RIETI Discussion Paper Series 16-E-098

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RIETI Discussion Paper Series 16-E-098
First Draft: November 2016
Revised: December 2017

Testing for Agglomeration Economies and Firm Selection in Spatial Productivity Differences: The Case of Japan*

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Abstract

This study explores why firms, on average, are more productive in larger cities. One major explanation is that the higher firm productivity in larger cities is the result of agglomeration economies. However, recent studies have proposed an alternative mechanism of selection; namely, tougher competition in larger cities forces less-productive firms to exit and, as a result, more-productive firms operate in such locations. To distinguish agglomeration economies from firm selection, this study applies a newly suggested quantile approach to the Japanese manufacturing sector. Overall, the empirical results show that agglomeration economies, rather than stronger selection in larger cities, better explain spatial productivity differences in the Japanese manufacturing sector. The findings also show that benefits from agglomeration economies in this sector have decreased as interregional accessibility has increased.

JEL classification: R12, C52, D24
Keywords: Productivity, Quantile Approach, Agglomeration, Firm Selection, Cities

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*I would like to thank Yoshiyuki Arata, Yoko Konishi, Masayuki Morikawa, Yukiko Saito, Makoto Yano, and participants of the RIETI Discussion Paper Seminar for their useful comments. Naturally, any remaining errors are my own. I am also grateful to the Ministry of Economy, Trade and Industry (METI) and the Ministry of Internal Affairs and Communications (MIC) for providing the micro-data of the Census of Manufacture (from METI) and the Economic Census for Business Activity (from METI and MIC). This is an outcome of the research conducted under the project "Data Management" at the RIETI. This research uses the establishment-level panel converter table developed by the aforementioned project.

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1 Introduction

As discussed by Marshall (1890), agglomeration economies are considered to generate numerous benefits as positive externalities. One of the stylized facts in the literature of urban economics and economic geography is that firms are, on average, more productive in larger cities (e.g., Ciccone and Hall, 1996; Combes et al., 2010, 2012; Combes and Gobillon, 2015).[1] For example, Combes et al. (2010) estimate the density elasticity of productivity using the French firm-level dataset from 1994 to 2002 and obtain 0.035 after controlling for variables at the area and sector levels. This means that a city twice as large shows, on average, 2.5% ($\approx 2^{0.035} - 1$) higher productivity. As such, numerous studies in this field have focused on agglomeration economies to explain why productivity is higher in larger cities.

Recent theoretical studies have proposed another hypothesis: *selection*. As introduced by Melitz (2003) in the international trade literature, selection is defined as that less-productive firms are unable to survive in the market. Further introducing the endogenous markup, Melitz and Ottaviano (2008) show that larger markets bring about stronger selection and consequently, aggregate productivity in larger cities is higher than that in smaller cities, since only more-productive firms survive in larger markets. Combes et al. (2012) extend the model of Melitz and Ottaviano (2008) to incorporate agglomeration economies as positive technological externalities, which is proportional to the population of one city and its neighboring cities. Their model nests selection and agglomeration economies, both of which affect average productivity for cities through different channels.

To simultaneously test for agglomeration economies and selection in spatial productivity differences, Combes et al. (2012) develop a new quantile approach that focuses on entire productivity distributions through three key parameters, (i.e., shift, dilation, and truncation), whereas the standard statistical approach only captures the shift and dilation through the mean and variance of distributions. Agglomeration economies are captured by the right-shift of productivity distributions between smaller and larger cities (i.e., the right-shift captures the difference in average productivity between smaller and larger cities). Furthermore, Combes et al. (2012) consider the dilation effect of agglomeration economies, which indicates that more-productive firms can enjoy greater benefits from agglomeration (i.e., the dilation examines whether productivity distributions in larger cities are more dispersed than those in smaller cities). An estimation issue related to these two effects is that, when stronger truncation exists in the productivity distribution for larger cities, the right-shift and

[1] Rosenthal and Strange (2004) and Melo et al. (2009) offer a comprehensive review of empirical studies in this literature.

dilation effects of agglomeration economies are overestimated and underestimated respectively, due to omitted truncation parameter.[2] Thus, the quantile approach suggested by Combes et al. (2012) offers a greater advantage since it simultaneously examines whether agglomeration or selection plays a more important role in explaining spatial productivity differences.[3] After applying their new quantile approach to the French firm-level dataset from 1994 to 2002, Combes et al. (2012) find that selection cannot explain spatial productivity differences in France and that agglomeration economies play a crucial role.

Limited empirical studies have attempted to distinguish agglomeration economies from firm selection, but several studies offer insightful empirical findings. Focusing on the pre-war Japanese silk-reeling industry, Arimoto et al. (2014) conclude that selection played a key role in explaining why aggregate productivity in silk industrial clusters was higher than that in non-clusters. Furthermore, they find that relatively less-productive firms enjoyed greater benefits from agglomeration economies, which means that productivity distribution for silk industrial cluster was less dispersed than that in non-clusters. Their findings are in contrast to Combes et al. (2012), who find that there is no stronger selection in terms of city size and that relatively more-productive firms enjoy greater benefits from agglomeration economies in France. Using the Italian manufacturing firm-level dataset, Accetturo et al. (2013) find that agglomeration economies better explain spatial productivity differences, which is quite similar to the findings of Combes et al. (2012). However, they conclude that selection is also a crucial factor to explain spatial productivity differences in some sectors, especially under different spatial scales that capture market size. Thus, the literature requires more empirical studies in order to deepen the understanding of spatial productivity differences.

The present study applies the quantile approach to the Japanese manufacturing sector from 1986 to 2014 and focuses on the temporal differences in benefits from agglomeration economies. Another key testable prediction of Combes et al. (2012) is whether benefits from agglomeration economies decrease

[2] A seminal paper on selection in productivity distributions is Syverson (2004), who shows that the strength of selection increases (and indirectly implies that the dispersion of productivity distribution decreases due to the selection) as local market size increases. His indirect identification approach to selection using inter-quantile range of distribution crucially depends on the assumption that the left-truncation of distribution leads to smaller variance. However, smaller variance of distribution in larger cities is not necessarily driven by selection. This occurs when agglomeration economies benefit relatively less-productive firms greater than relatively more-productive firms. For example, relatively less-productive firms enjoy greater benefits through transactions with more-productive firms in locally segmented markets. Furthermore, Arimoto et al. (2014) also point out the possibility of faster technological catch-up through imitation. Thus, one advantage of the quantile approach of Combes et al. (2012) is its ability to simultaneously estimate not only the relative strength of selection between larger and smaller cities but also the relative shift and dilation effects arising from agglomeration economies.

[3] A strong empirical assumption for identification is that there is a common underlying productivity distribution across cities, although this is commonly assumed in theoretical works (e.g., Melitz and Ottaviano, 2008).

as interregional accessibility increases. For example, information and communication technology facilitates exchanges of ideas across distant cities, which relatively decreases the extent of benefits from agglomeration economies. Since agglomeration simultaneously generates greater costs in bigger cites, it is important to assess the extent to which agglomeration economies benefit firm productivities over time.

Our main finding in the Japanese manufacturing sector is also similar to that of Combes et al. (2012), and we can hardly find stronger selection effects in larger cities (i.e., no stronger left-truncation of productivity distribution in larger cities).[4] Conversely, higher average productivity in larger cities is mostly explained in terms of the right-shift of productivity distribution, thus suggesting that agglomeration economies better explain spatial productivity differences in the Japanese manufacturing sector. In addition, the dilation effect of agglomeration economies shows greater variations across sectors. On the one hand, more-productive firms enjoy greater benefits from agglomeration in some sectors, while, on the other hand, less-productive firms enjoy greater benefits from agglomeration in other sectors. Furthermore, the findings show that benefits from agglomeration economies in the Japanese manufacturing sector have decreased in the recent decade. Therefore, it is suggested that, when regional economies are integrated into one another as communication and transportation costs decrease, the productivity advantage of agglomeration also decreases.

The remainder of this paper is organized as follows. Section 2 offers a brief review of the theoretical framework with firm selection and agglomeration economies following Combes et al. (2012). Section 3 explains the quantile approach. Section 4 describes the total factor productivity (TFP) estimation methodology and the dataset. Section 5 discusses the estimation results. Finally, Section 6 presents the conclusions.

2 Theory

2.1 Basic Setup

Based on Combes et al. (2012), the present study briefly reviews a theoretical model that includes both firm selection and agglomeration economies. Although mathematical details are omitted in this paper, the objective is to offer intuitive interpretations of their theoretical predictions.

Suppose that there are R cities in the economy, and city r includes population N_r. There are two

[4]Our estimation results are obtained by the Stata command of Kondo (2017), who develops a Stata package that easily implements the quantile approach suggested by Combes et al. (2012).

sectors producing homogeneous and differentiated goods, respectively. In addition, the homogeneous numéraire good is produced under a constant return to scale, whereas differentiated goods are produced under monopolistic competition. Labor is the only variable input used for the production, and it is assumed that spatial workers' distribution is exogenously given (i.e., we do not treat labor mobility). In addition, the homogeneous good requires one unit of labor to produce one unit of output. Given that the price of the homogeneous numéraire good is normalized to one, marginal cost (i.e., wage rate) is also equal to one. The differentiated goods are produced using h (> 0) units of labor per unit of output, and h can be seen as marginal cost since the cost of each unit of labor is equal to one unit of the homogeneous numéraire good. The homogeneous good is freely traded across cities, but differentiated goods are traded with the iceberg transportation costs τ (> 1).

Firms are heterogeneous in terms of labor input requirement h, which varies across firms and determines firm productivity distributions. In the sector of differentiated goods, firms need to pay the sunk cost in order to enter the market. After paying the sunk entry cost, the labor unit requirement h is randomly drawn for each of the firms from an *ex ante* known distribution, which includes common probability density function $g(h)$ and cumulative distribution function $G(h)$ across cities. Then, less-productive firms cannot survive because they cannot cover the sunk entry cost. As a result, only more-productive firms, with a marginal cost that is less than the marginal cost cutoff $\bar{h}$, survive in the market.

2.2 Heterogeneous Firms and Productivity

Firms producing differentiated goods require h unit of labor input per one unit of output, which gives total labor inputs $l_r(h)$ of the firm in city r as follows:

$$l_r(h) = h \sum_{s=1}^{R} Q_{rs}(h),$$

where $Q_{rs}(h)$ is the output produced by the firm with h unit of labor per one unit of output in city r and exported to city s. Then, the logarithm of TFP can be defined as the logarithm of the ratio of total production to total inputs as follows:

$$\phi_r(h) = \log\left(\frac{\sum_{j=1}^{R} Q_{rs}(h)}{l_r(h)}\right).$$

Thus, when agglomeration economies do not exist, the logarithm of TFP becomes

$$\phi_r(h) = \log\left(\frac{1}{h}\right).$$

Note that the value of h differs across firms with the assumption being that it is randomly drawn from a known distribution. In this literature, Melitz and Ottaviano (2008) assume that the productivity, $1/h$, follows a Pareto distribution. Moreover, Combes et al. (2012) generalize distributional assumption in the theoretical model setting and point out that the empirical productivity distribution is close to the log-normal distribution.

2.3 Selection

In the model, free entry condition regarding the expected operational profits prior to entry and the sunk entry cost determines the marginal cost cutoff $\bar{h}_r$ as a function of the sizes of each city, the marginal cost distribution, the sunk entry cost, and the product differentiation parameter in the model. This means that firms with a marginal cost higher than the cutoff cannot survive and they must exit the market. Thus, the proportion of firms that cannot sell their products is expressed as $S_r \equiv 1 - G(\bar{h}_r)$, whereas the *ex ante* probability of successful entry is $G(\bar{h}_r)$.

Instead of the distribution of labor input requirement h, we now define the distribution of the logarithm of TFP $\phi = \log(1/h)$ as an underlying productivity distribution. Let $\tilde{F}(\phi)$ denote the cumulative distribution function of the logarithm of TFP. Using the variable transformation $\phi = \log(1/h)$, the cumulative distribution function of productivity is $\tilde{F}(\phi) \equiv 1 - G(e^{-\phi})$. Hence, the proportion of firms that cannot sell their products is also expressed as $S_r \equiv \tilde{F}(\bar{\phi}_r)$, where $\bar{\phi}_r = \log(1/\bar{h}_r)$, whereas the *ex ante* probability of successful entry is $1 - S_r$.

Therefore, the cumulative distribution function of the *ex post* productivity distribution truncated on $[\bar{\phi}_r, \infty)$ is

$$F_r(\phi) = \begin{cases} \dfrac{\tilde{F}(\phi) - S_r}{1 - S_r}, & \text{if} \quad \phi \geq \bar{\phi}_r, \\ 0, & \text{otherwise}, \end{cases}$$

where $1 - S_r$ is the normalizing constant that ensures that the density adds up to 1. Combes et al. (2012) shows that $\bar{\phi}_r$ increases as city size increases, which means that the left-truncation S_r becomes greater as the city size increases. A key theoretical prediction is that larger cities show more left-truncated productivity distribution than smaller cities. Another prediction is that a decrease in transportation costs leads to stronger selection since firms in a city need to compete with more-productive firms from other cities as transportation costs decrease, which in turn, causes least productive firms to exit the market.

2.4 Agglomeration Economies

In this study, agglomeration economies are defined as that workers become more productive through interactions with other workers within a city. In other words, workers are *ex ante* identical, but city size determines *ex post* workers' productivity, which is captured by TFP in this model. This study also considers the interactions with workers in different cities, but the exchange of ideas with them is assumed to be spatially decayed by parameter δ ($0 \leq \delta \leq 1$). The degree of agglomeration economies can be mathematically expressed as $a(N_r + \delta \sum_{s \neq r} N_s)$, where $a(0) = 1$, $a' > 0$, and $a'' < 0$. The first case of benefits from agglomeration economies is assumed to be additive to the logarithm of TFP as $\log(1/h) + A_r$, where $A_r \equiv \log[a(N_r + \delta \sum_{s \neq r} N_s)]$. In other words, when benefits from agglomeration economies exist, total labor inputs can be expressed in effective labor unit as follows:

$$a\Big(N_r + \delta \sum_{s \neq r} N_s\Big) l_r(h) = h \sum_{s=1}^{R} Q_{rs}(h).$$

In this case, the cumulative distribution function of the *ex post* truncated productivity distribution is

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

A key prediction is that, since the value of A_r is greater as city size increases by the definition, larger cities show more right-shifted productivity distribution than smaller cities.

