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Yutaka Arimoto, Kentaro Nakajima, and Tetsuji Okazaki

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HITOTSUBASHI UNIVERSITY

Research Project **PRIMCED**
Institute of Economic Research
Hitotsubashi University
2-1 Naka, Kunitatchi Tokyo, 186-8601 Japan
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Productivity Improvement in the Specialized Industrial Clusters: The Case of the Japanese Silk-Reeling Industry*

Yutaka Arimoto† Kentaro Nakajima‡ Tetsuji Okazaki§

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Abstract

We examine two sources of productivity improvement in the 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 in 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
JEL classification: R12; O18; L10

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 economic literature. For example, labor density is known to have a positive effect on productivity in the United States (Ciccone and Hall, 1996) and in 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 review of the existing studies on

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†Institute of Economic Research, Hitotsubashi University, 2-1 Naka, Kunitachi, Tokyo 186-8603, Japan. Tel: +81-42-580-8346. E-mail: `arimotoy@ier.hit-u.ac.jp`

‡Faculty of Economics, Tohoku University, 27-1 Kawauchi Aobaku, Sendai 980-8576, Japan.Tel/Fax: +81-22-795-6305. E-mail: `nakajima.kentaro@gmail.com`

§Faculty of Economics, University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan. E-mail: `okazaki@e.u-tokyo.ac.jp`

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. However, recent theoretical developments in spatial economics with heterogeneous firms have suggested on another factor that could improve productivity: plant-selection. That is, in clusters, the 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. This effect was initially proposed in the field of international trade and later introduced into economic geography (Melitz, 2003; Melitz and Ottaviano, 2008; Behrens et al., 2009; Baldwin and Okubo, 2006). 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 were less likely to survive under increased competition. In the field of international trade, Corcos et al. (2010) have identified the selection effect induced by trade policy.

Which of these two effects, agglomeration or selection, is more important to the improvement of plant-level productivity in specialized industrial clusters? Recently, a pioneering work by Combes et al. (2009) measured the magnitudes of the two effects and found that agglomeration effects could mostly explain higher productivity in French *metropolitan areas*. However, can productivity improvement in *specialized* industrial clusters also be explained by agglomeration effects? It should be noted that the agglomeration effects in turn can be classified into two subcategories depending on the sources of the externalities: industry specific externalities and externalities through various industries. Glaeser et al. (1992) termed the former category Marshall-Arrow-Romer (MAR) externalities, and the latter category is termed Jacobs externalities (Jacobs, 1969). Because Combes et al. (2009) focused on the urban metropolitan employment areas and applied labor density in all of the sectors as the source of externalities, the agglomeration effect they detected was the mixed effect of both MAR and Jacobs externalities. In contrast, specialized industrial clusters of plants within the *same* industry, such as the high-tech cluster in the Silicon Valley (U.S.) or automobile clusters in Detroit (U.S.) and Toyota (Japan), are mainly representative of the MAR type of agglomeration economies.

The purpose of this paper is to identify the source of productivity improvement effects in specialized industrial clusters. Particularly, we focus on the Japanese silk-reeling industry during the period from 1908 to 1915. In this period, Japan became the largest exporter of raw silk, competing with Italy and China (Ishii 1972; Nakabayashi 2003). The Japanese silk-reeling industry then possessed a number of characteristics well-suited to the purposes of this work. First, clusters existed at the time: the Japanese silk-reeling industry formed huge clusters in the central and northeastern regions of Japan. These regions were mostly mountainous, peripheral areas with few plants other than the silk-reeling ones, implying that interactions between industries were limited. Second, besides the clustered plants, there existed numerous silk-reeling plants across Japan, allowing us to take regional variations into account in the empirical analysis. Third, the silk-reeling industry produced a single homogenous product— raw silk— with similar equipment and technologies using a simple production process. Moreover, our dataset includes the information regarding the physical output and not the value of raw-silk. These features allow us to estimate plant-level *physical* productivities more accurately than value-based productivities, which suffer from price and quality differences.

To distinguish between agglomeration and selection effects empirically, we follow the approach proposed by Combes et al. (2009), which examines the distribution of plant-level productivity. Combes et al. (2009) have developed a framework that nests selection and agglomeration by extending the model presented in Melitz and Ottaviano (2008) and introducing the agglomeration economies as done in Fujita and Ogawa (1982) and Lucas and Rossi-Hansberg (2002). The model provides empirical predictions that enable a distinction to be made between the two effects by examining the characteristics of 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 at a higher productivity level by expelling less productive plants from the market. Combes et al. (2009) have found that productivity differences among French metropolitan areas are explained mostly by agglomeration. While the agglomeration effect found in Combes et al. (2009) can be considered as a mixed effect of MAR and Jacobs externalities, we study MAR externalities by focusing on specialized industrial clusters.

We also contribute to the literature by developing a model of agglomeration and selection through a competition among plants over input procurement, rather than over output sales. The literature mostly relied on monopolistic competition in the output market to explain agglomeration or selection. However, the silk-reeling plants in our study were price-takers, that is, the price of raw silk was determined in the international market. Instead of competing in the output market, the plants aggressively competed over input procurement (cocoon) and labor forces (female workers). 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 the regional difference of entry cost can generate industrial clusters endogenously through selection. We then introduce an agglomeration economy into the model as done in Combes et al. (2009), and although our method differs, we obtain an identical result with respect to the density effects in the distributions of plant-level productivity.

Besides distinguishing agglomeration and selection effects by focusing on productivity distribution, we also investigate when productivity improvements occur. If the agglomeration effect is in place, we should observe a higher productivity growth of plants in clusters *after* they start operation. By focusing on the productivity growth rate, we can distinguish the two effects from a different perspective.

