Internal Migration Prediction for Economic Development in Japan by Considering the Spatial Dependencies

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Abstract: Japan is being into depopulation since 2009 with a super-aging society and rural-urban demographic disparity. These phenomena made reducing in the labor force which can directly impact on the economic growth of Japan. As social and economic divisions between rural areas and urban areas increased, the government faces difficulty in maintaining infrastructure and social services. To consider the implications for social sustainability, it is essential to understand the future movement of the population over the Japanese municipalities. In the national population prediction method of Japan made by Cohort-Component Analysis (CCA), migration is a difficult component since the geographical heterogeneity behind them. To clarify the significance of spatial dependencies in migration phenomena, this paper tribally applied the statistical model with spatial dependencies to predict the inter-regional migration in Japan. The estimated model clarified the significant spatial dependencies. Since the spatial distribution of industries is spatially agglomerated, our approach would result in more severe demographic disparities in Japan, comparing with the conventional population prediction by CCA.

Keywords: Population Distribution, Internal Migration, Aging Society, Spatial Dependencies, Spatial Autoregressive Model.

1. INTRODUCTION

Japan is being into depopulation since 2009 because of the declining fertility rate. On the other hand, emigration from rural areas to urban areas has been continued since the 1950s. In rural municipalities, population decline had started even earlier due to domestic migration. Domestic migration was peak during the mid-1960s until the early 1970s because of industrial development which caused the population movement for employment in the industrial sector. The internal migration in Japan came to be a major determinant of population growth in each region (Yorimitsu. 1987). According to the 2015 population census of Japan, eight prefectures (including three metropolitan areas-Tokyo, Osaka, and Nagoya) had positive net migration and the remaining thirty-nine prefectures had negative net migration. This shows people are highly mobile from rural to urbanized areas. The increase of population to developed cities leads to urban expansion which is a necessary part of the process of economic development.

Internal migration is a major force redistributing the population during development as a sectoral composition of the economy and the geographic distribution of employment change (Kuznets, 1966). In many countries, migration becomes a primary component of population change. Since internal migration shapes national patterns of human settlement, how internal migration adjusts the population composition of regions is essential for responding to housing, healthcare, education, transportation, and assessing the spatial distribution of labor. (Jorge Rodríguez-Vignoli & Francisco Rowe ; 2018).

On the other way, the connection between internal migration and industrial structures

has not been deeply explored in demographics study. The difference in regional economic growth influences on the distribution of population since the employment opportunities are main factors to cause migrants for job-searching (Zuo 2018). Thuku and Gideon (2013), discussed that population growth and economic growth are correlated. Therefore, internal migration and economic development are mutually dependent and reinforcing.

Current demographic trends are strongly affecting economic growth and all the developed economies are facing demographic slowdowns around the world. According to the UN world population aging report of 2015, population aging leads to a higher proportion of the elderly, which means more people in a situation of economic dependency, and relatively fewer people in the working-age population to support the aged people. Japan is denoted as a super-aged society according to United Nations Population Division (UNPD) recorded 26% of over-65 cohorts in 2015. The super-aged society is a striking issue in Japan, as to seek a higher rate of economic growth with social sustainability. Increasing life expectancy is another aspect of the aging trend. In Japan, life expectancy at birth was climbed to 84 years within fifty years. This raises policy concerns about the fiscal burden on the younger generation and the viability of social services. Therefore, concerning with elderly population is essential in population study for economic development nowadays.

The population studies concerning internal migration have been primarily focused on the migration rate of the region but not on the characteristics of spatial dependencies which are occurred to the spatial interaction existing between nearby geographic locations. Most of the previous studies either assume no spatial dependencies or allow the spatial dependencies in restrictive ways, sometimes without a precise definition of the parameters of interest or the conditions required to recover them (Vazquez-Bare, Gonzalo. 2017). In population prediction models, local area-specific effects are mostly discarded, however, correlations between spatial effects can be introduced for the geographically close areas. The model can insist on the variability and can stabilize the migration projection results by the credibility of assumed values. The spatial correlation is then likely to improve the quality of local estimates of the population (Pascal et al. 2018).

