Spatial Autocorrelation Analysis of Regional Direct Input Coefficients in China

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Abstract

The direct input coefficient is fundamental in the input-output(IO) model, reflecting the technical level of an economic system. Plenty of empirical studies have confirmed that there is significant spatial correlation of economic and technological innovation in China, but few scholars use the method of spatial econometrics to study direct input coefficients. Based on the theory and method of spatial autocorrelation, this paper selects key direct input coefficients from provincial IO tables to test the spatial correlation in three consecutive sessions(2002, 2007, 2012), makes a detailed analysis of manufacturing sectors characteristics and data characteristics for these direct input coefficients which present spatial autocorrelation. It is found that the relative geographical position is one of the influencing factors of direct input coefficients in China. The main contribution of this paper is helping researchers analyze the decision-making mechanism of direct input coefficients from the spatial perspective and improve the method to update IO tables.

Key words: Direct input coefficients; Spatial Correlation; Moran's I

1. BACKGROUND

The direct input coefficient, manifesting of the technical and economic relations among departments, is the core parameter of the input-output model. The researches on direct input coefficients mainly focus on the analysis of timing variation, the selection and determination of main coefficients, the updating and revision of coefficients and so on. As for the time series analysis, Zaman et al. (2010) verified the input-output coefficient of stability from the timing level, based on input-output tables of Romania in 2000 and 2006. Wang et al. (2010) used five input-output tables to analyz the changes of China's input-output tables during 1987-2005 from the perspectives of the stability and variability of coefficients, intermediate input ratio, intermediate usage ratio and changes of the direct input coefficient. In the selection of the main coefficients, Forssell (1989) chose Finnish input-output table as the research object, selected the key coefficients to research technological changes among industries. Shuntaro et al. (2000) took input-output tables of 45 countries and regions as the research object and selected direct input coefficients of key sectors to study the influence of population density, total output, energy consumption and other factors on the direct input coefficient. In terms of updating and revising coefficients, some scholars studied the process of coefficient changes by improving the compilation method and estimated the input-output matrix of different technical structures in a given year (Avelino,2017; Richard,2011; Ali,2000). Jiang (2011) improved the region's input-output tabulation method of non-investigation based on the single input-output coefficient of the table.

Although the research results of the direct input coefficient are relatively abundant, few scholars study the relationship between direct input coefficients of different regions from the perspective of space. The direct input coefficient reflects the technical and economic characteristics of the department's production activities. Do geographically closer regions, whose technical and economic characteristics are closer as a result of their interactions with each other, have closer direct input coefficients? From the perspective of the First Law of Geography, everything is related to everything else, but near things are more related than distant things.

In econometrics, spatial dimension is being paid more attention than before. By adding the normative descriptions of spatial relativity and spatial heterogeneity, hypothesis testing and setting to the classical econometric models, theories and methodologies of spatial econometrics have been formed and are used in the research widely (Anselin,1988). Some scholars used the theory and method of spatial autocorrelation to calculate the global spatial autocorrelation index and the local autocorrelation index in each province of China, revealing the evolution mechanism and law of carbon emission (Wu, 2015; Fu et al. 2015). Some scholars established a spatial econometrics model to analyze the impact of FDI on the environmental pollution in China (Jessie et al. 2006). Fischer et al. (2003), Li et al. (2010) used spatial metrology technology to study the spatial correlation of regional innovation. Long (2003) used the model of space lag to examine roles of labor, capital, FDI and other factors in the economic growth of China, pointing out that there was a strong mutual influence between regions in China's economic growth. Based on the result of Long, Han combined the spatial econometrics model with panel analysis method to study the coordinated development of the provincial economic growth and affected factors in China. A large number of empirical studies on the spatial correlation of economic, environmental and technological innovation in China's provincial administrative regions all show that the spatial correlation among regions is significant.

Based on above researches, it can be expected that the direct input coefficient that reflects the economic and technological characteristics of regions will also be spatially related to some degree. Confirmation and estimation of such a correlation have great significance both for a clearer understanding of inter-regional linkages at the industrial level to analyze the decision-making mechanism of direct input coefficients, and for the formulation and updating of regional input-output tables. China also possesses a regional input-output table with the same statistical size and comparatively high comparability, which provides a good data foundation for space research. Therefore, this paper introduces the theory and method of spatial autocorrelation into the input-output analysis innovatively and study the spatial correlation of direct input coefficients of different sectors in various provincial administrative regions in China. We also attempt to analyze the spatial effects of direct input coefficients and changes of them in detail and give economic explanations for spatial correlation.

