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Measuring and Spatio-Temporal Evolution for the Late-Development Advantage in China's Provinces

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Abstract: The coordinated development of regional economies is a major economic goal of many countries around the world. To that end, China has actively carried out a series of strategies to expedite the development of its late-developing regions. This study explores the issues raised by this coordinated development from the perspective of late-development advantages, which refer to a region's late-development advantages compared with the early-developing regions in the country. The 15 indicators applied for evaluating the late-development advantages fall into five categories including capital, technology, industrial structure, institutions and human resources. Then, the model of entropy-weighted technique for order preference by similarity to an ideal solution (EW-TOPSIS) is applied to evaluate the late-development advantages of China's provinces. Following this, ArcGIS and GeoDa are used to analyze the spatio-temporal evolution pattern of the late-development advantages of China's provinces, and to compare the spatio-temporal effect of these advantages between the provinces. The results show that the overall late-development advantages of China's provinces had a downward trend from 2006 to 2015, with the Eastern Region falling by 8.07%, the Central Region falling by 14.37% and the Western Region falling by 8.05%, indicating that the development gap between China's Eastern and Western Regions is still large. The temporal effect analysis shows the temporal autocorrelation changes from positive status to negative status with the increase of lagging order, which means the trend of late-development advantage will reverse over time. The spatial effect analysis shows there were only significant Low-Low and Low-High aggregation in 2006 and 2010, but significant High-High and High-Low aggregations emerge in 2012 and 2015, implying that the development environment has effectively promoted the use of the provincial late-development advantage. The research results could provide theoretical basis for the policy making of the accelerating development of late-developing regions in China.

Keywords: late-development advantage; spatio-temporal pattern; EW-TOPSIS; spatio-temporal effect; coordinated development

1. Introduction

As a major developing country, China has been in the economic pattern of 'Eastern strong and Western weak' for a long time, which means the development of Eastern regions are faster than the Western regions in China. Although the economic strength of Eastern, Central and Western regions in China has significantly been improved, there is still a big gap between the different regions. According to China's National Bureau of Statistics, the proportion of total economic output in the Eastern Region of China remained stable at around 57% from 1995 to 2015, consistently higher than the sum of the total economic output of the Central and Western regions. Therefore, accelerating economic development in the Central and Western regions, narrowing the development gap between the Eastern Regions and other regions, and realizing a coordinated economic development strategy across these three major regions have become a priority for the country. Due to the effects of geographical location, resource endowments and institutional structure, the speed of economic development differs greatly across China's regions, and thus forming 'early-developing' regions and 'late-developing' regions. The 'early-developing' regions are areas with early and high levels of development, leading or ahead of the development stage across the country, such as the Eastern regions of China. 'Late-developing' regions are those with late and low levels of development, such as China's Central and Western regions.

In 1962, Alexander Geschenkron, an American economic historian, proposed the theory of 'late-development advantage' (*LDA*) for the first time, arguing that the latter is a special advantage possessed by countries that are in a relatively late-developing state of development and in the process of industrialization. This kind of advantage is neither something that preemptive countries can possess, nor is it created by late-developing countries through their own efforts. Rather, it is completely symbiotic with the status of backward development [1]. Geschenkron's hypothesis of late-development advantage lays a theoretical foundation for late-developing countries to catch up with the preemptive countries.

In the same vein, Levy, an American economist, specifically analyzed the advantages of late-developing countries compared to the early-development countries in the process of modernization, which includes the aspects of recognition, technology, development stage, development path and seeking external aid. On the other hand, the disadvantages of a country's backwardness that coexist with the late-development advantage were also pointed out [2]. A related theory of "chasing hypothesis" based on the late-development advantage considers both the perspective of labor productivity and unit capital earning. A country's economic development speed is inversing to its initial economic development level. In addition, from the perspective of the late-development advantage of Japan compared to Europe and the USA in the 1960s, Japanese scholar [3] analyzed the motivations behind the great success achieved by Japan during its industrialization process, and the results verified the hypothesis of Geschenkron's theory of late-development advantage.

In recent years, many researchers [4–9] have conducted empirical studies on the theory of late-development advantage and obtain abundant results. Emst et al. [10] researched the impact of standards on the economic development of late-developing countries, and found that the latecomer countries should adopt assessment standards that are more fitted with themselves, which emphasized learning effects and building dynamic capabilities. Perkins et al., used event-history analysis to estimate the determinants of diffusion speed across a large panel of developed and developing countries for the technologies of continuous steel casting, shuttleless textile weaving looms and digital telephone mainlines. The results indicate that countries adopt new technology later or have a smaller existing capital stock diffuse new technology more rapidly than countries that adopt earlier or have more installed capacity [11].

Moreover, since China is the biggest developing country and has enormous late-development advantage, many scholars [12,13] divide their energy into the theory research of late-development advantage. Cai et al., took Chongqing, China as an example, analyzed the development model of Chongqing which is beyond late-development advantage model [14]. Xiao et al., proposed a theoretical framework for understanding late-comer firms' technology and predicting its outcome [15]. Wu et al., explored the new late-development advantage implied in the phenomena of overshooting and nonconsuming, and found that latecomer firms can successfully introduce disruptive technologies from advanced economies into emerging economies through secondary business-model innovations [16].

Previous studies [17–19] on countries' late-development advantage have mainly focused on exploring the specific advantages themselves, while paying little attention to the quantitative evaluation of late-development advantage. The quantitative evaluation of regional late-development advantage is a multi-index and comprehensive evaluation problem, whereby the comprehensive evaluation lies in the overall judgment of multi-attribute systems [20,21]. In other words, according to the given conditions, a certain method is used to judge the quality of the objects affected by a variety of factors. At present, there exist numerous multi-index comprehensive evaluation methods, such as the data envelopment analysis (DEA) model [22], principal component analysis (PCA), analytic hierarchy process (AHP) [23–25], and the fuzzy comprehensive evaluation method [26] among others. These methods contain strict restrictions and requirements, including the number of indexes, sample capacity and data distribution. In contrast, the TOPSIS method does not have the same limitations. Therefore, it is widely used either when having a small data sample and multiple objectives, or in the case of a large information system consisting of many modules. Moreover, this method can fully harness the raw data with less information loss and can compare specific evaluation objects either across space or time [27,28]. At the same time, the TOPSIS model employs the method of entropy weights, which can determine the weight of each index, comprehensively reflect the information implied in the data, and enhance the resolution significance and differences of the indicators, so as to avoid difficulties of analysis due to the small difference in the selection index [29].

The development of the regional will not only be affected by the resources, policies and technologies, etc., that we usually consider, but also by various factors in previous years. The effect of factors in previous years can be called the temporal effect, which is often quantitatively studied by temporal autocorrelation. Temporal autocorrelation originates from the relevant theoretical research of autoregression, which is widely used in the prediction of economics [30], informatics [31] and natural phenomena. Lanne et al., modeled the U.S. inflation by noncausal autoregressive models and found it shown a purely forward-looking dynamic [32]. Hyvärinen et al., illustrated how to combine the non-Gaussian instantaneous model with autoregressive models and proposed computationally efficient methods for estimating the model, as well as methods to assess the significance of the causal influences [33]. The *LDA* also has temporal effect, i.e., the current *LDA* of a region will have an impact on the region's future economic development. Therefore, it is necessary to quantitatively study the temporal effect of *LDA* by temporal autocorrelation.

Meanwhile, the economic development of the late-developing regions does not occur on its own, and is bound to be affected by neighboring regions. The power generated by the late-development advantage will not only promote rapid economic development in the late-developing regions, but also affect the speed of economic development in adjacent regions. Therefore, it is necessary to analyze the spatial effect of these late-development advantages. The most common method employed for spatial effect analysis is the spatial autocorrelation analysis. The method originated in biometric studies [34,35] and has become one of the basic methods of theoretical geography today. Due to the development of GIS technology, spatial autocorrelation analysis technology has also been fully developed and has become a core tool for spatial statistical analysis. Its application fields include geology [36], ecology [37,38], environmental detection [39] and epidemics [40], among others. For example, Peng et al., used geo-statistics combined with statistical analysis to study the spatial distribution of soil moisture in the dry season, in accordance with four vegetation types in southwest China [41]. Betts et al., compared the advantages and disadvantages of the spatial model and the common statistical model by simulating data of species distribution [42].

In sum, the previous studies [43–51] mainly used qualitative methods to study both the meaning and manifestation of late-development advantages. Such as Guo et al., consider the *LDA* from the perspective of development factors, and believe that China still has capital and technological *LDA* compared with developed countries [44]. Jian et al., believe that developing countries have *LDA* in technology introduction, institution innovation, structural change and human resources [49]. However, these studies are difficult to be operated, and lack a quantitative evaluation of late-development advantages. So, according to the existing scholars' researches on the *LDA* and uncoordinated status of China's provincial and regional development [50,51], we establish a measuring indicator system to evaluate the *LDA* of 31 provinces in the mainland of China from 2006 to 2015, which has 5 first-level indicators (capital, technology, industrial structure, institution and human resources) and 15 second-level indicators. Then the entropy weight TOPSIS (EW-TOPSIS) model is used to evaluate the late-development advantage of the provinces. Based on the data, we use ArcGIS to analyze the evolution of the spatial-temporal pattern of late-development advantage among Chinese provinces, and use coefficient of variation (CV) to explore the difference of regions' and provinces' *LDA*. Meanwhile, temporal autocorrelation coefficient and Moran's *I* are used to analyze the spatio-temporal effect of *LDA*. Based on the results, corresponding suggestions are then put forward to aid the coordinated development of China's regional economy. The specific research framework is shown in Figure 1.

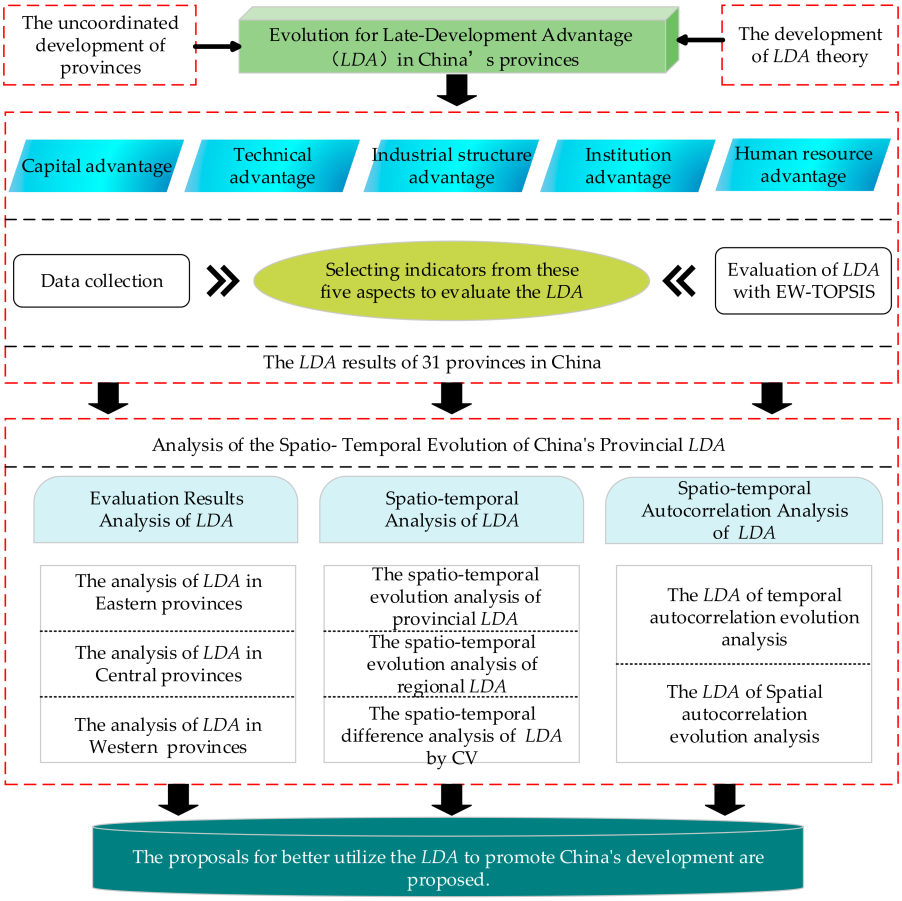

Figure 1. Research technology route.

The remainder of this paper is structured as follows. Section 2 describes the measuring index system and data source, the EW-TOPSIS model, the analysis method of temporal and spatial autocorrelation. Section 3 applies the proposed method to evaluate the late-development advantages of provinces in China, and analyzes the latter's spatial-temporal evolution patterns and the temporal autocorrelation as well as spatial autocorrelation among the regions' late-development advantages. Finally, Section 4 concludes the paper and highlights recommendations emerging from the research.

