Spatial Dependence, Social Networks, and Economic Structures in Regional Labor Migration

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Abstract

This study empirically analyzes the determinants of regional labor migration in Japan, where small towns are disappearing due to the shortage of labor. Using spatial models of origin-destination flows and considering network effects of labor and economic structures, we obtain results more consistent with the standard migration theory than previous studies. First, unlike previous studies, we find that migration decisions in Japan are based on economic motivations consistent with economic theories. Particularly, unemployment rates in origins and destinations and income in origins are found to be the determinants of labor migration. Second, we report that network effects, which help reduce migration costs, have encouraged relocation of labor. Third, considering spatial weights based on distance, goods flow, and economic structures, we show that neighbors can be most appropriately defined with economic structures; migration patterns are alike in regions with similar economic structures. (JEL J61, R23)

Keywords: labor migration; spatial models; regional economy; economic structures; network effects

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1 Introduction

Migration has been an important subject of study worldwide. While additional labor is believed to increase production, migrants are, today, considered to be causing serious socio-economic problems in many countries. As a result, the US plans to build a southern border wall between the US and Mexico against illegal immigrants. Similarly, since massive immigration from Middle East has resulted in socioeconomic conflicts, many European countries have imposed a cap on immigration; the UK decided to leave the European Union (Brexit) to control for their 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 movements of people and economic convergence among countries.

Thus, cross-border migration may be the main recent political focus; however, inter-regional migration has also drawn much interest of researchers and policymakers. In Japan, which has experienced rapid demographic changes, unidirectional movements of labor have widened regional heterogeneity. There is a tendency for people to move to urban areas where there are more job opportunities and easier access to medical facilities, shops, and public transportation. As a result, there are many rural regions known as *Genkai-shuraku* that face depopulation and the risk of disappearing in the near future. Moreover, policymakers in heterogeneous regions must consider the different impacts of monetary policies on regional economies, which are designed to fit in all regions.

Against this background, we attempt to identify socioeconomic factors affecting Japanese regional labor migration using spatial models of origin-destination flows. The distinguishing features of this study are as follows. First, even though there are many studies on human migration, this study is among the few that focus on labor migration (see the next section on related studies). Labor is an ingredient of production and economic activities, and, therefore, it is directly 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 focused on net migration, we use spatial models that distinguish between migration inflows and outflows. Since migration flows are known to be spatially correlated, regional dependence is modeled using spatial statistics to obtain consistent parameters.[1] Today, spatial statistics to model regional dependence has become a popular investigation approach in various research fields.[2] The consideration of the origin and the destination in spatial models enriches our understanding of labor movements.

In addition to spatial factors, we study inter-regional migration using a very comprehensive set of explanatory variables. Our regional characteristics to explain migration include economic variables, population, amenities such as weather conditions, and social networks. These characteristics reflect the fact that potential migrants consider many issues in deciding destination regions. After all, life is not only about work.

Finally, we introduce several definitions of spatial weight matrices to capture different types of regional dependence in the data. This approach departs from previous migration analyses that used only a single spatial weight matrix based on the geographical distance between regions. In particular, to our knowledge, this is the first study to look into regional heterogeneity in economic structures. Regional differences in economic structures are well documented in Japan (Nagayasu 2012), and labor mobility is expected to be influenced partly by employment opportunities in the destinations, which are normally related to industry-specific skills possessed by labor. Therefore, we attempt to fill the gap between the literature on migration and labor market research.

2 Related studies on migration

Here, we review previous studies relevant to labor migration. These studies tend to focus on the relationship between migration and determinants, such as regional economic conditions. Thus, according to previous research on Japanese migration, labor decisions on relocation are primarily

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

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

driven by economic motivations. Hence, we point out many other factors that potentially influence inter-regional migration decisions, such as amenities, social networks, and spatial dependence, which are often used to study migration in global markets. Furthermore, even when spatial models were used, net migration across regions was often analyzed by assuming one particular type of spatial dependence using the geographical distance between regions.

Unemployment rates: Labor market conditions are, probably, the most popular explanation of labor migration in previous studies. According to the migration theory (Karemera et al. 2000; Pedersen et al. 2008), the expected income is closely associated with unemployment rate; labor moves to low-unemployment-rate regions where economic conditions are better than the origin (Hunt 2006). Moreover, job security is considered high in these regions (Romer 2012) because the high unemployment rate increases risks of dismissal and reduces the chances of reemployment.

Among the Japanese migration studies, previous studies failed to establish the relationship between migration and the unemployment rate, consistent with the standard economic theory. Kondo (2015) analyzed labor inflows and outflows, without distinguishing between origin and destination regions. They found that the unemployment rate increased outflows. In studies on human migration using spatial autoregression models, Tsutsumi and Tamesue (2012) analyzed the effects of the unemployment rate in the origin and destination regions, separately. However, they concluded that unlike theoretical predictions, the higher unemployment rate in both regions increased 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 benefits from migration exceed costs. After subtracting migration costs, people compare real income that will be gained in the destination region with that in the origin region. They, then, relocate if they can maximize the present value of their lifetime income in the destination region. Using Japanese regional data, Kondo and Okubo (2015) confirmed that, consistent with this migration theory, net labor inflows have increased when regional income is high, without consideration of spatial correlation in migration flows.

Population: The population can be a proxy for market size. When a proportion of potential migrants is constant among regions, it is expected that more emigrants exist in populated regions.

Similarly, people tend to move to larger regions where employment opportunities are higher; thus, more immigrants are expected to exist in such regions (Bodvarsson et al. 2015).

Amenities: Amenities are not often included in the utility function of migrants. However, unlike the human capital investment theory of migration, the consumer theory of migration includes non-tradable goods like amenities in the utility function (Bodvarsson et al. 2015). When there are disparities in amenities, even if income is different among regions, the utility may not improve through migration. Therefore, in the presence of differences in amenities, regional economic disparities persist. Greenwood (1997) discussed that temperature is a typical amenity for migrants, and amenities increase when the temperature is higher. Likewise, Maddison and Bigano (2003) found that a low level of precipitation is regarded as an amenity.

Distance: In many migration analyses, the geographical distance between regions is used as a proxy for migration costs, such as transportation costs and costs from obtaining information on labor markets in the destination. It is considered that migration costs increase by distance.

Network effects: Bodvarsson et al. (2015) discussed that psychological and information costs decline if there are close contacts among migrants from the same origin. In the sociological migration theory, communities of families and friends and those of migrants in the destination who originally come from the same origin form a kinship and a migrant network, respectively. In empirical studies, 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 search costs of market information in the destination are low. Carrington et a. (1996) found that these networks decrease psychological and information costs, and migration costs can be proxied by past migration. Here, such communities are termed as social networks without distinguishing between kinship and migrant network.

