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Research Article

Analysis on the Spatial-Temporal Dynamics of Financial Agglomeration with Markov Chain Approach in China

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The standard approach to studying financial industrial agglomeration is to construct measures of the degree of agglomeration within financial industry. But such measures often fail to exploit the convergence or divergence of financial agglomeration. In this paper, we apply Markov chain approach to diagnose the convergence of financial agglomeration in China based on the location quotient coefficients across the provincial regions over 1993–2011. The estimation of Markov transition probability matrix offers more detailed insights into the mechanics of financial agglomeration evolution process in China during the research period. The results show that the spatial evolution of financial agglomeration changes faster in the period of 2003–2011 than that in the period of 1993–2002. Furthermore, there exists a very uneven financial development patterns, but there is regional convergence for financial agglomeration in China.

1. Introduction

Economic agglomeration is the single most dominant feature of industrial location patterns throughout the modern world. Empirical evidence brings out that industries are highly clustered in a limited number of regions or cities. The literature on measuring specialization and concentration in economic geography and spatial economics has been dramatically expanding in the last twenty years. Mori and Smith [1, 2] developed procedures for identifying spatial patterns of industrial agglomeration. Mori and Smith [3] applied the methodology to the case of manufacturing industries in Japan and shown a more detailed spatial representation of agglomeration patterns. Haedo and Mouchart [4] provided a fresh look at the measurement of concentration and specialization using the perspective of stochastic independence in the analysis of contingency tables. Haedo and Mouchart [5] developed new statistical and computational methods for the automatic detection of spatial clusters. In terms of empirical work, a substantial number of studies on industrial agglomeration have been published in the recent decades. Some of them have proposed indices of industrial agglomeration that allow testable comparisons of the degree of agglomeration among industries (see Duranton and Overman [6] and Mori et al. [1]). The results of these works suggest that industrial agglomeration is far more ubiquitous than previously believed and extends well beyond the traditional types of industrial agglomeration (such as information technology industries and manufacturing industries). Moreover, the degree of such agglomeration has been shown to vary widely across industries. However, few researches exploit the degree of agglomeration for financial industries.

Among the profound evolutions in development economics in recent decades has been the renewed interest in the role of financial systems in economic development. For example, Beck [7] proposed that the finance has a more important impact on growth through fostering productivity growth and resource allocation than through pure capital accumulation. Commendatore and Purificato [8] studied the impact of the degree of regional financial development on the spatial distribution of economic activity. Empirical research on the determinants of financial development encounters a similar model uncertainty problem to that on economic growth. New economic geographic (NEG) theories assume a continuing clustering and higher levels of concentration in the financial industry due to local embeddedness, network, face-to-face communication, knowledge spillovers, and spatial proximity for the organization of the industry (see Levine [9], Storper and Venables [10], and Cooper [11]). Generally, a financial center is a city where financial activities are concentrated. Financial service firms only serve customers within the cities and in adjacent areas. Despite the development of information technology during the last decades, contemporary definitions of financial centers have a clear spatial component. Among these factors, we think that geographical distance plays a key role, since it prevents to equalize credit conditions across regional financial market. Moreover, geographical distance not only affects credit decisions of banks but also their decisions to enter in a new market by opening a new branch; Felici and Pagnini [12] show that the empirical evidence is consistent with a strong negative correlation between geographical distance and entry decision.

Research has focused on the locational determinants of financial development and its influence on economic growth, but the extent to which financial development builds up across regions, leading to convergence or divergence, is rarely examined. The issue of divergence or convergence in regional financial development location is of interest, as financial development has assumed critical importance to economic growth of China. The purpose of this paper is to analyze the location of financial agglomeration across the regions of China from 1993 to 2011 in order to investigate divergence or otherwise. It is investigated in the framework of Markov chains, which is advantageous given the well-known difficulties of the β-convergence approach [13]. The Markov approach is appropriate as agglomeration is a dynamic process that implies transition in the regional financial agglomeration level.

