Productivity Improvement in the Specialized Industrial Clusters: The Case of the Japanese Silk-Reeling Industry*

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Abstract

We examine two sources of productivity improvements in specialized industrial clusters. Agglomeration improves the productivity of each plant through positive externalities, shifting plant-level productivity distribution to the right. Selection expels less productive plants through competition, truncating distribution on the left. By analyzing the data of the early twentieth century Japanese silk-reeling industry, we find no evidence confirming a right-shift of the distribution in clusters or that agglomeration promotes faster productivity growth. These findings imply that the plant-selection effect was the source of higher productivity in the Japanese silk-reeling clusters.

Keywords: Economic geography; Heterogeneous firms; Selection; Productivity

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1　Introduction

Plants located in industrial clusters are more productive than those not located in clusters. Indeed, a positive association between the spatial concentration of economic activities and productivity has been empirically confirmed in the literature. For example, labor density is known to have a positive effect on productivity in the U.S. (Ciccone and Hall, 1996) and in the EU countries (Ciccone, 2002) at the regional level. This also holds true at the plant-level in the U.S. high-tech industry (Henderson, 2003). Excellent reviews of the existing studies on spatial concentration and productivity can be found in Rosenthal and Strange (2004) and Melo et al. (2009).

The higher productivity of plants in industrial clusters has long been explained through *agglomeration effects*, which refer to positive localized externalities: transferring knowledge and innovating ideas among densely agglomerated workers, alleviating matching through thick labor markets, or reducing transaction costs by transacting with proximate firms. These positive externalities directly improve plant-level productivity in the form of "bonuses" in the agglomeration.

At the same time, recent theoretical developments in international trade and spatial economics with heterogeneous firms have suggested plant selection as another factor that could improve productivity (Melitz, 2003; Melitz and Ottaviano, 2008; Behrens et al., 2009; Baldwin and Okubo, 2006). That is, in clusters, intensification of competition expels less productive plants, and consequently, only the relatively productive plants survive. Thus, clusters have higher average regional productivity, even though they do not actually improve the productivity of each plant. Empirically, Syverson (2004) finds that higher plant density truncates the productivity distribution in the lower tail in the ready-mixed concrete industry, implying that low-productivity producers are less likely to survive under increased competition. Corcos et al. (2010) have identified the selection effect induced by trade policy.

Recent studies attempt to identify which of these two effects are in place. A pioneering work by Combes et al. (2012) developed an innovative method to measure the magnitudes of the two effects and found that agglomeration effects could mostly explain higher productivity in French metropolitan areas. Following Combes et al. (2012), Accetturo et al. (2011) too found the existence of agglomeration effects in most of the industries, and selection effects in a few industries in Italian metropolitan areas. These two studies suggest a stronger impact of

agglomeration effects in urban metropolitan clusters.

However, there remains a question of whether such agglomeration effects can also be found in specialized industrial clusters. Since urban metropolitan clusters typically consist of many diverse industries and that Combes et al. (2012) and Accetturo et al. (2011) applied labor density in all sectors as the source of externalities, the detected agglomeration effects contain both industry-specific externalities (Marshall-Arrow-Romer (MAR) externalities) and externalities through diversity (Jacobs externalities) as termed by Glaeser et al. (1992).[1] In contrast, specialized industrial clusters of plants within the same industry, such as the high-tech cluster in the Silicon Valley (U.S.), automobile clusters in Detroit (U.S.), and Toyota (Japan) typically concentrate on a smaller number of related industries, thereby, lacking the benefits from the diversity of industry. Moreover, given that agglomerated plants produce similar products, competition is likely to be fiercer. However, identifying the agglomeration effects or selection effects in specialized industrial clusters is problematic since many of these clusters are also localized in few areas, thus reducing the size of the observation.

In this paper, we aim to identify the sources of productivity improvement in the specialized industrial clusters of silk-reeling in Japan during the period from 1908 to 1915. The Japanese silk-reeling industry then possessed two key characteristics necessary for the purposes of this work. First, silk-reeling clusters, by the nature of the industry, were formed in mountainous, peripheral areas with few plants other than those for silk-reeling. For example, in Suwa County in Nagano Prefecture, one of the largest silk-reeling clusters in that period, 36,814 out of 37,161 total manufacturing workers (or 99.1%) belonged to the silk-reeling sector. Further, in county-level aggregation, the average and median shares of silk-reeling workers in total manufacturing workers is 87% and 94% respectively, in Nagano Prefecture. Therefore, the silk-reeling industry formed specialized clusters with limited interactions between diverse industries, allowing us to focus solely on MAR externalities. Second, besides the clustered plants, there existed numerous silk-reeling plants across Japan, which enable us to exploit sufficient regional variations for empirical analysis. In fact, more than half of the counties in Japan (354 of 680) had more than one silk-reeling plant in 1919.

To frame our empirics, we develop a model of agglomeration and selection through com-

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[1]Henderson (2003) finds using micro data in the U.S. machinery and high-tech industries that the plant density of the same sector significantly improves plant-productivity. While he attributes the bonus to agglomeration effects, it could be explained by selection effects.

petition among plants over input procurement. The literature mostly relied on monopolistic competition in the output market to model agglomeration or selection. However, the silk-reeling plants in our study were takers of price determined in the international market. Instead of competing in the output market, the plants aggressively competed over input procurement (cocoon). To take this feature into account, we modify Syverson's (2004) selection model on competition over the sales of homogeneous output, to competition over input procurement. While Syverson (2004) relies on demand density as the source of selection, we show that a regional difference in entry cost can generate industrial clusters endogenously through selection. Following Fujita and Ogawa (1982) and Lucas and Rossi-Hansberg (2002), we then introduce an agglomeration economy into the model as done in Combes et al. (2012). We obtain theoretical predictions identical with Combes et al. (2012), which enable a distinction between agglomeration and selection effects by examining the characteristics of plant-level productivity distributions. Intuitively, the agglomeration effect will shift the distribution to the right by improving the productivity of all plants in a region but keep the shape of the distribution unchanged. However, the selection effect will left-truncate the distribution by expelling less productive plants from the market. By using this theoretical identity in the characteristics of the distribution, we follow Combes et al. (2012)'s estimation method to estimate the agglomeration and selection effects from the productivity distribution.

Our main empirical conclusion is that selection improves productivity in clusters in the Japanese silk-reeling industry. We find strong evidence of the existence of selection effect. On the other hand, we do not find any evidence of the existence of agglomeration effect. These results are also supported by exploiting prefectural variations. We find that the width of the distribution for clusters was narrower and more severely left-truncated than that for non-clusters. However, we find no clear evidence of the right-shift of the distribution for clusters. Furthermore, we support this finding with the evidence that the extent of agglomeration did not affect the productivity growth rate. If the agglomeration effect is in place, we should observe higher productivity growth among plants in clusters. These results suggest that productivity improvements took place through selection before operation rather than through agglomeration economies after entry. Contrary to the results of Combes et al. (2012) and Accetturo et al. (2011), which emphasize the role of the agglomeration effect in urban metropolitan areas, our results suggest the importance of the selection effect in specialized industrial clusters.

The rest of this paper is organized as follows. The next section overviews the Japanese silk-reeling industry during the period from 1908 to 1915. Section 3 provides a theoretical explanation of industrial clusters and plant-level productivities. Section 4 describes the estimation strategy, and Section 5 describes the data. Section 6 provides our main results. Section 7 discusses the robustness of our findings by using a summary statistics approach and focusing on the timing of the cluster effects. Finally, Section 8 concludes the paper.

2 Overview of the Japanese silk-reeling industry

The silk-reeling industry was one of the major industries in pre-war Japan[2]. For example, in 1908, this industry employed 24.4% of the total factory workers in Japan,[3] and its product, raw silk, occupied 26.6% 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. For example, in 1908, Japan had more than 3,200 silk-reeling plants. Even the largest plant accounted for only 4.3% of the total silk production in 1908, and the median value of the market share was 0.058% (Ministry of Agriculture and Commerce, 1910). In this sense, the market structure of the silk-reeling industry was very competitive.

These silk-reeling plants formed several clusters, of which those in the Nagano, Aichi, and Gifu prefectures in the central region of Japan were the largest; 37.5% of the silk-reeling plants in Japan were located in these three prefectures in 1908. These silk-reeling clusters were highly specialized. According to the Census of Manufacturing in 1919, in Suwa County of Nagano Prefecture, the largest silk-reeling cluster in terms of employment, the share of the silk-reeling industry in the total manufacturing employment was a whopping 99.1%. In addition, in Shimo-Ina County, the second-largest cluster, and in Kami-Ina County, the third-largest cluster, the shares of silk-reeling employment were 98.5% and 96.7%, respectively.

Of these clusters, the cluster in Suwa County in Nagano Prefecture was the largest (Ministry of Agriculture and Commerce 1910). In 1930, to document the history of Hirano Village, the center of the Suwa silk-reeling cluster, the assigned editors conducted a survey of the major plant

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[2]Of the many studies on the development of the silk-reeling industry in Japan, Ishii (1972) and Nakabayashi (2003) are basic references.

[3]The denominator is the number of total factory workers in 1909 (Ministry of International Trade and Industry, 1962).

owners on the reasons behind the development of the silk-reeling industry in the village; one of the most common answers was that they could not secure their living only through agriculture as their land holdings were small and the soil was not fertile. Some respondents also cited the lack of good alternative occupations as a reason (Hirano Village Office 1932, pp.560–562). These answers imply that the opportunity cost for entering the silk-reeling industry was lower owing to the natural conditions in Suwa District. These first-nature characteristics were important causes that facilitated silk-reeling start-ups.

It is also notable that besides the large clusters, silk-reeling plants also operated in other areas, that is, in non-clusters. Figure 1 is the map of Japan, indicating the density of silk-reeling plants in 1908. The dark colored areas represent the prefectures where silk-reeling plants were densely located.

= Figure 1 =

The silk-reeling industry emerged in Japan in the Tokugawa Era, but its growth was accelerated by the opening of the economy in 1859. Under the free trade regime, the export of raw silk experienced a boom. Initially, raw silk was produced using the traditional hand-reeling technology (*zaguri*-reeling), but in the 1870s, a new technology, machine-reeling (*kikai*-reeling), was developed, which modified the imported European technology. While hand-reeling production stagnated owing to competition with Chinese products in the 1870s, machine-reeling production experienced growth in this period (Nakabayashi 2003, pp.66–68). Machine-reeling production exceeded hand-reeling production in 1894, and the latter witnessed a decline in 1900.