Our main empirical finding is that selection improves productivity in clusters in the Japanese silk-reeling industry. We first confirmed that plants in clusters had relatively higher productivity on average. Then, we applied the estimation method of Combes et al. (2009) and confirmed that silk-reeling clusters had a larger selection effect that do non-clustered silk-reeling plants, but not karger agglomeration (and dilation) effects. We then examined the productivity distributions via a summary statistics approach and by applying prefectural variations and found that the width of the distribution for clusters was narrower and more severely left truncated than that for non-clusters, a result that suggests selection. However, we found no clear evidence that confirmed the right-shift of the distribution for cluster. This evidence ais consistent with plant-selection but not the agglomeration effect. We also examined whether the productivity growth rate was higher in clusters, as implied by the agglomeration effect, and found that the extent of agglomeration did not affect the productivity growth rate. These results strongly suggest that productivity improvement took place through selection before operation rather than through agglomeration economies after entry. Contrary to the results of Combes et al. (2009), which emphasize the role of the agglomeration effect in 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 provides our main results. Section 6 discusses the robustness of our findings by using a summary statistics approach and focusing on the timing of the cluster effects. Finally, Section 7 concludes the paper.

2 Overview of Japanese silk-reeling industry

The silk-reeling industry was one of the major industries in pre-war Japan[1]. For example, in 1908, this industry employed 24.4% of the total factory workers in Japan,[2] 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. 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 for the major plant 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 by 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 United States. 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

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

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

and China. With 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.[3] 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.

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 management productivity and survivability of the silk-reeling plants essentially depended on the production and management the two basic inputs, cocoons and labor. Hence, especially in clusters, fierce competition and congestion characterized the markets of these inputs.

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 of 1908, the price of spring cocoons per koku (180.39 liter) 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 reduction, or they 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 of the workers were young women, who were primarily recruited from surrounding areas so that they could easily commute from their homes. However, the enormous labor demand in clusters forced plants to hire from remote areas and, therefore, pay a fixed cost for boarding, food, and even education, consequently increasing the 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 factories was prevalent in clusters, and the practice gradually proliferated throughout the country (Kambayashi, 2001; Nakabayashi, 2003; Tojo, 1990). Furthermore, Eguchi and Hidaka eds.(1937) observed that land prices rose sharply in Suwa because of the expansion of silk-reeling plants and an increase of workers (p.787).

In the silk-reeling industry, the performance-based wage system was widely used to provide workers with incentives to improve both productivity and product quality by the early twentieth century. A distinctive characteristic of this system was that the wage of each worker was determined on the basis of her relative performance compared to the average of all the workers in the same plant. The performance was evaluated by several measures including labor productivity, cocoon productivity and product quality, which were strategic for the competitiveness and prof-

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

itability of the plant. Nakabayashi (2003) reports the basic statistics of the worker-level wage at a plant in Suwa from the late nineteenth century to the early twentieth century. For example, sample mean, median, variance, and maximum and minimum values of wage per day in 1908 were 0.24, 0.25, 1.09, 0.62, and 0.018 yen, respectively (p.259). However, 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 facts imply that an unskilled female silk-reeling worker earned approximately the same amount as did an average agricultural worker, but highly skilled silk-reeling workers in clusters could earn higher wages depending on their productivity. It is notable that this wage system was first devised by Nakayama Co. in Suwa to diffuse within the district, and then was transmitted to other districts (Ishii, 1972, pp.291–307; Nakabayshi, 2003, pp.241–277). This diffusion process can be regarded as a case of rapid knowledge spillover in an industrial cluster.

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. 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 were 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 the plant side heterogeneity (i.e., the capability of the machines, management and incentive systems, training, etc.) to explain the plant-level productivity difference.[4]

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: higher h_i implies greater labor requirement and, hence, lower productivity. We normalize the cost of unit effective labor to unity.

The 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 purchase (cocoons).

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

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 payment, a plant draws the 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 the level of production q_i given one's own 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

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

so 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 profits, 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:

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

The 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 varied across regions owing to the first nature or opportunity costs of starting-up a new business. We show that a region with lower s imposes fiercer competition (i.e., lower cutoff unit labor requirement) but retains large number 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 $h_i \geq \hat{h}$. 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 $\{p, w, f\}$:

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

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, 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, *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 magnitudes 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*)**.** 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 lower s.

3.3 Agglomeration effects and productivity distributions

Following Combes et al. (2009), 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 $a'' < 0$. The improved productivity of workers should be compensated for by higher wages if the labor market is perfect.[5] However, 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 $A \equiv \ln[a(N_p)]$.

[5] Indeed, the performance-based wage system was prevalent in the silk-reeling clusters (Nakabayashi, 2003).

As discussed above, each plants' 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 slides the distribution rightward while maintaining its form.

Implication 3 (*Agglomeration effects*)**.** 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. (2009), although the method is different. Thus, we can apply their novel empirical strategy. To do so, we introduce additional notations.

Let $F_i(\phi)$ be the corresponding cumulative density function of $f(\phi)$. The proportion of firms that cannot survive in city i is defined as $S_i \equiv 1 - G(\bar{h}_i)$. The underlying cumulative density function of log productivities in all cities when there is no selection and no agglomeration effects ($\bar{h}_i \to \infty$ and $A_i = 0$, $\forall i$) can be defined as follows:

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

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

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}(\phi - A_i) - S_i}{1 - S_i}\right\}. \tag{20}$$

Because the results of productivity distribution from our model are identical to those of Combes et al. (2009), we can consider the following four polar cases with respect to the channels of productivity improvement, as did the Combes et al. (2009) model. For simplicity, we consider two regions $r = c$ (cluster) and $r = n$ (non-cluster).