2. Indicators Selection and Methodology

2.1. Indicators Selection

Some scholars have made a lot of researches about the *LDA* in different aspects [43–51], Guo et al., consider the *LDA* from the perspective of development factors, and believe that China still has capital and technological *LDA* compared with developed countries. Jian et al., believe that developing countries have *LDA* in technology introduction, institution innovations, structural change and human resources. Comprehensively considering these aspects and China's development status, we hold that the late-development advantage can be evaluated from five aspects of capital, technology, industrial structure, institutions and human resources, which constitute the first-level indicators. Based on these indicators, we further decompose them into 15 second-level indicators (see Table 1) which can reflect the first-level indicators. The source of the selection of these indicators is shown in Figure 2. According to these previous researches of *LDA* (Figure 2), we briefly explain the selection of the first-level and second-level indicators.

Table 1. Evaluation indicators of late-development advantage.

First-Level Indicators	Second-Level Indicators	Calculation Formula	Properties
Capital advantage	X_1: Growth rate of the ratio of Fixed Asset Investment to GDP (%)	$X_1 = \left(\frac{FAI_t}{GDP_t} \div \frac{FAI_{t-1}}{GDP_{t-1}} - 1\right) \times 100\%$	Positive
	X_2: Growth rate of Fixed Asset Investment (%)	$X_2 = \frac{FAI_t - FAI_{t-1}}{FAI_{t-1}} \times 100\%$	Positive
	X_3: Growth rate of capital formation rate (%)	$X_3 = \left(\frac{TI_t}{GDP_t} \div \frac{TI_{t-1}}{GDP_{t-1}} - 1\right) \times 100\%$	Positive
	X_4: Foreign investment growth rate (%)	$X_4 = \frac{TFI_t - TFI_{t-1}}{TFI_{t-1}} \times 100\%$	Positive
Technical advantage	X_5: Growth rate of patent ownership per 10,000 people (%)	$X_5 = \left(\frac{NP_t}{P_t} \div \frac{NP_{t-1}}{P_{t-1}} - 1\right) \times 100\%$	Positive
	X_6: Patent Growth Rate (%)	$X_6 = \frac{NP_t - NP_{t-1}}{NP_{t-1}} \times 100\%$	Positive
	X_7: Change rate of technological innovation level (%)	$X_7 = \left(\frac{ERD_t}{GDP_t} \div \frac{ERD_{t-1}}{GDP_{t-1}} - 1\right) \times 100\%$	Positive
Industrial structure advantage	X_8: Industrial development speed (%)	$X_8 = \frac{IVA_t - IVA_{t-1}}{IVA_{t-1}} \times 100\%$	Positive
	X_9: Growth rate of share of primary industry in GDP (%)	$X_9 = \left(\frac{VAP_t}{GDP_t} \div \frac{VAP_{t-1}}{GDP_{t-1}} - 1\right) \times 100\%$	Negative
	X_{10}: Growth rate of industrial development level (%)	$X_{10} = \left(\frac{\lvert RPI_t - RSI_t\rvert + \lvert RSS_t - RSI_t\rvert}{\lvert RPI_{t-1} - RSI_{t-1}\rvert + \lvert RSS_{t-1} - RSI_{t-1}\rvert} - 1\right) \times 100\%$	Positive
Institutions advantage	X_{11}: Change rate of degree of marketization (%)	$X_{11} = \left(\frac{FC_t + SC_t + OC_t}{FAI_t} \div \frac{FC_{t-1} + SC_{t-1} + OC_{t-1}}{FAI_{t-1}} - 1\right) \times 100\%$	Positive
	X_{12}: Change rate of openness to the outside world (%)	$X_{12} = \left(\frac{TIE_t}{GDP_t} \div \frac{TIE_{t-1}}{GDP_{t-1}} - 1\right) \times 100\%$	Positive
Human resources advantage	X_{13}: Growth rate of percentage of working-age population (%)	$X_{13} = \left(\frac{EP_t}{P_t} \div \frac{EP_{t-1}}{P_{t-1}} - 1\right) \times 100\%$	Positive
	X_{14}: Growth rate of average labor cost (%)	$X_{14} = \frac{WEU_t - WEU_{t-1}}{WEU_{t-1}} \times 100\%$	Negative
	X_{15}: Population growth rate of high school education and above (%)	$X_{15} = \frac{HP_t - HP_{t-1}}{HP_{t-1}} \times 100\%$	Positive

Serial number	Author	Indicators	Year of the literature
1	Caselli F and Feyrer J	Capital advantage	[2007]
2	LA. and Yang Zhen ning, et al.	Technical advantage	[1991,1993]
3	Wang Y and Guo X	Industrial structure advantage	[2008]
4	PB Doeringer	Institutions advantage	[2011]
5	Yao O,Hou G and JIAN Xin Hua	Human resources advantage	[2016,2009,2002]

Figure 2. The sources of late-development advantage indicators.

The *LDA* of capital is mainly derived from the marginal diminishing returns [43]. Developed regions are rich in capital, while late-developing regions have little capital, so the marginal return on capital of late-developing regions is higher than that of developed regions. This will lead to more capital flowing to the late-developing regions and thus forming the *LDA* of capital. The *LDA* of capital can be decomposed into 4 indicators of X_1, X_2, X_3 and X_4. The indicator of X_1 is the growth rate of the ratio of Fix Asset Investment (*FAI*) to Gross Domestic Product (*GDP*), which can reflect changes of fix assets in capital structure. The indicators of X_2, X_3 and X_4 are the growth rate of *FAI*, the growth rate of capital formation rate and the growth rate of foreign investment, respectively. They can reflect the speed of capital accumulation. The properties of indicator X_1, X_2, X_3 and X_4 are all positive, indicating that while these indicators increase, the capital late-development advantage is also increasing.

The *LDA* of technology means that late-developing regions can introduce the advanced technologies instead of developing new technologies, which will reduce the costs and shorten development time and thus forming the *LDA* of technology [45,46]. The *LDA* of technology can be decomposed into indicators of X_5 (Growth rate of patent ownership per 10,000 people), X_6 (Patent Growth Rate) and X_7 (Change rate of technological innovation level), and both of them can reflect the speed of technology development. The properties of X_5, X_6 and X_7 are all positive, indicating that while indicators of X_5, X_6 and X_7 increase, the *LDA* of technology is also increasing.

The *LDA* of industrial structure is mainly comes from the industrialization process [47]. In general, the productivity of the industrial sector is the highest in the three industries. Most late-developing regions have not completed the industrialization process. When they finish industrialization, they will accelerate the economic development and thus form the *LDA* of industrial structure. The *LDA* of industrial structure can be decomposed into three indicators of X_8, X_9 and X_{10}. The indicators of X_8 (industrial development speed) and X_{10} (growth rate of industrial development level) can reflect the industrial development level and development speed. The properties of X_8 and X_{10} are positive, indicating that while these indicators increase, the *LDA* of industrial structure is increasing. The indicator of X_9 (growth rate of share of primary industry in *GDP*) can reflect the industrial development stage. The property of X_9 is negative, indicating that while these indicators increase, the *LDA* of industrial structure is decreasing.

The *LDA* of institutions denotes that late-developing regions can learn from and imitate the institutions and policies of developed regions, especially modern market economic institutions and public management institutions, so that they can reduce trial and error costs and time in institution construction and thus form *LDA* of institution [48]. The *LDA* of institution can be decomposed into two indicators of X_{11} and X_{12}. The indicator of X_{11} (change rate of degree of marketization) can reflect the development speed of market institution. The indicator of X_{12} (change rate of openness to the outside world) can reflect the formation speed of opening up institution. The properties of X_{11} and X_{12} are positive, indicating that while these indicators increase, the *LDA* of institution is also increasing.

The *LDA* of human resources is mainly due to the low cost labor force. The late-developing regions usually possess a large amount of low cost labor that can promote the rapid development of labor-intensive industries and thus form the *LDA* of human resource [49,50]. The *LDA* of human resource can be decomposed into three indicators of X_{13}, X_{14} and X_{15}. The indicator of X_{13} (growth rate of percentage of working-age population) can reflect the growth rate of labor force. The indicator of X_{14} (growth rate of average labor cost) can reflect the changes in labor cost. The indicator of X_{15} (population growth rate of high school education and above) can reflect the changes in labor quality. The properties of X_{13} and X_{15} are positive, indicating that while indicators of X_{13} and X_{15} increase, the *LDA* of human resource is also increasing. However, the property of X_{14} is negative, indicating that while X_{14} increases, the *LDA* of human resource is decreasing.

In Table 1, FAI_t is the total social investment of fixed assets in the period t; GDP_t is the Gross Domestic Production of t period; TI_t is the total capital formation of the region; TFI_t is the total foreign investment; NP_t is the number of patents produced by the region; P_t is the population of the area; ERD_t is the expenditure on scientific research activities; IVA_t is the industrial added value in the period t; VAP_t is the first industry added value, and RPI_t, RSI_t and RSS_t account for the proportion of the first, second and third industry in period t, respectively. FC_t is the amount of foreign capital used in the fixed assets investment of the whole society in the period t; SC_t is the amount of self-financing in the fixed assets investment of the whole society in the period t; OC_t is the amount of other investment in the fixed assets investment of the whole society in the period t. TIE_t is the total imports and exports of the region in the period t. EP_t is the number of people aged 15–64 in the period t; WEU_t is the average wage of employees in urban businesses in the period t; and HP_t is the number of people with a high school education in the period t.

The data of the indicators were all collected from the National Bureau of Statistics of the People's Republic of China, which ensures the authority and credibility of the data. In addition, due to miss data in some years, we used the exponential smoothing method to compensate for the missing values of some indicators in individual years. By using the collected data and the formula in the third column of Table 1, the original values of the 15 indicators relating to the late-development advantage of 31 provinces in China from 2006 to 2015 were obtained.

2.2. Research Methods for Calculating the Late-development Advantage

TOPSIS is proposed by Hwang C L and Yoon K in 1981 [52] and is an effective method commonly used to evaluate multi-objective decisions. Although it has been widely used in practical research by scholars [53–58], the traditional TOPSIS method mainly relies on the expert's subjective opinion to determine the weight, which means that the evaluation results may deviate from reality. Therefore, according to the current scholars' research on the weight determination method, this study uses the entropy weight method to determine the index weight, and establishes an evaluation model of entropy weighted TOPSIS (EW-TOPSIS). The EW-TOPSIS model can more objectively reflect the ranking of the late-development advantages of China's provinces. The specific steps of EW-TOPSIS are as follows:

Step 1: Data standardization

The initial evaluation matrix of regional late-development advantage is as follows:

$$X^j = \begin{bmatrix} X_{11}^j & X_{12}^j & \dots & X_{1p}^j \\ X_{21}^j & X_{22}^j & \dots & X_{2p}^j \\ \dots & \dots & \dots & \dots \\ X_{m1}^j & X_{m2}^j & \dots & X_{mp}^j \end{bmatrix} \quad (1)$$

where X^j is the original index value matrix for evaluating the j-th region's late-development advantage, it is composed by the second level indicators in Table 1.

The standardized formulas for positive and negative indicators are shown in Formulas (2) and (3), respectively.

$$y_{it}^{j} = \frac{X_{it}^{j} - \min(X_{it}^{j})}{\max(X_{it}^{j}) - \min(X_{it}^{j})} \tag{2}$$

$$y_{it}^{j} = \frac{\max(X_{it}^{j}) - X_{it}^{j}}{\max(X_{it}^{j}) - \min(X_{it}^{j})} \tag{3}$$

where y_{it}^{j} is the standardized value of i-th index in the t year of the j-th province, which builds up the standardized matrix of the indicator $Y^j = [y_{it}^{j}]_{m \cdot p}$.

Step 2: Establishing the entropy-weight evaluation matrix

According to the information theory, entropy can used to measure the amount of indicator information [59]. Smaller indicator entropy represents a larger amount of information, and thus the weight (i.e., entropy weight) of this indicator should be higher. The calculation method of entropy weight of LDA indicators is as follows:

$$X_{it} = \sum_{j=1}^{n} X_{it}^{j} \qquad i = 1, 2, \ldots, m, \quad t = 1, 2, \ldots, p \tag{4}$$

$$r_{it} = \frac{X_{it}}{\sum\limits_{t=1}^{p} X_{it}} \qquad i = 1, 2, \ldots, m, \quad t = 1, 2, \ldots, p \tag{5}$$

$$e_i = \frac{1}{\ln n} \sum_{t=1}^{p} r_{it} \ln r_{it} \tag{6}$$

$$a_i = \frac{1 - e_i}{\sum\limits_{i=1}^{m} (1 - e_i)} \tag{7}$$

where e_i is the entropy value of indicator X_i, a_i is the weight of index X_i, i.e., entropy weight.

The entropy a_i constitutes the weight vector A, $A = (a_1, a_2, \ldots)^{\mathrm{T}}$. A and the standardization matrix Y^j yield the weighted standardized matrix V^j as the following formula:

$$V^j = A \cdot Y^j = [v_{it}^{j}]_{m \cdot p} \tag{8}$$

where Y^j is standardized matrix of the indicators; v_{it}^{j} represents the i-th indicator of j-th regoin in t-th year. m is the number of indicators; p is the time length.

