

# Determinants of Migration Networks in Japan during the COVID-19 Pandemic\*

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## Abstract

Owing to the spread of the novel coronavirus disease (COVID-19), the life-work balance has changed significantly. The paper conducts a social network analysis to clarify whether population movement trends have structurally changed before and after the COVID-19 pandemic as well as an econometric analysis is conducted to explore the determinants of population migration networks during the COVID-19 pandemic. The econometric results show that the structure of migration networks has not changed significantly. In addition, the determinants of the networks are mainly economic factors rather than the response to the COVID-19.

## 1. Introduction

Owing to the spread of the novel coronavirus disease (COVID-19), the life-work balance, which refers to the balance between individuals' lives and work, has changed significantly. Regarding daily life, individuals were requested to refrain from outing, limit movement, and support online classes to prevent the spread of COVID-19. Owing to the request to refrain

from outing, individuals spent more time at home, which resulted in the rapid spread of stay-at-home consumption and services, such as subscriptions.

Regarding work, an increasing number of companies are shifting from face-to-face work styles, such as commuting from home to work, to online work or telework, where employees work online from home via the Internet. As mentioned previously, lifestyles are changing, and it has become necessary to balance daily life at home with online work. However, various ingenuities were required for families whose house was not originally designed to accommodate this type of lifestyle. Furthermore, households requiring fundamental housing improvements would now have unprecedented options, such as relocating from the area.

Generally, the Tokyo area includes Tokyo, Kanagawa, Chiba, Saitama, and Ibaraki prefectures, or Tokyo, Kanagawa, Chiba, and Saitama, all of which are within 50–70 km of central Tokyo. In this study, the Tokyo area is defined as the latter.

Since the spread of COVID-19, an increase in population migration from the Tokyo area to rural areas was expected (Sadakiyo 2021). However, this expectation soon faded due to a decrease in relocation from the Tokyo area and an increase in immigration in 2022. Therefore, excess immigration did not change significantly. However, structural changes may have occurred, such as moving from one prefecture to another.

When discussing the population movement, other non-COVID-19 factors, which may have influenced population movement, should be considered. The factors influencing decisions regarding population movement can be divided into social and economic factors (Cadwallader 1996; Arakawa and Noyori 2023). Several previous studies have analyzed the relationship between the social and economic factors of the origin,

destination, or both and population migration to identify population migration determinants. However, when examining structural changes in population movement, the population movement between prefectures should be quantified and visualized.

This study, using prefectures as the unit of analysis, conducts a social network analysis to clarify whether population movement trends have structurally changed before and after the COVID-19 pandemic. In addition, an econometric analysis is conducted to explore the determinants of population migration networks during the COVID-19 pandemic.

The remainder of this paper is organized as follows: Section 2 summarizes extant literature on population movement analysis; Section 3 examines the methods of social network analysis; Section 4 provides the econometric analysis results to identify the impact of social and economic factors on migration networks in Japan; and Section 5 concludes the study.

## **2. Literature review**

Previous studies on population migration in Japan can be broadly divided into macro-level analyses, which focus on population migration as a group, and micro-level analyses, which focus on individual migration. Several previous studies have focused on population migration to prefectures, between prefectures, or between prefectures and large cities (Ito 2011; Wakasugi 2020; Sadakiyo 2021; Okuda 2022; Odazawa and Kashoji 2022; Kuribayashi et al. 2022; Koike 2022; Hatta et al. 2022; Fukuda 2022; Arakawa and Noyori 2023; Watanabe 2023).

Additionally, the direction of population movement is also important. Several studies have analyzed trends in the Kanto region, centered on Tokyo or in prefectures that have experienced excessive immigration.

However, when analyzing the population migration network, the prefectures from which the population migrated should be considered. Thus, information concerning both the source and destination is required.

## 2.1 Social factors

The determinants of population movements include social and economic factors. Social factors include educational and administrative services, amenities, and age. Economic factors include income and employment opportunities (Cadwallader 1996). This section examined the relationships between social factors and population migration at the macro level.

Education and administrative services were the primary social factors. First, regarding education, the larger the number of junior high schools as the source of relocation, the smaller the number of individuals moving out. Conversely, the larger the number of junior high schools as destinations, the greater the number of individuals moving in (Arakawa and Noyori 2023). This is explained by the fact that a large proportion of the analyzed population was between the ages of 20 and 49 years, who were likely to raise children in the future, or who were already raising junior high school students. Furthermore, the greater the educational investment in the source of relocation, the more likely young individuals are to relocate (Arakawa and Noyori 2023). Additionally, previous studies suggested a positive relationship between the number of destination universities and the number of transfers; however, it has been emphasized that this relationship depends on the target age group (Odazawa and Kashoji 2022; Fukuda 2022).

