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SPATIAL-TEMPORAL DYNAMICS OF REGIONAL CONVERGENCE AT COUNTY LEVEL IN JIANGSU

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ABSTRACT: The dynamics of regional convergence include spatial and temporal dimensions. Spatial Markov chain can be used to explore how regions evolve by considering both individual regions and their geographic neighbors. Based on per capita GDP data set of 77 counties from 1978 to 2000, this paper attempts to investigate the spatial-temporal dynamics of regional convergence in Jiangsu. First, traditional Markov matrix for five per capita GDP classes is constructed for later comparison. Moreover, each region's spatial lag is derived by averaging all its neighbors' per capita GDP data. Conditioning on per capita GDP class of its spatial lag at the beginning of each year, spatial Markov transition probabilities of each region are calculated accordingly. Quantitatively, for a poor region, the probability of moving upward is 3.3% if it is surrounded by its poor neighbors, and even increases to 18.4% if it is surrounded by its rich neighbors, but it goes down to 6.2% on average if ignoring regional context. For a rich region, the probability of moving down ward is 1.2% if it is surrounded by its rich neighbors, but increases to 3.0% if it is surrounded by its poor neighbors, and averages 1.5% irrespective of regional context. Spatial analysis of regional GDP class transitions indicates those 10 upward moves of both regions and their neighbors are unexceptionally located in the southern Jiangsu, while downward moves of regions or their neighbors are almost in the northern Jiangsu. These empirical results provide a spatial explanation to the "convergence clubs" detected by traditional Markov chain.
KEY WORDS: regional convergence; spatial-temporal dynamics; spatial Markov chain; Jiangsu Province

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1 INTRODUCTION

With the rapid development of China's economy, the research on regional convergence or divergence has attracted a lot of attention (SONG, 1996; LUO *et al.*, 2002; QIN, 2004). At present, the empirical analyses are often based on two concepts of regional convergence, σ- and β-convergence (BARRO and SALA-I-MARTIN, 1995). σ-convergence refers to a reduction of differences in the per capita GDP across regions over time and is typically measured as the standard deviation of the logarithm of per capita GDP at the regional level. β-convergence predicts that the growth rate of a region is positively related to the distance that separates it from its steady state and is usually investigated by regressing growth rates of per capita GDP on initial levels. Unfortunately, both coefficients fail to provide insights as to the behavior of the entire regional GDP distribution over time as well as other methodological problems (QUAH, 1993). In response to some of the criticisms, a number of researchers have adopted Markov chain to study the dynamics of regional convergence (QUAH, 1996; FINGLETON, 1997). Different from the measurements of σ-or β-convergence, this method can be used to identify an alternative concept of regional convergence—convergence clubs, which means an increase in the homogeneity within regions in the same groups and also an increase in the differences between different groups.

During the process of regional convergence, regional interdependences, such as trade between regions, technology and knowledge diffusion, are regarded as the main forces that drive regional convergence (REY and MONTOURI, 1999; LI, 1999). As we all know, if a region is surrounded by its richer neighbors, the possibility of moving upward might increase. On the contrary, the region would be put into poverty trap if surrounded by its poorer neighbors. In practice, regional growth poles are often encouraged to establish in order to pull the whole regional economy through trickle-down or spreading effects (YAO *et al.*, 2004). It

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is evident that the dynamics of regional convergence have both spatial and temporal dimensions. However, traditional Markov transition matrix can only portray the temporal characteristics of regional convergence and ignore the spatial dimension of regional distribution due to treating regions as if they were "isolated islands", while regional conditioning Markov chain can not portray transitions over time due to only quantifying the effects of spatial interaction (QUAH, 1996). How can we fully consider the spatial and temporal dimensions of regional convergence? Or how can we learn that the probabilities of regional moving upward or downward are related to the movements of their neighbors?