According to Nakabayashi (2003), the basic market condition was factored by the growth of the silk weaving industry in the U.S. The U.S. silk-weaving industry introduced its mass production system in the 1860s and preferred homogeneous raw silk in large lots; meeting this demand was a challenge for the traditional silk-reeling industries in both Japan and China. Using the machine-reeling technology, the emerging silk-reeling industry in Japan met the demand of the U.S. silk-weaving industry and thereby grew rapidly.[4] In the U.S. market, each silk-reeling plant in Japan, which as mentioned above, was very small, was basically a price-taker, and it could sell as much raw silk as it wanted to at the market price in Yokohama, the main exporting port.

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[4]For example, in 1908, the ratio of export to production was 98.9% with respect to machine-reeled raw silk and the share of export to U.S. was 74.0% (calculated from the statistics in Nakabayashi, 2003, pp.468–462).

According to Duran (1913), the typical machine-reeling process during that period was as follows. A silk-reeling plant purchased cocoons from sericulture peasants. Cocoons were boiled to unwind the cocoon filaments. Then, from a group of boiled cocoons, unwound filaments were bundled and reeled onto a small moving reel that was powered by water, steam, electricity, or gas. Young female workers played a key role in this production process. Each female worker was in charge of one reeling machine, and her ability and level of effort substantially affected the productivity and quality of the raw silk.

Owing to its relatively simple production process, the productivity and survivability of a silk-reeling plant essentially depended on the procurement and management of the two basic inputs, cocoons and labor. It is notable that competition in these input markets—the cocoon and labor markets—was substantially different.

In the cocoons market, competition for procurement was very severe in clusters, raising input prices not only in the clusters but also in the adjacent prefectures or prefectures farther away (Hirano, 1990; Ishii, 1972, ch.4; Matsumura, 1992). The competition was amplified by the temporal and technological constraint that raw cocoons had to be transported quickly or dried appropriately to ensure that their quality and condition were maintained, because they perished in moist environments. Drying was also necessary to prevent the metamorphosis of the pupa. As Kajinishi ed. (1964) states, "As the silk-reeling industry developed in Suwa, competition for raw materials and work force became harsh among plants, while loss due to transportation cost and damage of cocoons increased" (pp.304–306). Indeed, in March 1908, the price of spring cocoons per koku (180.39 liters) was 50 yen in Matsumoto City (close to Suwa), whereas it was 42 yen in Nagano City (Nagano Prefecture 1910, p.213). To relax competition, silk-reeling plants attempted (and often failed) to arrange cartels for the joint purchase of cocoons and production reductions, or engaged in vertical integration (*tokuyaku torihiki*) in the form of contract farming by concluding direct prior agreements with cocoon farmers with regard to price and quantity.

On the labor side, most silk-reeling workers were young women. As the enormous labor demand in clusters forced plants to hire those workers from rural areas around them, the plants would pay a fixed cost for boarding, food, and even education, which increased unit labor cost. Moreover, because silk-reeling required some experience and skill, recruiting and training new workers was expensive for the plants. Therefore, poaching trained workers from other plants was prevalent in clusters, and the practice gradually proliferated throughout the country

7

(Kambayashi, 2001; Nakabayashi, 2003; Tojo, 1990). In spite of this background, wages of silk-reeling workers did not largely increase on average, because of the abundant supply of young unemployed women in the agricultural areas around the clusters. Nakabayashi (2003) reports the basic statistics of worker-level wage at a plant in Suwa from the late nineteenth century to the early twentieth century. For example, the sample mean and median of wage per day in 1908 were 0.24 and 0.25 yen, respectively (p.259). Meanwhile, the average daily wage of female agricultural workers was 0.23 yen in the same year (Statistics Bureau, Management and Coordination Agency 1988, p.228). These data imply that unit labor cost for an average female silk-reeling worker in the largest cluster was approximately the same as that of the average agricultural worker, and there is little difference among regions.

3   Theoretical model and empirical strategy

We first develop a theoretical framework to model plant selection in the context of the Japanese silk-reeling industry by modifying Syverson's (2004) selection model. Then, we incorporate the agglomeration effect.

3.1   Market structure

We consider the entry and production decisions of silk-reeling plants that procure cocoons from farmers, reel silk, and sell the final product. Output is sold in the export market (Yokohama) at an exogenous price p set by the international market. Plants are price-takers and they can sell as much as they wish in Yokohama.

We assume that the production of q_i silk by plant i entails labor cost $h_i q_i$, input purchase cost $w(Q)q_i$ for cocoons, and fixed cost f. Silk production relied heavily on female workers who reeled unwound cocoon filaments, and their skill and effort were crucial determinants of plant-level productivity.

While workers' individual reeling skills would be inherently different, we assume that all plants faced the same skill distribution regardless of the plant's location. Thus, we ignore the heterogeneity of workers' productivity and rely solely on plant-side heterogeneity (i.e., the capability of the machines, management and incentive systems, training, etc.) to explain the plant-level productivity difference.[5]

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[5]While workers' inherent skills at the individual level may be different, there is no reason to assume that its

We let h_i denote the effective labor required to produce one unit of output (raw silk). This variable can be considered as the plant's productivity: a higher h_i implies greater labor requirement, and hence, lower productivity. Following the discussion on the female labor market in that period in Section 2, we can normalize the cost of unit effective labor to unity.

Input purchase price $w(Q)$ can be considered an aggregate inverse supply function, where $Q = \sum q_i$ is the total output in the region (or, in other words, factor demand). We assume that $w(Q)$ increases with Q because greater silk production requires a higher demand for cocoons. Therefore, unlike the plants modeled in Syverson (2004), for which demand density is the key variable of focus, plants in our model do not compete over output sales but rather over input purchases (cocoons).

The profit of a plant can be represented as

$$\pi_i = pq_i - h_i q_i - w(Q)q_i - f$$

For simplicity, we assume the linear marginal input purchase price as $w(Q) = wQ$:

$$\pi_i = pq_i - h_i q_i - wQq_i - f. \tag{1}$$

This model has two stages. In stage one, each potential plant decides whether to pay a sunk entry cost s to enter the market. After the payment, a plant draws labor unit requirement h_i from distribution $g(h)$ with support $[0, \overline{h}]$, where $\overline{h}$ is an arbitrary upper bound. In stage two, each plant decides its level of production q_i given its productivity parameter h_i, forming an expectation of the total output in a region, $E(Q)$.

The expected profit of an entrant plant at stage two is

$$E(\pi_i) = (p - h_i)q_i - wE(Q)q_i - f. \tag{2}$$

The first-order condition with respect to q_i is

$$\frac{\partial E(\pi_i)}{\partial q_i} = p - h_i - wq_i - wE(Q) = 0, \tag{3}$$

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distribution differed across regions. Moreover, *regional* migration based on reeling skill was unlikely except for experienced, top-ranked reelers who mostly engaged in training, which should be considered as the plant's effort for productivity improvement.

and as such, the optimal output of a plant with marginal cost h_i is

$$q_i^*(h_i) = \frac{p - h_i - wE(Q)}{w}. \tag{4}$$

Inserting q_i^* back into the expected profit yields

$$E[\pi_i(h_i)] = \frac{[p - h_i - wE(Q)]^2}{w} - f. \tag{5}$$

The expected profit decreases with h_i. Therefore, a critical labor unit requirement draw $\hat{h}$ exists such that entrants drawing $h_i > \hat{h}$ choose not to produce. This cutoff labor unit requirement draw can be solved by setting $E(\pi_i) = 0$:

$$\hat{h}(E(Q)) = p - wE(Q) - \sqrt{wf}. \tag{6}$$

Inserting $p - wE(Q) = \hat{h} + \sqrt{wf}$ obtained from (6) into $E(\pi_i)$ yields operating profit, conditional on $h_i \leq \hat{h}$:

$$E\left[\pi_i(h_i | h_i \leq \hat{h})\right] = \frac{\left(\hat{h} - h_i + \sqrt{wf}\right)^2}{w} - f. \tag{7}$$

We assume a free-entry condition so that plants enter the market (i.e., pay s and draw c_i) until the expected value of entry is equal to zero:

$$V^e = \int_0^{\hat{h}} \left[\frac{\left(\hat{h} - h + \sqrt{wf}\right)^2}{w} - f \right] g(h)dh - s = 0 \tag{8}$$

Equilibrium $\hat{h}$ is the value that solves this expression, and it is a function of $g(h)$ and parameters w, f, and s.

3.2   Entry cost, selection effect, and emergence of clusters

We now consider regions that are symmetric except for entry cost s. On the basis of the historical information in Section 2, we assume that s varies across regions owing to the first nature or opportunity costs of starting-up a new business. We show that a region with a lower s imposes fiercer competition (i.e., lower cutoff unit labor requirement) but retains a large number

10

of operating plants, resulting in the formation of a cluster.

We first consider the effect of entry cost s on the cut-off marginal unit labor requirement $\hat{h}$. The implicit function theorem implies that

$$\frac{d\hat{h}}{ds} = \frac{-(\partial V^e/\partial s)}{\partial V^e/\partial \hat{h}} = \frac{w}{2 \int_0^{\hat{h}} \left(\hat{h} - h + \sqrt{wf}\right) g(h)dh} > 0. \tag{9}$$

Implication 1 (*Selection effect*). Regions with a lower start-up cost have a lower cutoff labor unit requirement $\hat{h}$. This relationship implies that competition is more severe: high-cost (low-productivity) plants are not profitable in regions with a lower start-up cost.

Next, we investigate the effect of s on the number of plants in a region. Let N_e denote the number of *entrant plants* that had paid s and drawn h_i, and let N_p denote the number of *producing plants* with $h_i \leqslant \hat{h}$. Then,

$$N_p = N_e \int_0^{\hat{h}} g(h)dh = N_e G(\hat{h}). \tag{10}$$

By applying (4), the total production in a region can be represented as

$$Q = N_e \int_0^{\hat{h}} q_i^* g(h)dh = N_e \int_0^{\hat{h}} \frac{p-h}{w} g(h)dh - N_e E(Q) G(\hat{h}).$$

Since $Q = E(Q)$ in the equilibrium, we can represent Q as a function of N_e and $\hat{h}$:

$$Q(N_e, \hat{h}) = \frac{N_e}{1 + N_e G(\hat{h})} \int_0^{\hat{h}} \frac{p-h}{w} g(h)dh. \tag{11}$$

Additionally, rearranging (6) yields

$$Q = \frac{p - \hat{h} - \sqrt{wf}}{w}. \tag{12}$$

By applying (11) and (12), we can represent N_e as a function of $\hat{h}$ and $g(\cdot)$, and parameters $\{p, w, f\}$:

$$N_e = \frac{p - \hat{h} - \sqrt{wf}}{\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h)dh}. \tag{13}$$

11

Partial differentiation with respect to $\hat{h}$ yields

$$\frac{\partial N_e}{\partial \hat{h}} = \frac{-\int_0^{\hat{h}}(p-h)g(h)dh - (p-\hat{h}-\sqrt{wf})\sqrt{wf}g(\hat{h})}{\left[\int_0^{\hat{h}}(\hat{h}-h+\sqrt{wf})g(h)dh\right]^2} < 0. \tag{14}$$

Therefore, a lower $\hat{h}$ (fiercer selection) entails more entry.

