Regional income convergence in Japan after the bubble economy

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Abstract

With the collapse of the bubble economy in the early 1990s, economic disparities among both people and regions have arisen in Japan. Although developments in spatial econometrics have provided regional convergence studies with a strong tool to explicitly consider spatial dependence and heterogeneity, there has been no significant research on Japan's economic disparity using spatial econometrics. Moreover, most conventional regional convergence studies on Japan study the post-war high economic growth period before the economic bubble.

Hence, the objective of this study is to analyze regional income disparities at the municipality level in Japan after the bubble burst. We use annual data collected during the period 1989–2004. Note that for all the years, the number of municipalities is 1,841 and also that Japan has 47 prefectures. To the best of our knowledge, no research has been conducted to analyze the dynamical change in Japan's regional income disparities at the municipality level though some research has been done at the prefecture level.

First, the study shows that σ-convergence holds. Second, it demonstrates the dynamic change in Moran's I and indicates that the spatial dependence of income has weakened after 2000. Third, the study analyzes regional income convergence by applying the Spatial Durban Model to the β-convergence approach. The results show that β-convergence holds. The study also verifies that a lack of sufficient consideration of both spatial dependence and spatial heteroskedasticity can lead to serious mistakes in model estimation and interpretation.

Keyword: regional convegence, income inequality, spatial dubin model, β-convergence

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1. Introduction

With the collapse of the bubble economy in the early 1990s, economic disparities among both people and regions have arisen in Japan, and have now become a major social issue. One of the popular approaches to analyze economic disparities is testing the β-convergence hypothesis. β-convergence concepts are based on the neoclassical growth model (Solow 1956; Swan 1956), which was elaborated in the early 1990s by Barro (1991), Barro and Sala-i-Martin (1992a), and Mankiw *et al*. (1992). See Barro and Sala-i-Martin 2004 for details. In the neoclassical framework, a statistical model is built around the hypothesis that lower per capita income economies have a higher growth rate as compared higher per capita income economies. This hypothesis is tested using the estimate of the initial income's parameter. Consequently, it is important to note that Goodchild *et al*. (2000) points out that for building reliable statistical models, spatial dependence and heterogeneity of data have to be considered.

Many methods to consider spatial dependence have been developed in the field of *Spatial Econometrics* (e.g., Anselin 1988; Anselin and Florax 1995; Haining 2003; LeSage and Pace 2008). To the best of our knowledge, Rey and Montouri (1999) is the first literature to use spatial econometric models for β-convergence studies. After Rey and Montouri (1999), many empirical studies have been conducted for various countries and time periods (e.g., Fingleton 1999; Ertur *et al*. 2007; Battisti and De Vaio 2008). For more details, see Abreu *et al*. (2004).

To consider spatial heterogeneity, Islam (1995) proposed a method to control location-specific impacts omitted from the model as dummy variable effects (fixed effects) by using panel data. It is well known that omitted variables will result in spatial heteroscedasticity of errors, and this heteroscedasticity will lead to statistical problems involving coefficient estimates (e.g. Green 2008). Islam (1995)'s finding insists that the lack of sufficient consideration of the location can lead to serious mistakes in model estimation and interpretation. After Islam (1995), using panel data has become the "standard" for β-convergence studies (e.g., Arbia 2004; Arbia *et al*. 2005; Lopez-Rodriguez 2008). However, panel data suffer from availability, i.e., in many cases, it is difficult or almost impossible to prepare a sufficient panel data set of income and control variables. Hence, this paper uses cross-sectional data employing LeSage (1999)'s Bayesian approach that considers both spatial dependence and heterogeneity.

The objective of this study is to analyze the regional per capita income disparities at the municipality level in Japan after the bubble burst. We use annual data collected during the period 1989–2004. Note that the number of municipalities for each year is 1,841 and that Japan has 47 prefectures. To the best of our knowledge, no research has been conducted to analyze the dynamical change in Japan's regional income disparities at the municipality level; however, there have been several works on Japan's regional income disparities at the prefecture level (e.g., Barro and Sala-i-Martin 1992b; Kawagoe 1999).

This paper contains 5 sections. Section 2 contains a review of neoclassical growth models and some techniques of spatial economics. Section 3 describes the data used in this paper. Section 4 shows some results of the preliminary analysis. Section 5 is the main part of this paper and contains a discussion on income disparities in Japan after the bubble burst based on β-convergence. Finally, Section 6 concludes.

2. Neoclassical growth model

2.1. Neoclassical growth model and β-convergence

The neoclassical growth model based on cross-sectional data is given by

$$\ln\left[\frac{y_{i,T}}{y_{i,0}}\right] = \alpha + \beta \ln[y_{i,0}] + \boldsymbol{x}_i'\boldsymbol{\gamma} + \varepsilon_i\ , \tag{1}$$

where i ($i = 1, \ldots, n$), 0, T are the indices that denote region (municipality), initial period, and final period, respectively; y denotes the per capita income, and as such, $\ln(y_{i,T}/\ y_{i,0})$ is the growth rate over the entire period; $\boldsymbol{x}_i$ is a vector of region i that contains $m \times 1$ control variables and denotes the regional difference in the steady state; ε_i are *i.i.d.* errors; and α and β are the parameters (Jones 1998; Barro and Sala-i-Martin 2004; Arbia 2006). If β is negative and significant, the lower initial per capita income regions have a higher growth rate as compared to regions with a higher initial per capita income, and also the per capita income of all regions converges to one steady state (β-convergence). Further, $\beta = -(1 - e^{-bT})$ holds; note that here b denotes the speed of convergence. $\ln(2)/b$ indicates the so-called "half life time," which is the time required by the economies to fill the initial gap in income inequalities by half.

2.2. Neoclassical growth model and spatial econometrics

Eq. (1) implicitly assumes that there is no spatial interaction in the process of income evolvement, i.e., the economies evolve solely depending on their initial incomes. However, Rey (2001) points out that the regions neighboring rich regions grow faster than those neighboring poor regions. His finding clearly shows that the assumption of regional independence in eq. (1) is unrealistic. It seems to be natural to assume that "nearby" regions show similar growth patterns. With regard to this, Rey and Montouri (1999) uses some models developed in the field of spatial econometrics for the study of β-convergence. We briefly look at the spatial econometric models in the perspective of β-convergence.

