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Spatial Dependence and Social Networks in Regional Labor Migration*

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Abstract

This study empirically analyzes the determinants of regional labor migration in Japan. Using spatial models of origin-destination flows and considering the network effects of labor, we obtain results more consistent with standard migration theory than previous studies. First, unlike prior research, we find that migration decisions are made by economic motivations consistent with economic theories. In particular, the unemployment rate in the destination region and income in the origin are found to be driving forces of labor migration. Second, we report that network effects, which help reduce migration costs, have encouraged the relocation of labor. Third, by using several definitions of spatial weights, we show that spatial dependence in regional migration is more complex than what previous studies assumed.

Keywords: labor migration, spatial models, origin-destination flows, regional economy, network effects
JEL classification: C32, O47

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1 Introduction

Migration has been an important research topic globally. Massive immigration from the Middle East has resulted in socioeconomic conflicts in Europe. As a result, many European countries have imposed a cap on immigration; the United Kingdom has even decided to leave the European Union (Brexit) to control its own immigration policy. Blanchard and Katz (1992), Debelle and Vickery (1999), and Choy et al. (2002) discussed migration as a factor in reducing income disparities; however, the recent political trend is to prevent the free movement of people and economic convergence among countries.

While cross-border migration may have been the main political focus recently, inter-regional migration has also drawn the interest of researchers and policymakers. In Japan, which has experienced rapid demographic changes, the unidirectional movement of labor has widened regional heterogeneity and become a serious socioeconomic problem in recent decades. People tend to move to urban areas where there are more job opportunities and easier access to medical facilities, shops, and public transportation. As a result, many rural regions known as *Genkai-shuraku* face depopulation and risk disappearing in the near future. Moreover, policymakers need to consider the different impacts of monetary policies designed to fit all regions on regional economies.

Against this background, we attempt to identify the socioeconomic factors affecting regional labor migration in Japan by using spatial models of origin-destination flows. The distinguishing points in this study are threefold. First, although many studies of migration exist, this is one of the few focusing on labor migration (see the next section for previous studies). Labor is an ingredient of production and economic activities, and therefore, is closely related to household income and utility. Furthermore, as discussed, labor mobility is an important factor for economic and regional convergence.

Second, unlike most previous studies that have focused on net migration, we distinguish between migration inflows and outflows; moreover, because migration flows are known to be spatially correlated, we model regional dependence by using spatial statistics.[1] The consideration of the origin and destination in spatial models enriches our understanding of labor movement, and we use spatial statistics, which has become a pop-

[1] The study by Paelinck and Klaassen (1979) was the first comprehensive attempt to outline a field of spatial analyses and its distinct methodology. Spatial correlation is sometimes called spatial interaction.

ular investigation approach to obtain consistent parameters in various research fields, to model regional dependence.[2] Third, we introduce several definitions of spatial weight matrixes to capture the different types of regional dependence in the data. This departs from previous migration analyses that have used only a single spatial weight matrix based on the geographical distance between regions. Finally, we control for the network effects of migrants, which have often been omitted in previous studies. Our results suggest that the last two contributions particularly help reduce the bias in many of the parameters and make our estimates more consistent with standard economic theory.

2 Related studies of migration

Previous studies of labor migration tend to focus on the relationship between migration and determinants such as regional labor market conditions; therefore, labor decisions on relocation are driven largely by economic motivations. Such research also has some shortcomings; for example, even when spatial models are used, net migration across regions is often analyzed by assuming one particular type of spatial dependence. Furthermore, the social networks of labor have not been considered in previous studies of Japanese relocation decisions.

Unemployment rates: Labor market conditions are probably the most popular explanation of labor migration in previous studies. According to migration theory (Karemera et al., 2000; Pedersen et al., 2008), expected income is closely associated with the unemployment rate; labor moves to low-unemployment-rate regions in which the economic conditions are better than those in the origin (Hunt, 2006). Moreover, job security is considered to be high in these regions (Romer, 2012) because a low unemployment rate reduces the risks of dismissal for an individual and increases the chances of reemployment after being fired. Among Japanese migration studies, Kondo and Okubo (2015) analyzed

[2]For instance, in epidemiology, Grillet et al. (2010) studied the spatial pattern of malaria incidence and persistence in Venezuela using spatial statistics and geographically weighted regression. In veterinary science, Joly et al. (2006) analyzed the spatial distribution and correlation of epidemics in deer. In ecology, Getzin et al. (2008) analyzed the effect of environmental heterogeneity in the spatial dynamics of plant communities and confirmed that biological processes interact with spatial heterogeneity. Furthermore, in political sciences, Chen and Rodden (2010) confirmed that partisan bias arises from geographical factors, and in criminology, Vilalta (2010) analyzed the spatial distribution and correlation of drug possession in Mexico. In education, Gu (2012) confirmed that the admission score chosen by universities in China is spatially autocorrelated with their neighboring competitors.

labor inflows and outflows without distinguishing between origin and destination regions. They found that the unemployment rate increases outflows in some periods (1985–1990 and 1995–2000), but not in another (2005–2010). Tamesue and Tsutsumi (2012) and Tsutsumi and Tamesue (2012) studied inter-prefectural migration using a spatial autoregression model. They analyzed the effects of the unemployment rate in the origin and destination separately but concluded that, unlike the theoretical predictions, a higher unemployment rate in both regions increases migration flows.

Income: Income is another important labor market indicator. Sjaastad (1962) advocated the human capital investment theory of migration, and most modern migration studies use this analytical framework (Bodvarsson et al., 2015). According to this theory, people migrate if the benefits from migration exceed the costs. After subtracting the migration costs, people compare the real income that will be gained in the destination with that in the origin. Then, they relocate if they can maximize the present value of their lifetime income in the destination. Using Japanese regional data, Kondo and Okubo (2015) confirmed that consistent with migration theory, net labor inflows increase when regional income is high, without considering the spatial correlation in migration flows.

Amenities: Amenities are rarely included in the utility function of migrants; however, unlike the human capital investment theory of migration, the consumer theory of migration includes in the utility function non-tradable goods such as amenities (Bodvarsson et al., 2015). When there are disparities in amenities, even if income differs among regions, utility may not improve through migration. Therefore, in the presence of differences in amenities, regional economic disparities do not disappear but rather persist. Greenwood (1997) discussed that temperature is a typical amenity for migrants, finding that amenities increase when temperature is higher.

Age: In theory, migration decisions are influenced by the life-cycle of households; for example, younger people are more likely to migrate than older people. According to Becker (1965), the present value of benefits from migration declines by age because older people spend less time in a destination and thus stand to gain fewer benefits. Consequently, regions with younger households are expected to experience more emigration.

Distance: In many migration analyses, the geographical distance between regions is used as a proxy for migration costs, such as transportation costs and the costs of obtaining information on labor markets in the destination. Migration costs are assumed to increase by distance.

Network effects: Bodvarsson et al. (2015) found that psychological and information costs decline if there is close contact among migrants from the same origin. In sociological migration theory, communities of families and friends and those of migrants in the destination who come from the same origin are called kinship and migrant networks, respectively. Yap (1977) and Hugo (1981) reported that when the historical number of migrants from a specific origin to a destination is high, people tend to relocate to that destination because the costs of finding out market information in the destination are low. Carrington et al. (1996) found that these networks decrease psychological and information costs, and migration costs can be proxied by the size of past migration. Here, we name such community-level social networks without distinguishing between kinship and migrant networks.

3 Migration theory

Our analysis is based on a gravity model, which is a popular economic approach applied to a number of research areas such as international and regional economics. The name of the gravity model originates from the law of universal gravitation. We use this model because it can be extended to include the socioeconomic variables identified in Section 2. The gravity model in migration studies points to a negative relationship between distance (d_{od}) and migration flows (Y_{od}) from the origin (o) to the destination (d):

$$Y_{od} = K \frac{X_o^{\beta_1} X_d^{\beta_2}}{d_{od}^{\beta_3}} \tag{1}$$

where X_o and X_d represent the regional characteristics of o and d, respectively. K is a constant, and β_1, β_2, and β_3 are the parameters to be estimated. This allows us to model migration inflows and outflows separately. In empirical studies, researchers have often used the natural logarithm of Eq. (1):

$$\ln Y_{od} = \ln(K) + \beta_1 \ln X_o + \beta_2 \ln X_d - \beta_3 \ln d_{od} \tag{2}$$