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 cluster: $\hat{\phi_c} > \hat{\phi_n}$. This case is represented in Figure 2(a). The solid line represents the log productivity distribution in the cluster, while the dashed line represents that in the non-cluster. The log productivity distribution in the cluster is left truncated.

Case 2 (*Only the agglomeration effect matters*)**.** In this case, only the agglomeration effect improves the plants' productivity. To eliminate the selection effects, we impose $s_c = s_n = s$, 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 cluster and non-cluster, 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, the log productivity simply slides 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 the cluster and non-cluster, $s_c < s_n$, and the concentration of workers improves their productivity, $a' > 0$ and $a'' < 0$. Thus, both left truncations by selection and right slide by agglomeration occur in the cluster. 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, 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 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 of lower percentile points rather than higher percentile points of 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 effects are in place, both the higher and lower percentile points of the distribution should increase.

The above discussions are summarized in Table 1.

= Table 1 =

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

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

4 Empirical strategy

As we have shown in the previous chapter, our theoretical results in plant-level log of productivity distribution is identical to the Combes et al. (2009) results, although the theoretical set up is different. Thus, we can apply their novel empirical strategy for quantitatively measuring each density effect, selection and agglomeration. This section briefly describes the empirical strategy. For more detail, please see Combes et al. (2009).

Because the underlying baseline distribution function $\tilde{F}(\phi)$ is unknown, we cannot estimate exact values of A_i, D_i, and S_i for each region, but by comparing the distributions of log productivities across clusters and non-clusters, we can estimate the relative strength of those parameters.

Before describing the estimation strategy, we address the concern that the impact of the agglomeration effect varies by plant. For example, highly productive plants would tend to more rapidly benefit from agglomeration economies. To include this effect, we redefine the agglomeration economies by introducing heterogeneity of benefiting from agglomeration economy. By

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

introducing heterogeneity, the agglomeration economy $a(N_p)$ can be rewritten as $a(N_p)h^{-(D_i-1)}$, where $D_i \equiv \ln[d(N_p)]$, $d(0) = 1$, $d' > 0$, and $d'' < 0$. Then, the log productivity of a firm with unit cost h in region i is denoted by

$$\phi_i(h) = \ln\left(\frac{q_i(h)}{l_i(h)}\right) = A_i - D_i \ln(h). \tag{21}$$

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

$$F_i(\phi) = \max\left\{0, \frac{\tilde{F}(\frac{\phi-A_i}{D_i}) - S_i}{1 - S_i}\right\}. \tag{22}$$

This implies that agglomeration effects not only slides the distribution to the right by A_i, but also dilates the distribution by D_i; however, selection drops a share of S_i of entrants. It is worth noting that the heterogeneity also allows for the case that low productivity plants benefit more than do high productivity plants from the agglomeration economy. In this case, D_i takes a negative value.

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

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

By introducing these parameters, we can express the 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

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

Then, following the approach of Combes et al. (2009), we obtain estimators of A, S, and D.[7]

This approach do not separately estimate A_r, D_r, and S_r in each region, but instead estimates the relative strength of each variable that $A = A_c - DA_n$, $D = D_c/D_n$, and $S = (S_c - S_n)/(1 - S_n)$. That is, we estimate the relative strength of selection and agglomeration in the specialized clusters compared to the non-clusters. Intuitively, if we obtain $A > 0$, there is larger right shift in the clusters than in the non-clusters. Dilation by agglomeration is captured by D. If we

[7]For the detail of the estimation method, see Combes et al. (2009).

obtain $D > 1$, clusters have larger dilation of the distribution than the non-clusters. Selection is captured by S. If we obtain $S > 0$, there is more elimination of entrants in the clusters than in the non-clusters.

5 Data and the measure of plant-level productivity

5.1 Data

We compiled the data of the silk-reeling industry census data, *Zenkoku Seishi Kojo Chosa*, for the two data points 1908 and 1915. The data include plant-level information of plant name, location, year of foundation, number of pots, number of workers, number of business days per year, type of powers, 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 the 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 number of plants per km^2. Information regarding the regional area at the prefecture or county level was obtained from the GIS (Geographical Information System) 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 Total Factor Productivity (TFP) as the primary measure of plant-level productivity. In order to estimate TFP, we specify the firm-level production function as follows:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \delta Z_{it} + \omega_{it} + \epsilon_{it}, \tag{28}$$

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 the plant i's observable characteristics, ω_{it} and ϵ_i are the productivity terms that are unobservable to the econometrician. While ϵ_{it} is also unobserved by firms before they make their input decisions, ω_{it} is observable. We assume $\omega_{it} = \omega_i$, that is, the observable productivity for plants does not change through the study period (7 years). As the 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 the fixed effect model.[9]

The estimation results are reported in Table 2.

= Table 2 =

[8] The data is 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

[9] Alternative way of estimating TFP, 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 dataset that seven years apart each period makes difficult for application of the method of Levinsohn and Petrin (2003).

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 the output per pot (capital productivity) and output per worker (labor productivity) as alternative measures of plant-level productivity. In the Japanese silk-reeling industry, the 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 effects and selection effects.

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). 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*.

First, we estimate the kernel density functions[10] of the plant-level productivity for 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 the density of the non-clustered prefectures. In every figure, the estimated density in the lower tail of the distribution is lower for the clustered prefectures than for the non-clustered prefectures, while the density in the higher tail of the 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 the clustered prefectures slides 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 =

Panel A represents the statistics for 1908 and Panel B represents those for 1915. The mean productivities are significantly higher in the cluster for every productivity measure and period, indicating that plants located in the industrial clusters were indeed more productive than those in the 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 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 lower and higher tails of the distribution should shift to the right.