With regard to the Spatial Lag Model (SLM), which considers spatial interaction in terms of dependent variables, the neoclassical growth model is given by

$$\ln\left[\frac{y_{i,T}}{y_{i,0}}\right] = \rho \sum_j w_{ij} \ln\left[\frac{y_{i,T}}{y_{i,0}}\right] + \alpha + \beta \ln[y_{i,0}] + \boldsymbol{x}_i'\boldsymbol{\gamma} + \varepsilon_i\ , \tag{2}$$

where ρ is the autoregressive parameter and w_{ij} is the weight assigned to region j.

If ρ is positive (negative) and significant, positive spatial autocorrelation is (not) implied.

However, negative spatial autocorrelation exhibits the so-called checker board pattern, and is actually difficult to interpret. See Griffith (2006) for negative spatial autocorrelation.

If there is some dependence between the data in i and j, a non-zero value is assigned to w_{ij}. In many cases, the a priori specification of w_{ij} is needed. Some works have attempted automatic specification of w_{ij} (e.g., Kakamu 2005). One of the most popular specification methods for w_{ij} is as follows: if region j is one of the k-nearest regions of i, $w_{ij} = 1$; otherwise, $w_{ij} = 0$.

We can get the matrix form of SLM as

$$\boldsymbol{Y}^* = \rho \boldsymbol{W}\boldsymbol{Y}^* + \alpha \boldsymbol{\iota} + \beta \boldsymbol{Y}_0 + \boldsymbol{X}\boldsymbol{\gamma} + \boldsymbol{\varepsilon}, \tag{3}$$

where $\boldsymbol{Y}^*$ is an $n \times 1$ vector whose elements Y_i^* are given by $\ln(y_{i,T}/y_{i,0})$; $\boldsymbol{\iota}$ is an $n \times 1$ vector with all elements equal to 1; Y_0 is an $n \times 1$ vector whose element $Y_{i,0}$ are given by $\ln(y_{i,0})$; $\boldsymbol{X}$ is an $n \times m$ control variables matrix; $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of *NID* errors; $\boldsymbol{W}$ is the spatial weight matrix whose i, j element is w_{ij}; and $\boldsymbol{W}$ is a row-standardized matrix (with row sums equal to unity) that leads to a spatial lag for $\boldsymbol{Y}^*$ at i given by

$$\sum_j w_{ij} \ln\left[\frac{y_{i,T}}{y_{i,0}}\right]. \tag{4}$$

This can be interpreted as the weighted average of the per capita income of neighboring region.

After Rey and Montouri (1999) introduced spatial econometric models for β-convergence, many studies on β-convergence began using spatial econometrics (e.g., Fingleton 1999; Magalhães *et al.* 2005). This study follows these empirical studies. More precisely, the study adopts Spatial Durbin model (SDM) developed by LeSage and Fischer (2008) as the spatial econometric model. LeSage and Fischer (2008) insist that this model is very suitable for growth studies.

SDM is given by

$$\boldsymbol{Y}^* = \rho \boldsymbol{W}\boldsymbol{Y}^* + \alpha \boldsymbol{\iota} + \beta \boldsymbol{Y}_0 + \theta \boldsymbol{W}\boldsymbol{Y}_0 + \boldsymbol{X}\boldsymbol{\gamma} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\zeta} + \boldsymbol{\varepsilon}, \tag{5}$$

where θ is a scholar parameter and $\boldsymbol{\zeta}$ is an $m \times 1$ parameter vector. Then, let us assume that the error vector of eq. (5) obeys heteroscedastic multivariate normal distribution as below.

$$\boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \sigma_\varepsilon^2 \boldsymbol{V}),\ \boldsymbol{V} = diag(v_1, \ldots, v_n), \tag{6}$$

where $diag(\bullet)$ denotes the diagonal elements of the matrices. Eq. (6) allows heteroskedasticity in variance, and hence, location-specific impacts can be considered. In the neoclassical framework, the growth rate is explained using the initial per capita income and some control variables. However, it is very difficult to explain "growth rate" because it is determined by many unknown factors. Hence, outliers or heteroskedasticity are often observed in variance and these hinder the estimation of β. Eq. (6) can yield a robust estimation of β by estimating relative variance $v_1, \ldots, v_n$.

LeSage (1999) proposed a method to estimate relative variance in the framework of Bayesian Statistics, i.e., updating prior distribution assigned to each parameter by Bayes theorem. Like LeSage (1999), we adopt the following prior distributions:

$$\pi(\alpha) \sim N(a, r),\quad \pi(\beta) \sim (c, s),\quad \pi(\boldsymbol{\gamma}) \sim MN(\boldsymbol{g}, \boldsymbol{t}),\quad \pi(\boldsymbol{\zeta}) \sim MN(\boldsymbol{h}, \boldsymbol{u}),$$
$$\pi(\sigma_\varepsilon^2) \sim Ga(d, \nu),\quad \pi(v_i^{-1} \mid q) \sim i.i.d.\chi^2(q)/q, \text{ and } \pi(\rho) \sim Unif(-1, 1), \tag{7}$$

where $N(\bullet,\bullet)$, $MN(\bullet,\bullet)$, $Ga(\bullet,\bullet)$, $\chi^2(\bullet)$, and $Unif(\bullet,\bullet)$ denote the normal, multivariate normal, Gamma, Chi-squared, and uniform distribution, respectively. For the initial values, we use $a = c = d = \nu = 0$, $r = s = 10^{12}$, $\boldsymbol{g} = \boldsymbol{h} = \boldsymbol{0}_m$, and $\boldsymbol{t} = \boldsymbol{u} = 10^{12} \times \boldsymbol{I}_m$, where $\boldsymbol{0}_m$ is an $m \times 1$ zero vector and $\boldsymbol{I}_m$ is an $m \times m$ identity matrix. See LeSage (1999) for further details. In this paper, we refer to this model as the Bayesian Spatial Durbin Model (B_SDM); further, we refer to the model considering only spatial heteroskedasticity in eq. (1) as the Bayesian Basic Model (B_BM).

Needless to say, eq. (6) does not use temporal information; hence, it cannot consider time-variant impact.

2.3. Interpretation of SDM estimates

As shown in section 2.1., the traditional β-convergence approach concentrates on the estimates of β. However, as pointed by LeSage and Fischer (2008), this interpretation is no longer valid when SDM is used. Below, we present this problem in brief.