Now, since $N_p = N_e G(\hat{h})$, the effect of the entry cost on the number of producing plants is expressed by

$$\frac{dN_p}{ds} = \frac{dN_e}{d\hat{h}}\frac{d\hat{h}}{ds}G(\hat{h}) + N_e g(\hat{h})\frac{d\hat{h}}{ds}. \tag{15}$$

The effect of s on N_p consists of two effects. The first effect represented by the first term is the *entry effect*, which is negative. That is, a *lower s* entails that more plants will enter the market. The second effect represented by the second term is the *competition effect*, which is positive because $\frac{d\hat{h}}{ds} > 0$ from (9). Because lower s induces severe competition, the number of plants that can produce after entry will be smaller. The aggregate effect of a low entry cost on the number of producing plants depends on the relative magnitude of the (positive) entry effect and the (negative) competition effect. However, we can show that the entry effect always dominates the competition effect. Substituting (13) and (14) into (15) yields

$$\begin{aligned}\frac{dN_p}{ds} &= \left[\frac{dN_e}{d\hat{h}}G(\hat{h}) + N_e g(\hat{h})\right]\frac{d\hat{h}}{ds}\\ &= \frac{-(p-\hat{h})\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}}G(h)dh\right] - \left[G(\hat{h}) + \sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}}G(h)dh}{\left[\int_0^{\hat{h}}(\hat{h}-h+\sqrt{wf})g(h)dh\right]^2}\frac{d\hat{h}}{ds} < 0.\end{aligned} \tag{16}$$

This value is negative because $\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}}G(h)dh\right]$ is positive because $G(\hat{h}) \geq G(h)$ for all $h \in [0, \hat{h}]$, $G(\hat{h}) > g(\hat{h})$, and $\frac{d\hat{h}}{ds} > 0$ from (9).

Implication 2 (*Endogenous clusters*)**.** A lower entry cost s entails that more plants will enter the market (entry effect), but it imposes fiercer competition after entry and reduces the number of producing plants (competition effect). The former always dominates the latter, and therefore, the number of producing plants is greater in a region with a lower s.

3.3 Agglomeration effect and productivity distributions

Following Combes et al. (2012), we now introduce the agglomeration effect, which improves plants' productivities through the interaction between adjacent operating plants. We model this effect by assuming that when a plant interacts with N_p plants, the effective units of labor supplied by an individual worker during their unit time becomes $a(N_p)$, where $a(0) = 1$, $a' > 0$, and $a'' < 0$. Then, a plant with unit labor requirement h_i reduces the number of workers to $l(h_i) = q_i h_i / a(N_p)$ at a total cost of $a(N_p) l(h_i) = q_i h_i$. Thus, each plant's maximization problem is unchanged.

Given this agglomeration effect, the logarithm of a plant's productivity ϕ_i can be derived as follows:

$$\phi_i = \ln\left[\frac{q_i}{l}\right] = \ln\left[\frac{q_i}{q_i h_i / a(N_p)}\right] = \ln[a(N_p)] - \ln(h_i) \tag{17}$$

Then, the density function of the log productivities is as follows:

$$f(\phi) = \begin{cases} 0 & \text{for} \quad \phi < \hat{\phi} \equiv A - \ln(\hat{h}), \\ \frac{e^{A-\phi} g(e^{A-\phi})}{G(\hat{h})} & \text{for} \quad \phi \geqslant \hat{\phi}, \end{cases} \tag{18}$$

where $A \equiv \ln[a(N_p)]$.

As discussed above, each plant's maximization problem is unchanged regardless of the presence of the agglomeration effect. Thus, plugging the equilibrium cut-off unit labor requirement $\hat{h}$ obtained from eq. (8) into eq. (18) yields the equilibrium distribution of plant productivities. From this productivity density function and the assumption of $a' > 0$, it is clear that the increase in the number of operating plants shifts the distribution rightwards while maintaining its form.

Implication 3 (*Agglomeration effect*). An increase in the number of operating plants in a region N_p shifts the productivity distribution to the right.

Fortunately, the result of our model with respect to the productivity distribution is identical to that of Combes et al. (2012), although the theoretical set up is different. Thus, we can apply their novel empirical strategy. To do so, we introduce additional notations.

Now we introduce regions into the model explicitly using the index of r. Let $F(\phi)$ be the

corresponding cumulative density function of $f(\phi)$. The proportion of firms that cannot survive in region r is defined as $S_r \equiv 1 - G(\bar{h}_r)$, where $\bar{h}_r$ is the cutoff productivity in region r. Let $A_r \equiv \ln[a(N_{pr})]$ be the agglomeration effect in region r, where N_{pr} is the number of producing plants in region r. The underlying cumulative density function of log productivities in all regions when there are no selection or agglomeration effects ($\bar{h}_r \rightarrow \infty$ and $A_r = 0$, $\forall i$) can be defined as follows:

$$\tilde{F}(\phi) \equiv 1 - G(e^{-\phi}), \tag{19}$$

because $\phi = 0$, and if $A_r = 0$, then, $h = e^{-\phi}$ and there is a change of variables. Then, the cumulative density function of log productivities for survival firms in region r can be defined as follows:

$$F_r(\phi) = \max\left\{0, \frac{\tilde{F}(\phi - A_r) - S_r}{1 - S_r}\right\}. \tag{20}$$

Because the results of productivity distribution from our model are identical to those of Combes et al. (2012), we can consider the following four polar cases with respect to the channels of productivity improvement, as in the Combes et al. (2012) model. For simplicity, we consider two regions $r = c$ (clusters) and $r = n$ (non-clusters).

Case 1 (*Only the selection effect matters*)**.** When there is no agglomeration effect, only selection affects productivity. In this case, $a(N_p) = 1$ holds for any value of N_p. However, selection implies that $\hat{h}_c < \hat{h}_n$, where $\hat{h}_c$ ($\hat{h}_n$) is the cutoff unit labor requirement in region c (n). This raises the log productivity cut-off in the clusters: $\hat{\phi}_c > \hat{\phi}_n$. This case is represented in Figure 2(a). The solid line represents the log productivity distribution in clusters, while the dashed line represents that in non-clusters. The log productivity distribution in clusters is left-truncated.

Case 2 (*Only the agglomeration effect matters*)**.** In this case, only the agglomeration effect improves plants' productivity. To eliminate the selection effect, we impose $s_c = s_n = s$, where s_c (s_n) is the startup cost in region c (n). Then, the intention of the selection is the same in the both clusters and non-clusters, and therefore, $\hat{h}_c = \hat{h}_n$ and $N_{pc} = N_{pn}$, where N_{pc} (N_{pn}) is the number of plants in region c (n). To establish clusters and non-clusters, we assume $N_c > N_n$ by exogenous reasons that are outside the scope of our model. Only firms in clusters benefit from larger worker interactions, $\ln[a(N_{pc})] > \ln[a(N_{pn})]$. Thus, log productivity simply shifts to the right while maintaining its distribution form. This case is shown in Figure 2(b).

Case 3 (*Both the selection and agglomeration effects matter*). In this case, the fixed entry costs are different between clusters and non-clusters, $s_c < s_n$, and the concentration of workers improves their productivity, $a' > 0$ and $a'' < 0$. Thus, both left-truncation by selection and right-shift by agglomeration occur in clusters. This case is shown in Figure 2(c).

Case 4 (*Neither effect matters*). In this case, the fixed entry costs are the same for all regions and the concentration of workers does not improve their productivity, $a(N_p) = 1$. Then, the log productivity distribution is common across regions. Thus, there is no difference in the productivities across regions. This case is shown in Figure 2(d).

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

Intuitively, these four cases are distinguished by two measures that characterize the productivity distributions. The first measure is the interquartile range of the distribution, which was used by Syverson (2004). If no selection effect exists (cases 2 and 4), the shape of the distribution should be the same for clusters and non-clusters, and thus, the interquartile range should have no difference. However, if a selection effect exists (cases 1 and 3), the productivity distribution should be left-truncated in clusters and the interquartile range should be smaller than that for non-clusters. Hence, by comparing the interquartile range between clusters and non-clusters, we would be able to detect the presence of the selection effect.[6]

The second measure consists of the percentiles of the distribution. Because selection left-truncates the distribution, we should observe a rise in the lower percentile points rather than the higher percentile points of the log-productivity distribution. However, the agglomeration effect affects every percentile point of the distribution because it shifts the whole distribution rightwards. Thus, if the agglomeration effect is in place, both the higher and lower percentile points of the distribution should increase.

The above discussions are summarized in Table 1.

= Table 1 =

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[6]Of course, variance is also an informative measure of truncation. However, empirically, the interquartile range is more robust for outliers.

The table represents the direction of the shift for each measure of distribution in clusters relative to non-clusters for the four cases.

The next section describes the formal estimation strategy based on the theory.

4　Empirical strategy

As we have shown in the previous chapter, our theoretical results in the plant-level log of productivity distribution are identical to the Combes et al. (2012)'s results, although the theoretical set up is different. Thus, we can apply their quantile approach for quantitatively measuring selection and agglomeration effects. This section briefly describes the empirical strategy. For more detail, please see Combes et al. (2012).

Before describing the estimation strategy, we address the concern that the impact of the agglomeration effect varies by plant. For example, high-productivity plants would tend to more rapidly benefit from agglomeration economies. To include this effect, we redefine the agglomeration economies by introducing heterogeneity in the benefits from an agglomeration economy. By introducing heterogeneity, agglomeration economy $a(N_p)$ can be rewritten as $a(N_p)h^{-(D_r-1)}$, where $D_r \equiv \ln[d(N_p)]$, $d(0) = 1$, $d' > 0$, and $d'' < 0$. Then, the log productivity of a firm with unit cost h in region r is denoted by

$$\phi_r(h) = \ln\left(\frac{q_r(h)}{l_r(h)}\right) = A_r - D_r \ln(h). \tag{21}$$

Then, we can write the cumulative density function of the log of productivity in a survival firm in region r as

$$F_r(\phi) = \max\left\{0, \frac{\tilde{F}(\frac{\phi - A_r}{D_r}) - S_r}{1 - S_r}\right\}. \tag{22}$$

This implies that the agglomeration effect not only shifts the distribution to the right by A_r, but also dilates the distribution by D_r; however, selection drops a fraction S_r of entrants. It is worth noting that the heterogeneity also allows for the case wherein low-productivity plants benefit more than high-productivity plants from the agglomeration economy. In this case, D_r takes a negative value.