The second type of benefits from agglomeration economies is assumed multiplicative to the logarithm of TFP as $D_r \log(1/h)$, where $D_r \equiv \log[d(N_r + \delta \sum_{s \neq r} N_s)]$, where $d(0) = 1$, $d' > 0$, and $d'' < 0$. In this case, total labor inputs can be expressed in effective labor unit as follows:

$$\left(\frac{1}{h}\right)^{(D_r - 1)} l_r(h) = h \sum_{s=1}^{R} Q_{rs}(h),$$

and the cumulative distribution function of the *ex post* truncated productivity distribution is

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

where $D_r = 1$ indicates the case of no multiplicative benefits from agglomeration economies.

The interpretation of this second type is slightly complicated. In the empirical analysis, the absolute value of D_r cannot be estimated, and we compare the relative values of D_r between cities. As a relative value of D_r to D_s increases (decreases), a multiplicative type of agglomeration economies benefits more- (less-) productive firms than less- (more-) productive firms, thus making the distribution of city r more (less) dispersed relative to city s.[5] The second type of agglomeration economies includes heterogeneous effects across firms depending on the value of h within a city. A key prediction is that, since the value of D_r is greater as city size increases by the definition, larger cities show flatter productivity distribution than smaller cities.[6]

Finally, this study considers the case in which both types of agglomeration economies exist as $\phi_r = D_r \log(1/h) + A_r$. In this case, the cumulative distribution function of the *ex post* truncated productivity distribution is

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

A key prediction is that, since the values of A_r and D_r are greater as city size increases, larger cities show flatter and more right-shifted productivity distribution than smaller cities. In the present study, we assess these theoretical predictions by the quantile approach newly suggested by Combes et al. (2012).

3 Empirical Strategy

3.1 Basic Assumption

Suppose that the cumulative distribution functions F_r and F_s have some common underlying distribution $\tilde{F}$. As shown earlier, F_r can be obtained by shifting $\tilde{F}$ rightward by A_r, dilating $\tilde{F}$ by D_r, and left-truncating share $S_r \in [0, 1)$ of $\tilde{F}$. In the same manner, F_s can also be obtained by shifting $\tilde{F}$ rightward by A_s, dilating $\tilde{F}$ by D_s, and left-truncating share $S_s \in [0, 1)$ of $\tilde{F}$. Then, the following

[5]This is easily confirmed with a basic knowledge of statistics. Suppose that a random variable X has mean $\mathrm{E}(X)$ and variance $\mathrm{Var}(X)$. When a random variable X is multiplied by constant c, the mean and variance of cX are $c\mathrm{E}(X)$ and $c^2\mathrm{Var}(X)$, respectively, which means that variance is also augmented proportional to constant c. On the other hand, additive constant $X + c$ affect the mean as $\mathrm{E}(X) + c$, but it does not affect the variance.

[6]Although we assume that D_r is proportional to the city size as agglomeration economies, this is not necessarily supported in empirical studies (e.g., Arimoto et al., 2014).

relationship between F_r and F_s can be obtained:

$$F_r(\phi) = \max\left(0, \frac{F_s\left(\frac{\phi - A}{D}\right) - S}{1 - S}\right), \quad \text{if} \quad S_r > S_s, \tag{1}$$

$$F_s(\phi) = \max\left(0, \frac{F_r\left(D\phi + A\right) - \frac{-S}{1-S}}{1 - \frac{-S}{1-S}}\right), \quad \text{if} \quad S_r < S_s, \tag{2}$$

where $D \equiv D_r/D_s$, $A \equiv A_r - DA_s$, $S \equiv (S_r - S_s)/(1 - S_s)$. The first equation shows that F_r can be obtained by dilating F_s by D, shifting F_s by A, and left-truncating share S of F_s. Moreover, the second equation shows that F_s can be obtained by dilating F_r by $1/D$, shifting F_r by $-A/D$, and left-truncating share $-S/(1 - S)$ of F_r.

This relationship helps to compare the two cumulative distribution functions without directly specifying an ad hoc underlying distribution $\tilde{F}$. In addition to the relative degrees of shift A and dilation D, we can examine the relative strength of truncation S of city r compared to city s. in this case, parameter A measures how much stronger the right shift in city r is relative to city s, while parameter D measures the ratio of dilation in city r relative to city s. Finally, parameter S measures how much stronger the left truncation in city r is relative to city s.

3.2 Quantile Transformation

We transform equations (1) and (2) into quantile functions in order to estimate them. Suppose that the cumulative distribution functions F_r and F_s are invertible. Let $\lambda_r(u) = F_r^{-1}(u)$ and $\lambda_s(u) = F_s^{-1}(u)$ denote the quantile functions of cities r and s, respectively, and u is the uth quantile. The quantile function is defined for all $u \in [0, 1]$.

If $S > 0$, then the quantile function can be obtained from equation (1) as follows:

$$\lambda_r(u) = D\lambda_s\Big(S + (1 - S)u\Big) + A, \quad \text{for} \quad u \in [0, 1]. \tag{3}$$

If $S < 0$, then the quantile function can be obtained from equation (2) as follows:

$$\lambda_s(v) = \frac{1}{D}\lambda_r\left(\frac{v - S}{1 - S}\right) - \frac{A}{D}, \quad \text{for} \quad v \in [0, 1].$$

Then, we use the transformation of variable by $u = (v - S)/(1 - S)$ and thus, the quantile function can be rewritten as follows:

$$\lambda_s\Big(S + (1-S)u\Big) = \frac{1}{D}\lambda_r(u) - \frac{A}{D} \quad \text{for} \quad u \in \left[\frac{-S}{1-S}, 1\right] \tag{4}$$

Combining equations (3) and (4) for all S yields

$$\lambda_r(u) = D\lambda_s\Big(S + (1-S)u\Big) + A \quad \text{for} \quad u \in \left[\max\left(0, \frac{-S}{1-S}\right), 1\right].$$

This equation cannot be directly estimated since the set of ranks u includes the unknown true parameter S. Thus, additional variable transformation provides the following equation:

$$\lambda_r\Big(r_S(u)\Big) = D\lambda_s\Big(S + (1-S)r_S(u)\Big) + A \quad \text{for} \quad u \in [0, 1]\,, \tag{5}$$

where $r_S(u) = \max\Big(0, -S/(1-S)\Big) + \Big(1 - \max\Big(0, -S/(1-S)\Big)\Big)\,u$.

3.3 Estimating Quantile Functions

Let $\boldsymbol{\theta} = (A, D, S)$ denote the parameter vector. In order to estimate $\boldsymbol{\theta}$, we define the infinite set of equalities:[7]

$$m_{\boldsymbol{\theta}}(u) = \lambda_r\Big(r_S(u)\Big) - D\lambda_s\Big(S + (1-S)r_S(u)\Big) - A, \quad \text{for} \quad u \in [0, 1]. \tag{6}$$

To consider the asymmetric relationship between two distributions arising from the opposite transformation, we also define the following infinite set of equalities:

$$\tilde{m}_{\boldsymbol{\theta}}(u) = \lambda_s\Big(\tilde{r}_S(u)\Big) - \frac{1}{D}\lambda_r\left(\frac{\tilde{r}_S(u) - S}{1-S}\right) + \frac{A}{D}, \quad \text{for} \quad u \in [0, 1], \tag{7}$$

where $\tilde{r}_S(u) = \max\Big(0, S\Big) + \Big(1 - \max(0, S)\Big)u$.

The estimator of $\boldsymbol{\theta}$ can be obtained by minimizing the criteria function $M(\boldsymbol{\theta})$, which is defined as the sum of the squared values of $\hat{m}_{\boldsymbol{\theta}}(u)$ and $\hat{\tilde{m}}_{\boldsymbol{\theta}}(u)$, as follows:

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \arg\min_{\boldsymbol{\theta}}\ M(\boldsymbol{\theta}), \\ M(\boldsymbol{\theta}) &\equiv \int_0^1 \Big[\hat{m}_{\boldsymbol{\theta}}(u)\Big]^2 \mathrm{d}u + \int_0^1 \Big[\hat{\tilde{m}}_{\boldsymbol{\theta}}(u)\Big]^2 \mathrm{d}u, \end{aligned} \tag{8}$$

[7] One difficulty is that we have an infinite set of equalities due to continuous quantile u. Thus, we need to approximate them by a finite set of equalities for estimation. See Combes et al. (2012) for the details of the estimation methodology.

where $\hat{m}_{\boldsymbol{\theta}}(u)$ and $\hat{\tilde{m}}_{\boldsymbol{\theta}}(u)$ are obtained from the some quantile functions $\hat{\lambda}_i$ and $\hat{\lambda}_j$. Finally, to measure the fitness of the model, we define the pseudo R^2 as follows:

$$R^2 = 1 - \frac{M(\hat{A}, \hat{D}, \hat{S})}{M(0, 1, 0)}.$$

Note that this pseudo R^2 can take a small value even if the model specification correctly fits the data. A special case is when $\hat{A} = 0$, $\hat{D} = 1$, and $\hat{S} = 0$ are obtained, after which R^2 becomes 0. In other words, even if two distributions are correctly estimated as identical, pseudo R^2 cannot measure the exact goodness of fit in this special case.

Finally, in order to estimate the standard errors of the estimated parameters $\hat{\boldsymbol{\theta}}$, we use the bootstrap method. We draw observations of the same sample size as data with replacement and then estimate $\boldsymbol{\theta}$ for each bootstrap replication. In other words, when we have B bootstrap replications, there are B estimates for $\boldsymbol{\theta}$. Hence, the bootstrap standard errors $\widehat{\mathrm{SE}}_B(\hat{\theta}_k)$ are calculated as follows:

$$\widehat{\mathrm{SE}}_B(\hat{\theta}_k) = \sqrt{\frac{1}{B-1}\sum_{b=1}^{B}(\hat{\theta}_k^{(b)} - \bar{\theta}_k)^2}, \quad k \in (A, D, S)$$

where $\bar{\theta}_k$ is the mean of $\hat{\theta}_k^{(b)}$ obtained from each bootstrap sample ($\bar{\theta}_k = B^{-1}\sum_{b=1}^{B}\hat{\theta}_k^{(b)}$). Note that $\bar{\theta}_k$ is not equal to the $\hat{\theta}_k$ observed in the sample.

4 Data

4.1 TFP Estimation

Our TFP estimation procedure follows the method suggested by Levinsohn and Petrin (2003), Petrin and Levinsohn (2012), and Wooldridge (2009), who modify the method of Olley and Pakes (1996) with respect to lumpy investment. Consider the Cobb-Douglass production function as follows:

$$\log v_{irt} = \beta_t + \beta_\ell \log \ell_{irt} + \beta_k \log k_{it} + \phi_{irt} + e_{irt}$$

where v_{irt} is the value-added of establishment i in year t, ℓ_{irt} is the labor, and k_{irt} is the capital stock. The error term is assumed to consist of two components: ϕ_{irt} is a productivity shock which is unobserved by the econometricians but observable to the establishment i, and e_{irt} is a sequence of idiosyncratic shock which is not observable by the establishment i before the input decision-making.

An estimation issue is that the OLS estimators β_ℓ and β_k can be inconsistent due to the omitted variable bias, since k_{irt} is correlated with the productivity shock ϕ_{irt}. In addition, ℓ_{irt} might be inconsistent, as pointed out by Ackerberg et al. (2006). To solve the estimation issues, Levinsohn and Petrin (2003) uses intermediate inputs (e.g., material, fuel, and energy) to proxy for unobserved productivity. Wooldridge (2009) further modifies their approach solving issues raised by Ackerberg et al. (2006) and proposes an estimation procedure simplified by the generalized method of moments.

Obtaining consistent estimates $\hat{\beta}_\ell$ and $\hat{\beta}_k$ by the Wooldridge–Levinshon–Petrin approach, the present study estimates the logarithm of TFP as follows:

$$\log(\widehat{\text{TFP}}_{irt}) = \log v_{irt} - \hat{\beta}_t - \hat{\beta}_\ell \log \ell_{irt} - \hat{\beta}_k \log k_{irt}.$$

To consider heterogeneity in production technology across industries, we estimate the production function by two-digit level industry. In addition, to make TFP comparable across industries, industry-year effects η_{st} are removed by estimating the following regression: $\log(\widehat{\text{TFP}}_{irt}) = \eta_{st} + \varepsilon_{irt}$, where ε_{irt} is an error term. Then, we calculate the establishment-average TFP as follows:

$$\log(\widehat{\text{TFP}}_{ir}) = \log\left(\frac{1}{T_i}\sum_{t=1}^{T_i} \exp\Big(\log(\widehat{\text{TFP}}_{irt}) - \hat{\eta}_{st}\Big)\right),$$

where T_i is the number of years for establishment i observed during the study period. Note that this study calculates the arithmetic mean rather than the geometric mean.

4.2 Dataset

In this study, the data regarding the Japanese manufacturing sector are obtained from confidential datasets of the Census of Manufacture (CM), which is annually conducted by the Ministry of Economy, Trade and Industry.[8] In this case, the dataset ranges from 1986 to 2014. To consider the temporal differences in industrial structure, we divide the dataset into two time periods: 1986–2000 and 2001–2014.