Spatial Markov chain approach can be used to answer the above questions. By integrating traditional Markov chain with some recent developments in local spatial statistics, Spatial Markov matrices are constructed to analyze how the transitions of a region can be explained by its geographic environment and the extent to which this environment exerts impacts on the region's relative position within GDP cross-sectional distribution (REY, 2001; LE GALLO, 2004). Thus, we can investigate the role of geographic context in a dynamic setting. In this paper, we apply Spatial Markov chain to studying the spatial and temporal characteristics of regional convergence in Jiangsu at the county level over the time from 1978 to 2000, as well as calculating traditional Markov matrix for comparison.

2 METHODOLOGY

2.1 Markov Chain

Markov chain can be used to track the movement of each region's per capita GDP over time (QUAH, 1996; REY, 2001; LE GALLO, 2004; QIN, 2004). Assume that a set of k different per capita GDP classes provide a discrete approximation of the entire regional GDP distribution. The state probability vector P_t for year t, which represents the probability that a region will be a member of a GDP class, is a $1\times k$ vector $[P_{1,t}, P_{2,t}, ..., P_{k,t}]$. The dynamics of per capita GDP distribution are represented by a $k\times k$ transition probability matrix M, in which each element $m_{i,j}$ specifies the probability that a region in class i at year t ends up in class j in the following period. In the Markov model, if the transition probabilities are stationary, that is, the probabilities between two classes are time-invariant, then

$$P_{t+b} = P_t M^b \tag{1}$$

where M is a transition probability matrix, P_{t+b} or P_t is the probability vector for year $t+b$ or t, and b is time interval.

2.2 Spatial Autocorrelation

Spatial data are often characterized by spatial autocorrelation, which can be defined as the coincidence of value similarity with locational similarity (ANSELIN, 2001). There is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space, and there is negative spatial autocorrelation when geographic areas tend to be surrounded by neighbors with very dissimilar values. Recent work on the spatial analysis of regional income distribution has recognized the need for testing and, if necessary, accounting for spatial autocorrelation before drawing any inference on the nature of the process of regional convergence (REY and MONTOURI, 1999; REY, 2001; LE GALLO and ERTUR, 2003).

Spatial autocorrelation analysis of regional per capita GDP class transitions between initial and terminal years can answer the extent of a region's moving up or down in the classes of regional GDP distribution related to that of its geographic neighbors. Presently, Moran's I and Geary's C indices are two mostly used spatial autocorrelation statistics. But for ordinal data such as per capita GDP classes, BB statistic should be evaluated (CLIFF and ORD, 1981). BB is a count of joins for which two neighboring regions both experience upward or downward moves in GDP distribution. It is defined as follows:

$$BB=\frac{1}{2}\sum_i\sum_j w_{ij}(\delta_i\delta_j) \tag{2}$$

where w_{ij} is the element of a binary spatial weight matrix, $w_{ij}=1$ if region i is contiguous to region j; otherwise $w_{ij}=0$. δ_i or δ_j refers to the attribute value of region i or region j. $\delta_i=1$ if region i has moved up one per capita GDP class; otherwise $\delta_i=0$. Similarly, to test spatial autocorrelation for downward transitions, we define $\delta_i=1$ if region i has moved down one per capita GDP class; otherwise $\delta_i=0$.

2.3 Spatial Markov Chain

Spatial Markov chain is achieved by incorporating local spatial statistics into the framework of Markov chain (REY, 2001; LE GALLO, 2004). Spatial lag operator, that is, the product of observations (z) and a matrix of spatial weights (W), is the core concept of local spatial statistics (ANSELIN, 1995). A region's spatial lag is a weighted average of the values in neighboring regions, with the matrix W defining the sets of "neighbors". More precisely, if an observation on a variable z at location i is denoted by z_i, then its spatial lag is $\sum_{j=1}^{n} w_{ij}z_j$, with $i\neq j$, w_{ij} the elements of w, and $i, j = 1, ..., n$.