Regarding administrative services, it has been shown that the high density of parks, nursing care facilities, and hospitals in relocation

destinations increases the number of population migration in. In addition, previous studies have pointed out that the enhancement of support specific to the child-rearing generation, such as housing and childcare support, contributes to an increase in the number of population migration in (Ito 2011; Wakasugi 2020; Odazawa and Kashoji 2022; Arakawa and Noyori 2023). However, these effects are highly dependent on the age structure of the target population.

The second social factor is amenities. Amenity is a term often used in discussions of urban and town planning and refers to comfort in a living environment. In the analysis of population movement, amenities include indicators such as climate, nature (disasters), transportation convenience, safety, and security, as well as indicators of education and administrative services, which is part of the first factor (Ito 2011; Wakasugi 2020; Odazawa and Kashoji 2022; Koseki and Hato 2022; Fukuda 2022; Arakawa and Noyori 2023).

The third social factor is age. Some studies have analyzed population migration by age, based on the notion that a region's age structure affects population migration. For example, the determinants of relocation differ between adults and minors as well as between students and working adults. It is easy to imagine that young and older individuals make different decisions respectively regarding whether to relocate (Ito 2011; Wakasugi 2020; Sadakiyo 2021; Okuda 2022; Odazawa and Kashoji 2022; Kuribayashi et al. 2022; Koike 2022; Hatta and others 2022; Fukuda 2022; Arakawa and Noyori 2023; Watari Bei 2023).

Finally, recent population movement analyses have focused on population movements caused by COVID-19. Several studies have conducted analyses targeting the number of individuals infected with COVID-19, countermeasures, and population movements due to changes in

the life-work balance caused by the spread of COVID-19 (Sadakiyo 2021; Kinoshita 2022; Koike 2022; Watanabe 2023). However, owing to statistical data for the relevant period being limited and the need for micro-level analyses, there are few empirical analyses identifying the causal relationship between the social and economic factors of population migration.

## **2.2 Economic factors**

Economic factors are also determinants of population movement. Economic factors can be broadly classified into income level and employment opportunities. This section examines income level and employment opportunity as determinants of population migration at the macro level.

First, income level is expressed by variables such as nominal prefectural income per capita, real prefectural income, and price level at the relocation destination. Generally, while the content of a job is important, individuals tend to desire a job with a higher income. Furthermore, to seek real wealth rather than just income level, real income is emphasized, which considers changes in price levels. Thus, there is a positive relationship between population movement and the relocation destination's income level (Ito 2011; Okuda 2022; Kinoshita 2022; Hatta et al. 2022; Fukuda 2022; Arakawa and Noyori 2023).

Upgrading of the industrial structure is also important. Although it is an indirect indicator, the average income level generally tends to rise as primary, secondary, and tertiary industries become more sophisticated. Therefore, suggesting a positive relationship between the sophistication of the industrial structure of the relocation destination and population relocation.

Employment opportunity is expressed as the effective job openings-to-

applicants ratio and the unemployment rate for each prefecture. Irrespective of high income level, if there are few employment opportunities, population movement will slow down. Therefore, a positive relationship exists between population migration and employment opportunity in new locations (Okuda 2022; Odazawa and Kashoji 2022; Kinoshita 2022; Hatta et al. 2022).

Regarding employment opportunity, the number of companies, the number of companies per prefectural citizen, and the number of head offices are important variables. Regarding company attributes, the larger the company and the more it forms a group, the more likely it is to create local employment. However, owing to the spread of teleworking and online conferencing, an increasing number of jobs do not require proximity between homes and work.

To date, several studies have focused on the determinants of population movement. However, only a few have attempted to understand the characteristics of population movement by viewing it as a network and focusing on prefectures other than Tokyo. Furthermore, previous studies on population movement during the COVID-19 pandemic focused on fields that clarify the characteristics of population movement in Tokyo and other large cities, and no studies have examined the changes in population movement in Japan as a whole. Therefore, this study used prefectures as the unit of analysis and social network analysis to clarify whether population movement trends have changed before and after the COVID-19 pandemic. In addition, an econometric analysis was conducted to explore the determinants of population migration networks during the COVID-19 pandemic.

### 3. Social network analysis

Social network analysis refers to the analysis of the relationship structures between individuals or groups of individuals. For example, interpersonal networks include friendships, networks within project teams, and networks between job-seekers and employers. Networks between groups include international trade networks and population movements (Wasserman and Faust 1994; Kadushin 2003).

In social network analysis, individuals and groups are represented by nodes at the network apex. A network is expressed by connecting the related nodes using lines called edges. The number of edges of each node is called the degree, and a node with a large degree is called a hub (Wasserman and Faust 1994; Kadushin 2003).

When analyzing the network of population movement between prefectures, the nodes represent the prefectures and the edges represent the flow of population movement. In general, Tokyo, Kanagawa, Aichi, and Osaka prefectures are recognized as hubs in the field of population movement, and by identifying these hubs, it can be understood how they were formed and maintained.