The CM includes two forms: Form A (*Kou*), which covers establishments with 30 or more employees, and Form B (*Otsu*), which covers establishments with 29 or less employees. One issue regarding TFP estimation is that the data on capital stocks are only available for Form A. When we compare TFP distributions between larger and smaller cities, the distributions may be truncated by

[8]The Census of Manufacture was integrated into the Economic Census for Business Activity (ECBA) in 2012. The 2012 ECBA surveyed annual economic activities in 2011, and the survey was jointly conducted by the Ministry of Economy, Trade and Industry and the Ministry of Internal Affairs and Communications.

the establishment size stipulated in the CM. As a baseline analysis, we use the datasets of Form A to estimate establishment-level TFP, but we also use labor productivity including the establishments with 29 or less employees as a robustness check.[9]

As for TFP estimation, we use the value added as a dependent variable. In this case, the value added is calculated as total amount of production minus cost of raw materials, fuels and electricity consumed, subcontracting expenses for consigned production, and the internal tax on consumption[10]. Labor is considered as the total annual hours worked. In addition, our dataset includes the total annual number of workers. Using the average annual hours worked in the manufacturing sector, which are taken from the Monthly Labor Statistics (Ministry of Health, Labour and Welfare), the total annual hours worked are calculated by multiplying the annual number of workers by the hours worked.[11] Capital stocks are measured as end-of-year book values . All nominal values of outputs, intermediate inputs, and capital stocks are deflated by each price index. Finally, the deflators of output price, input price, and investment price are constructed by price indices available from the Bank of Japan (2011=100), and all monthly price indices are averaged yearly.

This study only focuses on establishments observed more than four times in each period in order to capture firm selection. Unproductive establishments also exist in the markets, but they might be unable to survive for long periods of time. Thus, it is important to control for establishments that enter and exit the market since these establishments make the detection of the left-truncation of distributions difficult. Thus, we exclude these establishments from the sample after calculating TFP.

Figure 1 presents the estimation results of the Cobb-Douglass production function. As a proxy variable for unobserved productivity, we use the total costs of energy consumed. Overall, the null hypothesis of constant return to scale is rejected for all sectors.

[Figure 1]

Table 1 presents the descriptive statistics of the estimated TFP. As a baseline of categorization for city size, we use employment density, and compare productivity distributions between below-

[9]Form B (*Otsu*) covers the establishments with 29 or less employees. However, the establishments with three or less employees are not covered each year. Thus, we use the establishments with four or more employees to calculate labor productivity.

[10]The estimated consumption tax is also included from 2001. Unlike the definition of value added in the Census of Manufacture, the depreciation is not subtracted from the value added in this paper

[11]The CM has distinguished workers into regular and non-regular workers since 2001. We calculated the hours worked adjusted for regular and non-regular workers in the 2001–2014 time period. However, we did not separate the annual hours worked between regular and non-regular workers as two explanatory variables. The logarithm of the sum of hours worked for regular and non-regular workers was used as an explanatory variable.

and above-median employment densities. Overall, above-median dense cities show higher TFP than below-median dense cities at any quantile in Table 1.

Note that, in the quantile approach, the logarithms of TFP are normalized to these averages in below-median dense cities in order for the relative shift parameter A to measure the average increase in productivity enjoyed by firms in above-median dense cities (relative to below-median dense cities).

The employment density, as a proxy of city size, is calculated by dividing the number of workers by inhabitable area (in km^2). The numbers of workers at the municipality level are taken from the 1985, 1990, 1995, 2000, 2005, and 2010 population censuses, and the linear interpolation is implemented between each five years. In addition, linear interpolation between 2010 and 2015 is implemented using the percentage change in population, not labor force, due to data limitations.[12] Then, instead of aggregating municipalities with respect to metropolitan areas, we utilize a potential approach, which aggregates neighboring municipalities located within the circle of d km radius from the center of the municipality, to control for dynamic change in urban employment areas from 1986 to 2014. In other words, we calculate spatially smoothed employment density based on the concept of potential. Let $\widetilde{x_r} = \sum_{s=1}^{R} I(d_{rs} < d) \cdot x_s$ denote the spatially local sum of municipality r; x_s is the raw data of municipality s; and $I(d_{rs} < d)$ is the indicator function that takes the value of 1 if the distance between municipalities r and s is less than d km or 0 otherwise.[13] We set $d = 30$ km, considering local labor markets and commuting distance. The spatially smoothed population density is calculated as $\text{Dens}_{rt} = \widetilde{\text{Emp}}_{rt}/\widetilde{\text{Area}}_{rt}$, where $\widetilde{\text{Emp}}_{rt}$ and $\widetilde{\text{Area}}_{rt}$ are the spatial local sums of population and area of municipality r, respectively.

[Table 1]

5 Estimation Results

5.1 Agglomeration Economies Better Explain Spatial Productivity Differences

Figure 2 illustrates the distributions between cities with below- and above-median employment densities for all of the sectors. Figure 2(a) shows the productivity distributions in the 1986–2000 time period, whereas Figure 2(b) shows such distributions in the 2001–2014 time period. A common feature between both panels is the right-shift of distributions between above- and below-median

[12]Population by municipality is available from the 2015 population census.

[13]The latitudes and longitudes of municipalities are obtained by GIS software and the bilateral distances between any two municipalities are calculated using the formula suggested by Vincenty (1975).

employment densities. A remarkable difference is that the degree of right-shift decreases in the most recent decade, although the difference between cities below- and above-median employment densities does not change significantly. Thus, we cannot visually judge the clear effects of the dilation and selection in Figure 2.

[Figure 2]

Figures 3 and 4 illustrate the productivity distributions between cities with below- and above-median employment densities by sector in the 1986–2000 and 2001–2014 time periods, respectively. Since there are greater heterogeneities across sectors, we can visually confirm that above-median dense cities show more right-shifted productivity distributions than below-median dense cities for almost all of the sectors, which suggests that there are additive benefits from agglomeration economies. However, it is difficult to visually conclude that larger cities show stronger selection than smaller cities.

[Figures 3–4]

Tables 2 and 3 present the estimation results of the quantile approach by sector in the 1986–2000 and 2001–2014 time periods, respectively. As shown earlier, almost all of the sectors show significantly positive estimates of the relative shift parameter A in Table 2. However, the relative shift parameter A is negative, but insignificant for Sector 4 (Pulp, paper and paper products) in Table 2 and Sector 10 (Non-ferrous metals and products) in Table 3. As a result, 14 of 16 sectors in our classification show significant positive estimates of relative shift parameter A in the 1986–2014 time period. In the 2001–2014 time period, 13 of the 16 sectors in our classification show significant positive estimates of relative shift parameter A.

Estimation results show that relative truncation parameter S is not significantly positive for almost all of the sectors except for Sector 1 (Food, beverages, tobacco, feed) in Table 3. Conversely, below-median dense cities show a stronger truncation than above-median cities in Sector 2 (Textile mill products, leather tanning, leather products, and fur skins) in Tables 2 and 3. Overall, the results suggest that firm selection is not a crucial factor to explain why firm productivity is higher in larger cities, but agglomeration economies better explain the spatial productivity differences in the Japanese manufacturing sector.

Significant dilation effects of agglomeration economies are also observed in the 1986–2000 time period for some sectors, but dilation effects are uncommon among sectors in the 2001–2014 time period. For all of the sectors, we obtain a significant estimate, $\hat{D} = 1.028$, in the 1986–2000 time period. In the 2001–2014 time period, we obtain $\hat{D} = 0.997$, which is not significantly different from $D = 1$. Moreover, a large portion of agglomeration economies result in the right-shift of productivity distributions, rather than dilation effects.

We can quantify the right-shift effects of agglomeration economies, based on the standard regression approach used in the literature on agglomeration economies. Consider the following regression:

$$\log(\mathrm{TFP}_r) = \alpha_1 + \alpha_2 \log(\mathrm{Dens}_r) + \varepsilon_r,$$

where TFP_r is the average firm TFP in city r, Dens_r is the employment density in city r, ε_r is an error term, and parameter α_2 captures the density elasticity of productivity.[14] For example, Morikawa (2011) estimates the density elasticity of productivity α_2 using the Japanese service industry dataset, after which the estimated elasticity ranges from 0.081 to 0.433 across industries.[15] Using the estimate of the relative shift parameter A, the density elasticity of TFP α_2 can be approximated as follows:

$$\hat{\alpha}_2 \approx \frac{\hat{A}}{\log(\overline{\mathrm{Dens}}_{above}) - \log(\overline{\mathrm{Dens}}_{below})}$$

where $\overline{\mathrm{Dens}}_{above}$ denotes the average employment density across above-median dense cities and $\overline{\mathrm{Dens}}_{below}$ denotes the average employment density across below-median dense cities. The differences in the logarithm of employment density for the 1986–2000 and 2001–2014 time periods are 1.598 and 1.550, respectively. For all of the sectors, the density elasticity of productivity is approximately 0.116 ($\approx 0.185/1.598$) for the 1986–2000 time period and 0.082 ($\approx 0.127/1.550$) for the 2001–2014 time period. As shown in Figure 2, our quantification reveals that the benefits from agglomeration economies tend to decrease over decades.

We also find heterogeneities across sectors. In the 1986–2000 time period, Sector 2 (Textile mill products, leather tanning, leather products, and fur skins), Sector 3 (Lumber, wood products, furniture, and fixtures), Sector 5 (Printing and allied industries), Sector 13 (Business oriented machinery), and Sector 16 (Miscellaneous manufacturing industries) enjoy greater benefits from agglomeration economies relative to all of the sectors. In the 2001–2014 time period, Sector 1 (Food, beverages, tobacco, feed), Sector 2 (Textile mill products, leather tanning, leather products, and fur skins), Sector

[14]Note that the control variables are not introduced in this framework in order to be comparable with the estimation results of the quantile approach.

[15]Morikawa (2016) estimates the density elasticity of labor productivity in the Japanese knowledge- and information-intensive business service and the mean value in 2010 is 0.078.

3 (Lumber, wood products, furniture, and fixtures), Sector 5 (Printing and allied industries), Sector 8 (Ceramic, stone and clay products), Sector 12 (General-purpose machinery), Sector 13 (Business oriented machinery), and Sector 14 (Electrical machinery, equipment and supplies, electronic parts, devices and electronic circuits; Information and communication electronics equipment) show greater benefits from agglomeration economies relative to all of the sectors.

[Tables 2–3]

5.2 Robustness Check 1: Different TFP measures

As for the robustness check, Table 4 presents the estimation results using different TFP measures. It is important to note that our estimation results might change if we use different TFP estimation methods. In this study, we apply four different approaches. First, we estimate the Cobb-Douglass production function by OLS estimation. Overall, the output elasticities of labor and capital are estimated higher than those of the Wooldridge-Levinsohn-Petrin method in Figure 1. Second, we estimated the trans-log production function by OLS to account for the variable output elasticities of labor and capital across establishments. Third, we estimated the Cobb-Douglass production function by fixed-effect estimation. Overall, the output elasticities of labor and capital are estimated to be lower than those of the Wooldridge-Levinsohn-Petrin method in Figure 1. Fourth, we estimated the Cobb-Douglass production function by Levinsohn-Petrin estimation method. the output elasticities of labor and capital are almost the same as those of the Wooldridge-Levinsohn-Petrin method in Figure 1. Roughly speaking, the elasticities of labor and capital estimated by the Wooldridge-Levinsohn-Petrin method fall between the OLS and fixed-effect estimates.

The estimation results in Table 4 show that the TFP estimation methods do not change our main findings, although the magnitudes slightly vary. In fact, the TFP estimates by OLS become lower since the OLS estimates of output elasticities are higher than those of the Wooldridge-Levinsohn-Petrin method, which reflects the differences in the magnitudes of the estimated relative shift parameter $\hat{A}$. A key message in Table 4 is that the spatial productivity difference is mostly explained by the relative shift parameter of agglomeration economies, not by the relative truncation parameter $\hat{S}$. Therefore, it is suggested that firm selection cannot explain the spatial productivity differences in the Japanese manufacturing sector.

[Table 4]

5.3 Robustness Check 2: Different Spatial Scales

Another robustness check is made using different spatial scales. We compared productivity distributions between cities with below- and above-median employment densities as a benchmark categorization. In this robustness check, we use three different spatial scales to capture the differences between bigger and smaller cities. The first case is the categorization at the 75th percentile point of employment density. The second case compares the below-25th percentile with the above-75th percentile. The third case compares the 25–50th percentile with the 50–75th percentile.

Table 5 presents the estimation results for all of the sectors. In both 1986–2000 and 2001–2014 time periods, the estimated relative truncation parameter $\hat{S}$ is not significant. Although the second categorization between the below-25th percentile and the above-75th percentile is stricter than our benchmark median-based categorization, larger cities do not show much stronger selection than smaller cities in terms of magnitude. In contrast, estimated relative shift parameter $\hat{A}$ shows larger magnitude than the benchmark case. This robustness check also indicates that agglomeration economies better explain spatial productivity differences through the right-shift of productivity distribution.[16]

[Table 5]

5.4 Discussion: Decreasing Communication and Transportation Costs

This section discusses why the benefits from agglomeration economies have decreased between the 1986–2000 and 2001–2014 time periods. One possible explanation is that, given that firms and workers are immobile across cities, the advantages of larger cities decrease as interregional accessibility increases. In addition, the spatial decay parameter δ plays a key role in measuring interregional accessibility. When $\delta = 1$ (i.e., the case of no spatial decay), location does not matter in terms of agglomeration economies. In this regard, workers can enjoy the benefits of interactions from any location, even if they live in smaller cities. Moreover, recent advancements in information and communication technology, and improved transportation infrastructure, have facilitated interactions between firms and workers across distant cities.

Another explanation is related to the decreasing spatial decay parameter of transportation costs, which is expressed by τ in the model of Combes et al. (2012). However, the fundamental concept of agglomeration economies differs from the former. A traditional approach to agglomeration economies

[16] Additional robustness checks are conducted in the Online Appendix.

is to assume technological externalities regarding city size. On the other hand, Krugman (1991) and Fujita et al. (1999, Chap. 4–5) introduce pecuniary externalities regarding increasing returns to scale. Regional economies are spatially segmented by iceberg transportation costs, and the total demand is expressed as the market potential, where transportation costs play a key role in determining the extent to which consumers can import differentiated goods from other cities. Even if the production technology is identical among firms, firms in regions with greater market potential show *ex post* higher productivity via increasing returns to scale. Furthermore, when regional markets become integrated as transportation costs decrease, regional differences in productivity also decrease.

