GRIPS Discussion Paper 14-19

Measuring the sorting effect of migration on spatial wage disparities

Kentaro Nakajima
Ryosuke Okamoto

October 2014

National Graduate Institute for Policy Studies
7-22-1 Roppongi, Minato-ku,
Tokyo, Japan 106-8677

Measuring the sorting effect of migration on spatial wage disparities*

Kentaro Nakajima[a], Ryosuke Okamoto[b]

[a]Graduate School of Economics, Tohoku University, 27-1 Kawauchi Aoba-ku, Sendai, 980-8576 Japan

E-mail: nakajima.kentaro@gmail.com

[b]National Graduate Institute for Policy Studies, 7-1 Roppongi, Minato-ku, Tokyo 106-8677 Japan

E-mail: rokamoto@grips.ac.jp

Abstract

Observed spatial wage disparities reflect not only disparities in regional productivity but also an uneven geographical distribution of heterogeneous worker skills. We measure spatial skill disparities in Japan and evaluate how migration contributes to these disparities. For this purpose, we regress the individual wage on the residential region dummy variables and a series of individual characteristics to decompose the wage into regional productivity and the workers' skills. The estimation illustrates that by removing the skill heterogeneities, the productivity disparity is approximately half of the observed wage disparity. Workers living in metropolitan areas have 9.7% higher skills than those in nonmetropolitan areas on average. The spatial skill disparity that stems from individuals' hometowns is approximately 4.2%. Hence, migration increases the spatial skill disparity from 4.2% to 9.7%, which is an increase of 5.5 percentage points. Furthermore, we investigate migration effects in terms of the workers' characteristics and find that most sorting effects of migration come from highly educated and regularly employed male workers.

Keywords: sorting; migration; spatial wage disparities; skill difference by residence; skill difference by hometown

JEL Classification: R23, J31, J61, R12

* We use the Japanese General Social Surveys for the analyses in this paper. The Japanese General Social Surveys (JGSS) were designed and carried out by the JGSS Research Center at Osaka University of Commerce (Joint Usage / Research Center for Japanese General Social Surveys accredited by Minister of Education, Culture, Sports, Science and Technology) in collaboration with the Institute of Social Science at the University of Tokyo. We would like to thank Koji Karato, Keisuke Kawata, Yasusada Murata, Makoto Okumura, Yasuhiro Sato, and the participants of various conferences and seminars for their helpful comments and discussions.

1 Introduction

Understanding the interregional productivity gap is one of the main issues in the field of urban and regional economics. Agglomeration economies have been considered a critical source of the interregional productivity gap, and many studies estimate the degree of agglomeration economies using the mean wage observed in each region as an indicator of regional productivity.[1] However, workers are heterogeneous in their skills, and the heterogeneous skills are unevenly distributed over geographical space. Furthermore, the regional mean wage is determined by the composition of heterogeneous workers and by the regional productivity. Thus, spatial skill disparities may cause significant bias in the degree of agglomeration economies. Many studies, such as those by Yankow (2006), Combes et al. (2008), Bacolod et al. (2009), De la Roca (2011), and Matano and Naticchioni (2012), demonstrate that highly skilled workers tend to agglomerate to large cities. This phenomenon is referred to as "spatial skill sorting". High wages in large cities may reflect not only high productivity premiums in the cities but also the concentration of highly skilled workers. This paper investigates the degree to which such spatial sorting increases spatial wage disparities.

There are two sources of spatial sorting. First, individuals bred in larger cities tend to acquire more skills. This effect can be identified using information about workers' hometowns. Second, migration also generates interregional differences in skills because migration changes the composition of heterogeneous workers in the regions. This paper quantifies these two sources of spatial sorting using Japanese individual-level data. Few papers have analyzed the effect of migration on spatial skill disparities based on a comparison of skill distributions with and without migration. To our knowledge, no such studies have been conducted in Japan.[2]

In our empirical strategy, we first estimate the wage equation using residential region dummy variables and individual characteristics. Then, we decompose individuals' wages into regional productivity and individual skills that are embedded in the individual. To evaluate the obtained geographical distribution of individual skills, we calculate the difference in the mean skills between metropolitan and nonmetropolitan areas, which is called the skill difference by residence in this paper.

Second, this paper analyzes the effect of migration on spatial skill disparities. For this purpose, information on individuals' residences in the counterfactual situation where there is no migration, i.e., hometowns, is required. We calculate the skill difference in the counterfactual situations. Through comparing the actual and counterfactual skill differences, we evaluate the effect of migration on skill sorting. To identify individuals' hometowns, we use Japanese General Social Surveys (JGSS), which

[1] See Rosenthal and Strange (2004). For the Japanese case, Tabuchi and Yoshida (2000) estimate the effect of agglomeration economies using per capita labor income in cities.

[2] Tabuchi (1988) analyzes causality between regional per capita income and interregional migration using Japanese prefecture-level panel data and concludes that migration does not cause regional income disparities. However, as prefecture-level data cannot count for worker heterogeneity between migrants and non-migrants, we analyze the effects of migration on spatial disparities using individual-level data.

are individual-level pooled cross-sectional data with information on residence at age 15. This type of identification of migration is based on a long-term view of migration. A typical method to identify the short-run migration is using information about moves during an interval of surveys of panel data. This method cannot generate the full effect of migration because "stayers" identified in this method might have originated from another region before the time of the survey. Based on long-term migration, Combes et al. (2012) examine the effect of migration as the source of spatial sorting using the information on place of birth.[3]

This paper shows that the productivity gap is considerably smaller than the observed wage disparity. The average productivity gap between the Tokyo Metropolitan Area (hereafter referred to MA) and the other regions is 12.0%, which accounts for only 51% of the observed wage gap of 23.4%.[4] This statistic suggests the substantial role of spatial skill sorting on spatial wage disparities. Indeed, our results show that the mean worker skill level in the Tokyo MA is 9.7% higher than that in other regions. In the counterfactual situation without migration, the skill level difference is 4.2%, implying that migration increases the skill level by 5.5 percentage points. Calculating the counterfactual wage without migration shows that migration enlarges the spatial wage disparity by 23.5%.

We also explore the sorting effect of migration within specific types of workers. The sorting effect is relatively weak for low-educated and female worker groups, illustrating that migrants from non-MAs have nearly the same mean skill level as stayers in the Tokyo MA. In the case of non-regular employees, migration is the negative selection from both the Tokyo MA and non-MAs. Thus, the positive sorting effect of migration mainly comes from the migration of highly skilled workers, specifically, highly educated and regularly employed male workers.

The remainder of this paper is organized as follows. Section 2 describes the outline of our methodology. We specify the wage equation and define several measures of spatial disparities used to evaluate the sorting effect of migration. Section 3 describes our dataset. Section 4 reports the results. Section 5 discusses the robustness of the results. Section 6 presents more detailed analyses and interpretations. Section 7 provides some conclusions.

2 Methodology

2.1 Overview

We consider local labor markets, each of which matches the supply and demand of specific

[3] Because self-selecting migration occurs after age 15 in almost all cases, our concept of counterfactual skill disparities corresponds to the "sorting at birth" concept of Combes et al. (2012).

[4] This result is in line with the result of Combes et al. (2008), who find that worker heterogeneity accounts for approximately half of the observed spatial wage disparities using French panel data. Using Italian data, Mion and Naticchioni (2009) show that the difference in mean worker fixed effects accounts for 75% of wage differences between denser and less dense areas. Matano and Naticchioni (2012) derive 77-79% as the corresponding value from Canadian data.

skilled labor types in a specific region. This implies that a worker's wage is determined by his/her workplace location and skills. We estimate the wage equation using individual-level data that identify individual characteristics and residential locations at the prefecture level.[5] From estimated parameters in the wage equation, we obtain effects of residences, referred to as *regional productivities,* and individual wage-earing abilities, referred to as *worker skills*.

