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Research Article

Regional Credit, Technological Innovation, and Economic Growth in China: A Spatial Panel Analysis

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Based on data of 31 provinces in China for the period 2007–2017, this paper establishes spatial models by means of a transcendental logarithmic production function and analyzes the impact of regional credit and technological innovation on regional economic growth. The Jenks natural breaks method, kernel density function, and Moran index are introduced for spatial statistical analysis. Spatial weight matrices are constructed from two aspects of geographical characteristics and innovative input characteristics. The empirical results show significant spatial heterogeneity and spatial autocorrelation in economic growth, regional credit, and technological innovation. Both regional credit and technological innovation are important impacts to economic growth, whereas the interaction of regional credit and technological innovation has a negative effect on provincial economic growth. Therefore, we argue that China should rationally allocate regional credit resources, strengthen technological innovation capabilities, and boost the integrated development of regional credit and technological innovation. It is a particularly important way to facilitate regional economic integration and sustainable development.

1. Introduction

Entering a new era, China is in a critical period of economic high-quality growth with the increase of uncertainties in the international economic situation and the competitive landscape. To successfully surmount this critical period, we must heighten the proportion of science and technology and knowledge-intensive industries, stimulate technical innovation as the "first driving force," and take the road of regional innovation-driven development. In the recent years, regional credit and technological innovation have brought into play more and more vital effect in the transformation and upgrading of China's economy [1,2]. In terms of the ranking of the World Intellectual Property Organization (WIPO), Chinese synthesize ranking of scientific and technological innovation was 14th in 2019. In addition, the value of contract deals in domestic technical markets by type of contracts of China increased by more than 26.56% in 2019. Furthermore, the contribution rate of scientific and technological progress to the GDP has risen to 58.5% in 2018. Accordingly, in the process of China's modernization, technological innovation as the main driving force of economic development should be placed at the core.

In this economic situation, having a solid financial system is essential to provide an effective financing, risk management, and the sustainable development of China's economy [3]. According to the National Bureau of Statistics of China, the outstanding loans in local and foreign currencies of all financial institutions in China reached 23 trillion dollar in 2019, an increase of 2.4 trillion dollar over 2018. Figure 1 serves as the trend of financial institution credit measured by the logarithm of loan-based metrics (lnRC), technological innovation measured by the logarithm of patent-based metrics (lnRD), and total economic output measured by the logarithm of the GDP (lnGDP) of China from 2007 to 2018. As can be seen from Figure 1, lnGDP and lnRC maintained steady and rapid growth. Actually, reasonable credit supply creates a favorable financial environment for high-quality economic development. lnRD has remained high, mainly because of China's increasing emphasis on technological innovation in the recent years [4]. Meanwhile, technological innovation highly depends on the support of credit supply [2,5,6]. Credit supply has a direct impact on technological innovation and its transformation efficiency. Analyzing financial dependence and technological innovation [5] shows that firms in external finance-dependent industries generate a better patent portfolio. By comparing the trends of lnGDP, lnRC, and lnRD, it is also found that there is a certain correlation and similarity among them.

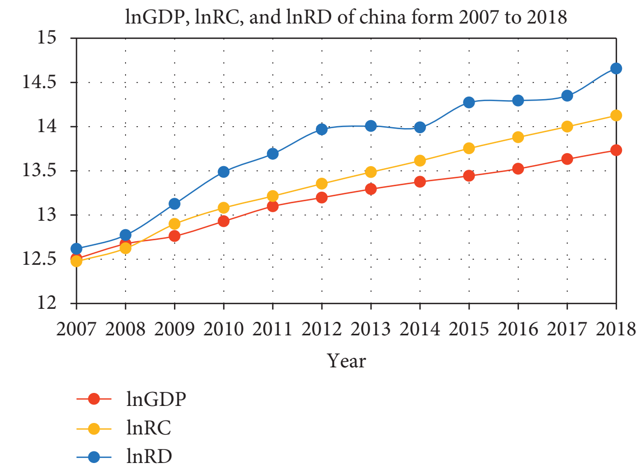


Figure 1: lnGDP, lnRC, and lnRD of China from 2007 to 2018.

Most researchers focus on the Chinese technological innovation surge, interestingly, while few have been known about the impact of regional credit and technological innovation on regional economic growth in China. From a regional perspective, is there spatial heterogeneity and a regional correlation in China's economic growth? Does China's regional credit level promote or restrain regional economic growth? How does regional credit affect regional economic growth through technological innovation? In the process of implementing an innovation-driven development strategy, exploring the influence of regional credit and technological innovation on economic growth is conducive to optimizing an innovation ecosystem and realizing the coordinated development of multiagent economy.

The following structure is arranged as follows. Section 2 is the literature review. Section 3 introduces the model specification and description of variables, including the spatial econometric model, variable selection, and spatial weight matrix construction. Section 4 uses spatial statistical analysis technology to analyze the dynamic evolution trend and spatial agglomeration effect of regional credit, technological innovation, and economic growth. Section 5 analyzes the empirical results of the static spatial model and dynamic spatial model. Section 6 draws the research conclusion and gives policy recommendations.

