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# Dynamic Benefits of Working in Large Cities: Evidence from Japanese matched employer–employee data*

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Abstract

This study estimates wage and labor productivity profiles using a matched employer-employee dataset of the Japanese service industry. Our main concern is to uncover how work experience in large cities helps workers dynamically accumulate human capital, by comparing wage and labor productivity profiles. This study finds that longer work experience in larger cities steepens wage and labor productivity profiles, suggesting that upgrading skills by working in large cities provides dynamic benefits of agglomeration economies. Interestingly, this study finds different growth patterns between wage and labor productivity premiums. Labor productivity grows rapidly with longer work experience in large cities, but the growth of the labor productivity premium stops at about 15-20 years of work experience; in contrast, the wage premium grows gradually until about 35 years of work experience.

*JEL classification*: J31, R12, R23
*Keywords*: Wage, Labor productivity, Agglomeration, Human capital accumulation



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# 1 Introduction

Large cities are attractive for workers. One reason is that workers can enjoy the benefits of agglomeration economies. Recent studies in the literature on urban and regional economics attempt to quantify these benefits (e.g., Combes and Gobillon, 2015). Whereas most existing studies are based on a static model of agglomeration economies, we still do not understand how agglomeration economies bring about dynamic benefits for workers. This study highlights how longer work experience in larger cities dynamically affects wage and labor productivity.

A recent study on the dynamic benefits of agglomeration economies by de la Roca and Puga (2017) finds that working in larger cities makes workers dynamically productive. Existing literature on the spatial sorting of skills (e.g., Combes et al., 2008) considers that the estimated workers' fixed effects reflect their innate abilities. However, de la Roca and Puga (2017) find that workers acquire skills *ex post* while working in large cities, which means that the estimated workers' fixed effects in previous studies include dynamic agglomeration benefits. In addition, Glaeser and Maré (2001) find higher wage growth in larger cities, where workers accumulate human capital faster. Gould (2007) also find that work experience in cities increases wages. An interesting finding is that white-collar workers continue to receive higher wages even after leaving cities.

Figure 1 presents wage and labor productivity profiles calculated from our matched employer–employee dataset of the Japanese service industry. In Panels (a) and (b), cities are classified into two groups: cities with above-75 percentile population (red line with circle markers) and cities with below-75 percentile population (blue line with square markers). A key difference between these two city groups is the steepness of the profiles. When workers begin their jobs, only a small difference in profiles exists between large and small cities. Afterwards, wages and labor productivity between large and small cities gradually diverge as workers accumulate work experience. This implies that dynamic benefits of working in larger cities exist.

[Figure 1]

This study aims to simultaneously estimate wage and labor productivity profiles using a matched employer–employee dataset of the Japanese service industry. In the literature on urban wage premiums, de la Roca and Puga (2017) implicitly consider that the wage rate exactly reflects workers' productivity. However, labor economics literature points out that a gap exists between wages and marginal labor productivity profiles (e.g., Becker, 1962; Lazear, 1979; Lazear and Moore, 1984; Hellerstein and Neumark, 1995; Hellerstein et al., 1999; Hellerstein and Neumark, 1999). The Japanese labor market, in particular, is characterized by long-term employment (*shushin koyo*) with tenure-based wage schedules (*nenko chingin*).[1] Under this tenure-based wage system, wages of older workers may be higher than their productivity. For example, in the Japanese manufacturing sector, Kawaguchi et al. (2007) find that younger workers' wages were higher than their productivity, while older workers' wages were lower than their productivity. Therefore, it is important to simultaneously consider wage and labor productivity profiles in our empirical analysis.

Our particular concern is how to quantify dynamic premiums of wage and labor productivity obtained by working in large cities. The static model of agglomeration economies considers that workers receive a constant urban wage premium, regardless of the length of their work experience. In contrast, the dynamic model of agglomeration economies considers that longer work experience in larger cities dynamically fosters human capital accumulation, which leads to dynamic wage and labor productivity premiums. This study empirically quantifies the extent to which working in larger cities generates higher wages and a labor productivity.

We find that working in larger cities causes steeper wage and labor productivity profiles, which suggests that working in large cities generates dynamic wage and labor productivity premiums. In addition, we find a different growth pattern between dynamic wage and labor productivity premiums. Labor productivity grows rapidly after an employee starts working in a large city, but growth of the labor productivity premium stops after about 15–20 years of work experience; in contrast, the wage premium grows gradually until about 35 years of work experience. Thus, our empirical results suggest that the static agglomeration model can underestimate the dynamic benefits of working in large cities.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical framework. Section 3 explains the empirical framework. Section 4 describes our matched employer–employee dataset and key variables. Section 5 discusses the estimation results. Finally, Section 6 concludes.

## 2 Theoretical Background

This section describes how workers' skills affect wage rate and labor productivity. Following Combes and Gobillon (2015), we discuss the basic theoretical predictions. The profit of a representative

[1]In this employment system, the mandatory retirement age is about 60 for almost all workers. After that, many workers receive a lump-sum retirement allowance. Hashimoto (1990), Ito (1991), and Kato (2016) provide detailed explanations of the Japanese employment system.

establishment $j$ operating in area $a$ is given by

$$\pi_{ja} = p_{ja}q_{ja} - w^{\ell}_{ja}\ell_{ja} - r_{ja}k_{ja},$$

where $p_{ja}$ is the price of the product in area $a$, $q_{ja}$ is the output, $\ell_{ja}$ is the amount of labor supply measured in effective labor ($\ell_{ja} = \sum_{i\in j} s_{ia}l_{ia}$), $w^{\ell}_{ja}$ is its wage rate in area $a$, and $s_{ia}$ and $l_{ia}$ represent workers' skills and the labor supply of worker $i$. In addition, $k_{ja}$ represents the other factors of production, and $r_{ja}$ is their price in area $a$.