While the gravity model is popular in economic analyses because of its simplicity, it is sometimes criticized for lacking theoretical foundations. Therefore, to add the micro-foundation to the standard gravity model, we use the random utility maximization model in line with McFadden (1974), Andersson and Ubøe (2012), and Beine et al. (2016). First, using the notation $\ln Y = y$, the migration equation can be defined as

$$y_{odt} = p_{odt} s_{ot} \tag{3}$$

where y_{odt} is the number of migrants who move from o to d at time t, s_{ot} is the population stock in o at t, and $p_{odt} \in [0,1]$ is the proportion of people who move from o to d at t. Next, we define the utility function of individual a associated with migration as

$$U_{aodt} = w_{odt} - c_{odt} + \epsilon_{aodt} \qquad\qquad d = 1, ..., n \tag{4}$$

where U_{aodt} is the utility of a arising from migration from o to d at time t, w_{odt} is the non-stochastic effect on utility, c_{odt} is the cost of migration from o to d, and ϵ_{aodt} is the stochastic and individual-specific effect on utility. Then, we can express the probability of individuals also migrating from o to d as p_{odt}:

$$\begin{aligned} p_{odt} &= P(U_{aolt} \leq U_{aodt}, \forall l \neq d) \\ &= P(w_{o1t} - c_{o1t} + \epsilon_{ao1t} \leq w_{odt} - c_{odt} + \epsilon_{aodt}, ..., w_{ont} - c_{ont} + \epsilon_{aont} \leq w_{odt} - c_{odt} + \epsilon_{aodt}) \\ &= P(\epsilon_{ao1t} \leq w_{odt} - c_{odt} - (w_{o1t} - c_{o1t}) + \epsilon_{aodt}, ..., \epsilon_{aont} \leq w_{odt} - c_{odt} - (w_{ont} - c_{ont}) + \epsilon_{aodt}) \\ &= \int_{-\infty}^{\infty} \prod_{\substack{l=1 \\ l \neq d}}^{n} P(\epsilon_{aolt} \leq (w_{odt} - c_{odt}) - (w_{olt} - c_{olt}) + x) f_{\epsilon}(x) dx \end{aligned}$$

Furthermore, assuming that ϵ_{aodt} follows the i.i.d. Gumbel distribution (type-I extreme value distribution), the cumulative distribution function of ϵ is

$$F_{\epsilon}(x) = P(\epsilon_{aodt} \leq x) = e^{e^{-x}}$$

Hence, we can express p_{odt} as

$$\begin{aligned}
p_{odt} &= \int_{-\infty}^{\infty} \prod_{\substack{l=1 \\ l \neq d}}^{n} P(\epsilon_{aolt} \leq (w_{odt} - c_{odt}) - (w_{olt} - c_{olt}) + x) f_{\varepsilon}(x) dx \\
&= \int_{-\infty}^{\infty} \prod_{\substack{l=1 \\ l \neq d}}^{n} e^{e^{(w_{olt}-c_{olt})-(w_{odt}-c_{odt})+x} e^{-x} e^{-e^{-x}}} dx \\
&= \int_{0}^{\infty} \prod_{\substack{l=1 \\ l \neq d}}^{n} e^{-e^{(w_{olt}-c_{olt})-(w_{odt}-c_{odt})} u} e^{-u} du \\
&= \int_{0}^{\infty} e^{-(1+\sum_{\substack{l=1 \\ l \neq d}}^{n} e^{(w_{olt}-c_{olt})-(w_{odt}-c_{odt})}) u} du \\
&= \frac{1}{1+\sum_{\substack{l=1 \\ l \neq d}}^{n} e^{(w_{olt}-c_{olt})-(w_{odt}-c_{odt})}} = \frac{e^{w_{odt}-c_{odt}}}{\sum_{l=1}^{n} e^{w_{olt}-c_{olt}}}
\end{aligned} \tag{5}$$

From Eqs. (3) and (5),

$$E(y_{odt}) = \frac{e^{w_{odt}-c_{odt}}}{\sum_{l=1}^{n} e^{w_{olt}-c_{olt}}} s_{ot} \tag{6}$$

Rewriting Eq. (6), $E(y_{odt})$ can be expressed as

$$E(y_{odt}) = \phi_{odt} \frac{x_{dt}}{\Omega_{ot}} s_{ot} \tag{7}$$

where $x_{dt} = e^{w_{odt}}$, $\phi_{odt} = e^{-c_{odt}}$, and $\Omega_{ot} = \sum_{l=1}^{n} \phi_{olt} x_{lt}$.

Similarly, $E(y_{oot})$ can be expressed as

$$E(y_{oot}) = \phi_{oot} \frac{x_{ot}}{\Omega_{ot}} s_{ot} \tag{8}$$

Now, assuming no living costs in o and $\phi_{oot} = 1$, the ratio of $E(y_{odt})$ to $E(y_{oot})$ can be written as

$$\frac{E(y_{odt})}{E(y_{oot})} = \phi_{odt} \frac{x_{dt}}{x_{ot}} \tag{9}$$

where Ω_{ot} is canceled out. This equation is the same as the gravity model because the left-hand side of Eq. (9) is decided by the migration costs associated with the move from o to d (ϕ_{odt}), non-stochastic factors in utility by migrating to d (x_{dt}), and non-stochastic factors influencing utility by not migrating from o (x_{ot}). By taking the natural logarithmic form, we can obtain a specification consistent with Eq. (2):

$$\ln\left(\frac{E(y_{odt})}{E(y_{oot})}\right) = \ln x_{dt} - \ln x_{ot} + \ln \phi_{odt} \tag{10}$$

where $\ln x_{dt}$, $\ln x_{ot}$, and $\ln \phi_{odt}$ correspond to $\ln X_d$, $\ln X_o$, and $\ln d_{od}$ in Eq. (2), respectively. As discussed in Section 2, x_{dt} and x_{ot} comprise regional data on the unemployment rate, income, temperature, and average age of labor. In addition, we consider the network effects between specific regions, which are expected to reduce overall migration costs and increase current migration. In an application of Eq. (10) to migration studies, Tamesue and Tsutsumi (2012), for example, focused on migration flows y_{odt} and used only y_{odt} as a dependent variable in Eq. (10).

4 Spatial models of origin-destination flows

There are many types of spatial models; however, unlike most previous studies on migration, we examine spatial dependence while distinguishing between origin and destination regions as well as between inter-prefectural and intra-prefectural migration. The separate treatment of origin and destination flows is important because a large flow in one particular direction (say, from the origin to the destination) will be ignored in net migration analyses when it is offset by a large flow in the opposite direction (i.e., from the destination to the origin). As it becomes clear in this study, such a distinction in migration flows helps us better understand labor movement.

Following LeSage and Pace (2008), the spatial model of origin-destination flows from the origin (o) to the destination (d) is expressed as follows:

$$\begin{aligned} y_{od} = {} & \rho_o W_o y_{od} + \rho_d W_d y_{od} + \rho_w W_w y_{od} + \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od}\gamma \\ & + \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{11}$$

where y_{od} is an $N \times 1$ matrix representing inter-prefectural labor migration ($N = n^2$) and n is the number of prefectures. ι_N is $N \times 1$ and consists of unity, and α is an intercept. X_o is an $N \times k$ matrix of o's characteristics, whose elements are zero when the corresponding dependent variables represent intra-prefectural migration. ι_i is an $N \times 1$ vector whose elements are equal to one, but zero when the corresponding dependent variables represent intra-prefectural migration. X_i is an $N \times l$ matrix where the elements are zero if the corresponding dependent variables capture inter-prefectural migration. $dist_{od}$ is an $N_1 \times 1$ matrix that measures the distance between o and d if the corresponding dependent variable is inter-prefectural migration, but takes zero otherwise. ε is an $N \times 1$ disturbance. ρ_d, ρ_o, and ρ_w represent the strength of spatial dependence, and β_o, β_d, α_i, and γ are the parameters.

W_o, W_d, and W_w are the spatial weight matrixes that are the origin-based dependence, destination-based dependence, and origin-to-destination dependence, respectively. The origin-based spatial dependence (W_o) measures the strength between migration from an origin to a particular destination and migration from the origin's neighbors to the same destination (Fig. 1). The destination-based dependence (W_d) measures the relationship between migration from o to d and migration from o to the destination's neighbor (Fig. 2). W_w is the origin-to-destination dependence, capturing migration flows from the origin's neighbors to the destination's neighbors (Fig. 3).