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 term gravity model originates from the law of universal gravitation, and we use this model because it can be extended to include the socioeconomic variables identified in Section 2. Furthermore, an extension of this model allows us to establish an theoretical link between inter- and intra-regional migration. Intra-regional migration was ignored in previous inter-regional migration studies.

Eq. (1) summarizes the main prediction from the gravity models in migration studies—a negative relationship between the distance (d_{od}) between regions 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 consist of the regional characteristics of o and d, respectively. K is a constant, and β_1, β_2, and β_3 are parameters to be estimated. It follows that people tend to move to regions close to the origin. This specification 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, this model is sometimes criticized because of its lack of a theoretical foundation. Therefore, to add a micro-foundation to the standard gravity model, we use the random utility maximization (RUM) 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, 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 effects on the utility, c_{odt} is the costs of migration from o to d, and ϵ_{aodt} is the stochastic and individual specific effects on the utility. Then, we can express the probability that individuals will migrate 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 ϵ_{aodt} follows the independent and identically distributed (i.i.d.) Gumbel distribution (type-I extreme value distribution), the cumulative distribution function of ϵ is

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

Thus, 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), we get:

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

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, $E(y_{oot})$, which represents intra-regional migration, 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 in Eq. (9) is determined by migration costs associated with the move from o to d (ϕ_{odt}), non-stochastic factors in the utility by migrating to d (x_{dt}), and non-stochastic influencing factors in the utility by not migrating from o (x_{ot}). Thus, 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, population, amenities (temperature and precipitation) and network effects between specific regions that are expected to reduce overall migration costs and increase current migration.

4 Spatial models of origin-destination flows

There are many types of spatial models. However, unlike most previous studies on migration, we study spatial dependence while distinguishing between origin and destination regions, as well as inter-prefectural and intra-prefectural migration. The separate treatment of origin and destination flow 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 of migration (from the destination to the origin). As it becomes clear in this study, such a distinction in migration flows helps us in understanding labor movements.

Similar to LeSage and Pace (2008), the spatial model of origin-destination flows from the origin (o) to the destination (d) is expressed as follows.[3]

$$y_{od} = \rho_o W_o y_{od} + \rho_d W_d y_{od} + \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od} \gamma + X_i \beta_i + \varepsilon, \tag{11}$$

where y_{od} is an $N \times 1$ matrix representing labor migration flows ($N = n^2$) and n is the number of regions. ι_N is an $N \times 1$ matrix and consists of unity, and α is an intercept. X_o is an $N \times k$ matrix of o's characteristics and X_d is an $N \times k$ matrix of d's characteristics whose elements are zero when corresponding dependent variables represent intra-prefectural migration. Thus, X_o and X_d have no effects on intra-prefectrual migration. X_i is an $N \times l$ matrix where elements are zero if corresponding dependent variables capture inter-prefectural migration and take some values of particular regions when corresponding dependent variables represent intra-prefectural migration. In this study, we use past intra-migration data as X_i. $dist_{od}$ is an $N_1 \times 1$ matrix and measures the distance between o and d if the corresponding dependent variable is an inter-prefectural migration but is zero otherwise. ε is an $N \times 1$ disturbance. ρ_d and ρ_o represent the strength of spatial dependence, and β_o, β_d, γ, δ and α_i are parameters.

W_o and W_d are spatial weight matrices that are the origin- and the destination-based spatial dependence, respectively. The origin-based spatial dependence (W_o) measures the level of strength between migration from an origin region to a particular destination and migration from the neighbors of the origin region 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).

[Fig. 1 & 2]

[3]The third spatial weight is also proposed to capture flows from the neighbors of the origin region to that of the destination region. The results from this spatial weight are not reported here because such a dependence is difficult to interpret in an economically meaningful way (LeSage and Pace 2008) and does not seem to fit into Japan's geography. However, the general conclusion remains unchanged.

For illustrative purposes, let us consider three regions, a, b, and c to explain W. In this example, a vector of 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 the intra-regional migration within a, and y_{ab} shows inter-regional migration from a to b. In the context of 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 rows of W is normalized. Thus, 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 demonstrated 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 captures 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.' In Fig. 1 there is a close neighbor (A) and a distant neighbor

(B) from o. 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 gray arrows expresses the strength of the effect of the gray arrows on the black arrow (that is, migration from 'o' to 'd'). Tokyo, the capital of Japan, may be a typical destination region to which labor tends to move from all other regions in Japan.

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

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

Therefore, $W_d y_{od}$ becomes

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

Thus, $w_{ab}y_{ab} + w_{ac}y_{ac}$ 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 flows 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 'region distant from d' is shown as a thin gray arrow from o to D. The thickness of the gray arrows expresses the strength of regional dependence. Kanto region, consisting, among others, of Chiba, Saitama, and Yokohama, which is adjacent to Tokyo, may be a typical migration destination of this spatial weight, where more attractive employment opportunities tend to exist compared to the origin.

5 Data

5.1 Dependent and independent variables

Our dataset covers 47 regions (prefectures) that comprise Japan. Regional labor migration data are obtained from Japan's National Census (*Kokusei Chosa*) in 2010.[4] Thus, unusual labor movements 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 has been conducted every five years. Migrant labor refers to labor who relocated residence from one prefecture to the other in the past five years.[5] The labor force consists of the employed and unemployed; the employed are those older than 15 years and gain income, and the unemployed are those seeking jobs. In 2010, there were about 65 million people in the labor force, out of which were 63 million people who were employed. Given the Japanese population of 128 million in 2010, half of the population can be regarded as the labor force, and this proportion is very low by international standards because Japan is one of the most aged countries in the world.

Net inter-prefectural labor migration in Japan from 2005 to 2010 is depicted in Fig. 3. A large amount of labor moved to the Aichi prefecture (a center of the automobile industry) and the Kanto region, which includes Tokyo. Within the Kanto region, net labor migration is higher in Saitama, Kanagawa, and Chiba than Tokyo because of the high land prices and housing costs in Tokyo. On the contrary, because of low income and the relatively low-toned industries, there are more emigrants than immigrants in rural areas, which implies the presence of *Genkai-shuraku*.

[Fig. 3]

Additional 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 the nominal GDP per capita (1000 yen) in 2005 divided by GDP deflator in 2005. Unemployment rates (%) and the regional population between the ages of 10 and 70 are calculated from the 2005 National Census. Regional

[4] As of this writing, this is the most recent data disseminated to the public.

[5] The National Census was conducted in October.

temperatures (°C) are the average temperatures between 2005 and 2010. Regional precipitation data (mm) are the amount of annual precipitation of each prefecture in 2005, and are obtained from the Statistics Bureau, Ministry of Internal Affairs and Communications (MIAC). Social networks are from the MIAC, and are proxied by the number of cumulative human migration between prefectures from October 2000 to September 2005.