The derivative of Y_i^* with respect to $Y_{j,0}$ is given by

$\frac{\partial Y_i^*}{\partial Y_{j,0}} = S(\boldsymbol{W})_{ij}$, where

$$S(\boldsymbol{W}) = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}(\beta\boldsymbol{I} + \theta\boldsymbol{W}) . \quad (8)$$

Clearly, $\partial Y_i^* / \partial Y_{i,0} \neq \beta, \forall i$ and $\partial Y_i^* / \partial Y_{j,0} \neq 0, \forall j \neq i$, i.e., the change in the initial per capita income of the neighboring region j (j = 1, …, n) affects the growth rate of region i; therefore, the convergence hypothesis cannot be tested using the estimates of β. In SDM, the growth rate of i is affected by the growth rate of j, and the growth rate of j is affected by the change in the initial per capita income of j. Hence, the growth rate of i is indirectly affected by the change in the initial par capita income of region j. LeSage and Fischer (2008) insist that there are two effects: one described by $\boldsymbol{W}\boldsymbol{Y}_0$ and the other, by the fact that the changes in $Y_{j,0}$ impact Y_j^*, which in turn impacts Y_i^*.

Then, the derivative of Y_i^* with respect to $Y_{i,0}$ is given by

$$\frac{\partial Y_i^*}{\partial Y_{i,0}} = S(\boldsymbol{W})_{ii} . \quad (9)$$

Y_i^* is affected directly by any change in $Y_{i,0}$, and is also affected by the feedback effect through Y_j^*. Thus, the impact of initial value varies with location and the neighborhoods described by $\boldsymbol{W}$; hence, it is difficult to interpret eq. (8) and (9) as they are. LeSage and Fischer (2008) propose the following summary measure:

$$M_{direct} = n^{-1} tr(S(\boldsymbol{W})) ,$$
$$M_{all} = n^{-1} \boldsymbol{\iota}' S(\boldsymbol{W}) \boldsymbol{\iota} \text{, and}$$

$$M_{indirect} = M_{all} - M_{direct}, \tag{10}$$

where M_{direct} indicates the average of the impact of the changes in $Y_{i,0}$ on Y_i^* over all regions, $M_{indirect}$ is the average of the impact of the changes in $Y_{j,0}$ on Y_i^* over all regions, and M_{all} is the total effect: the sum of M_{direct} and $M_{indirect}$.

This study adopts the abovementioned interpretation given in LeSage and Fischer (2008). It should be noted that there are many other interpretations for spatial econometric models. The differences among interpretations arise owing to the manner in which externalities from the neighboring regions are dealt with (e.g., Small and Steimetz 2007; Tsutsumi and Seya 2008).

3. Data

3.1. Per capita income data

For the per capita income data, we use annual data collected during the period 1989–2004. Note that the number of municipalities is 1,841 for each year. The data is made using the "Annual report on Municipal Tax" published by the Ministry of Internal Affairs and Communications, Japan. We do not deflate the data because the study period is short enough that the change in prices can be neglected (Fig. 1).

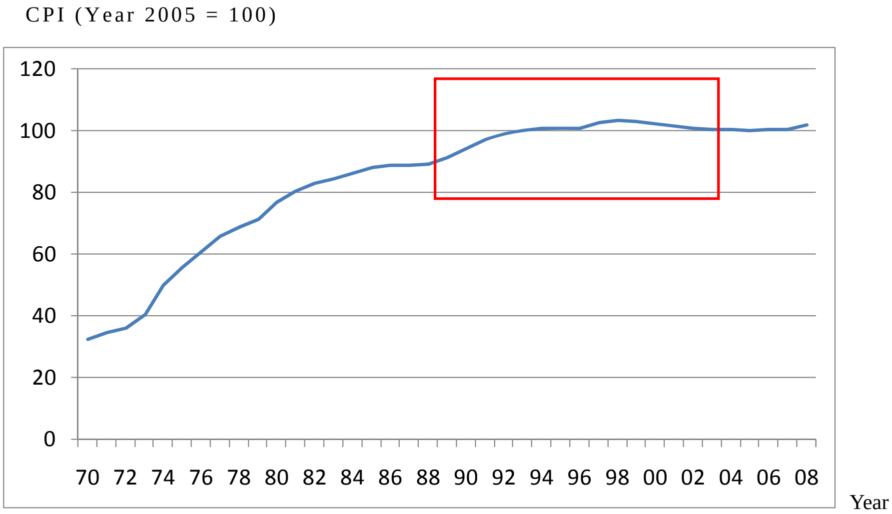

Fig. 1. Change in the consumer price index (CPI) in Japan

3.2. Descriptive of per capita income data

Table 1 shows the descriptive of per capita income (1,000 yen) during the period 1989–2004. The table includes the minima ($q1$), median, mean ($q3$), maxima, and interquartile range ($IQR = q3 - q1$).

The mean of the per capita income was increasing until 1998, and has been decreasing ever since. The peak of the *IQR* is in 1992, immediately after the collapse of the bubble economy. After 1992, IQR decreases.

Table 1. Descriptive of per capita income (1,000 yen)

Year	min	q1	median	mean	q3	max	IQR
89	279	698	870	914	1,074	3,814	376
90	266	735	927	985	1,163	4,627	428
91	236	822	1,039	1,101	1,305	5,022	483
92	368	893	1,129	1,190	1,420	5,198	527
93	391	928	1,135	1,179	1,374	4,081	447
94	418	956	1,165	1,208	1,402	3,941	446
95	431	993	1,195	1,236	1,427	3,904	434
96	433	993	1,197	1,239	1,439	3,791	446
97	425	1,028	1,229	1,275	1,481	3,791	453
98	460	1,033	1,238	1,280	1,489	3,860	456
99	460	1,020	1,219	1,258	1,454	3,617	435
00	478	1,004	1,203	1,234	1,429	3,841	426
01	471	981	1,183	1,215	1,410	4,032	430
02	408	958	1,154	1,188	1,375	4,199	417
03	450	918	1,110	1,143	1,318	4,153	400
04	445	898	1,089	1,124	1,304	4,305	406

4. Preliminary analysis of per capita income data

4.1. Geographic distribution of per capita income data

Fig. 2 and 3 show the geographic distribution of per capita income in the years 1989 and 2004, respectively. The data is classified by standard deviation into five categories. The high income regions in 1989 are concentrated along the so-called “Pacific Belt Zone,” where there is a concentration of the main production facilities. It is also notable that high income regions are located along the seashore for a similar reason. Although the geographic distribution in 2004 is similar to that in 1989, some peculiarities can be found. The per capita income in the Nagoya Metropolitan Area, where Toyota Motors has its headquarters and many motor industry factories are located, has increased. Further, the high income region around the Tokyo Metropolitan Area is moving eastwards.

Fig. 4 shows the growth rate over the period 1989–2004. The growth rates of rich regions—the Tokyo and Osaka Metropolitan Areas, the two major metropolitan areas in Japan—are low as expected. However, the growth rates of some mountainous regions are also low probably owing to aging and depopulation.