Therefore, it is essential to develop the population prediction method based not only on the characteristics of each region but on the neighborhood effects or spatial dependencies. Spatial models describe the spatial dependences due to neighborhood interactions. Among spatial statistic models, spatial autoregressive (SAR) models are appropriate for using datasets that contain observations on geographical areas or any units with a spatial representation. However, throughout the extant literature, there is an issue of how to scale the neighborhood spatial dependencies. Most often, the neighborhoods are defined by census tracts or census block groups. Regarding areal socio-economic characteristics, these have been demonstrated only at the prefectural level in the Japanese census. With this recent scalability of the neighborhood level, the migration phenomenon was not clearly examined. Therefore, smaller-scale units of neighborhood-level observation on migration phenomenon are required. In this study, spatial dependences of the regions are estimated with municipality scale.

In this paper, we develop the prediction procedure for migration phenomenon considering spatial dependencies among the municipalities, examine the significance of interactions between industrial characteristics and cohort-wise migrants. As the first step of such an approach, this paper examines whether the SAR model yields significant dependencies or not, so then the integration with the CCA model will be discussed in the following study. The rest of the paper is organized as follows. In section 2, we explained our proposed methodology (integration of CCA with SAR model) to analyze the migration structure. In section 3, we present the direct and indirect effect results of the SAR model for migration prediction and in section 4 we make some concluding remarks are presented.

2. POPULATION PREDICTION AND SPATIAL MODEL FOR MIGRANTS

In the national prediction method (conventional CCA), the average value of the age and sex-specific annual net migration rate of Japanese people between 2010 and 2015 is used to predict the future (using values for 4 years, excluding the maximum and minimum values for each age), smoothed out the rates to remove random fluctuations, and set the result as the net migration rate of Japanese people (Figure 1) for 2016 and onward. (Population Projections for Japan 2017 by National Institute of Population and Social Security Research Japan).

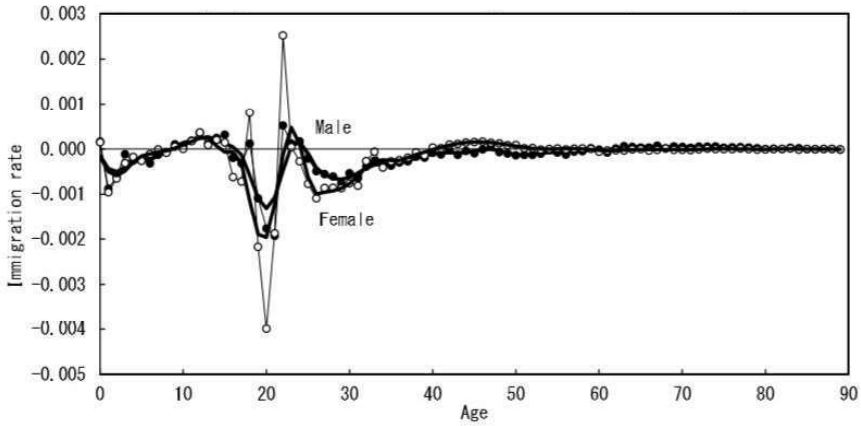

Figure 1. Age-specific Net Migration Rates by Sex for Japanese Population (Source: Portal Site of Official Statistics of Japan website (https://www.e-stat.go.jp))

In our approach, the migration phenomenon for CCA is calculated with spatial statistic modeling which we can examine the changes of immigration and emigration in every cohort interval throughout the entire prediction period. The illustrative steps are shown in (Figure 2).

The following part is the details of the SAR model. We applied the spatial statistic approach to predict the future demographic trend as the spatial data which means the influence of neighboring field values can make better predictions about human behavior and understand what variables may influence people's choices. By analyzing spatial data and how certain variables impacts, we can observe why certain spatial dependence exists. For example, infrastructure development, housing values, and income levels are more likely to be similar at two meters apart than at two kilometers apart. This similarity of attributes of point locations is called spatial autocorrelation. To analyze the spatial autocorrelation, spatial regression methods which can examine the relationship between the observations - dependent variable and one or more explanatory variables. These observations could be income, employment, population levels, and so on. The regression approach typically clarifies the relationship between the dependent variables and causal factors. And then the estimated relationship in the data period is applied to the projection period.