2. Literature Review

2.1. Regional Credit and Economic Growth. Finance is the core of modern economy and plays an important role in regulating the economy. The relationship between regional credit and economic growth has attracted great attention in the available theoretical and empirical literature. By comparing countries' economic growth performance, we summarize three main views on the relationship between regional credit and economic growth. First, financial credit has a positive effect on steady-state economic growth [7–10]. Diallo and Al-Titi [11] theoretically and empirically investigated the positive effect of bank credit on regional economic growth. Second, the link between regional credit and economic growth is not significant [12,13]. Zhang [13] explained that the contribution of bank credit development to economic growth was not significant in China. Third, financial credit has a negative effect on economic growth [14,15]. Sassi and Gasmi [14] explained the negative effect of credit on economic growth and the heterogeneity of the credit. Meanwhile, credit supply is unbalanced in the region [16], and it is not matched and not coordinated with the good situation of regional economic development, which restricts the development of regional economy to a certain extent. However, China's credit supply under the dominance of economic growth indicates that China is a puzzling example to the general financial credit literature.

2.2. Technological Innovation and Economic Growth. Statistical evaluation and quantitative analysis of technological innovation are the hot spots and trends of current scientific and technological research. Many studies focus on firms' capabilities for innovation [17], technological innovation output, the intensity of technological innovation [18], and sustainable innovation [19]. Innovation is the main engine of socioeconomic development for an increasing number of economic agents and countries. In particular, technological innovation is an important independent factor to reveal the change of economic growth [20,21]. Consequently, technological innovation has always been an intriguing research topic for scholars and policy makers. The existing literature has two main views on the impact of technological innovation on regional economic growth. First, an efficient regional innovation system plays a significant and positive role in promoting regional economic growth in China [22,23]. Zhou and Luo [24] analyzed that technological innovation had a delayed positive effect on economic growth. China hopes to stimulate the development of regional economy through the research of technological innovation. Second, there are significant regional differences in technological innovation [25,26]. Through econometric tools, Santana et al. [25] aimed to analyze the link between technological innovation and sustainable development in different countries and regions. The research indicated that technological innovation could produce different types of impacts according to the analysis of the development stages of different regions. The improvement of technological innovation capability is of great significance to innovation-driven development, innovation ecology, and regional economic synergy.

2.3. Regional Credit, Technological Innovation, and Economic Growth. A region's short-term growth depends on capital accumulation, while its long-term growth depends on technological innovation. A proper allocation of credit funds in a region can easily reduce transaction costs and achieve economies of scale. A well-developed and perfect credit mechanism can facilitate the intertemporal and inter-regional turnover of funds for the real economy, which is conducive to the growth and innovation of regional technologies. Technological innovation is the main driving force of regional economic growth in the new era. The integration of regional credit and technological innovation is a double-edged sword for economic growth.

Firstly, regional credit and technological innovation coordinate and play a synergistic effect to jointly promote regional economic growth. On the one hand, the deep integration of credit resources and technological innovation promotes the emergence and development of new nonbank credit institutions, breaks the monopoly of bank credit funds, and effectively optimizes the credit market system. On the other hand, the deep integration promotes financial innovation and provides diversified financing channels for innovative small and medium-size enterprises (SMES). Simultaneously, it reduces the financing transaction costs of SMES, improves their market profitability, and creates new advantages for regional economic growth. Therefore, the interactive integration of regional credit and technological innovation plays a role in economic growth. For example, Amore et al. [6] believe that the growth of financial credit could accelerate the accumulation of regional capital, enhance the financing capacity of enterprises in the region, and effectively promote the output of technological innovation. Pradhan et al. [23] explore the panel unit root test, panel cointegration test, and vector correction model to study the interaction among financial credit, economic development, and technological innovation of 49 European countries from 1961 to 2014. The results verify that, in the long run, both financial development and innovation are the causative factors of economic growth. Jia et al. [27] believe that innovation is the intermediate variable of financial development promoting economic growth.

Secondly, there are potential risks in the process of integration of regional credit and technological innovation, which will have an inhibitory effect on regional economic growth. On the one hand, the incentive of regional innovation policy makes some innovative enterprises exaggerate the economic effect of enterprises and expand blindly in order to obtain funds. As a result, enterprises fall into a vicious circle of "repaying old debts with new debts," which eventually leads to the bankruptcy of enterprises and increases the nonperforming loan rate of credit institutions. On the other hand, there is serious information asymmetry between credit institutions and innovative enterprises. It is difficult for credit institutions to grasp the core production technology and market competitiveness of enterprises in time and completely. As a result, it is unable to accurately evaluate the business performance and market prospects of enterprises, resulting in the mismatch of credit resources and increasing the potential risk of credit funds. Jiang and Ding [28] considered that the ratio of total financial deposits and loans to the local gross national product (GNP) inhibited the improvement of the quality of economic growth and was not conducive to technological innovation and the increase of economic growth. Zhang [29] used the spatial econometric model of 30 regions of China to study the positive effect of credit funds and technological innovation on regional economic growth, but the interaction between credit funds and technological innovation had no significant effect on economic growth. The prosperity of the technological innovation is a new development paradigm of global economy, while Brown et al. [30] considered that credit markets did not play an important role in funding its development. Also, they found that credit market development was not a major impediment to the expansion of the high-tech sector. Distortions in financial sector lower economic growth by reducing the speed of technological innovation [31,32]. These research studies provide various evidences for the role of regional credit in the process of innovation-driven regional economic growth.

2.4. Summary of the Aforementioned Literature. The aforementioned literature shows a significant gap in the conclusion of previous studies. Compared with the available literature, this paper makes three primary contributions.

Firstly, although regional credit, technological innovation, and economic growth have attracted great attention theoretically and empirically in the existing literature, most of the literature only considers two aspects of them. For example, Önder and Özyildirim [10], Diallo and Al-Titi [11], and Ouyang and Li [15] only explore the relationship between regional credit and economic growth. Santana et al. [25], Pradhan et al. [23], and Zhou and Luo [24] only explore the nexus between technological innovation and economic growth. However, only few researchers have studied the nexus among regional credit, technological innovation, and economic growth, such as Amore et al. [6], Pradhan et al. [23], Jiang and Ding [28], and Brown et al. [30]. This paper considers the impact of regional credit and technological innovation and their integration (coordination) on economic growth of China from the national perspective.