Based on the extended model, we describe the estimation strategy. As in the previous section, we consider two regions, $r = c$ (clusters) and $r = n$ (non-clusters), and the cumulative density

functions in each region as

$$F_c(\phi) = \max\left\{0, \frac{\tilde{F}(\frac{\phi - A_c}{D_c}) - S_c}{1 - S_c}\right\} \tag{23}$$

and

$$F_n(\phi) = \max\left\{0, \frac{\tilde{F}(\frac{\phi - A_n}{D_n}) - S_n}{1 - S_n}\right\} \tag{24}$$

Now, we introduce the following relative parameters:

$$D \equiv \frac{D_c}{D_n}, \quad A \equiv A_c - DA_n, \quad S \equiv \frac{S_c - S_n}{1 - S_n}. \tag{25}$$

Combes et al. (2012)'s method does not separately estimate A_r, D_r, and S_r in each region; instead, it estimates the relative strength of each variable: $A = A_c - DA_n$, $D = D_c/D_n$, and $S = (S_c - S_n)/(1 - S_n)$. Accordingly, we estimate the relative strength of selection and agglomeration in specialized clusters as compared to non-clusters. Intuitively, if we obtain $A > 0$, there is a larger right-shift in clusters than in non-clusters. Dilation by agglomeration is captured by D. If we obtain $D > 1$, clusters have larger dilation of the distribution than non-clusters. Selection is captured by S. If $S > 0$, there is more elimination of entrants in clusters than in non-clusters.

By introducing these parameters, we can express cumulative density functions $F_c(\phi)$ and $F_n(\phi)$ in terms of the other expression in such a way that clarifies their relationship. If $S_c > S_n$, F_c can also be obtained from F_n by dilating D, shifting by A, and left-truncating a share of S as follows:

$$F_c(\phi) = \max\left\{0, \frac{F_n(\frac{\phi - A}{D}) - S}{1 - S}\right\}. \tag{26}$$

If $S_c < S_n$, F_n can also be obtained from F_c by dilating $\frac{1}{D}$, shifting by $-\frac{A}{D}$, and left-truncating a share of $\frac{-S}{1-S}$ as follows:

$$F_n(\phi) = \max\left\{0, \frac{F_c(D\phi + A) - \frac{-S}{1-S}}{1 - \frac{-S}{1-S}}\right\}. \tag{27}$$

Then, to estimate relative parameters A, D, and S, we rewrite the cumulative density functions into quantiles, and combine them. If $S > 0$, (26) can be rewritten in the quantile form

as

$$\lambda_c(u) = D\lambda_n(S + (1-S)u) + A, \tag{28}$$

where $\lambda_c(u) \equiv F_c^{-1}(u)$ is the uth quantile of F_c and $\lambda_n(u) \equiv F_n^{-1}(u)$ is the uth quantile of F_n. Further, if $S < 0$, (27) can be rewritten as

$$\lambda_n(u) = \frac{1}{D}\lambda_c\left(\frac{u-S}{1-S}\right) - \frac{A}{D}. \tag{29}$$

By combining these two equations and using change of variable $u \to r_S(u)$, where $r_S(u) = \max(0, \frac{-S}{1-S}) + [1 - \max(0, \frac{-S}{1-S})]u$, we can obtain following expression:

$$\lambda_c(r_S(u)) = D\lambda_n(S + (1-S)r_S(u)) + A. \tag{30}$$

This equation implies how the quantiles of the productivity distribution in clusters relates to that in non-clusters through relative parameters A, D, S. Then, we define $m_\theta(u) = \lambda_c(r_S(u)) - D\lambda_n(S + (1-S)r_S(u)) + A$, where $\theta = (A, D, S)$. Finally, we can obtain the estimator of θ by minimizing the mean-square error on m_θ, as

$$\hat{\theta} = \arg\min_\theta \left(\int_0^1 [\hat{m}_\theta(u)]^2 \mathrm{d}u\right), \tag{31}$$

where $\hat{m}_\theta(u)$ is the empirical counterpart of $m_\theta(u)$, obtained by replacing λ_c and λ_n with their estimators.[7] However, this implementation compares the two distributions asymmetrically. That is, we compare the quantiles of actual region c's productivity distribution to the quantiles of the truncated, dilated, and shifted distribution of region n. Combes et al. (2012) took one more step to obtain a robust estimator to consider a way to symmetrically treat the quantiles of the two distributions. Combining (28) and (29) into one equation and using change of variable $u \to \tilde{r}_S(u)$, where $\tilde{r}_S(u) = \max(0, S) + [1 - \max(0, S)]u$, we obtain another equality condition:

$$\tilde{m}_\theta(u) = \lambda_n(\tilde{r}_S(u)) - \frac{1}{D}\lambda_c\left(\frac{\tilde{r}_S(u) - S}{1-S}\right) + \frac{A}{D}. \tag{32}$$

By using this condition, Combes et al. (2012)'s estimator $\hat{\theta} = (\hat{A}, \hat{D}, \hat{S})$ that we actually estimate

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[7]See Combes et al. (2012) for details on obtaining these estimators.

in this paper is described as follows:

$$\hat{\theta} = \arg \min_{\theta} M(\theta), \quad \text{where} \quad M(\theta) = \int_0^1 [\hat{m}_\theta(u)]^2 \mathrm{d}u + \int_0^1 [\hat{\tilde{m}}_\theta(u)]^2 \mathrm{d}u, \tag{33}$$

where $\hat{\tilde{m}}_\theta(u)$ is the empirical counterpart of $\tilde{m}_\theta(u)$ obtained by replacing the true quantiles, λ_c and λ_n by their estimators. The standard errors for the estimated parameters are obtained by 200 bootstrap iterations, including re-estimating TFP.

5 Data, and measures of plant-level productivity

5.1 Data

We compiled the silk-reeling industry census data, *Zenkoku Seishi Kojo Chosa*, for the two data points 1908 and 1915. The data include plant-level information: plant name, location, year of foundation, number of pots, number of workers, number of business days per year, types of power used, and output. This data set covers both hand-reeling and machine-reeling plants. Here, we focus on machine-reeling plants because hand-reeling and machine-reeling are completely different techniques. We matched plants over two periods and constructed an unbalanced panel data set by using plant name, location, and year of foundation. The number of machine-reeling plants in 1908 was 2385 and that in 1915 was 2263. The number of plants that existed in 1908 and survived until 1915 was 910. The extent of agglomeration is measured by regional plant density, computed as the number of plants per km^2. Information regarding the regional area at the prefecture or county level was obtained from the Geographical Information System (GIS) data for 1937, from "Taisho-Showa Gyoseikai Data."[8]

5.2 Measures of plant-level productivity

As discussed in the previous section, we focus on the shape of the productivity distributions to distinguish the channels of productivity improvement effects. For this purpose, we first estimate the productivity of each plant. We use TFP as the primary measure of plant-level productivity.

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[8]The data are published 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

In order to estimate TFP, we specify the firm-level production function as follows:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \delta Z_{it} + \omega_{it} + \epsilon_{it}, \tag{34}$$

where y_{it} is the log of output, k_{it} is the log of capital input (number of pots), l_{it} is the log of labor inputs (number of female workers), m_{it} is the log of intermediate input (quantity of cocoons used), Z_{it} is the vector of plant i's observable characteristics, and ω_{it} and ϵ_i are productivity terms unobservable to econometricians. While ϵ_{it} is also unobserved by firms before they make their input decisions, ω_{it} is observable. We assume that $\omega_{it} = \omega_i$; that is, observable productivity for plants does not change through the study period (7 years). As plant i's observable characteristics, we include the log of plant age, a dummy variable indicating that the plant used water power, and a dummy variable indicating that the plant used steam power. Given this assumption, we estimate this production function by fixed effects model.[9]

The estimation results are reported in Table 2.

= Table 2 =

The coefficients of ln(capital) and ln(worker) have expected signs and magnitudes with high statistical significance. The coefficient of ln(intermediate) is positive, but not significantly different from zero. We interpret $y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} + \hat{\beta}_m m_{it} - \hat{\delta} Z_{it}$ as the TFP of plant i in period t. 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 measures to evaluate plant-level productivity.

6   Main results

We now show the estimation results and distinguish the relative size of agglomeration and selection effects.

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[9]An alternative way of estimating TFP is the structural approach proposed by Levinsohn and Petrin (2003) that relaxes the assumption of $\omega_{it} = \omega_i$ is potentially useful, but the limitation of our data set is that the two periods are seven years apart, making it difficult for the application of the method of Levinsohn and Petrin (2003).

We use a prefecture as a unit of observation of regional productivity density to obtain sufficient observations. All prefectures in Japan are classified into two groups on the basis of regional plant densities (number of plants per km^2 in a region). We sorted prefectures according to the density of silk-reeling plants, and picked up the prefectures from the top until these prefectures had more than half of the total plants in Japan. We regard those prefectures with high plant density as *clustered prefectures*, and the other prefectures as *non-clustered prefectures*. There were 47 prefectures in total in Japan at that time, and of these, five are identified as clustered prefectures in each period (Aichi, Yamanashi, Nagano, Gifu, and Kyoto for 1909, while Gumma instead of Kyoto for 1916). The other 42 prefectures are regarded as non-clustered prefectures. Plant density in each prefecture in 1909 is illustrated in Figure 1. For instance, Nagano prefecture, the largest cluster, had over 18 plants per km^2.

First, we estimate the kernel density functions[10] of plant-level productivity for each group of prefectures. Figure 3 represents the kernel densities.

= Figure 3 =

The solid line refers to the density of clustered prefectures and the dashed line refers to the density of non-clustered prefectures. In every figure, the estimated density in the lower tail of the distribution is lower for clustered prefectures than for non-clustered prefectures, while density in the higher tail of distributions is similar for the two prefecture groups. Moreover, the shapes and positions of the two distributions seem to be similar except for the lower tails. There is no clear sign that the distribution of clustered prefectures shifts to the right. Given the predictions summarized in Table 1, these features of the two distributions suggest that a selection effect existed but an agglomeration effect did not.

These observations are also confirmed by the descriptive statistics of the productivity distributions shown in Table 3.

= Table 3 =

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[10]We estimate the density functions by using the Epanechnikov kernel with optimal bandwidth.

Panel A represents the statistics for 1908 and Panel B represents those for 1915. The mean productivities are significantly higher in clusters for every productivity measure and period, indicating that plants located in industrial clusters were indeed more productive than those in non-clusters.

Our conventional predictions in Table 1 suggest that the interquartile range is informative in detecting selection effects. If the productivity distribution is truncated by selection, we should observe a shorter interquartile range. We can also examine the existence of selection and agglomeration effects by looking at the percentiles of distribution at the lower and higher tails: while selection affects only the lower tail, agglomeration affects every support of the distribution because agglomeration shifts the whole distribution rightwards. Hence, if the agglomeration effect exists, both the lower and higher tails of the distribution should shift to the right.