The simplest forecasting model is the standard ordinary least squares (OLS) regression model, which can consider a variety of driving factors. However, OLS estimation will not converge to the true values of parameters if there is a spatial correlation. In case the spatial correlation is significant, a spatial regression model should be applied to estimate the consistent parameters (Chi and Voss 2011). Evaluating spatial dependency is a logical step in spatial analysis and understanding the spatial structure helps to tease apart the different potential influences on the spatial distribution of regions. Among spatial statistic models, the spatial autoregressive (SAR) model is widely applied to calculate the spatial dependency effects on the expected values of the objective variables.

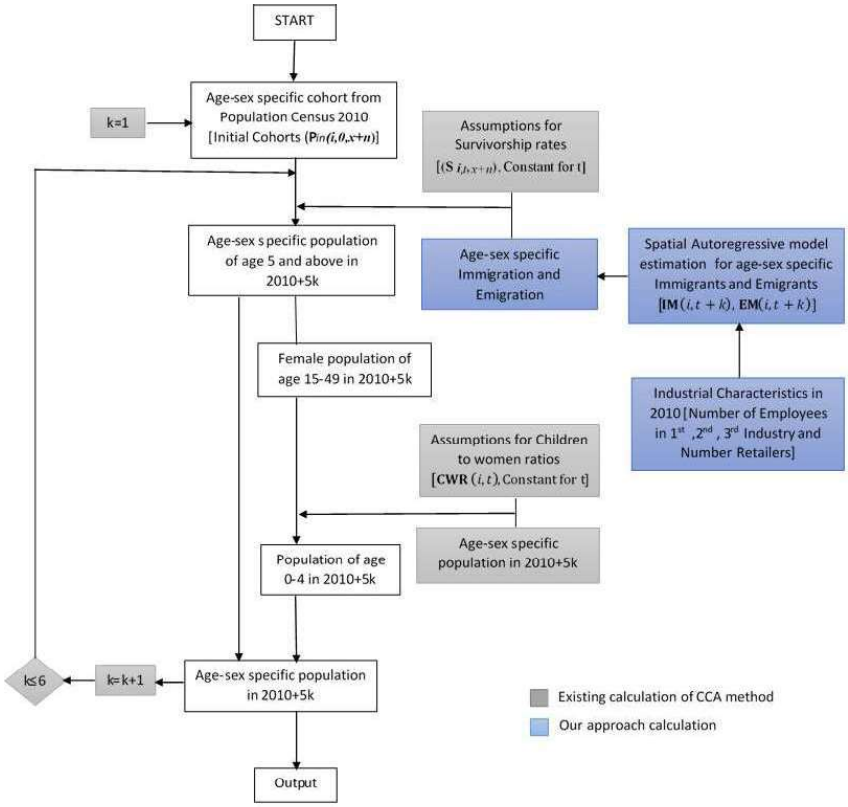

Figure 2. Prediction Methodology Flow (Integration of CCA with SAR Model)

To examine the necessity of the SAR model, standard global or local spatial statistics should be measured first. Global and local statistics of spatial autocorrelation can be measured by Moran's I, Local Moran's I statistics, etc. To examine the necessity of the SAR model, Moran's I should be estimated to confirm significant spatial dependency. Moran's I is a spatial correlation index to measure the spatial autocorrelation between a vector of a geo-referenced variable and its weighted average of the neighboring variables. A significant Moran's I indicate stronger spatial autocorrelation or a more evident clustering that should be modeled by the spatial statistic models.

Generally, the concept of the spatial autoregressive model is that neighboring regions have more influence on each other than on the distant regions. For example, region A has a new industry that could give several employment opportunities. The inflow of labors and their families to region A would increase the population in region A. Some employees and their families may choose region B connected to region A with frequent public transport services, where housing prices would be relatively lower. In this case, population growth in region B is caused by the employment opportunity in region A, but the increase is not caused by region B's employment opportunities.