#### 3.1 Population migration networks

This section attempts to visualize the population movement network using population movement statistics between prefectures. *The Basic Resident Register Population Movement Report* was used as the population movement statistics. These statistics publish data on population movement in prefectures, metropolitan areas, and large cities by sex and age. Among these, this study calculated the population movement network between prefectures by using the variable “Number of individuals moving between

prefectures by place of residence before movement to the prefecture.”

First, a matrix was calculated using real values of population movement between prefectures (Corten 2011; Yu et al. 2020).  $T_{ij}$  represents population movement from prefecture  $i$  to prefecture  $j$  in each year. The matrix for the 47 prefectures was as follows:

$$\begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1n} \\ T_{21} & T_{22} & \cdots & T_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{n1} & T_{n2} & \cdots & T_{nn} \end{bmatrix} \quad (1)$$

Where  $n$  refers to the number of prefectures and  $n = 47$ . In addition, if  $i = j$ , it refers to the same prefecture; therefore, the value of population movement is 0.

The adjacency matrix was calculated based on the values obtained in (1) (Yu et al. 2020). The following formula was used to determine whether the population movement from prefecture  $i$  to prefecture  $j$  was greater than the average population movement from prefecture  $i$  to all prefectures:

$$PN_{ij} = \begin{cases} 0 & \text{if } T_{ij} < \sum_{j=1}^n T_{ij} / 46 \\ 1 & \text{if } T_{ij} > \sum_{j=1}^n T_{ij} / 46 \end{cases} \quad (2)$$

$PN$  represents the population movement network and takes a value of 1 if it is larger than the average value from one prefecture to all prefectures and 0 if it is smaller. Thus, if the population movement from prefecture  $i$  to prefecture  $j$  exceeds the average population movement from prefecture  $i$  to all prefectures, a population movement network exists. Importantly, it does

not indicate the presence or absence of actual population movement but rather expresses the trend of population movement using a network.

### 3.2 Centrality of population migration

Centrality analysis is important to understand population migration networks. Centrality is an index used to evaluate the importance of nodes. This study analyzed population migration networks using degree centrality. Degree centrality is an indicator of the importance of nodes with numerous edges. A high degree of centrality indicates that networks are formed among several prefectures in terms of out-migration and in-migration.

This study utilized the *PN* index to calculate degree centrality. The *PN* has different meanings for row and column sums. The total in the column indicates the population movement network related to migration from other prefectures to prefecture *i*, and the total value of the column is defined as the population network inflow (*PNI*). The higher the *PNI* value, the more concentrated the transfer destinations in that prefecture.

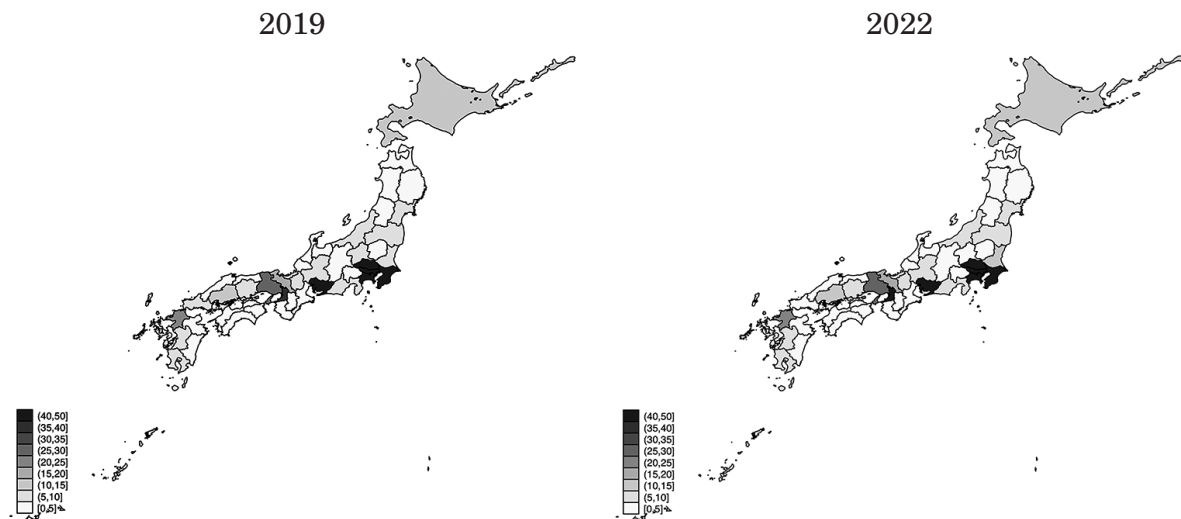
$$PNI_{it} = \sum_{j=1}^n T_{jit} \quad (3)$$

### 3.3 Migration networks in Japan

Figure 1 summarizes the *PNI* for each prefecture in 2019 and 2022. A prefecture with a dark color indicates the center of a population movements network concerning immigration, whereas a prefecture with a light color indicates the opposite. Regarding population and migration, the network centers were Tokyo, Kanagawa, Chiba, Aichi, and Osaka. This trend did not significantly change after the COVID-19 pandemic. Although the

spread of COVID-19 caused a momentary increase in population outflow from Tokyo, no major structural changes were identified. However, few studies have empirically analyzed whether this situation is due to social factors, economic factors, or COVID-19 countermeasures. In the next section, this study attempted to empirically clarify the determinants of population migration networks.

