solving a maximization problem subject to the budget constraint, we obtain the demand function for variety i. Since, marginal utility at zero consumption is bounded, the demand for a variety need not be positive. Let $\bar{\Omega}$ denote the set of varieties with positive consumption in equilibrium, ω the measure of $\bar{\Omega}$, and $P \equiv \frac{1}{\omega}\int_{j\in\bar{\Omega}} p_j dj$ the average price of varieties with positive consumption. Then, a demand function for variety i can be written as follows,

$$q^i = \begin{cases} \frac{1}{\gamma+\eta\omega}(\alpha + \frac{\eta}{\gamma}\omega P) - \frac{1}{\gamma}p^i & \text{if} \quad p^i \leqslant h^d \equiv P + \frac{\gamma(\alpha-P)}{\gamma+\eta\omega}, \\ 0 & \text{if} \quad p^i > h^d. \end{cases} \tag{2}$$

We then turn to the production side. Labor is the only factor of production, and its market is perfectly competitive. Composite good is produced under constant returns to scale technology on labor input, and be freely traded among regions. Then, wage of one unit labor is unity across regions.

Raw silk is produced under monopolistic competition. To enter the silk-reeling market, firms have to pay sunk entry cost s for product development and production start-up. Each firm learn its unit labor requirement h for production after making the irreversible investment. The unit labor requirement h is differs across firms and drawn from a common and known, continuously differentiable distribution G.

We can index firms by their unit labor requirement h instead of the specific variety i they produce, and we rewrite the individual consumer demand in terms of h^d and multiply the mass of consumers C. Then we obtain the following total sales of an firm,

$$Q(h) = Cq(h) = \begin{cases} \frac{C}{\gamma}[h^d - p(h)] & \text{if} \quad p(h) \leqslant h^d, \\ 0 & \text{if} \quad p(h) > h^d. \end{cases} \tag{3}$$

Since the entry cost is sunk, firms that can charge prices above marginal cost survive and produce. All other firms exit the silk-reeling industry immediately. Then, each surviving firm

[5] "Generalized" means that Melitz and Ottaviano (2008) assumed a specific distribution form on firm heterogeneity, Paleto distribution, then, Combes et al. (2009) extended their model to free from distribution form.

[6] This quadratic utility is extensively used in the previous literature on the location model following Ottaviano et al. (2002).

maximizes their profit,

$$\pi(h) = [p(h) - h]Q(h). \tag{4}$$

Maximization of this profit yields the optimal pricing rule,

$$p(h) = \frac{1}{2}(h + h^d), \tag{5}$$

and equilibrium operational profits, $\pi(h) = \frac{C}{4\gamma}(h^d - h)^2$.

Prior to entry, the expected firm profit is $\int_0^{h^d} \pi(h)dG(h) - s$. In the monopolistically competitive industry, entry takes place until this *ex-ante* expected profits becomes zero. We thus obtain a free-entry condition as follows,

$$\frac{C}{4\gamma}\int_0^{h^d}(h^d - h)^2 dG(h) = s. \tag{6}$$

At the cut-off point, h^d, zero-marginal profit, $h^d = p(h^d)$, have to be hold. Then, eq. (2) can be modified as follows,

$$h^d = \frac{1}{\eta\omega + \gamma}(\gamma\alpha + \eta\omega P). \tag{7}$$

Using optimal pricing rule (5), we can induce the zero cut-off profit condition,

$$N \equiv \omega = \frac{2\gamma}{\eta}\frac{\alpha - h^d}{h^d - H}, \tag{8}$$

where N is the mass of surviving firms which is equivalent to the mass of actually produced varieties and $H = \left[\int_0^{h^d} hdG(h)\right]/G(h^d)$ is the average unit labor requirement of surviving firms. Then, number of entrants is given by $N_E = N/G(h^d)$

Next, we introduce agglomeration economieses as in Fujita and Ogawa (1982); Lucas and Rossi-Hansberg (2002). We are assuming that each worker supplies a single unit of labor time inelastically. If the agglomeration effect present, then we assume that the workers' productivity increases with number of firms within a cluster. That is, effective labor supply by a single worker is $a(N)$, $a' > 0$, $a'' < 0$, and $a'(0) = 1$. On the other hand, if agglomeration of firms does not improve workers' productivity, for any value of N, we have $a(N) = 1$. We also assume that if agglomeration effect is present, it benefits workers across sectors in both silk-reeling and homogeneous composite good sector. In such case, the total labor income of each worker is $a(N)$ in both sectors.

Given agglomeration effects, a firm of unit labor requirement h hires $l(h) = Q(h)h/a(N)$ workers at a total cost of $a(N)l(h) = Q(h)h$. To taking logs, we obtain $\phi = \ln\left(\frac{Q}{l}\right) = \ln[a(N)] - \ln(h)$. By using the change of variable theorem, we can calculate the probability density of firms' log productivities,

$$f(\phi) = \begin{cases} 0 & \text{for} \quad \phi \leqslant A - \ln(h^d), \\ \frac{e^{A-\phi}g(e^{A-\phi})}{G(h^d)} & \text{for} \quad \phi > A - \ln(h^d), \end{cases} \tag{9}$$

where $A \equiv \ln[a(N)]$. Substituting h^d by solving free-entry condition (6), we can obtain the equilibrium distribution of log of firm productivities.

Next section applies this model into the silk-reeling industry.

3.2 Application to the silk-reeling industry

In order to adopt the model into the silk-reeling industry, we impose two more assumptions.

Assumption 1 (*Multi-region in production and regionally varied entry costs*)**.** As we discussed above, silk-reeling plants were broadly located around Japan. Thus we assume that silk-reeling plants located in region $r \in \{1, ..., R\}$. We further assume that fixed sunk entry costs are varied across regions, c_r,[7] based on the facts that we discussed in the above section.

Assumption 2 (*Limited accessibility to the market*)**.** Most of machine-reeled silk-reeling plants exported their products to US market through Yokohama port. Number of consumers, C_r, are varied across regions.[8]

From the assumption 1, free-entry condition (6) in region r is described as follows,

$$\frac{C_r}{4\gamma}\int_0^{h_r^d}(h_r^d - h)^2 dG(h) = s_r, \tag{10}$$

where h_r^d is the cut-off point of zero-profit in region r. Zero cut-off profit condition (8) is also regionally varied as follows,

$$N_r \equiv \omega_r = \frac{2\gamma}{\eta}\frac{\alpha - h_r^d}{h_r^d - H_r}, \tag{11}$$

where N_r is the mass of surviving firms, ω_r is the measure of produced varieties, and $H_r = \left[\int_0^{h_r^d} hdG(h)\right]/G(h_r^d)$ is the average unit labor requirement of surviving firms in region r.

Here, we made an assumption that firms' unit labor requirement draws $1/h$ follow a Pareto distribution[9]

$$G(h) = \left(\frac{h}{h^{max}}\right)^k, \tag{12}$$

with upper bound $m^{max} > 0$ and shape parameter $k > 1$.

Using this distributional assumption, we obtain closed-form solutions for the equilibrium cut-off (10) and mass of surviving firms (11),

$$h_r^d = \left[\frac{2(k+1)(k+2)\gamma(h^{max})^k s_r}{C_r}\right]^{1/(k+2)}, \tag{13}$$

$$N_r = \frac{2(k+1)\gamma}{\eta}\frac{\alpha - h_r^d}{h_r^d}. \tag{14}$$

Then, we can induce three important implications of the model.