It is assumed that the production function takes a Cobb–Douglas form with constant returns to scale as follows:

$$q_{ja} = A_a \ell^{\xi}_{ja} k^{1-\xi}_{ja}, \quad 0 < \xi \leq 1, \tag{1}$$

where $A_a$ is total factor productivity (TFP) related to local factors. Solving for profit maximization, we obtain an equation describing the relation among wage rate, TFP, and workers' skills as follows:

$$w_{ia} = A^{1/\xi}_a B_{ja} s_{ia}, \quad \text{where} \quad B_{ja} \equiv \xi(1-\xi)^{(1-\xi)/\xi} \left( \frac{p_{ja}}{r^{1-\xi}_{ja}} \right)^{1/\xi}.$$

Taking the logarithm of both sides, we obtain the following wage equation:

$$\log(w_{ia}) = \text{Const} + \frac{1}{\xi}\log(A_a) + \log(s_{ia}), \tag{2}$$

where Const = $\log(B_{ja})$ denotes the constant term. It is clear that, all other things being equal, higher skills $s_{ia}$ lead to higher wages.

We also consider how workers' skills affect labor productivity. It is assumed that effective labor can be expressed as $\ell_{ja} = \bar{s}_{ja} l_{ja}$, where $\bar{s}_{ja}$ represents average labor characteristics in establishment $j$ and $l_{ja}$ is the total labor supply in establishment $j$. Taking the logarithm of Equation (1) and subtracting $\log(l_{ja})$ from both sides, we can describe how workers' skills $\bar{s}_{ja}$ affect the labor productivity as follows:

$$\log(\text{LP}_{ja}) = \log(A_a) + (1-\xi)\log(k_{ja}) + (\xi - 1)\log(l_{ja}) + \xi\log(\bar{s}_{ja}), \tag{3}$$

where $\text{LP}_{ja} = q_{ja}/l_{ja}$ denotes labor productivity. Thus, all other things being equal, higher workers' skills, on average, lead to higher labor productivity.

Based on Equations (2) and (3), we investigate how workers' skills affect wages and productivity in terms of dynamic skill upgrading in cities. In other words, this study focuses on whether longer work experience in larger cities dynamically increases skills, which further leads to higher wages and labor productivity for urban workers and establishments.

# 3 The Empirical Framework

## 3.1 Regression Models

To derive regression models from theoretical models, we introduce static benefits of agglomeration economies as

$$\log(A_a) = \alpha \log(\mathrm{Pop}_a) + e_a, \tag{4}$$

where $\mathrm{Pop}_a$ is the variable of city size (in this study, population within a 30 km radius) and $e_a$ denotes other factors affecting TFP. This indicates that agglomeration economies increase local productivity. The term $\alpha$ captures wide-range effects of agglomeration economies, such as stronger input–output linkages, thicker labor markets, and knowledge spillover (e.g., Rosenthal and Strange, 2004).

A new feature in this study is the introduction of dynamic skill upgrading by working in large cities. As mentioned in Glaeser and Maré (2001), Gould (2007), and de la Roca and Puga (2017), work experience in large cities fosters human capital accumulation. To explicitly incorporate dynamic skill upgrading across cities, we consider that workers' skills depend on the length of work experience in cities as follows:

$$\log(s_{ia}) = \gamma_1\Big(\mathrm{Expr}_{ia} \times \log(\mathrm{Pop}_a)\Big) + \gamma_2\Big(\mathrm{Expr}_{ia}^2 \times \log(\mathrm{Pop}_a)\Big) + \gamma_3\Big(\mathrm{Expr}_{ia}^3 \times \log(\mathrm{Pop}_a)\Big) + \boldsymbol{X}_{ia}\boldsymbol{\beta}, \tag{5}$$

where $\mathrm{Expr}_{ia}$ denotes years of working in establishment $j$ for worker $i$ , and $\boldsymbol{X}_{ia}$ is the vector of individual characteristics of worker $i$ (age, gender, years of schooling, work experience, and a dummy variable for non-regular workers). The first three cross terms on the right hand side measure dynamic skill upgrading, which depends on the size of city where the employee works.

Inserting static benefits of agglomeration economies and workers' skills into Equation (2) and also considering sectoral heterogeneity $\pi_s$, we obtain the following wage regression model:

$$\begin{aligned} \log(w_{ias}) = \phi \log(\mathrm{Pop}_a) &+ \gamma_1\Big(\mathrm{Expr}_{ia} \times \log(\mathrm{Pop}_a)\Big) + \gamma_2\Big(\mathrm{Expr}_{ia}^2 \times \log(\mathrm{Pop}_a)\Big) \\ &+ \gamma_3\Big(\mathrm{Expr}_{ia}^3 \times \log(\mathrm{Pop}_a)\Big) + \boldsymbol{X}_{ia}\boldsymbol{\beta} + \pi_s + u_{ias}, \end{aligned} \tag{6}$$

where $\phi = \alpha/\xi$, and $u_{ia}$ is the error term.

This wage regression includes both static and dynamic benefits of agglomeration economies.

Parameter $\phi$ measures the static benefits of agglomeration economies, indicating that workers receive wage premiums from larger cities regardless of the length of work experience. Conversely, parameters $\gamma_1$, $\gamma_2$, and $\gamma_3$ measure the dynamic benefits of agglomeration economies, indicating that workers receive wage premiums through dynamic skill upgrading in cities.

Next, we consider labor productivity based on Equation (3). Inserting static benefits of agglomeration economies and average labor characteristics of the establishment into Equation (3), we obtain the following labor productivity regression model:

$$\begin{aligned}\log(\mathrm{LP}_{jas}) = \alpha \log(\mathrm{Pop}_a) + \delta_1\left(\overline{\mathrm{Expr}}_{ja} \times \log(\mathrm{Pop}_a)\right) + \delta_2\left(\overline{\mathrm{Expr}}^2_{ja} \times \log(\mathrm{Pop}_a)\right) \\ + \delta_3\left(\overline{\mathrm{Expr}}^3_{ia} \times \log(\mathrm{Pop}_a)\right) + \overline{\boldsymbol{X}}_{ja}\boldsymbol{\eta} + (1-\xi)\log(k_{ja}) + (\xi - 1)\log(l_{ja}) + \pi_s + v_{jas},\end{aligned} \tag{7}$$

where $\overline{\mathrm{Expr}}_{ja}$ is the average working years in establishment $j$, $\overline{\boldsymbol{X}}_{ja}$ is the vector of average labor characteristics at the establishment level, and $v_{ja}$ is the error term.