**Figure 1. Population migration networks in Japan (PNI)**



Note: This figure illustrates Japan's population migration networks (PNI) in 2019 and 2022. The PNI ranges from zero (white) to 46 (dark). Prefectures filled with darker shades indicate the center of a population movement network concerning immigration.

Source: *The Basic Resident Register Population Movement Report*, calculations by authors.

## 4. Determinants of population migration networks during the COVID-19 pandemic

### 4.1 Estimation model

This section consists of two steps. First, this study employed pooled OLS to

estimate the regressions, including all samples. Second, a difference analysis was used to examine the determinants of the change in the *PNI* in Japan during the COVID-19 pandemic.

In the first stage of the empirical analysis, the baseline specification was as follows:

$$\begin{aligned} \ln PNI_{it} = & \beta_1 \ln Population\ density_{it-1} + \beta_2 Salary\_regular_{it-1} \\ & + \beta_3 Salary\_part_{it-1} + \beta_4 Unemployment\ rate_{it-1} \\ & + \beta_5 Elementary\ School_{it-1} + \beta_6 Hospital_{it-1} + \beta_7 Land\ price_{it-1} \quad (4) \\ & + \beta_8 Temperature_{it-1} + \beta_9 Distance_i + \beta_{10} COVID-19_i \\ & + \beta_{11} Telework_{it-1} + \beta_{12} Telework\_wish_{it-1} + \eta_t + \varepsilon_{it} \end{aligned}$$

where  $i$  and  $t$  denote the prefecture and year, respectively.  $\ln PNI$  is the log of the *PNI* variable. The definitions and sources of the independent variables are summarized in Table 1. Tables 2 and 3 present the descriptive statistics and correlation matrix, respectively. Finally,  $\eta$  and  $\varepsilon$  are the fixed effect and error term, respectively.

**Table 1. Definition and source of variables**

Variables	Definition	Source
<i>IN</i>	Log of <i>PNI</i> variable	Statistics Bueru of Japan, <i>Annual report on internal migration in Japan derived from the basic resident registration</i>
<i>Population density</i>	Log of (population / habitable area)	Population: Statistics Bueru of Japan, <i>Population Estimates</i> Habitable area: Statistics Bueru of Japan, <i>Statistical observations of prefectures</i>
<i>Salary_regular</i>	Log of monthly contract cash earnings of regular worker	Ministry of Health, Labour and Welfare, <i>Basic Survey on Wage Structure</i>
<i>Salary_part</i>	Log of per-hour wage of part-time worker	Ministry of Health, Labour and Welfare, <i>Basic Survey on Wage Structure</i>
<i>Unemployment rate</i>	Unemployment rate	Statistics Bueru of Japan, <i>Labour Force Survey</i>
<i>Elementary School</i>	Log of the number of elementary schools per hundred thousand people	Ministry of Education, Culture, Sports, Science and Technology, <i>Basic School Survey</i>
<i>Hospital</i>	Log of the number of hospitals per hundred thousand people	Ministry of Health, Labour and Welfare, <i>Survey of Medical Institutions</i>
<i>Land price</i>	Residential land price index (Tokyo = 100)	Ministry of Land, Infrastructure, Transport and Tourism, <i>Publishment/publication of (market) value of standard sites by prefectural government</i>
<i>Temperature</i>	Log of average tempature	Statistics Bueru of Japan, <i>Labour Statistical observations of prefectures</i>
<i>Distance</i>	Log of average distance (sum of distance between a prefecture and all other prefectures / 46)	Geospatial Information Authority of Japan
<i>COVID-19</i>	Log of COVID-19 index in 2021 (maximam value = 423) COVID-19 index is the sum of 9 variables, which are related to medical system, vaccination, and PCR test. A higher value means appropriate response to the COVID-19.	Nihon Keizai Shimibun, "Korona Taiou Yuutouseini Manabe" (2021.10.23)
<i>Telework</i>	The share of the people who has experienced the telework.	Ministry of Internal Affairs and Communications, <i>Communications Usage Trend Survey</i>
<i>Telework_wish</i>	The share of the people who wants to work from home/ to do telework	Ministry of Internal Affairs and Communications, <i>Communications Usage Trend Survey</i>