Table 3 reveals that the interquartile range of the distribution in clustered prefectures is smaller than that in non-clustered prefectures. This suggests the truncation of the distribution implied by plant selection. This interpretation is further supported by the percentiles of the distribution. In the lower tails (the 10th and 25th percentiles), percentiles in clusters are much higher than in non-clusters. For example, in 1908, while the 10th percentile in cluster is –0.21, the same percentile in non-clusters is –0.33, and the difference is 0.1. However, in higher tails, the percentiles in both clusters and non-clusters are quite similar (the 90th percentile in both clusters and non-clusters are 0.18). These findings are consistent with Case 1 in Table 1: productivity distribution is left-truncated but no right-shift is observed. According to our theoretical prediction, this implies the existence of plant selection and non-existence of the agglomeration effect.

The estimation results are shown in Table 4.

= Table 4 =

These results are for three measures of productivities and for two periods. Column (1) in Table 4 reports our results for TFP in 1909. The point estimate of A is negative but not significantly different from zero, while that of D is greater than one but not statistically different from one. These values suggest that there is no larger rightwards shift of the distribution and dilations in silk-reeling clusters compared to non-clusters. However, the point estimate of S is positive and statistically different from zero, suggesting that there is more elimination of the distributions

22

in clusters compared to non-clusters. These results strongly suggest that the selection effect in clusters is larger compared to in non-clusters, while the agglomeration (and dilation) effect is not. That is, the higher plant-level productivity in silk-reeling clusters can be explained only by the selection effect. This result is the exact opposite of the result of Combes et al. (2012) that focuses on urban metropolitan areas.

This result is robust for the measure of productivities and periods. In every column, the point estimate of S is positive and statistically different from zero. However, the point estimate of A is negative but not significantly different from zero, while that of D is greater than one but not statistically different from one with the exception of column (3). These results suggest the robustness of our conclusion: the higher plant-level productivity in silk-reeling clusters can be explained only by the selection effect.

In sum, robustly, the selection effect was larger in specialized silk-reeling clusters than in the non-clusters, while there were no agglomeration or dilation effects. These results suggest that the higher plant-level productivity in silk-reeling clusters can be explained only by the selection effect.

Why were there no agglomeration economies in the silk-reeling clusters? One possible reason is that the major innovative knowledge for improving productivity had already spread by this period. Nakabayashi (2003) showed that the productivity of a silk-reeling plant in prewar Japan was principally determined by machines and the mode of labor management, and that substantial innovation occurred in the latter in Suwa District in the 1900s. That is, a sophisticated performance-based wage system was devised to provide appropriate incentives to female workers. In this system, the performance of each female worker was evaluated by several measures including labor productivity, cocoon productivity, and product quality, which were strategic for the competitiveness and profitability of a plant (pp.241-288). Notably, this wage system was first devised in Suwa, but had widely diffused in Japan by the early 1910s (Ishii, 1972, p.300). In this sense, there was little room for productivity improvement through learning in the 1910s.

7 Robustness checks

7.1 Prefectural variations

In the previous section, we found by the method developed by Combes et al. (2012) that there was larger selection but no agglomeration in silk-reeling clusters than in non-clusters. This method is theoretically and statistically rigorous, but it cannot fully utilize regional variations because the method compares two distributions of the log of productivities. However, our method to distinguish the agglomeration effect and the selection effect by the summary statistics of the log of productivity distribution as was done in Syverson (2004) and as described in Table 1 was not rigorously developed but can fully utilize the prefectural variations. Although the summary statistics approach cannot purely distinguish the agglomeration effect and the selection effect, it yields a useful approximation. This section adopts the summary statistics approach to check the robustness of the previous results.

Based on Table 1, we first investigate the effect of plant densities on the interquartile range of the productivity distribution. We index each prefecture by p and estimate the following equation:

$$\mathrm{IQR}_{pt} = \alpha + \beta \ln(\mathrm{D}_{pt}) + \mathrm{year}_t + \varepsilon_{pt} \tag{35}$$

where IQR_{pt} refers to the interquartile range of the plant-level productivity distribution in prefecture p in period t, D_{pt} is the plant density and year_t is the year fixed effects. Under the presence of selection effects, an increase in plant density will truncate the distribution and shorten the interquartile range; thus, we expect a negative sign for β. We estimate this equation by pooled OLS with year fixed effects. Because this estimation focuses on the productivity distribution and requires a certain number of observations (plants) in each prefecture, we restrict samples to prefectures that had more than 20 plants. The results are shown in columns (1) to (3) in Table 5.

= Table 5 =

In every result (columns 1–3), the coefficients of plant density are negative and statistically significant. This suggests the truncation of productivity distributions, which is consistent with the existence of the selection effect.

24

Next, we examine the role of the agglomeration effect by focusing on the percentiles of the productivity distribution. We estimate the following equation:

$$P_{pt}^u = \alpha + \beta \ln(D_{pt}) + \text{year}_t + \varepsilon_{pt}, \tag{36}$$

where P_{pt}^u is the u-th percentile of the log productivity distribution in prefecture p for period t. The equation is estimated by pooled OLS.

The results are shown in Table 6.

$$= \text{Table 6} =$$

Columns (1) to (4) use TFP as a measure of productivity while columns (5) to (8) and (9) to (12) use output per pot and output per worker, respectively. Regardless of the measure of productivity, the coefficients of plant density are positive and significant for the lower tail, that is, the 10th and 25th percentiles (columns 1, 2, 5, 6, 9, and 10). This result is consistent with both the agglomeration and selection effects. However, every coefficient of plant density is not statistically different from zero at the 75th or 90th percentiles (columns 3, 4, 7, 8, 11, and 12). This implies that higher plant density had no effect on the productivity distribution shifting rightwards. The evidence runs contrary to the existence of the agglomeration effect.

These results indicate that the increase in plant density truncated the log productivity distribution in the lower tail but had no effect in shifting the distribution rightwards. This is consistent with the existence of the selection effect and the non-existence of the agglomeration effect (Case 1 in Table 1). The results obtained in this section strongly support our main result that the higher plant-level productivity in silk-reeling clusters can be explained only by the selection effect.

7.2 Productivity growth after operation

According to the results obtained in the previous sections, there is no agglomeration effect in the clusters. Did the concentration of the plants actually have no positive externality to the plants located there? For the final robustness check, we examine the timing of the productivity growth.

Our strategy is as follows. If the agglomeration effect is in place and learning from leading

plants improves plant-level productivities, we would observe faster productivity growth in clusters than in non-clusters *after* the plants are operational.[11] Thus, we check the productivity growth after commencement of operations by comparing the productivity growth rates between plants in clusters and non-clusters.

Descriptive statistics of the productivity growth rate from 1908 to 1915 for three different productivity measures are shown in Table 7.

$$= \text{Table 7} =$$

Younger plants might tend to learn and improve their productivities faster than older plants. We report descriptive statistics for start-up plants separately. We define *start-up* plants as plants with age less than five years.

For every productivity measure, the average productivity growth rate is similar for clusters and non-clusters. Rather, the average growth rate in clusters is smaller than in non-clusters. We test the difference in the average productivity growth rate between clusters and non-clusters using a *t*-test, but the null hypothesis that the mean difference in the growth rates between clusters and non-clusters is zero is not rejected at the conventional levels of statistics for every measure of productivity. Furthermore, this relationship also holds even if we restrict samples to *start-up* plants. Overall, start-up plants grew faster than older plants in terms of every productivity measure. Meanwhile, the average productivity growth rate of *start-up* plants in clusters is again lower than in non-clusters, and we also cannot reject the null hypothesis that the mean difference in the growth rates between the clusters and non-clusters is zero in every measure of productivity. Thus, there is no evidence that plants learned faster in clusters than in non-clusters.

To control plant-level differences, we econometrically test the learning effects in clusters, by estimating the following equation:

$$\text{GrowthRate}_{icp} = \alpha + \beta D_{cp}^{1908} + \delta Z_{icp}^{1908} + \gamma \text{Productivity}_{icp}^{1908} + \text{pref}_p + \varepsilon_{icp}, \tag{37}$$

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[11]Such dynamics of productivity growth is not introduced into our theoretical model. However, technological externality does occur gradually rather than instantaneously. In a sense, this section considers the agglomeration economies separately from our baseline model.

where GrowthRate$_{icp}$ is the productivity growth rate of plant i located in county c in prefecture p from 1908 to 1915, D_{cp}^{1908} is the plant density at the county level in 1908, and Z_{icp}^{1908} is the vector of plant-level control variables (number of pots, number of workers, age, steam power dummy, and water power dummy) in 1908. To control low-productivity plants' faster learning and growth (catch-up), we include the initial productivity in 1908. Finally, pref$_p$ denotes prefectural fixed effects. Table 8 reports the results.

$$= \text{Table 8} =$$

Again, we use three measures for plant-level productivity. Column (1) gives the baseline result. Even after controlling for plant-level variables, the coefficient of plant density is not statistically different from zero. That is, plants in clusters did not improve their productivities faster than plants in non-clusters. Column (2) controls initial productivity in 1908. Interestingly, the coefficient of initial productivity in 1908 is negative and significant, suggesting a catch-up by low-productivity plants. However, the coefficient of plant density is still not statistically different from zero. Low-productivity plants did learn and catch-up, but their speed was not significantly different for clusters and non-clusters. This result is robust to the alternative measures of productivity (columns 3–6) or the restricted sample of *start-up* plants (columns 7–12). The coefficient of initial productivity in 1908 is significantly negative but plant density is not statistically different from zero. In sum, these results do not support the presence of learning implied by the agglomeration effect. Low-productivity plants did catch up, but we find no evidence that plants in clusters improved their productivity faster than did their counterparts in non-clusters. The concentration of plants did not have any productivity growth effect in these periods. This result also supports our main result that the higher plant-level productivity in silk-reeling clusters can be explained only by the selection effect.

8   Concluding remarks

This paper attempted to distinguish the two channels through which industrial clusters improve plant-level productivity, focusing on the Japanese silk-reeling industry in the period from 1908 to 1915. On the basis of a nested model of selection and agglomeration, we considered the

agglomeration effect, which improves the productivities of all plants in a region, and the plant-selection effect, which raises the average regional productivity by expelling less-productive plants through intense competition.