Similar to the wage regression, parameter $\alpha$ measures the static benefits of agglomeration economies, indicating that working in large cities provides a constant labor productivity premium regardless of the length of workers' average work experience. Conversely, parameters $\delta_1$, $\delta_2$, and $\delta_3$ measure the dynamic effects of skill upgrading across cities on labor productivity, indicating that large cities offer labor productivity premium through this dynamic skill upgrading.

## 3.2 Quantifying Dynamic Premium of Wage and Labor Productivities in Larger Cities

The main purpose of this study is to quantify the dynamic wage and labor productivity premiums by working in large cities. Based on Regression (6), we define the dynamic wage premium as the percentage change in wages between cities $a$ and $b$ as follows:

$$\frac{w_a - w_b}{w_b} = \left(\frac{\mathrm{Pop}_a}{\mathrm{Pop}_b}\right)^{\phi+\gamma_1\mathrm{Expr}+\gamma_2\mathrm{Expr}^2+\gamma_3\mathrm{Expr}^3} - 1, \tag{8}$$

where an important assumption is holding other things equal between cities.

Next, we also define the dynamic labor productivity premium based on Regression (7) as the percentage change in labor productivity between cities $a$ and $b$ as follows:

$$\frac{\mathrm{LP}_a - \mathrm{LP}_b}{\mathrm{LP}_b} = \left(\frac{\mathrm{Pop}_a}{\mathrm{Pop}_b}\right)^{\alpha+\delta_1\overline{\mathrm{Expr}}+\delta_2\overline{\mathrm{Expr}}^2+\delta_3\overline{\mathrm{Expr}}^3} - 1, \tag{9}$$

where an important assumption, again, is holding other things equal between cities.

The key feature of our quantification is that wage and labor productivity premiums depend on both the ratio of city size (in this study, the population ratio between cities $a$ and $b$) and the length of work experience. In contrast, if dynamic skill upgrading does not vary across cities, while a static urban premium exists, the urban wage and labor productivity premium depends only on the ratio of city size. Using parameter estimates of Regressions (6) and (7), this study clarifies how working in larger cities dynamically increases skills, leading to higher wage and labor productivity.

# 4 Data

## 4.1 Matched Employer–Employee Data of the Japanese Service Sector

We combine individual workers' data with those of their working establishments.[2] Individual workers' data are taken from the Basic Survey on Wage Structure (BSWS) conducted annually by the Ministry of Health, Labour and Welfare. In this study, to match workers' dataset with the service sector establishment data, we focus on workers in the service sector. Establishment-level data on the service sector are taken from the 2012 Economic Census for Business Activity (ECBA) conducted by the Ministry of Internal Affairs and Communications and the Ministry of Economy, Trade and Industry. Our service industry covers (G) information and communications, (I) wholesale and retail trade, (K) real estate and goods rental and leasing, (L) scientific research, professional and technical services, (M) accommodations, eating and drinking services, (N) living-related and personal services and amusement services, (O) education, learning support, (P) medical, health care and welfare, (Q) compound services, and (R) services (not elsewhere classified).[3]

The BSWS includes worker information, such as gender, age, educational background (i.e., junior high school, high school, junior college, and university), type of employment (regular or non-regular worker), monthly hours worked (actual number of scheduled hours worked and actual number of overtime worked), earnings (monthly contractual cash earnings and annual special cash earnings), occupation, years of working for the establishment as well as the working establishment information.[4]

[2] See Appendix A for details on the construction of matched data.

[3] These industrial classifications are based on the Japan Standard Industrial Classification (Rev. 12, November 2007).

[4] We do not fully control for occupation heterogeneity since occupational career information is available only for establishments with 100 or more employees. This study controls only for occupational career, such as division manager and section chief.

### 4.2 Variables

Our regression analysis has two dependent variables. The first is the hourly wage relative to the minimum wage. The BSWS includes total monthly earnings as the sum of monthly contractual cash earnings and per month annual special cash earnings and the monthly actual number of hours worked. Thus, the hourly wage is calculated by dividing total monthly earnings by actual number of hours worked per month. Hourly wages are deflated by the consumer price index (2010=1). In addition, control for spatial price difference is conducted by the minimum wage, which is stipulated at the prefecture level each year.[5]

The second dependent variable is labor productivity. In this study, we calculate it by simply dividing total sales by the annual number of workers. The ECBA includes the number of workers on February 1, 2012. The annual number of workers is estimated by multiplying this figure by 12.

Our key explanatory variable is work experience in cities. The BSWS includes working years in the firm. This study utilizes how long workers continue to work for the same firms, which is crucial for knowing the size of city where the workplace is located. To avoid an estimation issue regarding workers' location changes on their lives, we do not use potential work experience (i.e., age − years of schooling − 6) to measure work experience in cities. However, note that this issue may remain for firms with multiple establishments in several cities, whose workers move across cities within the same firm. Another issue arises if a worker changes jobs within the same city. In this case, our variable underestimates the length of the urban work experience. However, these issues cannot be controlled due to the data limitation in this study.

In line with the labor economics literature, we control for years of schooling, age, gender, and type of employment (regular or non-regular worker). Years of schooling are calculated as follows: 9 years for junior high school graduates, 12 years for high school graduates, 14 years for junior college graduates, and 16 years for university graduates. A limitation of the BSWS is that no educational information is available for part-time workers. Following Kawaguchi et al. (2007), we simply assume that part-time workers uniformly have 12 years of schooling (i.e., equivalent to high school graduates).