Step 3: Determining positive and negative ideal solutions of V^+ and V^-

The positive ideal solution of V^+ is the solution with the optimal value of each attribute value, and the negative ideal solution of V^- is the solution with the worst value of each attribute value. V^+ and V^- are calculated as follows:

$$V^+ = \left\{ \max v_{it}^{j} \middle| i = 1, 2, \ldots, m \right\} = \{V_1^+, V_2^+, \ldots, V_m^+\} \tag{9}$$

$$V^- = \left\{ \min v_{it}^{j} \middle| i = 1, 2, \ldots, m \right\} = \{V_1^-, V_2^-, \ldots, V_m^-\} \tag{10}$$

Step 4: Calculating distance

D_t^{j+} and D_t^{j-} the distance from the evaluation vector to the positive and negative ideal solutions of V^+ and V^-, were calculated from Formulas (11) and (12):

$$D_t^{j+} = \sqrt{\sum_{i=1}^{m} (V_i^+ - v_{it}^j)^2} \tag{11}$$

$$D_t^{j-} = \sqrt{\sum_{i=1}^{m} (V_i^- - v_{it}^j)^2} \tag{12}$$

Step 5: Calculating the degree of closeness

The degree of closeness indicates the proximity of the evaluation target to the optimal state. The value range is [0,1]. The larger the value, the stronger the region's late-development advantage is, and the weaker on the contrary. The formula used to calculate the degree of closeness is as follows:

$$C_t^j = \frac{D_t^{j-}}{D_t^{j+} + D_t^{j-}} \tag{13}$$

where C_t^j is the degree of closeness of the region j in the year t, indicating the degree of proximity between the weak late-development advantage and the strongest one in the region j and the year t. We used C_t^j to denote the strength of the late-development advantage of the region j in the year t.

2.3. Temporal Autocorrelation Theory

Temporal autocorrelation originates from the theory of correlation analysis, which means that the correlation between the time series data during a period and another period that lags a certain time. Temporal autocorrelation has different orders, which correspond to different lag times [60–64]. For example, if we had time series data of *LDA* from 2006 to 2015, then the 1st order temporal autocorrelation of this data can be defined as the correlation coefficient between the time series data from 2006 to 2014 and the time series data from 2007 to 2015. Similar to the calculation of the 1st order temporal autocorrelation, the k-th order temporal autocorrelation of *LDA* is calculated as follows:

$$\rho(k) = \frac{R(k)}{R(0)} \tag{14}$$

$$R(k) = \frac{1}{Q-k} \sum_{q=1}^{Q-k} (u_q - \overline{U})(u_{q+k} - \overline{U}) \tag{15}$$

where u_q represents the *LDA* of a certain province in year q, and $\overline{U}$ is the mean value of u. k is the order, $0 \leq k < Q$, and Q is the time length. $\rho(k)$ denotes the k-th order temporal autocorrelation coefficient.

The temporal autocorrelation coefficient $\rho(k)$ can indicate the strength of correlation, but it need to be tested for significance to show whether the correlation is significant. This can be achieved by a t test [65]. The formula is as follows:

$$t = \frac{\rho\sqrt{T-2}}{\sqrt{1-\rho^2}} \tag{16}$$

where ρ represents the temporal autocorrelation coefficient, T is the time length, (T-2) represents the degree of freedom (*df*).

Table 2 shows the correspondence between t-values and p-values.

Table 2. *t*-Values and *p*-values.

Degree of Freedom (*df*)	*t*-Value		
	$p < 0.10$	$p < 0.05$	$p < 0.01$
3	2.353	3.182	5.841
4	2.132	2.776	4.604
5	2.015	2.571	4.032
6	1.943	2.447	3.707
7	1.895	2.365	3.499

Note: In this study, there are 10 years of data, 1st order temporal autocorrelation corresponds to 9 years of data, 2nd, 3rd, 4th, 5th order correspond to 8, 7, 6, 5 years of data. So the corresponding degree of freedom of 1st order temporal autocorrelation is 7, 2nd order is 6, 3rd order is 5, 4th order is 4 and 5th order is 3.

2.4. Spatial Autocorrelation Theory

Tobler's first law of geography points out that things are interconnected, and those that are closer to each other are more closely connected than those that are farther apart. Spatial autocorrelation is an important expression of spatial relevance, referring to the existence of correlation between the research object and its spatial position. Spatial autocorrelation is also an important indicator for testing whether the attribute value of an element is significantly related to the attribute value of its adjacent spatial feature [66]. Spatial autocorrelation is divided into global spatial autocorrelation and local spatial autocorrelation. Global spatial autocorrelation uses a single value to reflect a certain range of autocorrelation. It indicates the average degree of spatial correlation between the region under consideration and its surrounding regions, but cannot fully describe the spatial connection patterns among all units in the region under consideration. Therefore, it is very important to perform a local spatial autocorrelation analysis.

1. Spatial weight matrix

To conduct a spatial autocorrelation analysis, it is necessary to define the spatial adjacency relationship between the research objects and to determine the weight of each spatial unit. The spatial weight matrix is determined either by the adjacency rule or distance rule [67]. We adopted the adjacency rule, i.e., when there is a shared edge or point of spatial unit i and j, then w_{ij} = 1; otherwise, w_{ij} = 0. The spatial weight matrix W is as follows:

$$W = \begin{bmatrix} w_{11} & \dots & w_{1n} \\ \dots & \dots & \dots \\ w_{n1} & \dots & w_{nn} \end{bmatrix} \tag{17}$$

$$w_{ij} = \begin{cases} 1, & spatial\ unit\ i\ is\ adjacent\ to\ j \\ 0, & spatial\ unit\ i\ is\ not\ adjacent\ to\ j \end{cases} \tag{18}$$

2. Global spatial autocorrelation

A global spatial autocorrelation analysis mainly focuses on the spatial distribution characteristics of attribute data of an entire region. Moran's I is one of the most commonly used statistical indicators for detecting global and local spatial autocorrelation [68,69]. Global Moran's I is calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{W_0\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{19}$$

where $\overline{x}$ is the mean of the variable x, x_i and x_j are the values of region i and j on the variable x, w_{ij} is the elements of the weight matrix, n is the number of space units, and W_0 is the sum of all elements of the weight matrix, i.e., $W_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$.

Moran's I generally ranges from -1 to 1. When $I > E(I)$, there is a positive spatial autocorrelation, indicating that there is a regional aggregation with high (or low) variable values. The closer I is to 1, the more significant the aggregation phenomenon. When $I < E(I)$, there is a negative spatial autocorrelation, indicating that there is an aggregation between areas with high variable values and areas with low variable values. The closer I is closer to -1, the more obvious this spatial difference is. When $I = E(I)$, there is no spatial correlation, and the values are spatially random [70].

3. Local spatial autocorrelation

Local spatial autocorrelation mainly analyzes the distribution pattern of each spatial unit, with the ability to measure the degree of local spatial association between each area and its surrounding areas. The commonly used statistic is Local Moran's I_i, calculated as follows:

$$I_i = \frac{x_i - \overline{x}}{s^2} \sum_{j=1}^{n} w_{ij}(x_j - \overline{x}) \tag{20}$$

$$s^2 = \frac{\sum_{j=1}^{n} (x_j - \overline{x})^2}{n-1} - \overline{x}^2 \tag{21}$$

If $I_i > E(I)$, this indicates that there is a positive local spatial autocorrelation between area i and its surrounding areas. The provinces with positive local spatial autocorrelation are distributed in the first and third quadrants of the Moran scatter plot, which represent High-High and Low-Low aggregations, respectively. If $I_i < E(I)$, this means that there is a negative spatial autocorrelation in attributes between area i and its surrounding areas. The provinces with negative local spatial autocorrelation are distributed in the second and fourth quadrants of the Moran scatter plot, representing the Low-High and High-Low aggregations, respectively.

4. Significance test

The significance of global spatial autocorrelation can be verified by z-score [71]. The formula is as follows:

$$z = \frac{I - E(I)}{\sqrt{V(I)}} \tag{22}$$

where $E(I)$ is the expectation value of I, i.e., $E(I) = -1/(n-1)$. $V(I)$ is the variance of I.

Table 3 shows the correspondence between z-scores, p-values and significance levels.

Table 3. z-Score, p-values and significance levels.

z-Score	p-Value	Significance Level
z-score < −1.65 or z-score > 1.65	<0.10	90%
z-score < −1.96 or z-score > 1.96	<0.05	95%
z-score < −2.58 or z-score > 2.58	<0.01	99%

The significance of local Moran's I_i spatial autocorrelation can be verified by permutation test, which is proposed by Fisher in 1930s. The permutation test is a method of recalculating the statistical test value, constructing the empirical distribution by sequentially replacing the samples, and then calculating the p-value based on this to infer the hypothesis. Because it is free to the overall distribution, so it is widely used, especially for small sample data with unknown overall distribution, and some hypothesis testing problems that are difficult to analyze data by conventional methods [72,73]. In this study, the permutation test of local Moran's I_i was done by GeoDa and finally the p-value was output. According to the p-value, we can judge whether the local spatial autocorrelation is significant.

3. Results and Discussions

3.1. Evaluation Results

The evaluation values of Chinese regions' late-development advantages were yielded by EW-TOPSIS. The results are shown in Table 4. The values in Table 4 represent the closeness of *LDA* and ideal *LDA* of each region in different years, while a larger value means greater closeness and a higher late-development advantage. For example, the closeness of Xinjiang in 2006 and 2007 calculated by Formula (13) are 0.436 and 0.419, so the *LDA* of Xinjiang in 2006 is more close to the ideal *LDA* than that in 2007, i.e., the *LDA* of Xinjiang is higher in 2006 than that in 2007.

Table 4. Evaluation of Chinese Regions' Late-development advantages.

Province	Late-Development Advantages Evaluation Values										
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Mean
Beijing	0.386	0.410	0.348	0.404	0.453	0.414	0.390	0.380	0.368	0.399	0.395
Tianjin	0.418	0.423	0.442	0.449	0.442	0.427	0.402	0.400	0.409	0.405	0.422
Hebei	0.425	0.427	0.441	0.423	0.442	0.424	0.423	0.416	0.404	0.414	0.424
Shanxi	0.438	0.461	0.411	0.495	0.453	0.427	0.426	0.424	0.395	0.410	0.434
Inner Mongolia	0.444	0.459	0.429	0.443	0.443	0.427	0.413	0.425	0.393	0.383	0.426
Liaoning	0.452	0.435	0.454	0.403	0.460	0.405	0.409	0.391	0.363	0.314	0.409
Jilin	0.462	0.471	0.457	0.425	0.455	0.378	0.433	0.370	0.408	0.405	0.426
Heilongjiang	0.442	0.441	0.437	0.425	0.468	0.426	0.439	0.405	0.357	0.401	0.424
Shanghai	0.391	0.399	0.372	0.399	0.394	0.424	0.371	0.371	0.375	0.395	0.389
Jiangsu	0.428	0.435	0.428	0.442	0.432	0.416	0.404	0.376	0.383	0.416	0.416
Zhejiang	0.416	0.410	0.402	0.415	0.428	0.415	0.430	0.391	0.395	0.433	0.413
Anhui	0.473	0.481	0.470	0.477	0.494	0.456	0.436	0.424	0.413	0.407	0.453
Fujian	0.429	0.451	0.426	0.418	0.474	0.441	0.427	0.430	0.411	0.433	0.434
Jiangxi	0.445	0.465	0.460	0.447	0.466	0.402	0.409	0.427	0.402	0.446	0.437
Shandong	0.424	0.414	0.426	0.414	0.436	0.398	0.405	0.396	0.395	0.404	0.411
Henan	0.459	0.463	0.456	0.450	0.444	0.408	0.437	0.406	0.407	0.430	0.436
Hubei	0.442	0.435	0.466	0.457	0.474	0.442	0.429	0.406	0.399	0.420	0.437
Hunan	0.458	0.454	0.464	0.441	0.490	0.444	0.427	0.414	0.410	0.421	0.442
Guangdong	0.409	0.418	0.406	0.427	0.445	0.422	0.390	0.413	0.406	0.430	0.417
Guangxi	0.496	0.492	0.476	0.482	0.503	0.437	0.419	0.389	0.418	0.408	0.452
Hainan	0.461	0.472	0.450	0.505	0.442	0.444	0.482	0.452	0.403	0.388	0.450
Chongqing	0.444	0.474	0.432	0.449	0.467	0.461	0.414	0.369	0.418	0.443	0.437
Sichuan	0.470	0.457	0.465	0.492	0.451	0.416	0.423	0.400	0.394	0.377	0.435
Guizhou	0.422	0.426	0.428	0.434	0.457	0.433	0.488	0.458	0.434	0.436	0.442
Yunnan	0.439	0.431	0.447	0.430	0.503	0.409	0.458	0.411	0.425	0.431	0.439
Tibet	0.469	0.355	0.466	0.511	0.437	0.407	0.509	0.419	0.380	0.393	0.434
Shaanxi	0.452	0.466	0.443	0.436	0.478	0.428	0.439	0.431	0.411	0.399	0.438
Gansu	0.432	0.441	0.418	0.435	0.500	0.424	0.438	0.403	0.415	0.443	0.435
Qinghai	0.459	0.476	0.410	0.490	0.453	0.498	0.408	0.437	0.427	0.428	0.449
Ningxia	0.403	0.397	0.478	0.445	0.446	0.401	0.416	0.458	0.459	0.418	0.432
Xinjiang	0.436	0.419	0.451	0.394	0.485	0.451	0.433	0.415	0.415	0.421	0.432
mean	0.439	0.441	0.437	0.444	0.459	0.426	0.427	0.410	0.403	0.411	0.430

Note: the EW-TOPSIS model is programed by MATLAB, then the original 15 indicators of 31 provinces from 2006 to 2015 are put into the program, and the results are obtained.