**Table 2. Descriptive statistics**

	Mean	p50	SD	p1	p99
<i>IN</i>	1.90	1.61	0.96	0.00	3.83
<i>Population density</i>	6.81	6.68	0.77	5.44	9.19
<i>Salary_regular</i>	5.71	5.72	0.09	5.55	5.99
<i>Salary_part</i>	7.10	7.09	0.11	6.89	7.47
<i>Unemployment rate</i>	2.26	2.30	0.47	1.30	3.50
<i>Elementary School</i>	2.93	2.95	0.29	2.25	3.50
<i>Hospital</i>	2.01	1.97	0.37	1.29	2.88
<i>Land price</i>	8.02	7.15	3.19	3.60	17.80
<i>Temperature</i>	2.77	2.81	0.15	2.28	3.17
<i>Distance</i>	5.31	5.35	0.39	4.37	5.92
<i>COVID-19</i>	9.80	9.10	6.26	1.80	33.70
<i>Telework</i>	15.31	15.50	3.80	7.90	28.00
<i>Telework_wish</i>	6.21	6.15	0.28	5.91	7.19

**Table 3. Correlation matrix**

	<i>Population density</i>	<i>Salary_regular</i>	<i>Salary_part</i>	<i>Unemployment rate</i>	<i>Elementary School</i>	<i>Hospital</i>	<i>Land price</i>	<i>Temperature</i>	<i>Distance</i>	<i>COVID-19</i>	<i>Telework</i>	<i>Telework_wish</i>
<i>Population density</i>	1.000											
<i>Salary_regular</i>	0.812	1.000										
<i>Salary_part</i>	0.735	0.726	1.000									
<i>Unemployment rate</i>	0.338	0.181	0.287	1.000								
<i>Elementary School</i>	-0.800	-0.771	-0.658	-0.436	1.000							
<i>Hospital</i>	-0.515	-0.612	-0.432	-0.190	0.711	1.000						
<i>Land price</i>	-0.442	-0.547	-0.390	-0.176	0.675	0.978	1.000					
<i>Temperature</i>	0.484	0.155	0.205	0.007	-0.095	0.124	0.187	1.000				
<i>Distance</i>	-0.385	-0.556	-0.427	0.375	0.238	0.292	0.265	-0.146	1.000			
<i>COVID-19</i>	-0.643	-0.608	-0.537	-0.511	0.766	0.583	0.511	-0.133	0.033	1.000		
<i>Telework</i>	0.601	0.562	0.675	0.515	-0.565	-0.358	-0.303	0.160	-0.138	-0.457	1.000	
<i>Telework_wish</i>	0.421	0.292	0.400	0.481	-0.390	-0.202	-0.158	0.235	0.162	-0.433	0.540	1.000

## 4.2 Results

Table 4 summarizes the analysis results for the baseline specifications. Population density and salary level were statistically significant and positive. Thus, even during the COVID-19 pandemic, prefectures with high population densities and high salary levels were at the center of the population movement network. Conversely, the unemployment rate was generally statistically significant and negative. Therefore, even if the unemployment rate was high, it remained the center of the network.

The number of elementary schools and hospitals was statistically significant and positive. Additionally, the price of land in the place of residence was statistically significant and positive. Because the correlation coefficients of these three variables were large, their robustness was

examined (see Appendix). The results revealed that only the number of elementary schools was statistically significant. Physical distance was generally statistically significant and positive. Therefore, it is necessary to add more specific variables, such as travel time rather than the physical straight-line distance.

**Table 4. Results (baseline specification)**

Variables								
<i>Population density</i>	0.229 (0.150)	0.462** (0.129)			0.437** (0.144)	0.596** (0.143)		
<i>Salary_regular</i>	2.652** (0.838)		3.625** (0.745)		2.713** (0.792)		3.724** (0.793)	
<i>Salary_part</i>	0.421 (0.652)			1.468** (0.544)	0.209 (0.573)			1.129* (0.565)
<i>Unemployment rate</i>	0.305* (0.131)	0.280* (0.135)	0.369** (0.125)	0.391** (0.131)	0.170 (0.127)	0.129 (0.131)	0.273* (0.126)	0.278* (0.132)
<i>Elementary School</i>	-1.523** (0.376)	-1.736** (0.353)	-1.810** (0.324)	-2.140** (0.330)	-1.141** (0.373)	-1.250** (0.371)	-1.537** (0.360)	-1.800** (0.383)
<i>Hospital</i>	-1.893** (0.621)	-2.168** (0.621)	-1.934** (0.607)	-2.557** (0.620)	-1.309+ (0.676)	-1.411* (0.668)	-1.361* (0.679)	-1.815* (0.713)
<i>Land price</i>	0.263** (0.072)	0.294** (0.073)	0.270** (0.069)	0.332** (0.071)	0.211** (0.077)	0.222** (0.077)	0.216** (0.077)	0.260** (0.081)
<i>Temperature</i>	-0.999+ (0.516)	-1.418** (0.498)	-0.535 (0.420)	-0.612 (0.445)	-1.274** (0.479)	-1.623** (0.500)	-0.481 (0.419)	-0.601 (0.447)
<i>Distance</i>	0.703* (0.276)	0.442 (0.270)	0.628* (0.264)	0.329 (0.272)	0.825** (0.255)	0.517+ (0.262)	0.648* (0.254)	0.276 (0.271)
<i>COVID-19</i>					-0.640** (0.174)	-0.734** (0.173)	-0.605** (0.181)	-0.635** (0.177)
<i>Telework</i>					-0.020 (0.015)	-0.011 (0.014)	-0.004 (0.013)	0.005 (0.013)
<i>Telework_wish</i>					-0.029* (0.014)	-0.025+ (0.014)	-0.024+ (0.014)	-0.018 (0.015)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141	141	141	141	141	141	141	141
R-squared	0.728	0.715	0.722	0.706	0.757	0.745	0.744	0.726