Secondly, although many scholars have analyzed the imbalance and incoordination of regional economic distribution, they seldom introduce spatial factors. Traditional econometric models, such as the ordinary least squares estimation, panel unit root test, panel cointegration test, and vector correction model, ignore the spatial effects and may be considered biased [4]. The spatial effect is the essential characteristic of spatial econometric analysis. Only Zhang [29] and Li and Zhou [32] introduce spatial models, while Zhang [29] does not consider spatial heterogeneity and dynamic evolution, and Li and Zhou [32] ignore the influence of other factors (institutional factors, open conditions, etc.) other than explanatory variables on the explained variables. This paper establishes static spatial panel models and dynamic spatial panel models by means of transcendental logarithmic production function and analyzes the impact of regional credit and technological innovation on regional economic growth in China. Simultaneously, the Jenks natural breaks method, kernel density function, and Moran index are introduced for spatial statistical analysis.

Thirdly, the spatial weight matrix setting form is limited. The spatial weight matrix is the main tool to abstract spatial and reflect a spatial effect. It is one of the core contents of the spatial econometric model. The setting and optimization of spatial weight matrices have always been the focus of attention. Li and Zhou [32] only constructed the weight matrix based on adjacency and geographical distance, and the spatial dependent structure of reaction variables had limitations. Spatial weight matrices are constructed from the spatial adjacency matrix, geographical distance weight matrix, and innovation capital input weight matrix in this paper.

3. Model Specification and Variables Description

3.1. Model Specification. Most of the existing literature is according to the Cobb–Douglas production function, which regards credit as an input factor. But, in the actual economic system, not only the input factors have an impact on output, but also the interaction of input factors will have an impact on output. Transcendental Logarithmic Production function is a variable substitution elastic production function model, which is generally used to analyze the interaction between input factors [33,34]. This paper establishes a transcendental logarithmic production function model to analyze the impact of regional credit, technological innovation, and their interaction on economic growth.

$$\begin{aligned}\ln \mathrm{GDP}_{it} = {} & \beta_1 \ln \mathrm{RC}_{it} + \beta_2 \ln \mathrm{RD}_{it} + \beta_3 \ln(\mathrm{RC}_{it}) * \ln(\mathrm{RD}_{it}) \\ & + \gamma \ln X_{it} + \varepsilon_{it},\end{aligned} \tag{1}$$

where GDP denotes the gross domestic product, RC denotes the regional credit, and RD denotes technological innovation. The interaction term, $\ln(\mathrm{RC}) * \ln(\mathrm{RD})$, denotes the influence of the integration of regional credit and technological innovation on economic growth. X denotes other control variables affecting economic growth, $\beta_1, \beta_2, \beta_3, \gamma$ denote the coefficients of each variable, respectively, ε denotes the error perturbation term, i represents a certain region, and t represents a certain year ranging from 2007 to 2017.

The output elasticity of regional credit is as follows:

$$Z = \frac{\partial(\ln \mathrm{GDP}_{it})}{\partial(\ln \mathrm{RC}_{it})} = \beta_1 + \beta_3 \ln(\mathrm{RD}_{it}). \tag{2}$$

The impact of regional credit on economic growth is not only related to the scale and structure of regional credit but also to technological innovation. When $\beta_3 \ln(\mathrm{RD}) > 0$, it says that technological innovation enhanced the impact of regional credit on economic growth. When $\beta_3 \ln(\mathrm{RD}) < 0$, it says that technological innovation restrained the impact of regional credit on economic growth. When $\beta_3 \ln(\mathrm{RD}) = 0$, it says that the impact of regional credit on economic growth had nothing to do with technological innovation.

In addition to regional credit and technological innovation, regional economic growth will be affected by a series of other factors, such as provincial material capital (K_{it}), labor input (L_{it}), and consumption level (C_{it}). By incorporating these control variables into the equation, equation (1) can be transformed into

$$\begin{aligned}\ln \mathrm{GDP}_{it} = {} & \beta_1 \ln \mathrm{RC}_{it} + \beta_2 \ln \mathrm{RD}_{it} + \beta_3 \ln(\mathrm{RC}_{it}) * \ln(\mathrm{RD}_{it}) + \gamma_1 \ln K_{it} \\ & + \gamma_2 \ln L_{it} + \gamma_3 \ln C_{it} + \varepsilon_{it}.\end{aligned} \tag{3}$$

Equation (3) is a traditional panel model. If the spatial effect of the gross domestic product is taken into consideration, the spatial lag is brought into equation (3) and the static spatial panel model is established. The basic models of static spatial panel models include spatial autoregressive models (SAR) and spatial error models (SEM). Equations (4) and (5) are the SAR and SEM.