Regional disparities in this paper are based on the comparison between MAs and non-MAs. We use three definitions of MAs in Japan: the Tokyo MA, three major MAs, and denser prefectures.[6]

We first calculate the *regional productivity difference* to clarify whether observed wages in large MAs overstate the regional productivity advantages. This difference accounts for the wage differences in the counterfactual situation, where all regions have the same composition of worker skills.

Second, to evaluate the difference in worker skill distribution, we calculate the ratio between the mean worker skill level in MAs and that in non-MAs, which is called the *skill difference by residence*. A positive correlation between regional productivity and regional mean skill level leads to positive spatial skill sorting.

Third, we consider a counterfactual situation in which there is no migration, i.e., all workers work in their hometowns, as a reference point. As discussed in Section 3, the surveys used in this paper contain information about the residential prefecture at age 15, which is called the *hometown*. Assigning individuals to their hometowns, we calculate the ratio between the mean skill level in MAs and that in non-MAs, which is called the *skill difference by hometown*. Because this measure indicates the skill disparity without migration, the effect of migration is the difference between the skill level by residence and by hometown.

Finally, to evaluate the effect of migration on the spatial wage disparity, we compute the *counterfactual wage in hometown* using the worker's skill level and the prefectural productivity of the worker's hometown. The comparison between actual and counterfactual wages indicates the contribution of migration to the spatial wage disparity.

2.2 Estimation of the wage equation

Local labor markets set the same wage for workers with the same skill in the same region. Thus, worker *i*'s wage, w_i, is determined by the worker's residence $r(i)$ and skill, s_i:

$$w_i = w\,(r(i), s_i) \tag{1}$$

The regional effects on wages are elucidated by residential region dummy variables at the

[5] We use residence as a proxy of workplace because no information on workplace location is available in the surveys used in the paper.

[6] The Tokyo MA is composed of Tokyo, Kanagawa, Saitama, and Chiba Prefectures. The three major MAs are the Tokyo MA, Osaka MA (Osaka, Kyoto, Hyogo, and Nara Prefectures) and Nagoya MA (Aichi, Gifu, and Mie Prefectures). Denser prefectures are prefectures with a higher population density that covers 50% of workers in the sample.

prefecture level. The worker skill represents the individual's ability to earn wages. It is related to variables such as standard worker characteristics, workplace characteristics, and household environment. In this paper, we assume a log-linear form of wage function, expressed as

$$\ln w_i = \beta^1_{r(i)} + \mathbf{x}_i \boldsymbol{\beta}^2 + e_i , \tag{2}$$

where $\beta^1_{r(i)}$ is the effect of a residence on wage, called *regional productivity*, and $\mathbf{x}_i$ is the vector of the variables that explain workers' wage-earning abilities. We use standard worker characteristics, workplace characteristics, and household variables. For standard worker characteristics, we use gender, education, and age. For workplace characteristics, we consider employment status, firm size, and industry.[7] The employment status variables include a regular employment dummy variable. For household variables, we use information on a dependent spouse and/or dependent child, the main source of household income, and the spouse's employment status. Because the social environment of the workers' hometown may directly affect their skills, which is not captured by the above characteristics, we add hometown dummy variables as explanatory variables. Unobserved skills that are not captured by these variables are included in the error term e_i. We list variables formally in the Appendix.

We define worker *i*'s skill by

$$s_i = \exp(\mathbf{x}_i \boldsymbol{\beta}^2 + e_i) .$$

Skill s_i represents *i*'s wage-earning ability that is independent of residential location.[8] To obtain consistent estimators of worker skills, it is sufficient to obtain consistent estimators for regional effects $\beta^1_{r(i)}$. For this purpose, we concentrate our attention on controlling heterogeneous attributes of workers that are unevenly distributed over regions.

2.3 Regional productivity difference

We measure the regional productivity difference between MAs and non-MAs using estimated coefficients for residential region dummy variables β^1_j. We calculate the ratio of mean prefectural productivity $\exp(\beta^1_j)$ in MAs and that in non-MAs, formally defined by the following expression:

[7] In a local labor market, different industries and firms with different sizes compete with each other for labor. Thus, workers with the same skill level earn the same wage rate in the same region regardless of the industry and firm size. This is implied by the fact that we define worker "skill" as the worker's wage-earning ability independent of residential regions. In this type of situation, the difference in the mean wage among industries in the same region evidences the difference in the mean skill among those industries.

[8] Our definition of "skill" is different from that of Mion and Naticchioni (2009) and Combes et al. (2012), who consider worker fixed effect to be skill level. These studies take worker fixed effect as unobserved skill level and discern it from observed skill levels represented by time-varying worker characteristic variables. We do not intend to identify such specific skill level; rather, we aim to identify a worker's "total skill level".

$$D_P = \frac{\frac{1}{N^M}\sum_{j\in\text{MAs}} N^j \exp\beta_j^1}{\frac{1}{N^O}\sum_{j\in\text{non-MAs}} N^j \exp\beta_j^1} - 1, \tag{3}$$

where N^j, N^M, and N^O are the number of workers in prefecture j, MAs, and non-MAs, respectively.

2.4 Skill difference by residence

Let I^M and I^O be the set of workers residing in MAs and non-MAs. Assigning workers to their residential prefectures, we calculate the skill difference by residence. Formally, we calculate following measure as the skill difference:

$$D_{RS} = \frac{\frac{1}{N^M}\sum_{i\in I^M} s_i}{\frac{1}{N^O}\sum_{i\in I^O} s_i} - 1. \tag{4}$$

Positive D_{RS} implies positive sorting that highly skilled workers concentrate in highly productive regions.

2.5 Skill difference by hometown

Our hypothesis is that migration is a major source of spatial skill disparities. A migrant is a person who resides in a different region from his/her hometown. We analyze how migration changes the geographical distribution of worker skills. For this, we consider the counterfactual skill distribution that is obtained when all workers reside in their hometowns. We compute the skill difference for this counterfactual skill distribution, referred to as the skill difference by hometown and denoted by D_{HS}. Then, we compare it with actual sorting, measured by D_{RS}. The difference between these two measures represents the effect of migration on skill sorting.

Formally, we first assign worker i's skill to either MAs or non-MAs based on his/her hometown $h(i)$. Let I_H^M and I_H^O be the set of workers whose hometowns are included in MAs and non-MAs, respectively. N_H^M and N_H^O denote the numbers of workers in I_H^M and I_H^O, respectively. Then, we calculate D_{HS}, defined as

$$D_{HS} = \frac{\frac{1}{N_H^M}\sum_{i\in I_H^M} s_i}{\frac{1}{N_H^O}\sum_{i\in I_H^O} s_i} - 1. \tag{5}$$

If D_{HS} is smaller than D_{RS}, migration has a positive effect on spatial skill disparities.

2.6 Difference in the counterfactual wage without migration

Finally, we evaluate the contribution of migration to the spatial wage disparity. The effect of migration measured by D_{RS} - D_{HS}, based on the comparison between MAs and non-MAs, cannot be directly compared with the actual wage difference because actual wages involve the regional effects identified at the prefecture level. For a direct comparison with actual wage difference, we must calculate the difference in the wage earned by each worker in his/her hometown, which is called *counterfactual wage in hometown*, using the productivity in the hometown prefecture and the worker skill.