Interregional firm mobility also plays an important role in determining the spatial distribution of economic activity in the long run. Unlike Krugman (1991), Helpman (1998) considers the housing/land sector as a dispersion force, which better explains the spatial distributions of workers in the Japanese manufacturing sector.[17] Decreasing transportation costs may also reduce the spatial productivity differences through firm mobility across cities in the long run.[18] The findings in the present study are consistent with these predictions.

6 Conclusion

This study has investigated why firms are, on average, more productive in larger cities. Whereas urban economists have long emphasized the role of agglomeration economies, recent theoretical studies have shed new light on an alternative mechanism of selection. In other words, less-productive firms cannot survive in larger cities because of tougher competition and, as a result, more-productive firms effectively operate in such locations. To distinguish agglomeration economies from firm selection, this study has applied the quantile approach suggested by Combes et al. (2012) to the Japanese manufacturing sector.

Overall, selection effects are hardly found in larger cities in terms of the left-truncation of productivity distribution. Our empirical results show that agglomeration economies, rather than firm selection, better explain the spatial productivity differences in the Japanese manufacturing sector. In particular, the right-shift of productivity distribution is the main driver of agglomeration economies

[17]Kondo and Okubo (2015) empirically investigate the relationship between the interregional labor mobility and real wage disparities by focusing on the theoretical model of Helpman (1998).

[18]Decreasing transportation costs simultaneously brings about tougher competition, which, in turn, causes the least-productive firms to exit the market. Ottaviano (2012) investigates how the firm heterogeneity affects the balance between agglomeration and dispersion forces in the presence of pecuniary externalities. However, the model of Combes et al. (2012) limits these two impacts of transportation costs only to the selection effect, while exogenously assuming agglomeration economies as technological externalities.

for all sectors. Although the dilation effects are significant in some industries in the 1986–2000 time period, they are not as significant as those in the 2001–2014 time period. Our results are robust in terms of different TFP measures and different spatial scales. Furthermore, we have found that the benefits from agglomeration economies in the Japanese manufacturing sector have decreased over recent decades, which is also consistent with the theoretical predictions.

Finally, this study includes the following limitation. It did not explore what factors generate the right-shift of productivity distributions. In the literature of agglomeration economies, it is often assumed that more active face-to-face communication in larger cities increases productivity as technological externalities. However, there are numerous factors internalized in larger cities, such as human capital externalities and increasing returns to scale, which also explain why firms are, on average, more productive in larger cities. In order to open the black box of agglomeration economies, future studies need to investigate why firms are, on average, more productive in larger cities, based on these wide-ranging perspectives.

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Table 1: Descriptive Statistics

Variables	Obs.	Mean	S.D.	p10	p25	p50	p75	p90
	Total Factor Productivity, Period: 1986–2000							
log(TFP)	79685	4.142	0.654	3.422	3.758	4.103	4.486	4.933
log(Dens)	79685	6.634	0.969	5.443	5.946	6.450	7.393	8.042
log(TFP), Below-Median Density	39842	4.050	0.637	3.362	3.677	4.005	4.380	4.812
log(TFP), Above-Median Density	39843	4.234	0.657	3.512	3.857	4.197	4.580	5.022
log(Dens), Below-Median Density	39842	5.835	0.468	5.180	5.566	5.946	6.178	6.342
log(Dens), Above-Median Density	39843	7.433	0.618	6.585	6.820	7.393	7.966	8.196
	Total Factor Productivity, Period: 2001–2014							
log(TFP)	60391	4.397	0.668	3.663	3.999	4.353	4.749	5.215
log(Dens)	60391	6.590	0.947	5.423	5.935	6.468	7.289	7.947
log(TFP), Below-Median Density	30195	4.331	0.668	3.606	3.930	4.281	4.682	5.158
log(TFP), Above-Median Density	30196	4.462	0.662	3.739	4.075	4.421	4.807	5.269
log(Dens), Below-Median Density	30195	5.815	0.496	5.125	5.562	5.935	6.168	6.351
log(Dens), Above-Median Density	30196	7.365	0.588	6.582	6.804	7.289	7.891	8.151

Notes: TFP is controlled for industry-year effects. Dens indicates employment density (workers/km^2). In the estimation, lowermost and uppermost 0.05% of productivity distribution are dropped by category.

Table 2: Estimation Results of TFP Distributions by Sector, 1986–2000, Below- vs. Above-Median Employment Density

Sectors	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
All Sectors	0.1851*	1.0275*	−0.0003	0.9926	39802	39803
	(0.0044)	(0.0073)	(0.0003)			
1. Food, beverages, tobacco, feed	0.1815*	1.0932*	0.0006	0.9861	6176	4942
	(0.0130)	(0.0181)	(0.0006)			
2. Textile mill products, leather tanning, leather products, and fur skins	0.6057*	0.9039*	−0.2447*	0.9692	6930	3118
	(0.0141)	(0.0215)	(0.0009)			
3. Lumber, wood products, furniture, and fixtures	0.2360*	1.1264*	0.0053*	0.9904	2014	1242
	(0.0206)	(0.0407)	(0.0027)			
4. Pulp, paper and paper products	0.0621*	0.9194+	−0.0001	0.8725	956	1449
	(0.0221)	(0.0475)	(0.0034)			
5. Printing and allied industries	0.3520*	1.2076*	0.0009	0.9854	1124	3051
	(0.0183)	(0.0375)	(0.0025)			
6. Chemical and allied products	−0.0340	0.9441	−0.0010	0.5385	980	1655
	(0.0251)	(0.0435)	(0.0026)			
7. Plastic products and rubber products	0.1049*	0.9581	−0.0021	0.9234	2295	2895
	(0.0194)	(0.0270)	(0.0015)			
8. Ceramic, stone and clay products	0.1302*	0.9965	−0.0012	0.9159	2134	1724
	(0.0194)	(0.0320)	(0.0018)			
9. Iron and steel	0.1024*	1.1764*	0.0045	0.8567	603	1037
	(0.0336)	(0.0555)	(0.0048)			
10. Non-ferrous metals and products	0.0548	0.9476	−0.0135	0.7460	453	598
	(0.0403)	(0.0773)	(0.0159)			
11. Fabricated metal products	0.1474*	0.9327*	−0.0010	0.9519	2657	3827
	(0.0156)	(0.0229)	(0.0014)			
12. General-purpose machinery	0.1665*	0.9828	−0.0005	0.9923	3429	4896
	(0.0132)	(0.0227)	(0.0009)			
13. Business oriented machinery	0.3530*	0.8322*	−0.0486*	0.9801	928	804
	(0.0321)	(0.0518)	(0.0050)			
14. Electrical machinery, equipment and supplies, electronic parts, devices and	0.1720*	1.1157*	−0.0001	0.9389	6693	4865
electronic circuits; Information and communication electronics equipment	(0.0113)	(0.0199)	(0.0008)			
15. Transportation equipment	0.1086*	0.9824	0.0021	0.9113	1632	2657
	(0.0211)	(0.0313)	(0.0017)			
16. Miscellaneous manufacturing industries	0.2127*	1.0957+	−0.0030	0.9267	778	1029
	(0.0275)	(0.0560)	(0.0046)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for below-median dense cities and Obs. (A) denotes the number of observations for above-median dense cities.

Table 3: Estimation Results of TFP Distributions by Sector, 2001–2014, Below- vs. Above-Median Employment Density

Sectors	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
All Sectors	0.1273*	0.9971	0.0004	0.9716	28738	28739
	(0.0062)	(0.0078)	(0.0003)			
1. Food, beverages, tobacco, feed	0.1628*	1.0747*	0.0022*	0.9765	5800	4635
	(0.0118)	(0.0186)	(0.0008)			
2. Textile mill products, leather tanning, leather products, and fur skins	0.3342*	1.0492	−0.0151*	0.9659	2492	1153
	(0.0247)	(0.0321)	(0.0023)			
3. Lumber, wood products, furniture, and fixtures	0.1817*	1.1136*	0.0070	0.9414	1092	709
	(0.0314)	(0.0491)	(0.0044)			
4. Pulp, paper and paper products	0.0151	0.8663*	−0.0020	0.8304	840	1131
	(0.0271)	(0.0436)	(0.0046)			
5. Printing and allied industries	0.2448*	0.9579	−0.0033	0.9293	928	2093
	(0.0224)	(0.0364)	(0.0020)			
6. Chemical and allied products	−0.1026*	0.9808	−0.0014	0.8309	1122	1486
	(0.0254)	(0.0388)	(0.0039)			
7. Plastic products and rubber products	0.0663*	0.9616	0.0006	0.9601	2347	2648
	(0.0174)	(0.0283)	(0.0017)			
8. Ceramic, stone and clay products	0.1168*	1.0122	0.0079*	0.9466	1343	1051
	(0.0239)	(0.0388)	(0.0038)			
9. Iron and steel	0.0984*	0.9678	−0.0119*	0.8936	594	876
	(0.0337)	(0.0570)	(0.0055)			
10. Non-ferrous metals and products	−0.0564	0.8927	−0.0151	0.6181	508	506
	(0.0417)	(0.0667)	(0.0097)			
11. Fabricated metal products	0.1134*	0.9680	−0.0020	0.9407	2409	3001
	(0.0179)	(0.0240)	(0.0014)			
12. General-purpose machinery	0.1411*	1.0138	−0.0004	0.9498	3228	3842
	(0.0161)	(0.0214)	(0.0014)			
13. Business oriented machinery	0.2250*	0.9545	−0.0242	0.8891	663	687
	(0.0406)	(0.0567)	(0.0237)			
14. Electrical machinery, equipment and supplies, electronic parts, devices and electronic circuits; Information and communication electronics equipment	0.1662*	0.9859	−0.0004	0.9104	4430	3201
	(0.0131)	(0.0223)	(0.0011)			
15. Transportation equipment	0.0894*	0.9507	0.0015	0.9143	1795	2497
	(0.0211)	(0.0304)	(0.0022)			
16. Miscellaneous manufacturing industries	0.1513*	0.9870	−0.0056	0.9152	556	632
	(0.0660)	(0.0712)	(0.1640)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for below-median dense cities and Obs. (A) denotes the number of observations for above-median dense cities.

Table 4: Comparison between Estimation Results for All Sectors Using Different TFP Measures

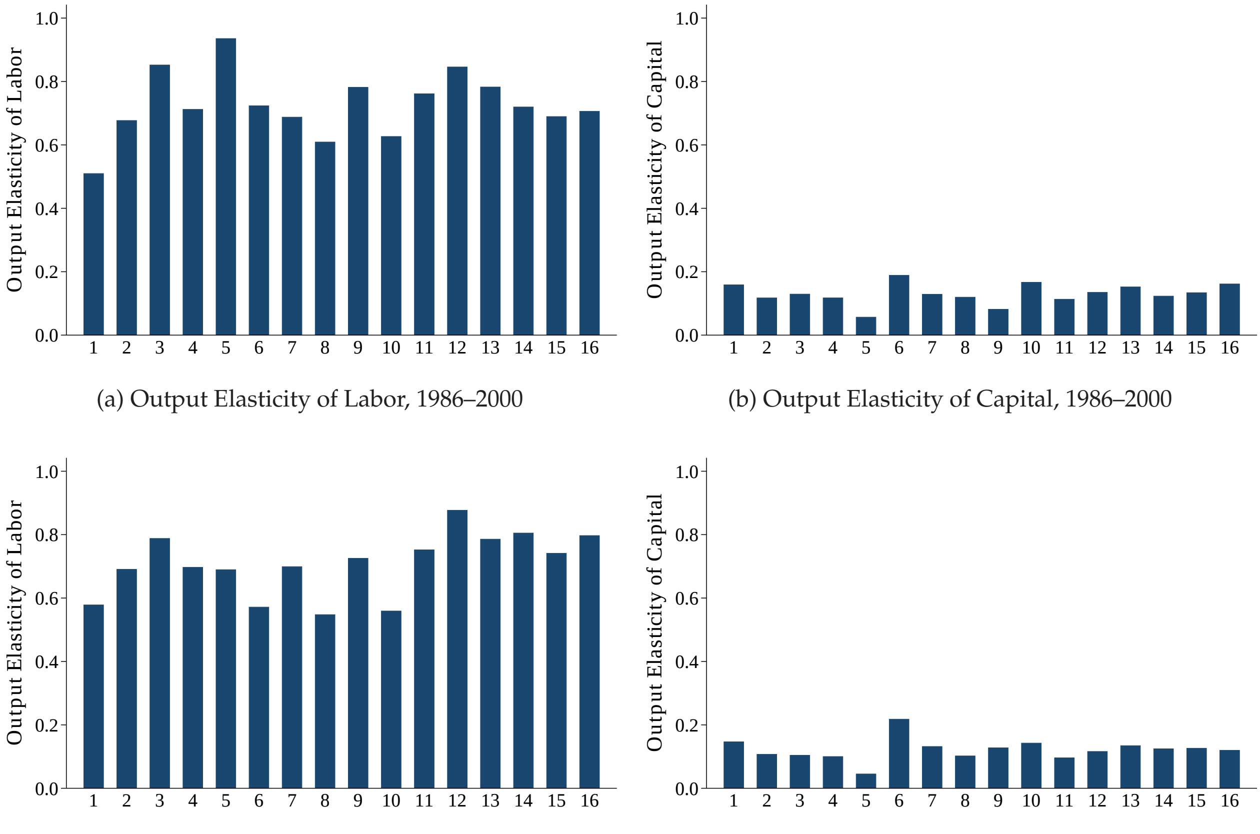
TFP Estimation Methods	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
	Employment Density, Period: 1986–2000					
OLS (Cobb-Douglass)	0.1614*	1.0404*	0.0001	0.9956	39802	39803
	(0.0042)	(0.0079)	(0.0003)			
OLS (Trans-Log)	0.1623*	1.0533*	0.0001	0.9954	39802	39803
	(0.0040)	(0.0080)	(0.0003)			
Fixed Effects (Cobb-Douglass)	0.1861*	1.0333*	−0.0003	0.9898	39802	39803
	(0.0047)	(0.0073)	(0.0003)			
Levinsohn–Petrin (Cobb-Douglass)	0.1851*	1.0275*	−0.0003	0.9926	39802	39803
	(0.0044)	(0.0073)	(0.0003)			
	Employment Density, Period: 2001–2014					
OLS (Cobb-Douglass)	0.1283*	1.0027	0.0001	0.9862	30163	30164
	(0.0042)	(0.0084)	(0.0004)			
OLS (Trans-Log)	0.1285*	1.0085	−0.0001	0.9854	30163	30164
	(0.0042)	(0.0084)	(0.0004)			
Fixed Effects (Cobb-Douglass)	0.1288*	0.9822*	−0.0002	0.9761	30163	30164
	(0.0059)	(0.0081)	(0.0005)			
Levinsohn–Petrin (Cobb-Douglass)	0.1273*	0.9971	0.0004	0.9716	28738	28739
	(0.0062)	(0.0078)	(0.0003)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for below-median dense cities and Obs. (A) denotes the number of observations for above-median dense cities.