Implication 1 (*Endogenous cluster*)**.** Regions which have lower sunk entry costs induce more firms and grow up as a cluster. From equations (13) and (14), we can show that $\partial N_r/\partial s_r > 0$. Then, *mass of surviving firms is increasing with the lower sunk entry costs.* Intuitively, in clusters, lower sunk entry cost induces more entrants. Even though part of them will exit the market by the intense competition, mass of survival plants are larger than in the non-clusters because

[7] Previous literature set the sunk cost in common among regions (Melitz, 2003; Melitz and Ottaviano, 2008; Behrens et al., 2009; Combes et al., 2009).

[8] This assured there is no inter-regional competition.

[9] Pareto distribution is widely used in the literature of heterogeneous firms (Helpman et al., 2008; Melitz and Ottaviano, 2008; Behrens et al., 2009).

of the large entrants.

Implication 2 (*Selection in cluster*)**.** From equation (13), we can show that $\partial h_r^d/\partial s_r > 0$. That is, *lower sunk entry cost decreases the cut-off of unit labor requirement of survival plants.* Then, the cut-off of unit labor requirement of survival plants in clusters is lower than in non-clusters. Intuitively, lower sunk entry cost induces more entry which makes the competition more intense in clusters and decreases the cut-off point of unit labor requirement level for survival. We refer to this as *selection.*

Implication 3 (*Agglomeration in cluster*)**.** Finally, equilibrium distribution of firm productivities (15) can be modified as follows,

$$f(\phi) = \begin{cases} 0 & \text{for} \quad \phi \leqslant A_r - \ln(h_r^d), \\ \frac{e^{A_r-\phi}g(e^{A_r-\phi})}{G(h_r^d)} & \text{for} \quad \phi > A_r - \ln(h_r^d), \end{cases} \tag{15}$$

where $A_r \equiv \ln[a(N_r)]$. Thus, increase of number of firms within a region slides the distribution of firms' log productivity to the right. We refer to this as *agglomeration.*

In summary, the observed distribution of plants' log-productivities would include the effects of both agglomeration and selection effects. In clusters, lower sunk entry cost attracts more entrants but induces severe competition between large number of entrants which raises the cut-off point of zero-profit condition. This selection effect truncates the left tail in the log-productivity distribution in clusters. Simultaneously, firms in clusters enjoy interaction with many other firms which improves the workers' productivity and slides the log-productivity distribution rightwards.

3.3 Empirical hypotheses and identification strategy

Based on the model, we consider the following four cases of the channel of productivity improvement in the silk-reeling clusters. For simplicity, we consider the two regions $r = c$ (cluster) and $r = n$ (non-cluster).

Case 1 (*Only selection effect matters*)**.** When there is no agglomeration effect, only selection affects productivity. In this case, $a(N_r) = 1$ holds for any value of N_r. On the other hand, selection implies $h_c^d < h_n^d$ and raises the log productivity cut-off $\ln[a(N_c)] - \ln(h_c^d) > \ln[a(N_n)] - \ln(h_n^d)$. This case is shown in Figure 2(a). Solid line refers to the log productivity distribution in cluster, while dashed line refers that in non-cluster. Log productivity distribution in cluster is left-truncated.

Case 2 (*Only agglomeration effect matters*)**.** In this case, only the agglomeration effect improves the plants' productivity. To eliminate the selection effects, we impose $s_c = s_n = s$ and $C_c = C_n = C$. Then, the intension of selection is the same in both cluster and non-cluster and therefore, $h_c^d = h_n^d$ and $N_c = N_n$. In order to establish clusters and non-clusters, we need to assume $N_c > N_n$ by exogenous reasons that are our outside the scope of our model. Only firms in clusters are benefited from larger worker interactions, $A_c > A_n$. Thus, the log productivity cut-off $\ln[a(N_c)] - \ln(h_c^d)$ simply slides to the right while keeping its distribution form. This case is shown in Figure 2(b).

Case 3 (*Both selection and agglomeration effects matter*)**.** In this case, fixed entry costs are different between cluster and non-cluster, $s_c < s_n$ (or accessible market in the cluster is larger,

$C_c > C_n$), and concentration of workers improves workers' productivity, $a' > 0$ and $a'' < 0$. Thus, both $h_c^d < h_n^d$ and $A_c > A_n$ holds. Then, the log productivity distribution in clusters is severely truncated and slides rightward. This case is shown in Figure 2(c).

Case 4 (*Neither effect matters*)**.** In this case, fixed entry costs and accessible market size are the same for all regions and concentration of workers does not improves workers' productivity, $a' = 0$. Then, log productivity distribution is in common across regions. Thus, there is no difference in productivities across regions. This case is shown in Figure 2(d).

= Figures 2(a) to 2(d) =

To distinguish these different cases, we utilize two measures of distributions. The first measure is the variance and interquartile range of the distribution. If there is no selection effects (case 2 and 4), the shape of the distribution should be the same for the clusters and non-clusters and thus, the variance and the interquartile range should have no difference. On the other hand, if there exists selection effects (case 1 and 3), the productivity distribution should be left-truncated in clusters and the variance and the interquartile range should be smaller than non-clusteres. Hence, by comparing the variance and the interquartile range between clusters and non-clusteres, we would be detect the presence of selection-effect.

The second measure is the percentile points of the distribution. Selection left-truncates the distribution, so we should observe a rise of lower percentile points of log-productivity distribution than higher percentile points. On the other hand, agglomeration effect affects every percentile points of the distribution, because agglomeration shifts the distribution itself rightward. Thus, if agglomeration effects are in place, higher percentile points of the distribution should also rise.

The above discussions are summarized in Table 1.

= Table 1 =

The table shows the direction of the shift of each measure of distributions in clusters relative to non-clusters in each case.

4 Estimation of the cluster effect

Based on the theoretical prediction—whereas both of agglomeration and selection effects improve the average productivity (mean effect), only selection effects reduce the variance of productivities (truncation effect)—this section identifies the agglomeration and selection effects.

4.1 Data

We compiled the data of the census of silk-reeling industry, *Zenkoku Seishi Kojo Chosa* for the two data points, 1909 and 1916. The data include plant-level information of plant name, location of the plant, year of foundation, number of pots, number of workers, number of business days per year, type of powers, output, and unit cost. This dataset covers both hand-reeling and machine-reeling plants. However, as the definition of the hand-reeling plants is ambiguous, we limit samples to machine reeling plants.

In order to compute regional plant density, we combine the location information in the *Zenkoku Seishi Kojo Chosa* with the GIS (Geographical Information System) data in period

1937, from “Taisho-Showa Gyoseikai Data”.[10] This GIS data provides county and prefectural-level geographical area data.

4.2 Mean effect

First, we examine whether productivity in clusters are higher than non-clusters (mean effect). Following Henderson (2003), we estimate a general production function for a plant as follows,

$$\ln(y_{icp}) = \alpha + \beta \ln D_{cp} + \ln Z_{icp}\delta + \mathrm{pref}_p + \varepsilon_{icp}. \tag{16}$$

We compute county-level plant density D_{cp} by dividing the number of plants in county c in prefecture p by its area. y_{icp} is the physical output of raw silk measured by weight ($kin = 0.6$ kg) of plant i located in county c in prefecture p, Z_{icp} is the vector of plant-level control variables (number of pot (pot), number of workers, plant age, steam power dummy, water power dummy), and pref_p is the prefecture fixed effect.