The remainder of this paper is arranged as follows: In Section 2, a spatial autocorrelation measurement method of direct input coefficients in a region is defined. Section 3 determines the scope of direct input coefficients to study and analyzes spatial features of key coefficients. Section 4 selects direct input coefficients of different spatial effects, summarizes and extracts the typical characteristics in different spatial models. Section 5 concludes the work.

2. SPATIAL AUTOCORRELATION MEASUREMENT

The indexes that characterize spatial autocorrelation mainly include Moran’s I, Geary's C as well as Getis-Ord. Because of the fixed range, it is convenient to visually judge the characteristics and intensity of the spatial correlation by Moran’s I. Therefore, this index is commonly used in literatures to measure the spatial autocorrelation (Wu 2015; Fu et al. 2015; Li et al. 2010). Based on the results of scholars and the excellent features of Moran’s I, we select it to test the spatial correlation of direct input coefficients in this paper.

Moran's I can be regarded as the correlation coefficient of an observation and its spatial lag, and it can be divided into global Moran's I and local Moran's I. Since this paper focuses on the aggregation of direct input coefficients across the nationwide space, the following discourse is based on the global Moran's I (all described below as the Moran's I). The range of Moran's I is from -1 to 1. If the observations of all regions show the positive spatial autocorrelation, that larger observations are gathering, meanwhile, the smaller have similar phenomenon, the value of Moran's I will be between 0 and 1. On the contrary, if the observations present the negative spatial autocorrelation, that the larger and the smaller is clustering, the Moran's I is between -1 and 0. The closer the absolute value of Moran's I to 1, the stronger the spatial autocorrelation of observations.

The first step in spatial correlation analysis is to choose a scientific method to measure the spatial distance among regions, and spatial weighting matrix is used to characterize the distance between regions. The spatial weighting matrix is usually constructed according to adjacency relation of regions.. At this stage, in necessary aspects of the manufacturing industry, such as the technological development, resource endowment and traffic condition, all the neighboring provinces in China have coordinated development or complementarity in each other's advantages. The economic and technological linkages between neighboring provinces are even closer. Based on the spillover effect and economic competition pattern among neighboring provinces in China, and considering the coordinated development of regional economy, the provincial space weighting matrix is constructed in this paper. We assign a value of 1 to all provinces which are contiguous with the aimed province and assign a value of 0 to these non-adjacent provinces.

3. EXISTENCE TEST OF SPATIAL AUTOCORRELATION

3.1 Filter key coefficients

The main data sources used in this paper are the 2002, 2007 and 2012 regional IO table for China to calculate direct input coefficients. The evaluation includes all provinces in mainland China except Tibet. Due to a large number of direct input coefficients, we need to select key t coefficients for spatial autocorrelation in order to avoid the occasional fluctuation of smaller numerical factors disturbing the result and ensure the representativeness of the research object. A single rule, that a key coefficient is larger than 0.05 in two of the three years in national tables, has been adopted for choosing key coefficients.. This paper focuses on the manufacturing industry. Therefore, at least one of the departments belonging to industry should be retained, and the direct input coefficient that satisfies the above conditions is the research object of this paper. After calculations, 67 coefficients satisfy the rule.

Table 1 shows 16 coefficients with significant spatial autocorrelation among the 67 direct input coefficients tested by the 5% significance level. In the time dimension, there are 7 coefficients showing spatial autocorrelation in 2002, the largest number in 2007, with 11 coefficients showing spatial correlation, and 8 coefficients showing spatial autocorrelation in 2012. In spatial dimension, most of the coefficients show positive spatial autocorrelation, and the absolute value of Moran's I concentrates between 0.2 to 0.3. This shows that the relative geographical location effects direct input coefficients of some departments, but the impact is limited. In general, the coefficients that have appeared spatial autocorrelation in the three years accounted for 23.88%(16/67). The direct input coefficient has a certain degree of spatial autocorrelation in China and deserves further attention and research.