In this study, the variable of city size is represented by the population, which is constructed from municipal data of population census. Municipal population are taken from the 2005, 2010, and 2015 population censuses, and a linear interpolation is implemented among them using the percentage change. An estimation issue is that geographical units of regional data correspond to administrative units, not to economic areas. Workers and consumers move across municipal borders by commuting

[5] One of the reasons for the minimum wage in Japan is to equalize living standards across prefectures.

and shopping, and a geographical mismatch takes place between their residence and their work and consumption locations. Using only municipal population suffers from border discontinuity and also does not consider potential people who can access from the surrounding municipalities.

To take into account potential people including surrounding municipalities, we calculate total population within a 30 km radius from the centroid of the municipality polygon. The local sum of population for municipality $a$ is expressed as $\sum_{b=1}^{R} I(d_{ab} < d) \cdot \mathrm{Pop}_b$, where $R$ stands for the number of municipalities and $I(d_{ab} < d)$ is the indicator function that takes the value of 1 if the distance between municipalities $a$ and $b$ is less than $d$ km and 0 otherwise.[6] We set $d = 30$ km, considering local labor markets and commuting distances.

Table 1 presents the descriptive statistics of variables for workers and establishments. Our sample includes 2,789,956 individual workers in pooled data between 2008 and 2015 and 91,210 establishments in the 2012 ECBA. Because our dataset lacks data on capital stock at the establishment level, for simplicity, we use financial capital in the estimation. Workers' skill variables at the establishment level are averaged within the establishments for working years, years of schooling, and age. For dummy variables of non-regular workers and female workers, we calculate the shares of these variables at the establishment level.[7]

[Table 1]

# 5 Estimation Results

## 5.1 Wage and Labor Productivity Profiles

Table 2 presents estimation results of the wage profile in Regression (6).[8] In Column (1) of Table 2, the static agglomeration model is estimated, and the city size elasticity of wages is 0.022 after controlling for individual characteristics. In this static agglomeration model, workers' wage profiles across cities have the same slope, regardless of their working locations. In contrast, workers in large cities enjoy constant benefits from agglomeration economies (i.e., upward shift of wage profile). In Columns (2) and (3), the dynamic agglomeration model is estimated. When the cross terms of city size and work experience are introduced into the regression, the static benefits of agglomeration

[6] Latitudes and longitudes of municipalities are obtained using a GIS software, and the bilateral distance between any two municipalities is calculated using the Vincenty formula.

[7] Dummy variables for occupational career are not considered for the labor productivity regression due to data limitation.

[8] Estimation results of the nominal wage profile are available in Appendix B.

economies decrease to 0.010. Except for the squared term in Column (2), these cross terms are estimated significant, which means that working in large cities dynamically affects wage profiles. In the existing literature, Morikawa (2011) introduces the cross terms of working years and city size (up to the working years squared) into the regressions and also finds that these cross terms significantly affect the wage profile. To check robustness, we control for area fixed effects instead of using the logarithm of the population in Column (3). However, estimation results in Column (2) do not change qualitatively.

Table 3 presents estimation results of the labor productivity profile in Regression (7). In Column (1) of Table 3, the static agglomeration model is estimated. The city size elasticity of labor productivity is 0.013 after controlling for average labor characteristics at the establishment level. The static agglomeration model in Column (1) indicates that working in larger cities leads to higher labor productivity as a constant premium. However, the slope of labor productivity profiles is not affected by work experience in large cities. Conversely, in Column (2), the cross terms of city size and work experience are introduced into the regression to consider the dynamic benefits of agglomeration economies. The static premium is a negative value, whereas the cross terms of working years and city size are significant, except for the cross term of city size and the working years cubed. Similar to the wage profile, estimation results of the labor productivity profile suggest that working in larger cities fosters human capital accumulation. To check robustness, area fixed effects are controlled in Column (3); however, the results do not change qualitatively. Our next step is to quantify the dynamic premiums of wage and labor productivity using these estimates.

[Tables 2–3]

### 5.2 Dynamic Premium of Wage and Labor Productivity in Larger Cities

The main focus of this study is to numerically evaluate whether longer work experience in larger cities leads to higher wage and labor productivity. Figure 2 presents the quantification results of dynamic premium of wage and labor productivity based on Equations (8) and (9). In this numerical analysis, we consider the case in which city $a$ is always twice as large as city $b$ (i.e., the city size ratio is two). It is assumed that the city size ratio is constant while workers accumulate work experience in both cities. An important assumption in the quantification is that all other things are equal.

Panel (a) measures the extent to which workers receive wage premiums by working in larger cities. The blue line with square markers indicates the numerical results of the static agglomeration model in Column (2) of Table 2. As explained earlier, workers in larger cities constantly receive 1.5%

($\approx 2^{0.022}-1$) higher wages. In Panel (a), the red line with circle markers indicates the numerical results of the dynamic agglomeration model in Column (3) of Table 2. Unlike the static model, working in large cities dynamically increases wage premiums. Indicating the static benefits of agglomeration economies, when workers start working in large cities, their wages are 0.7% higher than in small cities. Their wage premium gradually increases as they accumulate work experience in large cities. The estimated urban wage premium between two cities reaches 3.7% when a worker has 30 years of work experience in the city twice as large as the other, holding other things equal.

Panel (b) measures the extent to which working in larger cities generates a labor productivity premium. The blue line with square markers indicates the numerical results of the static agglomeration model in Column (2) of Table 3. Working in larger cities constantly generates a 0.9% ($\approx 2^{0.013}-1$) higher labor productivity premium. In Panel (a), the red line with circle markers indicates the numerical results of the dynamic agglomeration model in Column (3) of Table 3. Unlike the static model, the labor productivity premium shows a negative value for the first five years. Larger cities generate negative effects for workers who do not have enough large-city work experience. However, working in large cities drastically increases labor productivity premium for 15–20 years of working, and the labor productivity premium shows a positive value from the sixth year. The estimated labor productivity premium between two cities reaches 3.8% when workers in an establishment, on average, have 18 years of work experience in the city twice as large as the other, holding other things equal. A point to note that, unlike the dynamic wage premium, the dynamic labor productivity premium does not continuously grow after 15–20 years of working.