The Ordinary Least Squares (OLS) estimates of the equation (16) are shown in Table 2.

= Table 2 =

Columns (1) and (2) are the results for 1909 and 1916, respectively. In both columns, coefficients of ln(worker) and ln(number of pot) have expected signs and magnitudes with high statistical significance. In addition, in 1909 (Column 1), the coefficient of the county-level density of plants is positive and statistically significant at the 1 % level. This implies that plant-level productivities in clusters are higher than non-clusters. However, the coefficient of the plant-density is positive but not significant even at the 10 % level in 1916 (Column 2). This insignificance of the cluster effects in 1916 may be explained by the expansion of the clusters beyond each county. Thus, county-level plant density would not be appropriate to capture the cluster effect. To capture the cluster effects beyond the boundary of counties, we use prefecture-level plant density, which captures the cluster effect from the surrounding areas. The results are reported in Columns (3) and (4). In 1909 (column 3), coefficients of both county and prefectural-level plant densities are positive and statistically significant at the 1 % level. Furthermore, (column 4), the coefficient of prefecture-level plant density is positive and significant in 1916 as well. These results suggest that plant-density positively affected plant-level productivity at least at the prefecture-level.

In Columns (5)–(8) of Table 2, we estimate the equation by using the density of workers as the measure of cluster following Henderson (2003) since density of workers capture the externality in clusters such as labor matching efficiency. The coefficients of the densities of workers are positive and statistically significant for both county and prefectural-levels in all the specifications.

The results suggest that there were significant productivity improvement effects in clusters. We now turn to distinguish its channels.

4.3 Measures of plant-level productivity

As discussed in the previous section, we focus on the shape of productivity distributions to distinguish the channels of productivity improvement effects. For that purpose we first estimate

[10] It is publicized by Yuji Murayama, Division of Spatial Information Science, Graduate School of Life and Environmental Sciences, University of Tsukuba, URL: http://giswin.geo.tsukuba.ac.jp/teacher/murayama/data_map.html

the productivity of each plant. As the primary measure of plant-level productivity, we use TFP. TFP of each plant is obtained by estimating the following production function,

$$\ln(y_{icp}) = \alpha + \ln Z_{icp}\delta + \phi_{icp}. \tag{17}$$

where Z_{icp} is the vector of the inputs: the number of pot, the amount of labor inputs (number of female workers), and dummies indicating the types of powers adopted. The residual ϕ_{icp} is the TFP, which represents plant-level productivity. Following Combes et al. (2009), we estimate the production function (17) by OLS.[11]

The estimation results are reported in Columns (9) and (10) of Table 2. In both columns, the coefficients of ln (worker) and ln (number of pot) have expected signs and magnitudes with high statistical significance, and the large R-squared indicates good fit of this production function. We interpret the residual ϕ_{icp} as TFP of plant i.

Because this estimate of TFP by OLS may includes some endogeneity biases (Olley and Pakes, 1996), we also use output per pot, *capital productivity*, and output per worker (labor productivity), as alternative measures of plant-level productivity. In the Japanese silk-reeling industry, output per pot and output per worker were conventionally used as the measures to evaluate plant-level productivity. Those indicators, simple as they are, might be preferable when the TFP have a serious endogeneity problem. Hence, we use these three measures of the plant-level productivities, TFP, output per pot, and output per labor in the analyses as follows.

4.4 Truncation effect

We now proceed to distinguish between agglomeration effects and selection effects, by examining the shape of plant-level productivities estimated in the previous section with the theoretical predictions in section 3.

We use prefecture as a unit of observation of regional productivity density to obtain sufficient observations. All prefectures in Japan are classified into two groups based on plant densities. Prefectures with plant densities higher than the median value are classified into the *clustered-prefectures*, and the other prefectures are classified into the *non-clustered prefectures*.

Next, we estimate the kernel density functions on the plant-level productivity in each group of prefectures. Figure 3 represents the kernel densities.

= Figure 3 =

The solid line refers to the density of the clustered prefectures, and the dashed line refers to that of the non-clustered prefectures. In every figure, the kernel density of the clustered prefectures is lower than the non-clustered prefectures in the lower tail of the distributions, while the density of the clustered prefectures is higher than the non-clustered prefectures in the higher tail of the distribution. Moreover, the shapes and the positions of the two distributions except for the lower tails of them seems to be similar, and a slide of the distribution to the right in is not observed.

[11] It is well known that estimating a plant-level production function by OLS yields an endogeneity problem; ε_{icp} are not orthogonal to covariates. Recently, various methodologies which can settle the endogeneity problem are proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), or Blundell and Bond (1998). However, all of these methodologies require panel data. As we discuss later, in Japanese silk-reeling industry at those periods, extremely low survival rate of plants (48 % per 7 years) losses much observations, thus we do not adopt these methodologies. As the robustness check, using two periods panel data on survival plants (we discuss later), we estimate TFP by both OLS and the method of Levinsohn and Petrin (2003) with using cocoon-use as the input. The correlation coefficients of estimated TFPs are very high (0.95 in 1909 and 0.96 in 1916). Those high correlations justify using estimated TFP by OLS.

These features of the two distributions suggest that there were selection effects and that there were not agglomeration effects.

Next we confirm these observations by descriptive statistics shown in Table 3.

= Table 3 =

One key measure for distinguishing between agglomeration effects and selection effects are variance and interquartile range of the distribution (Syverson, 2004). By comparing the variance and the interquartile range between clustered prefectures and non-clustered prefectures, we would be able to distinguish the existence of the selection effect. Table 3 reveals that the interquartile range of the distribution in the clustered prefectures is smaller than that in the non-clustered area, and the variance is also smaller in clusters for every measure of productivity. These results support the existence of selection effects.

Next, we use prefectural variations to distinguish agglomeration effects and selection effects.

We first investigate the effect of cluster on the interquartile range of productivity distribution. We index each prefecture by p, and estimate the following equation,

$$\mathrm{IQR}_{pt} = \alpha + \beta \ln(\mathrm{D}_{pt}) + \varepsilon_{pt} \tag{18}$$

where IQR_{pt} refers to the interquantile range of plant-level productivity distribution in prefecture p in period t. Under the presence of selection effects, increase of the plant density will truncate the distribution and shorten the interquantile range. Thus, we expect the negative sign for β. We estimate this equation in three types of the specifications. The results are presented in Table 4. We report the estimation results for 1909 and 1916 in Panel A and B respetiviely. Pooled OLS results for both years with year fixed effect are reported in Panel C. The samples are restricted to the prefectures that had more than 20 plants. We use TFP, output per pot, and output per worker as a measure of plant-level productivity. three measures of the plant-level productivities.

= Table 4 =

Columns (1) to (3), report the results with the interquartile range of the productivity as the dependent variable. In most of the cases, the coefficients of $\ln(\mathrm{D}_{pt})$ are negative and statistically significant. This is consistent with the selection effect that concentration of plants induced severe competition and left-truncation of the productivity distribution narrowed the interquartile range (both Cases 1 and 3).