Note: Robust standard errors are indicated in parentheses. \*\*\*, \*\*, and \* indicate that the results are statistically significant at 1%, 5%, and 10%, respectively.

Regarding the variables related to the COVID-19 response and teleworking, only the COVID-19 variable was statistically significant and negative. Therefore, even in regions where the infection situation was more

serious and the response to the spread of COVID-19 was delayed, it remained the center of the network.

Notably, the possibility of a reverse causal relationship should be considered between network centrality and each variable.

**Table 5. Results (difference analysis)**

Variables												
<i>Population density</i>	2.958 (3.262)	3.073 (3.152)			3.722 (3.220)	3.753 (3.135)			3.625 (3.195)	3.646 (3.087)		
<i>Salary_regular</i>	1.664 (1.012)		1.705+ (0.993)		1.680+ (0.883)		1.674+ (0.906)		1.641+ (0.871)		1.635+ (0.894)	
<i>Salary_part</i>	0.0597 (0.146)			-0.045 (0.145)	0.110 (0.167)			-0.016 (0.165)	0.132 (0.181)			0.002 (0.174)
<i>Unemployment rate</i>	0.187 (0.140)	0.171 (0.136)	0.167 (0.138)	0.150 (0.136)	0.166 (0.127)	0.149 (0.123)	0.151 (0.131)	0.132 (0.129)	0.169 (0.129)	0.153 (0.126)	0.152 (0.132)	0.133 (0.130)
<i>Elementary School</i>	-0.504 (1.656)	-0.721 (1.550)	-0.170 (1.510)	-0.377 (1.468)								
<i>Hospital</i>					1.934 (1.526)	1.980 (1.460)	1.205 (1.162)	1.277 (1.152)				
<i>Housing price</i>									0.208 (0.162)	0.214 (0.154)	0.134 (0.131)	0.148 (0.136)
<i>COVID-19</i>	0.093 (0.105)	0.124 (0.106)	0.0374 (0.078)	0.066 (0.083)	0.083 (0.101)	0.110 (0.101)	0.026 (0.086)	0.051 (0.088)	0.081 (0.101)	0.107 (0.101)	0.026 (0.087)	0.049 (0.090)
<i>Telework</i>	-0.010 (0.010)	-0.010 (0.009)	-0.004 (0.005)	-0.004 (0.005)	-0.009 (0.009)	-0.009 (0.009)	-0.003 (0.005)	-0.003 (0.005)	-0.009 (0.009)	-0.009 (0.009)	-0.003 (0.005)	-0.003 (0.005)
Observations	45	45	45	45	45	45	45	45	45	45	45	45
R-squared	0.141	0.108	0.101	0.065	0.179	0.145	0.118	0.083	0.178	0.145	0.119	0.086

Note: Robust standard errors are indicated in parentheses. \*\*\*, \*\*, and \* indicate that the results are statistically significant at 1%, 5%, and 10%, respectively.

Table 5 summarizes the results of the difference analysis. Tokyo and Kanagawa are excluded from the estimation because their PNI value is 46, which means that PNI cannot increase. The results indicated that only the increase in the wages of general workers could explain the changes in the population migration network, suggesting that the centrality of the network may have changed owing to economic factors during the COVID-19 expansion period. Therefore, even during the COVID-19 expansion period, economic policies were required to encourage migration from a situation where individuals are concentrated in urban centers to rural areas.

### 4.3 Discussion

The COVID-19 pandemic had a limited impact on the structure of population movement in Japan. There are several reasons for this, including age, response to telework, economic factors, and the response to the COVID-19 pandemic (Sadakiyo 2021; Kinoshita 2022; Kuribayashi et al. 2022; Koike 2022; Watanabe 2023).