For illustrative purposes, let us consider three regions, a, b, and c, to explain W. In this example, the vector of the dependent variables becomes $y_{od} = [y_{aa}, y_{ab}, y_{ac}, y_{ba}, y_{bb}, y_{bc}, y_{ca}, y_{cb}, y_{cc}]'$, where y_{aa} is intra-regional migration within a and y_{ab} shows inter-regional migration from a to b. In the context of these three regions, W can be expressed as

$$W = \begin{pmatrix} 0 & w_{ab} & w_{ac} \\ w_{ba} & 0 & w_{bc} \\ w_{ca} & w_{cb} & 0 \end{pmatrix}$$

The elements in W indicate the strength of the contiguity between regions, and the sum of the rows of W is normalized. Then, the origin-based spatial weight W_o can be expressed as $W_o = W \otimes I_n$:

$$W_o = \begin{pmatrix} 0 & w_{ab} & w_{ac} \\ w_{ba} & 0 & w_{bc} \\ w_{ca} & w_{cb} & 0 \end{pmatrix} \otimes I_n = \begin{pmatrix} \mathbf{0} & w_{ab}I_n & w_{ac}I_n \\ w_{ba}I_n & \mathbf{0} & w_{bc}I_n \\ w_{ca}I_n & w_{cb}I_n & \mathbf{0} \end{pmatrix}$$

Therefore, $W_o y_{od}$ can be shown as

$$W_o y_{od} = \begin{pmatrix} 0 & 0 & 0 & w_{ab} & 0 & 0 & w_{ac} & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{ab} & 0 & 0 & w_{ac} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{ab} & 0 & 0 & w_{ac} \\ w_{ba} & 0 & 0 & 0 & 0 & 0 & w_{bc} & 0 & 0 \\ 0 & w_{ba} & 0 & 0 & 0 & 0 & 0 & w_{bc} & 0 \\ 0 & 0 & w_{ba} & 0 & 0 & 0 & 0 & 0 & w_{bc} \\ w_{ca} & 0 & 0 & w_{cb} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{ca} & 0 & 0 & w_{cb} & 0 & 0 & 0 & 0 \\ 0 & 0 & w_{ca} & 0 & 0 & w_{cb} & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} y_{aa} \\ y_{ab} \\ y_{ac} \\ y_{ba} \\ y_{bb} \\ y_{bc} \\ y_{ca} \\ y_{cb} \\ y_{cc} \end{pmatrix} = \begin{pmatrix} w_{ab}y_{ba} + w_{ac}y_{ca} \\ w_{ab}y_{bb} + w_{ac}y_{cb} \\ w_{ab}y_{bc} + w_{ac}y_{cc} \\ w_{ba}y_{aa} + w_{bc}y_{ca} \\ w_{ba}y_{ab} + w_{bc}y_{cb} \\ w_{ba}y_{ac} + w_{bc}y_{cc} \\ w_{ca}y_{aa} + w_{cb}y_{ba} \\ w_{ca}y_{ab} + w_{cb}y_{bb} \\ w_{ca}y_{ac} + w_{cb}y_{bc} \end{pmatrix}$$

where, for example, $w_{ab}y_{ba} + w_{ac}y_{ca}$ corresponds to y_{aa} and $w_{ab}y_{bb} + w_{ac}y_{cb}$ to y_{ab}. The origin-based dependence of y_{ab} is captured by $W_o y_{ab}$. W_o represents the fact that migration flows from o to d are affected (i) strongly by migration from "regions near o" to d and (ii) weakly by migration from "regions distant from o" to d. Fig. 1 illustrates their relationship, where region c is subdivided into a close neighbor (A) and a distant neighbor (B). For example, migration from "regions near o" to d is shown as a thick gray arrow from A to d and migration from "regions distant from o" to d is shown as a thin gray arrow from B to d. The thickness of the gray arrows expresses the strength of the effect of the gray arrows on the black arrow (i.e., migration from o to d). The capital of the country, Tokyo, may be a typical destination to which labor tends to move from all other regions in Japan.

[Figure 1]

Similarly, the destination-based spatial weight matrix (W_d) can be defined as $W_d = I_n \otimes W$, that is,

$$W_d = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \otimes W = \begin{pmatrix} W & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & W & \mathbf{o} \\ \mathbf{0} & \mathbf{0} & W \end{pmatrix}$$

Therefore, $W_d y_{od}$ becomes

$$W_d y_{od} = \begin{pmatrix} 0 & w_{ab} & w_{ac} & 0 & 0 & 0 & 0 & 0 & 0 \\ w_{ba} & 0 & w_{bc} & 0 & 0 & 0 & 0 & 0 & 0 \\ w_{ca} & w_{cb} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{ab} & w_{ac} & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{ba} & 0 & w_{bc} & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{ca} & w_{cb} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{ab} & w_{ac} \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{ba} & 0 & w_{bc} \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{ca} & w_{cb} & 0 \end{pmatrix} \begin{pmatrix} y_{aa} \\ y_{ab} \\ y_{ac} \\ y_{ba} \\ y_{bb} \\ y_{bc} \\ y_{ca} \\ y_{cb} \\ y_{cc} \end{pmatrix} = \begin{pmatrix} w_{ab}y_{ab} + w_{ac}y_{ac} \\ w_{ba}y_{aa} + w_{bc}y_{ac} \\ w_{ca}y_{aa} + w_{cb}y_{ab} \\ w_{ab}y_{bb} + w_{ac}y_{bc} \\ w_{ba}y_{ba} + w_{bc}y_{bc} \\ w_{ca}y_{ba} + w_{cb}y_{bb} \\ w_{ab}y_{cb} + w_{ac}y_{cc} \\ w_{ba}y_{ca} + w_{bc}y_{cc} \\ w_{ca}y_{ca} + w_{cb}y_{cb} \end{pmatrix}$$

Hence, $w_{ab}y_{ab}+w_{ac}y_{ac}$ corresponds to y_{aa} and $w_{ba}y_{aa}+w_{ac}y_{ac}$ to y_{ab}. The destination-based dependence of y_{ab} captured by $W_d y_{ab}$ is depicted in Fig. 2, and W_d indicates that y_{ab} is affected (i) strongly by migration from o to "regions near d" and (ii) weakly by migration from o to "regions distant from d." In Fig. 2, migration from o to "regions near d" is shown as a thick gray arrow from o to C and migration from o to "regions distant from d" is shown as the thin gray arrow from o to D. The thickness of the gray arrows expresses the strength of regional dependence. The Kanto region, consisting of, among others, Chiba, Saitama, and Yokohama, which are located adjacent to Tokyo, may be a typical migration destination of this spatial weight, where more attractive employment opportunities tend to exist than in the origin.

[Figure 2]

Finally, the origin-to-destination spatial weight is defined as $W_w = W \otimes W$:

$$W_w = \begin{pmatrix} 0 & w_{ab} & w_{ac} \\ w_{ba} & 0 & w_{bc} \\ w_{ca} & w_{cb} & 0 \end{pmatrix} \otimes W = \begin{pmatrix} \mathbf{0} & w_{ab}W & w_{ac}W \\ w_{ba}W & \mathbf{0} & w_{bc}W \\ w_{ca}W & w_{cb}W & \mathbf{0} \end{pmatrix}$$

Hence, $W_w y_{od}$ becomes

$$W_w y_{od} = \begin{pmatrix} 0 & 0 & 0 & 0 & w_{ab}w_{ab} & w_{ab}w_{ac} & 0 & w_{ac}w_{ab} & w_{ac}w_{ac} \\ 0 & 0 & 0 & w_{ab}w_{ba} & 0 & w_{ab}w_{bc} & w_{ac}w_{ba} & 0 & w_{ac}w_{bc} \\ 0 & 0 & 0 & w_{ab}w_{ca} & w_{ab}w_{cb} & 0 & w_{ac}w_{ca} & w_{ac}w_{cb} & 0 \\ 0 & w_{ba}w_{ab} & w_{ba}w_{ac} & 0 & 0 & 0 & 0 & w_{bc}w_{ab} & w_{bc}w_{ac} \\ w_{ba}w_{ba} & 0 & w_{ba}w_{bc} & 0 & 0 & 0 & w_{bc}w_{ba} & 0 & w_{bc}w_{bc} \\ w_{ba}w_{ca} & w_{ba}w_{cb} & 0 & 0 & 0 & 0 & w_{bc}w_{ca} & w_{bc}w_{cb} & 0 \\ 0 & w_{ca}w_{ab} & w_{ca}w_{ac} & 0 & w_{cb}w_{ab} & w_{cb}w_{ac} & 0 & 0 & 0 \\ w_{ca}w_{ba} & 0 & w_{ca}w_{bc} & w_{cb}w_{ba} & 0 & w_{cb}w_{bc} & 0 & 0 & 0 \\ w_{ca}w_{ca} & w_{ca}w_{cb} & 0 & w_{cb}w_{ca} & w_{cb}w_{cb} & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} y_{aa} \\ y_{ab} \\ y_{ac} \\ y_{ba} \\ y_{bb} \\ y_{bc} \\ y_{ca} \\ y_{cb} \\ y_{cc} \end{pmatrix}$$

$$= \begin{pmatrix} w_{ab}w_{ab}y_{bb} + w_{ab}w_{ac}y_{bc} + w_{ac}w_{ab}y_{cb} + w_{ac}w_{ac}y_{cc} \\ w_{ab}w_{ba}y_{ba} + w_{ab}w_{bc}y_{bc} + w_{ac}w_{ba}y_{ca} + w_{ac}w_{bc}y_{cc} \\ w_{ab}w_{ca}y_{ba} + w_{ab}w_{cb}y_{bb} + w_{ac}w_{ca}y_{ca} + w_{ac}w_{cb}y_{cb} \\ w_{ba}w_{ab}y_{ab} + w_{ba}w_{ac}y_{ac} + w_{bc}w_{ab}y_{cb} + w_{bc}w_{ac}y_{cc} \\ w_{ba}w_{ba}y_{aa} + w_{ba}w_{bc}y_{ac} + w_{bc}w_{ba}y_{ca} + w_{bc}w_{bc}y_{cc} \\ w_{ba}w_{ca}y_{aa} + w_{ba}w_{cb}y_{ab} + w_{bc}w_{ca}y_{ca} + w_{bc}w_{cb}y_{cb} \\ w_{ca}w_{ab}y_{ab} + w_{ca}w_{ac}y_{ac} + w_{cb}w_{ab}y_{bb} + w_{cb}w_{ac}y_{bc} \\ w_{ca}w_{ba}y_{aa} + w_{ca}w_{bc}y_{ac} + w_{cb}w_{ba}y_{ba} + w_{cb}w_{bc}y_{bc} \\ w_{ca}w_{ca}y_{aa} + w_{ca}w_{cb}y_{ab} + w_{cb}w_{ca}y_{ba} + w_{cb}w_{cb}y_{bb} \end{pmatrix}$$