$$\begin{aligned}\ln \mathrm{GDP}_{it} = {} & \rho W(\ln \mathrm{GDP}_{it}) + \beta_1 \ln(\mathrm{RC}_{it}) + \beta_2 \ln(\mathrm{RD}_{it}) \\ & + \beta_3 \ln(\mathrm{RC}_{it}) * \ln(\mathrm{RD}_{it}) \\ & + \gamma_1 \ln K_{it} + \gamma_2 \ln L_{it} + \gamma_3 \ln C_{it} + \varepsilon_{it},\end{aligned} \tag{4}$$

$$\begin{aligned}\ln \mathrm{GDP}_{it} = {} & \beta_1 \ln \mathrm{RC}_{it} + \beta_2 \ln \mathrm{RD}_{it} + \beta_3 \ln(\mathrm{RC}_{it}) * \ln(\mathrm{RD}_{it}) \\ & + \gamma_1 \ln K_{it} + \gamma_2 \ln L_{it} + \gamma_3 \ln C_{it} + \lambda W \varepsilon_{it} + \mu_{it},\end{aligned} \tag{5}$$

where ρ and λ, reflecting the spatial spillover of gross domestic product, respectively, represent the estimated parameters of spatial lag and spatial error. W is a spatial weight matrix, which reflects the spatial relationships among the various regions. If the dynamic effect and the spatial effect of the gross domestic product are taken into consideration, the first-order lag and spatial lag are brought into equation (3). The dynamic spatial panel models are established as follows:

$$\begin{aligned}\ln \mathrm{GDP}_{it} = {} & \tau \ln\mathrm{GDP}_{i(t-1)} + \rho W(\ln \mathrm{GDP}_{it}) \\ & + \beta_1 \ln(\mathrm{RC}_{it}) + \beta_2 \ln \mathrm{RD}_{it}(\mathrm{RD}_{it}) \\ & + \beta_3 \ln(\mathrm{RC}_{it}) * \ln(\mathrm{RD}_{it}) \\ & + \gamma_1 \ln K_{it} + \gamma_2 \ln L_{it} \\ & + \gamma_3 \ln C_{it} + \varepsilon_{it}\varepsilon_{it} = \lambda W \varepsilon_{it} + \mu_{it},\end{aligned} \tag{6}$$

where τ denotes the estimated parameter of first-order lag of the gross domestic product, which reflects the impact of the past relevant factors on the current gross domestic product.

3.2. Selection of the Spatial Weight Matrix

3.2.1. Spatial Adjacency Matrix (W1). In order to establish a spatial econometric model, this paper firstly defines the space distance. The distance here is generalized, and it can be geographic distance or can be other economic sense of the distance. The spatial data of n regions are expressed as $\{x_i\}_{i=1}^{n}$, where i denotes the region i. w_{ij} denotes the spatial distance between the region i and the region j, and then, the spatial weight matrix W can be defined as

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix}, \quad (7)$$

where $w_{ii} = 0\,(i = 1, \ldots, n)$. Because the distance from region i to region j is the same as that from region j to region i, that is, $w_{ij} = w_{ji}$, the spatial weight matrix W is a symmetric matrix. The most commonly used spatial weight matrix is the adjacency matrix (W_1). Specifically, if regions i and j have a common boundary, the weight is 1; otherwise, it is 0.

3.2.2. Geographical Distance Weight Matrix (W2). In order to enhance the robustness of the results, this paper not only constructs the spatial adjacency matrix (W_1) but also considers the geographical distance weight matrix (W_2) and the innovation capital input weight matrix (W_3). The geographical distance weight matrix (W_2) is constructed by the reciprocal of the spherical distance between provincial capitals. Namely,

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}}, & i \neq j, \\ 0, & i = j. \end{cases} \quad (8)$$

In formula (8), d_{ij} is the spherical distance between the provincial capital city of i province and that of j province, indicating that the closer the distance is, the closer the relationship between provinces is. The advantage of this approach is that it takes full account of the actual situation of interaction and interaction between provinces which are close but not adjacent in space.

3.2.3. Innovation Capital Input Weight Matrix (W3). The weight matrix based on spatial adjacency and geographical distance does not reflect the correlation of regional economic characteristics. Lin et al. [35] took the spatial correlation of social and economic characteristics into consideration and constructed the weight matrix of social and economic distance. Substantively, it mainly embodies the ability of transforming the research achievements of technological innovation into technologies and products, and it is the materialized achievement of technological innovation in promoting economic and social development. Naturally, we consider establishing the distance weight matrix (W_3) of innovation capital input. W_3 reflects the correlation between research and experimental development expenditure and geographical distance. Significantly, W_3 is beneficial to the robustness test of the results. The specific formula is as follows:

$$W_3 = W_1 \operatorname{diag}\left(\frac{\overline{T}_1}{\overline{T}}, \frac{\overline{T}_2}{\overline{T}}, \frac{\overline{T}_3}{\overline{T}}, \ldots, \frac{\overline{T}_n}{\overline{T}}\right), \quad (9)$$

where $\overline{T}_i = (1/(t_1 - t_0 + 1)) \sum_{t=t_0}^{t_1} T_{it}$ represents the average expenditure on research and experimental development (R&D) in Province i during the investigation period. $\overline{T} = (1/(n(t_1 - t_0 + 1))) \sum_{i=1}^{n} \sum_{t=t_0}^{t_1} T_{it}$ represents the average expenditure on total research and experimental development (R&D) during the investigation period, and t is in different periods.

3.3. Variables Description

3.3.1. Explained Variable: Economic Growth (GDP). In empirical analysis, there are generally two methods to measure regional economic growth. Firstly, the GDP of each region is adopted and converted into the real GDP expressed in terms of the base year constant price by the GDP index. Second is GDP per capita. GDP per capita can only approximate regional economic development. If regional growth is to be properly measured, the most direct measure is the real GDP at constant prices. Therefore, this paper uses the real GDP, expressed in constant prices on the basis of 2007, to reflect regional economic growth. Data source: China Statistical Yearbook (2007–2017).