First, population movement from the perspective of age is discussed. Age, which is a social factor, is important when considering population movement, and the same has been true during the COVID-19 pandemic. Compared with individuals  $\geq 40$  years of age, university students and young people move relatively easily between prefectures. It has been pointed out that the main population movement at this time was among young individuals, and, based on the population ratio, the structure of the population movement did not change (Watanabe 2023).

Regarding the spread of teleworking and online work. Although teleworking is more popular than before, few companies have employed teleworking as a result of the COVID-19 pandemic. Furthermore, the introduction of teleworking differs depending on the company and industry. Additionally, there are often restrictions on relocation, even when working from home. Therefore, structural changes in population movement are expected to be limited (Sadakiyo 2021; Kinoshita 2022; Kuribayashi et al. 2022; Koike 2022; Watanabe 2023).

Regarding economic factors, there has been no change in the disparities in income levels, effective job openings-to-applicants ratio, or the number of companies across Japan, and all prefectures have been negatively affected by the spread of COVID-19 to some extent (Sadakiyo 2021; Kinoshita 2022; Kuribayashi et al. 2022; Koike 2022; Watanabe 2023). Therefore, it is believed that the basic structure of population

movement has not changed.

Finally, the appropriate response to the COVID-19 pandemic could not change the inward migration networks in Japan. In fact, it had a negative impact on PNI. However, there could be a reverse causality. In other words, prefectures with higher PNI could not responded to the COVID-19 pandemic appropriately because of the population concentration.

Overall, although the spread of COVID-19 has significantly changed social and economic factors, it has not drastically changed the structure of population movement in Japan, and the balance between rural and urban areas remains the same. Therefore, it is necessary to draw on these experiences and develop measures that consider social and economic factors to advance future discussions on regional revitalization.

For the future works, city-level or individual-level analysis should be conducted. In addition, more precise econometric specifications are needed to identify the causality between migration networks and each factor.

## **5. Concluding remarks**

Due to the spread of the novel coronavirus disease (COVID-19), the life-work balance has changed significantly in Japan. The paper conducted a social network analysis to clarify whether population movement trends have structurally changed during the COVID-19 pandemic periods. In addition, an econometric analysis was conducted to explore the determinants of population migration networks during the COVID-19 pandemic.

The econometric results show that the structure of migration networks has not changed significantly, which indicates that the balance between rural and urban areas remains the same. In addition, the determinants of

the networks are mainly economic factors rather than the response to the COVID-19. Therefore, it is necessary to draw on these experiences and develop measures that consider social and economic factors as well as COVID-19 responses to advance future discussions on regional revitalization.

### Footnote

- \* The views in this paper are those of the author and not necessarily those of the College of Law, Nihon University. The author would like to thank an anonymous referee for helpful suggestions as well as Editage ([www.editage.jp](http://www.editage.jp)) for English language editing.
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## Appendices

### A. Results (baseline specification, *Elementary School*)

Variables								
<i>Population density</i>	0.287*	0.583**			0.435**	0.604**		
	(0.140)	(0.120)			(0.139)	(0.142)		
<i>Salary_regular</i>	3.316**		4.487**		2.856**		3.871**	
	(0.913)		(0.792)		(0.867)		(0.889)	
<i>Salary_part</i>	0.398			1.710**	0.200			1.027+
	(0.613)			(0.537)	(0.542)			(0.551)
<i>Unemployment rate</i>	0.338*	0.305*	0.418**	0.447**	0.203	0.157	0.303*	0.291*
	(0.135)	(0.139)	(0.130)	(0.139)	(0.132)	(0.135)	(0.128)	(0.130)
<i>Elementary School</i>	-1.014**	-1.268**	-1.338**	-1.894**	-0.495	-0.601*	-0.893**	-1.192**
	(0.344)	(0.324)	(0.303)	(0.267)	(0.299)	(0.298)	(0.279)	(0.288)
<i>Temperature</i>	-0.611	-1.114*	-0.018	-0.067	-0.819	-1.184*	-0.033	-0.165
	(0.528)	(0.532)	(0.426)	(0.463)	(0.495)	(0.535)	(0.420)	(0.452)
<i>Distance</i>	0.819**	0.501+	0.735*	0.317	0.862**	0.537+	0.685*	0.253
	(0.306)	(0.302)	(0.302)	(0.307)	(0.277)	(0.296)	(0.283)	(0.304)
<i>COVID-19</i>					-0.710**	-0.821**	-0.681**	-0.779**
					(0.177)	(0.175)	(0.178)	(0.180)
<i>Telework</i>					-0.009	0.000	0.006	0.020
					(0.015)	(0.014)	(0.013)	(0.012)
<i>Telework_wish</i>					-0.027+	-0.023	-0.023	-0.015
					(0.015)	(0.015)	(0.015)	(0.016)
<b>Year fixed effect</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
Observations	141	141	141	141	141	141	141	141
R-squared	0.694	0.673	0.685	0.655	0.726	0.713	0.713	0.692

Note: Robust standard errors are indicated in parentheses. \*\*\*, \*\*, and \* indicate that the results are statistically significant at 1%, 5%, and 10%, respectively.