Next, we examine the role of agglomeration effects by focusing on the percentile points of productivity distribution. We estimate the following equation,

$$\mathrm{P}^{u}_{pt} = \alpha + \beta \ln(\mathrm{D}_{pt}) + \varepsilon_{pt}, \tag{19}$$

where P^{u}_{pt} is the u-th percentile point of the log productivity distribution in prefecture p in period t. As we discussed in section 3.3 and Table 1, while selection affects only at the lower tail of the log-productivity distribution, agglomeration affects every points of the distribution because agglomeration shifts whose distribution rightwards. Hence, if agglomeration effect exists, both lower and higher tails of the distribution would shift to the right. We examine this hypothesis by estimating the effect of regional plant density on 10-th, 25-th, 75th, and 90-th percentile points of log productivity distribution.

The results are shown in Columns (4) to (15) in Table 4. Columns (4) to (7) use TFP as a measure of productivity while Columns (8) to (11) and (12) to (15) uses output per pot and worker respectively. Regardless of measure of productivity, coefficients of $\ln(D_{pt})$ are positive and significant for lower tail, i.e. 10-th and 25-th percentiles points (Columns 4, 5, 8, 9, 12, and 13). This result is consistent with both of the agglomeration effect and selection effect. On the other hand, many of the coefficients of plant density are not statistically different from zero for higher tail. i.e. 75-th or 90-th percentiles (Columns 6, 7, 10, 11, 14, and 15). This implies that higher plant density had no effect on shifting the productivity distribution rightwards. The evidence runs contrary to the existence of agglomeration effect.

These results indicate that the increase of plant density truncated the log productivity distribution at the lower tail but had no effect on shifting the distribution rightwards. According to the theoretical prediction in section 3, this is consistent with the existence of selection effect but no agglomeration effect (Case 1). In the rest of the paper, we examine the robustness of this finding.

5 Productivity growth effects in clusters

The validity of the interpretation of the evidences in the previous section depends on our theoretical predictions based on the agglomeration effects in the sense of Fujita and Ogawa (1982) and Lucas and Rossi-Hansberg (2002)—plant agglomeration affects every plant in a cluster in common, and hence, it only slides the distribution to the right and never skews the distribution form. However, plant agglomeration might also skew the distribution. For example, learning from leading plants might truncate the distribution—if low productive plants learn from high productive plants much more in clusters, the catch-up rate become higher in clusters, and it skews the productivity distribution in clusters. Thus, if such type of agglomeration effects is in place in clusters, truncation of productivity distribution does not necessarily imply the existence of selections.

To make a further progress on the identification of agglomeration and selection effects, we investigate the source of truncation of the productivity distribution by focusing on the timing of the truncation. First, if learning from leading plants improves plant-level productivities and truncates the productivity distribution in clusters (learning after start-up hypothesis), we should observe faster growth of plant-level productivity in clusters than non-clusters. Second, if the truncation is caused by selection, we should be able to observe the truncated distributions for restricted samples of young plants in clusters because selection occurs before operation.

To examine the above two hypotheses, we panelize the data for 1909 and 1916. By using plant's name, location, and year of foundation, we connect the datasets of the two years.

5.1 Existence of productivity growth after start-up

To examine the first hypothesis on the productivity growth after start-up, we compare the growth rate of plant-level productivities between plants in clusters and non-clusteres.

Descriptive statistics of productivity growth rate from 1909 to 1916 for three different productivity measures is shown in Table 5.

= Table 5 =

We report productivity growth rate separately for *incumbent* plants (plants with plant age equal to or more than three years) and *start-up* plants (plants with plant age less than three years). If start-up plants were able to learn intensively in clusters than non-clusters, we should observe faster productivity growth for start-up plants than incumbent plants in clusters compared to non-clusters.

The results of the t-test on the null hypothesis that the productivity of growth rate is different from zero indicate a mixed picture on productivity growth: there was productivity growth for output per pot but output per worker seems to had declined. Start-up plants grew faster than incumbents in terms of output per pot, but on the other hand, growth of output per worker declined faster for start-up plants. Nevertheless, we cannot reject the null hypothesis that the average growth rate of productivity is the same for clusters and non-clusters regardless of the measure of productivity or sample. Thus, there is no evidence that plants learnt faster in clusters than non-clusters.

We econometrically test the learning effects in clusters, by estimating the equation as follows,

$$\text{GrowthRate}_{icp} = \alpha + \beta D_{cp} + \delta Z_{icp} + \text{pref}_p + \varepsilon_{icp}, \tag{20}$$

where, GrowthRate_{icp} is the plant i's productivity growth rate from 1909 to 1916, D_{cp} is the plant density in county c where firm i was located, and Z_{icp} is the vector of plant-level control variables (number of pot, number of labor, age, steam power dummy, water power dummy). Table 6 reports the results.

= Table 6 =

We use three measures of the plant-level productivity. Columns (1) to (3) is the results on the start-up plants, and Columns (4) to (6) is the results on the incumbent plants. In every column, coefficients of the plant densities are insignificant from zero. Thus, plant densities do not seem to affect productivity growth rate.

These results reject the learning after start-up hypothesis. We found no evidence of newly start-up plants learning faster and catching up with leading plants in clusters. This finding is in support for the non-existence of agglomeration effect.

5.2 Start-up plants' productivity distributions

Now, we proceed to examine the second hypothesis on the truncation of younger plants due to selection before operation.

Figure 4 represents the kernel density of the productivities of start-up plants.

= Figure 4 =

The solid line refers to the density of the clustered prefectures, and the dashed line refers to the non-clustered prefectures. Even for restricted samples of start-up plants, we can observe the severe left-truncation of productivity distribution in clusters.

Table 7 reports the descriptive statistics of plant-level productivities for start-up plants.

= Table 7 =

In every measure of productivities, average productivity of start-up plants is higher in clusters than non-clusters. Moreover, in clusters, interquartile ranges are narrower and standard errors are smaller in clusters than in non-clusters. These suggest that productivity distribution is more severely truncated in clusters even for restricted samples of start-up plants, which is consistent with the selection effect that truncation occurred before plants' actual operation.

Finally, we estimate the cluster effects as described in equation (16).

= Table 8 =

Even for the restricted samples of start-up plants, the coefficient of density is significantly positive at 10 % level in both estimations using plant density and worker density as a measure of cluster. Start-up plants in clusters had significantly higher productivities on average.

These results suggest that the truncation of productivity distribution took place before plants' operation and therefore, the average regional productivity in cluster was higher. This is consistent with the selection under the assumption of perfect foresight which is broadly assumed in the model of selections (Melitz, 2003; Melitz and Ottaviano, 2008; Behrens et al., 2009).

5.3 Discussions

By focusing on the timing of truncation of productivity distribution, we obtained two results: i) there was no difference in productivity growth rate between clusters and non-clusters; and ii) average productivities of entrants in clusters were higher than in non-clusters.

Result i) rejects the presence of any skew of productivity distribution caused by learning after start-up, which is implied by the agglomeration effect. Plant-level productivity distribution was not truncated after plants start-up. Moreover, result ii) strongly supports the truncation before start-up. Thus, these two results provide further support for the truncation by selection rather than agglomeration.

Thus, we conclude that higher productivity in Japanese silk-reeling clusters in this periods was not caused by the Fujita and Ogawa (1982); Lucas and Rossi-Hansberg (2002) type of agglomeration effects. Lower start-up costs in clusters attracted more entrants and intensified the competition. The Melitz (2003); Melitz and Ottaviano (2008); Behrens et al. (2009) type of selection effect truncates the lower tail of the productivity distribution and improved average productivity by driving out plants with lower productivity in clusters. The higher average productivities in Japanese silk-reeling clusters were caused by selection rather than agglomeration.