Conditioning on the class of its spatial lag at the beginning of each year, spatial Markov matrices for different per capita GDP classes can be constructed. Essentially, spatial Markov matrix is the decomposition of a traditional $k \times k$ Markov matrix into k conditional matrices of dimension (k, k). If one considers the kth conditional matrix, an element $m_{ij}(k)$ is the probability that a region in class i in year t moves to class j in the next year given that its spatial lag was in class k in year t. This is illustrated in Table 1 for a simple case where $k = 2$. The bottom portion of this table is the marginal transition probabilities for the initial and terminal states, which represents the traditional Markov matrix obtained by aggregating the relevant cells from the conditional distributions above.

Table 1 can be used to test the negative or positive influence of geographic neighbors upon a region. More specifically, if we want to know the effect of poor neighbors on a region's upward or downward transition, we can analyze the elements in the conditional matrix where its spatial lag is low. For example, $m_{\mathrm{LH/L}}$ represents the possibility of a poor region moving up to a richer one with poor neighbors. In addition, the overall

Table 1 Spatial Markov matrix (k=2)

Spatial lag	t_0	t_1	
		Low	High
Low	Low	$m_{\mathrm{LL/L}}$	$m_{\mathrm{LH/L}}$
	High	$m_{\mathrm{HL/L}}$	$m_{\mathrm{HH/L}}$
High	Low	$m_{\mathrm{LL/H}}$	$m_{\mathrm{LH/H}}$
	High	$m_{\mathrm{HL/H}}$	$m_{\mathrm{HH/H}}$
Markov	Low	m_{LL}	m_{LH}
matrix	High	m_{HL}	m_{HH}

Note: "Low" for values below average and "High" for above average

influence of spatial dependence can be evaluated by comparing the elements in the traditional Markov matrix and the corresponding ones in spatial Markov matrix. For example, if $m_{\mathrm{LH}} > m_{\mathrm{LH/L}}$, then the probability of an upward move for a poor region, irrespective of its neighbors, is higher than the probability of an upward move for a poor region with poor neighbors. Similarly, if $m_{\mathrm{LH}} < m_{\mathrm{LH/H}}$, then poor regions with rich neighbors have a higher probability of moving upward than poor regions on average. More generally, if geographic context did not matter for transition probabilities, then the conditional probabilities would be equal to the initial probabilities:

$$m_{ij/1}=m_{ij/2}=\cdots=m_{ij/k}=m_{ij} \quad \forall\, i, j=1,\cdots,k \tag{3}$$

During the process of regional convergence, Spatial Markov matrix not only analyzes the dynamics of regional GDP distribution, but also provides the geographic dimension of regional dynamics. Therefore, it can answer whether a region's probability of moving up or down the distribution is related to the movement of its neighbors.

3 EMPIRICAL ANALYSES

Jiangsu is one of the most developed provinces in China, but the whole regional development is severely unbalanced. In 2002, GDP per capita in the richest city at the county level—Kunshan reached 52 078 yuan (RMB), while that of the poorest county—Suining was only 3648 yuan (JPSB, 2003). The ratio of the maximum and minimum GDP at the county level within Jiangsu is up to 14:1. The research on the obvious regional disparities within Jiangsu has been paid much attention to (WEI and FAN, 2000; LONG and NG, 2001; OU and GU, 2004). Our question is whether the development of Kunshan or Suining is related to its geographic neighbors as well as its own feature.

Regional per capita GDP data from 1978 to 2000 are extracted from the *Jiangsu Reform and Development for 20 Years* (1978–1998) (SONG and ZHANG, 1999) and *Statistical Yearbook of Jiangsu* (JPSB, 2000, 2001). In 2000, there were 13 prefecture cities and 64 counties (cities) at the county level in Jiangsu. Within the framework of Markov chain, this paper divides per capita GDP data into five different classes according to provincial average in each year: 1) Poor (P): less than 65% of the provincial average, 2) Lower (L): between 65% and 95% of the provincial average, 3) Middle (M): between 95% and 110% of the provincial average, 4) Upper (U): between 110% and 125% of the provincial average, and 5) Rich (R): more than 125% of the provincial average.