Therefore, $y_{aa} = w_{ab}w_{ab}y_{bb} + w_{ab}w_{ac}y_{bc} + w_{ac}w_{ab}y_{cb} + w_{ac}w_{ac}y_{cc}$ and $y_{ab} = w_{ab}w_{ba}y_{ba} + w_{ab}w_{bc}y_{bc} + w_{ac}w_{ba}y_{ca} + w_{ac}w_{bc}y_{cc}$. W_w indicates that y_{od} is affected (i) strongly by migration from "regions near o" to "regions near d" and (ii) weakly by migration from "regions distant from o" to "regions distant from d." In Fig. (3), migration from "regions near o" to "regions near d" is shown as the thickest gray arrow from A to C and migration from "regions distant from o" to "regions distant from d" is shown as the thinnest gray arrow from B to D. Because $W_w y_{od}$ involves multiple origins and destinations, the interpretation of this weight is complicated. Hence, we do not have any particular expected relationship with migration from o to d unlike the other two spatial weights.[3]

[Figure 3]

[3]See LeSage and Pace (2008) on the difficulties of interpreting this spatial weight matrix in an economically meaningful way.

5 Data

Our dataset covers the 47 regions (i.e., prefectures) of Japan. Regional labor migration data are obtained from Japan's National Census (*Kokusei Chosa*) in 2010,[4] and therefore unusual labor movement due to the 2011 earthquakes and tsunami are not covered here. The Census is the most comprehensive dataset that collects details of residents in Japan and is conducted every five years. Migrant labor refers to workers who have relocated residences from one prefecture to another in the past five years.[5] The labor force consists of employed and unemployed people; employed workers are those older than 15 years earning income, and the unemployed are those who do not have earnings but are seeking work. In 2010, about 65 million people were in the labor force, of which 63 million people were employed. Given Japan's population of 128 million in 2010, half the population can thus be regarded as in the labor force. This proportion is very low by international standards because Japan is one of the most aged countries.

Other data are collected from various sources. Real GDP per capita, which is a proxy for income, is obtained from the Japanese Cabinet Office and is equal to nominal GDP per capita (1000 yen) in 2005 divided by a GDP deflator in 2005. Unemployment rates (%) are calculated from the National Census in 2010. Regional temperatures (°C) are the average temperatures between 2005 and 2010, and are obtained from the Statistics Bureau, Ministry of Internal Affairs and Communications (MIAC). The average age of prefectural labor is calculated based on information in the National Census in 2010,[6] and the geographical distance between prefectures is from Japan's Geospatial Information Authority. Social networks are from the MIAC, and are proxied by cumulative migration between prefectures from October 2000 to September 2005. Finally, regional goods flows in 2005, which are used to construct the spatial weight, are collected from the Logistics Census of the Ministry of Land, Infrastructure and Transport.

Table 1 presents the descriptive statistics of the data, showing regional disparities in many statistics. For example, Fig. 4 shows the unemployment rate of each prefecture. The highest unemployment rate (11.9%) is recorded for Okinawa and the lowest (4.24%) for Fukui. The gap in these regional unemployment rates is about 8 percentage points,

[4] This is the most recent data disseminated to the public.
[5] The National Census was conducted in October.
[6] In this dataset, workers older than 85 years are treated as 85 years old.

implying that significant regional disparities exist in the labor market conditions. In addition, Fig. 5 reports the income of each prefecture. The highest real GDP per capita of 5.17 million yen is recorded for Tokyo and the lowest (2.04 million yen) for Okinawa. The regional difference is about 3.13 million yen.

[Table 1 & Figs. 4 and 5]

The importance of spatial dependence in migration studies has been underlined, but what are elements of W (i.e., w) that determines the definition of neighbors? Here, we use three definitions of a spatial weight matrix based on 1) the distance between prefectural capitals, 2) past migration, and 3) goods flows. The majority of previous studies have used geographical distance, assuming that the proximity of regions indicates a tight economic relationship with each other. Further, we use additional definitions to check the robustness of our findings because there are three metropolitan areas in Japan (i.e., Tokyo, Osaka, and Aichi) to which many people and goods flow—even from distant rural regions.

Thus, the first definition of a spatial weight is based on the geographical distance between regions: W_o, W_d, and W_w. This definition is the most popular in previous spatial analyses and assumes that spatial dependence is related to the physical proximity between regions. Let us define a 47×47 spatial weight matrix W consisting of w_{od}:

$$w_{od} = \begin{cases} \dfrac{dist_{od}^{-p}}{\sum_{d=1}^{47} dist_{od}^{-p}}, & if \quad o \neq d \\ 0, & otherwise \end{cases}$$

where $dist_{od}$ is the distance between prefectural capitals and p can take any real positive value (p=1, 2, or 3 in this study). Then, we can construct spatial weight matrixes by using the Kronecker product as $W_o = W \otimes I$, $W_d = I \otimes W$, and $W_w = W \otimes W$, where I is a 47×47 identity matrix.

The second spatial weight utilizes the size of cumulative migration ($\overline{W}_o$, $\overline{W}_d$, and $\overline{W}_w$). According to this spatial weight, when many migrants have relocated to particular destinations in the past, labor migration to these regions is also expected to be high today. Assuming a 47×47 spatial weight matrix $\overline{W}$, it consists of $\overline{w}_{od}$ where the elements of the rows are normalized.

$$\overline{w}_{od} = \begin{cases} \dfrac{(\overline{z}_{od,t-1} + \overline{z}_{do,t-1})}{\sum_{d=1}^{47}(\overline{z}_{od,t-1} + \overline{z}_{do,t-1})}, & if \quad o \neq d \\ 0, & otherwise \end{cases}$$

where $\overline{z}_{do,t-1}$ is past migration from o to d. As before, we can define three spatial weight matrixes by using the Kronecker product as $\overline{W}_o = \overline{W} \otimes I$, $\overline{W}_d = I \otimes \overline{W}$, and $\overline{W}_w = \overline{W} \otimes \overline{W}$.

The final definition of spatial weight matrixes utilizes the size of goods flows between prefectures ($\tilde{W}_o$, $\tilde{W}_d$, and $\tilde{W}_w$), which are constructed using a 47×47 spatial weight matrix $\tilde{W}$ that consists of $\tilde{w}_{od}$, where the sum of the rows is normalized:

$$\tilde{w}_{od} = \begin{cases} \dfrac{(g_{od,t-1} + g_{do,t-1})}{\sum_{d=1}^{47}(g_{od,t-1} + g_{do,t-1})}, & if \quad o \neq d \\ 0, & otherwise \end{cases}$$

where $g_{od,t-1}$ is the past goods flow between o and d. We assume that the higher the past goods flow between regions, the greater is the importance of their relationship. Therefore, this spatial matrix is closely related to regional relationships through trading economic goods. These three spatial weight matrixes are again obtained by using the Kronecker product as $\tilde{W}_o = \tilde{W} \otimes I$, $\tilde{W}_d = I \otimes \tilde{W}$, and $\tilde{W}_w = \tilde{W} \otimes \tilde{W}$.

6 Empirical results

6.1 Results from the non-spatial models

Initially, we estimate a cross-sectional migration model without considering spatial dependence. Maintaining the notations of the variables used in the previous section and in line with LeSage and Pace (2008, 2009), this basic model can be written as Eq. (12) but includes past cumulative migration ($\overline{z}_{od,t-1}$) as a proxy for social networks:

$$y_{od} = \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od} \gamma + \overline{z}_{od,t-1} \delta + \varepsilon \tag{12}$$

The OLS results in Table 2 show that the treatment of social networks influences the empirical outcomes. In Column (1-1), which does not control for social networks, the unemployment rate in both o and d has a positive and significant effect on labor migration. By contrast, in Column (1-2), which controls for social networks, the unemployment rate in o is insignificant, but this rate in d has a negative and significant effect on labor migration. This negative sign is consistent with the theoretical predictions and suggests that labor moves to low-unemployment-rate regions. Because the parameter of the network effects is fairly large (0.962) and the Akaike information criterion (AIC) in Column (1-2) is smaller than that in Column (1-1), controlling for social networks improves the model performance significantly, suggesting a large omitted bias in the estimates reported in Column (1-1). From the fact that labor does not react to the origin's unemployment rate but to the destination's unemployment rate, it is conceivable that labor migrates if the labor market conditions of the destination are seen to be good—regardless of the origin's unemployment rate. Such a phenomenon, which can be represented as "the grass is always greener on the other side," is confirmed by Dinger et al. (2012) and can be used to explain our results.