A typical spatial statistic model SAR is defined as follows.

$$\boldsymbol{Y} = \rho \boldsymbol{WY} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{1}$$

The spatial autoregressive structure can be transferred into an induced form which clearly shows the generating process of the dependent variable shown in eq(2). Anselin (1988) noted the model is as "mixed regressive or spatial autoregressive" model.

$$\boldsymbol{Y} = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \boldsymbol{X}\beta + (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \varepsilon \tag{2}$$

Vector $\boldsymbol{Y}$ is a geo-referenced dependent variable. Matrix $\boldsymbol{X}$ contains exogenous explanatory vectors, and the β are associated regression parameters vectors. In our approach, model will result in spatial correlation of explanatory variable and error term. Therefore, SAR specification can include the spatial correlation in "$\boldsymbol{X}\beta$". The reason why we adopt the spatial correlation in Y is adopted is because we assumed the dependent variable Y (number of migration) will be an index of regional attractiveness, or the opportunities of the offered jobs.

$\boldsymbol{W}$ is a weighting matrix with neighboring regions, and the associated scalar parameter ρ reflects the strength of spatial dependence. The spatial weight matrix, $\boldsymbol{W}$, is an n-by-n nonnegative matrix that has an element of $\boldsymbol{W}_{ij}$, which is the weight at location i, j. In this model, $(\boldsymbol{I}\text{-}\rho\boldsymbol{W})^{-1}$ is non-singular and the product $\sigma^2(\boldsymbol{I}-\rho\boldsymbol{W})^{-1}\ ((\boldsymbol{I}-\rho\boldsymbol{W})^{-1})^t$ equals the variance-covariance matrix is positive-definite. For spatial correlation, we considered the observations as being independent of one another and each identically distributed. For creating standard weighting matrices, such as inverse distance or nearest neighbor, or create custom matrices is essential in spatial autoregressive model, and this study, we used contiguity matrices as the boundaries shared between spatial units play an important role in determining the degree of "spatial influence". For Contiguity matrices, an element w[i,j] is one of the units i and j share a common border, and 0 otherwise.

$$W[i,j] = \begin{cases} 1 \text{ if i shares a boundary with j} \\ 0\ otherwise \end{cases} \tag{3}$$

In defining the spatial-weighting matrices, if there is too much dependence, existing statistical theory is not applicable, that mean the estimation of spatial economic models become difficult or even impossible. Therefore, normalization of the spatial-weighting matrices is necessary. In our estimation, we designed the spatial-weighting matrices based on spectral normalization which is created by dividing the entries by the absolute value of the largest eigenvalue of the matrix and this normalization is easier to interpret than the traditional row normalization.

$$w[i,j] = \left(\frac{1}{\tau}\right) w[i,j]^* \tag{4}$$

where τ is the largest of the moduli of the eigenvalues of the unnormalized spatial-weighting matrix w*.

The proposed prediction procedure represents the interaction between the population distribution and the industrial distribution. Such the interaction is sometimes referred to that the population distribution affects somewhat on the spatial distribution of industrial activities, and that also it is true for vice versa. As the model to describe such the interactions, we adopt the following specification that the lagged / future population is explained by the industrial characteristics at present, and the lagged / future industrial characteristics are explained by the population (actually cohort), considering spatial dependency. Of course, such the model would be more complex, but it is another issue to be discussed. Therefore, for the simplicity of our study, the basic equation eq (2) is developed to the immigration and emigration models to eq (5) and (6).

$$\boldsymbol{EM}_{(t+k)} = \rho\boldsymbol{WEM}_{(t+k)} + \boldsymbol{X}_{(t+k)}\beta + \varepsilon \tag{5}$$

$$\boldsymbol{IM}_{(t+k)} = \rho\boldsymbol{WIM}_{(t+k)} + \boldsymbol{X}_{(t+k)}\beta + \varepsilon \tag{6}$$

The dependent variables are immigration and emigration by cohort for each municipality. [Migration population, (2 types)] × [5-year-old Class (19 class)] × [gender (2 types)] = 76 models were estimated. The explanatory variables are the number of retailers and the change in

the number of employees of 2nd industries. In our calculation, the effect of parent migration (20 and overs) is also considered on the migration of children population (0-4,5-9,10-14,15-19). In this study, the estimation of migration models is made for immigration, emigration, and industrial characteristics to clarify the lagged impact of the explanatory variable in t on the dependent variable in $t + 1$. Once the model is estimated, the prediction of the dependent variable is repeatedly made until the projected years (it is 2040 in our study).