It is worth discussing the different growth patterns between dynamic wage and labor productivity premiums. Figure 2 shows that workers in larger cities receive a higher wage premium compared to their productivity premium when they start to work in larger cities. Also, when workers have more than 20 years of work experience, they receive a higher wage premium, compared to their productivity premium. Our empirical results suggest that the dynamic wage premium does not fully capture learning effects by working in larger cities in terms of human capital accumulation. During the first 10 years, the dynamic labor productivity premium grows much faster than the dynamic wage premium. As pointed out by Becker (1962) and Lazear (1979), wages do not necessarily correspond to workers' productivity. It is important to measure workers' productivity from several points of view.

[Figure 2]

Like Figure 1, Figure 3 compares estimated profiles between static and dynamic agglomeration models. Panels (a) and (b) illustrate wage and labor productivity profiles, respectively. Red lines (with circle markers) indicate wage and labor productivity profiles in cities with above-75 percentile population, while blue lines (with square markers) indicate wage and labor productivity profiles in cities with below-75 percentile population. In addition, solid and dashed lines indicate dynamic and static agglomeration models, respectively. A key difference between the static and dynamic agglomeration models in Figure 3 is that the static model may underestimate dynamic benefits of working in larger cities. In other words, longer work experience in larger cities separates wage profiles between cities with below- and above-75 percentile population. Furthermore, labor productivity profiles between static and dynamic agglomeration models in Panel (b) also show a similar aspect to the wage profiles. The dynamic agglomeration model suggests that workers upgrade their skills dynamically as they accumulate work experience in large cities.

[Figure 3]

# 6 Conclusion

This study has estimated wage and labor productivity profiles using a matched employer–employee dataset of the Japanese service sector. Recent literature on agglomeration economies has emphasized their dynamic benefits. Thus, the main concern of this study was to uncover how longer work experience in larger cities dynamically affects wage and labor productivity profiles.

This study has found that working in larger cities makes wage and labor productivity profiles steeper, suggesting that working in large cities generates dynamic wage and labor productivity premiums. More interestingly, we have found a different growth pattern between dynamic wage and labor productivity premiums. Labor productivity grows rapidly after begin working in large cities, but growth of the labor productivity premium stops after about 15–20 years of work experience; in contrast, the wage premium grows gradually until about 35 years of work experience. Our empirical results suggest that the static agglomeration model may underestimate the dynamic benefits of working in large cities.

Our findings have important policy implications. Although most previous studies have focused primarily on the static benefits of agglomeration economies, our findings emphasize their dynamic benefits. Working in larger cities offers greater opportunities for workers to upgrade their skills. Where one works plays an important role in enhancing skills, which also has a large impact on lifetime income. In addition, it should be noted that this could be one of the reasons for the expanding income inequality between urban and rural areas.

Finally, this study has some limitations regarding identification issues. Our matched employer–employee data are not panel data for workers and establishments. To exactly identify the dynamic benefits of urban work experience, long-term workers' panel data are required. Further studies need to uncover the role of cities and human capital accumulation using such rich panel data.

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## Appendix A Constructing Matched Employer–Employee Data

The sampling design of the BSWS is based on the establishment level; thus, individual workers have an establishment ID. The establishment lists obtained by the Establishment and Enterprise Census, the Economic Census for Business Frame, and the Economic Census for Business Activity are used for sampling and we can easily match them with individual worker-level data via the establishment ID.

The 2009 Economic Census for Business Frame includes establishment IDs allocated in the 2006 Establishment and Enterprise Census when the establishments were surveyed. Similarly, the 2012 Economic Census for Business Activity includes establishment IDs allocated in the 2009 Economic Census for Business Frame when the establishments were surveyed. To use the information on establishments' economic activities, we construct a panel dataset of establishments surveyed in the

2012 Economic Census for Business Activity. In other words, this study focuses on establishments that existed in the three periods (2006, 2009, and 2012), in the two periods (2009 and 2012), or in the one period (2012).

Data construction proceeds as follows. First, we construct an establishment-level panel dataset using the establishment IDs of the 2006 Establishment and Enterprise Census, the 2009 Economic Census for Business Frame, and the 2012 Economic Census for Business Activity. Second, we match the individual worker-level datasets of the 2008–2015 BSWS with the establishment IDs of these three establishment surveys. Note that our establishment data with economic activities are limited to the the 2012 Economic Census for Business Activity.

Table A.1 presents the schema for constructing matched data between workers and establishments. This study only focuses on establishments surveyed in the 2012 ECBA, which includes detailed economic activities at the establishment level. Using an establishment-level panel structure among the 2006 EEC, the 2009 ECBF, and the 2012 ECBA, worker-level data from the 2008–2012 BSWS are matched with establishment-level data from the 2012 ECBA. Note that this study uses a sample of workers and establishments matched between the 2008–2015 BSWS and the 2012 ECBA.

[Table A.1]

## Appendix B Estimation Results of Nominal Wage Profile

Table B.1 presents estimation results of wage profile using nominal wages. Note that wages are deflated by the consumer price index (2010=1) in terms of time-series, but spatial price differences are not controlled. In Column (1) of Table B.1, the static agglomeration model is estimated, and the city size elasticity of wages is 0.068 after controlling for individual characteristics. In Columns (2) and (3), the dynamic agglomeration model is estimated. When the cross terms of city size and work experience are introduced into the regression, the static benefits of agglomeration economies decrease to 0.057. In Column (2), these cross terms are estimated significant, which means that working in large cities dynamically affects wage profiles. When area fixed effects are controlled in Column (3), the estimates of these cross terms are almost similar to those of Table 2.