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

Table 3 reveals that the interquartile range of the distribution in the clustered prefectures is smaller than that in the 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 the cluster is –0.21, the same percentile in the non-cluster is –0.33, and the difference is 0.1. However, in higher tails, percentiles in both the cluster and non-cluster are quite similar (the 90th percentile in both cluster and non-cluster 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 the 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 rightward shift of the distribution and dilations in the silk-reeling clusters compared to the non-clusters. However, the point estimate of S is positive and statistically different from zero, suggesting that there is more elimination of the distributions in the clusters compared to the non-clusters. These results strongly suggest that there are larger selection effects and no larger agglomeration (and dilation) effects in the silk-reeling clusters than in the non-clusters. That is, the higher plant-level productivity in the silk reeling clusters can be explained only by the selection effects. This result is the exact opposite of the result of Combes et al. (2009) that focuses on the urban metropolitan area.

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: that the higher plant-level productivity in the silk reeling clusters can be explained only by the selection effects.

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

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 productivity of a silk-reeling plant in prewar Japan was principally determined by machines and the mode of labor management, and that a substantial innovation occurred in the latter in the 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, 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 the 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. (2009), that there was larger selection but no agglomeration in the silk-reeling cluster than in the non-clusters. This method is theoretically and statistically rigorous, but it cannot fully utilize regional variations because the method compares two distributions of 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 the 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 productivity distribution. We index each prefecture by p and estimate the following equation:

$$\mathrm{IQR}_{pt} = \alpha + \beta \ln(\mathrm{D}_{pt}) + \mathrm{year}_t + \varepsilon_{pt} \tag{29}$$

where IQR_{pt} refers to the interquartile range of 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 the 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.

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

$$\mathrm{P}^u_{pt} = \alpha + \beta \ln(\mathrm{D}_{pt}) + \mathrm{year}_t + \varepsilon_{pt}, \tag{30}$$

where P^u_{pt} 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.

= 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, 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 effect 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 of 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 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 the silk reeling clusters can be explained only by the selection effects.

7.2 Productivity growth after operation

According to the results obtained in the previous sections, there is no agglomeration effects 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 operation by comparing the productivity growth rates between plants in clusters and non-clusters.

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

= Table 7 =

Younger plants might tend to learn and improve their productivity 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 the cluster and non-cluster. Rather, the average growth rate in the cluster is smaller than in the non-cluster. We test the difference of average productivity growth rate between the cluster and non-cluster using a t-test, but the null hypothesis that the mean difference of growth rate between the cluster and non-cluster 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 the cluster is again lower than in the non-cluster, and we also cannot reject the null hypothesis that the mean difference of the growth rate between the cluster and non-cluster 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,

$$\text{GrowthRate}_{icp} = \alpha + \beta D_{cp} + \delta Z_{icp} + \gamma \text{Productivity1908}_{icp} + \text{pref}_p + \varepsilon_{icp}, \qquad (31)$$

where GrowthRate_{icp} is the productivity growth rate of plant i located in county c in prefecture p from 1908 to 1915, D_{cp} is the plant density at county level, and Z_{icp} is the vector of plant-level

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

control variables (number of pots, number of workers, age, steam power dummy, water power dummy). To control low-productivity plants' faster learning and growth (catch-up), we include the initial productivity in 1908. Table 8 reports the results.

= Table 8 =

Again, we use three measures for the plant-level productivity. Column (1) is 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 productivity 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 restricted samples of *start-up* plants (columns 7–12). The coefficient of initial productivity in 1908 is significantly negative but the 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 the silk reeling clusters can be explained only by the selection effects.

8 Concluding remarks

In this paper, we attempted to distinguish the two channels through which industrial clusters improved plant-level productivity, focusing on the Japanese silk-reeling industry during the period from 1908 to 1915. On the basis of nested model of selection and agglomeration, we considered the agglomeration effect, which improves the productivities of all the plants in a region and the plant-selection effect, which raised the average regional productivity by expelling less productive plants through intense competition.

Using plant-level data, we distinguished the channels of productivity improvement on the basis of the estimation method proposed by Combes et al. (2009). We found on one hand that there was left-truncation of the log of the productivity distribution in the clusters relative to the non-clusters, and on the other hand, that there was no rightward 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. It 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 implied 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 the low-productivity plants, and consequently, only relatively more productive plants survived.

Our finding is contrary to that of Combes et al. (2009), who found that productivity differences between French metropolitan areas are explained mostly by agglomeration. This difference suggests the density effect is different in the metropolitan areas and specialized industrial clusters. That is, agglomeration economies in the metropolitan areas are larger than those in specialized clusters, whereas more severe competition and selection occur in the specialized clusters than in the metropolitan areas. This finding suggests the importance of competition in improving productivity in specialized industrial clusters.

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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 OLS with plant fixed effects.
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: 1909								
Measure of Productivity	Cluster vs. Non-cluster	Mean	Interquartile range	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
TFP								
	All	-0.03	0.22	-0.27	-0.14	-0.01	0.09	0.18
	Cluster	-0.002	0.19	-0.21	-0.09	0.01	0.1	0.18
	Non-cluster	-0.05	0.26	-0.33	-0.18	-0.04	0.08	0.18
		(4.288)						
Output per pot								
	All	3.95	0.71	3.2	3.62	4.03	4.33	4.57
	Cluster	4.07	0.57	3.44	3.82	4.07	4.39	4.57
	Non-cluster	3.82	0.82	2.96	3.43	3.92	4.25	4.56
		(10.031)						
Output per Worker								
	All	3.92	0.66	3.16	3.63	4.00	4.29	4.51
	Cluster	4.04	0.55	3.44	3.81	4.06	4.35	4.54
	Non-cluster	3.8	0.79	2.96	3.44	3.93	4.23	4.47
		(10.113)						
Panel B: 1916								
Measure of Productivity	Cluster vs. Non-cluster	Mean	Interquartile range	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
TFP								
	All	0.03	0.28	-0.27	-0.1	0.06	0.18	0.29
	Cluster	0.04	0.24	-0.2	-0.07	0.07	0.18	0.28
	Non-cluster	0.004	0.34	-0.34	-0.15	0.05	0.19	0.29
		(3.218)						
Output per pot								
	All	4.17	0.87	3.22	3.78	4.29	4.65	4.93
	Cluster	4.26	0.79	3.53	3.87	4.34	4.66	4.93
	Non-cluster	4.05	1.04	2.93	3.59	4.19	4.63	4.94
		(7.180)						
Output per Worker								
	All	4.14	0.83	3.24	3.76	4.26	4.6	4.86
	Cluster	4.23	0.77	3.49	3.85	4.31	4.61	4.88
	Non-cluster	4.02	0.94	2.91	3.62	4.18	4.56	4.83
		(7.581)						