From Table 4, the annual mean of late-development advantage weakens from 2006 to 2015, indicating that China is gradually making use of the late-development advantage to promote rapid economic development. However, from a local point of view (see Figure 3), the *LDA* in the Eastern, Central and Western regions decreased by 0.034 (8.07%), 0.065 (14.37%) and 0.036 (8.05%), indicating that the major declines in late-development advantage have occurred mainly in the Central provinces. The decline of *LDA* in Eastern and Western regions is relatively small, implying that the development gaps between the Eastern and Western regions of China are still large during the period of 2006 to 2015. Therefore, the coordinated development of the country's regional economy is not optimistic. In order to further understand the specific changes of Chinese regions' late-development advantages, ArcGIS are used to analyze the temporal and spatial evolution patterns of the Chinese provincial late-development advantages.

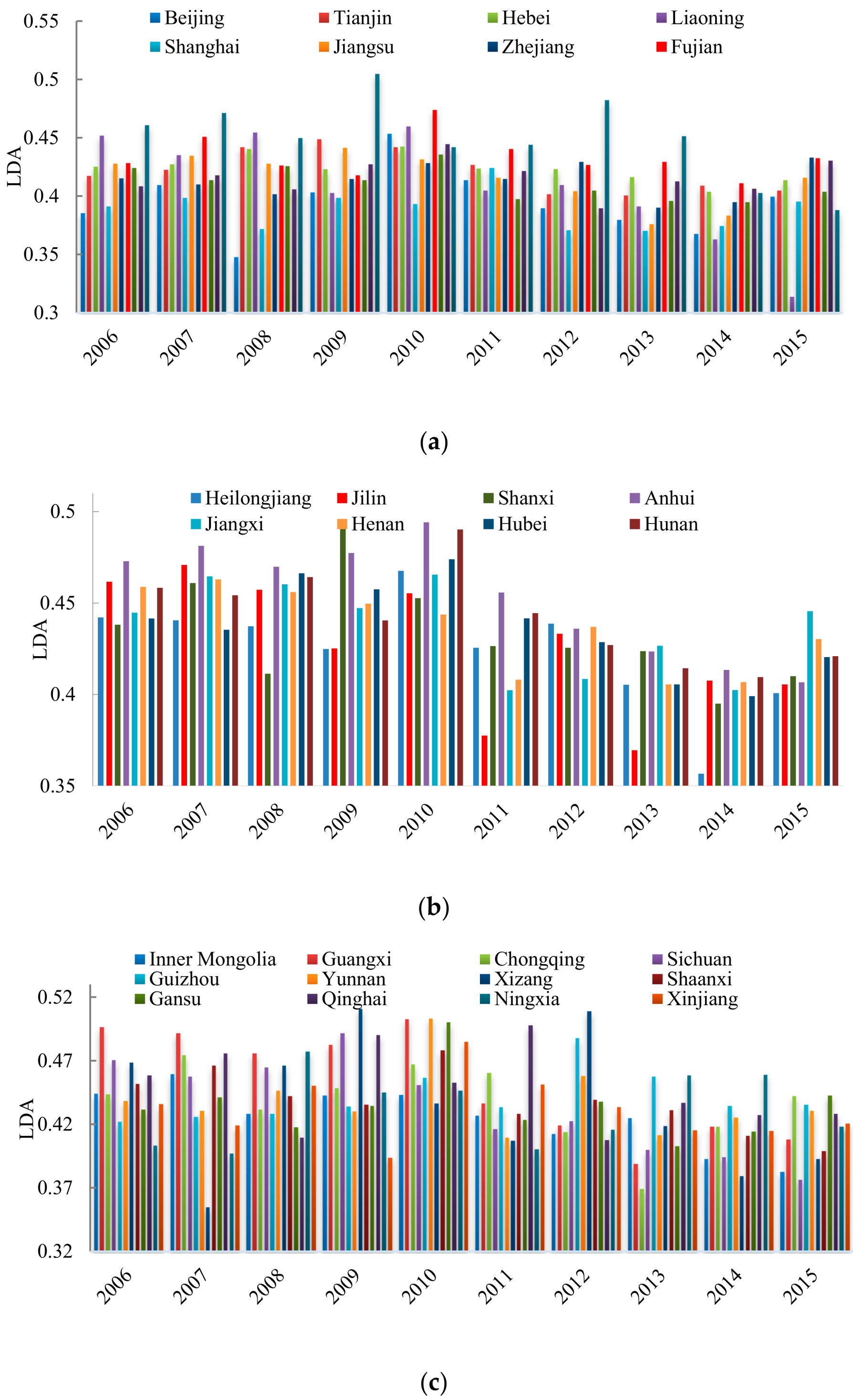

Figure 3. The *LDA* of Eastern, Central, Western provinces in China. (**a**) The *LDA* of Eastern provinces; (**b**) The *LDA* of Central provinces; (**c**) The *LDA* of Western provinces.

3.2. Spatio-Temporal Analysis of Late-Development Advantages

The values of the late-development advantage of the Chinese regions in 2006, 2009, 2012 and 2015 are processed by ArcGIS, with a range of 0.300–0.550, to obtain the spatial evolution pattern in the corresponding years (Figure 4). As shown in Figure 4, most of the regions' late-development advantages are weakened from 2006 to 2015, especially in the Central regions. Late-development advantages declined significantly between 2009 and 2012, and a large number of late-development advantages also decreased from the interval of 0.450–0.500 to the interval of 0.400–0.450. According to the original data of each index, we find this is mainly due to the rapid accumulation of capital in the Central regions, the advances in technology, and the increase in labor costs. In contrast, the late-development advantages in the Western region fluctuate greatly from 2006 to 2015, and the difference is large in different Western provinces. The *LDA* of Inner Mongolia, Guangxi, Sichuan, Shaanxi, Qinghai has been weakening during the period, while the *LDA* of Chongqing, Gansu, Ningxia is always in the interval of 0.400–0.450, and the *LDA* of Guizhou, Yunnan, Xizang increases first and then decreases. These results show that, on one hand, most Western provinces have consistently stronger late-development advantages. On the other hand, the findings indicate that these provinces have a weaker ability to make full use of its late-development advantage.

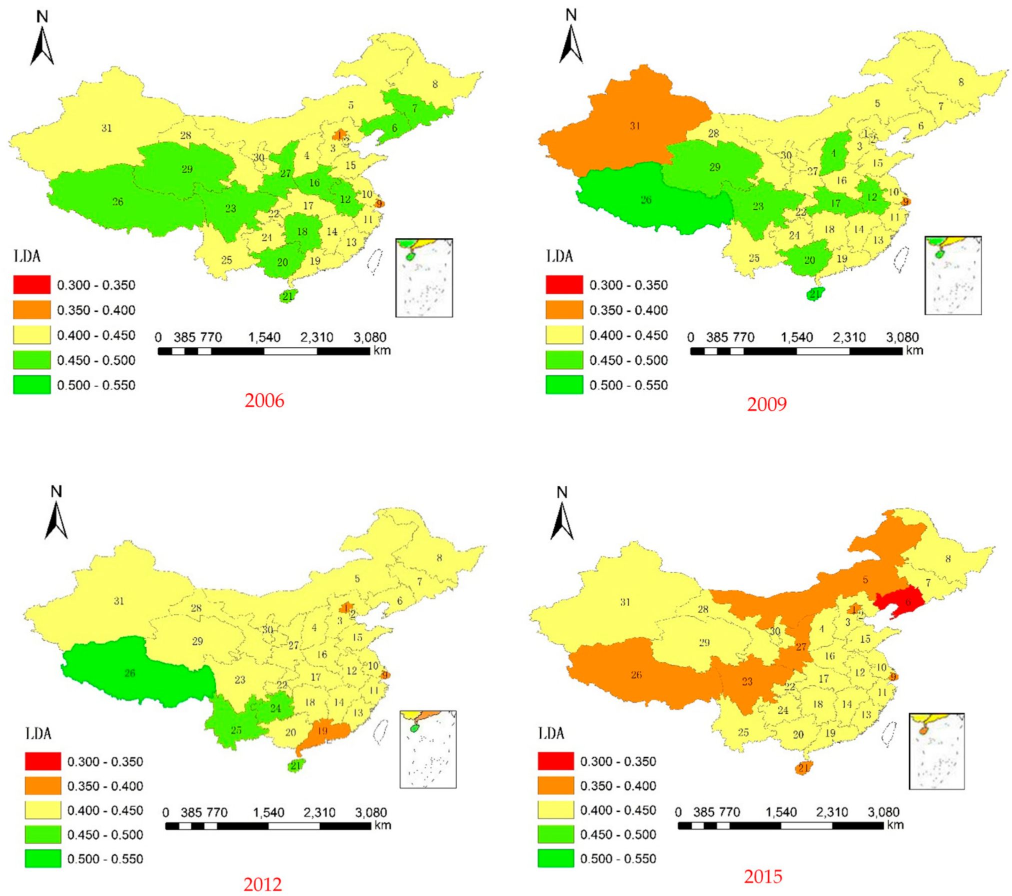

Figure 4. Spatial distribution of Chinese provinces' late-development advantage. Note: numbers represent the following provinces: 1. Beijing; 2. Tianjin; 3. Hebei; 4. Shanxi; 5. Inner Mongolia; 6. Liaoning; 7. Jilin; 8. Heilongjiang; 9. Shanghai; 10. Jiangsu; 11 .Zhejiang; 12. Anhui; 13. Fujian; 14. Jiangxi; 15. Shandong; 16. Henan; 17. Hubei; 18. Hunan; 19. Guangdong; 20. Guangxi; 21. Hainan; 22. Chongqing; 23. Sichuan; 24. Guizhou; 25. Yunnan; 26. Tibet; 27. Shaanxi; 28. Gansu; 29. Qinghai; 30. Ningxia; 31. Xinjiang.

With regard to the mean value of the regions' late-development advantages from 2006 to 2015, the mean *LDA* of most provinces is in the interval of 0.400–0.450. Only Beijing and Shanghai emerged as under 0.400. Through analyzing in conjunction with Figure 4, we can find that the *LDAs* of Beijing and Shanghai are relatively stable in the interval of 0.350–0.400, indicating that the *LDAs* of these two provinces are always weak. It is mainly due to these two provinces have relatively high levels of economic development, strong capital accumulation, leading technological capabilities, good industrial structure and well-functioning market mechanisms and thus be classified as the relative early-developing areas. Their late-development advantages are relatively weak. The three provinces with the highest mean *LDA* are Anhui, Guangxi and Hainan, and the mean *LDA* values are 0.453, 0.452 and 0.450, respectively. From Figure 4, we can see that both these three provinces have strong late-development advantage before 2012. Then the *LDAs* of these three provinces are still in the interval of 0.400–0.450 in 2015, indicating that these three provinces have strong late-development advantage for a long time, but without favorable conditions to bring out the late-development advantage.

From the perspective of temporal and spatial change, the overall late-development advantage in China shows a fluctuating downward trend from 2006 to 2015 (Figure 5). The mean value of late-development advantage decreases from 0.439 in 2006 to 0.411 in 2015, with a decrease of 6.38% and an average annual drop of 0.638%. The trend of mean *LDA* in Eastern, Central and Western China is similar to the overall trend, which can be divided into several stages. From 2006 to 2010, the mean *LDAs* of Eastern, Central and Western regions increase by 0.045, 0.034 and 0.048, with an increase of 10.8%, 7.6% and 10.7%, respectively. According to the data of indicators, the main reason for this trend is the acceleration of China's industrialization process, capital accumulation and technological innovation, the further improvement of the market economy institution, and the fact that labor costs have not increased significantly from 2006 to 2010. During the period of 2010 to 2014, the mean *LDAs* of these three regions decrease by 0.049, 0.069 and 0.053, with a decrease of 11.1%, 14.8% and 11.3%, respectively. The main reason for this trend is the adjustment of China's industrial structure, the decline in capital accumulation speed, and the significant increase in labor costs from 2010 to 2014. During the period of 2014 to 2015, the mean *LDAs* of Eastern and Central regions increase by 0.011 and 0.019, with an increase of 2.78% and 4.69% respectively, while the mean *LDA* of Western region decreases slightly by 0.001, with a decrease of 0.23%. The reason for the former is the acceleration of technological innovation and institutional improvement, and the main reason for the latter is the rise in labor cost.