Formally, the counterfactual wage in the hometown is derived by replacing the productivity of the residential region in Equation (2) with that of the hometown. Hence, the counterfactual wage of worker i, denoted by $\hat{w}_i = w(h(i), s_i)$, is defined by

$$\ln \hat{w}_i = \beta^1_{h(i)} + \mathbf{x}_i \boldsymbol{\beta}^2 + e_i \,, \tag{6}$$

where $\beta^1_{h(i)}$ is the regional productivity of hometown prefecture $h(i)$.

We compare the mean counterfactual wage in MAs and that in non-MAs. The difference in the counterfactual wage, D_{HW}, is formulated as

$$D_{HW} = \frac{\frac{1}{N^M} \sum_{j \in \text{MAs}} \sum_{i \in I(j)} \frac{N^j \exp(\hat{w}_i)}{N^j_H}}{\frac{1}{N^O} \sum_{j \in \text{non-MAs}} \sum_{i \in I(j)} \frac{N^j \exp(\hat{w}_i)}{N^j_H}} - 1 \,, \tag{7}$$

where $I(j) = \{i \mid h(i) = j\}$ and N^j_H is the number of workers whose hometown is prefecture j. In this equation, we use prefectural weight based on the number of residents, but not the number of natives, to keep the prefectural weights identical to those in the other measures of disparities.[9]

Table 1 summarizes the measures of spatial disparities analyzed in this paper. These measures are characterized by the designation of regional effects and skill distribution.

Table 1 Measures of spatial disparities

	Regional effect	Skill distribution
Wage difference: D_W	actual	actual
Regional productivity difference: D_P	actual	national average
Skill difference by residence: D_{RS}	national average	actual
Skill difference by hometown: D_{HS}	national average	counterfactual (hometown)
Counterfactual wage difference: D_{HW}	actual	counterfactual (hometown)

[9] There are disparities in regional productivity among prefectures included in non-MAs. If we use regional weights based on the number of natives, we lower the weights for highly productive prefectures in non-MAs that gain migrants from the other non-MA prefectures. To exclude the effect of such migration unrelated to the difference between MAs and non-MAs, we use the same weights as the other measures of disparities.

3. Data

We use Japan General Social Surveys (JGSS) designed and carried out by the JGSS Research Center at the Osaka University of Commerce, which are individual-level surveys on economics and sociology. The surveys were carried out from 2000 to 2010. In this paper, we use surveys in 2002, 2003, 2005, 2006, 2008, and 2010 that include information required for our analyses.

The surveys ask about the prefectures of the present residence and the residence at age 15. We refer to the latter prefecture as "hometown". A migrant is defined as an individual whose present residence is different from his/her hometown. This definition is based on the concept of long-term migration.[10] Nearly all self-selecting migrations occur after age 15, and hometowns are exogenously determined by their parents' location choices. Although we cannot describe a situation without migration using the pre-migration locations identified by the panel data, we can do so using information on long-term migration extracted from the JGSS data.[11] We cannot capture migration within the prefecture from this dataset. However, intra-prefectural migration is not important for analyzing the effect of migration on the spatial disparities between MAs and non-MAs.

We limit the sample to workers aged 20-59. To exclude the effect of workers with low working incentive, we trim the lowest 10% workers in terms of working hours, which corresponds to approximately 20 hours per week. Further, because we limit our attention to salary only, we exclude self-employers and workers with a similar status, whose income may contain profits from their businesses.[12]

Table 2 shows the sample statistics for the main variables. The share of regular employees is larger than that obtained from the Labor Force Surveys of 2008, which is due to the exclusion of workers with the lower tail of working hours. The surveys report the income from the respondents' main job during the previous year.[13] It also reports the hours of work during the previous week. Using these data, we calculate the wage per hour, which is the dependent variable in the wage equation estimation.

Before the analyses, we calculate the spatial wage disparities simply from row data. Table 3 reports the wage disparity between MAs and non-MAs. Depending on the definition of MAs, the disparity ranges from 22.4% to 23.5%. These values are comparable to the values obtained from prefectural accounting: hence, the data reflect the overall aspect of the regional structure in Japan.

---

[10] Ohta (2007) estimates the wage equation using a Japanese dataset with information on respondents' hometown, which is similar to the JGSS data. He classifies workers into four groups using combinations of residences and hometowns. However, because he does not identify worker skills using residential prefecture dummy variables in the wage estimation, the features of the spatial skill difference are ambiguous in his analysis.

[11] Migration identified as a move during an interval of surveys in panel data cannot generate the full effect of migration because "stayers" might have originated from another region before the time of the surveys. Therefore, we cannot investigate the total effect of migration using such data.

[12] For example, we exclude farmers, doctors, artists, and chief executives.

[13] In the surveys, a respondent chooses his/her annual income among several classes. We use the median values of the intervals. For the highest income class over 23 million yen, we cannot assign a median value. Because the reduction of a high-income class leads to underestimates for wages in large cities, we compute the expected values of income class in each prefecture by assuming Pareto distributions for high-income classes.

Table 2 Sample statistics

	Male	Graduation	Regular	Migration	Age	Wage (yen/hour)
Mean	0.588	0.272	0.744	0.211	44.5	1850
Standard deviation	0.492	0.445	0.436	0.408	11.0	1385

Note: See the Appendix for detailed definitions of the variables.

Table 3 Wage difference between MAs and non-MAs

Definition of MAs	JGSS	2010 Prefectural Accounting
Tokyo MA	0.235	0.230
Three Major MAs	0.226	0.209
Denser Prefectures	0.224	0.198

Table 4 Average wage by residence and hometown

	Tokyo MA (hometown)	Other regions (hometown)
Tokyo MA (residence)	2098 (1054)	2304 (536)
Other regions (residence)	1820 (122)	1754 (5200)

Note: Unit is yen/hour. The number of observations is in parentheses.

Table 4 shows the mean wage in the Tokyo MA and others by residence and hometown. Among Tokyo residents, migrants receive higher wages than Tokyo natives. Similarly, among residents in the other regions, migrants from Tokyo receive higher wages than workers from non-Tokyo areas. These data suggest a positive migration selection. However, because wage level depends on regional productivity, we must abstract regional effects and worker skills by estimating the wage equation. The effect of migration also depends on the volume of migration between MAs and non-MAs. The number of observations is shown in parentheses. The inflow to Tokyo is approximately five times larger than the outflow from Tokyo (536 vs. 122). If there is a positive selection of migration, it contributes to the expansion of the spatial disparity.

4 Results

4.1 Wage equation estimation

With regard to the determinants of worker skill, we use four categories of variables. The first category consists of the standard worker characteristics: a male dummy variable, a college graduate dummy variable, a logarithm of age, and the interaction terms between the former two and the logarithm of age. The second category is composed of workplace characteristics, such as employment status, the worker's industry, and the employment size classification of the organization to which the worker belongs. Among them, the regular employment dummy variable is important in the analysis. We account for the interaction term between the regular employment dummy variable and the logarithm of age. The third category is the household information that may represent the worker's unobservable skills or affect the worker's working incentive. For this consideration, we use a dependent spouse dummy variable with a value of one if the worker has a dependent spouse and zero otherwise, a dependent child dummy variable with a value of one if he/she has a dependent child and zero otherwise, and a dependent dummy variable with a value of one if the main income source of the household is not the respondent's income and zero otherwise.[14] The fourth category includes hometown dummy variables to account for possible heterogeneities in the hometown environment that affect unobservable skills. We also include year fixed effects. Detailed definitions of the variables are provided in the Appendix.