Note: TFP is estimated by the fixed effect OLS. The t-values of the t-test are presented in parentheses. The null hypotheses of the t-test is that the average productivities is not different 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	1909	1916	1909	1916	1909	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	4479	4479	4479	4479	4479	4479
R^2	0.649	0.576	0.338	0.439	0.509	0.457

Note: Estimation method proposed by Combes et al. (2009) is used. Standard errors are calculated by 100 bootstrapping iterations. TFP is estimated by the fixed effect OLS.
Bootstrapped standard errors in square parentheses.
**: for A and S significantly different from 0 at the 5 percent, for D significantly different from 1 at 5 percent.

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 effect OLS.
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 effect OLS.
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								
	All plants				Start-up plants			
Cluster vs. Non-cluster	Obs.	Mean	Standard deviation	t-value	Obs.	Mean	Standard deviation	t-value
Cluster	448	0.279	0.680		115	0.417	0.829	
Non-cluster	461	0.311	1.053		83	0.640	1.842	
All	909	0.295	0.888		198	0.510	1.350	
Difference (Cluster/Non-cluster)		0.032	0.059	0.535		0.223	0.194	1.148
Panel B. Measure of productivity: Output per pot								
	All plants				Start-up plants			
Cluster vs. Non-cluster	Obs.	Mean	Standard deviation	t-value	Obs.	Mean	Standard deviation	t-value
Cluster	448	0.471	1.011		115	0.676	1.219	
Non-cluster	461	0.494	1.568		83	1.053	3.014	
All	909	0.482	1.323		198	0.834	2.163	
Difference (Cluster/Non-cluster)		0.023	0.088	0.265		0.377	0.311	1.213
Panel C. Measure of productivity: Output per worker								
	All plants				Start-up plants			
Cluster vs. Non-cluster	Obs.	Mean	Standard deviation	t-value	Obs.	Mean	Standard deviation	t-value
Cluster	448	0.459	1.049		115	0.652	1.198	
Non-cluster	461	0.489	1.551		83	1.009	2.973	
All	909	0.474	1.327		198	0.802	2.131	
Difference (Cluster/Non-cluster)		0.030	0.088	0.337		0.357	0.307	1.164

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

Table 8: Estimation of growth effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent: Measure of productivity growth	TFP	TFP	Output per pot	Output per pot	Output per worker	Output per worker	TFP	TFP	Output per pot	Output per pot	Output per worker	Output per worker
Samples	All	All	All	All	All	All	Start-up	Start-up	Start-up	Start-up	Start-up	Start-up
ln(density)	-0.0148	-0.00968	-0.0138	-0.00820	0.0105	0.0165	-0.0589	-0.0911	-0.119	-0.165	-0.0949	-0.142
	(0.0284)	(0.0258)	(0.0410)	(0.0389)	(0.0391)	(0.0370)	(0.0919)	(0.0832)	(0.151)	(0.145)	(0.147)	(0.143)
ln(pot)	0.968**	0.877**	1.435**	0.300	-0.691**	-0.600**	2.393**	2.240**	3.552**	1.989**	0.322	0.346
	(0.393)	(0.377)	(0.585)	(0.634)	(0.259)	(0.229)	(0.438)	(0.432)	(0.605)	(0.950)	(0.436)	(0.439)
ln(worker)	-0.340	-0.274	-0.391	-0.130	1.751**	0.732**	-0.816	-0.806	-0.914	-0.657	2.063*	0.700
	(0.418)	(0.389)	(0.652)	(0.644)	(0.466)	(0.318)	(0.638)	(0.573)	(1.129)	(1.101)	(1.076)	(0.924)
ln(cocoon)	-0.552**	-0.511**	-0.962**	-0.0380	-1.009**	-0.0282	-1.472**	-1.297**	-2.535**	-1.144	-2.407**	-0.981
	(0.183)	(0.134)	(0.309)	(0.200)	(0.317)	(0.194)	(0.554)	(0.479)	(1.113)	(0.953)	(1.114)	(0.912)
ln(age)	-0.0783*	-0.133**	-0.128*	-0.121*	-0.132*	-0.124*	-0.182	-0.231	-0.437	-0.417	-0.498	-0.477
	(0.0415)	(0.0431)	(0.0714)	(0.0691)	(0.0721)	(0.0697)	(0.222)	(0.206)	(0.400)	(0.369)	(0.398)	(0.368)
Steam power dummy	0.0531	0.0933	0.0720	0.122	0.101	0.154	0.398	0.370	0.542	0.508	0.688*	0.653
	(0.0791)	(0.0753)	(0.114)	(0.111)	(0.120)	(0.115)	(0.262)	(0.257)	(0.418)	(0.413)	(0.407)	(0.403)
Water power dummy	-0.0316	-0.0732	-0.0214	-0.00273	0.00137	0.0212	0.701*	0.671**	1.395**	1.437**	1.421**	1.465**
	(0.0811)	(0.0764)	(0.128)	(0.127)	(0.131)	(0.129)	(0.355)	(0.339)	(0.692)	(0.687)	(0.692)	(0.687)
ln(TFP) in 1909		-1.100**						-1.114**				
		(0.203)						(0.483)				
ln(Output per pot) in 1909				-1.221**						-1.587*		
				(0.273)						(0.822)		
ln(Output per worker) in 1909						-1.296**						-1.627**
						(0.277)						(0.780)
Constant	1.370**	1.337**	2.567**	5.179**	2.781**	5.554**	2.870**	2.401**	5.301**	8.077**	5.433**	8.279**
	(0.420)	(0.350)	(0.737)	(1.142)	(0.757)	(1.175)	(1.225)	(1.114)	(2.489)	(3.413)	(2.499)	(3.382)
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 effect OLS. 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.