The descriptive statistics of the data are presented in Table 1. We can observe 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 rate (4.24%), for Fukui. The gap of these regional unemployment rates is about 8%, implying significant regional disparities in the regional 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 income (2.04 million yen), for Okinawa. The regional difference is about 3.13 million yen.

[Table 1 & Fig. 4 and 5]

5.2 Spatial weight matrices

We have highlighted the importance of spatial dependence in migration studies, but what are the elements of W (that is, w) that determine the definition of neighbors? Here, we use three definitions of a spatial weight matrix. They are based on 1) the distance between prefectural capitals, 2) goods flow, and 3) economic structures. The majority of previous studies used geographical distances by assuming that the proximity of regions indicates tight economic and labor movements. Moreover, we use extra definitions to check the robustness of our findings. Goods flow is used because there are three metropolitan areas in Japan (Tokyo, Osaka, and Aichi) to which many people and goods flow even from distant rural regions. Economic structures are used to capture relevant labor skills that are required for seeking new jobs and are closely linked with employment and wages (Van Reenen 2011). Labor skills are related to job matching in labor markets.

The first definition of a spatial weight is based on the geographical distance between the origin and destination regions: W_o and W_d. This definition of a weight matrix assumes that spatial dependence is related to physical proximity between regions. Thus, neighbors are considered regions geographically close to the origin. Let us define a 47×47 spatial weight matrix W

consisting of w_{od}.

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

where $dist_{od}$ is 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 matrices using the Kronecker product as $W_o = W \otimes I$ and $W_d = I \otimes W$, where I is a 47×47 identity matrix.

The second definition of spatial weight matrices utilizes the volume of goods flow traded between the origin and destination regions. They are constructed using a 47×47 spatial weight matrix W that consists of w_{od} where the sum of rows is normalized.

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

where $g_{od,t-1}$ is the past goods flow between o and d. We assume that the larger the goods flow between regions, the greater the importance of their relationship. As before, origin- and destination-based spatial weight matrices are obtained again by the Kronecker product as $W_o = W \otimes I$ and $W_d = I \otimes W$.

The third definition of spatial weight matrices utilizes a proxy for the similarities of the importance of particular economic sectors in the prefectures. In this context, we measure similarities of regional economic structures using the number of firms and GDP of the primary, secondary, and tertiary sectors in each prefecture. Assuming that each economic sector calls for labor with industry-specific skills, labor with similar work experiences tends to search a job in similar destination regions. Allen and van der Velden (2001) found that skill mismatches can predict job search better than educational mismatches. More specifically, the origin- and destination-based spatial weight matrices are obtained by the Kronecker product as $W_o = W \otimes I$ and $W_d = I \otimes W$. A 47×47 spatial weight matrix W consists of w_{od}^{i} where the sum of rows is normalized. The elements of the spatial matrix for the primary sector are:

$$w_{od}^{i1} = \begin{cases} \dfrac{1 - |i1_o - i1_d|/(i1_o + i1_d)}{\sum_{d=1}^{47}(1 - |i1_o - i1_d|/(i1_o + i1_d))}, & \texttt{if } o \neq d \\ 0, & \texttt{otherwise}, \end{cases}$$

where $i1_o$ and $i1_d$ are ratios of the number of firms or GDP of the primary industry to that of all industries in o and d, respectively. The specification à la $1 - |A_i - A_j|/(A_i + A_j)$ is from Kelejian and Piras (2017), and becomes large if regional characteristics are similar. Thus, w_{od}^{i1} becomes large if the economic structure in terms of the primary industry is homogeneous between prefectures.

Alternatively, we can construct a spatial weight matrix for the secondary sector. In this case, the elements of the second matrix become:

$$w_{od}^{i2} = \begin{cases} \dfrac{1 - |i2_o - i2_d|/(i2_o + i2_d)}{\sum_{d=1}^{47}(1 - |i2_o - i2_d|/(i2_o + i2_d))}, & \texttt{if } o \neq d \\ 0, & \texttt{otherwise}, \end{cases}$$

where $i2_o$ and $i2_d$ are ratios of the number of firms or GDP of the secondary industry to that of all industries in o and d. w_{od}^{i2} becomes large if ratios of firms or GDP of the secondary sector are homogeneous between prefectures.

Similarly, we can obtain a spatial weight for the tertiary sector.

$$w_{od}^{i3} = \begin{cases} \dfrac{1 - |i3_o - i3_d|/(i3_o + i3_d)}{\sum_{d=1}^{47}(1 - |i3_o - i3_d|/(i3_o + i3_d))}, & \texttt{if } o \neq d \\ 0, & \texttt{otherwise}, \end{cases}$$

where $i3_o$ and $i3_d$ are ratios of the number of firms or GDP in the tertiary sector to that of all sector in o and d. w_{od}^{i2} becomes large if these ratios are homogeneous between prefectures.

Finally, the elements of the spatial weight matrix based on overall economic structures can be expressed as:

$$w_{od}^{i123} = \begin{cases} \dfrac{I_{123}}{\sum_{d=1}^{47} I_{123}}, & \texttt{if} \quad o \neq d \\ 0, & \texttt{otherwise}, \end{cases}$$

where $I_{123} = 1 - \{|i1_o - i1_d|/(i1_o + i1_d) + |i2_o - i2_d|/(i2_o + i2_d) + |i3_o - i3_d|/(i3_o + i3_d)\}/3$, and w_{od}^{i123} becomes large if ratios of firms or GDP in three industries are homogeneous between prefectures.

Thus, to construct spatial weights, the geographical distance between prefectures is obtained from Japan's Geospatial Information Authority. Furthermore, regional goods flow (quantity unit) in 2005, GDP in 2005, and the number of firms in 2004 are collected from the Ministry of Land, Infrastructure, and Transport; the Japanese Cabinet Office; and the MIAC, respectively, in order to construct different definitions of neighbors. Distance is, obviously, exogenous in the model. Similarly, since the dependent variable is labor migration from October 2005 to October 2010, past goods flowed in 2005, and economic structures that are from data in 2004 and 2005 are, also, exogenous. In Table 2, we conduct the Moran's I test for migration. Since the null hypotheses are rejected (p-value < 0.001) for all spatial matrices, we confirm that labor migration in Japan is spatially interactive as described above.

[Table 2]

6 Empirical results

6.1 Results from non-spatial models

Initially, we estimate a cross-sectional migration model by the OLS without considering spatial dependence. Maintaining the notations of variables used in Eq. (11) in line with LeSage and Pace (2008) and LeSage and Pace (2009), this basic model for migration from the origin to destination regions (y_{od}) for region i can be written as Eq. (12) where $\overline{z}_{od,t-1}$ is a proxy for social networks.