To summarize the effects of the industrial characteristics on the age composition of migrants, we constructed the population pyramid charts. In spatial statistic models which contain spatial lags of the dependent variables, interpretation of the parameters is more complicated as models expand to include the information from neighbors. This may lead to erroneous conclusions if we make the direct interpretation of the coefficients of the models like linear regression models which can directly give the relation among the dependent and the explanatory variable. Previous studies (Kim, Phipps, and Anselin 2003; Anselin and Legallo 2006) suggested that models containing spatial lags of the dependent variable require special interpretation of the parameters. Therefore, the output of the models is in the form of direct effect indicating the effect of explanatory variables from own region and indirect effect indicating the effect of the surrounding regions. These effects are obtained as the estimated parameters in eq (6) or eq (7). For simplicity, we combined the direct and indirect effect as a total effect to see the clear attractiveness of cohorts on the explanatory variables. The output effects are summarized up and averaged over the regions to show in the charts.

We used the 2010 initial population data from the population census of Japan and the estimated period is from 2015 to 2040 every 5 years. Usage data is from Geographic Data (ArcGIS Data Collection 2015, Esri Japan) and e-Stat of Japan. The target areas are 1 prefecture (Fukushima Prefecture) and 1799 municipalities. Due to the impacts of the Great East Japan Earthquake that occurred in March 2011, Fukushima Prefecture had -1.93 % with the highest rate of decrease in population according to the population estimates of October-1, 2011. Unfortunately, only the prefectural data was published and the municipal data for Fukushima could not be available as population census survey was not conducted due to the damage caused by the Great East Japan Earthquake. Therefore, we deliberately excluded municipal data and considered the Fukushima Prefecture as one region. Table 1 is the descriptive statistics of the variables which we used in our proposed method.

Table 1. Descriptive statistics

Dependent Variable	Explanatory Variable	Mean	Std.Dev	Min	Max
Population		66763.36	97183.621	178	903,346
Net Migration		29.337	1685.814	-8,279	68,917
Male Net Migration		17	776.239	-1,044	31,822
Male Immigration		1,660	8,195	0	337,629
Male Emigration		2,401	13,230	6	547,290
Female Net Migration		19	903.962	-896	37,095
Female Immigration		1,460	7,506	2	309,618
Female Emigration		1,387	6,297	6	258,300
	Working Age Population (15-64)	27,390	46094.009	0	573,317
	Number of Employees in 2nd Industry	7426.012	9922.661	13	96,761
	Number of Retailers	10949.84	7716.154	4	18670

3. DISCUSSION

3.1 Interregional Migration Prediction with Industrial Indexes

Before the estimation of the SAR model, we calculated Moran's I to test the necessity of the spatial dependent model. For the evaluation of the statistical stability of Moran's I, the statistical significance of standard errors is shown as * p <0.05, ** p <0.01, and *** p <0.001, respectively. According to the significance of Moran's I test in our analysis (Table 2), it is appropriate to apply the spatial statistic approach in our estimation. The spatial correlation parameter ρ was positive and significant in the 65 out of 76 models with significant ρ of almost all children migration, the male immigration cohorts from 20 to 49 and from 60 to 90 over cohorts, all of the male emigration and female immigration cohorts, the emigration of female cohorts from 25 to 59 and from 65 to 79 (Table 3). According to the results, all the working-age cohort's spatial correlation parameters ρ are positive and highly significant. Therefore, it becomes clear that migration of working-age cohorts is indeed affected by industrial characteristics.