**B. Results (baseline specification, *Hospital*)**

Variables								
<i>Population density</i>	0.564**	1.010**			0.653**	0.848**		
	(0.146)	(0.118)			(0.147)	(0.145)		
<i>Salary_regular</i>	4.201**		7.360**		3.301**		5.211**	
	(0.852)		(0.686)		(0.834)		(0.942)	
<i>Salary_part</i>	0.448			3.749**	-0.079			1.496*
	(0.667)			(0.597)	(0.556)			(0.606)
<i>Unemployment rate</i>	0.410**	0.395**	0.668**	0.858**	0.160	0.119	0.372**	0.404**
	(0.143)	(0.147)	(0.129)	(0.147)	(0.139)	(0.143)	(0.141)	(0.147)
<i>Hospital</i>	0.0372	-0.0627	-0.120	-0.564**	0.365+	0.322	0.209	0.025
	(0.194)	(0.194)	(0.187)	(0.197)	(0.195)	(0.196)	(0.195)	(0.205)
<i>Temperature</i>	-1.201+	-1.932**	0.0111	0.102	-1.474**	-1.891**	-0.274	-0.392
	(0.615)	(0.669)	(0.490)	(0.614)	(0.561)	(0.605)	(0.485)	(0.552)
<i>Distance</i>	0.931**	0.551+	0.827**	0.178	0.850**	0.504+	0.610*	0.008
	(0.305)	(0.317)	(0.309)	(0.403)	(0.258)	(0.279)	(0.285)	(0.366)
<i>COVID-19</i>					-0.970**	-1.098**	-1.002**	-1.171**
					(0.180)	(0.170)	(0.186)	(0.188)
<i>Telework</i>					-0.011	-0.000	0.016	0.040**
					(0.015)	(0.015)	(0.013)	(0.013)
<i>Telework_wish</i>					-0.028+	-0.023	-0.021	-0.011
					(0.014)	(0.015)	(0.015)	(0.018)
<b>Year fixed effect</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
Observations	141	141	141	141	141	141	141	141
R-squared	0.673	0.639	0.638	0.555	0.731	0.714	0.700	0.659

Note: Robust standard errors are indicated in parentheses. \*\*\*, \*\*, and \* indicate that the results are statistically significant at 1%, 5%, and 10%, respectively.

**C. Results (baseline specification, *Land price*)**

Variables								
<i>Population density</i>	0.595** (0.144)	1.059** (0.118)			0.672** (0.147)	0.871** (0.147)		
<i>Salary_regular</i>	4.306** (0.819)		7.661** (0.677)		3.287** (0.822)		5.271** (0.938)	
<i>Salary_part</i>	0.403 (0.666)			3.973** (0.634)	-0.036 (0.551)			1.501* (0.610)
<i>Unemployment rate</i>	0.407** (0.141)	0.391** (0.147)	0.677** (0.128)	0.903** (0.148)	0.164 (0.138)	0.120 (0.142)	0.377** (0.140)	0.403** (0.147)
<i>Land price</i>	0.017 (0.020)	0.009 (0.021)	-0.000 (0.019)	-0.045* (0.022)	0.048* (0.021)	0.044* (0.021)	0.029 (0.021)	0.012 (0.022)
<i>Temperature</i>	-1.345* (0.602)	-2.117** (0.644)	-0.055 (0.485)	0.053 (0.608)	-1.584** (0.557)	-2.011** (0.600)	-0.334 (0.488)	-0.461 (0.555)
<i>Distance</i>	0.927** (0.297)	0.538+ (0.302)	0.825** (0.302)	0.101 (0.387)	0.855** (0.251)	0.505+ (0.270)	0.603* (0.281)	-0.019 (0.354)
<i>COVID-19</i>					-0.960** (0.177)	-1.096** (0.167)	-1.006** (0.184)	-1.206** (0.185)
<i>Telework</i>					-0.013 (0.015)	-0.002 (0.0154)	0.015 (0.013)	0.040** (0.012)
<i>Telework_wish</i>					-0.029* (0.014)	-0.024 (0.014)	-0.021 (0.014)	-0.010 (0.018)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141	141	141	141	141	141	141	141
R-squared	0.675	0.639	0.637	0.538	0.735	0.719	0.702	0.660

Note: Robust standard errors are indicated in parentheses. \*\*\*, \*\*, and \* indicate that the results are statistically significant at 1%, 5%, and 10%, respectively.