We studied the spatial characteristics and the driving force of the financial agglomeration location by analyzing the panel data of the financial agglomeration for 31 provinces from 1993 to 2011 with Markov chain models. Our results showed that the financial agglomeration in each province exhibits convergence. In the periods from 1993 to 2002, the financial agglomeration is mainly distributed in economic-developed eastern coastlands such as Zhejiang, Guangzhou, and Jiangsu provinces. However, financial agglomeration in China shows the tendency to shift from the coastal regions to inland regions from a long time. This shows that the central and western regions of China have the potential to become the new financial agglomeration center.

The paper begins in the next section by considering the data and regional financial agglomeration location pattern. Section 3 briefly outlines the nature of the Markov approach, Section 4 conducts the Markov analysis, and Section 5 concludes.

2. Data

The dataset is a balanced panel consisting of 31 provinces of China from 1993 to 2011. The data are collected from various

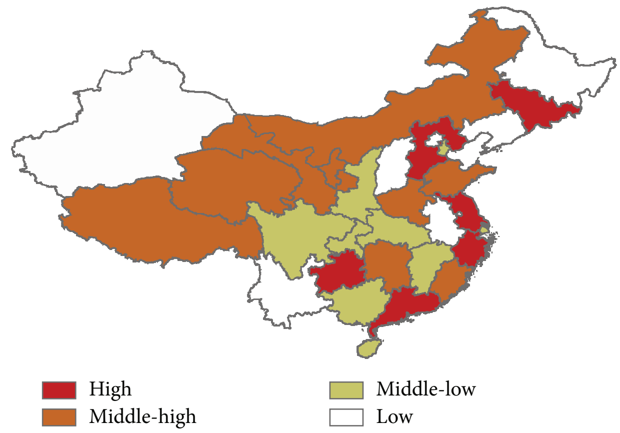

FIGURE 1: Spatial distribution for the degree of financial agglomeration based on province data in China in 1993.

issues of the Statistical Yearbook of China and the Provincial Statistical Yearbook. In order to identify the presence of clusters, scholars have developed a number of metrics from simple concentration ratios such as location quotients (LQ) to summary metrics for spatial concentration (e.g., Gini, Herfindahl, entropy, or Ellison-Glaeser indices). For the purposes of detecting industrial specialization, the simple LQ remains the metric of choice. The location quotient is an easy to use and often used indicator for identifying the clustering of financial industry [14, 15]. The LQ for a subregion i can be shown as follows:

$$\mathrm{LQ}_i = \frac{E_{i,r}/E_r}{E_{i,n}/E_n}, \tag{1}$$

where $E_{i,r}$ denotes financial industry employment in subregion r, E_r denotes overall employment in subregion r, $E_{i,n}$ denotes financial industry employment in region n, and E_n denotes overall employment in region n. A LQ above 1 (below 1) indicated an employment share of the observed industry above (below) the average. Values above one are therefore often interpreted as indicators for a cluster because of the concentration of the employment [15]. The financial LQ based on province data in China are classified into four different classes (low, middle-low, middle-high, and high). The dynamic distribution of financial agglomeration level across China from 1993 to 2011 is shown in Figures 1–3.

Figure 1 indicates that there is a distinction between the eastern and western regions. By observing the map of China, it can be easily found that financial resources in China concentrated in coastal provinces with developed economy except for Guizhou province. This implies that variables like geographic location and economies have internal causality with the spatial distributions of financial agglomeration in 1993.

From Figure 2, we can observe some changes in financial agglomeration spatial pattern at 2002. As the development of economic, the patterns and locations of financial agglomeration have also undergone profound changes, with new features displayed in its spatial layout in China. As can be seen from Figure 2, the degree of financial agglomeration in

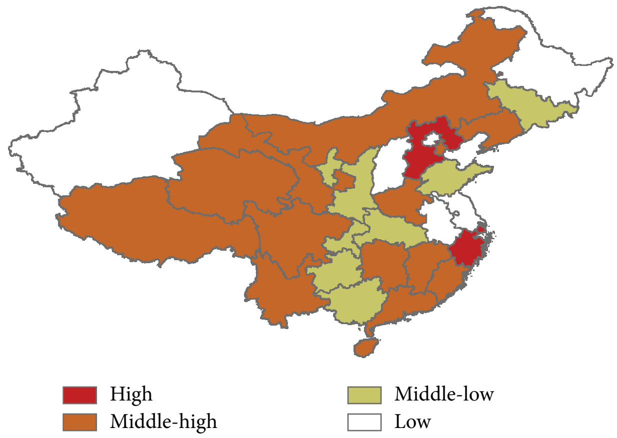

Figure 2: Spatial distributions for the degree of financial agglomeration based on province data in China in 2002.