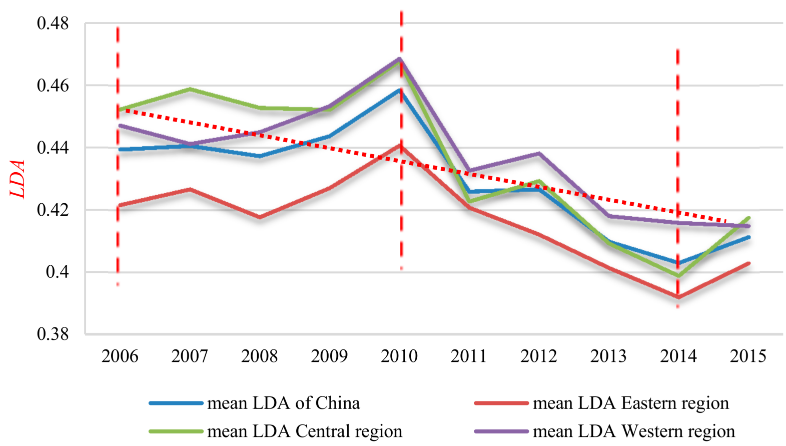

Figure 5. The changes of mean *LDA* in China and the three regions.

For analyzing the difference of *LDA* in China and the three regions, we calculate the coefficient of variation (CV) on the late-development advantage from 2006 to 2015 (Figure 6). From the overall point of view, the CV of *LDA* in China increases slightly from 0.056 to 0.062, indicating that the difference of *LDA* in China's provinces is slightly enlarged. From a local perspective, there is a big increase in the CV of *LDA* in Eastern region (from 0.053 to 0.082), with an increase of 55.3% in 2006–2015. The *LDA* fluctuates greatly during this period, which indicates that the development difference of Eastern provinces becomes more and more large, and the speed of development in Eastern provinces is quite different. The CV of *LDA* in Central region increases from 0.027 to 0.036, with an increase of 31.8%, and shows a trend of increasing first and then decreasing. It declares that the difference of *LDA* in Central region increases but this difference will narrow in the future. The CV of *LDA* in Western region almost do not increase in 2006–2015, and the difference of CV in different years becomes smaller and smaller, indicating that the difference of *LDA* in Western provinces is getting more and more stable. Moreover, the mean CV of *LDA* in China is 0.061, while the mean CV of *LDA* in Eastern, Central and Western regions is 0.059, 0.040 and 0.062, respectively, which implies that the difference of *LDA* in Western provinces is great and the development coordination between these provinces is poor.

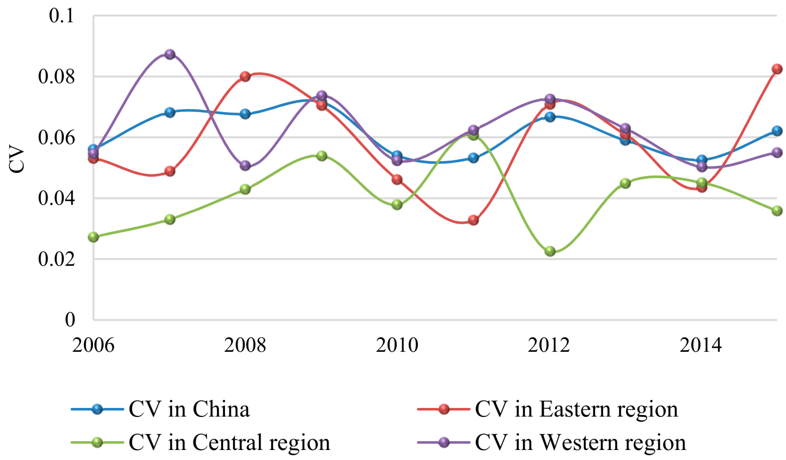

Figure 6. The changes of CV in China and the three regions.

3.3. *Temporal Autocorrelation Analysis of the Late-Development Advantage*

In Section 3.2, we have qualitatively analyzed the changes in *LDA* of China and its three regions over time. In this Section, we further quantitatively analyze the time effect of *LDA*. According to the calculating method of temporal autocorrelation coefficient in Section 2.3, the results of temporal autocorrelation of *LDA* obtained and showed in Table 5.

From Table 5, we can find that some provinces have significant positive 1st order temporal autocorrelations, including Tianjin, Inner Mongolia, Liaoning, Jiangsu, Anhui, Hubei, Guangxi and Sichuan. The temporal autocorrelation coefficients are all positive, which indicates that the *LDA* of these provinces has a significant positive correlation with their *LDA* lagged one year. Similar to the 1st order, the 2nd order temporal autocorrelations that pass the 90% significance test are also positive, but the provinces are partially different from the 1st order. It means that some provinces like Inner Mongolia, Liaoning, Anhui and Sichuan have a continuous correlation of *LDA* in the adjacent three years. While in the province of Jilin that only passes the 2nd order significant test, the correlation of *LDA* has a two year lag period. In 3rd order, only Inner Mongolia and Shanghai pass the significant test and show positive temporal autocorrelation and negative temporal autocorrelation, respectively. Moreover, Inner Mongolia also has a significant 1st and 2nd order positive temporal autocorrelation, which implies the *LDA* of Inner Mongolia has strong continuity. The negative temporal autocorrelation of Shanghai indicates that the *LDA* of Shanghai has opposite trend in different time periods. In 4th order, only one province of Tianjin passes the significant test and shows a negative temporal autocorrelation. In 5th order, only Tibet passes the significant test and shows a negative temporal autocorrelation. These phenomena denote that after several years of development in Tianjin and Tibet, these two provinces have reversed the trend of their *LDA*.

Table 5. The temporal autocorrelation of *LDA* in China's 31 provinces.

Provinces	1st Order	*t*-Value	2nd Order	*t*-Value	3rd Order	*t*-Value	4th Order	*t*-Value	5th Order	*t*-Value
Beijing	0.088	0.234	−0.373	−0.984	−0.340	−0.809	−0.362	−0.777	0.231	0.412
Tianjin	0.740 **	2.914	0.225	0.566	−0.279	−0.650	−0.838 **	−3.070	−0.542	−1.116
Hebei	0.340	0.957	0.515	1.473	0.086	0.194	−0.388	−0.843	0.024	0.042
Shanxi	0.084	0.222	0.240	0.606	0.147	0.331	−0.056	−0.113	−0.769	−2.081
Inner Mongolia	0.670 **	2.386	0.627 *	1.973	0.836 **	3.412	0.564	1.367	−0.176	−0.309
Liaoning	0.595 *	1.958	0.796 **	3.221	0.406	0.994	0.506	1.174	−0.097	−0.169
Jilin	0.216	0.587	0.726 **	2.589	0.066	0.147	0.220	0.450	0.043	0.075
Heilongjiang	0.415	1.207	0.314	0.809	0.088	0.198	−0.408	−0.894	0.344	0.635
Shanghai	−0.091	−0.241	−0.103	−0.255	−0.677 *	−2.054	0.389	0.845	0.116	0.202
Jiangsu	0.690 **	2.521	0.334	0.867	0.065	0.145	−0.581	−1.430	−0.278	−0.502
Zhejiang	−0.144	−0.385	−0.508	−1.444	−0.122	−0.276	−0.558	−1.346	0.651	1.486
Anhui	0.854 ***	4.347	0.664 *	2.178	0.484	1.236	0.047	0.095	−0.557	−1.162
Fujian	−0.125	−0.333	−0.314	−0.809	0.227	0.522	−0.454	−1.019	0.348	0.642
Jiangxi	0.309	0.860	0.295	0.755	0.184	0.418	−0.663	−1.773	0.723	1.813
Shandong	0.251	0.686	0.567	1.684	−0.044	−0.098	0.097	0.194	0.203	0.360
Henan	0.558	1.781	0.571	1.704	0.571	1.555	−0.087	−0.175	0.042	0.073
Hubei	0.666 **	2.365	0.393	1.046	−0.293	−0.685	−0.652	−1.721	−0.595	−1.283
Hunan	0.465	1.390	0.418	1.127	0.035	0.077	−0.125	−0.252	0.103	0.179
Guangdong	0.096	0.256	−0.358	−0.941	−0.493	−1.268	−0.165	−0.334	0.351	0.649
Guangxi	0.767 **	3.167	0.592	1.798	0.371	0.894	0.406	0.890	0.531	1.085
Hainan	0.315	0.877	−0.102	−0.252	0.171	0.387	0.419	0.923	−0.048	−0.083
Chongqing	0.380	1.087	−0.217	−0.545	−0.316	−0.745	0.293	0.612	0.374	0.699
Sichuan	0.825 ***	3.865	0.649 *	2.087	0.605	1.699	0.542	1.289	0.067	0.116
Guizhou	0.193	0.522	0.099	0.245	−0.097	−0.218	−0.386	−0.836	−0.372	−0.695
Yunnan	−0.486	−1.472	0.439	1.198	−0.413	−1.013	−0.008	−0.017	−0.043	−0.074
Tibet	−0.108	−0.288	−0.555	−1.634	0.301	0.706	0.385	0.834	−0.908 **	−3.760
Shaanxi	0.322	0.899	0.307	0.789	0.545	1.452	0.042	0.084	−0.232	−0.412
Gansu	−0.086	−0.229	−0.137	−0.339	−0.250	−0.577	−0.354	−0.757	0.793	2.257
Qinghai	−0.319	−0.891	0.394	1.050	−0.459	−1.156	0.408	0.895	−0.175	−0.309
Ningxia	0.018	0.047	−0.593	−1.804	−0.636	−1.843	0.283	0.590	0.793	2.255
Xinjiang	−0.261	−0.715	0.127	0.313	−0.336	−0.798	−0.165	−0.335	−0.039	−0.068

Note: The calculation method and significant test of temporal autocorrelation of *LDA* is programed by MATLAB, and then put the *LDA* value of 31 provinces from 2006 to 2015 into the program, the results of different order autocorrelation and its significance obtained. * indicates a 90% confidence level; ** indicates a 95% confidence level and *** indicates a 99% confidence level following the test method in (16).

From the comparison of different orders (Table 6), we can find that the higher the order, the less the provinces that pass significant test. This implies the *LDA* is less likely relevant in two years with long interval. Meanwhile, low order (1st and 2nd) temporal autocorrelations are mainly positive temporal autocorrelations, while high order (3rd, 4th and 5th) temporal autocorrelation are mainly negative temporal autocorrelations. It indicates that the trend of *LDA* is consistent in a short term, but it is likely to reverse in a long run. From the perspective of the Eastern, Central and Western regions, the significant temporal autocorrelations in different orders have no significant distribution law, denoting the correlation between the temporal effect of *LDA* and spatial location is not obvious.

Table 6. The provinces with significant temporal autocorrelation in different orders.

Order	The Provinces with Significant Positive Temporal Autocorrelation	The Provinces with Significant Negative Temporal Autocorrelation
1	Tianjin, Inner Mongolia, Liaoning, Jiangsu, Anhui, Hubei, Guangxi, Sichuan	—
2	Inner Mongolia, Liaoning, Jilin, Anhui, Sichuan	—
3	Inner Mongolia	Shanghai
4	—	Tianjin
5	—	Tibet

3.4. Spatial Autocorrelation Analysis of the Late-Development Advantage

In Figure 4, the provinces with late-development advantage falling between 0.400 and 0.450 manifest a clear aggregation phenomenon, which indicates that there may be spatial autocorrelation among these provinces. In order to test the existence and significance of this spatial autocorrelation, global Moran's I indices of the 31 provinces are calculated using Formula (17)–(22). The global Moran's I index value and the significance analysis of results is presented in Table 7.

Table 7. Global Moran's I index for testing late-development advantage.

Time	Global Moran's I	p-Value	z-Value	$E(I)$
2006	0.140 *	0.066	1.512	−0.033
2007	−0.026	0.424	0.093	−0.033
2008	0.026	0.258	0.598	−0.033
2009	0.030	0.278	0.526	−0.033
2010	0.165 *	0.052	1.649	−0.033
2011	0.019	0.304	0.464	−0.033
2012	0.115 *	0.089	1.366	−0.033
2013	0.065	0.171	0.910	−0.033
2014	0.087	0.164	0.990	−0.033
2015	0.117 *	0.076	1.466	−0.033
mean	0.289 **	0.007	2.849	−0.033

Note: * indicates a 90% confidence level and ** indicates a 95% confidence level following the test method in (22).

As shown in Table 7, the global Moran's I indices of the late-development advantage from 2006 to 2015 are all greater than $E(I)$ except 2007, and the significance test of a 90% confidence level is passed in 2006, 2010, 2012 and 2015. Together, these indicate the existence of a significant positive spatial autocorrelation in China's regional areas in these four years, i.e., provinces with a strong late-development advantage tend to be surrounded by others that also have a strong late-development advantage. Likewise, provinces with a weak late-development advantage tend to surrounded by those with a weak one. This phenomenon implies that there has been a certain degree of coordination and consistency in terms of economic development in China's regions over the past ten years, for better or for worse.

In terms of changing trends, the global Moran's *I* indices of Chinese provinces' late-development advantage show fluctuating growth during 2006–2015 (Figure 7), indicating that the correlation between late-development advantage and spatial distribution was on the rise. Since the global Moran's *I* index represents the mean value of the local Moran's *I* index, the global Moran's *I* index is thus significantly greater than $E(I)$, indicating that the local spatial autocorrelations of most provinces are positive. However, the available data do not make it possible to determine whether there exists a negative spatial autocorrelation. Therefore, in order to further analyze the local spatial autocorrelation of late-development advantage in China's regions, we select four years of 2006, 2010, 2012 and 2015 that pass significance test of a 95% confidence level, and then map the provinces onto a Moran scatter plot for the years of 2006, 2010, 2012 and 2015, as shown in Figure 8. The corresponding permutation test results are shown in Table 8.