3.1 Temporal Transition

In order to investigate the behavior of the transition of regional GDP distribution over time, we first calculate the traditional Markov transition probability matrix for per capita GDP classes at the county level in Jiangsu from 1978 to 2000 (Table 2). The estimates of transition probabilities ($\hat{m}_{ij}$) are defined as follows (LE GALLO, 2004):

$$\hat{m}_{ij}=\frac{n_{ij}}{n_i} \tag{4}$$

where n_{ij} is the total number of regions moving from class i in year t to class j in year t+1 over all 22 years of transitions, and n_i is the total sum of regions ever in class i over the 22 years.

Several points can be inferred from Table 2. First, the transition probabilities on the main diagonal are relatively high. If a region is in the ith class, the probability

Table 2 Markov matrix (annual) for per capita GDP classes at the county level in Jiangsu (1978–2000)

t_0	n	t_1				
		P (%)	L (%)	M (%)	U (%)	R (%)
P	726	93.8	6.2	0	0	0
L	441	10.0	84.3	5.2	0.5	0
M	70	0	15.7	55.7	20.0	8.6
U	50	0	0	20.0	56.0	24.0
R	407	0	0	0.2	1.5	98.3

of being in the same class the year after is at least 55.7%, and at most up to 98.3%. In addition, the transition probabilities of the poorest and richest extreme classes dominate the diagonal. During the 22-year period, 93.8% for poor regions and 98.3% for rich regions remained in that class in the next year. These estimates indicate that the poorest and the richest regions do not seem to change their relative positions over time. Second, there is no spectacular move between different classes from year to year. The positive elements on the non-diagonal are extremely less than the diagonal ones, and are only observed around the diagonal. The least transition probability between different classes is 0.2% and the largest one is 24% which is less than the half of the minimum (55.7%) being in the same class in the following years. Lastly, little sign of converging to the mean indicates there exist two different convergence clubs in Jiangsu during the period from 1978 to 2000. The extremely high probability in the same rich class (98.3%) and very low probability moving downward between different classes in the following years (1.7%) would imply convergence to the rich, while concentration in the poor class (93.8%) and 6.2% upward moves would imply convergence to the poor.

The tendency that a rich or poor region in Jiangsu over the whole period remained in its initial state can be interpreted as follows. As a coastal province, some more developed regions in Jiangsu (such as Suzhou, Wuxi and Changzhou prefecture cities) have been designated as open zones and have been provided with preferential policies to stimulate economic growth rapidly since 1985 (LI *et al*., 1999). Their local governments and enterprises have been given greater autonomy in the investment decision-making and a greater access to different sources of investments. In contrast, under such a climate of allowing some people and places to become rich first, those less developed regions (including Suining County), unlike state-designated open zones, apparently do not have the same opportunity to develop quickly. In order to promote efficiency and comparative advantage, the richer regions will get much richer and the poorer ones much poorer with uneven regional development strategy.

It is not surprising that Suining, a poor county in 1978, still remained to be poor in 2002 as a result of cumulative causation. But for Kunshan, originally a lower region of Suzhou, why did it rank first in 2002? According to the above empirical results, the probability of Kunshan moving upward is only 5.7%, even lower than that of Suining (6.2%). One important answer to the rapid economic growth observed in Kunshan lies in the spread effects generated by growth poles. Traditional Markov chain, due to not considering spatial interaction between regions, cannot explain the spatial mechanism of the process of regional convergence or divergence.

3.2 Spatial-temporal Dynamics

3.2.1 Spatial and temporal transitions

Spatial Markov matrix offers much more information regarding the transitions of regions and the possible association between the direction and the rate of the transitions and the geographic context faced by each region. The results of conditioning the transition probabilities on the spatial lag of a given region in Jiangsu at the beginning of each year are reported in Table 3.