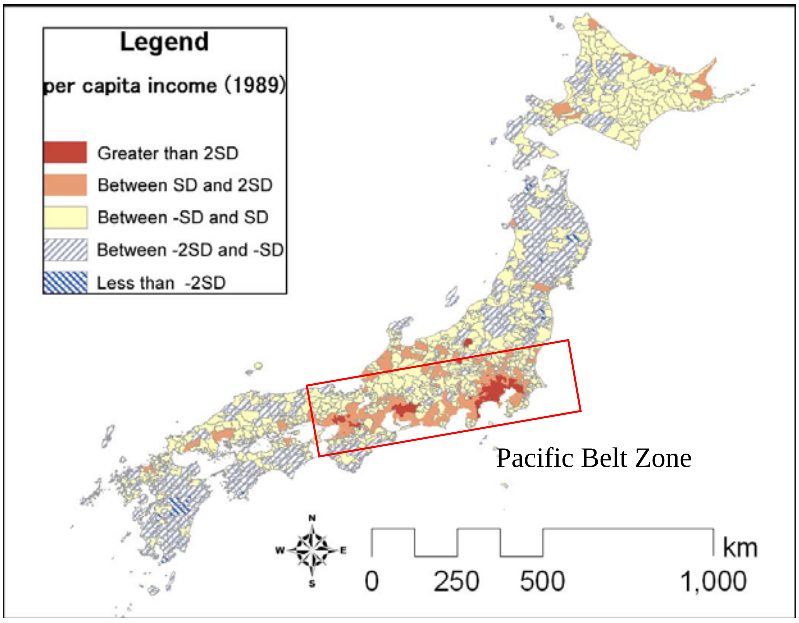

Fig. 2. Geographic distribution of per capita income in 1989

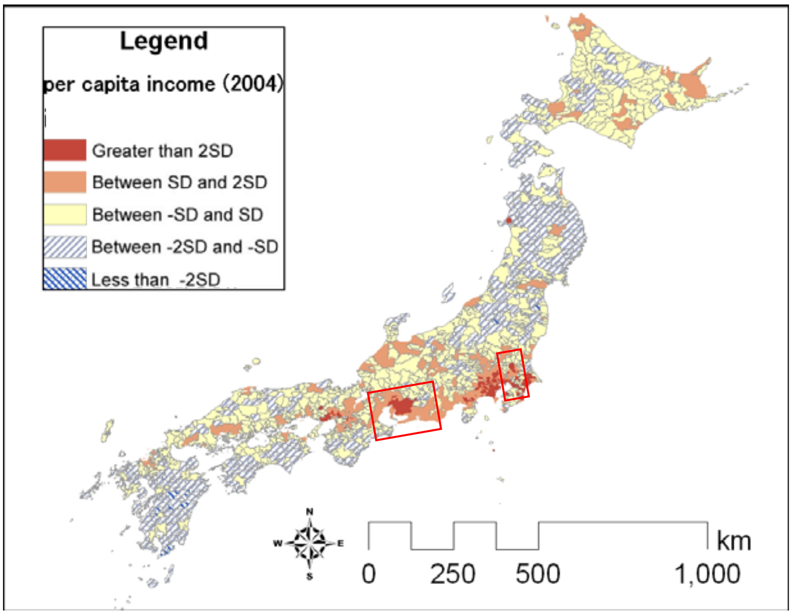

Fig. 3. Geographic distribution of per capita income in 2004

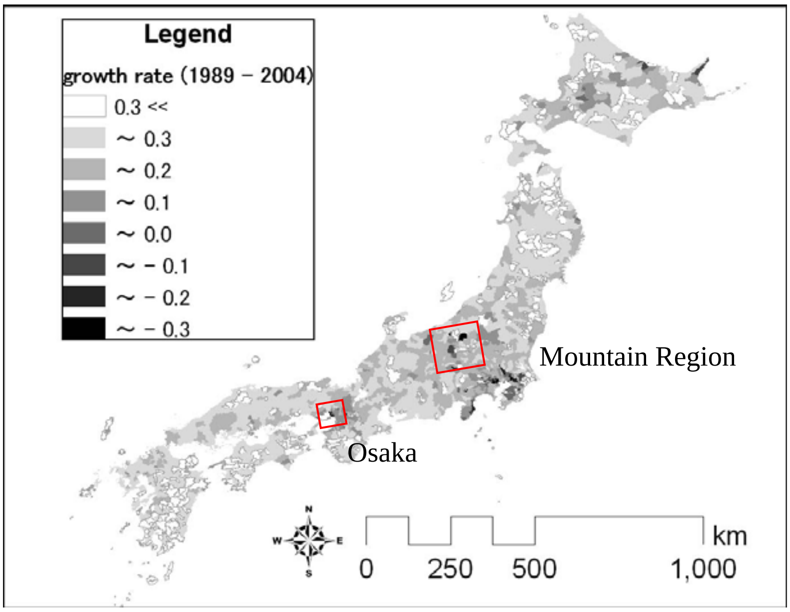

Fig. 4. Growth rate of per capita income over the period 1989–2004

4.2. Gini Coefficient

The Gini coefficient is one of the most popular measures of income inequality. The Gini coefficient lies in the range [0, 1). In this paper, the Gini coefficients are calculated for two cases. (1) Case A: per capita income not weighted by the population of municipalities. (2) Case B: per capita income weighted by the population of municipalities. Gini coefficient is calculated using the Space-Time Analysis of Regional Systems (STARS) package (Rey and Janikas 2006).

Fig. 5 shows the Gini Coefficient for Case A. The coefficient was relatively high during the bubble period. After the collapse of the bubble economy, the Gini coefficient has fallen to around 0.14 by 2000. However, the coefficient has increased since 2000, i.e., the economy has moved toward disparity. The coefficient for Case B is shown in Fig. 6, which shows that the Gini coefficient was very high (0.73–0.75) during the bubble period. This may be owing to the fact that the high per capita regions are concentrated in the high population regions. This is shown in Fig. 7. It is notable that income disparity has risen in recent years.