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

The OLS results with and without social network effects are reported in Table 3. We find that most parameters are reported to be statistically significant. However, the treatment of social networks influences empirical outcomes for some explanatory variables, and this can be seen clearly in the origin-destination models.

For example, in Column (A), which does not control social networks, income in both o and d has a negative and significant effect on labor migration. This result, where labor tends to migrate to a low-income destination, is inconsistent with the migration theory. In contrast, in Column (B), which controls social network effects, income in o has a negative and significant effect, and income in d has a positive and insignificant effect on labor migration. This result is more consistent with theoretical predictions and provides evidence that labor moves from low-income regions. Similarly, two parameters of unemployment rates are correctly marked with statistical significance in (B), suggesting that labor, indeed, moves from high to low unemployment rate regions.

Therefore, social networks are important to explain inter-regional migration and are factors to improve the model performance significantly. The parameter of network effects is fairly large (0.977), and the Akaike Information Criterion (AIC) in (B) is smaller than that in (A); it implies that there is a large omitted bias in the estimates in (A). In short, we conclude that human relationships are important factors in relocation decisions and have acted to increase labor migration. Next, we consider spatial dependence that is absent in our analyses so far.

[Table 3]

6.2 Results from spatial models

6.2.1 A spatial weight based on geographical distance

Here, the level of regional ties is determined by their physical location; labor is expected to move to destinations close to the origin in terms of the distance between regions. More specifically, spatial weights considered here are based on the inverse-distance, the square of inverse-distance, and the cubic form of the inverse-distance (p =1, 2, or 3) as specified in Section 5. This equation is an extension of Eq. (12) by introducing spatial weight matrices (W). We estimate such spatial migration models by the Spatial Two-Stage Least Squares (S2SLS) method to deal with a potential endogeneity problem (see the Appendix) because migration flows may influence the explanatory variables, such as income and unemployment rates.

$$y_{od} = \rho_o W_o y_{od} + \rho_d W_d y_{od} + \iota_N \alpha + X_o \beta_o + X_d \beta_d + dist_{od} \gamma + \overline{z}_{od,t-1} \delta + X_i \beta_i + \varepsilon. \quad (13)$$

Tables 4 and 5 show the empirical results of Eq. (13) that provide evidence that migration flows have a very complex spatial dependence. In Column (2) in Table 4 and (3) and (4) in Table 5, where social network effects are controlled, all origin-based spatial matrices (W_o) based on the inverse-distance, the square of inverse-distance, and the cubic form of inverse-distance are reported to be statistically significant. In addition, these W_o are positive, confirming that labor migration from o to d is strongly associated with migration from o to prefectures close to d. However, we fail to obtain a significant destination-based spatial dependence (W_d) in Column (2) in Table 4 and (3) and (4) in Table 5. These results indicate that distance may not be the best factor to capture regional dependence. Among different forms of spatial matrices, the spatial model with the inverse-distance ($p = 1$) fits the data best because the AIC is the smallest; furthermore, this spatial model explains labor migration better than the non-spatial model (Table 3) based on the AIC.

Thus, let us look more closely at the results in Table 4 ($p = 1$). We again confirm the importance of social networks in migration decisions and a large omitted bias in Column (1), which does not consider network effects. In this column, the unemployment rate in o has a positive and significant effect on labor migration, and this rate in d does not have a significant effect. Furthermore, income in both o and d has a negative and significant effect. This result, where labor tends to migrate to a low-income destination, is inconsistent with the economic theory. In contrast, in Column (2), the unemployment rate in o has a positive and significant effect, and this rate in d has a negative and significant effect. Furthermore, income in o has a negative and significant effect, and income in d does not have a significant effect on labor migration. These results do not conflict with theoretical predictions.

Therefore, our findings from (2) fit the standard economic theory more than any previous studies. Kondo (2015) reported that the unemployment rate has insignificant effects on immigration. Tsutsumi and Tamesue (2012) demonstrated that high unemployment rates in both the origin and destination region increased human migration. Tamesue and Tsutsumi (2016) found that high income in both origin and destination regions reduces human migration. Our findings imply that it is important to control both regional dependence and social network effects in migration studies.

[Tables 4 and 5]

6.2.2 A spatial weight based on goods flows

Next, we use spatial weights based on the volume of regional goods flow. Therefore, the regional relationship is not determined by geographical distance but economic ties. This departs from most previous studies. For example, LeSage and Pace (2008, 2009), Tsutsumi and Tamesue (2012), and Tamesue and Tsutsumi (2016) used a spatial weight based on the square of inverse-distance only and often reported statistical evidence inconsistent with the migration theory. This definition of neighbors may be more appropriate in Japan where metropolitan areas are scattered across a country, and regions physically close to each other may not have as strong an economic relationship as often assumed.

Column (5) in Table 5 shows the S2SLS results of the model, Eq. (13), which uses spatial weight matrices based on goods flow. Only results from the inverse-goods weight matrix are reported because, like using distance information, it offers the best specification. The general conclusion remains the same as before. Social networks play a positive and significant role in labor migration. Similarly, W_o is statistically significant, maintaining the marks of a positive parameter. Therefore, migration flows are closely related to the size of trades, not only between two particular regions under consideration but also between their neighbors. However, a destination-based spatial dependence (W_d) is again found to be statistically insignificant.

Other explanatory variables are also reported to be statistically significant. For example, the unemployment rate in o has a positive and significant effect on labor migration, and the rate in d has a negative and significant effect. Income in o has a negative and significant effect. These results are consistent with the migration theory. According to the AIC, the performance of this model is better than spatial models in Columns (3) and (4) but is worse than the model in Column (2) in Table 4 based on the inverse-distance spatial weight. Thus, neighbors can be defined better by the distance between prefectures in Japan.

6.2.3 A spatial weight based on economic structures

Finally, we consider economic structures to define neighboring regions. To capture such regional similarities, spatial weights are constructed based on the number of firms and GDP, and their results are reported in Tables 6 and 7, respectively. We find that most W_o and W_d are statistically significant with a mark of a positive parameter. Furthermore, the AIC of Columns (9) and (13) is smaller than that of spatial models based on geographical distance and goods flow. In this regard, neighbors can be most appropriately defined by similarities of industry structures in prefectures rather than geographical distance and goods flow. Notably, the model performance of Column (13) with the spatial weight matrix that uses GDP of entire economic sectors is the best of all according to the AIC. Our finding of the relevance of economic sectors to job search is consistent with labor market research (Allen and van der Velden 2001: Van Reenen 2011).