3.3.2. Core Explanatory Variables. Regional credit (RC): in previous studies, credit supply is considered as an important financial service to promote economic growth and is often used as an important indicator of credit. Credit supply is the main source of enterprise financing, which can measure the important role of financial credit in economic growth. Because of considering the availability and validity of the data, the balance of credit funds of financial institutions is used to reflect regional credit development. Data sources: the Statistical Yearbook of each province, Statistical Bulletin of National Economic and Social Development of each province, and Regional Financial Operation Report of the People's Bank of China.

Technological innovation (RD): as for the measurement index of technological innovation, the research literature mainly selects the input index and output index of technological innovation. In practice, there is great uncertainty from R&D input to output. The patent data can reflect the application value of technological innovation and the provincial technological innovation information, so most literature adopts the number of patents granted as the measurement index of the technological innovation output, such as [6]. Following the general practice, this paper adopts the number of patents granted in each province as the measurement index of technological innovation in the province. Data source: China Statistical Yearbook (2007–2017).

3.3.3. Control Variables. According to economic theory and the availability and validity of data, the control variables are as follows: provincial capital investment (K) is expressed by total investment in fixed assets in the whole country, labor input (L) is expressed by the number of employed persons in urban units, and consumption level (C) is expressed by total retail sales of regional social consumer goods. In order to reduce the influence of heteroscedasticity on the model, we take the logarithmic form of all variables to be dimensionless. Table 1 shows descriptive statistics of all the variables used. All variables have good statistical characteristics.

4. Spatial Feature Analysis

This section firstly describes geospatial distribution characteristics of regional credit, technological innovation, and economic growth from a macro perspective. Secondly, the kernel density function is used to reflect the dynamic evolution trend of regional credit, technology innovation, and economic growth. Finally, the Moran index and LISA are adopted to depict whether the spatial agglomeration phenomenon exists in the regional credit, technological innovation, and economic growth in Chinese provinces.

4.1. Geospatial Characteristics Analysis. The Jenks natural breaks classification is designed to place variable values into naturally occurring data categories [36]. We utilize the Jenks natural breaks method to distinguish logical breakpoints in economic datasets by grouping similar values of "minimizing differences in the sum of squares within a class and maximizing differences in the sum of squares between groups" [36,37]. We employ GeoDa to yield the geospatial distribution characteristics of regional credit, technological innovation, and economic growth of Chinese 31 provinces. The 31 provinces are itemized according to the Jenks natural breaks algorithm [38,39], which is shown in Figures 2–4. Different colors indicate different levels of geospatial distribution. As the color deepens, the level of development of regional credit, technological innovation, and economic growth increases gradually. If the classification value is superior to the average value, the development level of the region will have a spillover effect. Conversely, if the value is less than the average, the development level of this region has a weak impact on the development of neighboring provinces.

(1) Figure 2 shows the geospatial distribution of regional economic growth. As can be seen, the regions with high economic growth are mainly concentrated in the eastern and central regions of China. The lower economic growth is concentrated in northwest China. Also, this concentration is continuously changing in a ladder form from west to east, which shows that the economic growth of neighboring provinces influences each other. Furthermore, this proves the existence of the spatial spillover effect of economic growth.

(2) Figure 3 shows the geographic spatial distribution of regional credit. Clearly, the areas with large credit supply are mainly concentrated in the southeast coastal areas of China, where the economy is relatively developed, forming a financial cluster. In addition, Sichuan, Henan, and Hubei have higher credit level, but no obvious agglomeration area.

(3) Figure 4 shows the geospatial distribution of technological innovation levels. It can be seen that Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong have higher technological innovation levels. The lower technological innovation levels are concentrated in the western and northern parts of China.

4.2. Spatiotemporal Dynamic Evolution. For the spatial heterogeneity feature measure, the existing literature usually uses the kernel density estimation method, Dagum Gini coefficient, Theil index, and coefficient of variation. Although the calculation methods and processes are different, the conclusions are not much different. The kernel density estimation method is the most popular method now. The main idea of kernel density estimation is to reflect its evolution trend by dynamic changes of specific graphical features such as kurtosis, skewness, and symmetry in the index distribution map. On the basis of the practice of Jiang et al. [40], Ma et al. [41], Yang et al. [42], and Zhao [43], taking 2007, 2009, 2011, 2013, 2015, and 2017 as measuring time points, this paper adopted the kernel density estimation method to comprehensively depict the spatial distribution characteristics and spatiotemporal dynamic evolution of regional credit, technology innovation, and economic growth. By comparing the kernel density estimation curves (Figures 5–7), we come to the following conclusion:

(1) The overall economic growth level of China's provinces has grown steadily. During the inspection period, the center of the distribution curve of real GDP logarithm showed a trend of gradually shifting to the right, indicating that China's provincial economic growth level is gradually increasing. This feature is consistent with the overall description. The peak value of the main peak increases gradually, and the width of the main peak shows a weak trend of narrowing, indicating that the gap of economic growth between provinces in China tends to be narrow. The density distribution curve always has a trailing phenomenon, and its distribution tends to extend to the right, indicating that the provinces with higher economic growth show an upward trend, and some provinces have a lower level of economic growth. From the shape of the curve, the unipolarization phenomenon of the distribution is obvious, and its peak value first increases and, then, decreases, but the decrease range is small, indicating that the economic growth level of each province is advancing smoothly as a whole.

(2) The spatial distribution of credit levels in various provinces in China tends to converge. During the inspection period, the center of the density distribution curve of the credit funds of 31 provincial financial institutions gradually shifted to the right, indicating that the overall credit level of China's

Table 1: Statistical description of variables.