TABLE 1. Direct Consumption Coefficient with Spatial Autocorrelation

	Moran's I	p-value	Moran's I	p-value	Moran's I	p-value	Moran's I	p-value
KC	a2,11		a6,6		a7,21		a12,20	
2002	0.221	0.016	0.286	0.008	0.237	0.010	0.162	0.045
2007	0.196	0.027	0.349	0.004	0.335	0.001	0.223	0.021
2012	0.181	0.050	0.352	0.001				
KC	a1,7		a12,12		a13,13		a19,18	
2002								
2007	0.205	0.029	0.299	0.003	0.266	0.005	0.229	0.018
2012	0.284	0.004	0.396	0.000	0.222	0.020	0.24	0.010
KC	a12,36		a14,16		a14,21		a3,11	
2002	0.188	0.041	0.285	0.005	0.224	0.021		
2007							0.254	0.010
2012								
KC	a7,7		a12,21		a6,29		a14,14	
2002								
2007	0.210	0.030	0.376	0.000				
2012					-0.210	0.025	0.309	0.002

(Sector codes are listed in appendix.)

3.2 Interpretations and explanations

In this part, we analyze sectoral characteristics and other data characteristics of the direct input coefficient with spatial autocorrelation features, give economic interpretations for the spatial autocorrelation.

As for sectors, firstly, four sectors, the chemical products, metal smelting and rolling processing, food and tobacco and textile are more likely to have geographical and economic spatial connection, in which numbers of coefficients showing spatial autocorrelation are larger than the overall average 23.88%(16/67). 4 coefficients from sector chemical products present significant results in the test of spatial autocorrelation, accounting for 26.67% of all 15 coefficients whose row sector belongs to chemical products. Meanwhile, 3 coefficients from sector metal smelting and rolling processing accounting for 37.50% of 8 same-sector coefficients, 2 coefficients from sector food and tobacco accounting for 50% of all four coefficients, 2 from sector textile accounting for 66.67% of all three coefficients show familiar results. That means, neighboring provinces have more similar structure of consumption to the above four departments. Secondly, there are 16 diagonal coefficients among all 67 direct input coefficients, and five of them show spatial autocorrelation characteristics, accounting for 31.25%, while this proportion in different row and column sectors is 21.57%. That means, in the current industrial layout and market structure, there is a spatial self-correlation between the manufacturing sector and the consumption of its own products.

TABLE 2. Main Sectors with the Spatial Autocorrelation

No.	Sector	Numbers		Proportion
		Key Coefficients	Spatial autocorrelation	
6	Food and tobacco	4	2	50.00%
7	Textile	3	2	66.67%
12	Chemical products	15	4	26.67%
14	Metal smelting and rolling processing	8	3	37.50%

As for numerical characteristics, the mean of the medians among 16 spatial autocorrelation coefficients is 0.1703, while the mean of the medians among other non-spatial autocorrelation coefficients is 0.1034. The key direct input coefficient which shows spatial autocorrelation feature has larger value. In addition, among 16 coefficients showing significant spatial autocorrelation, 13 of them are greater than 0.05 in all three statistical years and only three have medians which are less than 0.05. We can make a preliminary judgment that the spatial correlation of direct input coefficient is related to the value itself. The larger direct input coefficients, the easier they show spatial dependencies and correlations.

4. SPATIAL AUTOCORRELATION PATTERN ANALYSIS

In general, provincial data of direct input coefficients show three spatial correlation patterns. They are positive spatial autocorrelation, negative spatial autocorrelation and spatial irrelevance. In this paper, we select representative direct input coefficients of these three spatial correlation patterns and analyze their characteristics. To maintain the consistency of the time dimension, we choose representative direct input coefficients from the same year. a6,29 presents negative spatial autocorrelation in 2012, which is regarded as the representative of negative autocorrelation coefficient in space. a6,6 has the largest value of Moran's I in 2012, so it is chosen as the representative of positive spatial autocorrelation. The Moran's I of a18,16 is the closest to 0 and its test is not significant, so a18,16 represents the space-independent coefficient.

Features of the spatial correlation can be observed by the Moran scatterplot. The abscissa of Moran scatterplot is the value of the direct input coefficient from provinces, the ordinate is the spatial lag of this coefficient. Spatial lag is the weighted average of adjacent values of a variable in space, and Moran's I is the slope of the regression line about this scatterplot. The Moran scatterplot divides the spatial pattern into four quadrants. The spatial attributes of regions which stand in the first or the third quadrant are positive autocorrelation, and the other two quadrants mean negative spatial autocorrelation.