Fig. 5 Gini coefficient for case A

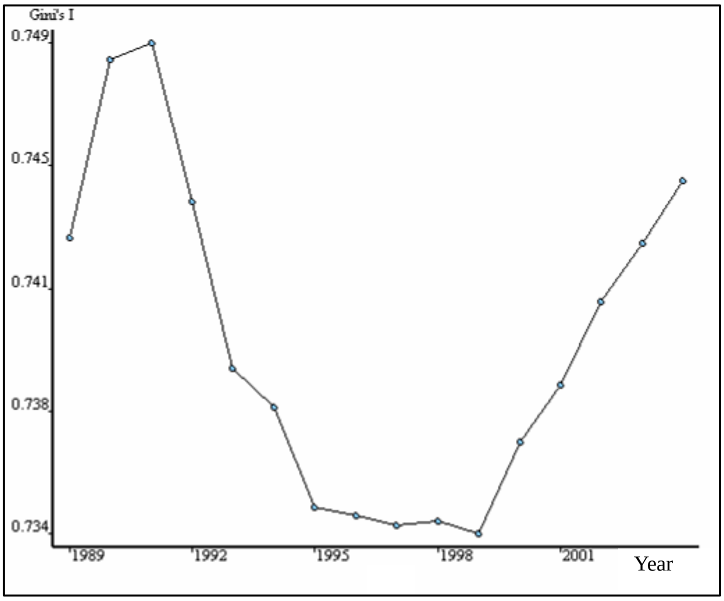

Fig. 6. Gini coefficient for case B

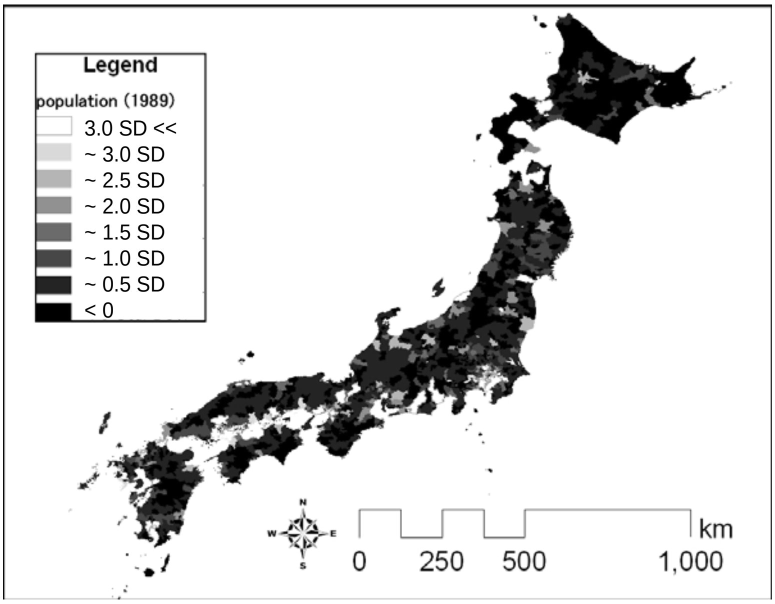

Fig. 7. Geographic distribution of population in 1989

4.2. Theil index

The Theil index is also one of the most popular measures of income inequality. The advantage of this index is that it can be decomposed into the sum of the indices of the intra-region and inter-region inequalities (Akita 2003; Adelman and Levy 2005). We will decompose the Theil index of per capita income in Japan into intra-prefecture and inter-prefecture inequalities. As stated above, the number of municipalities used in this study is 1,841 for each year, and the number of prefectures is 47.

Suppose that there are n municipalities and two prefectures. The per capita income of each municipality is given as $y_1, \ldots, y_n$. The share of municipality i (i = 1, …, n)—denoted by s_i—against all municipalities is given by $y_i = y_k / \sum_k y_k$ (k = 1, …, n). Then we define two sets—$\{s_1, \ldots, s_j\} \equiv A$ and $\{s_{j+1}, \ldots, s_n\} \equiv B$—where A and B denote the prefectures. The next step is to calculate the average s_i for each prefecture—denoted by μ_A and μ_B. Then, the Theil index of each prefecture is given by

$$T(A) = \sum_{i=1}^{j} \frac{s_i}{j\mu_A} \ln \frac{s_i}{\mu_A} \quad \text{and} \tag{11}$$

$$T(B) = \sum_{i=j+1}^{n} \frac{s_i}{(n-j)\mu_B} \ln \frac{s_i}{\mu_B} . \tag{12}$$

The inter-prefecture Theil index is given by

$$T(A,B) = \ln n + j\mu_A \ln \mu_A + (n-j)\mu_B \ln \mu_B . \tag{13}$$

Using (11)–(13), the Theil index for all samples is given by

$$T(S) = j\mu_A T(A) + (n-j)\mu_B T(B) + T(A,B) . \tag{14}$$

Thus, the Theil index is decomposed into the sum of each prefecture's Theil index (intra-prefecture) weighted by the sample size and inter-prefecture Theil index.

Fig. 8 shows the calculated Theil index mentioned above. The intra-prefecture and inter-prefecture Theil indices show similar patterns as a whole. However, the inter-prefecture index reduced during the period 1993–2000 while intra-prefecture index remained constant. After 2000, the intra-prefecture index remained at the same level while the intra-prefecture index increased. It can be interpreted that the per capita income disparity of recent years detected by the Gini coefficient is caused by the intra-prefecture disparity.

Fig. 9 shows the intra-prefecture Theil index for the years 1990, 1995, 2000, and 2004. We can observe that the income disparities in the Chiba prefecture, located east of Tokyo, are expanding; this is as stated in Section 3.2. This result coincides with the result that income inequality during these years has been high in Tokyo and low in the prefectures located along the Japan Sea side.