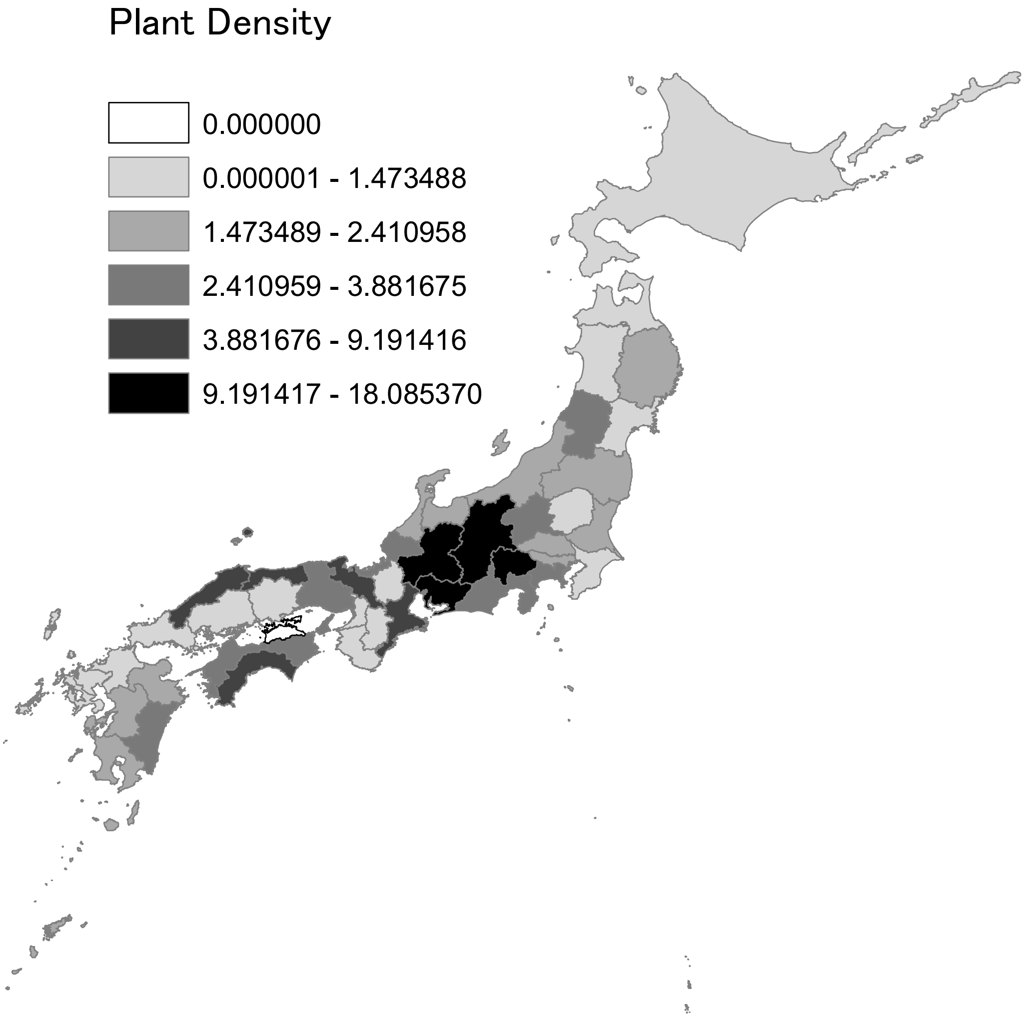
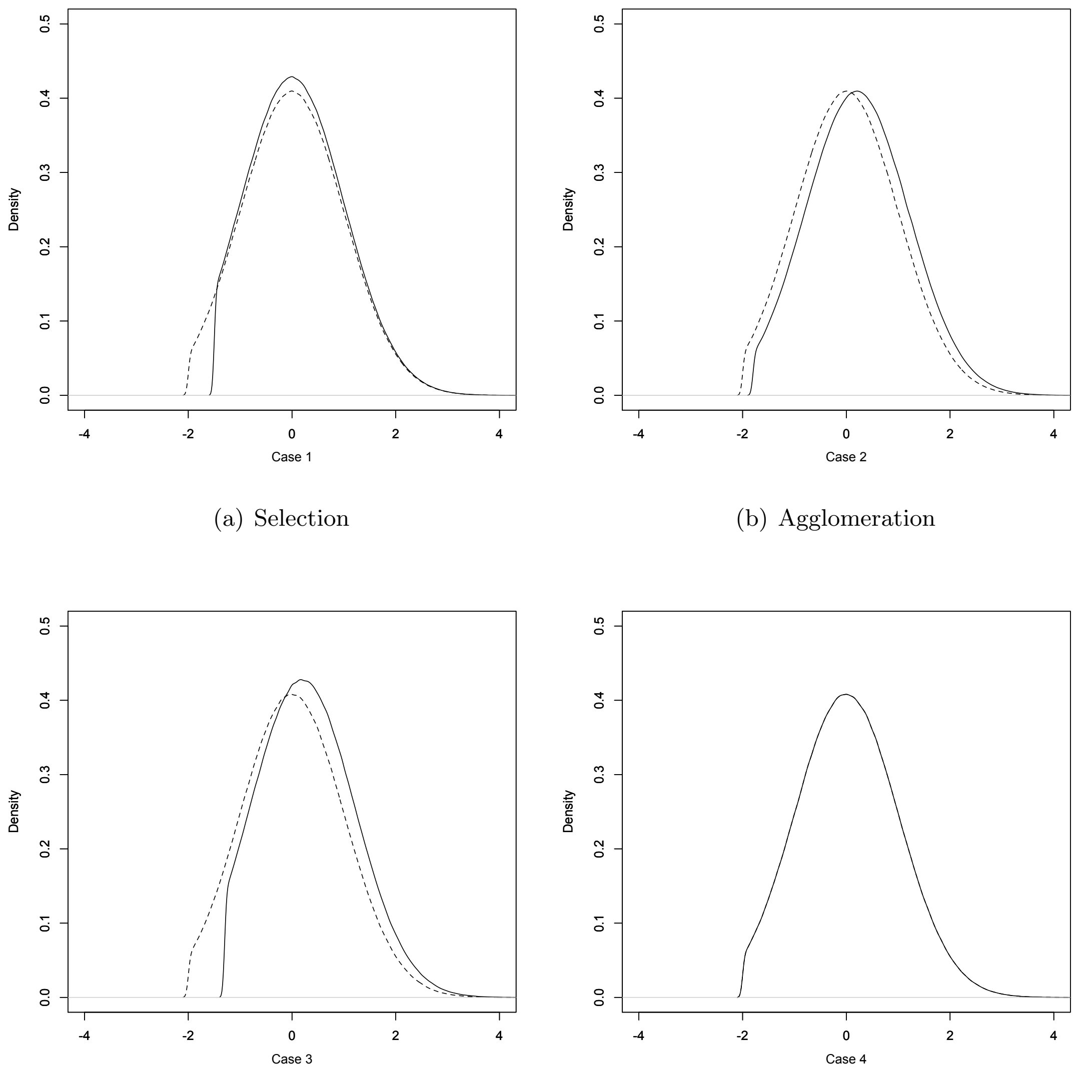