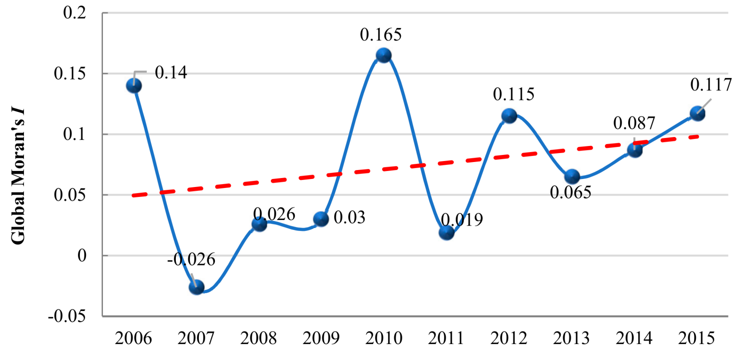

Figure 7. Global Moran's *I* from 2006 to 2015.

In Figure 8, over 70% of the provinces are lie in the first and third quadrants in the years 2006, 2010, 2012 and 2015, which shows that most of these provinces' late-development advantage has a positive spatial autocorrelation, i.e., both the regions with a strong late-development advantage and weak late-development advantage manifest a significant aggregation phenomenon. However, some provinces are also distributed in the second and fourth quadrant of the Moran scatter plot during the study period, which shows that in the case of overall positive spatial autocorrelation, there are still some local areas with a negative spatial autocorrelation.

The Figure 8 also shows some different trends over the years. In 2006, most provinces are in the first quadrant, while the number of provinces in the first quadrant and the third quadrant is basically equal in 2010. By 2012, most provinces leapfrog to the third quadrant. However, the provinces are distributed almost evenly in four quadrants in 2015. These phenomena mean that the positive spatial autocorrelation in 2006 and 2015 is mainly due to the aggregation of high *LDA* provinces, and the positive spatial autocorrelation in 2010 is due to the aggregation of high *LDA* provinces and the aggregation of low *LDA* provinces, while the positive spatial autocorrelation in 2012 is mainly due to the aggregation of low *LDA* provinces. It also implies that China made effective use of its late-development advantage between 2006 and 2012, which mainly due to the adjustment of industrial structure and the improvement of technical level.

Out of the three major regions, the distributions of the three regions' provinces in four quadrants are very different. Most Eastern provinces (red dots in Figure 8) distributed in the third quadrant (Low-Low) in 2006, 2010 and 2012, indicating that the development of the Eastern provinces is relatively coordinate, and the late-development advantage can be effectively utilized. In 2015, the Eastern provinces are almost evenly distributed in four quadrants, which imply that the difference in the development speed of Eastern provinces is expanding. Unlike the Eastern region, most Central provinces (blue dots in Figure 8) distributed in the first quadrant (High-High) in 2006 and 2010, denoting that the late-development advantage of Central region is relatively strong (see Table 4), but the development environment in the Central region is not conducive to the utilization of *LDA*. After

2010, most Central provinces gradually leapfrog to the fourth quadrant (High-Low) in 2012, and then the Central provinces evenly distributed in four quadrants in 2015. These changes show that some Central provinces effectively utilize the late-development advantage in 2012, which leads to the expanding development differences in Central region. Similar to the Central region, most Western provinces distributed in the first quadrant (High-High) in 2006 and 2010, indicates that the Western provinces have great development potential, but they need more favorable development conditions. However, some Western provinces leapfrog to the second quadrant (Low-High) in 2012, and then most Western provinces almost evenly distributed in the first and second quadrant (High-High and Low-High) in 2015. This phenomenon implies that some Western provinces like Chongqing and Sichuan etc. have effectively utilized the late-development advantage, thus expand the gap with the rest of the Western provinces.

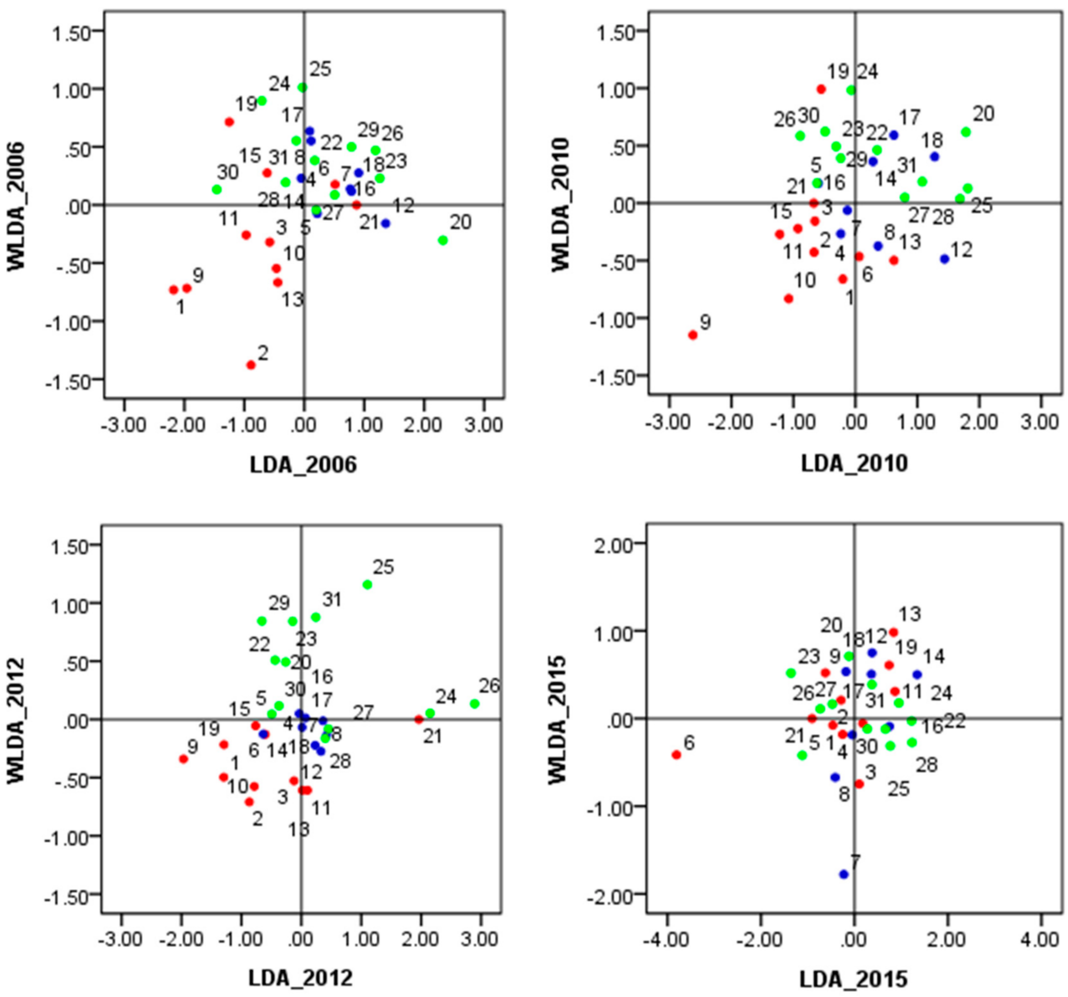

Figure 8. Moran scatter plot of late-development advantage in 2006, 2010, 2012 and 2015. Note: *LDA*_year represents the standardized value of late-development advantage in different year, *WLDA*_year indicates the spatial lag of standardized Late-Development Advantage in different year. The red dots represent Eastern provinces, blue dots represent Central provinces, and green dots represent Western provinces. Numbers represent the following provinces: 1. Beijing; 2. Tianjin; 3. Hebei; 4. Shanxi; 5. Inner Mongolia; 6. Liaoning; 7. Jilin; 8. Heilongjiang; 9. Shanghai; 10. Jiangsu; 11 .Zhejiang; 12. Anhui; 13. Fujian; 14. Jiangxi; 15. Shandong; 16. Henan; 17. Hubei; 18. Hunan; 19. Guangdong; 20. Guangxi; 21. Hainan; 22. Chongqing; 23. Sichuan; 24. Guizhou; 25. Yunnan; 26. Tibet; 27. Shaanxi; 28. Gansu; 29. Qinghai; 30. Ningxia; 31. Xinjiang.

Table 8. Permutation tests for local Moran's I_i.

Provinces	2006		2010		2012		2015	
	I_i	*p*-Value	I_i	*p*-Value	I_i	*p*-Value	I_i	*p*-Value
Beijing	0.035	0.099	0.134	0.160	0.641	0.164	0.035	0.383
Tianjin	0.045 *	0.018	0.286	0.237	0.615	0.104	0.045	0.297
Hebei	−0.074	0.164	0.297	0.086	0.065 *	0.045	−0.074 *	0.025
Shanxi	0.009	0.336	0.063	0.272	−0.001	0.439	0.009	0.293
Inner Mongolia	0.470	0.423	−0.108	0.338	−0.022	0.459	0.470	0.091
Liaoning	1.581	0.394	−0.027	0.188	0.077	0.410	1.581	0.098
Jilin	0.405	0.294	0.008	0.425	−0.051	0.393	0.405 **	0.006
Heilongjiang	0.277	0.211	−0.136	0.327	−0.055	0.487	0.277	0.115
Shanghai	−0.324	0.113	3.016	0.054	0.672	0.269	−0.324	0.230
Jiangsu	−0.010	0.112	0.897 *	0.033	0.451	0.084	−0.010	0.391
Zhejiang	0.268	0.231	0.331	0.201	−0.061 *	0.048	0.268	0.204
Anhui	−0.096	0.380	−0.699	0.118	−0.090	0.233	−0.096	0.063
Fujian	0.820	0.118	−0.309	0.190	−0.009	0.138	0.820 **	0.008
Jiangxi	0.670	0.418	0.102	0.169	0.081	0.360	0.670	0.057
Shandong	−0.060	0.292	0.205	0.282	0.041	0.479	−0.060	0.386
Henan	−0.066	0.366	−0.103	0.394	−0.004	0.495	−0.066	0.401
Hubei	0.181	0.054	0.368	0.052	0.001	0.469	0.181	0.063
Hunan	0.282	0.333	0.515	0.115	−0.001	0.470	0.282 **	0.004
Guangdong	0.452	0.081	−0.549 *	0.014	0.281	0.290	0.452	0.076
Guangxi	−0.085	0.267	1.101	0.071	−0.130	0.184	−0.085	0.053
Hainan	0.000 **	0.001	0.000 **	0.001	0.000 **	0.001	0.000 **	0.001
Chongqing	−0.035	0.203	0.163	0.149	−0.222	0.131	−0.035	0.459
Sichuan	−0.702	0.243	−0.154	0.091	−0.122 **	0.009	−0.702	0.054
Guizhou	0.168 *	0.015	−0.064 **	0.007	0.116	0.316	0.168	0.332
Yunnan	−0.240 *	0.012	0.234	0.346	1.276 *	0.015	−0.240	0.213
Tibet	−0.080	0.151	−0.520	0.132	0.390	0.267	−0.080	0.490
Shaanxi	−0.077	0.392	0.040	0.407	−0.036	0.443	−0.077	0.355
Gansu	−0.337	0.329	0.060	0.425	−0.064	0.378	−0.337	0.251
Qinghai	−0.080	0.143	−0.093	0.238	−0.556	0.053	−0.080	0.335
Ningxia	−0.033	0.468	−0.305	0.149	−0.044	0.415	−0.033	0.372
Xinjiang	0.143	0.192	0.201	0.367	0.210	0.067	0.143	0.238

Note: * indicates a 95% confidence level and ** indicates a 99% confidence level of permutation tests that contains 999 permutations.

As shown in Table 8, although the global Moran's I passed the significance test in 2006, 2010, 2012 and 2015, there are few provinces with significant local spatial aggregation in these years. In order to further explore the significant aggregations of provincial *LDA* from a local perspective, GeoDa was used to draw a LISA cluster map of China's provincial late-development advantages in the four years of 2006, 2010, 2012 and 2015 as shown in Figure 9.

The provinces marked with color in Figure 9 are those that passed the significance test of 95% confidence. Figure 9 shows some different changes of significant aggregation over the past ten years. In 2006 and 2010, the significant aggregations are Low-High and Low-Low aggregations. The former means the low *LDA* provinces surrounded by high *LDA* provinces, and the latter indicates that the low *LDA* provinces surrounded by low *LDA* provinces. The situation changes in 2012 and 2015, the aggregation of High-Low and High-High emerges. The former denotes that the high *LDA* provinces surrounded by low *LDA* provinces, and the latter implies that the high *LDA* provinces surrounded by high *LDA* provinces (the corresponding *LDA* can be find in Table 4). The changes from 2006 to 2015 indicate that the development environment has effectively promoted the use of the provincial late-development advantage. From the data of indicators, we find this is mainly due to the perfection of institutions and the improvement of industrial development level. Moreover, during the four years of study, most provinces have no significant aggregation, which means that the coordination of development between provinces is poor. China should strengthen the link of economic development between provinces, and promote the development of late-developing regions with the developed regions.