Figures below are Moran scatterplots of three coefficients(left) by GeoDa and colored maps classified according to quantiles by ArcGIS (data of Tibet and Taiwan are filled with 0). By observing the three sets of graphs, characteristics of the three spatial patterns can be summarized:

a6,6 shows positive spatial autocorrelation, so the regression line in the Moran scatterplot tilts to the upper right with positive slope, and most of data is distributed in the first and third quadrants. There are 22 points at the first and third quadrants in the Moran scatterplot, accounting for 64.71% of all data. On the colored map, except the value of Xinjiang, values of coefficient a6,6 larger than the mean are concentrated in the eastern and central provinces in the spatial distribution and are adjacent to each other. The smaller coefficients are mainly concentrated in the central, western and northeastern regions of China.

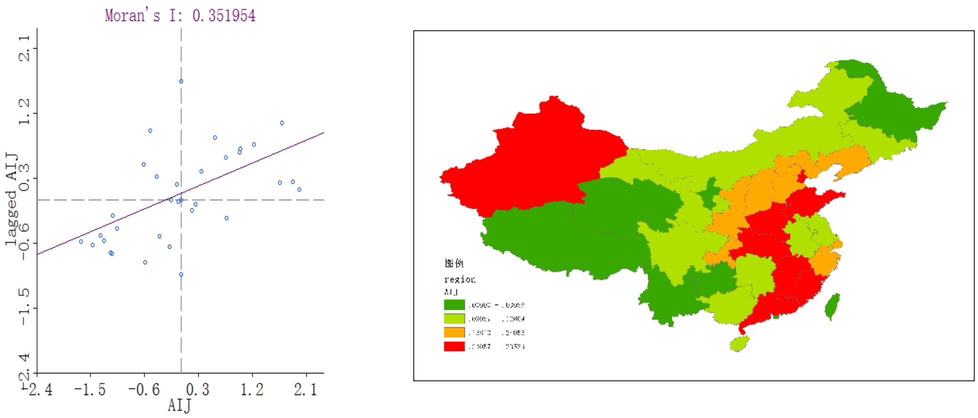

FIGURE 1. Moran scatterplot and colored map of a6,6

a6,29 shows negative spatial autocorrelation, so the regression line in the Moran scatterplot is downward sloping. There are 20 points at the second and fourth quadrants in the Moran scatterplot, accounting for 58.82% of all data, and there is no point in the third quadrant. According to the colored map, although larger values of a6,29 appear to accumulate in some provinces, all provinces whose coefficients are larger than the average have at least one neighboring province whose coefficient is less than the average. The numerical distribution of a6,29 in space is consistent with the Moran scatterplot.

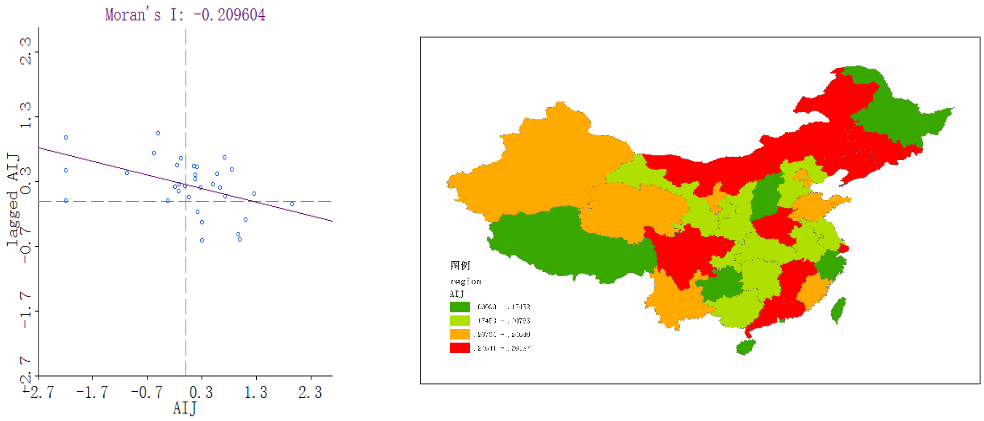

FIGURE 2. Moran scatterplot and colored map of a6,29

Values of a18,16 from provinces do not present spatial relevance. The regression line in the Moran scatterplot is similar to a horizontal ray, and data present a random distribution of irregularity. There is no trend of scatter points, with 15 points at the first and third quadrants in the Moran scatterplot, while 19 points at the second and fourth quadrants. Coefficients greater than the average with those less than the average show staggered distribution, no any regular information reflecting.