Using plant-level data, we distinguished the channels of productivity improvement by the estimation method proposed by Combes et al. (2012). We found on one hand that there was left-truncation of the log of the productivity distribution in clusters relative to non-clusters, and on the other hand, that there was no rightwards shift and dilation of the distribution. These findings suggest that the higher plant-level productivity in the silk-reeling clusters can be explained only by the selection effect. These main findings were robust for the alternative method to detect those effects via prefectural variations and summary statistics of the distribution. The observation is further supported by the finding that there was no difference in the productivity growth rate of individual plants between clusters and non-clusters. This result implies that productivity growth through learning suggested by the agglomeration effect was not evident. We suspect that the possible reason for this lack of agglomeration effect is that the major innovative knowledge for improving productivity (i.e., performance-based wage system) had already spread by this period.

We therefore conclude that in the Japanese silk-reeling industry, higher average productivity in clusters was not caused by the agglomeration effect but through selection; that is, the intensification of competition in clusters expelled low-productivity plants, and consequently, only relatively more productive plants survived.

Our finding is contrary to that of Combes et al. (2012) and Accetturo et al. (2011), which find agglomeration effects in French and Italian metropolitan areas, respectively. The difference implies that the source of productivity improvement may be different in urban metropolitan areas and specialized industrial clusters. In particular, plants in specialized industrial clusters are less likely to enjoy the benefits of "Jacobs externality," while facing severe competition compared to those in urban metropolitan clusters. Further investigation of the difference between urban metropolitan clusters and specialized industrial clusters remains for future research.

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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 result of plant-level productivity

ln(capital)	ln(labor)	ln(intermediates)	ln(age)	Water power dummy	Steam power dummy	Constant	No. obs.	R^2
0.152**	0.153**	0.719**	0.056**	0.053*	0.004	2.170 **	4479	0.955
(0.056)	(0.074)	(0.076)	(0.022)	(0.032)	(0.035)	(0.134)		

Note: The dependent variable represents the log of output: The capital represents the number of pots, labor represents the number of workers, and intermediates represents the quantity of cocoons. Estimated by the fixed effects model.
Robust standard errors in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.

Table 3: Descriptive statistics of plant-level productivity

Panel A: 1908

Measure of productivity	Clusters vs. Non-clusters	Obs.	Mean	Interquartile range	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
TFP									
	All	2232	-0.03	0.22	-0.27	-0.14	-0.01	0.09	0.18
	Clusters	1119	-0.002	0.19	-0.21	-0.09	0.01	0.1	0.18
	Non-clusters	1113	-0.05	0.26	-0.33	-0.18	-0.04	0.08	0.18
			(4.288)						
Output per pot									
	All	2233	3.95	0.71	3.2	3.62	4.03	4.33	4.57
	Clusters	1119	4.07	0.57	3.44	3.82	4.07	4.39	4.57
	Non-clusters	1114	3.82	0.82	2.96	3.43	3.92	4.25	4.56
			(10.031)						
Output per Worker									
	All	2234	3.92	0.66	3.16	3.63	4.00	4.29	4.51
	Clusters	1119	4.04	0.55	3.44	3.81	4.06	4.35	4.54
	Non-clusters	1115	3.8	0.79	2.96	3.44	3.93	4.23	4.47
			(10.113)						

Panel B: 1916

Measure of productivity	Clusters vs. Non-clusters	Obs.	Mean	Interquartile range	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
TFP									
	All	2247	0.03	0.28	-0.27	-0.1	0.06	0.18	0.29
	Clusters	1263	0.04	0.24	-0.2	-0.07	0.07	0.18	0.28
	Non-clusters	984	0.004	0.34	-0.34	-0.15	0.05	0.19	0.29
			(3.218)						
Output per pot									
	All	2263	4.17	0.87	3.22	3.78	4.29	4.65	4.93
	Clusters	992	4.26	0.79	3.53	3.87	4.34	4.66	4.93
	Non-clusters	1271	4.05	1.04	2.93	3.59	4.19	4.63	4.94
			(7.180)						
Output per Worker									
	All	2263	4.14	0.83	3.24	3.76	4.26	4.6	4.86
	Clusters	992	4.23	0.77	3.49	3.85	4.31	4.61	4.88
	Non-clusters	1271	4.02	0.94	2.91	3.62	4.18	4.56	4.83
			(7.581)						

Note: TFP is estimated by the fixed effects estimation. The t-values of the t-test are presented in parentheses. The null hypotheses of the t-test is that average productivity is the same for clusters and non-clusters.

Table 4: Main estimation results

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of productivity	TFP	TFP	Output per pot	Output per pot	Output per worker	Output per worker
Year	1908	1916	1908	1916	1908	1916
A (relative agglomeration)	−0.016	−0.029	−0.603**	−0.071	−0.192	−0.153
	[0.159]	[0.140]	[0.177]	[0.232]	[0.253]	[0.203]
D (relative dilation)	1.023	1.012	1.200**	1.042	1.089	1.073
	[0.069]	[0.057]	[0.044]	[0.053]	[0.063]	[0.046]
S (relative selection)	0.024**	0.013**	0.022**	0.024 **	0.018 **	0.027 **
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.003]
Observations	2232	2247	2233	2263	2234	2263
R^2	0.649	0.576	0.338	0.439	0.509	0.457

Note: Estimation method proposed by Combes et al. (2012) is used. Standard errors are calculated by 200 bootstrapping iterations. TFP is estimated by the fixed effects estimation.
Bootstrapped standard errors in square parentheses.
**: for A and S significantly different from 0 at the 5 percent level, for D significantly different from 1 at the 5 percent level.

Table 5: Plant density and interquartile range of productivity distribution

	(1)	(2)	(3)
Measure of productivity	TFP	Output per pot	Output per worker
ln(density)	-0.0276*	-0.129**	-0.130**
	(0.0151)	(0.0453)	(0.0539)
Constant	0.256**	0.860**	0.811**
	(0.0280)	(0.0876)	(0.104)
Observations	45	45	45
Adjusted R^2	0.071	0.111	0.102

Note: The dependent variables are the interquartile range of the productivity distribution at the prefectural level.
TFP is estimated by the fixed effects estimation.
Robust standard errors in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.

Table 6: Plant density and percentiles of productivity distribution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Measure of productivity	TFP	TFP	TFP	TFP	Output per pot	Output per pot	Output per pot	Output per pot	Output per worker	Output per worker	Output per worker	Output per worker
Percentiles	10th	25th	75th	90th	10th	25th	75th	90th	10th	25th	75th	90th
ln(density)	0.0506*	0.0430*	0.0154	0.0189	0.197**	0.181**	0.0527	0.0546	0.191**	0.169**	0.0387	0.0672
	(0.0290)	(0.0243)	(0.0155)	(0.0141)	(0.0772)	(0.0764)	(0.0560)	(0.0475)	(0.0801)	(0.0804)	(0.0535)	(0.0473)
Constant	-0.286**	-0.168**	0.0875**	0.166**	3.122**	3.432**	4.292**	4.557**	3.138**	3.453**	4.264**	4.473**
	(0.0509)	(0.0422)	(0.0254)	(0.0224)	(0.139)	(0.136)	(0.0901)	(0.0788)	(0.147)	(0.145)	(0.0825)	(0.0724)
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	45	45	45	45	45	45	45	45	45	45	45	45
Adjusted R^2	0.031	0.046	0.145	0.292	0.115	0.117	0.202	0.318	0.075	0.087	0.227	0.385

Note: Dependent variables are percentile points of the productivity distribution at the prefectural level. TFP is estimated by the fixed effects estimation.
Robust standard errors in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.

Table 7: Plant-level productivity growth rate, 1909 to 1916

Panel A. Measure of productivity: TFP

| Clusters vs. Non-clusters | All plants | | | | Start-up plants | | | |
	Obs.	Mean	Standard deviation	t-value	Obs.	Mean	Standard deviation	t-value
Clusters	448	0.279	0.680		115	0.417	0.829	
Non-clusters	461	0.311	1.053		83	0.640	1.842	
All	909	0.295	0.888		198	0.510	1.350	
Difference		−0.032	0.059	−0.535		−0.223	0.194	−1.148
(Clusters/Non-clusters)								

Panel B. Measure of productivity: Output per pot

| Clusters vs. Non-clusters | All plants | | | | Start-up plants | | | |
	Obs.	Mean	Standard deviation	t-value	Obs.	Mean	Standard deviation	t-value
Clusters	448	0.471	1.011		115	0.676	1.219	
Non-clusters	461	0.494	1.568		83	1.053	3.014	
All	909	0.482	1.323		198	0.834	2.163	
Difference		−0.023	0.088	−0.265		−0.377	0.311	−1.213
(Clusters/Non-clusters)								

Panel C. Measure of productivity: Output per worker

| Clusters vs. Non-clusters | All plants | | | | Start-up plants | | | |
	Obs.	Mean	Standard deviation	t-value	Obs.	Mean	Standard deviation	t-value
Clusters	448	0.459	1.049		115	0.652	1.198	
Non-clusters	461	0.489	1.551		83	1.009	2.973	
All	909	0.474	1.327		198	0.802	2.131	
Difference		−0.030	0.088	−0.337		−0.357	0.307	−1.164
(Clusters/Non-clusters)								

Note: TFP is estimated by the fixed effects estimation. The t-value columns show the results of the t-test. The null hypotheses of the t-test is that average productivity growth is not different for clusters and non-clusters.