The ordinary least-squares estimation results are shown in Column 1 of Table 5. The purpose of this estimation is to decompose wages into worker effects and residential prefecture effects. In this sense, we do not have considerable interest in each point estimate of the coefficient. By using the estimation results, we calculate worker skills and the indices of spatial disparities.

4.2 Regional productivity difference

If there is positive spatial skill sorting, the observed actual wage difference overstates the regional productivity advantage in MAs. This section explores the pure regional productivity difference by controlling for skill heterogeneity.

Figure 1 is the scatterplot between the logarithm of average wage and the logarithm of regional productivity for all 47 prefectures in Japan. For the comparison with wage, we adjust the regional productivity in prefecture *j* to the wage of the worker who lives in prefecture *j* and has an average skill level of Japanese workers. This operation can be described by the following equation:

$$\ln \tilde{w}^j = \beta_j^1 + \tilde{S} \,, \tag{8}$$

where $\tilde{w}^j$ is the productivity in prefecture *j* and $\tilde{S}$ is the average skill level of Japanese workers. In the calculation, we normalize worker skills to the 2010 values using the estimated year effects. The positively sloped line in Figure 1 is the fitted line with a gradient of 0.601. A gradient of less than one implies that the prefectural productivity difference is smaller than the actual wage

[14] If there is another main income source of the household, the worker's working incentive will be smaller. If the worker has non-regular employment and if his/her spouse has regular employment, the working incentive will be considerably smaller. To consider this effect, we include a dummy variable with a value of one if the worker is in the above status and zero otherwise.

difference.

Table 5 Wage estimation results

Dependent variable: ln(wage)	(1)	(2)	(3)
Male	-0.655**	-0.644**	-0.620**
	(0.196)	(0.220)	(0.221)
College graduates	-0.743**	-0.574**	-0.637**
	(0.210)	(0.229)	(0.232)
Junior and technical college graduates	0.110**	0.0924**	0.0900**
	(0.0181)	(0.0198)	(0.0199)
Regular employment	0.367	0.481*	0.482*
	(0.251)	(0.286)	(0.289)
ln(age)	0.185**	0.202**	0.230**
	(0.0535)	(0.0611)	(0.0623)
Male × ln(age)	0.250**	0.248**	0.241**
	(0.0531)	(0.0595)	(0.0596)
College graduates × ln(age)	0.231**	0.183**	0.197**
	(0.0567)	(0.0619)	(0.0626)
Regular employment × ln(age)	0.00396	-0.0355	-0.0360
	(0.0636)	(0.0731)	(0.0737)
Household variables	Yes	Yes	Yes
Residential prefecture	Yes	Yes	Yes
Hometown prefecture	Yes	Yes	Yes
Workplace characteristics	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Urban experience	No	Yes	Yes
Migration variables	No	No	Yes
Constant	-3.060**	-2.980**	-3.117**
	(0.265)	(0.311)	(0.329)
Observations	6912	5665	5665
Adjusted R-squared	0.544	0.538	0.538

Note: Robust standard errors in parentheses. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

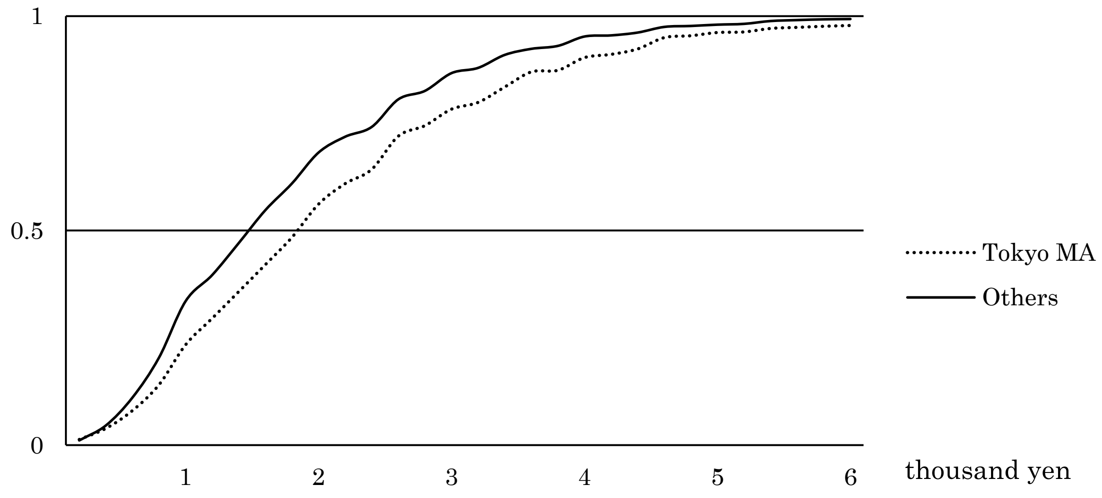
Figure 1 Actual wage and regional productivity

Table 6 Disparities in regional productivity and worker skills

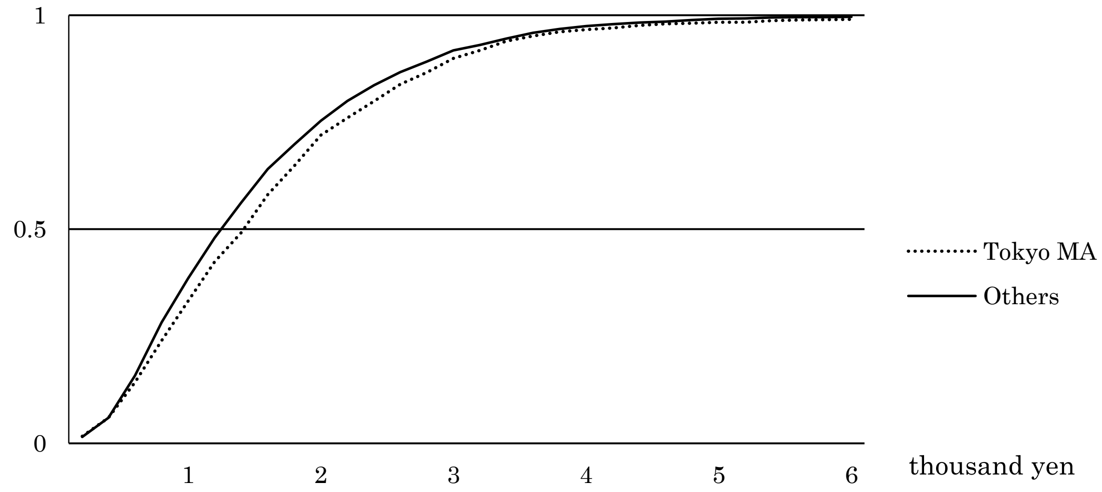
Definition of MAs	(1) D_W	(2) D_P	(3) D_{RS}	(4) D_{HS}	(5) D_{HW}
Tokyo MA	0.234	0.120	0. 097	0.042	0.189
Three major MAs	0.227	0.126	0. 083	0.049	0.186
Denser prefectures	0.223	0.111	0.092	0.058	0.182

Note: Calculated by the results in Column 1 of Table 5. Wages and skills are normalized to the 2010 values by year fixed effects. Hence, D_W is not equal to the wage difference in Table 2. D_W, D_P, D_{RS}, D_{HS}, and D_{HW} represent the actual wage disparity, regional productivity difference, skill difference by residence, and skill difference by hometown, respectively (see Table 1).