Table 1: Descriptive Statistics

| Variables | Obs. | Mean | S.D. | Median |
|---|---|---|---|---|
| *Individual Characteristics* | | | | |
| Log(Hourly Wage Relative to Minimum Wage) | 2789956 | 0.655 | 0.501 | 0.530 |
| Log(Population) | 2789956 | 14.492 | 1.457 | 14.217 |
| Working Years $\times$ Log(Population) | 2789956 | 51.757 | 57.791 | 31.173 |
| Working Years | 2789956 | 7.785 | 8.520 | 5.000 |
| Years of Schooling | 2789956 | 12.900 | 1.703 | 12.000 |
| Age | 2789956 | 40.900 | 14.330 | 40.000 |
| Dummy (1=Non-Regular Worker) | 2789956 | 0.493 | 0.500 | 0.000 |
| Dummy (1=Female) | 2789956 | 0.480 | 0.500 | 0.000 |
| Dummy (1=Division Manager) | 2789956 | 0.010 | 0.098 | 0.000 |
| Dummy (1=Section Chief) | 2789956 | 0.023 | 0.150 | 0.000 |
| *Establishment Characteristics* | | | | |
| Log(Labor Productivity) | 91210 | 4.510 | 1.193 | 4.331 |
| Log(Population) | 91210 | 14.446 | 1.466 | 14.216 |
| Mean Working Years | 91210 | 7.598 | 5.053 | 6.368 |
| Mean Working Years $\times$ Log(Population) | 91210 | 108.837 | 72.574 | 91.026 |
| Mean Years of Schooling | 91210 | 12.755 | 1.015 | 12.381 |
| Mean Age | 91210 | 40.615 | 9.142 | 40.872 |
| Share of Non-Regular Workers | 91210 | 0.489 | 0.369 | 0.520 |
| Share of Female Workers | 91210 | 0.481 | 0.267 | 0.500 |
| Log(Financial Capital) | 91210 | 8.595 | 2.496 | 8.006 |
| Log(Employment) | 91210 | 5.678 | 0.973 | 5.529 |

Note: The uppermost and lowermost 0.1 percentile of the distribution of the relative hourly wage to the minimum wage is excluded from the sample as extreme outliers. Hourly wage (unit: JP yen) is deflated by the consumer price index (2010=1).

Table 2: Estimation Results for Wage Profile

| | Dependent Variable: $\log(w_{ijat})$ | | |
|---|---|---|---|
| Explanatory Variables | (1) | (2) | (3) |
| **Log(Population)** | 0.022*** | 0.010*** | |
| | (0.001) | (0.001) | |
| **Working Years × Log(Population)** | | 0.001*** | 0.001*** |
| | | (0.000) | (0.000) |
| **Working Years Squared × Log(Population)** | | 0.003 | 0.003** |
| | | (0.002) | (0.002) |
| **Working Years Cubed × Log(Population)** | | −0.009** | −0.009*** |
| | | (0.004) | (0.003) |
| Working Years | 0.020*** | −0.000 | 0.006** |
| | (0.000) | (0.003) | (0.003) |
| Working Years Squared | −0.003 | −0.044* | −0.053** |
| | (0.002) | (0.025) | (0.022) |
| Working Years Cubed | −0.019*** | 0.114** | 0.119*** |
| | (0.005) | (0.052) | (0.045) |
| Years of Schooling | 0.049*** | 0.048*** | 0.044*** |
| | (0.001) | (0.001) | (0.000) |
| Age | 0.026*** | 0.026*** | 0.026*** |
| | (0.000) | (0.000) | (0.000) |
| Age Squared | −0.031*** | −0.031*** | −0.030*** |
| | (0.000) | (0.000) | (0.000) |
| D(1=Non-Regular Worker) | −0.286*** | −0.286*** | −0.285*** |
| | (0.002) | (0.002) | (0.002) |
| D(1=Female) | −0.191*** | −0.191*** | −0.191*** |
| | (0.001) | (0.001) | (0.001) |
| D(1=Division Manager) | 0.496*** | 0.485*** | 0.479*** |
| | (0.005) | (0.005) | (0.005) |
| D(1=Section Chief) | 0.351*** | 0.343*** | 0.335*** |
| | (0.005) | (0.005) | (0.004) |
| Industry Dummy | Yes | Yes | Yes |
| Year Dummy | Yes | Yes | Yes |
| Area Dummy | No | No | Yes |
| Number of Observations | 2789956 | 2789956 | 2789956 |
| Adjusted $R^2$ | 0.683 | 0.684 | 0.697 |

Note: Heteroskedasticity-consistent standard errors clustered at the establishment level are in parentheses. Working years squared and cubed are multiplied by 1/100 and 1/10000, respectively. Age squared is multiplied by 1/100. Constant term is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3: Estimation Results for Labor Productivity Profile

| | Dependent Variable: log($LP_{ja}$) | | |
|---|---|---|---|
| Explanatory Variables | (1) | (2) | (3) |
| **Log(Population)** | 0.013*** | −0.058*** | |
| | (0.002) | (0.008) | |
| **Mean Working Years × Log(Population)** | | 0.016*** | 0.016*** |
| | | (0.003) | (0.003) |
| **Mean Working Years Squared × Log(Population)** | | −0.068** | −0.081** |
| | | (0.034) | (0.035) |
| **Mean Working Years Cubed × Log(Population)** | | 0.089 | 0.126 |
| | | (0.105) | (0.106) |
| Mean Working Years | 0.043*** | −0.185*** | −0.196*** |
| | (0.005) | (0.046) | (0.046) |
| Mean Working Years Squared | −0.225*** | 0.794 | 0.962* |
| | (0.053) | (0.488) | (0.496) |
| Mean Working Years Cubed | 0.373** | −1.026 | −1.510 |
| | (0.158) | (1.482) | (1.505) |
| Mean Years of Schooling | 0.191*** | 0.183*** | 0.174*** |
| | (0.004) | (0.004) | (0.004) |
| Mean Age | 0.089*** | 0.085*** | 0.085*** |
| | (0.002) | (0.002) | (0.002) |
| Mean Age Squared | −0.111*** | −0.107*** | −0.107*** |
| | (0.003) | (0.003) | (0.003) |
| Share of Non-Regular Workers | −0.529*** | −0.532*** | −0.530*** |
| | (0.014) | (0.014) | (0.015) |
| Share of Female Workers | −0.620*** | −0.622*** | −0.607*** |
| | (0.014) | (0.014) | (0.014) |
| Log(Financial Capital) | 0.098*** | 0.098*** | 0.099*** |
| | (0.001) | (0.001) | (0.001) |
| Log(Employment) | −0.131*** | −0.133*** | −0.138*** |
| | (0.004) | (0.004) | (0.004) |
| Industry Dummy | Yes | Yes | Yes |
| Area Dummy | No | No | Yes |
| Number of Observations | 91210 | 91210 | 91210 |
| Adjusted $R^2$ | 0.533 | 0.534 | 0.536 |