Table 5: Comparison of Different Spatial Scales for All Sectors

Comparison of Different Spatial Units	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
	Employment Density, Period: 1986–2000					
Below- vs Above-Median	0.1851*	1.0275*	−0.0003	0.9926	39802	39803
	(0.0044)	(0.0073)	(0.0003)			
Below- vs Above-75th percentile	0.1886*	1.0083	−0.0006	0.9935	59701	19904
	(0.0049)	(0.0092)	(0.0004)			
Below-25th vs Above-75th percentile	0.3010*	1.0656*	−0.0002	0.9980	19901	19904
	(0.0080)	(0.0165)	(0.0007)			
25–50th vs 50–75th percentile	0.0684*	1.0014	−0.0002	0.9274	19901	19899
	(0.0091)	(0.0143)	(0.0006)			
	Employment Density, Period: 2001–2014					
Below- vs Above-Median	0.1273*	0.9971	0.0004	0.9716	28738	28739
	(0.0062)	(0.0078)	(0.0003)			
Below- vs Above-75th percentile	0.1254*	0.9685*	0.0000	0.9851	45247	15082
	(0.0059)	(0.0090)	(0.0005)			
Below-25th vs Above-75th percentile	0.2187*	0.9918	0.0003	0.9924	15081	15082
	(0.0097)	(0.0161)	(0.0009)			
25–50th vs 50–75th percentile	0.0438*	0.9930	−0.0003	0.8391	15082	15082
	(0.0105)	(0.0177)	(0.0008)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for smaller cities and Obs. (A) denotes the number of observations for larger cities.



(a) Output Elasticity of Labor, 1986–2000

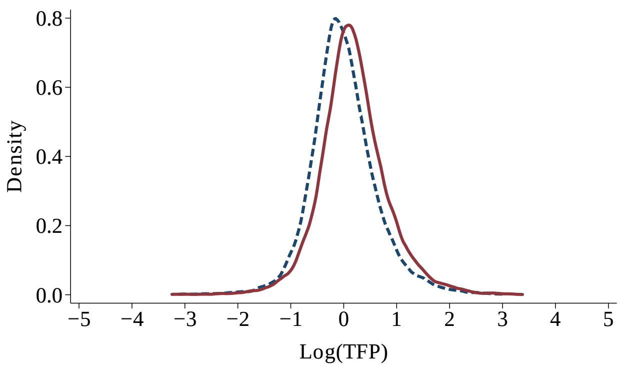
(b) Output Elasticity of Capital, 1986–2000

(c) Output Elasticity of Labor, 2001–2014

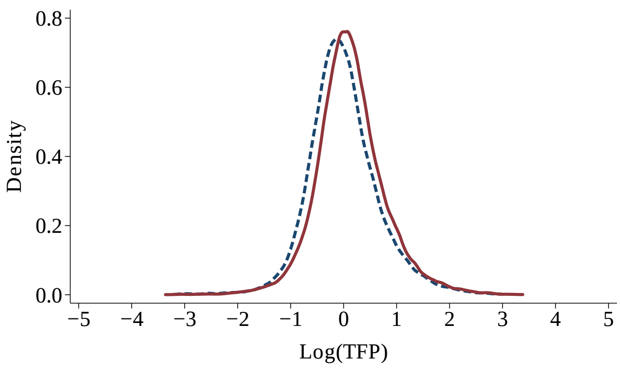
(d) Output Elasticity of Capital, 2001–2014

Figure 1: Estimated Output Elasticities of Labor and Capital

Note: Created by author. Numbers correspond to sector numbers used in Table 2.



(a) Employment Density, 1986–2000



(b) Employment Density, 2001–2014

Figure 2: TFP Distributions for All Sectors

Note: Created by author. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.

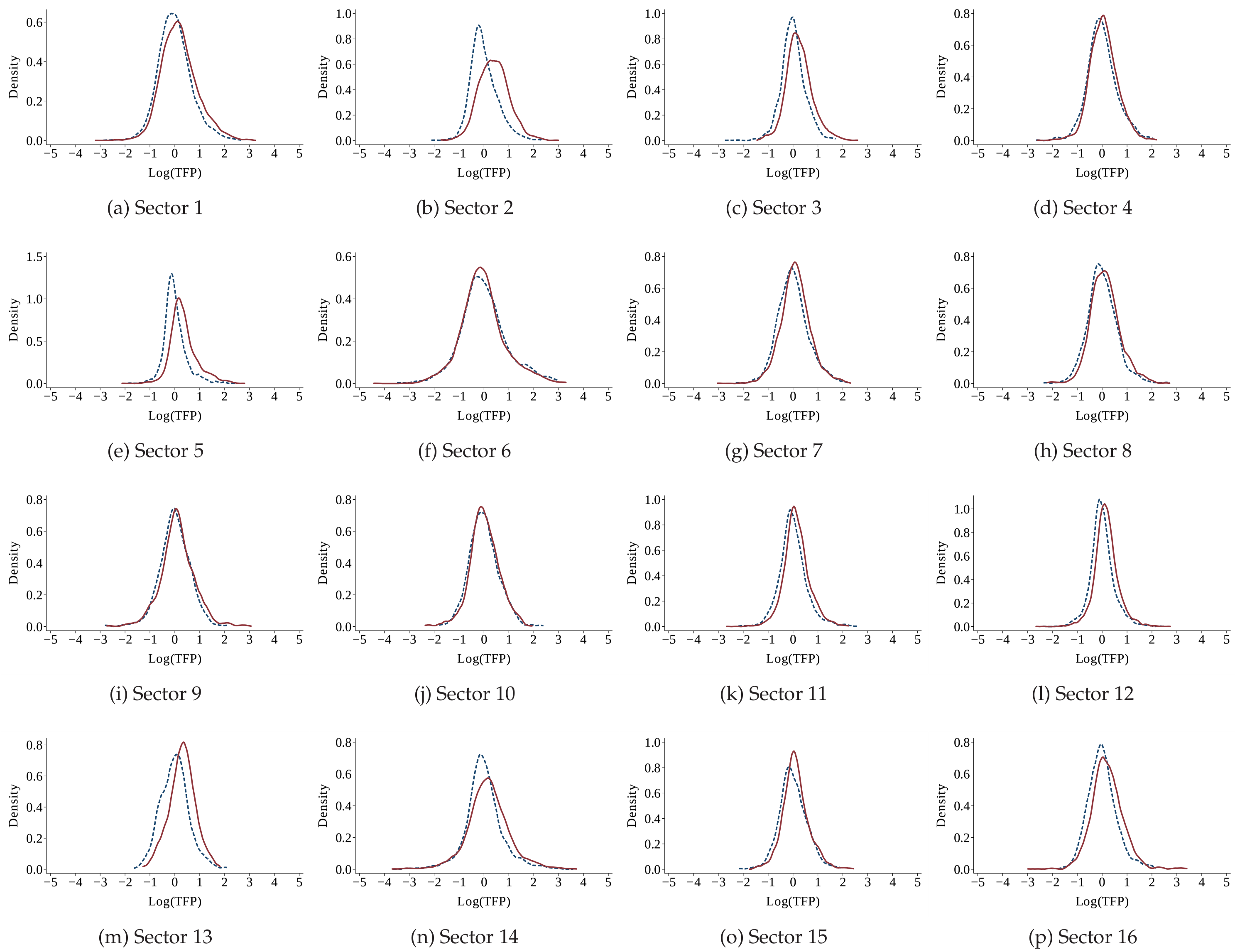
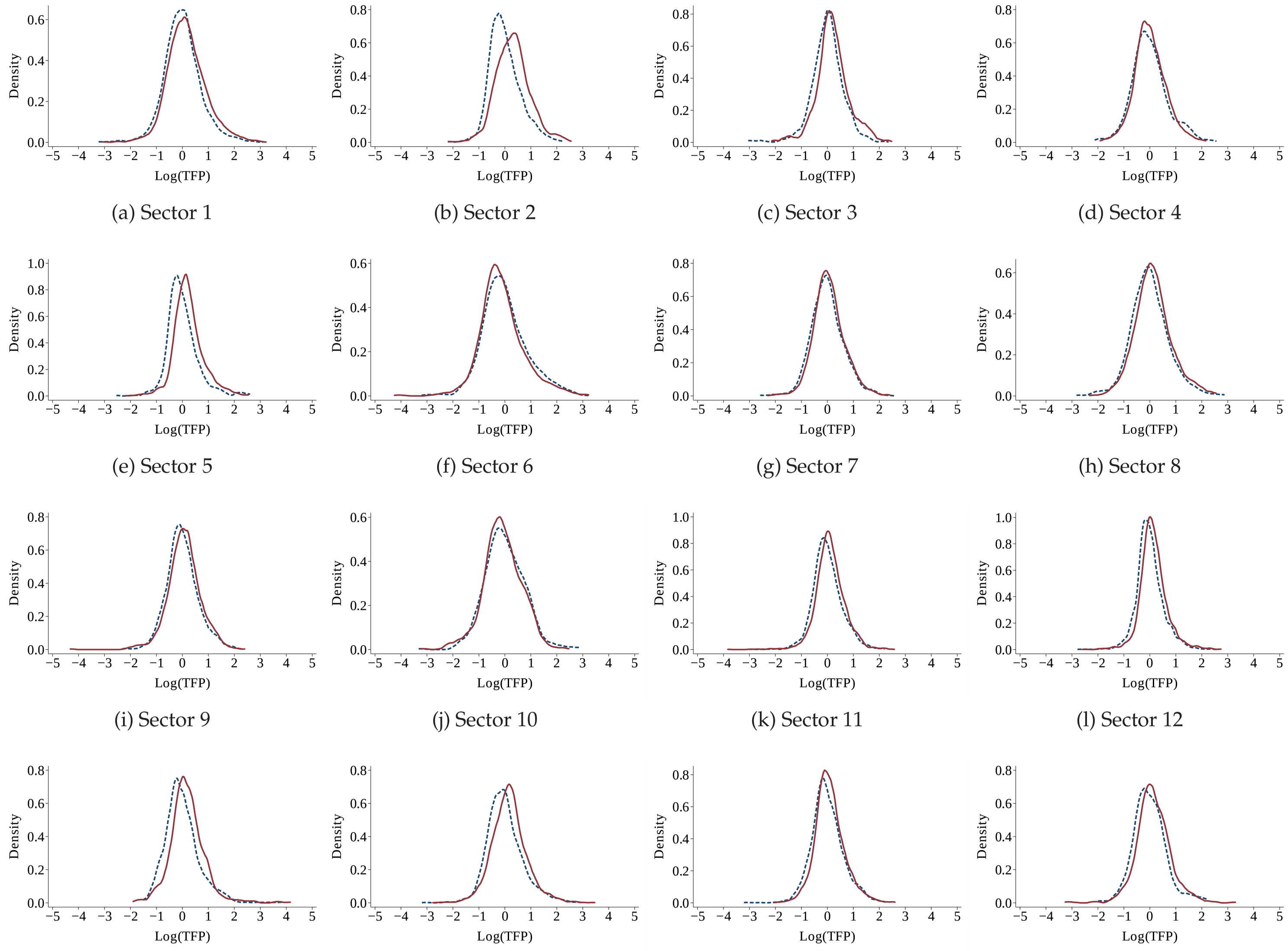


Figure 3: TFP Distributions by Sector, 1986–2000, Employment Density

Note: Created by author. Sector numbers correspond to those used in Table 2. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.



(a) Sector 1 (b) Sector 2 (c) Sector 3 (d) Sector 4

(e) Sector 5 (f) Sector 6 (g) Sector 7 (h) Sector 8

(i) Sector 9 (j) Sector 10 (k) Sector 11 (l) Sector 12

(m) Sector 13 (n) Sector 14 (o) Sector 15 (p) Sector 16

Figure 4: TFP Distributions by Sector, 2001–2014, Employment Density

Note: Created by author. Sector numbers correspond to those used in Table 2. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.

Online Appendix for

Testing for Agglomeration Economies and Firm Selection in Spatial Productivity Differences: The Case of Japan

Keisuke Kondo*

This online appendix offers additional robustness checks.

Robustness Check 3: Market Potential

This study also offers estimation results by comparing between the below- and above-median market potential instead of employment density. The market potential is defined as $\mathrm{MP}_r = \sum_{s=1}^{R} Y_s d_r$, where Y_r is the total income in city r and d_r is the bilateral distance between r.[1]

Table OA.1 presents the descriptive statistics of the estimated TFP between below- and above-median market potentials. Similar to the case of the employment density, overall, cities with above-median market potential show higher TFP than cities with below-median market potential at any quantile in Table OA.1.

[Table OA.1]

Figure OA.1 illustrates the distributions between cities with below- and above-median market potential for all of the sectors. Figures OA.2 and OA.3 illustrate the productivity distributions between cities with below- and above-median market potential by sector in the 1986–2000 and 2001–2014 time periods, respectively.