[Table 6 and 7]

Otherwise, the general conclusion obtained from these spatial weights remains the same as before. That is, social networks play a positive and significant role in labor migration. The unemployment rate in o has a positive and significant effect on labor migration, and this rate in d has a negative and significant effect. Income in o has a negative and significant effect in all columns in Table 6 and 7. These results are consistent with the migration theory. Thus far, we have explained the empirical results by focusing mainly on the relationship between labor migration and economic motivations of labor.

Other control variables are also often found to be statistically significant in Table 7. For example, we report common results that the higher the temperature in o, the less the labor migration from o, and the higher the temperature in d, the larger the labor migration to d, as expected from the theory. Furthermore, the higher the precipitation in o, the more the labor migration from o, and the higher the precipitation in d, the less the labor migration to d. Since amenities of labor in Japan are expected to increase with temperatures and decrease with precipitation, we confirm that relocation decisions are sensitive to weather conditions of residential sites.

Concerning the prefectural population in spatial models with economic structures, we generally find that the population in o has an insignificant effect on labor migration, but the population in d has a negative and significant effect. This result is contrary to our expectation that migrants move to populated regions. In this regard, Barro and Sala-I-Martin (1992) discussed that people prefer to move to areas near highly populated regions but avoid costs of highly congested areas, and they confirmed that population density influenced migration negatively in Japan. Our findings on the negative result for the population in destinations reflects labor behaviors in avoiding costs because populated regions often have high population densities. As mentioned before, Kanto is the typical destination for net migration, but prefectures adjacent to Tokyo are more popular destinations for immigrants than Tokyo (Figure 3).

Furthermore, the distance between o and $d$and social network effects are also reported to be significant. These results imply that migration to distant regions is considered to incur higher costs and uncertainty, but human relationships help reduce such costs.

7 Conclusion

This study empirically analyzes effects of regional characteristics on inter-prefectural labor migration using spatial models of the origin-destination flows. The consideration of network effects and the different types of spatial dependence lead us to empirical results that are more consistent with theoretical predictions than previous studies. More specifically, we find that social networks of migrants, which help reduce costs of gathering information and uncertainty about the destination, encouraged migration. Second, many spatial migration analyses have used only the inverse-distance based spatial weight matrix. However, this paper indicates that spatial dependence is more complicated than conventionally thought, and regions are also closely linked through economic structures. The specification of our spatial weights implies that labor tends to move to prefectures with similar economic structures, implying the importance of industry-specific skills of labor in the search for a job.

In summary, we have shown that socioeconomic factors can explain regional labor mobility in Japan, and, thus, the recent trend of decoupling between urban and rural regions is a natural outcome of migration decisions of labor. The government considers *Genkai-shuraku* as a significant socioeconomic loss to the country. In this regard, the decoupling process cannot be slowed down or prevented by the market forces; the intervention of the public sector seems to be indispensable to make rural regions attractive enough to be considered as destination regions.

Highlights

1. Labor migration decisions are influenced by socioeconomic factors and social networks.

2. Network effects, which reduce migration costs, have encouraged relocation of labor.

3. Three definitions of regional dependence are introduced here, and regional dependence is shown to be more complex than what previous studies assumed.

4. Empirical results consistent with economic theories can be obtained only when spatial dependence and network effects are considered.

Appendix

Spatial Two Stage Least Squares (S2SLS)

Following LeSage and Pace (2008), we construct a spatial regime model and estimate it by the S2SLS (Spatial Two Stage Least Squares). Spatially lagged variables $W_o y_{od}, W_d y_{od}$ in this study may be endogenous variables in a migration function. Therefore, we use the S2SLS following Badinger and Egger (2011). Defining Z as consisting of all exogenous explanatory variables in the model, instrumental variables of endogenous variables $W_o y_{od}$ and $W_d y_{od}$ are, thus, $H = (Z, W_o Z, W_d Z, W_o W_d Z, W_o^2 Z, W_d^2 Z)$.

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Table 1
Descriptive statistics

	Mean	SD	Min	Max
Inter- and intra-prefectural migration	6.28	1.81	2.48	13.9
Unemployment rates of prefectures	5.94	1.36	4.24	11.9
Real GDP per capita of prefectures	7.93	0.16	7.62	8.55
No. of population of prefectures	14.2	0.77	13.0	16.1
Average annual temperature of prefectures	2.73	0.16	2.23	3.15
Annual precipitation of prefectures	7.34	0.25	6.87	7.82
Past inter-prefectural migration	7.36	1.61	2.64	12.9
Distance between prefectures	5.98	0.80	2.35	7.72
Past intra-prefectural migration	12.2	0.93	10.8	14.5

Note: Standard deviation (SD). All variables are in natural log except unemployment rates that are expressed in terms of percentage.

Table 2
Moran's I tests for migration

Spatial weight matrix	Moran's I statistic	Expectation	SD	p-value
W_o (Inverse-distance)	0.411	-0.0005	0.0064	0.000
W_d (Inverse-distance)	0.454	-0.0005	0.0064	0.000
W_o (Square of inverse-distance)	0.603	-0.0005	0.0122	0.000
W_d (Square of inverse-distance)	0.626	-0.0005	0.0122	0.000
W_o (Cubic form of inverse-distance)	0.691	-0.0005	0.0167	0.000
W_d (Cubic form of inverse-distance)	0.704	-0.0005	0.0167	0.000
W_o (Past goods flow)	0.422	-0.0005	0.0081	0.000
W_d (Past goods flow)	0.467	-0.0005	0.0081	0.000
W_o (First industry_establishments)	0.241	-0.0005	0.0046	0.000
W_d (First industry_establishments)	0.292	-0.0005	0.0046	0.000
W_o (Secondly industry_establishments)	0.210	-0.0005	0.0044	0.000
W_d (Secondly industry_establishments)	0.269	-0.0005	0.0044	0.000
W_o (Tertiary industry_establishments)	0.208	-0.0005	0.0044	0.000
W_d (Tertiary industry_establishments)	0.267	-0.0005	0.0044	0.000
W_o (All industries_establishments)	0.215	-0.0005	0.0044	0.000
W_d (All industries_establishments)	0.272	-0.0005	0.0044	0.000
W_o (First industry_GDP)	0.264	-0.0005	0.0048	0.000
W_d (First industry_GDP)	0.309	-0.0005	0.0048	0.000
W_o (Secondly industry_GDP)	0.207	-0.0005	0.0044	0.000
W_d (Secondly industry_GDP)	0.266	-0.0005	0.0044	0.000
W_o (Tertiary industry_GDP)	0.208	-0.0005	0.0044	0.000
W_d (Tertiary industry_GDP)	0.266	-0.0005	0.0044	0.000
W_o (All industries_GDP)	0.216	-0.0005	0.0044	0.000
W_d (All industries_GDP)	0.273	-0.0005	0.0044	0.000

Note: Expectation and SD express the expectation value and standard deviation of the null distribution in Moran's I test. W_o and W_d are origin- and destination-based spatial matrices, respectively.