Table 3. Results of Spatial Correlation Parameter for Both Genders with Cohorts

Cohorts	Spatial Correlation Parameter (ρ)			
	Male Immigration	Male Emigration	Female Immigration	Female Emigration
0_4	0.196***	0.238***	0.195***	0.056
5_9	0.0868*	0.113*	0.121**	0.0949*
10_14	0.0848*	0.130**	0.152**	0.0895
15_19	0.157**	0.126*	0.11*	0.0688
20_24	0.137***	0.199***	0.145***	0.0693
25_29	0.142***	0.199***	0.210***	0.185***
30_34	0.210***	0.294***	0.234***	0.196***
35_39	0.209***	0.242***	0.234***	0.127***
40_44	0.117***	0.213***	0.144***	0.0693*
45_49	0.0746*	0.135***	0.0987**	0.129***
50_54	0.0599	0.146***	0.181***	0.172***
55_59	0.0748	0.111**	0.212***	0.0979**
60_64	0.0908*	0.0913*	0.131***	0.0657
65_69	0.173***	0.198***	0.161***	0.176***
70_74	0.220***	0.259***	0.292***	0.204***
75_79	0.284***	0.334***	0.221***	0.101*
80_84	0.349***	0.304***	0.236***	0.0863
85_89	0.284***	0.345***	0.168***	0.0348
90_over	0.456***	0.514***	0.193***	0.0934
Total	0.338***	0.524***	0.415***	0.416***

Table 2. Global Moran's I Analysis of Total Migration and Industrial Variables

Variable	Moran's Index	Expected Index	Variance	Z-score	p-value
Male Total Immigration	0.39692***	-0.00072	0.00856	45.28304	0.00000
Male Total Emigration	0.41763***	-0.00072	0.00859	48.67499	0.00000
Female Total Immigration	0.39061***	-0.00072	0.00857	45.66852	0.00000
Female Total Emigration	0.37421***	-0.00072	0.00556	43.8016	0.00000
Number of Employees in 2nd Industry	0.34752***	-0.00072	0.00726	47.94531	0.00000
Number of Retailers	0.34389***	-0.00072	0.00726	47.44475	0.00000

Significance level parenthesis
* ρ <0.05, ** ρ <0.01, *** ρ <0.001

To observe the influence of industrial characteristics, the estimated results about the number of retailers on male and female migrant cohorts are shown in Fig.3(a) and Fig.3(b). Since we considered the number of retailers can represent the geographical characteristics of urban agglomeration, the SAR model explained by the retailer will show the cohort characteristics whether they are attracted to urban agglomeration, or not. For this variable, we omitted to estimate the models from infants and children (0-4,5-9 cohorts) because these cohorts will not be directly influenced the retailers. Even the impact of retailers on 10-14 and 15-19 cohorts of both genders are also insignificant as shown in Fig.3(a) and Fig.3(b).

From Fig.4(a), the direct effects of male immigration between 20 to 54 cohorts are greater than the emigration however, the indirect effects are opposite. Hence, the number of retailers from the own region will affect the 20 to 54 male cohorts to cause more immigrants and the number of retailers from neighboring regions will attract the male cohorts. According to the total effects, the younger male cohort will be closer to the retailer sides and elderly people tend to be apart from the location of retailers. From Fig.3(b), both the direct and indirect effects of female immigration between 20 to 49 cohorts are greater than the emigration. This result suggests that the number of retailers in the own region and surounding regions will attract the female younger cohort. From the total effects, we can observe that the tendency of migration is weak for female cohorts. Similar with male cohorts, female younger cohorts will be more attracted to the retailer's location. By comparing Fig.3(a) and 3(b), we observed that the younger generation (10 to 54 male cohorts and 10 to 49 female cohorts) will more attract by the retailers and move to the urbanized regions, while elderly cohorts (55 to 90 over male cohorts and 50 to 90 over female cohorts) will not attract by retailers and they would remain at the local regions. The female elderly generation is much closer to the retailers' location rather than the male elderly cohorts.