Figure 1: Map of Japan and the density of silk-reeling plants in 1909



(a) Selection (b) Agglomeration

(c) Both selection and agglomeration (d) Neither effect

Figure 2: Four considerable cases of cluster effects

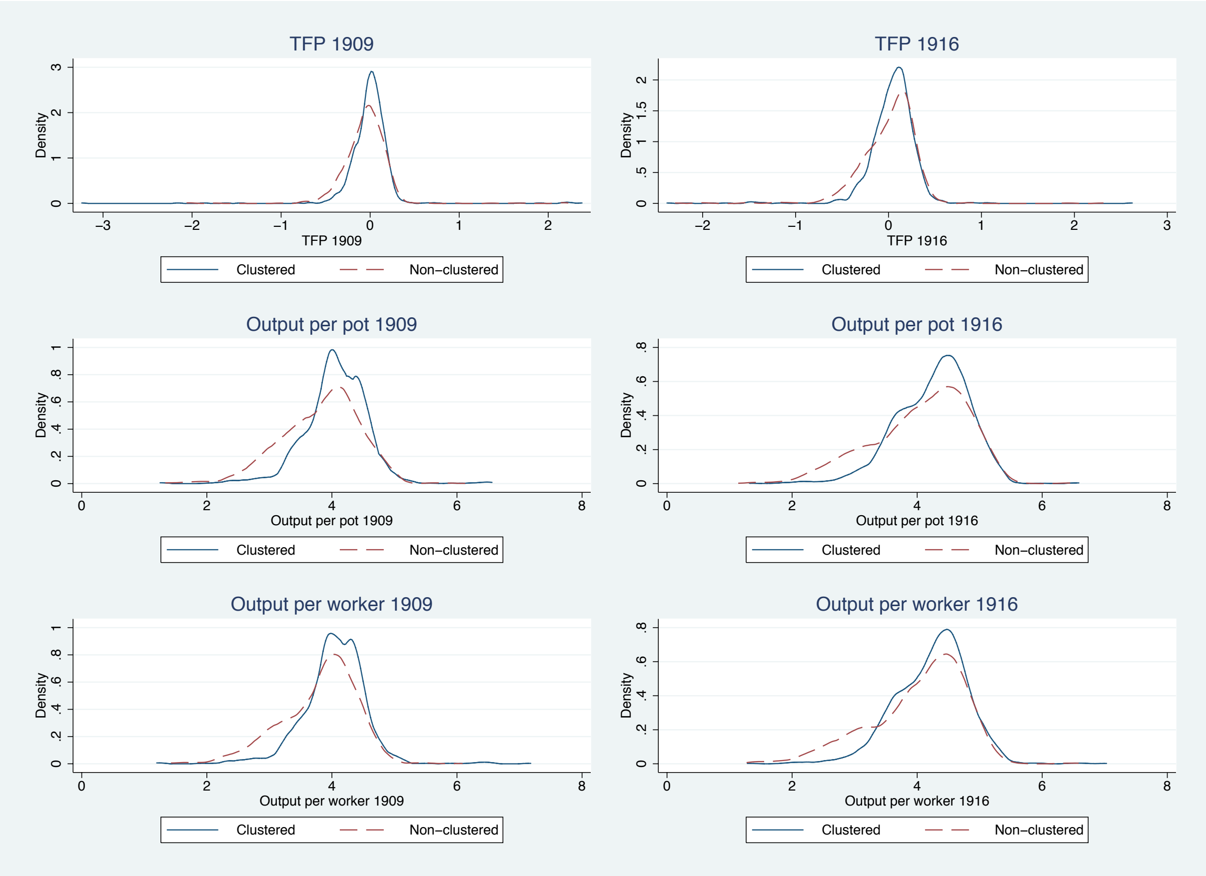


Figure 3: Kernel densities of plant-level productivity

A Mathematical Appendix (not for publication)