A similar outcome is obtained from the other variables. For example, in Column (1-1), income in both o and d has a positive and significant effect on labor migration. This result, that labor migration increases with high income in o, is inconsistent with migration theory. By contrast, in Column (1-2), both the income parameters are correctly signed, although they no longer have statistical significance. Together with these results and the positive and significant parameter for the social network effects, we conclude that social networks are important factors in relocation decisions and act to increase labor migration. Next, we consider the spatial dependence absent from our analyses so far.

[Table 2]

6.2 Results from the spatial models

6.2.1 A spatial weight matrix based on geographical distance

Here, the level of regional ties is determined by their physical location; labor is expected to move to destinations near the origin in terms of the distance between regions. Because migration flows may influence the explanatory variables such as income and unemployment rates, we estimate such spatial migration models by using the spatial two-stage least squares (S2SLS) method to deal with the potential endogeneity problem (see the Appendix for more details on the S2SLS). Tables 3, 4, and 5 show the empirical results of Eq. (13) that uses the spatial weights based on the distance between prefectures. More specifically, the spatial weights considered here are based on the inverse distance (Table 3), the square of the inverse distance (Table 4), and the cubic form of the inverse distance (Table 5):

$$\begin{aligned} y_{od} =& \rho_o W_o y_{od} + \rho_d W_d y_{od} + \rho_w W_w y_{od} + \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od}\gamma + \overline{z}_{od,t-1}\delta \\ &+ \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{13}$$

In these tables, all ρ_o, ρ_d, and ρ_w are reported to be statistically significant, suggesting that migration flows have complex spatial dependence. In particular, the first two parameters are positive and confirm that labor migration from o to d is highly associated with migration from o to prefectures close to d as well as with migration from prefectures near o to d. The negative ρ_w implies that regional heterogeneity is prominent in Japan. Among the different forms of spatial matrixes, the spatial model with the square of the inverse distance ($p = 2$) fits the data best because the AIC is the smallest; furthermore, this spatial model explains labor migration better than the non-spatial model (Table 2) based on their AICs.

Let us look more closely at the results in Table 4 ($p = 2$) with the smallest AIC. We again confirm the importance of social networks in migration decisions and large omitted bias in Column (3-1) that does not consider this effect. There, the unemployment rate in both o and d does not affect labor migration significantly. In Column (3-2), the unemployment rate in o does not have a significant effect on labor migration, but the rate in d has a negative and significant effect. Therefore, it is important to distinguish between immigrants and emigrants; otherwise, we could not conclude that only the unemployment rate of the destination has a significant and negative effect on labor migration. Our finding concurs more closely to migration theory than those of Kondo and Okubo (2015), who reported that the unemployment rate has no significant effect on migration between 2005 and 2010, and Tamesue and Tsutsumi (2012) and Tsutsumi and Tamesue (2012) who reported that the unemployment rate in both the origin and the destination increases migration.

Similarly, omitted bias is reported for the other variables in Column (3-1). Income in both o and d has a significant effect on labor migration in Column (3-1), but in Column (3-2) income in o has a negative and significant effect on labor migration. Since lower income in the origin should motivate workers there to consider relocation, it is important to control for both spatial dependence and the social network effects in migration studies. The result that only income in the destination has a significant negative effect is more consistent with the theoretical predictions than previous studies (e.g., Tamesue and Tsutsumi, 2016) that have found that high income in both the origin and the destination regions reduces migration. Our results from the spatial models are also in contrast to those obtained from the non-spatial models and thus confirm the importance of regional dependence in migration studies.

[Tables 3, 4, and 5]

6.2.2 A spatial weight matrix based on past migration

Column (5) in Table 6 shows the S2SLS results of the model (Eq. (14)) that uses the weight matrixes based on past migration. Thus, neighboring regions are defined by the historical number of migrants between regions:

$$\begin{aligned} y_{od} =& \overline{\rho_o}\overline{W}_o y_{od} + \overline{\rho}_d \overline{W}_d y_{od} + \overline{\rho}_w \overline{W}_w y_{od} + \iota_N \alpha + X_o\beta_o + X_d\beta_d + dist_{od}\gamma + \overline{z}_{od,t-1}\delta \\ &+ \iota_i\alpha_i + X_i\beta_i + \varepsilon \end{aligned} \tag{14}$$

In general, the empirical results are similar to those obtained by using the distance-based spatial weight matrixes. Again, $\overline{\rho}_o, \overline{\rho}_d$, and $\overline{\rho}_w$ are all statistically significant with the same parameter signs obtained from the distance-based matrixes. This outcome indicates that current labor migration flows are influenced by historical movement. On the effects of the unemployment rate in Table 6, this rate of o does not have a significant effect on labor migration, whereas the unemployment rate of d has a negative and significant effect on labor migration to d. Moreover, the income of o has a negative effect on labor migration from o, whereas the income of d does not have a significant effect on labor migration. These results are the same as those in Column (3-2), which used the square of the inverse distance-based weight matrix; however, the model performance is not as good as that when using the distance-based spatial weight matrix. Indeed, the AIC of this model is larger than that for the model using the distance-based weight matrix with $p = 2$.

[Table 6]

6.2.3 A spatial weight matrix based on goods flows

Column (6) in Table 6 shows the S2SLS results of the model, Eq. (15), which uses the spatial weight matrixes based on goods flows. This is an alternative way to define neighbors; here, neighboring regions are determined by the volume of trade between regions. This definition of neighbors is expected to be relevant in Japan where metropolitan areas are scattered across a country and regions physically close to each other may not have a direct economic relationship:

$$\begin{aligned} y_{od} =& \tilde{\rho}_o \tilde{W}_o y_{od} + \tilde{\rho}_d \tilde{W}_d y_{od} + \tilde{\rho}_w \tilde{W}_w y_{od} + \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od} \gamma + \overline{z}_{od,t-1} \delta \\ &+ \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{15}$$

The general conclusion remains the same as before. Social networks play a positive and significant role in labor migration, and similarly $\tilde{\rho}_o$, $\tilde{\rho}_d$, and $\tilde{\rho}_w$ are statistically significant and maintain the same parameter signs; therefore, migration flows are closely related to the size of trade not only between two regions but also among their neighbors. Furthermore, the unemployment rate in o does not have a significant effect on labor migration, whereas this rate in d has a negative and significant effect on labor migration flows to d. These results are the same as those in Column (3-2) based on the square of the inverse distance-based weight matrix and Column (5) based on the past migration weight matrix. Moreover, the income of o has negative effects on labor migration from o, whereas the income of d does not. However, the performance of this model is not as good as that of the other spatial models using weight matrixes based on distance and past migration according to the AICs.

6.2.4 A combination of the spatial weight matrixes

So far, we have assumed only one type of spatial weight matrix in a spatial model following the conventional approach. Here, we consider different combinations and definitions of the spatial weights used in this section (i.e., Eqs. (16)–(19)) because spatial dependence may be more complicated than previous studies have assumed. While maintaining the same notations as before, Eq. (16) contains the spatial weight matrixes based on distance and past migration (W and $\bar{W}$), Eq. (17) on distance and goods flows (W and $\tilde{W}$), and Eq. (18) on past migration and goods flows ($\bar{W}$ and $\tilde{W}$). Eq. (19) contains all types of spatial weights:

$$\begin{aligned} y_{od} =& \rho_o W_o y_{od} + \rho_d W_d y_{od} + \rho_w W_w y_{od} + \overline{\rho_o}\overline{W}_o y_{od} + \overline{\rho}_d \overline{W}_d y_{od} + \overline{\rho}_w \overline{W}_w y_{od} \\ &+ \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od}\gamma + \overline{z}_{od,t-1}\delta + \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{16}$$

$$\begin{aligned} y_{od} =& \rho_o W_o y_{od} + \rho_d W_d y_{od} + \rho_w W_w y_{od} + \tilde{\rho}_o \tilde{W}_o y_{od} + \tilde{\rho}_d \tilde{W}_d y_{od} + \tilde{\rho}_w \tilde{W}_w y_{od} \\ &+ \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od}\gamma + \overline{z}_{od,t-1}\delta + \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{17}$$

$$\begin{aligned} y_{od} =& \overline{\rho_o}\overline{W}_o y_{od} + \overline{\rho}_d \overline{W}_d y_{od} + \overline{\rho}_w \overline{W}_w y_{od} + \tilde{\rho}_o \tilde{W}_o y_{od} + \tilde{\rho}_d \tilde{W}_d y_{od} + \tilde{\rho}_w \tilde{W}_w y_{od} \\ &+ \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od}\gamma + \overline{z}_{od,t-1}\delta + \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{18}$$

$$\begin{aligned} y_{od} =& \rho_o W_o y_{od} + \rho_d W_d y_{od} + \rho_w W_w y_{od} + \overline{\rho_o}\overline{W}_o y_{od} + \overline{\rho}_d \overline{W}_d y_{od} + \overline{\rho}_w \overline{W}_w y_{od} \\ &+ \tilde{\rho}_o \tilde{W}_o y_{od} + \tilde{\rho}_d \tilde{W}_d y_{od} + \tilde{\rho}_w \tilde{W}_w y_{od} + \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od}\gamma + \overline{z}_{od,t-1}\delta \\ &+ \iota_i \alpha_i + X_i \beta_i + \varepsilon \end{aligned} \tag{19}$$

Table 7 summarizes the S2SLS results of these models. Column (7) uses the spatial matrixes based on distance and past migration, Column (8) uses those on distance and goods flows, Column (9) uses those on past migration and goods flows, and Column (10) uses all three types of the weight matrixes. The AICs of these models in Table 7 except Column (9) are smaller than those of the models with one weight matrix reported in Tables 3–6, indicating that the goodness of fit has improved by using several types of weight matrixes.