Table 3
OLS results for migration equations

Dependent variable: log of inter-prefectural labor migration		
Explanatory variable	(A)	(B)
Intercept	−6.656***	−0.146
	(0.952)	(0.300)
Unemployment rate_o	0.063***	0.012**
	(0.014)	(0.004)
Unemployment rate_d	−0.025	−0.068***
	(0.014)	(0.004)
Real GDP per capita_o	−1.458***	−0.143***
	(0.116)	(0.037)
Real GDP per capita_d	−1.075***	0.014
	(0.116)	(0.037)
No. of population_o	1.232***	0.026*
	(0.023)	(0.011)
No. of population_d	1.280***	0.027*
	(0.023)	(0.011)
Average temperature_o	0.017**	−0.012***
	(0.006)	(0.002)
Average temperature_d	0.058***	0.018***
	(0.005)	(0.002)
Annual precipitation_o	0.318***	0.082***
	(0.060)	(0.019)
Annual precipitation_d	0.168**	−0.084***
	(0.060)	(0.019)
Social network effects		0.977***
		(0.007)
Distance between prefectures	−1.114***	−0.046***
	(0.018)	(0.009)
Past intra-prefectural migration	1.518***	0.990***
	(0.078)	(0.024)
Sample size	2209	2209
AIC	4128.083	−1025.536

Note: ***p<0.001, **p<0.01, *p<0.05. Subscripts 'o' and 'd' represent origin and destination regions, respectively.

Table 4
S2SLS results for migration equations with spatial weights based on distance

Dependent variable: log of inter-prefectural labor migration		
Explanatory variable	(1)	(2)
Intercept	1.872*	0.421
	(0.806)	(0.315)
Unemployment rate_o	0.026*	0.010*
	(0.011)	(0.004)
Unemployment rate_d	−0.010	−0.067***
	(0.011)	(0.004)
Real GDP per capita_o	−1.117***	−0.159***
	(0.091)	(0.037)
Real GDP per capita_d	−1.067***	−0.008
	(0.091)	(0.037)
No. of population_o	0.505***	−0.026
	(0.041)	(0.015)
No. of population_d	0.554***	0.022
	(0.044)	(0.016)
Average temperature_o	0.003	−0.013***
	(0.004)	(0.002)
Average temperature_d	0.022***	0.018***
	(0.005)	(0.002)
Annual precipitation_o	0.143**	0.074***
	(0.047)	(0.018)
Annual precipitation_d	0.080	−0.089***
	(0.046)	(0.018)
Social network effects		0.946***
		(0.009)
Distance between prefectures	−0.419***	−0.015
	(0.030)	(0.011)
Past intra-prefectural migration	0.166*	0.882***
	(0.079)	(0.031)
W_o (Inverse-distance)	0.594***	0.080***
	(0.035)	(0.014)
W_d (Inverse-distance)	0.558***	0.028
	(0.036)	(0.014)
Sample size	2209	2209
AIC	2993.813	−1091.322

Note: ***p<0.001, **p<0.01, *p<0.05. Subscripts 'o' and 'd' represent origin and destination regions, respectively.

Table 5
S2SLS results for migration equations with spatial weights based on distance and goods flows

Dependent variable: log of inter-prefectural labor migration			
Explanatory variable	(3)	(4)	(5)
Intercept	−0.101	−0.149	−0.119
	(0.300)	(0.300)	(0.297)
Unemployment rate_o	0.010*	0.010*	0.010*
	(0.004)	(0.004)	(0.004)
Unemployment rate_d	−0.067***	−0.066***	−0.066***
	(0.004)	(0.004)	(0.004)
Real GDP per capita_o	−0.142***	−0.142***	−0.170***
	(0.037)	(0.037)	(0.037)
Real GDP per capita_d	0.009	0.013	0.047
	(0.037)	(0.037)	(0.038)
No. of population_o	0.011	0.017	−0.031*
	(0.012)	(0.011)	(0.015)
No. of population_d	0.038**	0.036**	0.054***
	(0.012)	(0.012)	(0.015)
Average temperature_o	−0.012***	−0.012***	−0.013***
	(0.002)	(0.002)	(0.002)
Average temperature_d	0.019***	0.018***	0.019***
	(0.002)	(0.002)	(0.002)
Annual precipitation_o	0.076***	0.077***	0.073***
	(0.019)	(0.019)	(0.018)
Annual precipitation_d	−0.086***	−0.081***	−0.077***
	(0.019)	(0.019)	(0.018)
Social network effects	0.968***	0.975***	0.951***
	(0.009)	(0.008)	(0.009)
Distance between prefectures	−0.036***	−0.044***	−0.035***
	(0.011)	(0.011)	(0.010)
Past intra-prefectural migration	0.974***	0.988***	0.943***
	(0.026)	(0.025)	(0.027)
W_o (Square of inverse-distance)	0.026***		
	(0.007)		
W_d (Square of inverse-distance)	−0.008		
	(0.008)		
W_o (Cubic form of inverse-distance)		0.013*	
		(0.006)	
W_d (Cubic form of inverse-distance)		−0.010	
		(0.006)	
W_o (Past goods flow)			0.073***
			(0.012)
W_d (Past goods flow)			−0.004
			(0.012)
Sample size	2209	2209	2209
AIC	−1040.679	−1027.840	−1079.945

Note: ***p<0.001, **p<0.01, *p<0.05. Subscripts 'o' and 'd' represent origin and destination regions, respectively. W is a spatial weight matrix.

Table 6
S2SLS results for migration equations with spatial weights based on economic structures