Regarding the aggregation effect, some provinces manifest a significant leapfrogging phenomenon. For example, Yunnan leapfrogs from Low-High quadrant in 2006 to High-High quadrant in 2012, Hebei leapfrogs from Low-Low quadrant in 2012 to High-Low quadrant in 2015, and Fujian leapfrogs from High-Low quadrant in 2012 to High-High quadrant in 2015. These phenomena imply that the utilization speed of *LDA* in different provinces is very different. Considering the appearance and disappearance of the aggregation phenomenon, Guizhou's late-development advantage shows a significant Low-High aggregation in 2006 and 2010, but it disappeared afterwards. It indicates that Guizhou has utilized its late-development advantage well in 2006 and 2010, but thereafter returns to a situation similar to its surrounding provinces. The changes of *LDA* aggregation in Guangdong and Sichuan are similar to Guizhou. Moreover, Tianjin's *LDA* shows a significant Low-Low aggregation in 2006, the *LDA* of Zhejiang and Shanghai shows a significant Low-Low aggregation in 2010, and Jilin's *LDA* shows a Low-Low aggregation in 2015, but these aggregations disappeared afterwards. This indicates that the development of these provinces is coordinate with their surrounding provinces in the corresponding year.

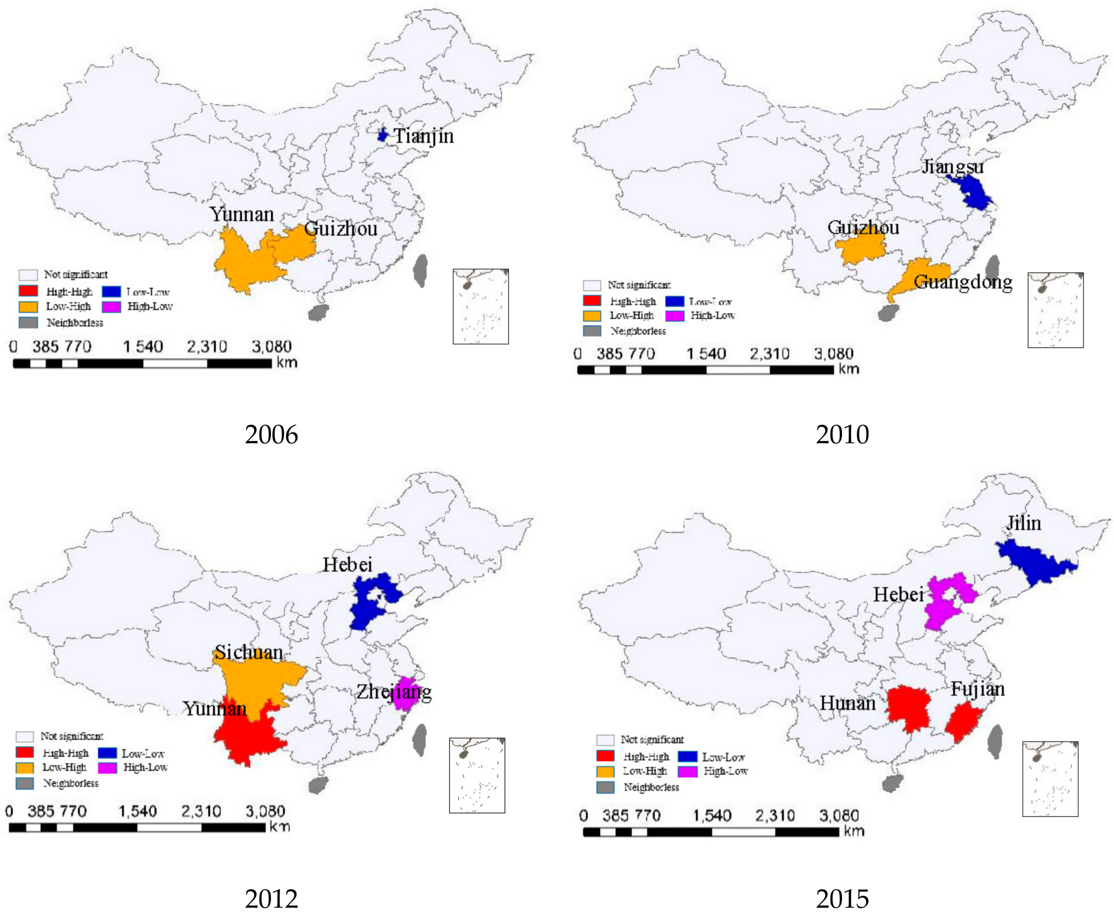

Figure 9. LISA aggregation map of late-development advantage in China's regions. Note: "High-High" represents the province with high *LDA* is surrounded by the provinces who also has high *LDA*; "Low-Low" indicates the province with low *LDA* is surrounded by the provinces who also has low *LDA*; "Low-High" represents the province with low *LDA* is surrounded by the provinces who has high *LDA*; "High-Low" indicates the province with high *LDA* is surrounded by the provinces who has low *LDA*; "Not significant" express the spatial agglomeration effect is not significant and "Neighborless" indicates the province without neighbor provinces.

4. Conclusions and Recommendations

This paper constructs a set of evaluation indicators of regional late-development advantages reflecting the aspects of capital, technology, industrial structure, institutions and human resources. Then, the late-development advantage values of 31 provinces in China between 2006 and 2015 were calculated using the EW-TOPSIS method, and the results were applied to an analysis of spatio-temporal evolution patterns and spatio-temporal autocorrelation.

According to the evaluation results of *LDA*, the annual mean value of late-development advantage weakens from 2006 to 2015, indicating that China is gradually making use of the late-development advantage to promote rapid economic development. The declines in *LDA* of Eastern and Western regions are almost equal, implying that the development gaps between the Eastern and Western regions are still large. Therefore, the coordinated development of the China's regional economy should be given more attention, and the government should make some favorable policies to promote the utilization of *LDA* in the Western regions. Moreover, the three provinces with the highest mean *LDA* are Anhui, Guangxi and Hainan. Their *LDA* has been at a high level over the past ten years, mainly due to the lack of capital and the backward industrial structure as well as technical level. For utilizing the *LDA* to promote their rapid economic development, China should increase investment in these provinces, adjust their industrial structure to improve the industrialization level, and accelerate the introduction of advanced technologies to these provinces in the recent future.

From the perspective of spatio-temporal evolution of *LDA*, we find that the overall trend of mean *LDA* in Eastern, Central and Western regions is decreasing, and the trend can be divided into three stages. The first stage is from 2006 to 2010, and the mean *LDA* shows an increase of 10.8%, 7.6% and 10.7%, respectively. This is mainly caused by the low labor cost, the acceleration of capital accumulation, technological innovation and industrialization process. The second stage is from 2010 to 2014, and the mean *LDA* shows a decrease of 11.1%, 14.8% and 11.3% in the three regions, which is caused by the significant rise in labor cost, the speed decline in capital accumulation and adjustment of industrial structure. The third stage is from 2014 to 2015, and the mean *LDA* of Eastern and Central regions shows an increase of 2.78% and 4.69% respectively, while that of Western region shows a decrease of 0.23%. The reason for the former is the acceleration of technological innovation and institutional improvement, and the main reason for the latter is the rise in labor cost. According to these analysis results, China's three regions should continue to improve the speed of technological innovation and institutional progress for better utilizing the *LDA* to promote the accelerated economic development.

The calculation results of CV show that the difference of *LDA* in China's provinces enlarged slightly in 2006–2015, while it increased by 55.3% and 31.8% in the Eastern and Western regions, and it was almost unchanged in the Western region. Meanwhile, the mean CV of Eastern, Central and Western regions is 0.059, 0.040 and 0.062, respectively. This indicates that the difference of development in Eastern Central provinces is expanding, but the average difference in Central provinces is smaller than that of Eastern provinces. The development difference in Western provinces has not expanded, but it is at a relatively high level. Based on the changes of CV, China should take measures to prevent the further expand of development difference in Eastern and Western provinces, and strengthen economic relations between the Western provinces to reduce their developmental differences.

In terms of the results of temporal autocorrelation, Tianjin, Inner Mongolia, Liaoning, Jiangsu, Anhui, Hubei, Guangxi and Sichuan have significant positive 1st order temporal autocorrelations, which indicates the *LDA* is the same high or low in adjacent two years. Some provinces like Inner Mongolia, Liaoning, Anhui and Sichuan pass the 1st and 2nd order significant test, denoting that they have a continuous correlation of *LDA* in the adjacent three years. In 3rd order, only Inner Mongolia and Shanghai pass the significant test and show positive temporal autocorrelation and negative temporal autocorrelation, while in 4th and 5th order, Tianjin and Xizang pass the significant test and show negative temporal autocorrelations. These phenomena imply that after several years of development in Tianjin and Tibet, these two provinces have reversed the trend of their *LDA*.

The comparison of temporal autocorrelation with different orders shows that the number of provinces passing the significance test shows a decreasing trend with the increase of the order. This means that the *LDA* is less likely relevant over time. Meanwhile, low order (1st and 2nd) temporal autocorrelations are mainly positive temporal autocorrelations, while high order (3rd, 4th and 5th) temporal autocorrelation are mainly negative temporal autocorrelations. It indicates the temporal autocorrelation changes from positive status to negative status with the increase of lagging order, which means the trend of late-development advantage will reverse over time. According to this law, different provinces can adjust their development plans to adapt or reverse the trend of *LDA*.

The global Moran's I indices of the *LDA* are significantly greater than $E(I)$ in 2006, 2010, 2012 and 2015, indicating the existence of a significant positive spatial autocorrelation in China's regional areas in these four years. Meanwhile, the global Moran's I indices show fluctuating growth during 2006–2015. This indicates a positive spatial autocorrelation in China's provinces and is increasing with time. China can make full use of this autocorrelation, drives the development of the Western region with the Eastern region, realizes the transfer of technology and capital from Eastern region to Western region, and improve the institution system of Western region.

Moreover, the Moran scatter plots show that the aggregations of *LDA* in Eastern provinces are mainly Low-Low aggregations in 2006, 2010 and 2012. The aggregations of *LDA* in Central provinces are mainly High-High aggregations in 2006 and 2010, while they are mainly High-Low aggregation in 2012. The aggregations of *LDA* in Western provinces are mainly High-High aggregations in 2006 and 2010, while they are mainly Low-High aggregation in 2012. In 2015, the provinces of the Eastern, Central and Western regions are almost evenly distributed in four quadrants, indicating that there is no obvious aggregation law in this year. At the same time, from the LISA agglomeration map we can find the significant aggregations are Low-Low and Low-High aggregations in 2006 and 2010. The situation changes in 2012 and 2015, the aggregation of High-Low and High-High emerges. These changes indicate that the development environment has effectively promoted the use of *LDA*. Therefore, we recommend that the government should instigate a development strategy to maintain this good trend, and transform the *LDA* into a realistic development momentum as soon as possible to promote the rapid development of economics.

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References

1. Gerschenkron, A. *Economic Backwardness in Historical Respective*; Harvard University Press: Cambridge, MA, USA, 1962; pp. 1–456.
2. Levy, M.J. Modernization and the structure of societies: A setting for international affairs. *Am. Sociol. Rev.* **1966**, *31*, 97–102.
3. Alexander, A. *The Arc of Japan's Economic Development*; Routledge: Abingdon, UK, 2008; Volume 10, p. 124.
4. Yu, F.L. Economic Development in Latecomer Economies: An Entrepreneurial Perspective. *Dev. Policy Rev.* **2010**, *16*, 353–372.
5. Chu, W.W. Knowledge production in a latecomer: Reproducing economics in Taiwan. *Inter-Asia Cult. Stud.* **2009**, *10*, 275–281. [CrossRef]
6. Lin, Y.F.; Zhang, P.F. The Advantage of Latter Comers, Technology Imports, and Economic Growth of Developing Countries. *CEQ* **2005**, *5*, 53–74.
7. Dan, P. Utility model patent regime "strength" and technological development: Experiences of China and other East Asian latecomers. *China Econ. Rev.* **2017**, *42*, 50–73.