Variables	Mean	Std. dev.	Min	Max
Economic growth (lnGDP)	9.289	1.051	5.833	11.293
Regional credit (lnRC)	9.568	1.104	5.390	11.886
Technological innovation (lnRD)	9.371	1.713	4.220	13.078
Intersection of regional credit and technological innovation (lnRC * lnRD)	91.470	25.501	22.831	155.435
Capital investment of provinces (lnK)	9.068	1.019	5.600	10.959
Labor input (lnL)	5.907	0.926	2.178	7.947
Consumption level (lnC)	8.423	1.145	4.724	10.584

Data source: China Statistical Yearbook.

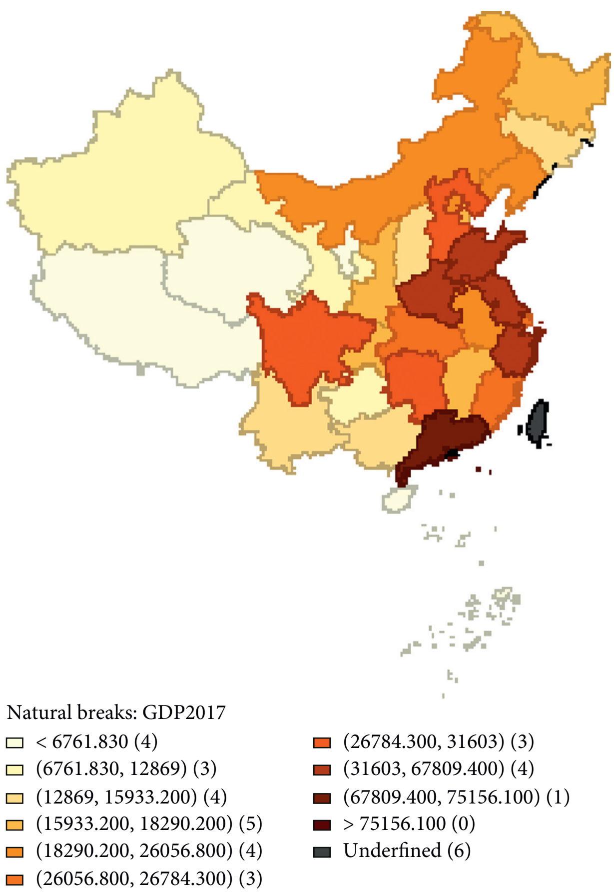


Figure 2: Geospatial distribution of economic growth in Chinese 31 provinces in 2017.

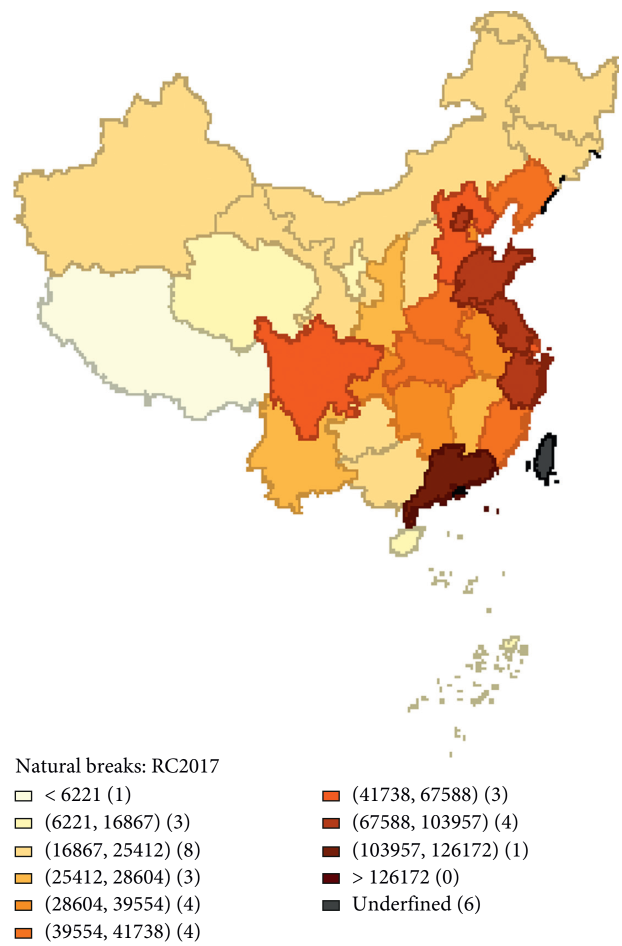


Figure 3: Geospatial distribution of regional credit in Chinese 31 provinces in 2017.

provinces showed a gradual upward trend. The main peak of the distribution curve showed a significant upward trend, and the main peak width decreased year by year. It shows that the absolute gap of credit levels in various provinces is shrinking. The distribution curve shows a tailing phenomenon to the left, and its distribution ductility tends to converge from broadening, indicating that the provinces with high credit levels are on the rise and the gap with the average level is shrinking year by year. The ductility gap has been shrinking year by year. The single polarization phenomenon of distribution has always existed, and its peak value rises stepwise, indicating that the polarization phenomenon of provincial credit level is gradually alleviated and controlled over time.