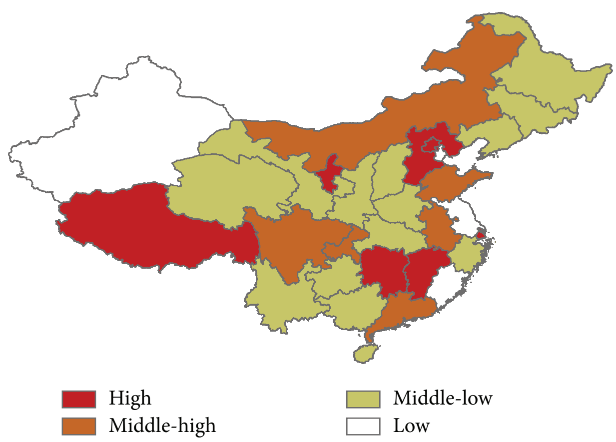

Figure 3: Spatial distributions for the degree of financial agglomeration based on province data in China in 2011.

coastal provinces in 2002 is still high but decreases when compared with 1993 in some provinces, such as Zhejiang. However, with the improvement of financial agglomeration in China, financial agglomeration in the central regions is still at an adjustment and optimization stage.

From 1993 to 2011, financial agglomeration in China shows a tendency to shift from the coastal regions to inland regions, with the financial agglomeration level decreased in Fujian and Zhejiang and Jiangsu provinces, but increased in central and western regions of Hunan, Jiangxi, Xizang, and Ningxia provinces. This shows that the central and western regions of China have the potential to become the new agglomeration center for financial development. The shift of financial agglomeration to the central region and western region lie in the implementation of the western development strategy and the rise of central China plan, which make financial agglomeration continuously tilt to the central and western regions of China.

3. Methodology

Markov chain methods are often used to examine convergence in per capita incomes [16]. However, we know of no attempt to use these methods to examine the dynamics of banking location, so that this represents a novel and important contribution to the paper. The issues at stake are whether China regions have diverged or converged in their financial agglomeration over time, and how it varies by time space.

For the total number of financial agglomeration located at the provincial level we consider the distribution of financial agglomeration across regions $r = 1, 2, \ldots, R$, at each time $t = 0, 1, 2, \ldots$. The basic approach is to specify a vector of state probabilities that represent the probability that an economy will be a member of a particular financial agglomeration class in a given year, which specifies the probability that an economy that was in state i in time period t ends up in state j in the next time period. Assuming there are N such classes and T such periods. Let T be any countable set, referred to as time. A sequence of random variables $(X_t)_{t\in T}$, where $X_t \in S$, is called a discrete time stochastic process with state S. A probability distribution $\pi = (\pi_i)_{i\in S}$ over S is called initial distribution if

$$\Pr[X_0 = i] = \pi_i, \quad \forall i \in S. \tag{2}$$

A stochastic process X satisfying the Markov condition

$$\begin{aligned} \Pr[X_t = i_t \mid X_{t-1} = i_{t-1}, \ldots, X_0 = i_0] \\ = \Pr[X_t = i_t \mid X_{t-1} = i_{t-1}] \end{aligned} \tag{3}$$

for all $t \in T$ is called a discrete time Markov chain.

The dynamics of the evolution of the financial agglomeration distribution are represented by the transition probability matrix with elements p_{ij}. In the basic Markov model the transition probabilities are assumed to be time invariant. A Markov chain X is called time invariant if the equality $\Pr[X_t = j \mid X_{t-1} = i] = \Pr[X_{t'} = j \mid X_{t'-1} = i]$ holds for all times $t, t' \in T$ and all state pairs $i, j \in S$. It then allows us to define

$$p_{ij} = \Pr[X_t = j \mid X_{t-1} = i]. \tag{4}$$

As the (1-step) transition probability is moving from state i to state j. This obviously induces a matrix