6 Concluding remarks

In this paper, we attempted to distinguish the two channels through which industrial clusters improved plant productivity in the Japanese silk-reeling industry in the period from 1909 to 1916. Based on the nested model of selection and agglomeration (Combes et al., 2009), we considered agglomeration effect, which improves productivities of all the plants in a region (Fujita and Ogawa, 1982; Lucas and Rossi-Hansberg, 2002) and plant-selection effect, which raised average regional productivity by driving out less productive plants by intense competition (Melitz, 2003; Melitz and Ottaviano, 2008; Behrens et al., 2009).

Using plant-level data, we confirmed that the plants located in clusters had higher productivities than those located in the non-clusters. Then, we distinguished the channels of productivity improvement, based on the theoretical prediction that plant-selection effect would truncate the distribution of plant-level productivity and hence the variance of the distribution would be smaller clusters. We found that the interquantile range of the productivity distribution was significantly smaller in the clustered-prefectures than that in the non-clustered prefectures, and prefectural plant density had a significant negative effect on the interquantile range. This suggests the existence of selection effect. Moreover, we confirmed that plant density had no effect in sliding the productivity distribution to the right. This suggests non-existence of agglomeration effect.

We provide further support on these findings by focusing on the timing of which the truncation occurred. Using plant-level paned dataset, we obtained two results: i) there was no difference in productivity growth rate between clusters and non-clusters; and ii) average productivities of entrants in clusters were higher than in non-clusters. These two results suggest that truncation of less productive plants in clusters occurred before the operation and that higher productivity in clusters was not caused by the agglomeration effect in the sense of Fujita and Ogawa (1982); Lucas and Rossi-Hansberg (2002). Truncation and average productivity improvement effects in clusters was through the Melitz (2003); Melitz and Ottaviano (2008) type of selection process which drove out less productive plants in clusters before they started-up.

Thus, we conclude that in the Japanese silk-reeling industry, higher average productivity in clusters was not caused by the direct agglomeration effect, but was caused by the selection effect—intensification of competition in clusters shook out low productive plants, and consequently only relatively more productive plants can be observed. This suggests the importance of competition in improving productivities.

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Table 1: Measures of distribution in clusters relative to non-clusters

Cases	Mean	Interquartile range	Lower percentile	Higher percentile
Case 1: Selection	+	–	+	+
Case 2: Agglomeration	+	0	+	++
Case 3: Selection & agglomeration	+	–	+	++
Case 4: Neither effect	0	0	0	0

Table 2: Estimation of mean effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
year	1909	1916	1909	1916	1909	1916	1909	1916	1909	1916
ln(worker)	0.842	0.807	0.792	0.761	0.826	0.804	0.771	0.756	0.766	0.767
	(0.123)***	(0.105)***	(0.103)***	(0.102)***	(0.122)***	(0.104)***	(0.102)***	(0.101)***	(0.104)***	(0.106)***
ln(No. of pot)	0.370	0.471	0.457	0.486	0.373	0.467	0.436	0.472	0.490	0.497
	(0.123)***	(0.108)***	(0.102)***	(0.104)***	(0.122)***	(0.106)***	(0.101)***	(0.103)***	(0.103)***	(0.109)***
ln(age)	0.049	0.001	0.043	0.031	0.050	-0.000	0.050	0.036	0.049	0.024
	(0.014)***	(0.013)	(0.014)***	(0.013)**	(0.014)***	(0.013)	(0.014)***	(0.013)***	(0.014)***	(0.013)*
Steam power dummy	0.137	-0.004	0.139	-0.020	0.137	-0.004	0.141	-0.015	0.118	-0.033
	(0.032)***	(0.037)	(0.032)***	(0.034)	(0.032)***	(0.037)	(0.031)***	(0.034)	(0.034)***	(0.034)
Water power dummy	-0.061	-0.084	-0.115	-0.295	-0.052	-0.068	-0.131	-0.280	-0.081	-0.235
	(0.033)*	(0.040)**	(0.033)***	(0.038)***	(0.034)	(0.040)*	(0.033)***	(0.037)***	(0.035)**	(0.037)***
County-level plant density	0.039	0.018	0.041	0.002						
	(0.012)***	(0.013)	(0.011)***	(0.012)						
Pref-level plant density			0.088	0.111						
			(0.014)***	(0.016)***						
County-level worker density					0.045	0.034	0.044	0.018		
					(0.011)***	(0.011)***	(0.010)***	(0.010)*		
Pref-level worker density							0.087	0.083		
							(0.013)***	(0.014)***		
Constant	3.096	3.117	2.863	3.037	2.981	3.047	2.484	2.749	2.813	3.140
	(0.077)***	(0.087)***	(0.076)***	(0.095)***	(0.064)***	(0.078)***	(0.088)***	(0.110)***	(0.057)***	(0.077)***
Pref. fixed effects	yes	yes	no	no	yes	yes	no	no	no	no
Observations	2232	2247	2232	2247	2232	2247	2232	2247	2232	2247
R-squared	0.87	0.83	0.83	0.78	0.87	0.83	0.84	0.78	0.82	0.77

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Descriptive statistics on plant-level productivity

year		1909				1916			
		Obs	Mean	SD	IQR	Obs	Mean	SD	IQR
TFP									
	Non-cluster	1106	-0.130	0.512	0.586	1160	0.058	0.635	0.785
	Cluster	1126	0.128	0.458	0.489	1087	0.259	0.554	0.727
	Total	2232	0.000	0.502	0.552	2247	0.155	0.605	0.737
Output per pot									
	Non-cluster	1107	3.824	0.626	0.826	1169	4.059	0.747	0.927
	Cluster	1126	4.065	0.506	0.567	1094	4.285	0.573	0.817
	Total	2233	3.945	0.581	0.707	2263	4.169	0.678	0.868
Output per labor									
	Non-cluster	1108	3.803	0.603	0.789	1169	4.024	0.728	0.859
	Cluster	1126	4.041	0.503	0.547	1094	4.259	0.569	0.776
	Total	2234	3.923	0.567	0.659	2263	4.138	0.666	0.833