Dependent variable: log of inter-prefectural labor migration				
Explanatory variable	(6)	(7)	(8)	(9)
Intercept	1.051**	0.965**	0.977**	1.121**
	(0.383)	(0.373)	(0.378)	(0.379)
Unemployment rate_o	0.013**	0.015***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)	(0.00)
Unemployment rate_d	−0.062***	−0.058***	−0.058***	−0.058***
	(0.005)	(0.005)	(0.005)	(0.005)
Real GDP per capita_o	−0.160***	−0.149***	−0.150***	−0.152***
	(0.037)	(0.038)	(0.038)	(0.038)
Real GDP per capita_d	−0.029	−0.021	−0.020	−0.026
	(0.038)	(0.039)	(0.039)	(0.039)
No. of population_o	−0.033	−0.037	−0.038	−0.044
	(0.022)	(0.024)	(0.025)	(0.025)
No. of population_d	−0.034	−0.043	−0.042	−0.049*
	(0.023)	(0.024)	(0.025)	(0.025)
Average temperature_o	−0.015***	−0.015***	−0.015***	−0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Average temperature_d	0.013***	0.013***	0.013***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
Annual precipitation_o	0.095***	0.091***	0.092***	0.093***
	(0.019)	(0.018)	(0.018)	(0.018)
Annual precipitation_d	−0.061**	−0.063***	−0.063***	−0.060**
	(0.019)	(0.019)	(0.019)	(0.019)
Social network effects	0.974***	0.969***	0.969***	0.969***
	(0.007)	(0.007)	(0.007)	(0.007)
Distance between prefectures	−0.045***	−0.052***	−0.054***	−0.052***
	(0.009)	(0.009)	(0.009)	(0.009)
Past intra-prefectural migration	0.836***	0.825***	0.825***	0.809***
	(0.039)	(0.041)	(0.042)	(0.042)
W_o (First industry_firms)	0.056**			
	(0.019)			
W_d (First industry_firms)	0.056**			
	(0.019)			
W_o (Secondly industry_firms)		0.071**		
		(0.022)		
W_d (Secondly industry_firms)		0.075***		
		(0.021)		
W_o (Tertiary industry_firms)			0.071**	
			(0.023)	
W_d (Tertiary industry_firms)			0.073***	
			(0.022)	
W_o (All industries_firms)				0.076***
				(0.022)
W_d (All industries_firms)				0.078***
				(0.021)
Sample size	2209	2209	2209	2209
AIC	−1081.363	−1086.962	−1087.114	−1092.518

Note: ***p<0.001, **p<0.01, *p<0.05. Subscripts 'o' and 'd' represent origin and destination regions, respectively. W is a spatial weight matrix.

Table 7
S2SLS results with spatial weights based on different definitions of economic structures

Dependent variable: log of inter-prefectural labor migration				
Explanatory variable	(10)	(11)	(12)	(13)
Intercept	1.091**	1.144**	1.159**	1.246***
	(0.378)	(0.372)	(0.376)	(0.374)
Unemployment rate_o	0.013**	0.015***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
Unemployment rate_d	−0.056***	−0.056***	−0.055***	−0.056***
	(0.005)	(0.005)	(0.005)	(0.005)
Real GDP per capita_o	−0.185***	−0.141***	−0.138***	−0.149***
	(0.038)	(0.038)	(0.038)	(0.037)
Real GDP per capita_d	−0.030	−0.038	−0.045	−0.038
	(0.038)	(0.039)	(0.039)	(0.039)
No. of population_o	0.018	−0.030	−0.022	−0.039
	(0.021)	(0.024)	(0.025)	(0.025)
No. of population_d	−0.071**	−0.068**	−0.076**	−0.065**
	(0.022)	(0.024)	(0.024)	(0.025)
Average temperature_o	−0.014***	−0.014***	−0.014***	−0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Average temperature_d	0.011***	0.011***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Annual precipitation_o	0.097***	0.092***	0.094***	0.094***
	(0.019)	(0.018)	(0.018)	(0.018)
Annual precipitation_d	−0.058**	−0.058**	−0.058**	−0.057**
	(0.019)	(0.019)	(0.019)	(0.019)
Social network effects	0.972***	0.968***	0.968***	0.969***
	(0.007)	(0.007)	(0.007)	(0.007)
Distance between prefectures	−0.047***	−0.054***	−0.055***	−0.053***
	(0.009)	(0.009)	(0.009)	(0.009)
Past intra-prefectural migration	0.840***	0.802***	0.801***	0.793***
	(0.037)	(0.041)	(0.042)	(0.041)
W_o (First industry_GDP)	0.004			
	(0.019)			
W_d (First industry_GDP)	0.094***			
	(0.018)			
W_o (Secondly industry_GDP)		0.065**		
		(0.022)		
W_d (Secondly industry_GDP)		0.098***		
		(0.021)		
W_o (Tertiary industry_GDP)			0.057*	
			(0.023)	
W_d (Tertiary industry_GDP)			0.106***	
			(0.021)	
W_o (All industries_GDP)				0.071**
				(0.022)
W_d (All industries_GDP)				0.094***
				(0.021)
Sample size	2209	2209	2209	2209
AIC	−1086.399	−1086.279	−1089.104	−1093.990

Note: ***p<0.001, **p<0.01, *p<0.05. Subscripts 'o' and 'd' represent origin and destination regions, respectively. W is a spatial weight matrix.