$$P = (p_{ij})_{i,j\in S}. \tag{5}$$

For all $t \in T$, where $\pi(0)$ is the initial distribution, P is the transition probability matrix that is of dimension $N \times N$. We denote a time invariant Markov chain X with initial distribution π and the transition matrix P by $M(P, \pi)$. The transition matrix can be estimated by a maximum likelihood (ML) approach. Assume that there is only one transition period, with the initial distribution n_i/n being given, and let n_{ij} denote the empirically observed absolute number of transitions from i to j. Then, maximize

$$\ln L = \sum_{i,j=1}^{N} n_{ij} \ln p_{ij}, \quad \text{s.t.} \sum_i p_{ij} = 1, \quad p_{ij} \geq 0. \tag{6}$$

Table 1: Markov transition probability matrix for financial agglomeration at the province level in China.

Periods	Class	Initial distribution	L (%)	ML (%)	MH (%)	H (%)	Limiting distribution
1993–2011	L	0.25	**90.99**	9.01	0.00	0.00	0.1641
	ML	0.25	4.49	**80.49**	14.61	0.00	0.3220
	MH	0.25	0.00	13.40	**81.82**	4.78	0.3560
	H	0.25	0.00	0.00	10.99	**89.01**	0.1579
1993–2002	L	0.25	**93.30**	6.70	0.00	0.00	0.1921
	ML	0.25	4.50	**81.10**	14.40	0.00	0.2861
	MH	0.25	0.00	10.00	**86.40**	3.60	0.4119
	H	0.25	0.00	0.00	13.50	**86.50**	0.1099
2003–2011	L	0.25	**88.20**	11.80	0.00	0.00	0.1442
	ML	0.25	4.50	**80.70**	14.80	0.00	0.3780
	MH	0.25	0.00	17.20	**76.80**	6.00	0.3253
	H	0.25	0.00	0.00	12.80	**87.20**	0.1579

The elements p_{ij} of M can be defined as follows:

$$\widehat{p}_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}, \qquad (7)$$

where n_{ij} is the sum of areas when i type at t moment and j type at $t+1$ moments. $\widehat{p}_{ij}$ is the asymptotically unbiased and normally distributed maximum likelihood estimator of p_{ij}. The standard deviation of the estimators can be estimated as

$$\widehat{\sigma}_{\widehat{p}_{ij}} = \left(\frac{\widehat{p}_{ij}\left(1-\widehat{p}_{ij}\right)}{n_i} \right)^{1/2}, \qquad (8)$$

where n_i is the sum of areas being in state i in all of studying periods of time. Obviously, the reliability of estimated transition probabilities depends on two aspects. First, the data-generating process must be Markovian, that is, to meet the assumptions of Markov chain theory (Markov property, time invariance). Otherwise, the estimators $\widehat{p}_{ij}$ are not allowed to be interpreted as Markov transition probabilities and cannot be used to derive a stationary distribution. And second, the estimates have to be based on a sufficiently large number of observations. Otherwise, the uncertainty of estimation is too high to allow for reliable inferences.

The Markov approach supposes that for a region in class i at time $t-1$ there is a transition probability $p_{ij}(t) = \Pr[X_t = j \mid X_{t-1} = i]$ of it being in class j at time t, where $i, j \in N$, $p_{ij}(t) \geq 0$ and $\sum_i p_{ij}(t) = 1$. With this assumption the state vector period t can be mapped into the state vector for period $t+1$ as

$$\pi_{t+1} = P\pi_t. \qquad (9)$$

Comparison of π with the initial distribution $\pi(0)$ reveals if there is convergence, divergence, or possibly neither. Thus, if $\pi_i < \pi_i(0)$ in the middle-low and middle-high classes but $\pi_i \geq \pi_i(0)$ in low and high classes, it suggests divergence, and conversely there is convergence. On the other hand, if $\pi_i < \pi_i(0)$ in the middle-low and low classes but $\pi_i \geq \pi_i(0)$ in middle-high and high classes, it suggests a somewhat higher probability of moving up the financial agglomeration level than that of moving down, and conversely it is right.