The calculated indices of spatial disparities defined in Table 1 are shown in Table 6. The productivity difference D_P, defined by Equation (4), between the Tokyo MA and the other regions is 12.0%, which corresponds to 51% of the wage difference. We obtain similar results by using the three major MAs (55%) and denser prefectures (50%) as definitions of MAs. These results are quantitatively similar to the findings by Combes et al. (2008). Our result also supports the implication of Combes et al. (2008) that one would overestimate the regional productivity advantage in large cities using observed wages without considering sorting effects.



(a) Actual wage



(b) Skill by residence

Figure 2 Cumulative distributions of wage and skill in the Tokyo MA and other regions

4.3 Skill difference by residence

Section 4.2 demonstrates the importance of considering the sorting effects on spatial wage disparities, so we inspect the skill disparities formally using the estimated skills. Figure 2 shows the cumulative distributions of (a) the actual wage and (b) the estimated skill of the resident. The dashed and solid lines represent the cumulative distribution in the Tokyo MA and that in the other regions, respectively. For the comparison of the actual wage, we adjust the worker skill using the following equation:

$$\ln \overline{w}_i = \overline{\beta}^1 + \mathbf{x}_i \boldsymbol{\beta}^2 + e_i , \tag{9}$$

where $\overline{\beta}^1$ is the adjustment term that equalizes the national average skill to the national average actual wage in Japan. Thus, $\overline{w}_i$ is interpreted as worker i's wage when he/she lives in the region that has average regional productivity in Japan.

Figure 2b illustrates that the Tokyo MA tends to have more highly skilled workers than other regions, i.e., there is a spatial skill disparity. In comparing Figures 2a and 2b, however, the disparity in worker skill appears smaller than that in the actual wage.

As shown in Table 6, the skill difference by residence between the Tokyo MA and the other regions is 9.7%, implying positive spatial sorting. This positive sorting can be found in other definitions of MAs, including the three major MAs (8.3%) and denser prefectures (9.2%).[15]

4.4 Sorting effect of migration

In Section 4.3, we find positive sorting that highly skilled workers are concentrated in MAs. This section investigates the role of migration in spatial skill sorting by calculating the prefectural mean skills by assigning workers to their hometowns. That is, we calculate the wages in the counterfactual situation wherein migrants had stayed in their hometowns. Figure 3 depicts the cumulative distribution of skill in the counterfactual situation. As in the case with Figure 2, the dashed and solid lines correspond to the Tokyo MA and other regions. The difference between the two lines is considerably smaller than in the case of the resident skills shown in Figure 2b.

To evaluate the effect of migration, we calculate the skill difference by hometown, D_{HS}. As shown in Table 6 (Column 4), the D_{HS} between the Tokyo MA and the other regions is 4.2%, which is smaller than the skill difference by residence (9.7%). Thus, migration increases the skill disparity by 5.5 percentage points. This finding is robust to the other definitions of MAs. Migration increases the skill disparity by 3.4 percentage points using the three major MAs and denser prefectures.[16]

[15] Assuming that the population distribution of worker skill is a log-normal distribution, we derive the 95% confidence intervals of the skill difference to be [4.2%, 14.7%], [4.3%, 13.0%], and [5.0%, 13.7%] using the Tokyo MA, the three major MAs and denser prefectures as a definitions of MAs, respectively. In all cases, the confidence interval ranges to the positive region, and hence, the null hypothesis of zero difference is rejected.

[16] Similar to the skill differences by residence, we calculate the 95% confidence intervals for these values. The confidence intervals go down ([-1.5%, 9.6%] for the Tokyo MA vs. other regions; [1.2%, 9.8%] for the three major MAs vs. other regions; [1.7%, 10.2%] for denser prefectures vs. other regions). We cannot reject the null hypothesis of zero difference for Tokyo vs. other regions.

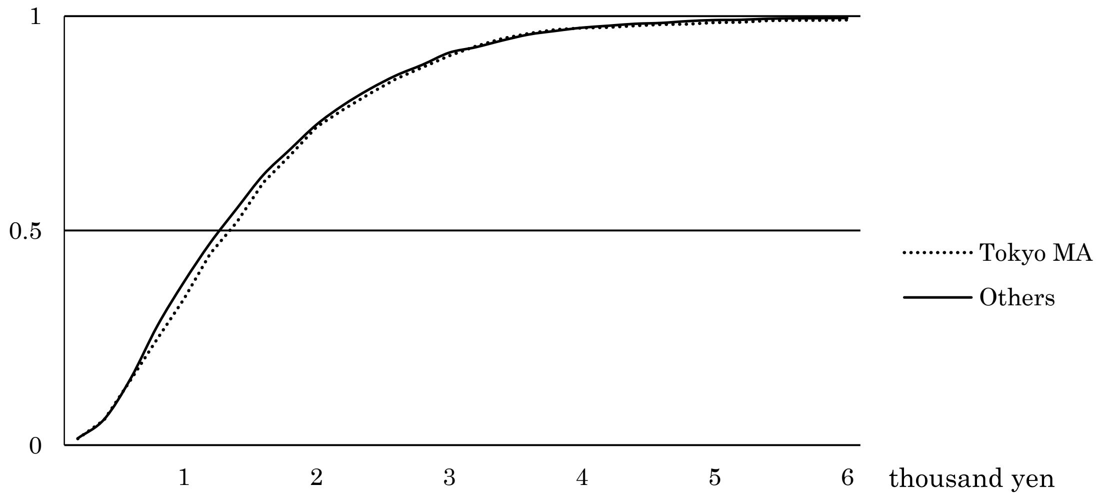


Figure 3 Cumulative distribution of skill at hometown

Table 7 Average skill by residence and hometown

	Tokyo MA (hometown)	Other regions (hometown)	Total
Tokyo MA (residence)	1603	1755	1654
Other regions (residence)	1527	1507	1508
Total	1595	1531	1542

Note: Skill is defined by Equation (9). Unit is yen/hour.

Table 7 compares four categories of workers classified by the combination of hometown and residential regions. Workers in the Tokyo MA from the other regions have the highest skills on average (1,755 yen per hour). This suggests that the migration of highly skilled workers from non-MAs to MAs plays a major role in the sorting effect of migration.[17] Among the residents outside Tokyo, migrants from Tokyo have higher skills (1,527 yen per hour) than do natives (1,507 yen per hour). This implies that migrants from Tokyo increase the average skill in the other regions. However, because the skills of migrants from Tokyo are lower than the stayers in Tokyo, the outflow

[17] There is no information on the timing of migration in our dataset. However, there was a large young worker migration flow from rural to large MAs in Japan in the 1960s (Tabuchi, 1988; Fujita and Tabuchi, 1997). The migrants in the 1960s are now senior workers and earn higher wages than the younger workers. Then, the estimated high skill levels of migrants into Tokyo in Table 7 may reflect the cohort effects of the large share of senior workers who migrated from rural regions in the 1960s. Thus, we compare the average age of migrant and native residents in Tokyo. The average age of the migrants from outside Tokyo is 46.5, whereas the average age of the Tokyo MA natives is 42.8. However, our wage estimation results suggest that this difference causes only 2.2% of the skill differences for high school graduate male workers, which is quite smaller than the skill difference observed in Table 7. This implies that the estimated skill level difference between migrants and natives cannot be explained solely by the cohort effect.

from Tokyo increases the average skill level in Tokyo. As a result, migration causes large skill disparities.[18]

Figure 4 illustrates the aspect of skill disparities at the prefecture level. It shows the relationship between the logarithm of mean skill level at the place of residence (horizontal axis) and at the hometown (vertical axis). The positively sloped line is the fitted line with a gradient of 0.837. This means that the variability in the prefectural mean skills in the actual situation (with migration) is larger than that in the counterfactual situation, where all workers work in their hometowns (without migration).