Regarding the influence of the industrial characteristics on migration, we also assumed that the 1st, 2nd, 3rd, and overall industrial employee forces can be explanatory variables in our model. However, our discussion only focused on the effects of the number of employees from the 2nd industry since the 2nd industries are located in limited areas such as manufacturing or industrialized zones. Fig.4(a) and Fig.4(b) are the summaries of the effects of 2nd industry employees on migrants, which have a significant impact on male and female cohorts' migration. From Fig.4(a), the direct effects on immigration for almost all-male cohorts (expect 0-4 and 15-19 cohorts) are greater than that on the emigration. Therefore, the effect of employees in the 2nd industry of their own region will attract the male cohorts. Indirect effects on the emigration of all-male cohorts, on the other hand, are larger than that on immigration. Therefore, in the surrounding region of manufacturing employees, male cohorts will make more emigrates. From

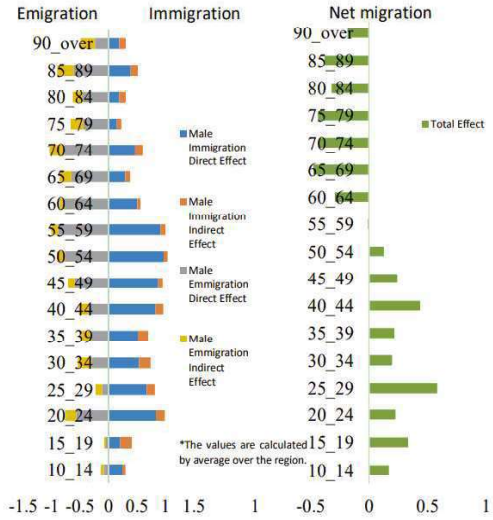

Figure 3(a). Male Immigration, Emigration and Net Migration Effected by Number of Retailers

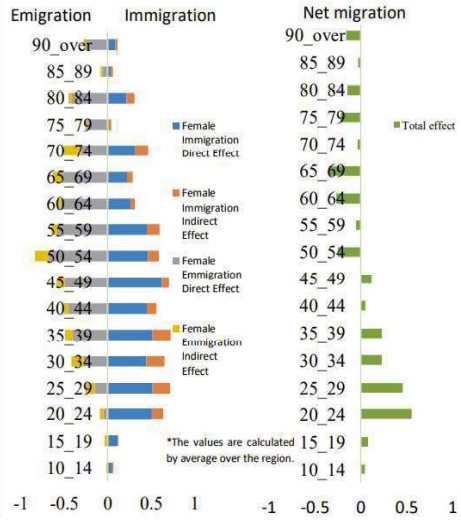

Figure 3(b). Female Immigration, Emigration and Net Migration Effected by Number of Retailers

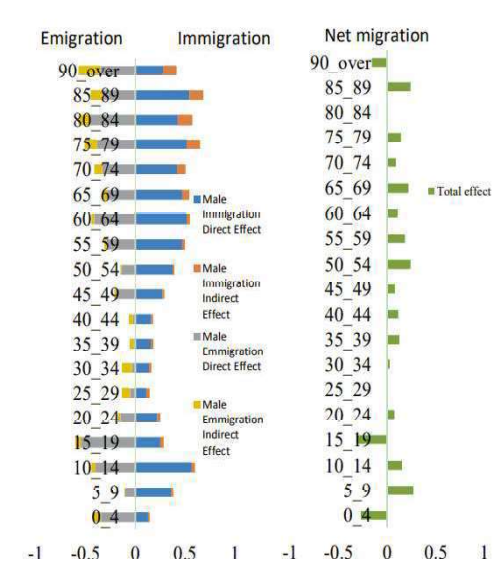

Figure 4(a). Male Immigration, Emigration and Net Migration Effected by Number of Employees from 2nd Industry

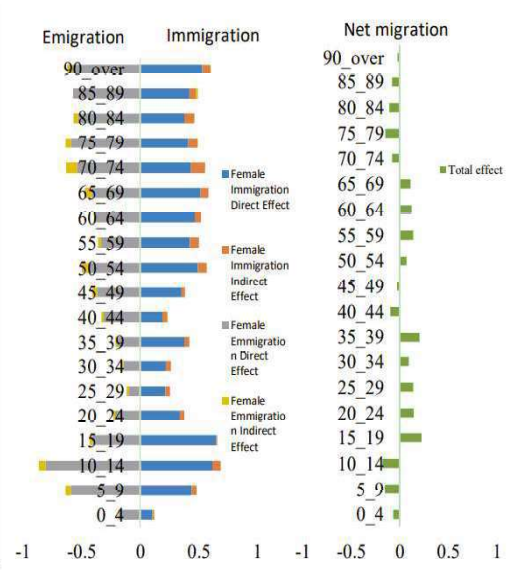

Figure 4(b). Female Immigration, Emigration and Net Migration Effected by Number of Employees from 2nd Industry.

the total effects, infant cohort, 15-19 and 90 over cohorts will not be attracted by the manufacturing industrial employees and these cohorts will be distributed in the specific industrial zones.