[Table 7]

The common results from Columns (7)–(9) are that the unemployment rate of d has a negative effect on labor migration to d and that income in o has a negative and significant effect on labor migration from o. Furthermore, the social network effects are reported to increase labor migration, consistent with the theoretical predictions. Moreover, in Columns (7) and (8), whose AICs are smaller than that of Column (9), two types of weight matrixes are statistically significant, suggesting that using only one spatial weight matrix is inadequate to fully capture the spatial dependence in migration flows.

In Column (10), which uses all three types of weights, all three distance-based spatial weight matrixes and all three past migration-based spatial weight matrixes are statistically significant. Furthermore, we find that the unemployment rate of d has a negative and significant effect on labor migration to d and that the income of o has a negative and significant effect on migration from o. Because the AIC is the smallest, the results of Column (10) are considered to be the most reliable.

In short, we find that not only the distance between regions, but also past migration and goods flows are important factors for capturing the spatial correlation, which is an original contribution of this study. For example, LeSage and Pace (2008, 2009), Tamesue and Tsutsumi (2012, 2016), and Tsutsumi and Tamesue (2012) used a spatial weight matrix based on inverse distance only and often reported statistical evidence inconsistent with migration theory. Therefore, regional dependence is more complex than researchers have thought, and it is important to consider several types of spatial correlations when modeling labor migration.

We have explained the empirical results by focusing on the relationship between labor migration and economic motivations; however, other control variables are also often found to be statistically significant. For example, in Columns (7)–(10), we report that the higher the temperature in o, the lower is the migration from o and that the higher the temperature in d, the higher is the migration to d, as expected from the theory. Because amenities of labor are expected to increase in warmer regions in Japan, we confirm that relocation decisions are sensitive to temperature.

With respect to the age of labor, Columns (7)-(10) show that the younger the average age in o, the higher is the migration from o. As explained in Section 2, when the proportion of young labor is high in a region, migrants tend to move from there. Similarly, the younger the average age in d, the higher is the migration to d. This finding reflects the fact that many young people live in urban areas that are typical destination regions for migrants.

The distance between o and d is also reported to be significant in Columns (7)–(10), suggesting that the longer distance between prefectures has resulted in less migration from o to d. This finding implies that migration to a distant region is considered to incur higher costs and uncertainty. Similarly, we find that regions with high intra-regional migration often experienced high inter-regional migration during our sample period. Thus, there seems to be regional differences in attitudes toward the relocation of residence.

7 Conclusion

This study empirically analyzes the effects of regional characteristics on inter-prefectural labor migration by using spatial models of origin-destination flows. The consideration of network effects and different types of spatial dependence leads us to empirical results more consistent with the theoretical predications than previous studies. More specifically, we find that labor is more likely to react to the destination's unemployment rate and origin's income. Second, social networks of migrants, which help reduce the costs of gathering information and uncertainty about the destination, are important factors when making migration decisions. Third, many spatial migration analyses have used only a distance-based spatial weight matrix, whereas we find that spatial dependence is more complicated than conventionally thought; regions are also closely linked to, for example, economic goods flows.

In short, based on a comprehensive migration model, we show that regional labor mobility can be explained by socioeconomic factors in Japan, and thus the recent widening of the gap between urban and rural regions is a natural outcome of migration decisions. In this regard, this decoupling process cannot be slowed or prevented by market forces; the intervention of the public sector seems to be indispensable to make rural regions sufficiently attractive to be considered to be destination regions by workers.

Appendix

S2SLS model

Following LeSage and Pace (2008), we construct a spatial regime model and estimate it by using S2SLS. The spatial lagged variables $W_o y_{od}, W_d y_{od}, W_w y_{od}$, $\overline{W}_o y_{od}, \overline{W}_d y_{od}, \overline{W}_w y_{od}$, $\tilde{W}_o y_{od}, \tilde{W}_d y_{od}$, and $\tilde{W}_w y_{od}$ in this study may be endogenous variables in a migration function, and therefore we use S2SLS in accordance with Badinger and Egger (2011). Defining Z that consists of all the exogenous explanatory variables in the model, the instrumental variables of the endogenous variables of $W_o y, W_d y$, and $W_w y$ are $H = (Z, W_o Z, W_d Z, W_w Z, W_o^2 Z, W_d^2 Z, W_w^2 Z, W_o W_w Z, W_d W_w Z)$ in model (14). Similarly, the instrumental variables of $\overline{W}_o y_{od}, \overline{W}_d y_{od}$, and $\overline{W}_w y_{od}$ are
$\overline{H} = (Z, \overline{W}_o Z, \overline{W}_d Z, \overline{W}_w Z, \overline{W}_o^2 Z, \overline{W}_d^2 Z, \overline{W}_w^2 Z, \overline{W}_o \overline{W}_w Z, \overline{W}_d \overline{W}_w Z)$, and the instrumental variables of $\tilde{W}_o y_{od}, \tilde{W}_d y_{od}$, and $\tilde{W}_w y_{od}$ are
$\tilde{H} = (Z, \tilde{W}_o Z, \tilde{W}_d Z, \tilde{W}_w Z, \tilde{W}_o^2 Z, \tilde{W}_d^2 Z, \tilde{W}_w^2 Z, \tilde{W}_o \tilde{W}_w Z, \tilde{W}_d \tilde{W}_w Z)$.

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Table 1: Descriptive Statistics

	Mean	SD	Min	Max
Log of inter-prefectural migration	6.16	1.62	2.48	11.8
Unemployment rate	5.94	1.34	4.24	11.9
Log of real GDP per capita	7.93	0.16	7.62	8.55
Average annual temperature	15.5	2.38	9.26	23.4
Log of average age of labor	3.80	0.02	3.73	3.84
Log of distance	5.98	0.80	2.35	7.72
Log of past inter-prefectural migration	7.32	1.60	2.64	12.9
Log of inter- and intra-prefectural migration	6.28	1.81	2.48	13.9
Log of past intra-prefectural migration	12.2	0.92	10.8	14.5

Note: Standard deviation (SD).

Table 2: OLS results

Dependent variable: log of inter-prefectural labor migration		
Explanatory variable	(1-1)	(1-2)
Intercept	177.979***	16.689***
	(8.614)	(1.597)
Unemployment rate_o	0.140***	0.006
	(0.022)	(0.004)
Unemployment rate_d	0.058**	−0.066***
	(0.022)	(0.004)
Log of real GDP per capita_o	1.615***	−0.057
	(0.209)	(0.032)
Log of real GDP per capita_d	2.003***	0.029
	(0.190)	(0.035)
Average annual temperature_o	−0.057***	−0.015***
	(0.010)	(0.002)
Average annual temperature_d	−0.023*	0.007***
	(0.010)	(0.002)
Log of average age of labor_o	−24.001***	−1.377***
	(1.276)	(0.233)
Log of average age of labor_d	−27.169***	−2.973***
	(1.268)	(0.227)
Log of distance between prefectures	−0.992***	−0.062***
	(0.031)	(0.006)
Log of past human migration		0.962***
		(0.004)
Sample size	2162	2162
Adjusted R^2	0.657	0.987
AIC	5914.839	−1184.446

Note: ***p<0.001, **p<0.01, *p<0.05

Heteroscedasticity robust standard errors are shown in ()

Table 3: S2SLS results (Inverse-distance based weight matrix)