Table 8: Estimation of growth effects

Dependent: Measure of productivity growth	(1) TFP	(2) TFP	(3) Output per pot	(4) Output per pot	(5) Output per worker	(6) Output per worker	(7) TFP	(8) TFP	(9) Output per pot	(10) Output per pot	(11) Output per worker	(12) Output per worker
Samples	All	All	All	All	All	All	Start-up	Start-up	Start-up	Start-up	Start-up	Start-up
ln(density) in 1908	-0.0148 (0.0284)	-0.00968 (0.0258)	-0.0138 (0.0410)	-0.00820 (0.0389)	0.0105 (0.0391)	0.0165 (0.0370)	-0.0589 (0.0919)	-0.0911 (0.0832)	-0.119 (0.151)	-0.165 (0.145)	-0.0949 (0.147)	-0.142 (0.143)
ln(pot) in 1908	0.968** (0.393)	0.877** (0.377)	1.435** (0.585)	0.300 (0.634)	-0.691** (0.259)	-0.600** (0.229)	2.393** (0.438)	2.240** (0.432)	3.552** (0.605)	1.989** (0.950)	0.322 (0.436)	0.346 (0.439)
ln(worker) in 1908	-0.340 (0.418)	-0.274 (0.389)	-0.391 (0.652)	-0.130 (0.644)	1.751** (0.466)	0.732** (0.318)	-0.816 (0.638)	-0.806 (0.573)	-0.914 (1.129)	-0.657 (1.101)	2.063* (1.076)	0.700 (0.924)
ln(cocoon) in 1908	-0.552** (0.183)	-0.511** (0.134)	-0.962** (0.309)	-0.0380 (0.200)	-1.009** (0.317)	-0.0282 (0.194)	-1.472** (0.554)	-1.297** (0.479)	-2.535** (1.113)	-1.144 (0.953)	-2.407** (1.114)	-0.981 (0.912)
ln(age) in 1908	-0.0783* (0.0415)	-0.133** (0.0431)	-0.128* (0.0714)	-0.121* (0.0691)	-0.132* (0.0721)	-0.124* (0.0697)	-0.182 (0.222)	-0.231 (0.206)	-0.437 (0.400)	-0.417 (0.369)	-0.498 (0.398)	-0.477 (0.368)
Steam power dummy in 1908	0.0531 (0.0791)	0.0933 (0.0753)	0.0720 (0.114)	0.122 (0.111)	0.101 (0.120)	0.154 (0.115)	0.398 (0.262)	0.370 (0.257)	0.542 (0.418)	0.508 (0.413)	0.688* (0.407)	0.653 (0.403)
Water power dummy in 1908	-0.0316 (0.0811)	-0.0732 (0.0764)	-0.0214 (0.128)	-0.00273 (0.127)	0.00137 (0.131)	0.0212 (0.129)	0.701* (0.355)	0.671** (0.339)	1.395** (0.692)	1.437** (0.687)	1.421** (0.692)	1.465** (0.687)
ln(TFP) in 1908		-1.100** (0.203)						-1.114** (0.483)				
ln(Output per pot) in 1908				-1.221** (0.273)						-1.587* (0.822)		
ln(Output per worker) in 1908						-1.296** (0.277)						-1.627** (0.780)
Constant	1.370** (0.420)	1.337** (0.350)	2.567** (0.737)	5.179** (1.142)	2.781** (0.757)	5.554** (1.175)	2.870** (1.225)	2.401** (1.114)	5.301** (2.489)	8.077** (3.413)	5.433** (2.499)	8.279** (3.382)
Prefectural FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	909	909	909	909	909	909	198	198	198	198	198	198
Adjusted R^2	0.157	0.265	0.160	0.219	0.159	0.226	0.534	0.574	0.405	0.435	0.401	0.435

Note: The dependent variables represent the growth rate of the plant-level productivity from 1909 to 1916. TFP is estimated by the fixed effects estimation. A start-up is a plant with age less than five years.
Robust standard errors in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.

Plant Density

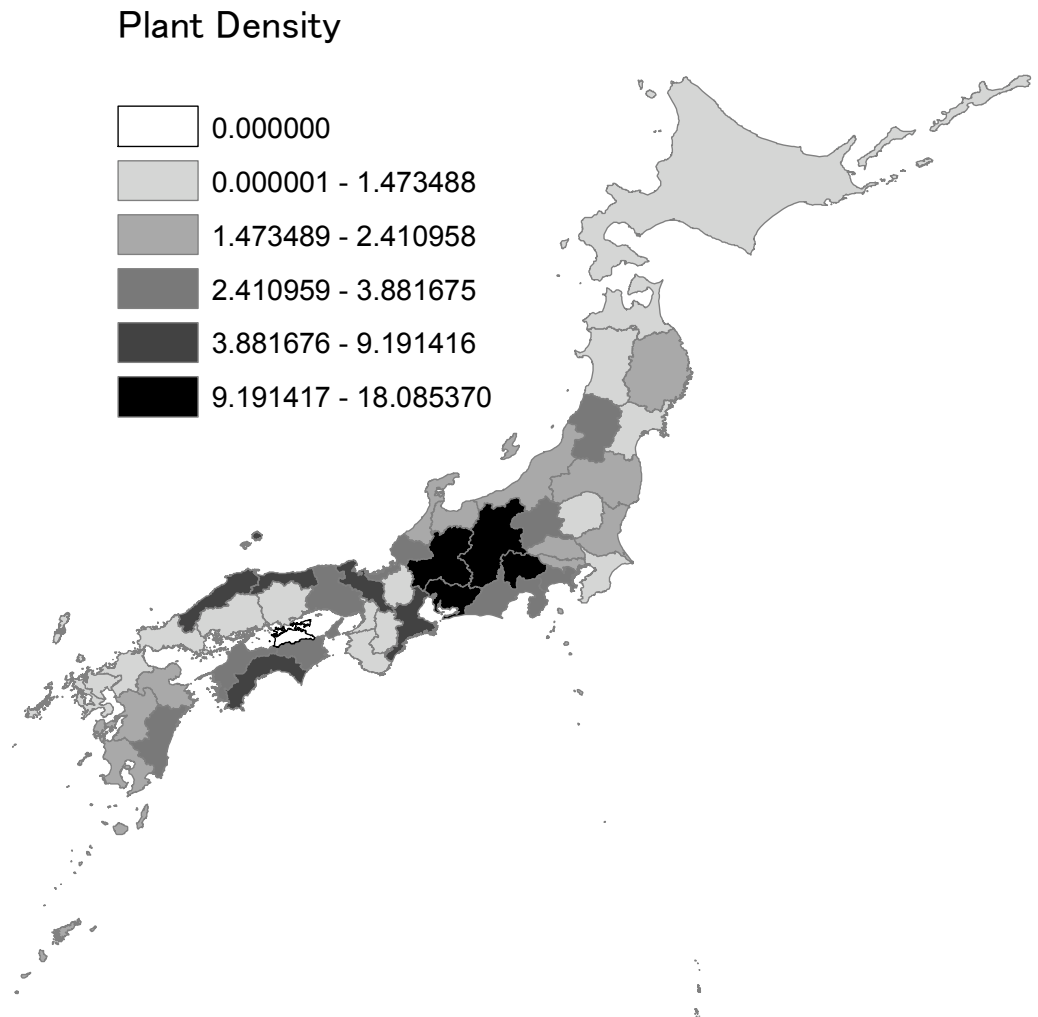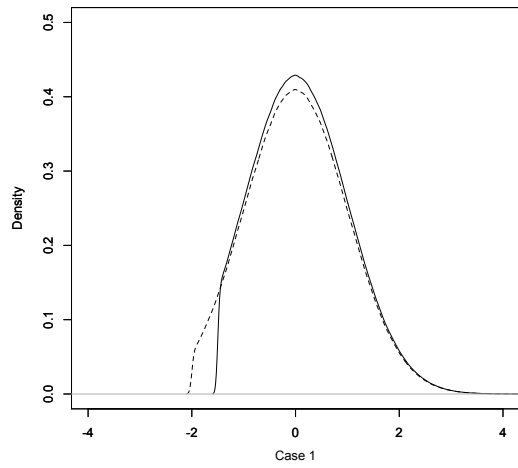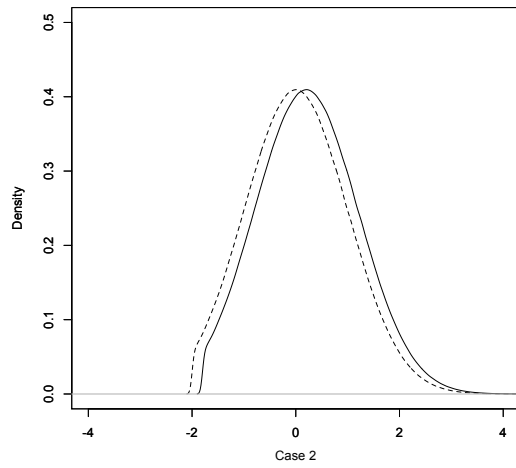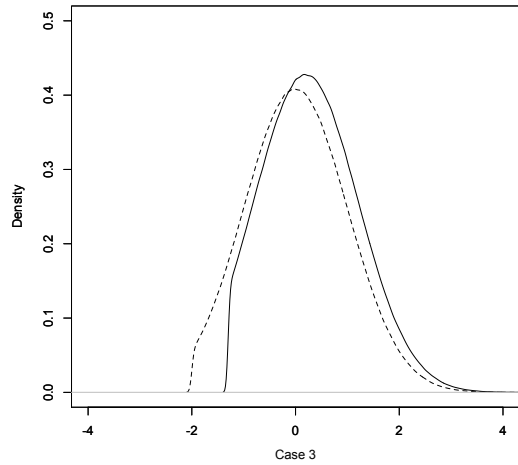|	
☐	0.000000
▨	0.000001 - 1.473488
▨	1.473489 - 2.410958
▨	2.410959 - 3.881675
▨	3.881676 - 9.191416
■	9.191417 - 18.085370

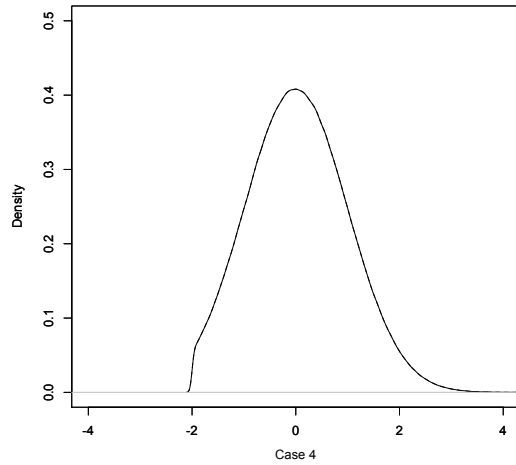Figure 1: Map of Japan and the density of silk-reeling plants in 1909