Table 4: Estimation of truncation effects

Dependent	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Productivity	TFP	Pot	Labor	TFP	TFP	TFP	TFP	Pot	Pot	Pot	Pot	Labor	Labor	Labor	Labor
Percentile	IQR	IQR	IQR	10p	25p	75p	90p	10p	25p	75p	90p	10p	25p	75p	90p
Panel A (In 1909)															
lndensity	-0.0624**	-0.132**	-0.137**	0.163**	0.229**	0.106**	0.0763	0.166**	0.169**	0.0363	0.0277	0.164*	0.162*	0.0250	0.0387
	(0.0257)	(0.0331)	(0.0464)	(0.0704)	(0.0923)	(0.0455)	(0.0448)	(0.0693)	(0.0699)	(0.0584)	(0.0447)	(0.0834)	(0.0799)	(0.0537)	(0.0455)
Constant	0.589**	0.800**	0.754**	-0.749**	-0.617**	0.0755	0.309**	3.113**	3.379**	4.179**	4.434**	3.140**	3.395**	4.149**	4.354**
	(0.0471)	(0.0692)	(0.0858)	(0.121)	(0.155)	(0.0663)	(0.0627)	(0.129)	(0.122)	(0.0944)	(0.0764)	(0.154)	(0.139)	(0.0850)	(0.0660)
Observations	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
Panel B (In 1916)															
lndensity	-0.0611	-0.125*	-0.122	0.233**	0.225**	0.134**	0.151**	0.229**	0.194*	0.0691	0.0815	0.217**	0.175*	0.0524	0.0958
	(0.0600)	(0.0722)	(0.0746)	(0.0913)	(0.0771)	(0.0595)	(0.0624)	(0.108)	(0.0995)	(0.0696)	(0.0590)	(0.102)	(0.0988)	(0.0670)	(0.0580)
Constant	0.730**	0.929**	0.876**	-0.960**	-0.703**	0.0984	0.352**	3.137**	3.495**	4.425**	4.703**	3.141**	3.520**	4.396**	4.614**
	(0.109)	(0.146)	(0.151)	(0.156)	(0.131)	(0.0841)	(0.101)	(0.187)	(0.175)	(0.107)	(0.0957)	(0.182)	(0.174)	(0.0946)	(0.0928)
Observations	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
Panel C (Pooled with year dummy)															
lndensity	-0.0618	-0.129**	-0.130**	0.198**	0.227**	0.120**	0.114**	0.197**	0.181**	0.0527	0.0546	0.191**	0.169**	0.0387	0.0672
	(0.0404)	(0.0453)	(0.0539)	(0.0709)	(0.0754)	(0.0469)	(0.0492)	(0.0772)	(0.0764)	(0.0560)	(0.0475)	(0.0801)	(0.0804)	(0.0535)	(0.0473)
Constant	0.655**	0.860**	0.811**	-0.851**	-0.657**	0.0851	0.326**	3.122**	3.432**	4.292**	4.557**	3.138**	3.453**	4.264**	4.473**
	(0.0703)	(0.0876)	(0.104)	(0.123)	(0.132)	(0.0690)	(0.0735)	(0.139)	(0.136)	(0.0901)	(0.0788)	(0.147)	(0.145)	(0.0825)	(0.0724)
Observations	45	45	45	45	45	45	45	45	45	45	45	45	45	45	45

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$

Table 5: Plant-level productivity growth rate, 1909 to 1916

Panel A: TFP	All				Incumbent				Start-up				Start-up – Inc.	
	Obs.	Mean	SD	p-value	Obs.	Mean	SD	p-value	Obs.	Mean	SD	p-value	Diff.	p-value
All	904	1.636	69.807	0.481	846	1.850	72.150	0.456	58	–1.474	4.155	0.009***	–3.323	0.726
Non-cluster	467	4.915	95.022	0.264	436	5.326	98.334	0.259	31	–0.854	2.796	0.099*	–6.180	0.727
Cluster	437	–1.868	20.449	0.057*	410	–1.847	21.072	0.077	27	–2.184	5.277	0.041	–0.338	0.934
Diff. (Cluster–Non-cluster)		–6.783	4.643	0.144		–7.172	4.960	0.149		–1.330	1.089	0.227		

Panel B: Output per pot	All				Incumbent				Start-up				Start-up – Inc.	
	Obs.	Mean	SD	p-value	Obs.	Mean	SD	p-value	Obs.	Mean	SD	p-value	Diff.	p-value
All	907	0.063	0.179	0.000***	849	0.057	0.157	0.000***	58	0.160	0.359	0.001***	0.103	0.000***
Non-cluster	469	0.059	0.169	0.000***	438	0.052	0.169	0.000	31	0.150	0.157	0.000	0.098	0.002***
Cluster	438	0.069	0.188	0.000***	411	0.062	0.144	0.000***	27	0.172	0.504	0.089*	0.110	0.003***
Diff. (Cluster–Non-cluster)		0.010	0.012	0.397		0.010	0.011	0.366		0.022	0.095	0.821		

Panel C: Output per worker	All				Incumbent				Start-up				Start-up – Inc.	
	Obs.	Mean	SD	p-value	Obs.	Mean	SD	p-value	Obs.	Mean	SD	p-value	Diff.	p-value
All	907	-0.136	0.597	0.000***	849	–0.125	0.607	0.000***	58	–0.293	0.407	0.000***	–0.168	0.038**
Non-cluster	470	–0.107	0.421	0.000***	439	-0.094	0.427	0.000***	31	–0.288	0.407	0.000***	–0.194	0.013**
Cluster	437	–0.168	0.741	0.000***	410	–0.159	0.753	0.000	27	–0.300	0.528	0.007***	–0.141	0.339
Diff. (Cluster–Non-cluster)		–0.060	0.040	0.128		–0.064	0.042	0.122		–0.012	0.108	0.913		

Note: p-values are the two-tailed p-values of the t-test where the null is mean (difference) of growth rate is zero.

Table 6: Estimation of growth effects

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of productivity growth	TFP	Output per pot	Output per labor	TFP	Output per pot	Output per labor
ln(density)	0.487	-0.079	-0.008	0.936	-0.006	-0.009
	(0.556)	(0.069)	(0.055)	(0.959)	(0.005)	(0.016)
ln(No. of pot)	-0.423	0.108	0.169	3.820	0.207	0.260
	(2.936)	(0.186)	(0.198)	(11.113)	(0.085)**	(0.126)**
ln(worker)	-0.650	-0.191	-0.105	-4.936	-0.216	-0.234
	(2.745)	(0.137)	(0.217)	(11.266)	(0.082)***	(0.122)*
ln(age)	-0.920	0.084	0.238	-1.006	-0.014	0.035
	(3.608)	(0.125)	(0.244)	(1.164)	(0.009)	(0.027)
Steam power dummy	1.648	0.006	0.049	6.436	-0.010	-0.054
	(2.937)	(0.113)	(0.206)	(4.848)	(0.020)	(0.050)
Water power dummy	1.292	0.147	0.057	2.291	-0.021	-0.042
	(2.773)	(0.248)	(0.218)	(3.490)	(0.019)	(0.049)
Constant	3.177	0.117	-0.766	7.417	0.127	-0.285
	(4.809)	(0.239)	(0.534)	(7.536)	(0.040)***	(0.113)**
Pref fixed effects	yes	yes	yes	yes	yes	yes
Start-up vs. Incumbent	Start-up	Start-up	Start-up	Incumbent	Incumbent	Incumbent
Observations	58	58	58	846	849	848
R-squared	0.37	0.42	0.22	0.05	0.13	0.05

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Descriptive statistics on start-up plants' productivities

	Obs.	Mean	SD	IQR
TFP				
Non-cluster	87	-0.121	0.572	0.550
Cluster	117	0.159	0.558	0.450
Total	204	0.028	0.580	0.585
Output per pot				
Non-cluster	87	3.703	0.660	0.759
Cluster	117	3.953	0.606	0.540
Total	204	3.837	0.643	0.635
Output per labor				
Non-cluster	87	3.688	0.653	0.815
Cluster	117	3.983	0.604	0.488
Total	204	3.846	0.643	0.593

Table 8: Estimation on start-up plants' productivities

	(1)	(2)
ln(density)	0.075	
	(0.041)*	
ln(workerdensity)		0.091
		(0.049)*
ln(No. of pot)	0.565	0.593
	(0.179)***	(0.178)***
ln(worker)	0.726	0.677
	(0.176)***	(0.179)***
ln(age)	-0.897	-0.874
	(0.774)	(0.733)
Steam power dummy	0.082	0.071
	(0.087)	(0.087)
Water power dummy	-0.103	-0.076
	(0.127)	(0.132)
Constant	3.629	3.379
	(0.593)***	(0.538)***
Pref fixed effects	yes	yes
Observations	204	204
R-squared	0.83	0.83