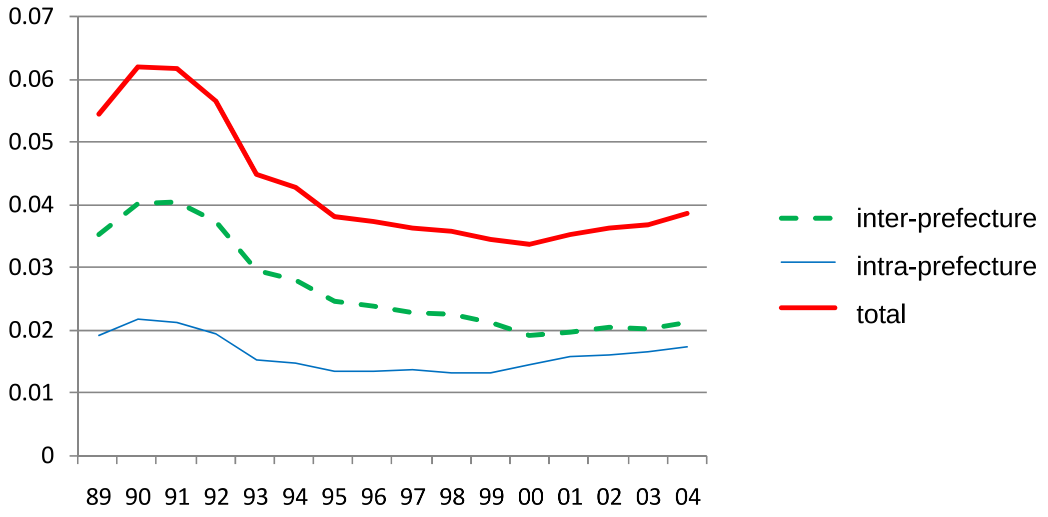

Fig. 8. Theil index

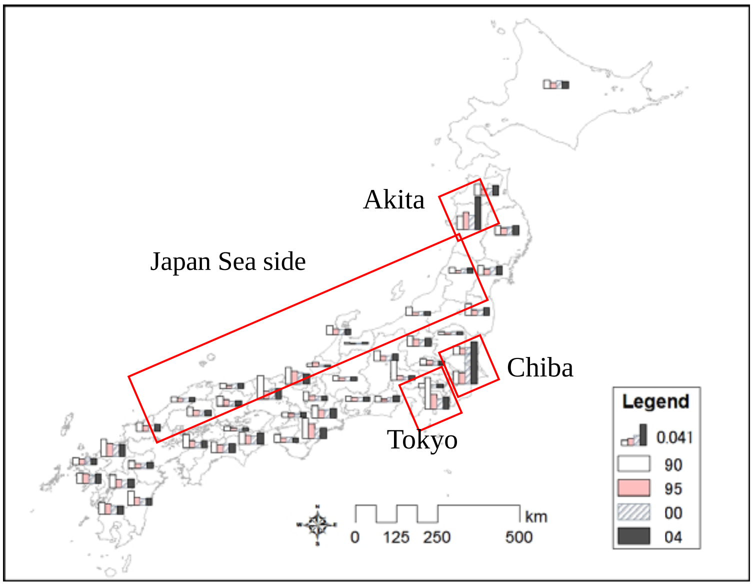

Fig. 9. Geographical distribution of inter-prefecture Theil index

4.4. σ-convergence and Moran's I

According to Young *et al*. (2008), when the disparity of real per capita income across a group of economies falls over time, *σ*-convergence holds. More specifically, the variance of log-income shown in eq. (15) falls over time.

$$\sigma_t^2 = \frac{1}{n}\sum_{i=1}^{n}\left[\ln(y_{t,i}) - \mu_t\right] \tag{15}$$

Fig. 10 shows the process of σ_t^2 in our case. The change in this process is similar to that of the Gini coefficient. Like the Gini coefficient (for case A), σ_t^2 is almost constant after 1995, and as such, it can be interpreted that *σ*-convergence holds. Note that Young *et al*. (2008) demonstrated that *σ*-convergence is a necessary but not sufficient condition for *β*-convergence. Hence, both hypotheses must be examined to discuss income disparity.

Even if *σ*-convergence holds, the geographic distribution pattern may change. Hence, we examine the change in the geographic distribution by Moran's *I* given by

$$I_t = \frac{n}{S_0}\sum_i\sum_j \frac{w_{ij}(y_{t,i} - \bar{y}_t)(y_{t,j} - \bar{y}_t)}{(y_{t,i} - \bar{y}_t)^2}, \tag{16}$$

where n is the number of regions, S_0 indicates the sum of all the elements of the spatial weight matrix, and $\bar{y}_t$ denotes the average per capita income in year t. Moran's I lies between –1 and 1, with 1 indicating strong positive spatial autocorrelation. We use k nearest neighbors to specify w_{ij}. In this paper, we set k = 4 based on Akaike's Information Criteria (AIC).

Fig. 10 shows the value of Moran's I. For all years, the null hypotheses of the non-existence of spatial autocorrelation were rejected at the 1% significance level, and strong spatial autocorrelation was suggested. This implies that rich regions are located close to rich regions, and poor regions are located close to poor regions.

However, the value of Moran's I has fallen since 1999 implying that this dependence has weakened. Especially after 2000, when the total amount of defaulted liabilities in business failures reached its peak, the value of Moran's I has fallen even though the sigma squared value has increased. This can be interpreted to imply that the trend of the clustering of regions with similar income levels is reversing.

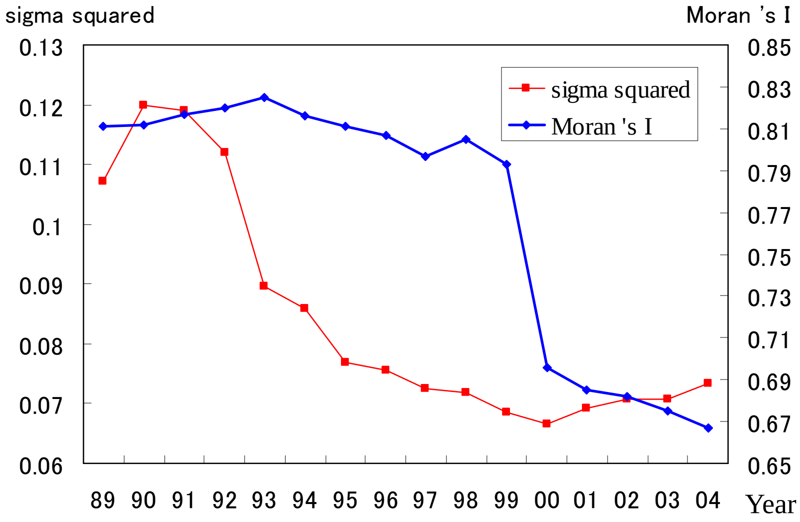

Fig. 10. σ-convergence and Moran's I

5. Analysis of income disparity using a neoclassical growth model

To test the convergence of the economy, we built four models: Basic Model (BM), B_BM, SDM, and B_SDM. The parameters of BM are estimated by the ordinary least squares (OLS) method, and those of SDM by the maximum likelihood method. As for B_BM and B_SDM, the Bayesian estimation method is used with the abovementioned priors and initial values. We adopt population density (per km^2), average age (years), the ratio of people engaged in tertiary industries (%), and district dummy variables as the control variables.

Table 2 shows the result of the parameter estimation. For all models, β is negative, and β-convergence holds. The control variables are all significant. As a result, high population density, low average age, and a low ratio of people engaged in tertiary industries affect the growth rate positively.