Note: Heteroskedasticity-consistent standard errors are in parentheses. Working years squared and cubed are multiplied by 1/100 and 1/10000, respectively. Age squared is multiplied by 1/100. Constant term is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table A.1: Common Establishment ID Between Worker- and Establishment-Level Datasets

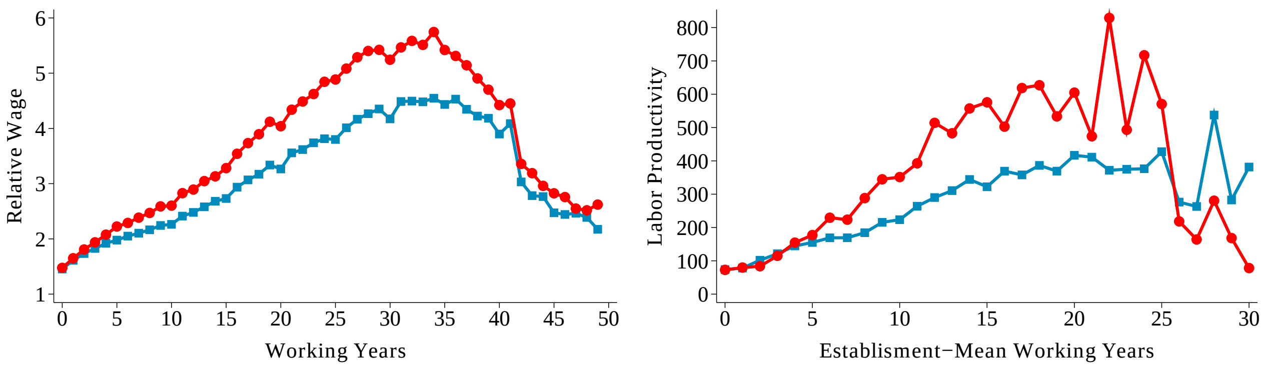
| Unit: Worker | Unit: Establishment | | |
|---|---|---|---|
| BSWS | 2006 EEC | 2009 ECBF | 2012 ECBA |
| 2008 | ✔ | | |
| 2009 | ✔ | | |
| 2010 | ✔ | | |
| 2011 | ✔ | | |
| 2012 | | ✔ | |
| 2013 | | ✔ | |
| 2014 | | | ✔ |
| 2015 | | | ✔ |

Note: BSWS denotes the Basic Survey of Wage Structure. EEC denotes the Establishment and Enterprise Census. ECBF denotes the Economic Census for Business Frame. ECBA denotes the Economic Census for Business Activity. This study focuses on establishments surveyed in the 2012 ECBA. Using the establishment-level panel structure between the 2006 EEC, 2009 ECBF, and 2012 ECBA, the worker-level data of the 2008–2012 BSWS are matched with the establishment-level data of the 2012 ECBA. This study uses the sample of workers and establishments matched between the 2008–2015 BSWS and the 2012 ECBA. The 2015 BSWS does not have establishment ID corresponding to the 2012 ECBA. Using the common establishment ID of the business register, which is included in the 2014 and 2015 BSWS, establishments are complementary linked between 2014 and 2015.

Table B.1: Estimation Results for Wage Profile without Spatial Price Difference Control

| | Dependent Variable: $\log(w_{ijat})$ | | |
|---|---|---|---|
| Explanatory Variables | (1) | (2) | (3) |
| **Log(Population)** | 0.068*** | 0.057*** | |
| | (0.001) | (0.001) | |
| **Working Years × Log(Population)** | | 0.001*** | 0.001*** |
| | | (0.000) | (0.000) |
| **Working Years Squared × Log(Population)** | | 0.006*** | 0.003* |
| | | (0.002) | (0.002) |
| **Working Years Cubed × Log(Population)** | | −0.015*** | −0.008*** |
| | | (0.004) | (0.003) |
| Working Years | 0.021*** | 0.006** | 0.004 |
| | (0.000) | (0.003) | (0.003) |
| Working Years Squared | −0.005** | −0.092*** | −0.044** |
| | (0.002) | (0.026) | (0.022) |
| Working Years Cubed | −0.016*** | 0.201*** | 0.106** |
| | (0.005) | (0.054) | (0.045) |
| Years of Schooling | 0.050*** | 0.049*** | 0.044*** |
| | (0.001) | (0.001) | (0.000) |
| Age | 0.026*** | 0.026*** | 0.026*** |
| | (0.000) | (0.000) | (0.000) |
| Age Squared | −0.031*** | −0.031*** | −0.030*** |
| | (0.000) | (0.000) | (0.000) |
| D(1=Non-Regular Worker) | −0.288*** | −0.288*** | −0.285*** |
| | (0.002) | (0.002) | (0.002) |
| D(1=Female) | −0.192*** | −0.192*** | −0.191*** |
| | (0.001) | (0.001) | (0.001) |
| D(1=Division Manager) | 0.498*** | 0.487*** | 0.479*** |
| | (0.005) | (0.005) | (0.005) |
| D(1=Section Chief) | 0.354*** | 0.346*** | 0.335*** |
| | (0.005) | (0.005) | (0.004) |
| Industry Dummy | Yes | Yes | Yes |
| Year Dummy | Yes | Yes | Yes |
| Area Dummy | No | No | Yes |
| Number of Observations | 2789956 | 2789956 | 2789956 |
| Adjusted $R^2$ | 0.689 | 0.690 | 0.709 |