Dependent variable: log of inter-prefectural labor migration		
Explanatory variable	(2-1)	(2-2)
Intercept	5.499	15.529***
	(3.741)	(1.633)
Unemployment rate_o	0.010	0.003
	(0.009)	(0.004)
Unemployment rate_d	0.014	−0.062***
	(0.009)	(0.004)
Log of real GDP per capita_o	−0.419***	−0.132***
	(0.074)	(0.035)
Log of real GDP per capita_d	−0.457***	0.031
	(0.074)	(0.037)
Average annual temperature_o	−0.010**	−0.015***
	(0.004)	(0.002)
Average annual temperature_d	−0.013***	0.006***
	(0.003)	(0.002)
Log of average age of labor_o	0.300	−0.875***
	(0.553)	(0.247)
Log of average age of labor_d	0.297	−2.950***
	(0.571)	(0.266)
Log of distance between prefectures	−0.121***	−0.066***
	(0.021)	(0.006)
Log of past human migration		0.903***
		(0.013)
ι_i	17.080***	−14.983***
	(4.473)	(1.766)
Log of the number of labor_i	−1.279	0.424***
	(0.703)	(0.094)
Log of past migration_i	−0.012	0.433***
	(0.628)	(0.075)
ρ_o	1.098***	0.096***
	(0.014)	(0.016)
ρ_d	1.092***	0.062***
	(0.014)	(0.016)
ρ_w	−1.181***	−0.124***
	(0.032)	(0.021)
Sample number	2209	2209
AIC	1880.203	−1342.174

Note: ***p<0.001, **p<0.01, *p<0.05

Heteroscedasticity robust standard errors are shown in ()

Table 4: Result of S2SLS (Square of inverse-distance based weight matrix)

dependent variable: log of inter-prefectural labor migration		
explanatory variable	(3-1)	(3-2)
Intercept	17.387∗∗∗	15.242∗∗∗
	(3.864)	(1.565)
Unemployment rate_o	0.009	0.001
	(0.008)	(0.004)
Unemployment rate_d	−0.004	−0.062∗∗∗
	(0.008)	(0.004)
Log of real GDP per capita_o	0.335∗∗∗	−0.079∗
	(0.079)	(0.032)
Log of real GDP per capita_d	0.364∗∗∗	0.056
	(0.081)	(0.034)
Average annual temperature_o	−0.004	−0.013∗∗∗
	(0.003)	(0.002)
Average annual temperature_d	−0.000	0.007∗∗∗
	(0.003)	(0.002)
Log of average age of labor_o	−2.629∗∗∗	−1.060∗∗∗
	(0.575)	(0.224)
Log of average age of labor_d	−3.302∗∗∗	−2.913∗∗∗
	(0.609)	(0.236)
Log of distance between prefectures	0.043∗	−0.048∗∗∗
	(0.022)	(0.007)
Log of past human migration		0.886∗∗∗
		(0.017)
ι_i	−2.063	−14.899∗∗∗
	(4.547)	(1.675)
Log of the number of labor_i	−1.067	0.396∗∗∗
	(0.600)	(0.097)
Log of past migration_i	0.384	0.462∗∗∗
	(0.521)	(0.076)
ρ_o	0.886∗∗∗	0.103∗∗∗
	(0.023)	(0.017)
ρ_d	0.880∗∗∗	0.074∗∗∗
	(0.023)	(0.018)
ρ_w	−0.877∗∗∗	−0.108∗∗∗
	(0.031)	(0.018)
Sample size	2209	2209
AIC	1628.63	−1411.023

Note: ***p<0.001, **p<0.01, *p<0.05

Heteroscedasticity robust standard errors are shown in ()

Table 5: Result of S2SLS (Cubic form of inverse-distance based weight matrix)

Dependent variable: log of inter-prefectural labor migration		
Explanatory variable	(4-1)	(4-2)
Intercept	57.240∗∗∗	16.710∗∗∗
	(6.883)	(1.576)
Unemployment rate_o	0.042∗∗∗	0.001
	(0.012)	(0.004)
Unemployment rate_d	0.012	−0.064∗∗∗
	(0.011)	(0.004)
Log of real GDP per capita_o	0.759∗∗∗	−0.079∗
	(0.117)	(0.033)
Log of real GDP per capita_d	0.901∗∗∗	0.050
	(0.124)	(0.034)
Average annual temperature_o	−0.016∗∗	−0.013∗∗∗
	(0.005)	(0.002)
Average annual temperature_d	−0.005	0.007∗∗∗
	(0.005)	(0.002)
Log of average age of labor_o	−8.113∗∗∗	−1.277∗∗∗
	(0.988)	(0.224)
Log of average age of labor_d	−9.596∗∗∗	−3.059∗∗∗
	(1.090)	(0.229)
Log of distance between prefectures	−0.173∗∗∗	−0.059∗∗∗
	(0.033)	(0.007)
Log of past human migration		0.924∗∗∗
		(0.012)
ι_i	−47.774∗∗∗	−17.271∗∗∗
	(7.516)	(1.633)
Log of the number of labor_i	−0.660	0.471∗∗∗
	(0.411)	(0.073)
Log of past migration_i	0.552	0.476∗∗∗
	(0.351)	(0.055)
ρ_o	0.634∗∗∗	0.058∗∗∗
	(0.040)	(0.011)
ρ_d	0.621∗∗∗	0.033∗∗
	(0.042)	(0.011)
ρ_w	−0.597∗∗∗	−0.061∗∗∗
	(0.046)	(0.011)
Sample size	2209	2209
AIC	2909.507	−1354.176

Note: ***p<0.001, **p<0.01, *p<0.05
Heteroscedasticity robust standard errors are shown in ()

Table 6: S2SLS results (Past migration based and goods flow based weight matrixes)

Dependent variable: log of inter-prefectural labor migration		
Explanatory variable	(5)	(6)
Intercept	15.115∗∗∗	15.411∗∗∗
	(1.571)	(1.574)
Unemployment rate_o	0.002	0.003
	(0.004)	(0.004)
Unemployment rate_d	−0.060∗∗∗	−0.061∗∗∗
	(0.004)	(0.004)
Log of real GDP per capita_o	−0.172∗∗∗	−0.179∗∗∗
	(0.035)	(0.036)
Log of real GDP per capita_d	0.034	0.036
	(0.039)	(0.041)
Average annual temperature_o	−0.014∗∗∗	−0.013∗∗∗
	(0.002)	(0.002)
Average annual temperature_d	0.006∗∗	0.006∗∗∗
	(0.002)	(0.002)
Log of average age of labor_o	−0.639∗∗	−0.670∗∗
	(0.241)	(0.245)
Log of average age of labor_d	−3.015∗∗∗	−3.072∗∗∗
	(0.267)	(0.261)
Log of distance between prefectures	−0.072∗∗∗	−0.071∗∗∗
	(0.006)	(0.006)
Log of past human migration	0.865∗∗∗	0.895∗∗∗
	(0.022)	(0.015)
ι_i	−14.230∗∗∗	−14.967∗∗∗
	(1.740)	(1.679)
Log of the number of labor_i	0.356∗∗	0.385∗∗∗
	(0.120)	(0.104)
Log of past migration_i	0.448∗∗∗	0.469∗∗∗
	(0.098)	(0.082)
$\overline{\rho}_o$	0.127∗∗∗	
	(0.021)	
$\overline{\rho}_d$	0.084∗∗∗	
	(0.023)	
$\overline{\rho}_w$	−0.116∗∗∗	
	(0.023)	
$\tilde{\rho}_o$		0.098∗∗∗
		(0.016)
$\tilde{\rho}_d$		0.055∗∗∗
		(0.017)
$\tilde{\rho}_w$		−0.086∗∗∗
		(0.018)
Sample size	2209	2209
AIC	−1378.606	−1341.942

Note: ***p<0.001, **p<0.01, *p<0.05

Heteroscedasticity robust standard errors are shown in ()

Table 7: S2SLS results (Combination of weight matrixes)