4. Empirical Results

4.1. Markov Transition. In order to observe the transition behavior of financial agglomeration spatial patterns over time, we calculate the traditional Markov transition probability matrix for classes of financial agglomeration at the province level in China from 1993 to 2011. Broadly, this involves portioning the overall study period into two subperiods. The first subperiod is from 1993 to 2002 and the second subperiod is from 2003 to 2011. The initial distribution is uniform by construction. Table 1 depicts the 4×4 Markov transition matrix and the limiting distribution for the whole China. Comparing the limiting distribution to the initial distribution, the limiting distribution shows somewhat higher probabilities in the middle-high and middle-low classes and somewhat lower probabilities in the high and low classes. It indicates that there has been a rather convergence across the China provinces during the last about two decades.

Several points can be inferred from Table 1. Firstly, the transition possibilities on the main diagonal are relatively high. If the financial agglomeration in a region is in the ith class, the probability of being in the same class the year after is at least 76.80% at the second stage and at most up to 93.30% at the first stage, which suggests that the interannual variation of financial agglomeration was little during the period of research. On the other hand, the transition probabilities on the main diagonal in the second stage are lower than that of the first stage. It implies that the transition probability between class i and class j increases after 2002. It implies that the spatial distribution of financial agglomeration at the province level in china changes faster at the second stage than that of the first stage.

Secondly, there is no obvious moving among different classes from year to year. The elements on the nondiagonal are extremely less than the diagonal, and the more deviation from main diagonal is, the smaller the value is. In the whole studying periods, the biggest transition probability among different classes is 14.61%, which occurs in the transition from middle-low class to middle-high class. At the first stage, the biggest transition probability among different classes is 14.40%, which occurs in the transition from middle-low class to middle-high class. At the second stage, the biggest transition probability among different classes is 17.20%, which occurs in the transition from middle-high class to middle-low class. On the whole, for middle-low class regions, the upward transfer probability is greater than the opposite direction one except for the second stage, but for the middle-high class it is converse; the downward transition from high class is larger than that of upward transition from low class. In a word, the financial development in China has been promoted.

Comparing the limiting distribution with initial distribution, several points can be inferred. In the period of 1993 to 2011, the limiting probability is less than initial probability for middle-high and high classes, but the limiting probability is higher than initial probability for low and middle-low classes. Moreover, the probability transition characteristic of the subperiod of 2003 to 2011 is similar to that of the subperiod of 1993 to 2002. We can conclude that there is convergence for financial agglomeration in China region.

The estimated transition matrix offers more detailed insights into the mechanics of this evolution process. Generally, a financial center is a city where financial activities are concentrated. Financial service firms only serve customers within the cities and in adjacent areas. Despite the development of information technology during the last decades, contemporary definitions of financial centers have a clear spatial component. In general, the more the economy develops, the higher degree of the financial agglomeration is. The unbalanced economic pattern brings about the imbalanced distribution of financial development. The high degree of spatial concentration in the financial sector illustrates the importance of local embeddedness, network, face-to-face communication, knowledge spillovers, and spatial proximity for the organization of the industry. These effects are well illustrated by considering the spatial effects of transportation costs in simple "core-periphery" models of industrial location.

4.2. Regional Mobility and Time Homogeneity. Convergence may be associated with a smooth flow of financial agglomeration to the regions in which it was previously underrepresented, or it might be accompanied by relatively large changes in the regional financial agglomeration, suggesting a high degree of mobility in regional location. It is worthy of closer inspection. Clearly, the leading diagonal of P is interesting, and it is investigated by the using of the Shorrocks' (1978) Index as follows:

$$\mathrm{SI} = \frac{N - \operatorname{tr} P}{N}, \tag{10}$$

where $N = 4$ and $\operatorname{tr} P$ is the trace operator of P. SI has a minimum value of zero when $P = I$ so there is no mobility, but $\mathrm{SI} = 1$ when the leading diagonal has zeros. The Shorrocks Index SI is calculated based on the transition matrices in Table 1. Overall, $\mathrm{SI} = 0.1442$ for the whole study period, which indicated some reasonable degree of mobility. Moreover, $\mathrm{SI} = 0.1317$ for the first stage and $\mathrm{SI} = 0.1677$ for the second stage, which implied that the mobility of the second stage is larger than that of the first stage.