Figure 1
Origin-based dependence of y_{od}

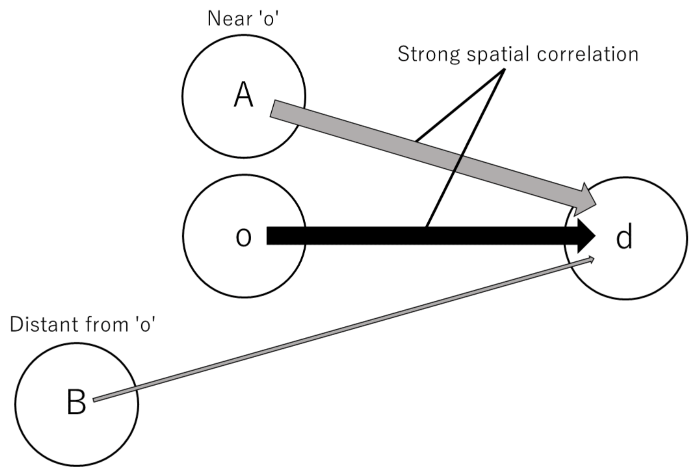


Figure 2
Destination-based dependence of y_{od}

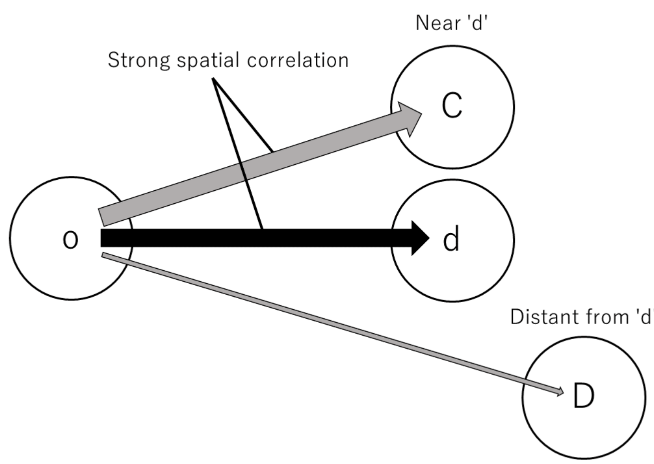
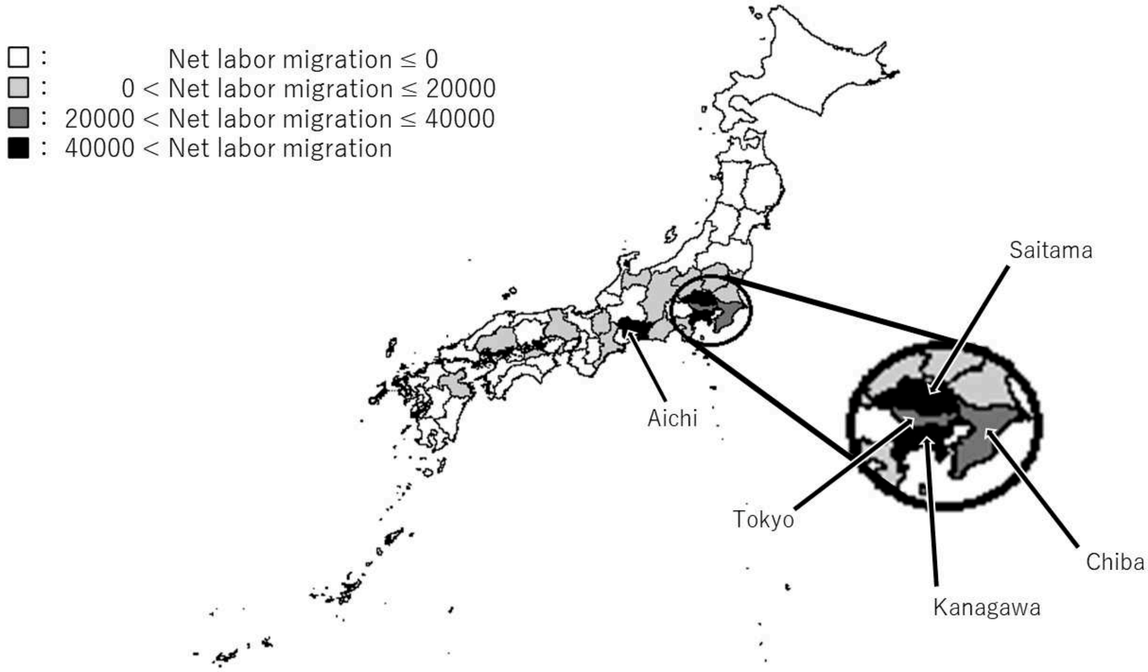
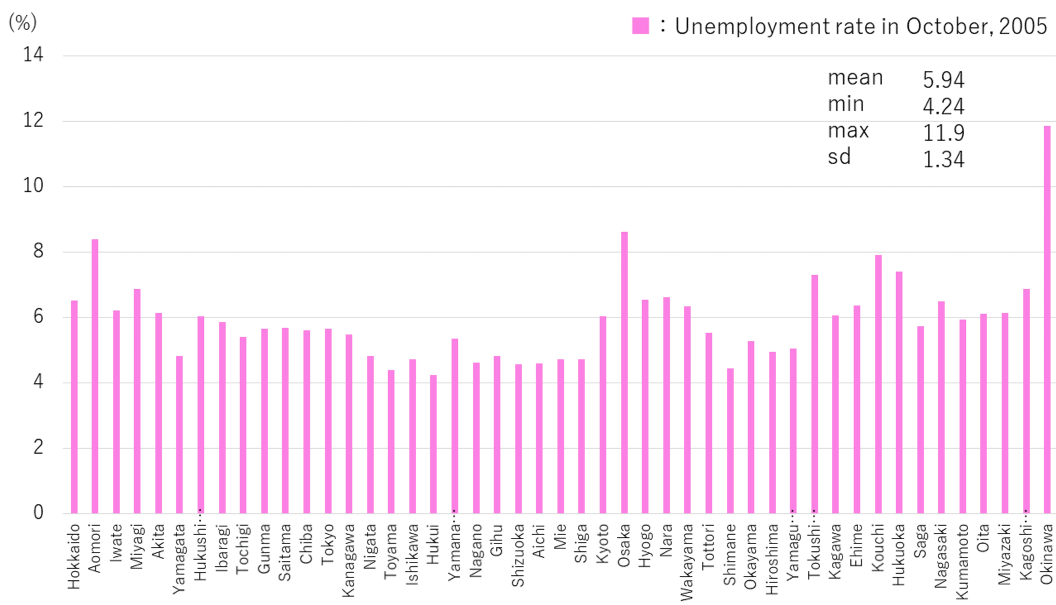


Figure 3
Net labor migration from 2005 to 2010



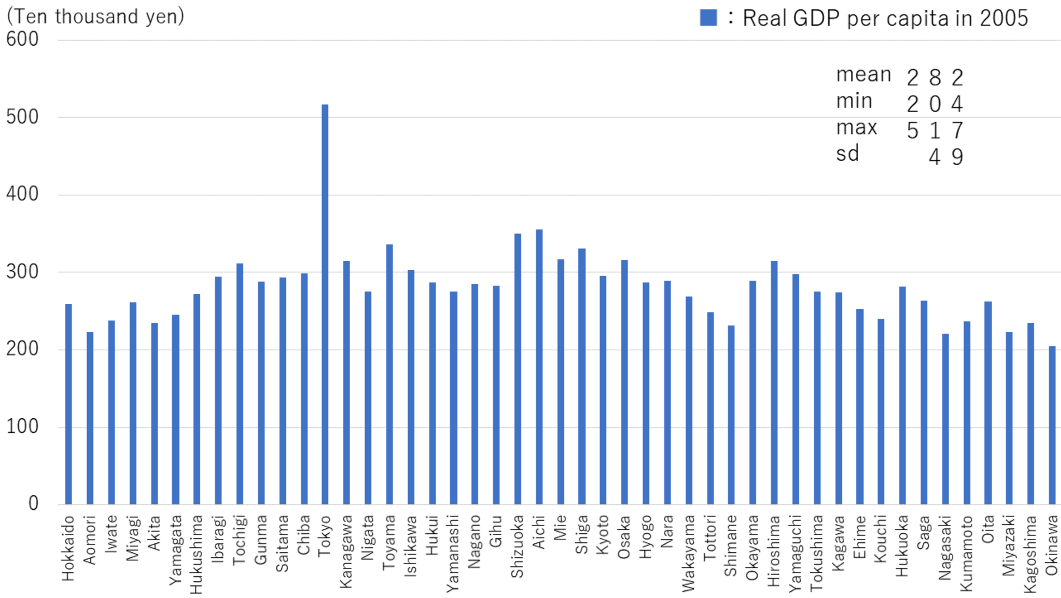
Note: The data source is the National Census of Heisei 22nd

Figure 4
Unemployment rate (%) in October, 2005



Note: The data source is the National Census of Heisei 22nd

Figure 5
Real GDP per capita (ten thousand yen) in 2005



Note: The data source is the report on prefectural accounts produced by the Japanese Cabinet Office