From Fig.4(b) in the female child cohorts (0-4,5-9,10-14), middle-aged cohort (40 to 49) and elderly cohort (70 to 90 overs), the direct effects of emigration are greater than the effects of immigration. In opposite, the direct effects on immigration of cohorts between (15 to 39, 50 to 69) are greater than the emigration. For indirect effects, the results are similar for both migrations. Therefore, the surrounding manufacturing industrial employees will influence both emigration and emigration of the region. According to the total effects, the younger cohort (15 to 39) and middle-aged cohort (50 to 69) are going to be attracted by manufacturing industrial employees and will be located close to the specific industrial zones. In Fig.4(a) and 4(b), the

immigrant and emigrant of female cohorts are more fluctuated than the male cohorts. Male cohorts including elderly cohorts will be strongly attracted by manufacturing industrial employees than the female cohorts, except the younger female cohort.

In manufacturing employees, the estimated parameters were fairly larger for both migrants, while the total effects (i.e., the effects on net migrants) were not so large comparing with that of retailers. In other words, even the migrants around the industrialized employee's location seem to be large, its net effect on the population is limited. On the other hand, the net effect of retailers which is introduced as an index of urban agglomeration would have a stable impact on migrants, resulting in the attraction of younger cohorts to the retailers, i.e., to the urbanized areas.

4. CONCLUSION

This study developed the prediction models for migration phenomenon considering spatial dependencies among the municipalities, examined the significance of interactions between industrial characteristics and cohort-wise migrants through the comparison with conventional Cohort Component Method (CCA). Interregional migrants and emigrants for each cohort are modeled with spatial dependency recursive specification, which will be incorporated with population prediction by CCA adopted as the national population prediction method. The target municipalities are 1 prefecture (Fukushima Prefecture) and 1799 municipalities. In CCA, the spatial factors and industrial characteristics in migration modeling are missing. To clarify the necessity to consider the spatial dependencies in population prediction, migration was modeled by the spatial statistic approach which can include spatial factors such as industrial characteristics of surrounding municipalities and the interaction between the spatial distribution of population and that of industries. The findings obtained in this study are summarized as follows.

The results of spatial parameters indicated that spatial dependencies should not be ignored in the analysis of population prediction. In our models, immigration and emigration depended positively on that of surrounding municipalities, respectively, especially in working-age cohorts (15 to 64). The net migration for younger cohorts would be more attracted by the retailers and the cohorts moved to the urbanized regions. Elderly cohorts, however, would not be attracted by retailers, so then they remain in the original regions. This can cause social problems for elderly cohorts in rural areas such as shopping. For the effect of industrial factors, the male and female migration was different. For males, almost all of the male cohorts (expect infant cohort, 15-19 and 90 overs cohorts) will be attracted by the manufacturing industrial factors and would be attracted more at the industrial zones which might be located around the metropolitan areas or developed regions. For females, the younger generation and middle-aged cohorts are going to be attracted by the manufacturing industrial factors. Female child cohort cohorts and elderly cohorts were not attracted by the manufacturing industrial factors. In our model, male cohorts made much amount of emigrants than female cohorts.

The above results give strong evidence to consider the spatial dependencies shown in Fig.2. Therefore, the simulation analysis of the population following to proposed approach should be tried in next step. Other remaining issues are as follows. The treatment of Fukushima prefecture will be revised in order to avoid the potential bias brought by the difference in the size of regions. The explanatory variables in the SAR models should be checked with caring. The lag of immigrant and emigrant models is also the target of research. In the SAR model, the specification of the spatial weight matrix requires more tests. For example, the inter-regional travel time by HSR or airline can be used as the weight. Finally, the validation of model structure can be checked by the actual population prediction. For this purpose, the proposed model can be applied to the past data, then the outputs could be tested by the present dataset.

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