[Figures OA.1–OA.3]

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[1]Although Accetturo et al. (2013) also mention the spatial productivity distributions in terms of market potential, the definition follows that of population potential as $\mathrm{PP}_r = \sum_{s=1}^{R} P_s d_r$, where P_r is population in city r.

Tables OA.2 and OA.3 present the estimation results of TFP by sector based on the market potential. These estimation results are qualitatively similar to the baseline case of employment density in Tables 2 and 3 presented in the paper. In other words, cities with greater market potential show higher productivity than cities with smaller market potential through the right-shift of productivity distribution. However, selection is not a major factor that can explain the spatial productivity differences in the Japanese manufacturing sector.

[Tables OA.2–OA.3]

Robustness Check 4: Labor Productivity

Table OA.4 presents the descriptive statistics of labor productivity. As a baseline of categorization for city size, we use employment density, and compare productivity distributions between below- and above-median employment densities. Overall, above-median dense cities show higher labor productivity than below-median dense cities at any quantile in Table OA.4. These observations suggest that establishments in larger cities enjoy the benefits from agglomeration economies.

[Table OA.4]

The CM includes no information on capital stocks for establishments with 29 employees or less, which does not allow us to estimate TFP. In order to additionally include small and medium-sized establishments into the sample, we use labor productivity instead of TFP. In this case, the labor productivity, $\log(\mathrm{LP}_{it})$, is calculated as $\log(v_{it}/\ell_{it})$, where v_{it} is value added and ℓ_{it} is labor. However, the definitions of both variables differ from those used for TFP estimation. In addition, establishments with 29 employees or less have no information on inventories and semi-manufactuerd goods, and thus the value added is calculated as the value of manufactured goods shipments minus the cost of raw materials, fuel, and electricity consumed, as well as the subcontracting expenses for production outsourcing. Furthermore, labor is the annual number of workers, not the annual hours worked.[2] Hence, establishments with negative value added are dropped.

Figure OA.4 illustrates the distributions of labor productivity between cities with below- and above-median employment densities. Figures OA.5 and OA.6 present labor productivity distributions by sectors. Overall, above-median dense cities enjoy the benefits of agglomeration economies,

[2]Form B includes no information regarding the annual number of workers, but it includes the monthly number of workers at the end of the year. Thus, we calculated the annual number of workers by multiplying it by 12.

which is similar to the case of TFP. As discussed earlier, cities with above-median dense cities are, overall, characterized by the right-shift of the productivity distribution. However, since the degree of the right-shift has decreased in the most recent decade, we cannot conclude the left-truncation of the labor productivity distributions from the visualization.

[Figure OA.4–OA.6]

Tables OA.5 and OA.6 present the estimation results of labor productivity by sector for the 1986–2000 and 2001–2014 time periods, respectively. Although some sectors show a significantly positive relative truncation parameter $\hat{S}$, our main results using TFP estimates appear to be robust. The magnitude of $\hat{S}$ is not so big as to explain a large part of spatial productivity differences. On the other hand, unlike the case of TFP, we cannot determine the dilation effects of agglomeration economies for some sectors. The opposite dilation effects ($\hat{D} < 1$) can be also observed, suggesting that relatively inefficient establishments in larger cities enjoy the benefits from agglomeration economies, such as transactions with efficient firms. As a result, the estimated relative shift parameter $\hat{A}$ better explains the spatial productivity differences.

[Tables OA.5–OA.6]

As a robustness check, we compare productivity distributions using three different spatial scales. The first case is the categorization at the 75th percentile point of employment density. The second case compares the below-25th percentile with the above-75th percentile. The third case compares the 25–50th percentile with the 50–75th percentile. Table OA.7 presents the estimation results of labor productivity for all of the sectors. In both 1986–2000 and 2001–2014 time periods, the estimated relative truncation parameter $\hat{S}$ is quite small. In contrast, estimated relative shift parameter $\hat{A}$ is a significantly positive. This robustness check also indicates that agglomeration economies better explain spatial productivity differences through the right-shift of productivity distribution.

[Table OA.7]

References

[1] Accetturo, Antonio, Valter Di Giacinto, Giacinto Micucci, and Marcello Pagnini (2013) "Geography, productivity and trade: Does selection explain why some locations are more productive than others?". Temi di Discussione (Working Papers) No. 910, Bank of Italy.

Table OA.1: Descriptive Statistics of TFP and Market Potential

Variables	Obs.	Mean	S.D.	p10	p25	p50	p75	p90
	Labor Productivity, Period: 1986–2000							
log(TFP)	79685	4.142	0.654	3.422	3.758	4.103	4.486	4.933
log(MP)	79685	13.848	0.672	12.986	13.359	13.831	14.330	14.757
log(TFP), Below-Median Potential	39842	4.027	0.620	3.351	3.664	3.985	4.354	4.771
log(TFP), Above-Median Potential	39843	4.257	0.666	3.530	3.881	4.217	4.603	5.050
log(MP), Below-Median Potential	39842	13.296	0.361	12.798	13.070	13.359	13.570	13.732
log(MP), Above-Median Potential	39843	14.399	0.404	13.919	14.051	14.330	14.670	15.021
	Labor Productivity, Period: 2001–2014							
log(TFP)	60391	4.397	0.668	3.663	3.999	4.353	4.749	5.215
log(MP)	60391	13.916	0.630	13.103	13.466	13.923	14.317	14.731
log(TFP), Below-Median Potential	30195	4.314	0.662	3.600	3.921	4.270	4.661	5.122
log(TFP), Above-Median Potential	30196	4.479	0.663	3.749	4.086	4.435	4.824	5.292
log(MP), Below-Median Potential	30195	13.406	0.360	12.880	13.201	13.466	13.662	13.842
log(MP), Above-Median Potential	30196	14.425	0.382	13.995	14.116	14.317	14.637	14.998

Notes: TFP is controlled for industry-year effects. MP indicates market potential. In the estimation, lowermost and uppermost 0.05% of productivity distribution are dropped by category.

Table OA.2: Estimation Results of TFP Distributions by Sector, 1986–2000, Below- vs. Above-Median Market Potential

Sectors	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
All Sectors	0.2319*	1.0654*	−0.0006	0.9968	39802	39803
	(0.0041)	(0.0081)	(0.0004)			
1. Food, beverages, tobacco, feed	0.2733*	1.1150*	0.0008	0.9917	6647	4471
	(0.0124)	(0.0188)	(0.0007)			
2. Textile mill products, leather tanning, leather products, and fur skins	0.4627*	1.0847*	0.0010	0.9871	7124	2924
	(0.0123)	(0.0217)	(0.0012)			
3. Lumber, wood products, furniture, and fixtures	0.3004*	1.1153*	−0.0001	0.9910	2096	1160
	(0.0209)	(0.0335)	(0.0027)			
4. Pulp, paper and paper products	0.0689*	0.9333	0.0004	0.8325	965	1440
	(0.0274)	(0.0440)	(0.0032)			
5. Printing and allied industries	0.3537*	1.2284*	0.0014	0.9839	1393	2782
	(0.0192)	(0.0375)	(0.0020)			
6. Chemical and allied products	0.0410	1.1013*	0.0050*	0.6443	938	1697
	(0.0262)	(0.0408)	(0.0020)			
7. Plastic products and rubber products	0.1720*	0.9859	−0.0010	0.9787	1998	3194
	(0.0151)	(0.0309)	(0.0016)			
8. Ceramic, stone and clay products	0.2119*	1.0777*	0.0006	0.9475	2139	1719
	(0.0197)	(0.0318)	(0.0022)			
9. Iron and steel	0.1568*	1.1997*	−0.0009	0.8575	680	960
	(0.0338)	(0.0570)	(0.0050)			
10. Non-ferrous metals and products	0.0794	0.9069	−0.0073	0.7839	402	649
	(0.1001)	(0.0858)	(0.2423)			
11. Fabricated metal products	0.1901*	0.9707	−0.0005	0.9694	2672	3812
	(0.0162)	(0.0230)	(0.0012)			
12. General-purpose machinery	0.1916*	1.0262	−0.0005	0.9923	3353	4972
	(0.0133)	(0.0257)	(0.0009)			
13. Business oriented machinery	0.3563*	0.8744*	−0.0616*	0.9827	812	920
	(0.0314)	(0.0494)	(0.0052)			
14. Electrical machinery, equipment and supplies, electronic parts, devices and	0.1948*	1.1508*	−0.0013	0.9435	6152	5406
electronic circuits; Information and communication electronics equipment	(0.0115)	(0.0214)	(0.0010)			
15. Transportation equipment	0.1335*	0.9901	0.0035*	0.9852	1654	2635
	(0.0199)	(0.0334)	(0.0014)			
16. Miscellaneous manufacturing industries	0.2649*	1.0982+	−0.0021	0.9684	759	1048
	(0.0306)	(0.0551)	(0.0062)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for cities with below-median market potential and Obs. (A) denotes the number of observations for cities with above-median market potential.

Table OA.3: Estimation Results of TFP Distributions by Sector, 2001–2014, Below- vs. Above-Median Market Potential

Sectors	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
All Sectors	0.1611*	1.0152+	0.0004	0.9941	28737	28740
	(0.0048)	(0.0081)	(0.0003)			
1. Food, beverages, tobacco, feed	0.2372*	1.0982*	0.0042*	0.9815	6186	4247
	(0.0104)	(0.0178)	(0.0010)			
2. Textile mill products, leather tanning, leather products, and fur skins	0.3505*	1.0203	−0.0086*	0.9741	2545	1100
	(0.0221)	(0.0335)	(0.0020)			
3. Lumber, wood products, furniture, and fixtures	0.2578*	1.1002*	0.0051	0.9563	1130	671
	(0.0279)	(0.0505)	(0.0039)			
4. Pulp, paper and paper products	−0.0032	0.8929*	−0.0013	0.7247	847	1124
	(0.0230)	(0.0441)	(0.0044)			
5. Printing and allied industries	0.2552*	1.0113	0.0011	0.9643	1113	1910
	(0.0217)	(0.0383)	(0.0020)			
6. Chemical and allied products	−0.0631*	1.0444	0.0021	0.5729	1068	1540
	(0.0239)	(0.0379)	(0.0029)			
7. Plastic products and rubber products	0.1040*	0.9737	0.0018	0.9741	2108	2887
	(0.0167)	(0.0284)	(0.0017)			
8. Ceramic, stone and clay products	0.1747*	1.0511	0.0130*	0.9677	1259	1135
	(0.0255)	(0.0395)	(0.0029)			
9. Iron and steel	0.1534*	0.8682+	−0.0150	0.8647	643	827
	(0.0360)	(0.0679)	(0.0300)			
10. Non-ferrous metals and products	−0.0646+	0.8040*	−0.0076	0.7005	455	559
	(0.0383)	(0.0744)	(0.0089)			
11. Fabricated metal products	0.1437*	0.9906	−0.0008	0.9637	2388	3022
	(0.0174)	(0.0285)	(0.0013)			
12. General-purpose machinery	0.1282*	1.0792*	0.0010	0.9729	3250	3820
	(0.0167)	(0.0221)	(0.0011)			
13. Business oriented machinery	0.2330*	1.1858*	−0.0026	0.8371	574	776
	(0.0364)	(0.0645)	(0.0050)			
14. Electrical machinery, equipment and supplies, electronic parts, devices and	0.1922*	0.9822	−0.0009	0.9391	4216	3415
electronic circuits; Information and communication electronics equipment	(0.0153)	(0.0240)	(0.0011)			
15. Transportation equipment	0.0726*	0.9786	−0.0004	0.9024	1844	2448
	(0.0193)	(0.0294)	(0.0017)			
16. Miscellaneous manufacturing industries	0.2287*	1.0703	−0.0041	0.9531	519	669
	(0.0341)	(0.0636)	(0.0052)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for cities with below-median market potential and Obs. (A) denotes the number of observations for cities with above-median market potential.

Table OA.4: Descriptive Statistics of Labor Productivity and Employment Density

Variables	Obs.	Mean	S.D.	p10	p25	p50	p75	p90
	Labor Productivity, Period: 1986–2000							
log(LP)	468090	3.669	0.667	2.861	3.257	3.672	4.068	4.461
log(Dens)	468090	6.812	0.989	5.616	6.066	6.686	7.882	8.160
log(LP), Below-Median Density	234045	3.578	0.674	2.775	3.166	3.574	3.975	4.383
log(LP), Above-Median Density	234045	3.760	0.647	2.963	3.361	3.771	4.145	4.523
log(Dens), Below-Median Density	234045	5.966	0.495	5.276	5.736	6.066	6.330	6.487
log(Dens), Above-Median Density	234045	7.657	0.530	6.828	7.202	7.882	8.081	8.291
	Labor Productivity, Period: 2001–2014							
log(LP)	306643	3.707	0.739	2.825	3.285	3.734	4.140	4.545
log(Dens)	306643	6.740	1.001	5.502	6.010	6.629	7.761	8.146
log(LP), Below-Median Density	153306	3.652	0.756	2.760	3.226	3.672	4.086	4.511
log(LP), Above-Median Density	153337	3.762	0.716	2.893	3.349	3.794	4.186	4.573
log(Dens), Below-Median Density	153306	5.895	0.538	5.161	5.642	6.010	6.294	6.476
log(Dens), Above-Median Density	153337	7.584	0.534	6.792	7.162	7.761	8.008	8.276

Notes: TFP is controlled for industry-year effects. Dens indicates employment density (workers/km^2). In the estimation, lowermost and uppermost 0.05% of productivity distribution are dropped by category.