(3) China's provincial technological innovation capability has shown an overall upward trend year by year. During the inspection period, the center of the density distribution curve of the 31 provincial patent application grants gradually shifted to the right, indicating that the technological innovation capability of China's provinces showed an upward trend. The distribution curve had a tailing phenomenon, and the distribution curve always had a single polarization phenomenon. The peak value of the main

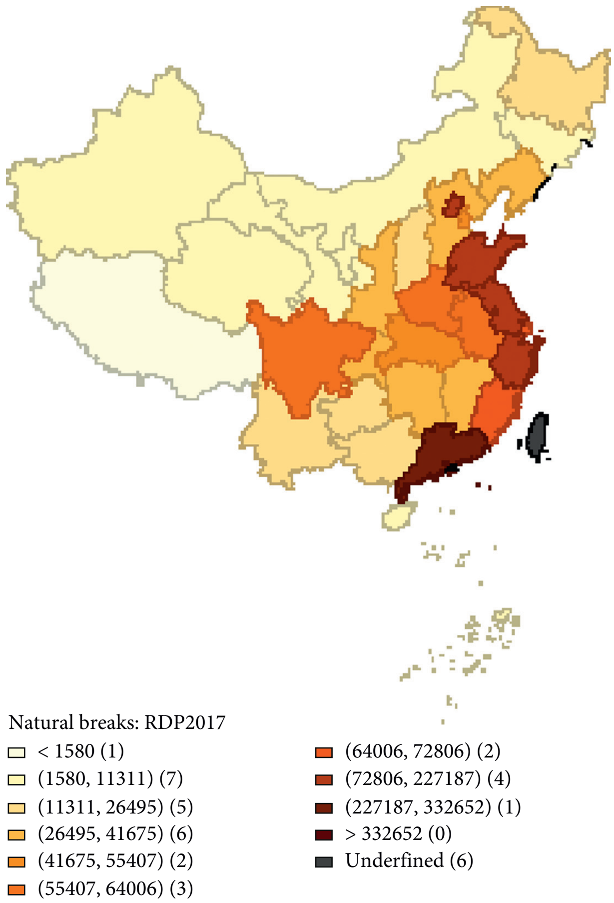


FIGURE 4: Geospatial distribution of technological innovation in Chinese 31 provinces in 2017.

peak first rises and then rises, and the width of the main peak does not change much, indicating that the technical innovation ability of each province has progressed smoothly.

4.3. Spatial Autocorrelation Analysis. Spatial heterogeneity (spatial structure) mainly examines the spatial imbalance of regional credit, technological innovation, and economic growth, while spatial autocorrelation (spatial interaction) mainly reflects the spatial agglomeration effect of regional credit, technological innovation, and economic growth. If the spatial characteristics of the data are strongly influenced by the observation location, the adjacent spatial units interact with each other, and the adjacent areas tend to have more similarities than the remote areas. The Moran index (*Moran's I*) [44] is the most popular method for estimating spatial autocorrelation in the literature.

4.3.1. Global Spatial Autocorrelation Analysis. For the purpose of testing the spatial correlation of economic growth, regional credit, and technological innovation, this paper uses the spatial adjacent weight matrix and global *Moran's I* to estimate. From Table 2, we find that *Moran's I* of economic

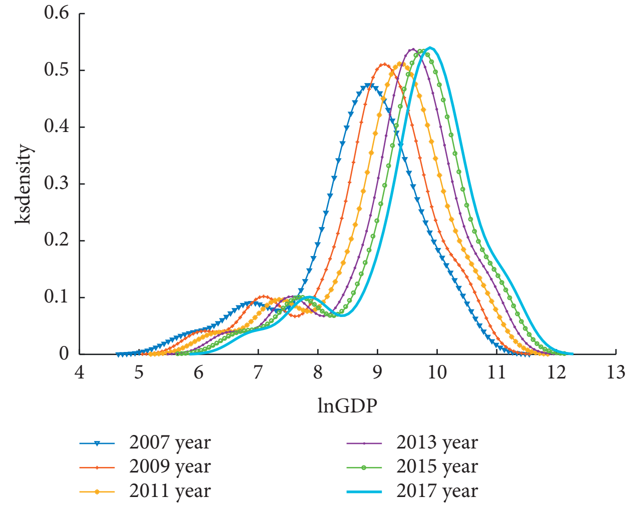


FIGURE 5: Kernel density distribution of 31 provincial lnGDP.

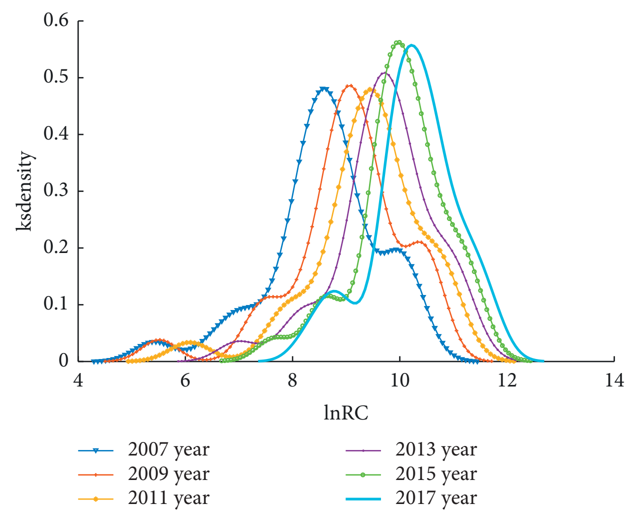


FIGURE 6: Kernel density distribution of 31 provincial lnRC.