Some evidences can be seen. First, regional context plays an important role in the dynamics of regional convergence. That is to say, the neighbors of a region influence its transitions over time. Obviously, the transition probabilities of a region with different neighbors are different. If the regional context did not matter, then the five conditional matrices in Table 3 would be the same, and each would equal to the traditional Markov matrix in Table 2. The fact is evidently not the case. Second, different regional contexts play different roles in the transitions of a region. Specifically, if a region is adjacent to richer regions, the possibility of moving upward will increase. Otherwise, the possibility of moving upward will decrease if it is contiguous to relatively poorer regions. For example, the probability of a poor region moving out of the bottom averages 6.2% ignoring regional context (cell [1, 2] of Table 2), while it increases to 18.4% if it is proximate to rich regions and drops to 3.3% when it is surrounded by poor neighbors. Similarly, the richest region ignoring regional context moves to the next lowest per capita GDP class with a probability of 1.5% (cell [5, 4] of Table 2). However, the probability decreases to 1.2% if it is surrounded by other rich regions and increases to 3.0% if the neighbors are poor regions. Third, the possibility of a region moving upward or downward is not proportional to the difference between a region and its neighbors. For a poor region, the probability of upward moves increases by 5.6% when it

Table 3 Spatial Markov matrix (annual) for per capita GDP classes conditioning on its spatial lag at county level in Jiangsu (1978–2000)

Spatial lag	t_0	n	t_1				
			P (%)	L (%)	M (%)	U (%)	R (%)
P	P	481	96.7	3.3	0	0	0
	L	84	19.1	80.9	0	0	0
	M	6	0	0	83.3	16.7	0
	U	9	0	0	33.3	55.6	11.1
	R	67	0	0	0	3.0	97.0
L	P	183	90.2	9.8	0	0	0
	L	186	9.7	86.0	3.8	0.5	0
	M	10	0	30.0	50.0	20.0	0
	U	2	0	0	0	100.0	0
	R	105	0	0	0	0	100.0
M	P	13	84.6	15.4	0	0	0
	L	44	6.8	77.3	15.9	0	0
	M	16	0	25.0	50.0	18.8	6.2
	U	6	0	0	33.3	16.7	50.0
	R	31	0	0	0	3.2	96.8
U	P	11	81.8	18.2	0	0	0
	L	45	2.2	93.3	4.5	0	0
	M	15	0	6.7	46.7	26.6	20.0
	U	8	0	0	25.0	75.0	0
	R	30	0	0	3.3	3.3	93.4
R	P	38	81.6	18.4	0	0	0
	L	82	7.3	82.9	8.5	1.3	0
	M	23	0	13.0	60.9	17.4	8.7
	U	25	0	0	12.0	64.0	24.0
	R	174	0	0	0	1.2	98.8

is surrounded by middle regions compared with lower neighbors, while it only increases by 0.2% when contiguous to rich neighbors in comparison with upper ones. For a rich region, the probability of a downward move does not change much wherever its poor or middle neighbors surround it. This may reflect that the influence of neighboring regions on a rich region is not as significant as that of relatively rich neighbors on a poor region.

Finally, these empirical results illustrate a spatial explanation to those convergence clubs in Jiangsu detected in the traditional and a-spatial analysis of Markov chain since poor regions are negatively affected by being co-located with other poor regions, while rich regions are positively affected when rich neighbors surround them. Specifically, the probability of being the same class for a poor region surrounded by poor neighbors is 96.7% compared with 93.8% on average (cell [1, 1] of Table 2). Similarly, for a rich region with rich neighboring units, the probability of being in the same class increases to 98.8% compared with 98.3% on average (cell [5, 5] of Table 2).

When considering the spatial effects of neighboring regions in the process of regional development, the prosperity of Kunshan can be explained to a large extent. The probability of Kunshan's upward moves has greatly increased from 5.7% ignoring regional context (the sum of cell [2, 3] and [2, 4] of Table 2) to 15.9% being surrounded by middle neighbors (cell [2, 3] of Table 3 with its spatial lag of "M"). What's more, once Kunshan and its neighbors evolve into a higher class, the upward probability will increase to 46.6% (the sum of cell [3, 4] and [3, 5] of Table 3 with its spatial lag of "U"). Here, the trickle-down effect of growth poles has been observed in the spatial Markov matrices. Undoubtedly, Kunshan City has been benefited a lot from this beneficial effect due to adjacency to other more developed cities, such as Suzhou and Shanghai. Conversely, the probability that Suining moves up has decreased from 6.2% ignoring regional context (cell [1, 2] of Table 2) to 3.3% being surrounded by poor neighbors (cell [1, 2] of Table 3 with its spatial lag of "P"). It suggests that the relative position of Suining in the cross-sectional distribution is highly constrained by its geographic environment.