Dependent variable: log of inter-prefectural labor migration				
Explanatory variable	(7)	(8)	(9)	(10)
Intercept	13.799***	13.351***	14.299***	12.836***
	(1.551)	(1.560)	(1.568)	(1.554)
Unemployment rate_o	0.000	0.001	0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Unemployment rate_d	−0.059***	−0.058***	−0.058***	−0.056***
	(0.004)	(0.004)	(0.004)	(0.004)
Log of real GDP per capita_o	−0.141***	−0.138***	−0.180***	−0.135***
	(0.034)	(0.035)	(0.035)	(0.035)
Log of real GDP per capita_d	0.059	0.061	0.007	0.049
	(0.038)	(0.040)	(0.040)	(0.039)
Average annual temperature_o	−0.011***	−0.012***	−0.014***	−0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
Average annual temperature_d	0.007***	0.006***	0.005**	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Log of average age of labor_o	−0.627**	−0.599*	−0.552*	−0.553*
	(0.242)	(0.247)	(0.242)	(0.246)
Log of average age of labor_d	−2.858***	−2.805***	−2.804***	−2.682***
	(0.269)	(0.268)	(0.266)	(0.269)
Log of distance between prefectures	−0.063***	−0.056***	−0.075***	−0.064***
	(0.008)	(0.007)	(0.006)	(0.008)
Log of past human migration	0.810***	0.828***	0.830***	0.782***
	(0.022)	(0.019)	(0.022)	(0.022)
ι	−12.277***	−12.114***	−12.738***	−10.971***
	(1.737)	(1.732)	(1.748)	(1.746)
Log of the number of labor_i	0.284*	0.3148**	0.303*	0.266
	(0.124)	(0.120)	(0.141)	(0.138)
Log of past human migration_i	0.429***	0.426***	0.429***	0.397***
	(0.102)	(0.098)	(0.119)	(0.118)
ρ_o	0.077***	0.094***		0.090***
	(0.018)	(0.018)		(0.019)
ρ_d	0.083***	0.096***		0.095***
	(0.018)	(0.018)		(0.019)
ρ_w	−0.117***	−0.130***		−0.138***
	(0.017)	(0.018)		(0.018)
$\overline{\rho}_o$	0.111***		0.172***	0.135***
	(0.023)		(0.038)	(0.036)
$\overline{\rho}_d$	0.066**		0.115***	0.085*
	(0.024)		(0.035)	(0.034)
$\overline{\rho}_w$	−0.053*		−0.162***	−0.105**
	(0.023)		(0.039)	(0.038)
$\tilde{\rho}_o$		0.081***	−0.009	−0.005
		(0.016)	(0.028)	(0.027)
$\tilde{\rho}_d$		0.041*	0.009	0.004
		(0.018)	(0.025)	(0.026)
$\tilde{\rho}_w$		−0.026	0.009	0.044
		(0.020)	(0.031)	(0.031)
Sample size	2209	2209	2209	2209
AIC	−1480.389	−1468.255	−1391.960	−1489.003

Note: ***p<0.001, **p<0.01, *p<0.05

Heteroscedasticity robust standard errors are shown in ()

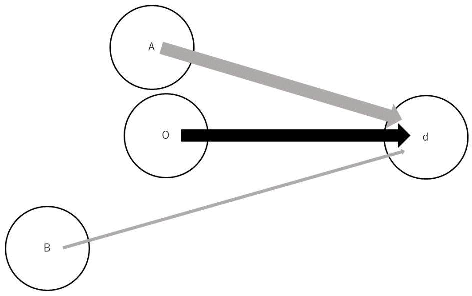

Figure 1: Origin-based dependence of y_{ab}

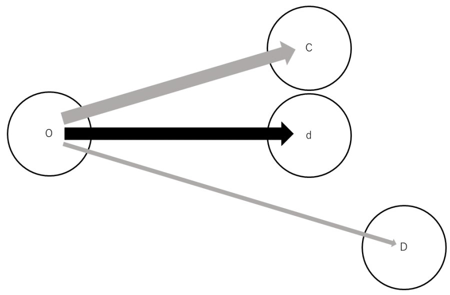

Figure 2: Destination-based dependence of y_{ab}

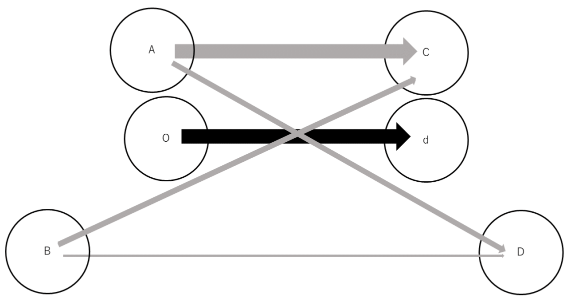

Figure 3: Origin to destination dependence of y_{ab}

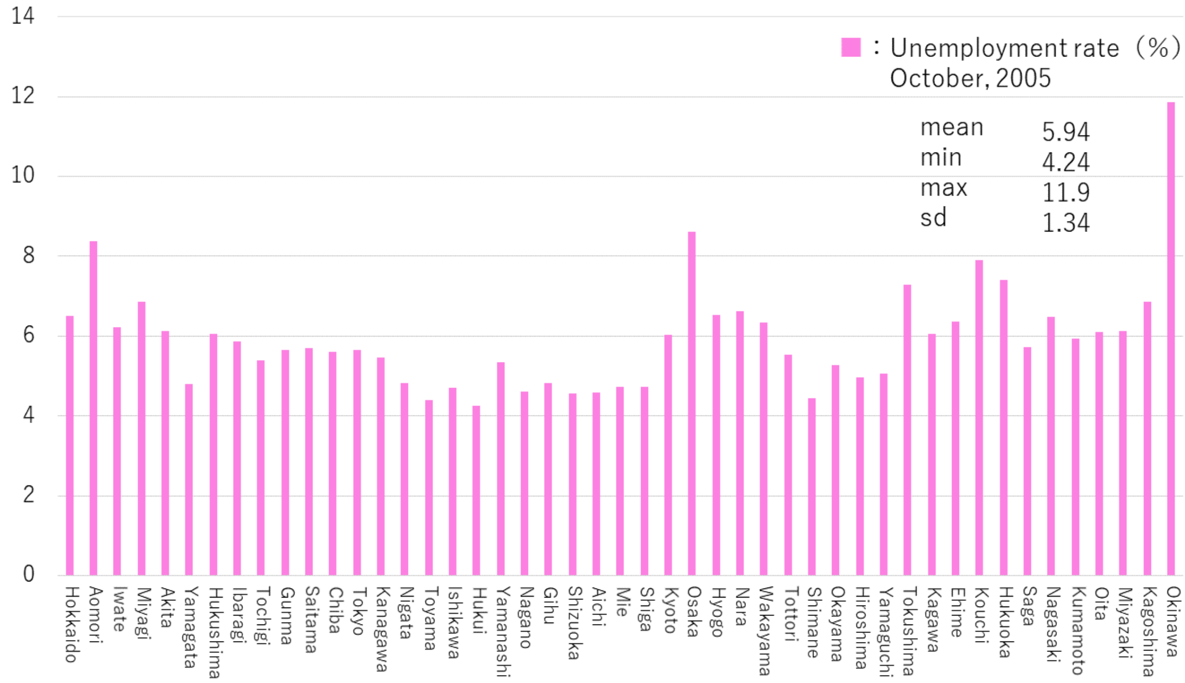

Figure 4: Unemployment rate (%) in October, 2005 from national census of 22th year of the Heisei period

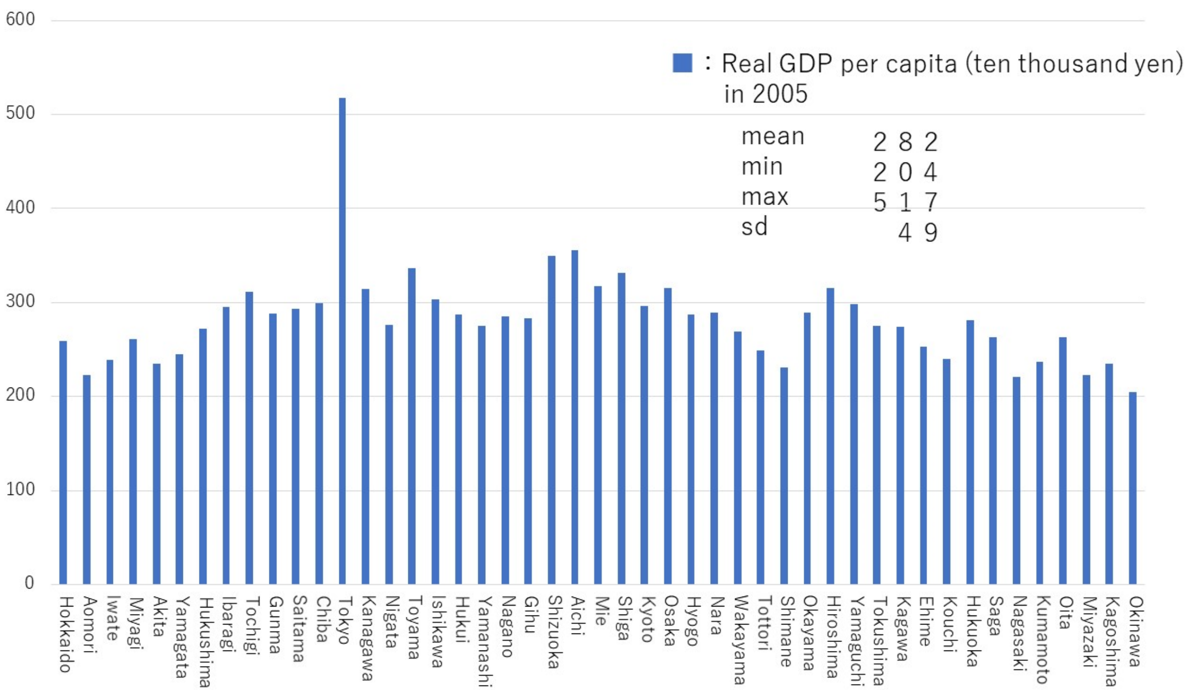

Figure 5: Real GDP per capita (ten thousand yen) in 2005 from GDP created by the Japanese cabinet office