To evaluate the distribution of prefectural mean skills, rather than the dichotomy, we focus on quartiles. Because we have only 47 prefectures, the quartiles are highly sensitive to the estimation errors. Thus, we use the expectations of the prefectural mean skills at the hometown on the fitted line. Whereas the difference in skills at the place of residence between the maximum and minimum is 62.8%, it is estimated to be 50.4% at the hometown. This means that migration increases the skill difference by 24.8%. Between the third and first quartiles, we find a 14.4% difference in skill level at residence and 11.9% in skill level at the hometown. The effect of migration on the skill level difference is 20.9% in this case. Thus, migration increases the skill level disparities between prefectures by at least 20.9%.

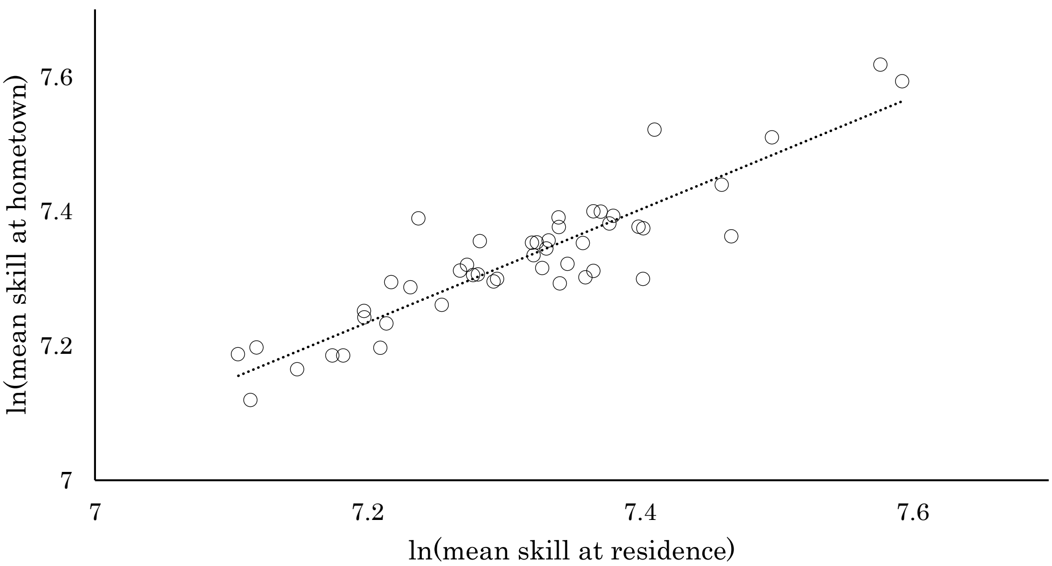


Figure 4　Skill by residence vs. skill by hometown

[18] The sorting effect of migration becomes higher in the case of the Tokyo MA because the Tokyo MA absorbs highly skilled workers from the Osaka and Nagoya MAs. The mean skill of migrants from Osaka and Nagoya is 1,933, which is considerably higher than that of average migrants.

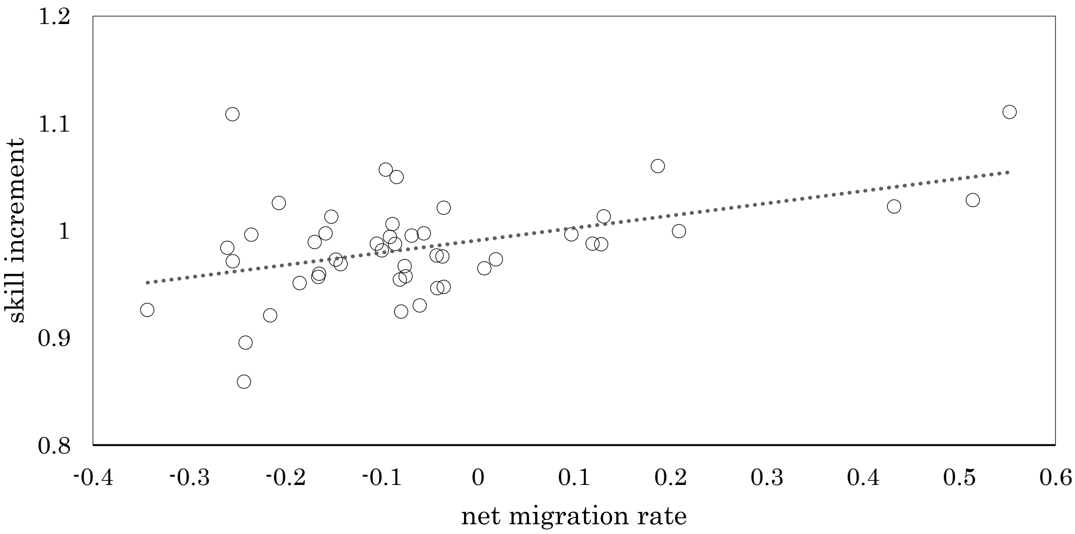


Figure 5 Net migration rate and skill growth rate

Figure 5 shows the relationship between net-migration inflow and the sorting effect of migration. The horizontal axis is the inflow minus the outflow divided by the number of natives. The vertical axis is the ratio of mean skill level at the place of residence and at the hometown, which illustrates the degree to which the prefectural mean skill level is raised by migration. We find a positive relationship between these two variables, which suggests that the effect of highly skilled migrants between prefectures dominates that of low-skilled migrants. The migration inflows (outflows) of highly skilled workers increase (decrease) the prefectural mean skill level. Because highly productive prefectures tend to attract more migrant inflow, migration is the major source of disparities in spatial skill level.

4.5 Counterfactual wage in hometown

For the direct comparison of the sorting effect of migration and the actual wage disparity, in this section, we calculate the counterfactual wage difference, D_{HW}, defined by Equation (7). As illustrated by Table 6 (Column 5), the counterfactual wage difference is 18.9% between the Tokyo MA and the other regions. Migration increases the wage disparity from 18.9% to 23.4% (D_W). Hence, the contribution of migration to the spatial wage disparity is 23.5% [(23.4-18.6)/18.6]. We obtain nearly the same values for the effect of migration using the three major MAs (22.0%) and denser prefectures (22.5%). Thus, migration has a non-negligible effect on spatial wage disparity in Japan.

5. Robustness

5.1 Human capital accumulation in large MAs

The regional effects identified in Section 4.2 are the effects that change the wages of workers instantaneously when they enter the regional labor markets and are called "level effects". However, some studies (e.g., Glaeser, 1999; Glaeser and Mere, 2001; Gould, 2007; Yankow, 2007; Glaeser and Resseger, 2010; Baum-Snow and Pavan, 2012) point out that working experiences in urban environments raise the workers' speed of human capital accumulation. Such effects are called "growth effects". In this paper, regional productivities are estimated as prefectural fixed effects based on the average urban experience of the workers. We are interested in identifying workers' potential skills, which are independent of the residential environment, rather than the skills that are obtained by living in urban environments. Urban growth effects may lead to underestimates of the potential skills of migrants, given that migrants from rural areas tend to have less urban experience.