(a) Selection

(b) Agglomeration

(c) Both selection and agglomeration

(d) Neither effect

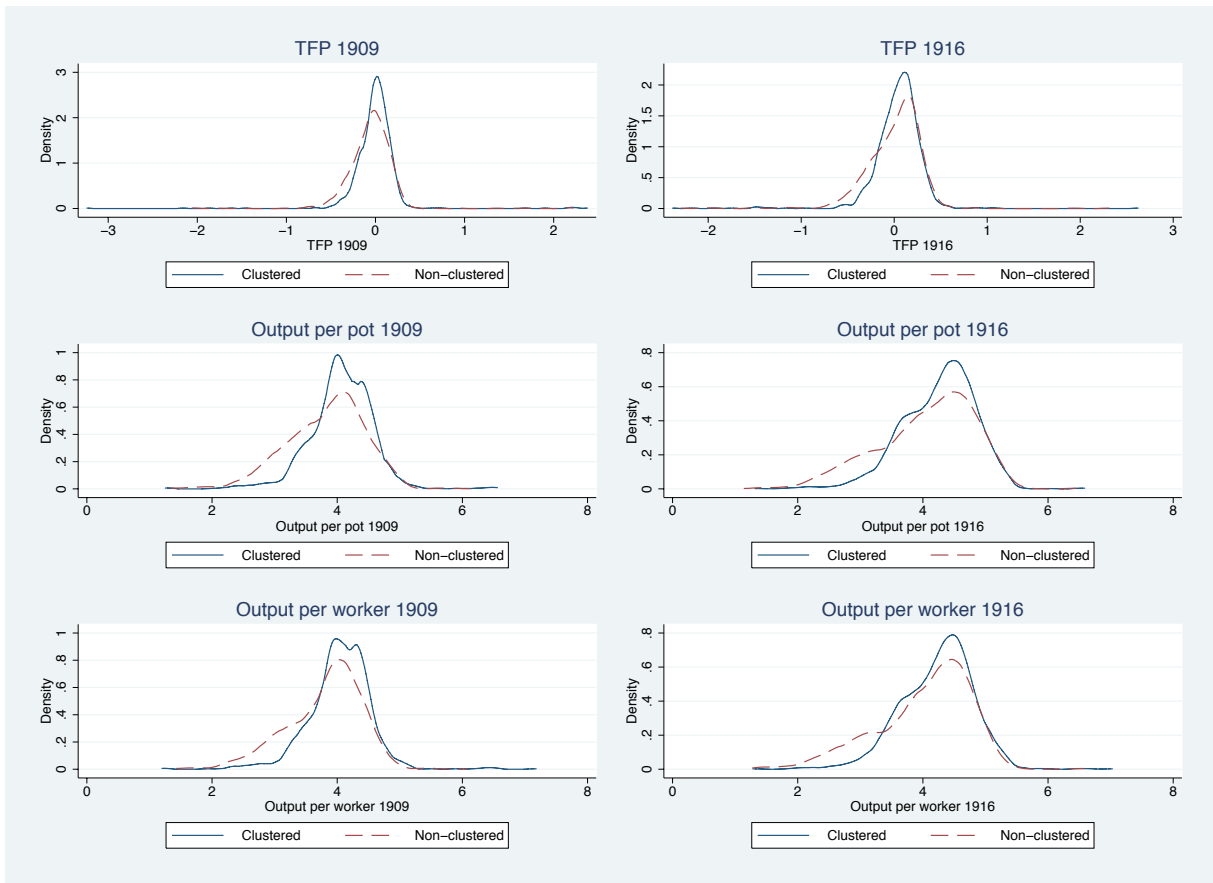Figure 2: Four considerable cases of cluster effects

Figure 3: Kernel densities of plant-level productivity

A Mathematical Appendix (not for publication)

A.1 Derivation of $\frac{d\hat{h}}{ds}$ (eq.(9))

The implicit function theorem implies that

$$\frac{d\hat{h}}{ds} = \frac{-(\partial V^e/\partial s)}{\partial V^e/\partial \hat{h}}.$$

$-(\partial V^e/\partial s) = 1$ is immediate from eq.(8). The denominator is

$$\frac{\partial V^e}{\partial \hat{h}} = \left[\frac{\left(\hat{h} - \hat{h} + \sqrt{wf} \right)^2}{w} - f \right] g(\hat{h}) + 2 \int_0^{\hat{h}} \left[\frac{\hat{h} - h + \sqrt{wf}}{w} \right] g(h) dh$$

$$= 2 \int_0^{\hat{h}} \left[\frac{\hat{h} - h + \sqrt{wf}}{w} \right] g(h) dh > 0.$$

Therefore,

$$\frac{d\hat{h}}{ds} = \frac{-(\partial V^e/\partial s)}{\partial V^e/\partial \hat{h}} = \frac{w}{2 \int_0^{\hat{h}} \left(\hat{h} - h + \sqrt{wf} \right) g(h) dh} > 0.$$

A.2 Derivation of N_e (eq.(13))

Total production in a region is

$$Q = N_e \int_0^{\hat{h}} q_i^* g(h) dh.$$

Inserting q_i^* from eq.(4) yields

$$Q = N_e \int_0^{\hat{h}} q_i^* g(h) dh$$

$$= N_e \int_0^{\hat{h}} \frac{p - h - wE(Q)}{w} g(h) dh$$

$$= N_e \int_0^{\hat{h}} \frac{p - h}{w} g(h) dh - N_e E(Q) G(\hat{h}).$$

Since $Q = E(Q)$ in the equilibrium, we can write Q as a function of N_e and $\hat{h}$:

$$Q(N_e, \hat{h}) = \frac{N_e}{1 + N_e G(\hat{h})} \int_0^{\hat{h}} \frac{p - h}{w} g(h) dh.$$

Further, by rearranging eq.(6) ($\hat{h} = p - wQ - \sqrt{wf}$), we get another expression of

$$Q = \frac{p - \hat{h} - \sqrt{wf}}{w}.$$

As such, we have

$$\frac{N_e}{1 + N_e G(\hat{h})} \int_0^{\hat{h}} \frac{p - h}{w} g(h) dh = \frac{p - \hat{h} - \sqrt{wf}}{w}$$

$$\Rightarrow \; N_e \int_0^{\hat{h}} (p - h) g(h) dh = [1 + N_e G(\hat{h})](p - \hat{h} - \sqrt{wf})$$

$$\Rightarrow \; N_e \left[\int_0^{\hat{h}} (p - h) g(h) dh - (p - \hat{h} - \sqrt{wf}) G(\hat{h}) \right] = p - \hat{h} - \sqrt{wf}$$

$$\Rightarrow \; N_e \left[\int_0^{\hat{h}} (p - h) g(h) dh - \int_0^{\hat{h}} (p - \hat{h} - \sqrt{wf}) g(h) dh \right] = p - \hat{h} - \sqrt{wf}$$

$$\Rightarrow \; N_e \left[\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh \right] = p - \hat{h} - \sqrt{wf},$$

and hence

$$N_e = \frac{p - \hat{h} - \sqrt{wf}}{\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh}.$$

A.3   Derivation of $\frac{\partial N_e}{\partial \hat{h}}$

$$\frac{\partial N_e}{\partial \hat{h}} = \frac{-\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh - (p - \hat{h} - \sqrt{wf}) \left[\sqrt{wf} g(\hat{h}) + \int_0^{\hat{h}} g(h) dh \right]}{\left[\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh \right]^2}$$

$$= \frac{-\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh - \int_0^{\hat{h}} (p - \hat{h} - \sqrt{wf}) g(h) dh - (p - \hat{h} - \sqrt{wf}) \sqrt{wf} g(\hat{h})}{\left[\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh \right]^2}$$

$$= \frac{-\int_0^{\hat{h}} (p - h) g(h) dh - (p - \hat{h} - \sqrt{wf}) \sqrt{wf} g(\hat{h})}{\left[\int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf}) g(h) dh \right]^2} < 0.$$

A.4   Derivation of dN_p/ds

Since $N_p = N_e G(\hat{h})$,

$$\frac{dN_p}{ds} = \frac{dN_e}{d\hat{h}} \frac{d\hat{h}}{ds} G(\hat{h}) + N_e g(\hat{h}) \frac{d\hat{h}}{ds} = \left[\frac{dN_e}{d\hat{h}} G(\hat{h}) + N_e g(\hat{h}) \right] \frac{d\hat{h}}{ds}.$$

By using eqs.(13) and (14), and letting

$$\xi \equiv \int_0^{\hat{h}} (\hat{h} - h + \sqrt{wf})g(h)dh,$$

the term in the brackets is

$$\frac{dN_e}{d\hat{h}}G(\hat{h}) + N_e g(\hat{h}) = \frac{-G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh - (p - \hat{h} - \sqrt{wf})\sqrt{wf}g(\hat{h})G(\hat{h})}{\left[\int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]^2} + \frac{(p - \hat{h} - \sqrt{wf})g(\hat{h})}{\int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh}$$

$$= \frac{-G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh - (p - \hat{h} - \sqrt{wf})\sqrt{wf}g(\hat{h})G(\hat{h}) + (p - \hat{h} - \sqrt{wf})g(\hat{h})\xi}{\left[\int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]^2}$$

$$= \frac{-G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh - (p - \hat{h} - \sqrt{wf})g(\hat{h})\left[\sqrt{wf}G(\hat{h}) - \xi\right]}{\left[\int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]^2}$$

$$= \frac{-G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh - (p - \hat{h} - \sqrt{wf})g(\hat{h})\left[\sqrt{wf}G(\hat{h}) - \int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]}{\left[\int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]^2}.$$

Let J denote the numerator:

$$J = -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh - (p - \hat{h} - \sqrt{wf})g(\hat{h})\left[\sqrt{wf}G(\hat{h}) - \int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]$$

$$= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p - \hat{h} - \sqrt{wf})g(\hat{h})\int_0^{\hat{h}}\left(\hat{h} - h\right)g(h)dh$$

$$= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p - \hat{h} - \sqrt{wf})g(\hat{h})\hat{h}G(\hat{h}) - (p - \hat{h} - \sqrt{wf})g(\hat{h})\int_0^{\hat{h}}hg(h)dh$$

$$= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p - \hat{h} - \sqrt{wf})g(\hat{h})\hat{h}G(\hat{h}) - (p - \hat{h} - \sqrt{wf})g(\hat{h})\left[\hat{h}G(\hat{h}) - \int_0^{\hat{h}}G(h)dh\right]$$

$$= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p - \hat{h} - \sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(c)dh$$

$$= -pG(\hat{h})^2 + G(\hat{h})\int_0^{\hat{h}}hg(h)dh + (p - \hat{h} - \sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(h)dh$$

$$= -pG(\hat{h})^2 + G(\hat{h})\left(\hat{h}G(\hat{h}) - \int_0^{\hat{h}}G(h)dh\right) + (p - \hat{h} - \sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(h)dh$$

$$= -pG(\hat{h})^2 + \hat{h}G(\hat{h})^2 - G(\hat{h})\int_0^{\hat{h}}G(h)dh + (p - \hat{h} - \sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(h)dh$$

$$= -(p - \hat{h})G(\hat{h})^2 - \left[G(\hat{h}) + \sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}}G(h)dh + (p - \hat{h})g(\hat{h})\int_0^{\hat{h}}G(h)dh$$

$$= -(p - \hat{h})\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}}G(h)dh\right] - \left[G(\hat{h}) + \sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}}G(h)dh.$$

Therefore, we have

$$\frac{dN_p}{ds} = \left[\frac{dN_e}{d\hat{h}} G(\hat{h}) + N_e g(\hat{h})\right] \frac{d\hat{h}}{ds}$$

$$= \frac{-(p - \hat{h})\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}} G(h)dh\right] - \left[G(\hat{h}) + \sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}} G(h)dh}{\left[\int_0^{\hat{h}}(\hat{h} - h + \sqrt{wf})g(h)dh\right]^2} \frac{d\hat{h}}{ds} < 0. \quad (38)$$

This is negative because $\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}} G(h)dh\right]$ is positive, since $G(\hat{h}) \geq G(h)$ for all $h \in [0, \hat{h}]$ and $G(\hat{h}) > g(\hat{h})$.