Table OA.5: Estimation Results of Labor Productivity Distributions by Sector, 1986–2000, Below- vs. Above-Median Employment Density

Sectors	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
All Sectors	0.1810*	0.9640*	0.0004*	0.9938	233809	233809
	(0.0018)	(0.0031)	(0.0001)			
1. Food, beverages, tobacco, feed	0.2385*	0.9898	0.0031*	0.9781	39109	16796
	(0.0054)	(0.0079)	(0.0003)			
2. Textile mill products, leather tanning, leather products, and fur skins	0.2360*	1.1048*	0.0017*	0.9829	39986	31743
	(0.0039)	(0.0056)	(0.0001)			
3. Lumber, wood products, furniture, and fixtures	0.1906*	1.0039	0.0009*	0.9965	26059	14114
	(0.0060)	(0.0083)	(0.0002)			
4. Pulp, paper and paper products	0.1013*	0.8615*	0.0009	0.9778	4494	7960
	(0.0115)	(0.0153)	(0.0007)			
5. Printing and allied industries	0.3625*	1.0742*	0.0009*	0.9971	10356	21483
	(0.0073)	(0.0105)	(0.0003)			
6. Chemical and allied products	−0.1590*	0.9170*	−0.0004	0.9605	2411	3504
	(0.0177)	(0.0240)	(0.0012)			
7. Plastic products and rubber products	0.0724*	0.9285*	0.0001	0.9117	10460	17954
	(0.0081)	(0.0118)	(0.0004)			
8. Ceramic, stone and clay products	−0.1020*	1.1651*	0.0347*	0.6902	14163	8398
	(0.0081)	(0.0118)	(0.0004)			
9. Iron and steel	0.1421*	1.0852*	−0.0016	0.9827	2904	4067
	(0.0147)	(0.0225)	(0.0012)			
10. Non-ferrous metals and products	0.0726*	0.8393*	−0.0054*	0.9090	1885	2786
	(0.0185)	(0.0264)	(0.0024)			
11. Fabricated metal products	0.1350*	0.9645*	0.0004	0.9765	21903	34031
	(0.0058)	(0.0077)	(0.0003)			
12. General-purpose machinery	0.1392*	0.9842+	−0.0001	0.9962	19023	30465
	(0.0057)	(0.0086)	(0.0003)			
13. Business oriented machinery	0.3552*	0.8326*	−0.0389*	0.9911	3685	4298
	(0.0137)	(0.0198)	(0.0010)			
14. Electrical machinery, equipment and supplies, electronic parts, devices and electronic circuits; Information and communication electronics equipment	0.2955*	1.0048	−0.0007*	0.9368	20165	18023
	(0.0064)	(0.0093)	(0.0002)			
15. Transportation equipment	0.1339*	0.9580*	−0.0065*	0.9425	8249	8788
	(0.0102)	(0.0129)	(0.0005)			
16. Miscellaneous manufacturing industries	0.2502*	0.9700*	0.0010*	0.9947	8939	9383
	(0.0090)	(0.0128)	(0.0005)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for below-median dense cities and Obs. (A) denotes the number of observations for above-median dense cities.

Table OA.6: Estimation Results of Labor Productivity Distributions by Sector, 2001–2014, Below- vs. Above-Median Employment Density

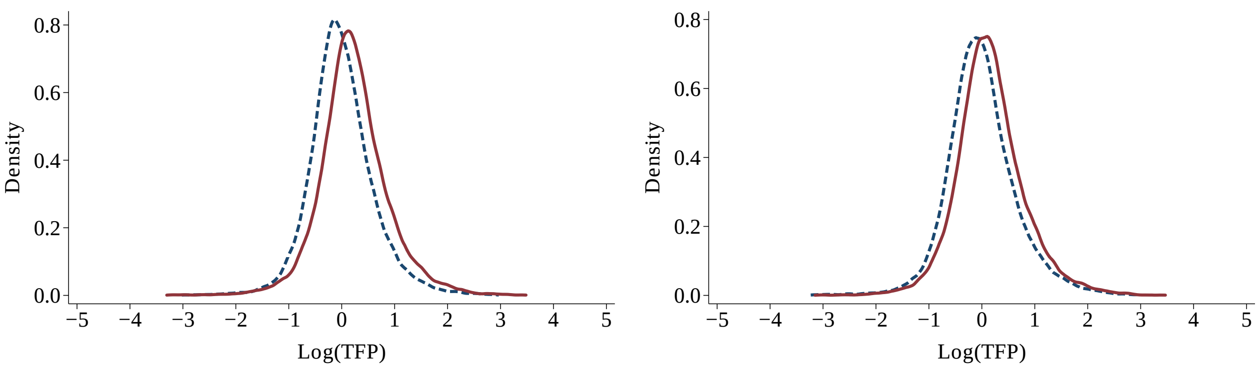
Sectors	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
All Sectors	0.1103*	0.9486*	0.0002	0.9759	153152	153183
	(0.0027)	(0.0039)	(0.0002)			
1. Food, beverages, tobacco, feed	0.2141*	0.9794*	0.0009*	0.9673	30444	13402
	(0.0061)	(0.0095)	(0.0003)			
2. Textile mill products, leather tanning, leather products, and fur skins	0.1386*	1.0950*	−0.0003	0.9224	15555	12782
	(0.0078)	(0.0103)	(0.0004)			
3. Lumber, wood products, furniture, and fixtures	0.1315*	0.9907	0.0007	0.9782	13628	7633
	(0.0093)	(0.0126)	(0.0006)			
4. Pulp, paper and paper products	−0.0003	0.8920*	−0.0015+	0.8400	3287	5512
	(0.0132)	(0.0209)	(0.0009)			
5. Printing and allied industries	0.2354*	1.0464*	0.0003	0.9662	6962	13057
	(0.0092)	(0.0120)	(0.0005)			
6. Chemical and allied products	−0.2284*	0.9483*	0.0047*	0.8298	2458	3076
	(0.0213)	(0.0246)	(0.0014)			
7. Plastic products and rubber products	0.0238*	0.9414*	0.0003	0.8757	8969	13076
	(0.0085)	(0.0126)	(0.0005)			
8. Ceramic, stone and clay products	−0.0607*	1.1751*	0.0090*	0.7235	9792	5758
	(0.0110)	(0.0151)	(0.0007)			
9. Iron and steel	0.1110*	0.9640	0.0011	0.9487	2139	2943
	(0.0217)	(0.0250)	(0.0013)			
10. Non-ferrous metals and products	−0.0046	0.8615*	−0.0046*	0.7695	1579	1968
	(0.0252)	(0.0302)	(0.0022)			
11. Fabricated metal products	0.0726*	0.9740*	0.0001	0.9003	16150	23713
	(0.0066)	(0.0095)	(0.0003)			
12. General-purpose machinery	0.0623*	1.0103	0.0001	0.9212	15764	22900
	(0.0073)	(0.0098)	(0.0004)			
13. Business oriented machinery	0.1954*	0.9585	−0.0039*	0.9121	2201	2867
	(0.0201)	(0.0285)	(0.0015)			
14. Electrical machinery, equipment and supplies, electronic parts, devices and electronic circuits; Information and communication electronics equipment	0.2261*	0.8876*	−0.0136*	0.8812	11782	11196
	(0.0086)	(0.0116)	(0.0005)			
15. Transportation equipment	0.0799*	0.9976	0.0006	0.8637	6701	7007
	(0.0136)	(0.0167)	(0.0008)			
16. Miscellaneous manufacturing industries	0.1608*	0.9740	0.0001	0.9631	5727	6281
	(0.0132)	(0.0166)	(0.0009)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for below-median dense cities and Obs. (A) denotes the number of observations for above-median dense cities.

Table OA.7: Labor Productivity Comparison of Different Spatial Scales for All Sectors

Comparison of Different Spatial Units	$\hat{A}$	$\hat{D}$	$\hat{S}$	R^2	Obs. (B)	Obs. (A)
	Employment Density, Period: 1986–2000					
Below- vs Above-Median	0.1810*	0.9640*	0.0004*	0.9938	233809	233809
	(0.0018)	(0.0031)	(0.0001)			
Below- vs Above-75th Percentile	0.1875*	0.9162*	0.0002	0.9953	350695	116925
	(0.0020)	(0.0031)	(0.0002)			
Below-25th vs Above-75th Percentile	0.2914*	0.9336*	0.0009*	0.9970	116813	116925
	(0.0040)	(0.0060)	(0.0003)			
25–50th vs 50–75th Percentile	0.0700*	0.9974	0.0002	0.9876	116996	116884
	(0.0042)	(0.0055)	(0.0002)			
	Employment Density, Period: 2001–2014					
Below- vs Above-Median	0.1103*	0.9486*	0.0002	0.9759	153152	153183
	(0.0027)	(0.0039)	(0.0002)			
Below- vs Above-75th Percentile	0.1174*	0.9161*	0.0002	0.9847	229718	76617
	(0.0027)	(0.0043)	(0.0002)			
Below-25th vs Above-75th Percentile	0.1837*	0.9109*	0.0006	0.9838	76548	76617
	(0.0051)	(0.0069)	(0.0005)			
25–50th vs 50–75th Percentile	0.0358*	0.9893	0.0000	0.8373	76602	76564
	(0.0054)	(0.0072)	(0.0003)			

Note: Bootstrap standard errors are in parentheses, and 100 times of bootstrap sampling with replacement are conducted. The same sample size is used for each bootstrap sampling. * (+) denotes that $\hat{A}$ and $\hat{S}$ are significantly different from 0 at the 5% (10%) level, and $\hat{D}$ is significantly different from 1 at the 5% (10%) level. Obs. (B) denotes the number of observations for smaller cities and Obs. (A) denotes the number of observations for larger cities.

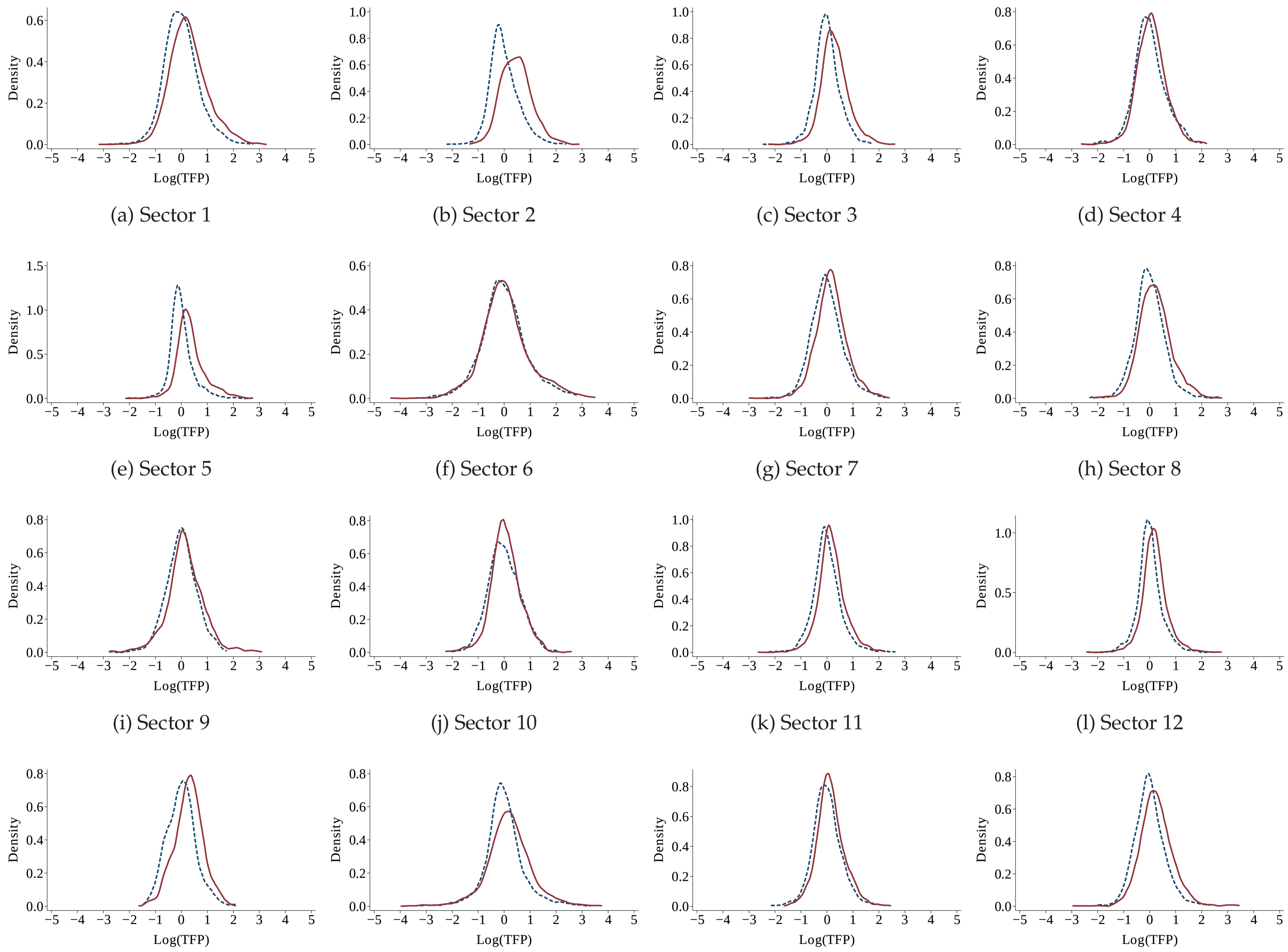


(a) Market Potential, 1986–2000

(b) Market Potential, 2001–2014

Figure OA.1: TFP Distribution for All Sectors between Cities with Below- and Above-Median Market Potential

Note: Created by author. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.