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

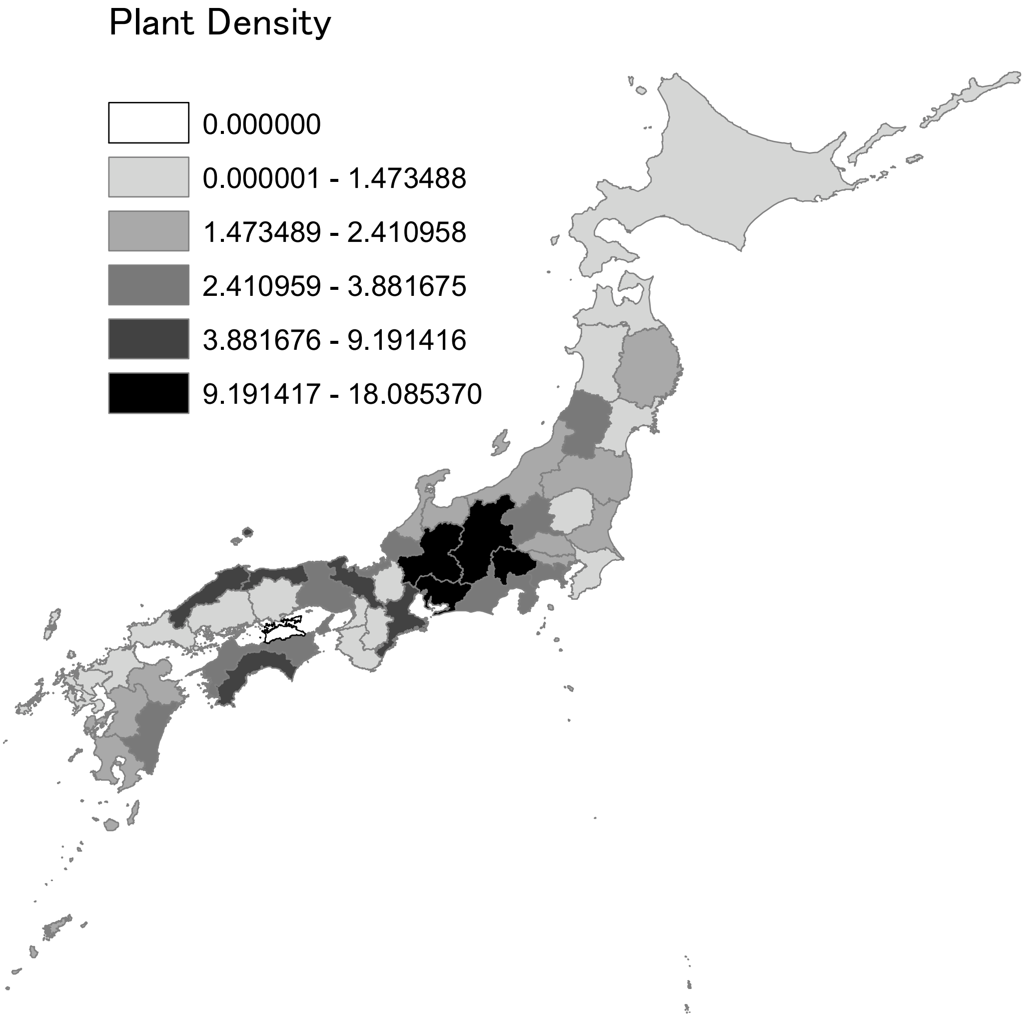
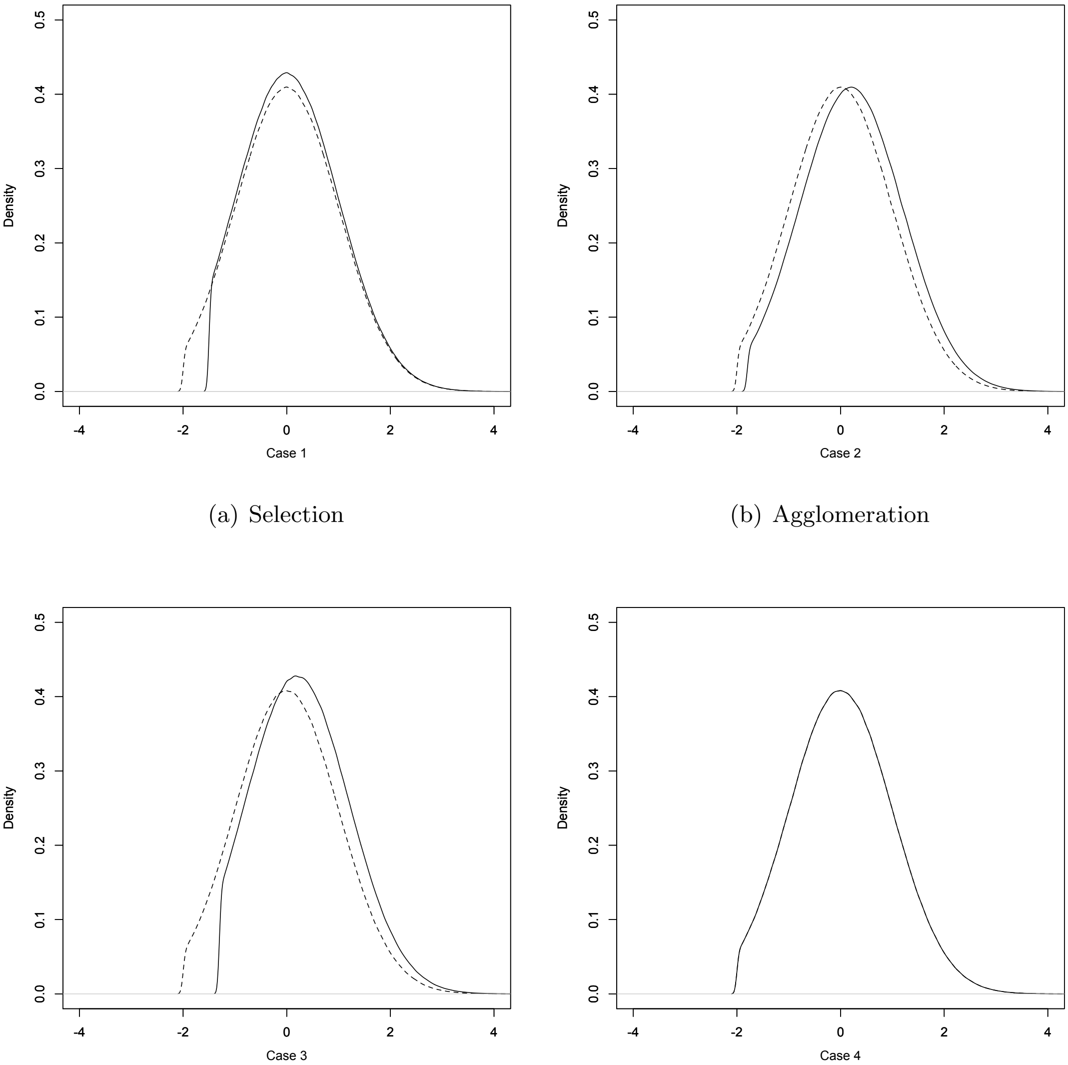