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

The implicit function theorem implies

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

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

$$\begin{aligned}\frac{\partial V^e}{\partial \hat{h}} &= \left[\frac{\left(\hat{h} - \hat{h} + \sqrt{wf}\right)^2}{w} - f\right] g(\hat{h}) + 2\int_0^{\hat{h}} \left[\frac{\hat{h} - h + \sqrt{wf}}{w}\right] g(h)dh \\ &= 2\int_0^{\hat{h}} \left[\frac{\hat{h} - h + \sqrt{wf}}{w}\right] g(h)dh > 0\end{aligned}$$

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 producution in a region is

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

Inserting q_i^* from (4) yields:

$$\begin{aligned}Q &= N_e \int_0^{\hat{h}} q_i^* g(h)dh \\ &= N_e \int_0^{\hat{h}} \frac{p - h - wE(Q)}{w} g(h)dh \\ &= N_e \int_0^{\hat{h}} \frac{p - h}{w} g(h)dh - N_e E(Q) G(\hat{h})\end{aligned}$$

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

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

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

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

So, we have

$$
\begin{aligned}
&\frac{N_e}{1+N_e G(\hat{h})}\int_0^{\hat{h}} \frac{p-h}{w} g(h)dh = \frac{p-\hat{h}-\sqrt{wf}}{w} \\
\Rightarrow\ & N_e \int_0^{\hat{h}} (p-h)g(h)dh = [1+N_e G(\hat{h})](p-\hat{h}-\sqrt{wf}) \\
\Rightarrow\ & N_e \left[\int_0^{\hat{h}} (p-h)g(h)dh - (p-\hat{h}-\sqrt{wf})G(\hat{h})\right] = p-\hat{h}-\sqrt{wf} \\
\Rightarrow\ & N_e \left[\int_0^{\hat{h}} (p-h)g(h)dh - \int_0^{\hat{h}} (p-\hat{h}-\sqrt{wf})g(h)dh\right] = p-\hat{h}-\sqrt{wf} \\
\Rightarrow\ & N_e \left[\int_0^{\hat{h}} (\hat{h}-h+\sqrt{wf})g(h)dh\right] = p-\hat{h}-\sqrt{wf}
\end{aligned}
$$

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 $\frac{\partial N_e}{\partial \hat{h}}$

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

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 (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

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

Let J denote the numerator.

$$
\begin{aligned}
J &= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh - (p-\hat{h}-\sqrt{wf})g(\hat{h})\left[\sqrt{wf}G(\hat{h}) - \int_0^{\hat{h}}(\hat{h}-h+\sqrt{wf})g(h)dh\right] \\
&= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p-\hat{h}-\sqrt{wf})g(\hat{h})\int_0^{\hat{h}}\left(\hat{h}-h\right)g(h)dh \\
&= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p-\hat{h}-\sqrt{wf})g(\hat{h})\hat{h}G(\hat{h}) - (p-\hat{h}-\sqrt{wf})g(\hat{h})\int_0^{\hat{h}}hg(h)dh \\
&= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p-\hat{h}-\sqrt{wf})g(\hat{h})\hat{h}G(\hat{h}) - (p-\hat{h}-\sqrt{wf})g(\hat{h})\left[\hat{h}G(\hat{h}) - \int_0^{\hat{h}}G(h)dh\right] \\
&= -G(\hat{h})\int_0^{\hat{h}}(p-h)g(h)dh + (p-\hat{h}-\sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(c)dh \\
&= -pG(\hat{h})^2 + G(\hat{h})\int_0^{\hat{h}}hg(h)dh + (p-\hat{h}-\sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(h)dh \\
&= -pG(\hat{h})^2 + G(\hat{h})\left(\hat{h}G(\hat{h}) - \int_0^{\hat{h}}G(h)dh\right) + (p-\hat{h}-\sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(h)dh \\
&= -pG(\hat{h})^2 + \hat{h}G(\hat{h})^2 - G(\hat{h})\int_0^{\hat{h}}G(h)dh + (p-\hat{h}-\sqrt{wf})g(\hat{h})\int_0^{\hat{h}}G(h)dh \\
&= -(p-\hat{h})G(\hat{h})^2 - \left[G(\hat{h})+\sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}}G(h)dh + (p-\hat{h})g(\hat{h})\int_0^{\hat{h}}G(h)dh \\
&= -(p-\hat{h})\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}}G(h)dh\right] - \left[G(\hat{h})+\sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}}G(h)dh.
\end{aligned}
$$

Therefore, we have

$$
\begin{aligned}
\frac{dN_p}{ds} &= \left[\frac{dN_e}{d\hat{h}}G(\hat{h}) + N_e g(\hat{h})\right]\frac{d\hat{h}}{ds} \\
&= \frac{-(p-\hat{h})\left[G(\hat{h})^2 - g(\hat{h})\int_0^{\hat{h}}G(h)dh\right] - \left[G(\hat{h})+\sqrt{wf}g(\hat{h})\right]\int_0^{\hat{h}}G(h)dh}{\left[\int_0^{\hat{h}}(\hat{h}-h+\sqrt{wf})g(h)dh\right]^2}\frac{d\hat{h}}{ds} < 0. \qquad (32)
\end{aligned}
$$

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 $G(\hat{h}) > g(\hat{h})$,