To control for the skills accumulated in large cities, we introduce the variables defined by using the information on "years living in the present region of residence" available in our dataset. The estimated equation is redefined as

$$\ln w_i = \beta^1_{R(i)} + \mathbf{x}_i \boldsymbol{\beta}^2 + \mathbf{u}_i \boldsymbol{\beta}^3 + e_i , \qquad (10)$$

where $\mathbf{u}_i$ is a vector of years living in the present residence of the Tokyo, Osaka, and Nagoya MAs.[19]

The estimation results are shown in Column 2 in Table 5. Using the results of this estimation, we calculate the potential worker skills defined by

$$s_i = \exp\left(\mathbf{x}_i \boldsymbol{\beta}^2 + e_i\right),$$

which is the same as that used before. The growth effect, $\mathbf{u}_i \boldsymbol{\beta}^3$, includes the region effect but not the worker effect. Table 8 reports the calculated skill differences. The disparities tend to be higher between the Tokyo MA and the other regions. The effect of migration, D_{RS}-D_{HS}, is 0.066, which is slightly higher than the baseline result (0.055). The results are almost the same as the corresponding baseline results when using the other definitions of MAs.

Table 8 Skill differences by residence and hometown: controlling for urban experiences

Definition of MAs	(1) D_W	(2) D_{RS}	(3) D_{HS}
Tokyo MA	0.257	0.127	0.061
Three major MAs	0.238	0.087	0.049
Denser prefectures	0.234	0.092	0.051

Note: Because region effects depend on the workers' urban experiences, the productivity difference is reduced in this table and Table 9.

[19] The JGSS include information on years of residence in the present location; hence, $\mathbf{u}_i$ has at most one positive element. The survey in 2002 does not report this information and is thus excluded from the analysis.

If the growth effects were caught up in the baseline skill disparities, when controlling them, we should have lower values of the disparities in Table 8. However, we obtain rather high values, especially for the Tokyo MA. Hence, we do not find solid evidence for growth effects.

5.2 Unobserved skills and the self-selection of migration

Another concern of the wage estimation is the self-selection of migration. Workers choose their residence by comparing the wages and costs of living between the potential residential regions and their hometowns. Furthermore, their potential wage will depend on their skills (observed and unobserved). For example, workers with high unobserved skills may have more opportunities to obtain new jobs with higher wages outside their hometowns. Workers with low unobserved skills may have fewer employment opportunities, which forces them to search for jobs outside their hometowns. Hence, there should be a difference in the distribution of unobserved skills between migrants and stayers. Unobserved skills may be unevenly distributed between MAs and non-MAs because of the different share of migrants. That is, even if we fully utilize observed worker characteristics, the unobservable heterogeneity correlating to the migration choice will remain and cause bias in the estimates of worker skills.

To account for the unobservable skills revealed by migration behaviors, we include migration variables in the wage equation and reestimate it. As for migration variables, we include a migration dummy variable that has a value of one if the worker's residential prefecture is different from his/her hometown and zero otherwise. In a case where migration distance affects the degree of self-selection, we use the logarithm of distance between the hometown and residential prefectures.[20] Considering the heterogeneity in migration behavior, noted by Greenwood (1975) and Deteng-Dessendre et al. (2004), we include the interaction terms of migration dummy variable and logarithm of distance with dummy variables for male, college graduate, and regular employment and the logarithm of age (see the Appendix). We estimate the following wage equation:

$$\ln w_i = \beta^1_{R(i)} + \mathbf{x}_i\boldsymbol{\beta}^2 + \mathbf{u}_i\boldsymbol{\beta}^3 + \mathbf{m}_i\boldsymbol{\beta}^4 + e_i\,, \tag{11}$$

where $\mathbf{m}_i$ is the vector of the migration variables. The worker skill level analyzed here is defined by

$$s_i = \exp\left(\mathbf{x}_i\boldsymbol{\beta}^2 + \mathbf{m}_i\boldsymbol{\beta}^4 + e_i\right).$$

Because migration variables represent the worker's unobservable skill, $\mathbf{m}_i\boldsymbol{\beta}^4$ is the component of

[20] Workers migrate if and only if they have larger gains than the cost of migration. Migration requires several types of costs, such as moving costs, searching costs for job and housing, and non-monetary costs from the differences in the cultures and natural environments. These monetary and non-monetary costs will correlate with the migration distance. We measure the great circle distances between the prefectural offices. We assign zero to distances between prefectures within the Tokyo and Osaka MAs. Because a non-negligible number of workers commute across prefectures in these MAs, migration within these MAs may be only a residential move, not a change of workplace. We are not concerned with such migration unrelated to worker skills. We add one to distance to avoid a logarithm of zero distance.

the worker's skill. The results are shown in Column 3 of Table 5.

Table 9 reports the calculated skill disparities. Although introducing migration variables changes the value of the skill disparities, D_{RS}-D_{HS} is nearly the same as the baseline. Therefore, we confirm the robustness of our result that migration plays significant roles in spatial skill disparities.

Table 9 Skill differences: considering the self-selection of migration

Definition of MAs	(1) D_W	(2) D_{RS}	(3) D_{HS}
Tokyo MA	0.257	0.125	0.059
Three major MAs	0.238	0.075	0.037
Denser prefectures	0.234	0.082	0.042

6 Further results: types of migrants

Migration behavior would differ among the worker characteristics. Thus, the sorting effect of migration would be heterogeneous among them. We investigate the sorting effects of migration for each of following three subgroups of workers: female, low-educated, and non-regular employee groups. For analyses, we use the baseline estimation to maintain the sample size (see footnote 19).

Table 10 shows the mean skills of female workers by residence and hometown in the same manner as Table 7 for all workers. Workers in Tokyo from other regions have the highest skill level. However, there is nearly no difference between the migrants and natives residing in Tokyo. Migrants from Tokyo have the lowest average skill level, which strongly contrasts the results of sorting workers as a whole. The positive selection of migration from non-MAs along with the negative selection from Tokyo generates skill disparities similar to those in all workers: D_{RS} =9.4% and D_{HS} =4.4%. The migration inflow of female workers to MAs itself has a negative effect on spatial disparity because female workers have lower skills than males on average.

Table 10 Average skill level by residence and hometown: female workers

	Tokyo MA (hometown)	Other regions (hometown)	Total
Tokyo MA (residence)	1064	1076	1068
Other regions (residence)	791	981	976
Total	1033	989	997

Note: The skill level is defined by Equation (9). Unit is yen/hour.

Table 11 Average skill level by residence and hometown: low-educated workers

	Tokyo MA (hometown)	Other regions (hometown)	Total
Tokyo MA (residence)	1353	1355	1354
Other regions (residence)	1163	1351	1348
Total	1333	1352	1349

Note: The skill is defined by Equation (9). Unit is yen/hour.

Table 12 Average skill level by residence and hometown: non-regular employees

	Tokyo MA (hometown)	Other regions (hometown)	Total
Tokyo MA (residence)	831	787	816
Other regions (residence)	724	802	800
Total	817	801	804

Note: The skill is defined by Equation (9). Unit is yen/hour.

Tables 11 reports the mean skill levels of low-educated workers. Focusing on the residents in the Tokyo MA, there is a negligible difference between migrants and natives. Among residents outside Tokyo, migrants from Tokyo tend to have lower skill levels than natives. Interestingly, the mean skill levels by hometown are lower in Tokyo (1,333 vs. 1,352), implying a negative D_{HS}. This may reflect a higher college enrollment rate in Tokyo. Because high school graduates in Tokyo with high potential skill levels enroll in college, highly skilled workers are rare in the low-educated group.

Table 12 shows the skill differences among non-regular employees. The results are quite different from those of all workers. Migrants, regardless of their source regions, have lower skills than stayers in the hometowns; i.e., migration is negative selection. Because low-skilled workers tend to be unemployed, they tend to migrate to search for better employment opportunities. As a result, D_{RS} and D_{HS} have nearly the same value (2.04% and 2.06%, respectively).