Furthermore, there are several properties of Markov process that can be tested for in the context of a data set pooled across several periods of time and several regions. The high degree of mobility of regions across classes indicated by the Shorrocks index suggests convergence may not be a stationary process, and that it varies over time. The time homogeneity of the transition probabilities for the Markov process was examined by using the Pearson χ^2 test statistic.

First, homogeneity over time (time-stationarity) can be checked by dividing the entire sample into T periods, and testing whether or not the transition matrices estimated from each of T subsamples differ significantly from the matrix estimated from the entire sample. Broadly, this involves portioning the overall study period into a finite number of subperiods $k = 1, 2, \ldots, Q$ estimating a transition matrix of each of these, and then for each row of each matrix, $i = 1, 2, \ldots, N$ for each subperiod, comparing the transition probabilities $p_{ij}(k)$ with that for the period as a whole p_{ij}. Let A_i denote the nonzero transition probabilities in the ith row and $n_{ij}(k)$ the number of regions transiting from class i to j in subperiod k. In particular, it tests $H_0 : \forall k,\ p_{ij}(k) = p_{ij},\ k = 1, 2, \ldots, Q$ against the alternative of transition probabilities differing between periods: $H_1 : \forall k,\ p_{ij}(k) \neq p_{ij}$. Then an asymptotically equivalent test statistic for the likelihood ratio test statistic is given by

$$\begin{aligned} T_\chi &= 2 \sum_{k=1} \sum_{i,j} n_{ij}(k) \left[\ln\left(\hat{p}_{ij}(k)\right) - \ln\left(\hat{p}_{ij}\right)\right] \\ &\sim asy\chi^2 \left(N(Q-1)(N-1)\right), \end{aligned} \tag{11}$$

where T_χ has an asymptotic Chi-square distribution with degrees of freedom equal to the number of $N(Q-1)(N-1)$. If this test is rejected, the process cannot be assumed to be time-homogeneous. To examine time homogeneity, two subperiods are chosen, 1993–2001 and 2003–2011 (i.e., $Q = 2$). The likelihood ratio test statistics is $T_\chi^* = 22.4325$ and $\chi^2_{0.99} = 26.217$, which indicates that time homogeneity is accepted at the 1% level. It indicates that the process is time-homogeneous.

5. Conclusions

The purpose of this paper is to investigate the location of financial agglomeration across the regions of China over 1993 to 2011. It is the first time that the issue of financial agglomeration location has been analyzed in the framework of Markov chains. The estimation of Markov transition probability matrix offers more detailed insights into the mechanics of financial agglomeration evolution process in China during the research period. In the periods from 1993 to 2002, the financial agglomeration is mainly distributed in economic-developed eastern coastlands such as Zhejiang, Guangzhou, and Jiangsu provinces. However, financial agglomeration in China shows the tendency to shift from the coastal regions to inland regions from a long time. This shows that the central and western regions of China have the potential to become the new financial agglomeration center. Moreover, we can conclude that there is convergence for financial agglomeration in China region.

Based on the provincial financial agglomeration data from 1993 to 2011, we make an analysis on the spatial dynamic evolution characteristics of financial agglomeration and then draw the following conclusion. Firstly, although the regional concentration rate of financial sector decreases currently, it still remains relatively high. And the effect of financial agglomeration on the eastern coastal areas is not very obvious. Secondly, as the regional policies of China give different priorities in different periods, making spatial evolutions of interregional financial agglomeration obviously difference in patterns. Although the spatial evolutions of financial agglomeration are complex, they have their own specific patterns no matter in the process of agglomeration or distribution. Thus, we can see that, only by adapting to economic laws rather than simply relying on the regional competitive preferential policy, the government can seek a coordinated development among various regions in the long term, if the government hopes to induce financial resources to transfer their investment from developed regions to the backward regions to narrow the economic gap. Besides, we find that the new economic geography and geographical factors play an important role in determining the distribution and spatial evolutions of financial agglomeration. And this can also serve as reference for policy making. In the process of attracting financial agglomeration in backward regions and accelerating the economic development, different regions should make full use of their geographical advantages and take the initiative in the industrial gradient transfer; especially, the labor-intensive industries transfer according to their own industrial foundation.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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