However, the OLS residual of BM seems to be spatially autocorrelated (Fig. 10). The standardized Moran's I statistic for the residuals of BM is 7.7 and the null hypotheses of the non-existence of spatial autocorrelation were rejected at the 1% significance level. The Breusch-Pagan test was also conducted to examine the hetereskedasticity of OLS residual variance. The BP statistic is 103 and the null hypotheses of the non-existence of hetereskedasticity were rejected at the 1% significance level. Hence, the BM estimate of β is unreliable. (The I test assumes the non-existence of hetereskedasticity, and the BP test assumes the non-existence of spatial autocorrelation; further, both the tests are not robust to the existence of hetereskedasticity or spatial autocorrelation (e.g. Anselin 1988). Hence, these tests must be co-used with the residual plot).

Table 2 indicates that the adjusted r-squared values of SDM are higher than those of BM. Further, the adjusted r-squared values of the robust models—B_BM and B_SDM—are expectedly lower than those of BM and SDM. The estimate of ρ is positive; hence we can interpret that the neighboring regions have evolved similarly. Fig. 11 shows that the relatively large estimate for the variance of B_SDM corresponds with the large OLS residuals of the regions.

Table 2. Result of parameter estimation

	BM			B_BM				SDM			B_SDM			
Variable	Coef.	Std. error	p	Coef.	Std. error	p	Geweke	Coef.	Std. error	p	Coef.	Std. error	p	Geweke
Intercept	3.1105	0.1424	0.000	2.4827	0.0946	0.000	0.088	2.3533	0.1357	0.000	2.1367	0.1500	0.000	0.526
Initial income	−0.3698	0.0182	0.000	−0.2819	0.0120	0.000	0.055	−0.3889	0.0183	0.000	−0.2862	0.0136	0.000	0.890
Pop. dens.	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.092	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.186
Average age	−0.0101	0.0012	0.000	−0.0088	0.0008	0.000	0.922	−0.0111	0.0012	0.000	−0.0090	0.0009	0.000	0.183
Tertiary industry ratio	−0.0011	0.0004	0.003	−0.0009	0.0002	0.000	0.286	−0.0011	0.0003	0.002	−0.0008	0.0003	0.001	0.108
Hokkaido	0.0564	0.0130	0.000	0.0275	0.0081	0.000	0.616	0.0087	0.0403	0.828	−0.0088	0.0247	0.358	0.329
Tohoku	−0.0270	0.0118	0.023	−0.0330	0.0070	0.000	0.680	−0.0601	0.0448	0.180	−0.0634	0.0276	0.011	0.254
Kanto	0.0611	0.0138	0.000	−0.0164	0.0085	0.028	0.401	−0.0028	0.0469	0.952	−0.0594	0.0287	0.020	0.055
Chubi	0.0423	0.0138	0.002	0.0122	0.0082	0.069	0.103	0.0176	0.0366	0.631	−0.0318	0.0228	0.081	0.898
Kinki	0.0249	0.0132	0.060	−0.0175	0.0079	0.013	0.370	0.0081	0.0272	0.765	−0.0326	0.0172	0.029	0.366
Chugoku or Shikoku	0.0487	0.0128	0.000	0.0309	0.0073	0.000	0.339	0.0098	0.0367	0.789	0.0044	0.0215	0.418	0.858
W initial income								0.0990	0.0133	0.000	0.0462	0.0202	0.010	0.563
W pop. dens.								0.0000	0.0000	0.000	0.0000	0.0000	0.025	0.166
W average age								0.0053	0.0015	0.000	0.0011	0.0013	0.190	0.196
W tertiary industries ratio								0.0004	0.0006	0.540	−0.0001	0.0004	0.358	0.124
W Hokkaido								0.0430	0.0413	0.298	0.0316	0.0258	0.111	0.178
W Tohoku								0.0396	0.0461	0.390	0.0341	0.0283	0.114	0.090
W Kanto								0.0231	0.0479	0.629	0.0428	0.0300	0.077	0.186
W Chubi								0.0114	0.0377	0.762	0.0450	0.0242	0.031	0.739
W Kinki								−0.0047	0.0291	0.872	0.0141	0.0189	0.228	0.861
W Chugoku or Shikoku								0.0257	0.0381	0.501	0.0240	0.0229	0.147	0.990
rho								0.1810	0.0272	0.000	0.1463	0.0256	0.000	0.289
Variance of error	0.0157			0.0041			0.038	0.0145			0.0040			0.312
Adjusted r^2	0.4525			0.4328				0.4751			0.4682			