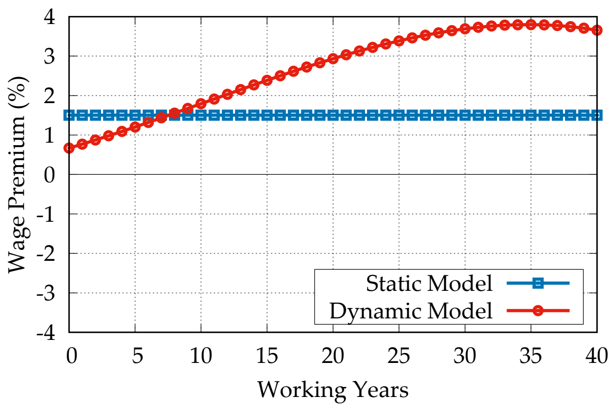
Note: Heteroskedasticity-consistent standard errors clustered at the establishment level are in parentheses. Working years squared and cubed are multiplied by 1/100 and 1/10000, respectively. Age squared is multiplied by 1/100. Constant term is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Note that wages are deflated by the consumer price index (2010=1) in terms of time-series, but spatial price differences are not controlled.



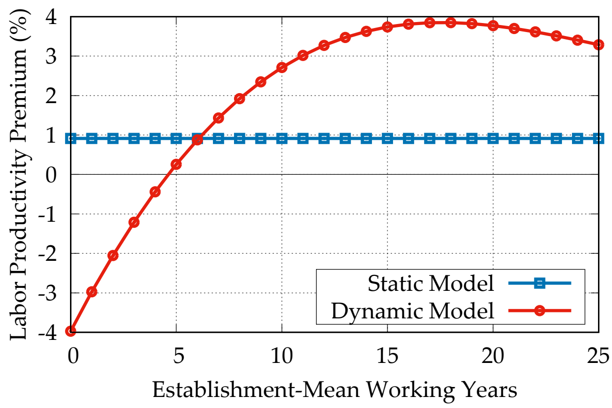

(a) Wage Profile (b) Labor Productivity Profile

Figure 1: Wage and Labor Productivity Profiles between Cities with Below- and Above-75 Percentile Population

Note: Created by author. Red and blue lines indicate wage and productivity profiles between cities with above- and below-75 percentile population, respectively. Sample in Table 1 is used, but it is extended up to 50 in Panel (a) and up to 40 in Panel (b). The relative wage denotes the real hourly wage (2010=1) divided by the prefecture minimum wage. The unit of the labor productivity (output divided by the number of workers) is 10 thousand JP.



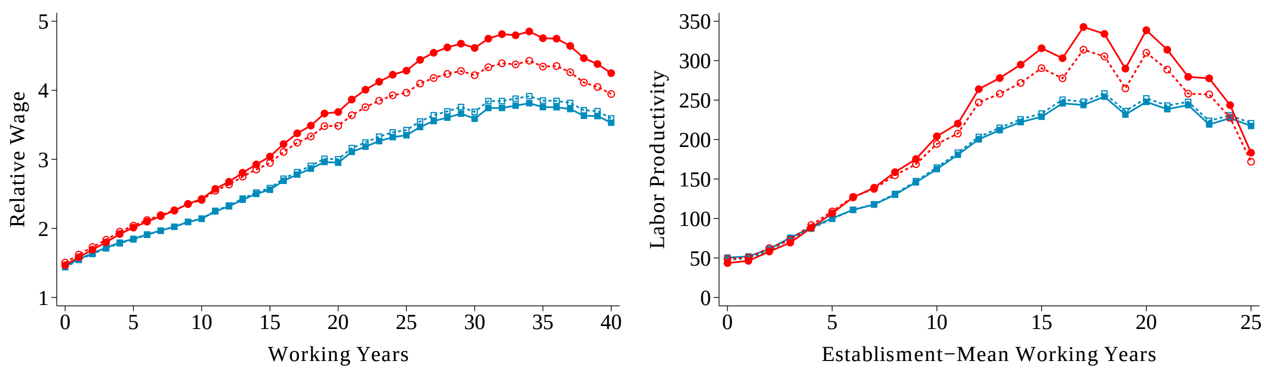

(a) Wage Relative to Minimum Wage




(b) Labor Productivity

Figure 2: Static and Dynamic Premium of Wage and Labor Productivity in Larger Cities

Note: Created by author. Panels (a) and (b) are depicted using the estimates in Tables 2 and 3, respectively. Red and blue lines are drawn from the dynamic and static models, respectively. The wage and labor productivity premium is, respectively, calculated from Equations (8) and (9), as the extent to which working in a city twice as large (i.e., the population ratio is two between cities) makes wage or labor productivity higher, holding other things equal.




(a) Wage Profile

(b) Labor Productivity Profile

Figure 3: Model Comparison between Static and Dynamic Models of Agglomeration Economies

Note: Created by author. The hourly wage relative to the minimum wage and labor productivity predicted from the regression models are used in Figure 1. Red lines with circle markers indicate wage and labor productivity profiles in cities with above-75 percentile population. Blue lines with square markers indicate wage and labor productivity profiles in cities with below-75 percentile population. Solid and dashed lines indicate dynamic and static agglomeration models, respectively. Static and dynamic agglomeration models for wage profile correspond to Columns (1) and (2) of Table 2, respectively. Static and dynamic agglomeration models for labor productivity profile correspond to Columns (1) and (2) of Table 3, respectively. The unit of the labor productivity (output divided by the annual number of workers) is 10 thousand JP yen.