3.2.2 Spatial patterns

To summarize the overall amount of change in the per capita GDP class distribution at the county level in Jiangsu, Table 4 reports the movement of each region from its initial per capita GDP class to that in 2002. From this table, the change in the per capita GDP distribution in Jiangsu over this period is dramatic. The number of regions higher than 125% of the provincial average doubled from 11 to 22, while that of regions lower than 65% of the provincial average hardly varied, just decreased by 1 from 34 to 33 at the end of the period. Moreover, there were 22 regions experiencing upward mobility from a lower per capita GDP class to a higher class. Among them, more than half of the regions (12) moved to richer clubs. At the same time, there were 10 regions experiencing downward moves over the time.

Table 4 Per capita GDP class transitions at the county level in Jiangsu in 1978 and 2000

	t_{1978}	t_{2000}				
		P	L	M	U	R
P	34	25	5	2	2	0
L	29	8	10	1	0	10
M	1	0	0	0	0	1
U	2	0	1	0	0	1
R	11	0	0	1	0	10
Total	77	33	16	4	2	22

Fig. 1 provides visual evidence that regional transitions in Jiangsu over the period are spatially clustered. Specifically, the 22 regions moving upward are mainly located in the southern and central Jiangsu with only one region (Suqian) in the northern Jiangsu; whereas those 10 regions moving downward are almost found in the northern Jiangsu. When considering the movements of a region's neighbors, those spatial patterns displayed in Fig. 1 are further strengthened in Fig. 2. Among 22 regions experiencing upward moves, 10 regions with their neighbors moving upward are unexceptionally found in the southern Jiangsu, while the downward moves of regions or their neighbors are almost located in the northern Jiangsu.

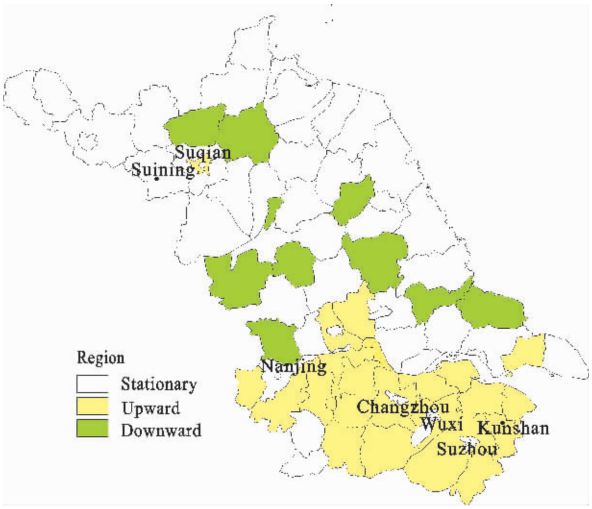

Fig. 1 Spatial patterns of per capita GDP class transitions in Jiangsu (1978–2000)

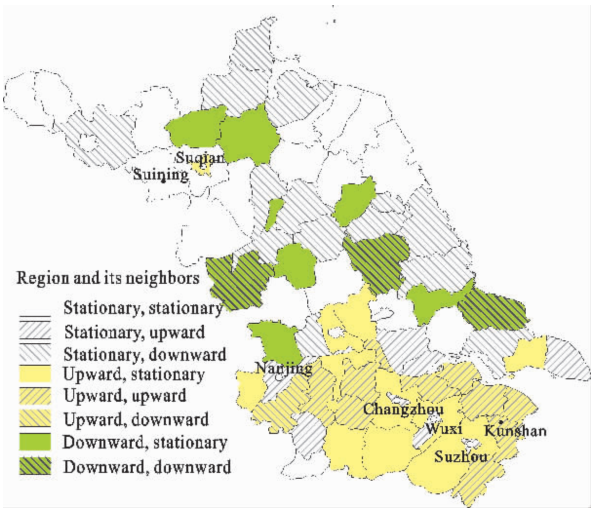

Fig. 2 Spatial patterns of per capita GDP class transitions concerning neighbors in Jiangsu (1978–2000)