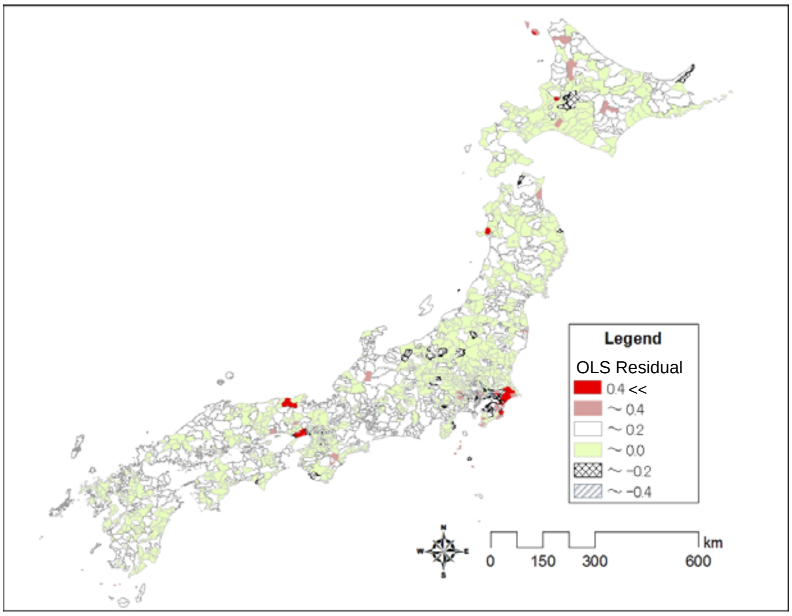

Fig. 10 Geographic distribution of OLS residual

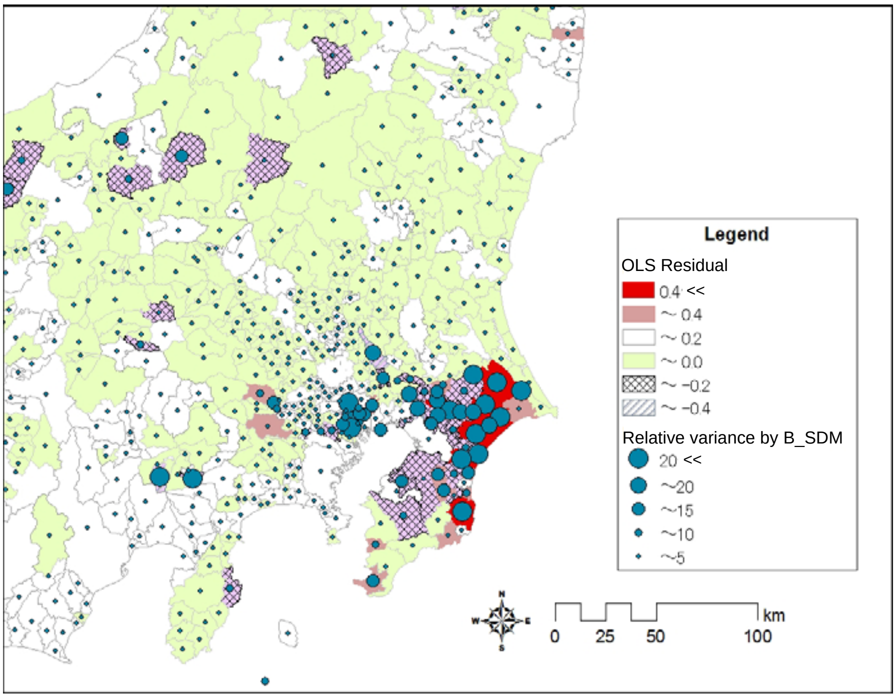

Fig. 11. OLS residual and relative variance by B_SDM

As mentioned above, for SDM and B_SDM, we cannot test the convergence hypothesis using the estimate for β; hence we calculate the direct effect, indirect effect, and total effect based on eq. (10). Fig. 12 and 13 show the results. The total effects calculated by both SDM and B_SMD are negative except for the period 2000–2004. Further, the per capita income disparity, as a whole, has fallen during the period 1984–2004. The total effect over 2000–2004 is slightly positive; hence, the disparity seems to have increased in this period. This result is coincident with the results of σ-convergence analysis. The indirect effect is weaker than the direct effect and positive over some periods. Hence, there is a negative direct effect and positive indirect effect. This indicates that regions with lower initial income and those neighboring higher income regions will have a higher growth rate. This result is plausible.

The half-life time (year) of BM, B_BM, SDM, and B_SDM are 21, 29, 29, and 22 years, respectively. Here, the half-life time of SDM and B_SDM is calculated using M_{all}. Thus, the estimated half-life is quite different for the four models. Further, this result shows that using only one model for the test of β-convergence can lead to serious mistakes in model estimation and interpretation.

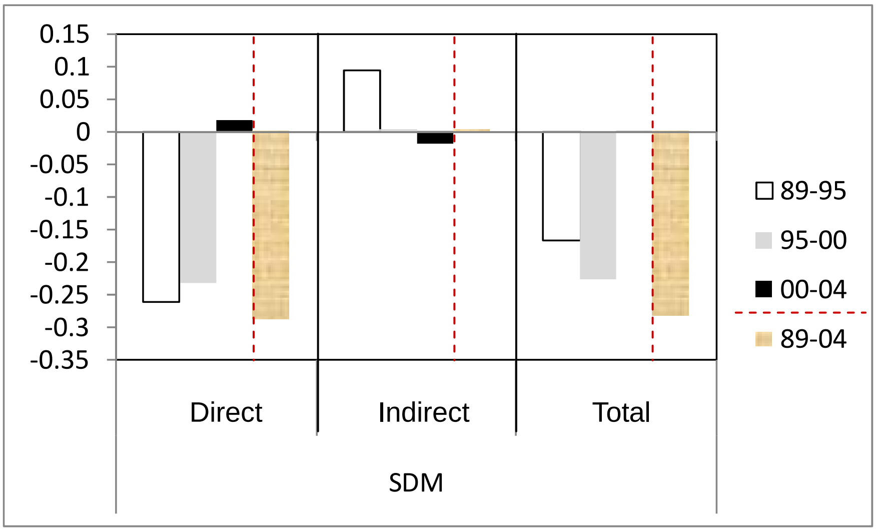

Fig. 12. SDM and convergence hypothesis

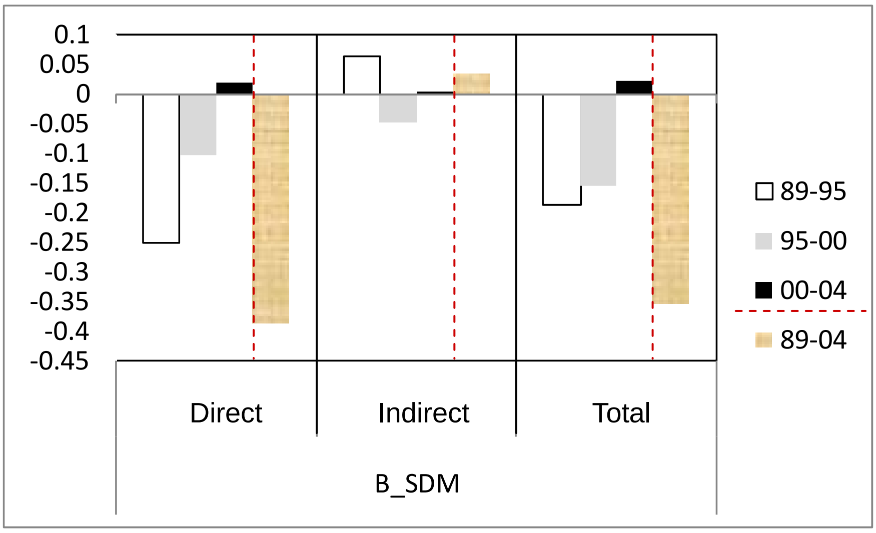

Fig. 13. B_SDM and convergence hypothesis

6. Concluding Remarks

This study analyzed the regional income disparities at the municipal level in Japan after the economic bubble burst. First, the study shows that σ-convergence holds. Second, it demonstrates the dynamic change in Moran's I and indicates that the spatial dependence of income has been weakening since 2000. Third, the study analyses the regional income convergence applying SDM to the β-convergence approach. The results show that the β-convergence holds and also verifies that using only one model for testing β-convergence can lead to serious mistakes in model estimation and interpretation.

The following are left for future research. First, in this study, we use the simple case of 4 nearest neighbors for the spatial weight matrix. However, the detailed transportation network and economic relationship among the municipalities need to be considered. Second, we did not consider the existence of club convergence (as in Quah 1993; Stirb¨ock and Fischer 2006). However, the assumption that all economies converge to one steady state is strong; hence, considering the plural convergence state is important. Third, the selection of control variables using the Bayesian model averaging technique (e.g., LeSage and Olivier 2007; Deller *et al*. 2008) can be examined further.

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