Figure 1: Map of Japan and the density of silk-reeling plants in 1909



(a) Selection

(b) Agglomeration

(c) Both selection and agglomeration

(d) Neither effect

Figure 2: Four considerable cases of cluster effects

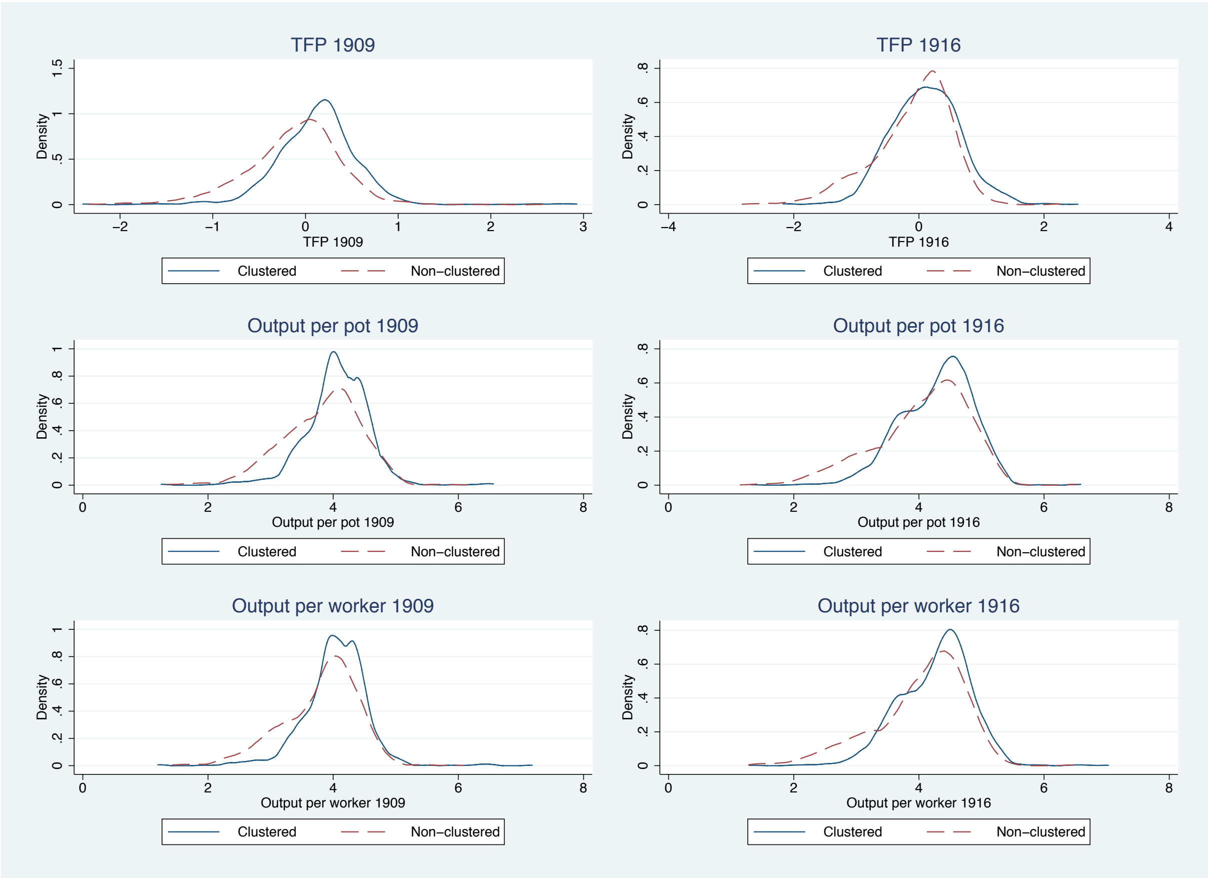


Figure 3: Kernel densities on plant-level productivity

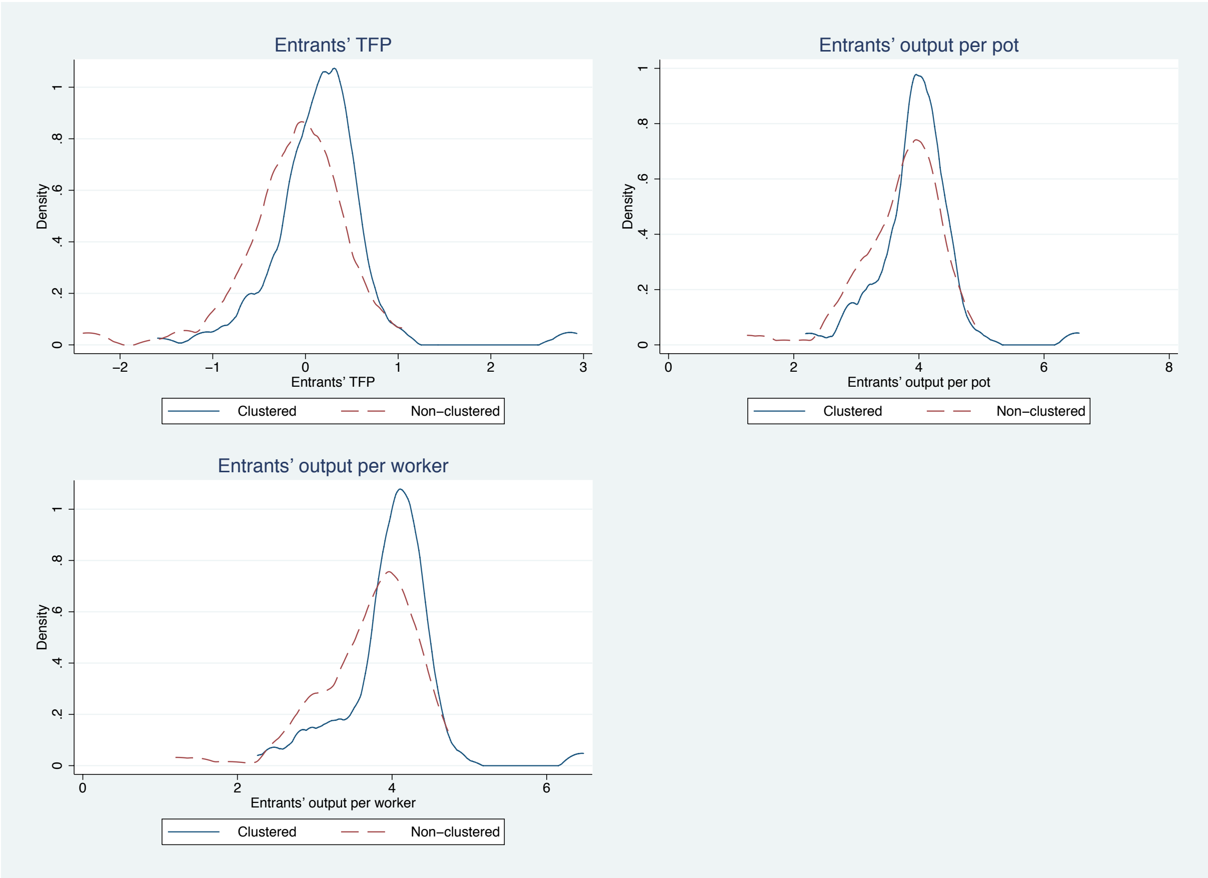


Figure 4: Productivity distribution of younger plants