To summarize the above analyses, we do not find a greater effect of positive selection of migration among low-skill workers. Spatial skill disparities tend to become lower for low-skill workers, indicating that most of the sorting effects of migration originate from highly educated and regularly employed male workers.

7 Concluding remarks

We have analyzed spatial skill sorting using Japanese individual-level data. By estimating the wage equation, we have identified workers' skills and regional productivity. Using the estimation results, first, we have shown that observed wage differences overstate the difference in regional productivity. This implies that spatial sorting is important in analyzing regional economic inequalities. Second, to determine these sorting effects, we have compared the skill distributions of workers between MAs and non-MAs. Workers in MAs have 8.3% to 9.7% higher skill levels on average than those in non-MAs depending on the definition of MAs. These findings suggest that the observed mean wages in MAs are increased by spatial skill sorting. Third, we have quantified the effect of migration on the skill sorting based on the comparison between the actual skill distribution and the counterfactual skill distribution without migration. Migration increases the spatial skill difference by 3.4 to 5.5 percentage points. These effects of migration correspond to a 22.0% to 23.5% increase in wage differences depending on the definition of MAs. Hence, migration plays significant role in spatial wage disparities in Japan.

We have also investigated how the aspect of sorting differs across worker characteristics. For female workers, migrants from MAs tend to have lower skills than natives residing in non-MAs. For low-educated workers, we have not observed positive skill sorting in term of workers' hometown. Among non-regular employees, migration is negative selection. These findings demonstrate that most of the sorting effects of migration originate from highly educated and regularly employed male workers.

Appendix List of variables

Prefecture effects

(1) Residential prefecture dummy variables: Dummies for prefectures of present residences. There are 47 prefectures in Japan.

Standard worker characteristics

(2) Male dummy variable.
(3) College graduate dummy variable: a dummy variable for workers with a college degree.
(4) Junior and technical college dummy variable: a dummy variable for workers who graduated junior or technical college but without a college degree.
(5) Logarithm of age.
(6) Interaction terms: (2) and (5); (3) and (5).

Workplace characteristics

(7) Regular employment dummy variable: a dummy variable that has a value of one for a regular employee and zero for a non-regular employee.

(8) Employment status dummy variables: We have 6 categories of employment status for regular employees, i.e., no title, foreman, assistant manager, manager, department chief, and other.

(9) Industry dummy variables: dummy variables for industries where the worker is employed. We have 17 industry classifications.

(10) Employment size classifications: dummy variables of classification of the size of the organization where the worker is employed. We define 3 categories for employment size: one to 99, 100 to 999, and over 999.

(11) Multiple establishment dummy variable: This takes on a value of one if the organization where the worker is employed has multiple establishments and zero otherwise.

(12) Interaction terms: (6) and (7); (8) and (10); (9) and (10).

Household characteristics

(13) Dependent spouse dummy variable: This takes on a value of one if the worker has a dependent spouse and zero otherwise.

(14) Dependent child dummy variable: This takes on a value of one if he/she has a dependent child and zero otherwise.

(15) Dependent dummy variable: This takes on a value of one if the respondent's income is not the main income source of the household and zero otherwise.

(16) Interaction term: (6) and (15).

Hometown dummy variables

(17) Hometown dummy variables: dummy variables for prefectures where the workers resided at age 15.

Urban experiences

(18) Logarithm of residential years in the Tokyo MA: logarithm of years of residence in the Tokyo MA if the present residential location is in the Tokyo MA and zero otherwise.

(19) Logarithm of residential years in the Osaka MA: logarithm of years of residence in the Osaka MA if the present residential location is in the Osaka MA and zero otherwise.

(20) Logarithm of residential years in the Nagoya MA: logarithm of years of residence in the Nagoya MA if the present residential location is in the Nagoya MA and zero otherwise.

Migration variables

(21) Migration dummy variable: This takes on a value of one if the prefecture of present residence is different from that of the prefecture at age 15 and zero otherwise.

(22) Logarithm of migration distance: logarithm of the distance between the prefectural offices of the present residence and the hometown. To avoid a logarithm of zero, we add one to distances.

(23) Interaction terms: (2) and (21); (2) and (22); (3) and (21); (3) and (22); (5) and (21); (5) and (22); (6) and (21); (6) and (22).

Year effects

(24) Survey year dummy variables.

References

Bacolod, Marigee, Bernardo S. Blum, and William C. Strange (2009), Skills in the city, Journal of Urban Economics 65, 136-153.

Baum-Snow, Nathaniel and Pavan Ronni (2012), Understanding the city size wage gap, Review of Economic Studies79, 88-127.

Charlot, Sylvie and Gilles Duranton, (2004), Communication externalities in cities, Journal of Urban Economics 56, 581-613.

Combes, Pierre-Philippe, Gilles Duranton, and Laurent Gobillon (2008), Spatial wage disparities: Sorting matters!, Journal of Urban Economics 63, 723-742.

Combes, Piierre-Philippe, Gilles Duranton, Laurent Gobillon, and Sébastien Roux (2012), Sorting and local wage and skill distribution in France, Regional Science and Urban Economics 42, 913-930.

De la Roca, Jorge (2011), Selection in initial migration: Evidence from moves across Spanish cities, IMDEA Working Paper Series 2011/21.

Fujita, Masahisa, Tomoya Mori, J. Vernon Henderson, and Yoshitsugu Kanomoto (2004), Spatial distribution of economic activities in Japan and China, in J. Vernon Henderson and Jacques-François Thisse ed. Handbook of Regional and Urban Economics Vol. 4, 2911-2977, Elsevier.

Fujita, Masahisa and Takatoshi Tabuchi, (1997),Regional growth in postwar Japan, Regional Science and Urban Economics 27, 643-670.

Glaeser, Edward L. (1999), Learning in cities, Journal of Urban Economics 46, 254-277.

Glaeser, Edward L. and David C. Maré (2001), Cities and Skills, Journal of Labor Economics 19, 316-342.

Gould, E. D. (2007), Cities, workers, and wages: A structural analysis of the urban wage premium, Review of Economic Studies 74, 477-506.

Greenwood, Michael J. (1975), Research on Internal Migration in the United States: A Survey, Journal of Economic Literature 13, 397-433.

Matano, Alessia and Paolo Naticchioni, (2012) Spatial externalities and wage distribution: The role of sorting, Journal of Economic Geography 12, 379-408.

Mion, Giordano and Paolo Naticchioni (2009), The spatial sorting and matching of skills and firms, Canadian Journal of Economics 42, 28-55.

Nakosteen, Robert A., Olle Westertlund, and Michael Zimmer (2008), Migration and self-selection: measured earnings and latent characteristics, Journal of Regional Science 48, 769-788.

Ohta, Souichi. (2007) Interregional earnings differentials and the effect of hometown on earnings in Japan, ESRI2006 International Collaboration Projects Paper, 69-99.

Rosenthal, Stuart S. and William C. Strange (2004), Evidence on the nature and sources of agglomeration economies, in J.V. Henderson and J.-F. Thisse ed. *Handbook of Regional and Urban Economics*, Vol. 4 (Amsterdam: Elsevier-North-Holland), Ch4, 2119-2171.

Tabuchi, Takatoshi (1988), Interregional income differentials and migration: their interrelationship, Regional Studies 22-1, 1-10.

Tabuchi, Takatoshi and Atsushi Yoshida (2000), Separating urban agglomeration economies in consumption and production, Journal of Urban Economics 48, 70-84.