The spatial patterns of per capita GDP class transitions in Jiangsu between 1978 and 2000 can be further confirmed by a formal spatial autocorrelation test. Statistical inference on the spatial randomness of per capita GDP class transitions is based on the conditional permutation approach with 999 random permutations of the regions. There is very strong evidence of spatial autocorrelation in the upward transitions when not considering the movements of neighbors, but the case is not for downward transition, since the null hypothesis of no spatial autocorrelation in the upward transitions is rejected (p-value is 0.0001). In contrast, when considering the movements of neighbors, regional transitions for upward or downward moves are significantly autocorrelated across space (p-values are 0.0000).

Geographic concentrations of regional upward and downward transitions indicate that the process of regional convergence in Jiangsu have been characterized by two convergence clubs. Broadly speaking, separated by the Changjiang (Yangtze) River, those regions on the south can be considered as the rich convergence club, while those areas on the north the poor convergence club. The nature of regional convergence clubs in Jiangsu is the spatial manifestation of regional disparities. That is, the unbalanced regional development across space has resulted in spatial polarization (ZHEN *et al*., 2000; OU and GU, 2004). Since the economic reforms of 1978, the well-developed regions in the southern Jiangsu have taken advantages of their preferential locations as well as preferential policies to stimulate economic growth. By now, these developed regions have exerted two distinct forces on their neighbors. One is the beneficial influence produced by growth centers. The booming of Kunshan is a good example. The other is the polarizing effect, since these geographically dependent areas join into a big core area to absorb factors, capital and labor from the periphery, that is, to a large extent, those regions in the northern Jiangsu. The regional polarization in Jiangsu increases with the widening of the regional economic difference (OU and GU, 2004).

Without the rapid economic growth in the northern Jiangsu, there will be no feasibility of turning the entire province into a whole "well-off" society. Under the framework of regional common development strategy in Jiangsu, it is extremely urgent to cultivate several growth poles in the northern Jiangsu to reduce the process of regional divergence and eventually promote regional growth in Jiangsu.

4 CONCLUSIONS

This paper applies the recently developed spatial Markov chain approach to analyzing the spatial-temporal evolution of regional convergence in Jiangsu over the time from 1978 to 2000. Empirical results indicate that the process of regional convergence in Jiangsu is characterized by two different convergence clubs: one converges to the rich, and the other to the poor. The nature of regional convergence in Jiangsu since 1978 is the process of spatial polarization. Although traditional

Markov matrix has shown that there exist two convergence clubs, it can not provide any information on the spatial mechanism of regional convergence due to supposing regions are geographically independent. Spatial Markov chain method solves this problem by considering each region's geographic neighbors.

Growth or development poles are often encouraged to establish in our practice to promote regional economic growth according to Growth Pole theory. In our empirical analyses, the diffusion or trickle-down effect of much more developed regions is indeed observed because a region's possibility of moving upward increases when adjacent to its richer neighbors. But simultaneously, polarization effect at a larger spatial scale is also found in that these growth poles are spatially clustered into a great core area in the southern Jiangsu. Even under regional common development strategy implemented in 1994, the persistence of spatial polarization in Jiangsu will be anticipated since the initial advantages and disadvantages will be maintained by circular and cumulative causation. In order to promote the regional development between the northern and southern Jiangsu in a harmonized way, it is necessary to cultivate growth poles in the northern Jiangsu.

In addition, several issues deserve further attention. First, the robustness of empirical results should be tested under different specifications of spatial weight matrix since spatial Markov chain is the extension of local spatial statistics. Second, the temporal stability of the convergence process in Jiangsu over the whole period should also be verified since China made it explicit in 1992 that the objective of its reforms was to establish a system of socialist market economy.

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