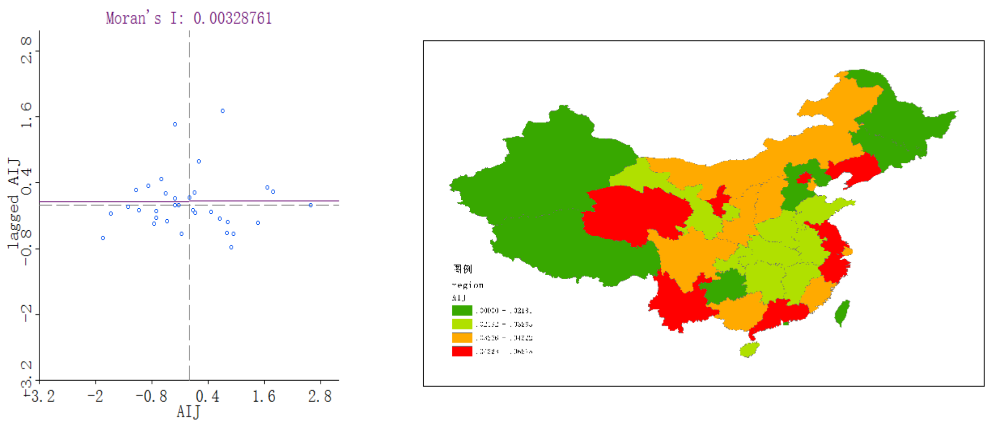

FIGURE 3. Moran scatterplot and colored map of a18,16

5. CONCLUSION

In this paper, we have tested the spatial direct correlation carried out on 67 important direct input coefficients of input-output tables, analyze departmental characteristics and data characteristics of these direct input coefficients showing the spatial autocorrelation, and summarize different spatial patterns. It is found that out of these 67 direct input coefficients accepted spatial autocorrelation tests, 16 coefficients show spatial correlation in at least one statistical year, accounting for 23.88% of the total number of samples. It shows that under the existing market environment and industrial structure, the relative geographical position is one of the factors that affect the direct input coefficient. The spatial correlation violates the hypothesis that explanatory variables in the traditional econometrics are strictly independent and the residual disturbance is independent and distributed identically, so we should establish relevant spatial econometric models to explain the influence factors of the regional differences about direct input coefficients.

We also found that the spatial correlation of the direct input coefficient is related to the row sector and the value of a coefficient itself. An analysis of the 16 coefficients with spatial correlation found that, across the country, sectors chemical products, metal smelting and rolling processing, food and tobacco and textiles in industrial production are more likely to have economic linkages in space. The manufacturing sector is easier to link to the consumption of its own products spatially. In addition, these key direct input coefficients which show spatial autocorrelation features have larger scales. And it is found that the most of 16 coefficients showing significant spatial autocorrelation have larger median scales. From this, we can make a preliminary conclusion that the spatial correlation of the direct input coefficient is related to the value itself, and the larger the direct input coefficient, the easier it shows spatial dependencies and correlations.

There is room for further research in this paper. Factors influencing the direct input coefficient are various, such as the technology, management, the internal product structure of a sector and the price movement. Why do some direct consumption factors show the spatial correlation? What is the relationship between these factors above and the spatial correlation of direct input coefficients? How does the relative geographical location affect direct input coefficients? All of these will be further explored in the following study.

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Appendix

TABLE A.1. Sectors after adjustment

No.	Sector	No.	Sector
1	Agriculture and agricultural services	21	Other manufacturing
2	Coal mining products	22	Scarp processing
3	Oil and gas products	23	Production and supply of electricity and heat
4	Metal mining	24	Gas production and supply
5	Non-metallic mining	25	Water production and supply
6	Food and tobacco	26	Construction
7	Textile	27	Wholesale and retail
8	Textile, leather and feather products	28	Transportation, storage and postal service
9	Wood products and furniture	29	Accommodation and catering
10	Paper, printing, stationery and sporting goods	30	Information transmitting, software and IT service
11	Petroleum, coking and nuclear fuel processing	31	Finance
12	Chemical products	32	Real estate
13	Non-metallic mineral products	33	Rental and business service
14	Metal smelting and rolling processing	34	R&D and technical service
15	Metal Products	35	Education
16	General and special equipment	36	Health and social work
17	Transportation equipment	37	Sports and entertainment
18	Electrical machinery and equipment	38	Public management, social security and social organizations
19	Communication, computer and other electronic equipment	39	Others
20	Instrumentation		