(a) Sector 1 (b) Sector 2 (c) Sector 3 (d) Sector 4

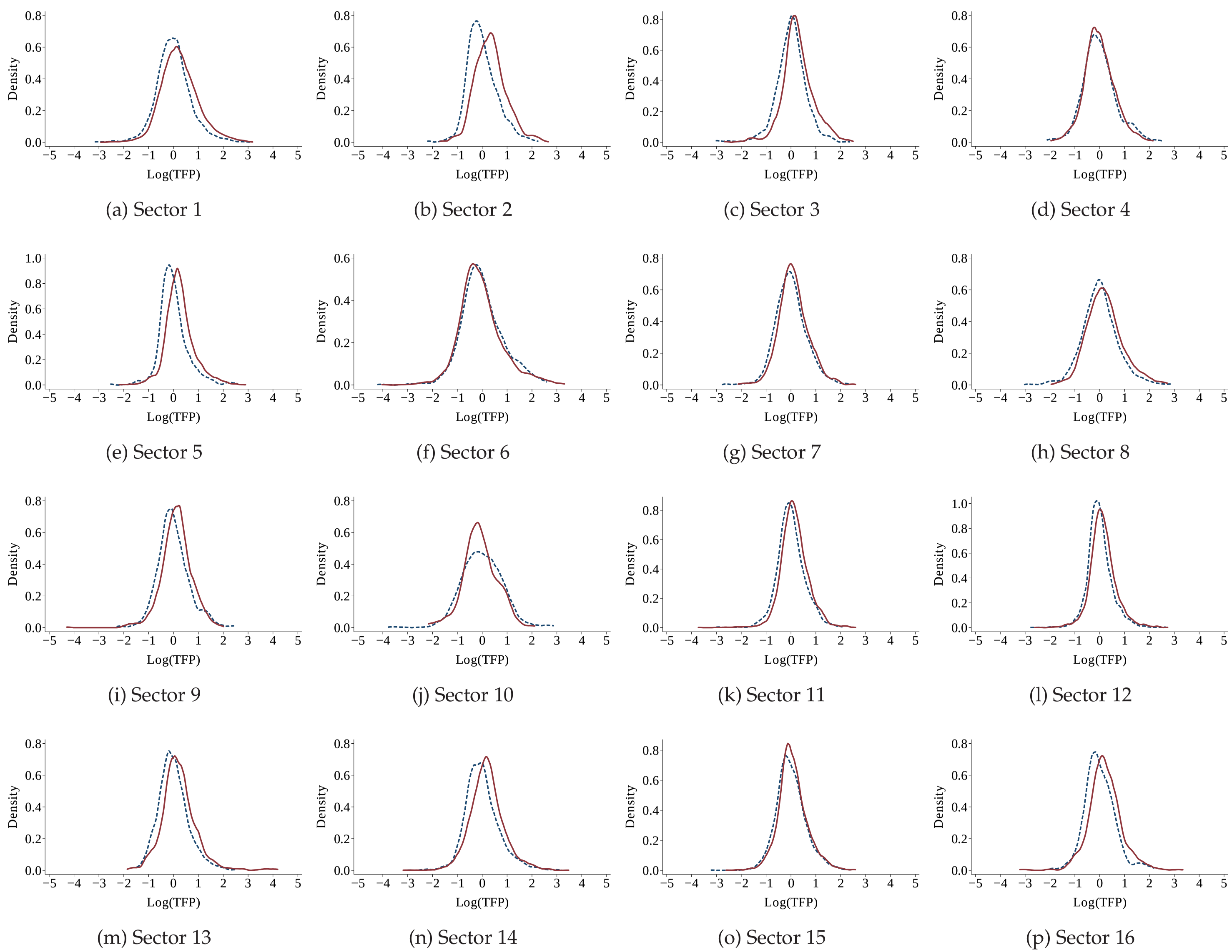
(e) Sector 5 (f) Sector 6 (g) Sector 7 (h) Sector 8

(i) Sector 9 (j) Sector 10 (k) Sector 11 (l) Sector 12

(m) Sector 13 (n) Sector 14 (o) Sector 15 (p) Sector 16

Figure OA.2: TFP Distributions by Sector, 1986–2000, Market Potential

Note: Created by author. Sector numbers correspond to those used in Table **??**. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.



(a) Sector 1 (b) Sector 2 (c) Sector 3 (d) Sector 4

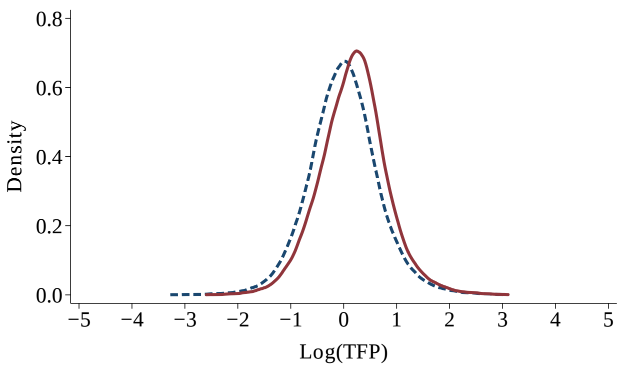
(e) Sector 5 (f) Sector 6 (g) Sector 7 (h) Sector 8

(i) Sector 9 (j) Sector 10 (k) Sector 11 (l) Sector 12

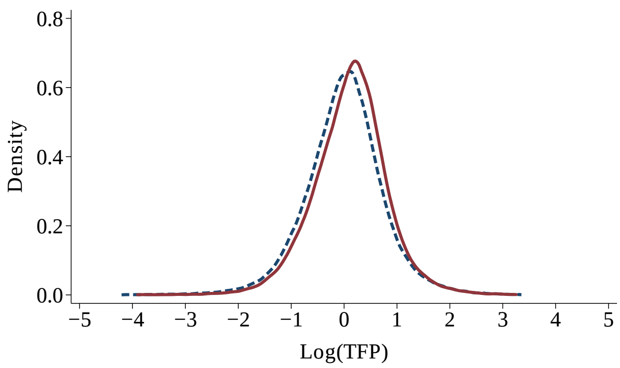
(m) Sector 13 (n) Sector 14 (o) Sector 15 (p) Sector 16

Figure OA.3: TFP Distributions by Sector, 2001–2014, Market Potential

Note: Created by author. Sector numbers correspond to those used in Table **??**. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.



(a) Employment Density, 1986–2000



(b) Employment Density, 2001–2014

Figure OA.4: The Case of Labor Productivity for All Sectors, Employment Density

Note: Created by author. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.

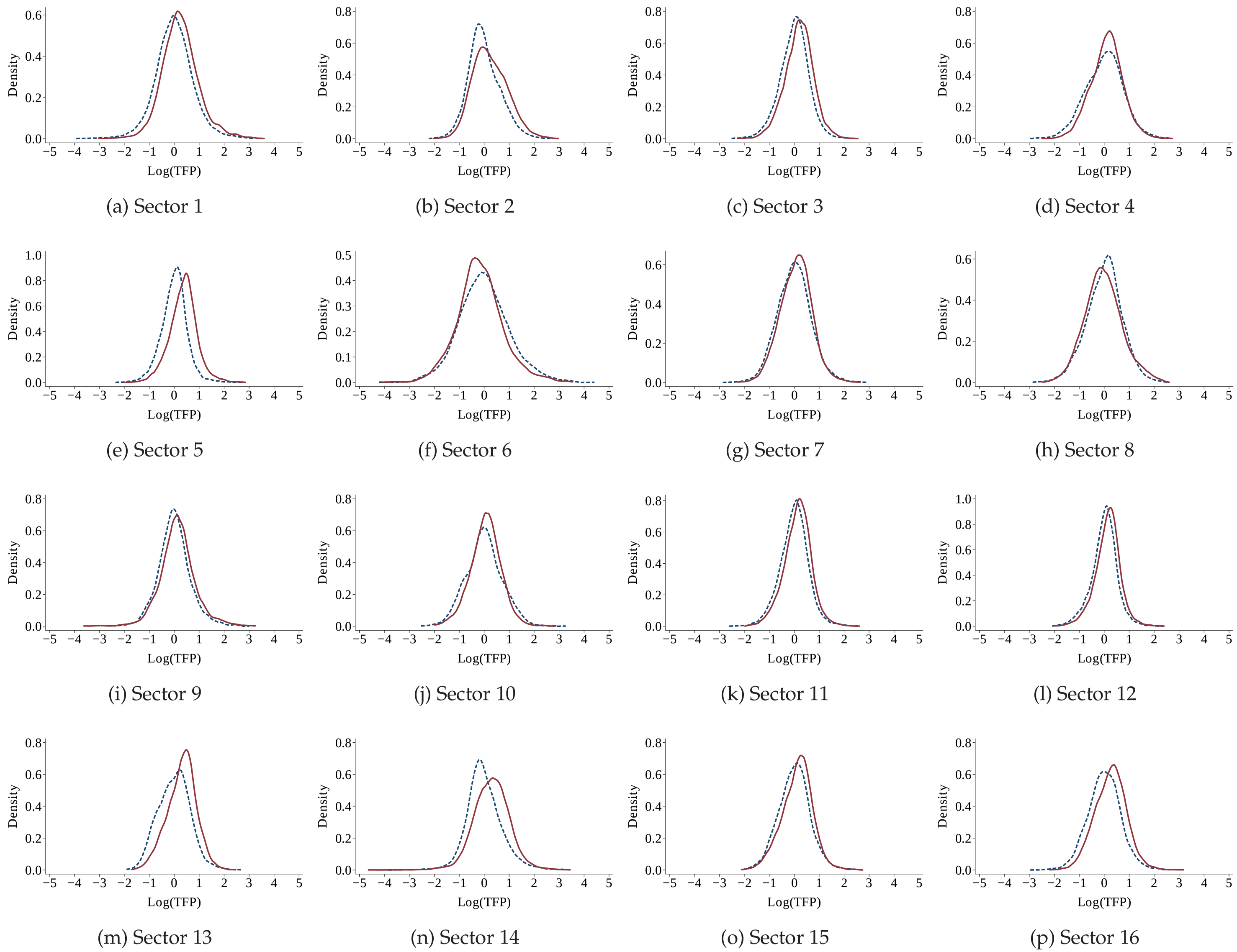
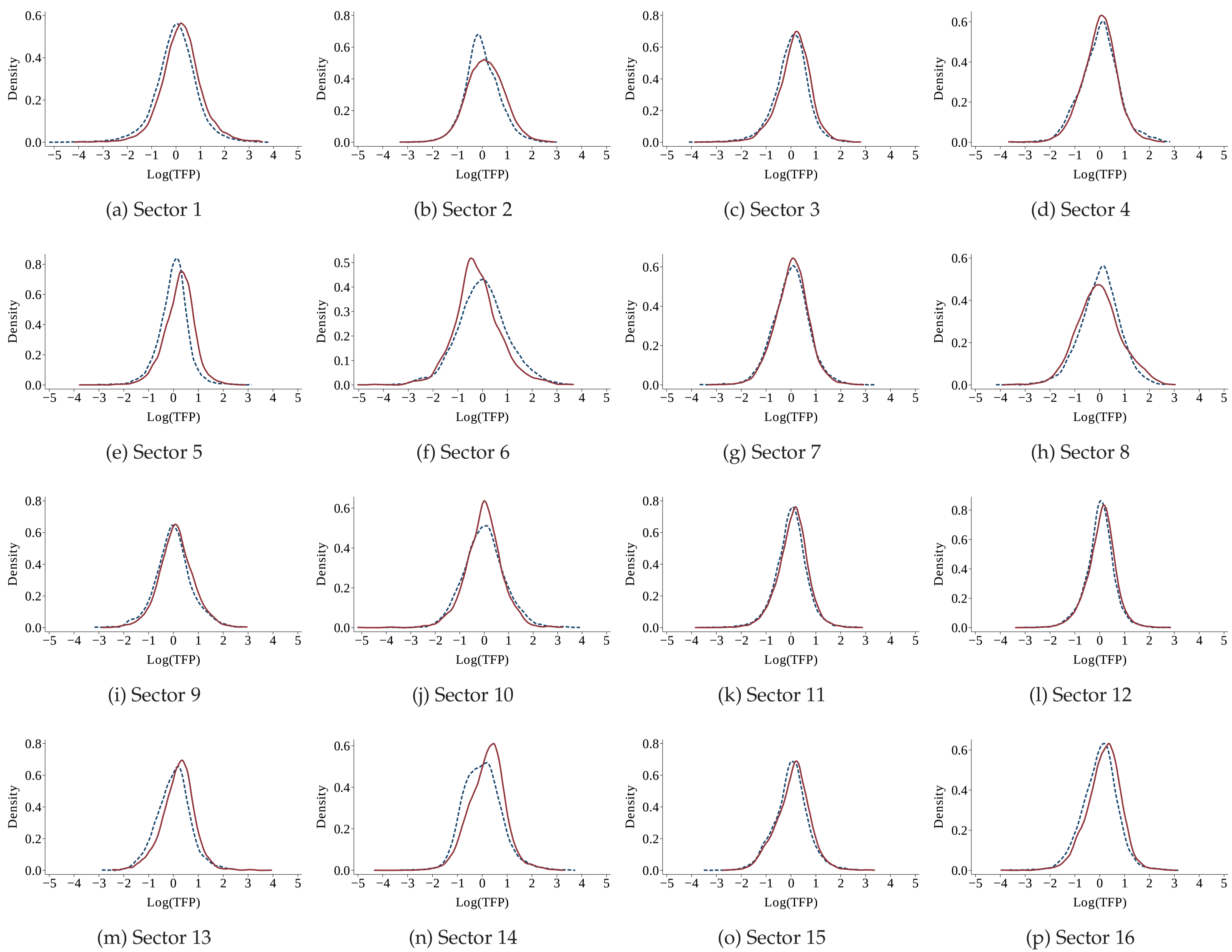


Figure OA.5: Labor Productivity Distributions by Sector, 1986–2000, Employment Density

Note: Created by author. Sector numbers correspond to those used in Table **??**. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.



(a) Sector 1 (b) Sector 2 (c) Sector 3 (d) Sector 4

(e) Sector 5 (f) Sector 6 (g) Sector 7 (h) Sector 8

(i) Sector 9 (j) Sector 10 (k) Sector 11 (l) Sector 12

(m) Sector 13 (n) Sector 14 (o) Sector 15 (p) Sector 16

Figure OA.6: Labor Productivity Distributions by Sector, 2001–2014, Employment Density

Note: Created by author. Sector numbers correspond to those used in Table **??**. The solid (dashed) line is the productivity distribution of cities with above-median (below-median) employment density.