8. Hayami, Y. Japan in the new world confrontation: A historical perspective. *Jpn. Econ. Rev.* **2010**, *46*, 351–357. [CrossRef]
9. Ishida, S. Exploratory research on the mechanism of latecomer advantages in the Asian LCD industry. *Int. J. Technol. Manag.* **2017**, *75*, 208–233. [CrossRef]
10. Ernst, D.; Lee, H.; Kwak, J. Standards, innovation, and latecomer economic development: Conceptual issues and policy challenges. *Telecommun. Policy* **2014**, *38*, 853–862. [CrossRef]
11. Perkins, R.; Neumayer, E. The International Diffusion of New Technologies: A Multitechnology Analysis of Latecomer Advantage and Global Economic Integration. *AAAG* **2005**, *95*, 789–808. [CrossRef]
12. He, G.Y.; Xu, C.S. Comparative Advantage, Advantage as Latecomer and the New Pattern of Industrialization in China. *Economist* **2004**, *5*, 16–22.
13. Hu, M.C.H.; Wu, C.Y. Exploring technological innovation trajectories through latecomers: Evidence from Taiwan's bicycle industry. *Technol. Anal. Strateg.* **2011**, *23*, 433–452. [CrossRef]
14. Cai, J.; Yang, Z.; Webster, D. Chongqing: Beyond the latecomer advantage. *Asia Pac. Viewp.* **2012**, *53*, 38–55. [CrossRef]
15. Xiao, Y.; Tylecote, A.; Liu, J. Why not greater catch-up by Chinese firms? The impact of IPR, corporate governance and technology intensity on late-comer strategies. *Res. Policy* **2013**, *42*, 749–764. [CrossRef]
16. Wu, X.; Ma, R.; Shi, Y. How do Latecomer Firms Capture Value from Disruptive Technologies? A Secondary Business-Model Innovation Perspective. *IEEE Trans. Eng. Manag.* **2010**, *57*, 51–62. [CrossRef]
17. Mobaraki, M.D. The benefits of being late?—An empirical analysis on the validity of the concept of "Advantages of Backwardness". *Marble* **2017**, *2*, 84–99.
18. Selwyn, B. Trotsky, Gerschenkron and the political economy of late capitalist development. *Econ. Soc.* **2011**, *40*, 421–450. [CrossRef]
19. Weede, E. The Rise of India: Overcoming Caste Society and Permit-License-Quota Raj, Implementing Some Economic Freedom. *Asian J. Political Sci.* **2010**, *18*, 129–153. [CrossRef]
20. Zhang, Q.W.; Zhang, Y.Z.; Ming, Z.A. Cloud model based approach for multi-hierarchy fuzzy comprehensive evaluation of reservoir-induced seismic risk. *J. Hydraul. Eng.* **2014**, *45*, 87–95.
21. Wang, X.; Li, X.; Wang, J. Urban Water Conservation Evaluation Based on Multi-grade Uncertain Comprehensive Evaluation Method. *Water Resour. Manag.* **2017**, *32*, 1–15. [CrossRef]
22. Lim, S.; Zhu, J. DEA cross-efficiency evaluation under variable returns to scale. *J. Oper. Res. Soc.* **2015**, *66*, 476–487. [CrossRef]
23. Westerhuis, J.A.; Kourti, T.; Macgregor, J.F. Analysis of multiblock and hierarchical PCA and PLS models. *J. Chemom.* **2015**, *12*, 301–321. [CrossRef]
24. Moreno-Jiménez, J.M.; Salvador, M.; Gargallo, P.; Altuzarra, A. Systemic decision making in AHP: A Bayesian approach. *Ann. Oper. Res.* **2016**, *245*, 261–284. [CrossRef]
25. Ejaz, N.; Baik, S.W. Weighting low level frame difference features for key frame extraction using Fuzzy comprehensive evaluation and indirect feedback relevance mechanism. *Coronary Artery Dis.* **2011**, *14*, 381–386.
26. Gelisli, K.; Kaya, T.; Babacan, A.E. Assessing the factor of safety using an artificial neural network: Case studies on landslides in Giresun, Turkey. *Environ. Earth Sci.* **2015**, *73*, 1–8. [CrossRef]
27. Anisseh, M.; Piri, F.; Shahraki, M.R.; Agamohamadi, F. Fuzzy extension of TOPSIS model for group decision making under multiple criteria. *Artif. Intell. Rev.* **2012**, *38*, 325–338. [CrossRef]
28. Mir, M.A.; Ghazvinei, P.T.; Sulaiman, N.M.N.; Basri, N.E.A.; Saheri, S.; Mahmood, N.Z.; Jahan, A.; Begum, R.A.; Aghamohammadi, N. Application of TOPSIS and VIKOR improved versions in a multi criteria decision analysis to develop an optimized municipal solid waste management model. *J. Environ. Manag.* **2016**, *166*, 109.
29. Li, X.G.; Wei, X.; Huang, Q. Comprehensive entropy weight observability-controllability risk analysis and its application to water resource decision-making. *Water SA* **2012**, *38*, 573–580. [CrossRef]
30. Hansen, B.E. Threshold autoregression in economics. *Stat. Interface* **2011**, *4*, 123–127. [CrossRef]
31. Tong, H.; Lim, K.S. Threshold Autoregression, Limit Cycles and Cyclical Data. *J. R. Stat. Soc.* **1980**, *42*, 245–292.
32. Lanne, M.; Saikkonen, P. Noncausal Autoregressions for Economic Time Series. *J. Time* **2010**, *3*. [CrossRef]
33. Hyvärinen, A.; Zhang, K.; Shimizu, S.; Hoyer, P.O. Estimation of a structural vector autoregression model using non-Gaussianity. *J. Mach. Learn. Res.* **2010**, *11*, 1709–1731.

34. Moran, P.A.P. The interpretation of statistical maps. *J. R. Stat. Soc. B* **1948**, *37*, 243–251.
35. Ma, F.; Wang, W.L.; Sun, Q.P.; Liu, F.; Li, X.D. Ecological pressure of carbon footprint in passenger transport: Spatio-temporal changes and regional disparities. *Sustainability* **2018**, *10*, 317. [CrossRef]
36. Austin, J.R.; Blenkinsop, T.G. Local to regional scale structural controls on mineralisation and the importance of a major lineament in the eastern Mount Isa Inlier, Australia: Review and analysis with autocorrelation and weights of evidence. *Ore Geol. Rev.* **2009**, *35*, 298–316. [CrossRef]
37. Shurin, J.B.; Cottenie, K.; Hillebrand, H. Spatial autocorrelation and dispersal limitation in freshwater organisms. *Oecologia* **2009**, *159*, 151–159. [CrossRef] [PubMed]
38. Ma, F.; Li, X.D.; Sun, Q.P.; Liu, F.; Wang, W.L.; Bai, L.B. Regional Differences and Spatial Aggregation of Sustainable Transport Efficiency: A Case Study of China. *Sustainability* **2018**, *10*, 399. [CrossRef]
39. Elhorst, J.P.; Zigova, K. Competition in Research Activity among Economic Departments: Evidence by Negative Spatial Autocorrelation. *Geogr. Anal.* **2014**, *46*, 104–125. [CrossRef]
40. Azil, A.H.; Bruce, D.; Williams, C.R. Determining the spatial autocorrelation of dengue vector populations: Influences of mosquito sampling method, covariables, and vector control. *J. Vector Ecol.* **2014**, *39*, 153–163. [CrossRef] [PubMed]
41. Peng, W.; Song, T.; Zeng, F.; Wang, K.; Du, H.; Lu, S. Spatial distribution of surface soil water content under different vegetation types in northwest Guangxi, China. *Environ. Earth Sci.* **2013**, *69*, 2699–2708. [CrossRef]
42. Betts, M.G.; Ganio, L.M.; Huso, M.M.P.; Som, N.A.; Huettmann, F.; Bowman, J.; Wintle, B.A. Comment on "Methods to account for spatial autocorrelation in the analysis of species distributional data: A review". *Ecography* **2009**, *32*, 374–378. [CrossRef]
43. Caselli, F.; Feyrer, J. The Marginal Product of Capital. *Q. J. Econ.* **2007**, *122*, 535–568. [CrossRef]
44. Guo, X.B.; Hu, H.C. New Explanation on Late-development Advantages & China's Economic Development. *Wuhan Univ. J. (Phil. Soc. Sci.)* **2004**, *57*, 351–357.
45. Rivera-Batiz, L.A.; Romer, P.M. International trade with endogenous technological change. *Eur. Econ. Rev.* **1991**, *35*, 971–1001. [CrossRef]
46. Yang, Z.N.; Dong-Hong, L.I.; Chen, L. On Industrial Catching-up Mechanisms in Chinese Manufacturing under the Uncertainty of Technology Change. *J. Financ. Econ.* **2013**, *39*, 123–135.
47. Wang, Y.; Guo, X. Meaning & Realization Mechanism of Advantage of Late-development in Industrial Structures. *Wuhan Univ. J. (Philos. Soc. Sci.)* **2008**, *5*, 620–625.
48. Doeringer, P.B. *"First-Mover" and "Late-Developer" Advantages: Institutions and Market Design in the New York and Los Angeles Garment Districts, 1900–1960*; Boston University: Boston, MA, USA, 2011; Volume 5, pp. 1–39.
49. Jian, X.H.; Xu, H. Advantages and Disadvantages as Late Starters and Development by Leaps and Bounds. *Economist* **2002**, *6*, 30–36.
50. Yao, O. *Case: Human Capital Advantages of Late-Developing Large Countries*; Spinger: Singapore, 2016.
51. Hou, G. To Parse Generalized Concept of Late-Development Advantage. *Ref. Strategy* **2009**, *5*, 59–61.
52. Hwang, C.L.; Yoon, K. *Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1981; Volume 375, pp. 1–531.
53. Chamodrakas, I.; Martakos, D. A utility-based fuzzy TOPSIS method for energy efficient network selection in heterogeneous wireless networks. *Appl. Soft Comput. J.* **2011**, *11*, 3734–3743. [CrossRef]
54. Minarčíková, E. Hodnocení rozvoje regionů Visegrádské čtyřky v kontextu politiky soudržnosti Evropské unie. *DSpace VŠB-TUO* **2016**, *5*, 12.
55. Li, N.; Wang, Y. Measuring the Development Level of Chinese Regional Service Industry: An Empirical Analysis based on Entropy Weight and TOPSIS. *World Acad. Sci. Eng. Technol.* **2012**, *68*, 159.
56. Torlak, G.; Sevkli, M.; Sanal, M.; Zaim, S. Analyzing business competition by using fuzzy TOPSIS method: An example of Turkish domestic airline industry. *Expert Syst. Appl.* **2011**, *38*, 3396–3406. [CrossRef]
57. Yue, Z. A method for group decision-making based on determining weights of decision makers using TOPSIS. *Appl. Math. Model.* **2011**, *35*, 1926–1936. [CrossRef]
58. Büyüközkan, G.; Çifçi, G. A combined fuzzy AHP and fuzzy TOPSIS based strategic analysis of electronic service quality in healthcare industry. *Expert Syst. Appl.* **2012**, *39*, 2341–2354. [CrossRef]
59. Shannon, C.E. Mathematical theory of communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423. [CrossRef]
60. Bence, J.R. Analysis of Short Time Series: Correcting for Autocorrelation. *Ecology* **1995**, *76*, 628–639. [CrossRef]

61. Vecchia, A.V.; Ballerini, R. Testing for Periodic Autocorrelations in Seasonal Time Series Data. *Biometrika* **1991**, *78*, 53–63. [CrossRef]
62. Haugen, M.A.; Rajaratnam, B.; Switzer, P. Extracting Common Time Trends from Concurrent Time Series: Maximum Autocorrelation Factors with Application to Tree Ring Time Series Data. *Statistics* **2015**, 1–24.
63. Hart, T.; Coulson, T.; Trathan, P.N. Time series analysis of biologging data: Autocorrelation reveals periodicity of diving behaviour in macaroni penguins. *Anim. Behav.* **2010**, *79*, 845–855. [CrossRef]
64. Dégerine, S.; Lambert-Lacroix, S. Characterization of the partial autocorrelation function of nonstationary time series. *J. Multivar. Anal.* **2003**, *87*, 46–59. [CrossRef]
65. Box, J.F. Guinness, Gosset, Fisher, and Small Samples. *Stat. Sci.* **1987**, *2*, 45–52. [CrossRef]
66. Moran, P.A. Notes on continuous stochastic phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
67. Griffith, D.A. Spatial Autocorrelation. *Int. Encycl. Soc. Behav. Sci.* **2001**, *14*, 14763–14768.
68. Anselin, L. Local indicator of spatial association-LISA. *Geogr. Anal.* **1995**, *27*, 91–115. [CrossRef]
69. Dormann, C.; Mcpherson, J.M.; Araujo, M.B.; Bivand, R.; Bolliger, J.; Carl, G.; Davies, R.G.; Hirzel, A.; Jetz, W.; Kissling, W.D.; et al. Methods to account for spatial autocorrelation in the analysis of species distributional data: A review. *Ecography* **2007**, *30*, 609–628. [CrossRef]
70. Mcmillen, D.P. Probit with Spatial Autocorrelation. *J. Reg. Sci.* **2010**, *32*, 335–348. [CrossRef]
71. Tiefelsdorf, M.; Griffith, D.A. Semiparametric filtering of spatial autocorrelation: The eigenvector approach. *Environ. Plan. A* **2015**, *39*, 1193–1221. [CrossRef]
72. Oden, A.; Wedel, H. Arguments for Fisher's Permutation Test. *Ann. Stat.* **1975**, *3*, 518–520. [CrossRef]
73. Ludbrook, J.; Dudley, H. Why Permutation Tests Are Superior to t and F Tests in Biomedical Research. *Am. Stat.* **1998**, *52*, 127–132. [CrossRef]