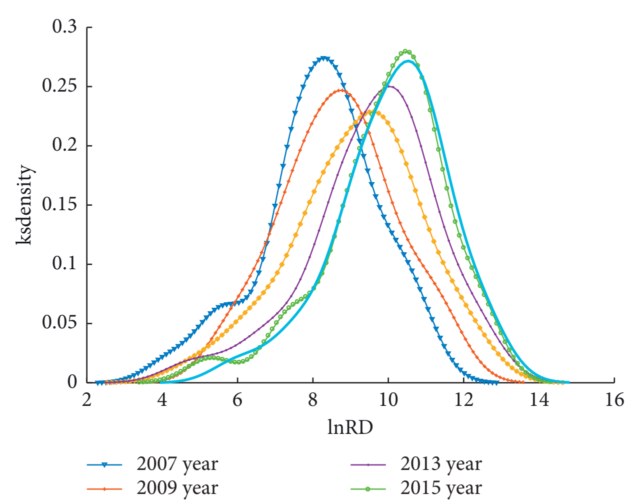


FIGURE 7: Kernel density distribution of 31 provincial lnRD.

Table 2: Global *Moran's I* in China from 2007 to 2017.

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
lnGDP	0.359***	0.358***	0.367***	0.362***	0.357***	0.350***	0.346***	0.346***	0.361***	0.378***	0.371***
lnRC	0.384***	0.380***	0.349***	0.350***	0.347***	0.353***	0.356***	0.353***	0.348***	0.367***	0.388***
lnRD	0.349***	0.362***	0.396***	0.397***	0.422***	0.415***	0.402***	0.420***	0.411***	0.430***	0.439***

***, **, and *denote statistical significance levels at 1%, 5%, and 10%, respectively.

growth in 2007–2017 is concentrated in 0.346–0.378 and passed the significance level test of 1%. In 2016, *Moran's I* of economic growth reached its highest value of 0.378. It shows that the economic growth of 31 provinces in China is not randomly distributed in space, but has positive autocorrelation in space and presents strong spatial agglomeration in geographical space. From 2007 to 2017, *Moran's I* of regional credit concentrated between 0.347 and 0.388 and passed the significance test under 1% level. It shows that a positive spatial autocorrelation exists in the credit of the provinces and regions. From 2007 to 2017, *Moran's I* of technological innovation concentrated between 0.349 and 0.464, and all of them passed the significance test at the level of 1%. The lowest *Moran's I* was 0.349 in 2007 and the highest was 0.464 in 2017. The results show that there is a strong positive autocorrelation in the space of technological innovation in 31 provinces in China, and the trend is strengthening year by year. Compared with economic growth and regional credit, technological innovation has the strongest positive spatial autocorrelation and shows stronger spatial agglomeration characteristics in geographic space.

By comparing *Moran's I* of the economic growth, regional credit, and technological innovation, we find that they have similar spatial agglomeration characteristics. That is to say, the provinces with the high *Moran's I* value are close to the provinces with high index value, and the provinces with low *Moran's I* value are close to the provinces with low index value. This agglomeration indirectly reflects the imbalance of economic growth, regional credit, and technological innovation in China's provinces. In addition, this paper also finds that there are certain correlations and similarities among the three trends of economic growth, regional credit, and technological innovation.

4.3.2. Local Spatial Autocorrelation Analysis. In order to further analyze the local agglomeration characteristics of economic growth, regional credit, and technological innovation in different provinces of China, this paper took the year of 2017 as an example and undertook a local indicator of spatial association (LISA) analysis [45]. The LISA agglomeration maps allowed us to explore the local spatial autocorrelation (Figures 8–10). Local *Moran's I* scatter plots were divided into four quadrants. The positive spatial correlation is distributed in the first and third quadrants, while the negative spatial correlation is distributed in the second and fourth quadrants.

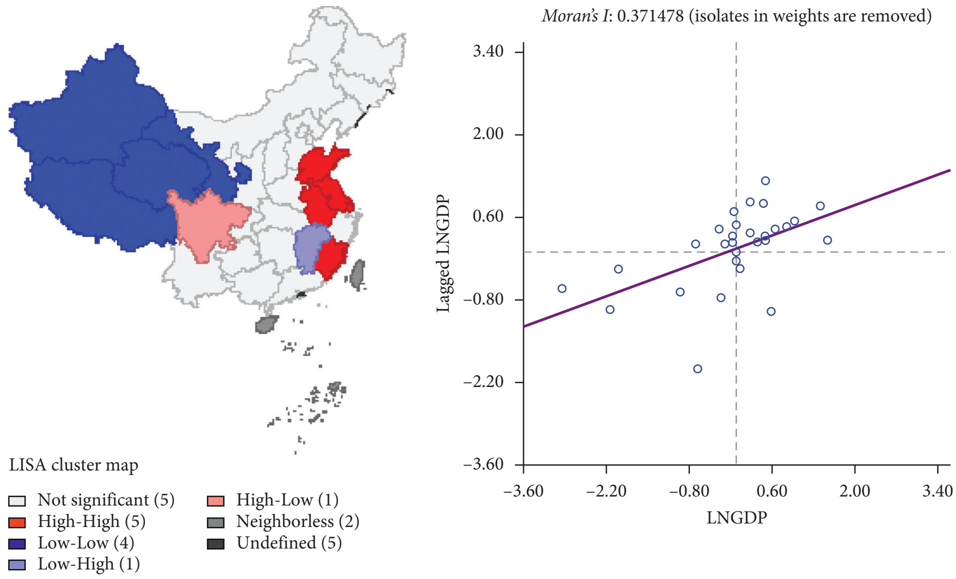
From Figure 8, we can see that the high-high agglomeration, are mostly distributed in Shandong, Jiangsu, Shanghai, Anhui, and Fujian of eastern coastal areas of China. The provinces with low-low agglomeration are Xinjiang, Tibet, Qinghai, and Gansu provinces of northwest China. As can be seen from *Moran's I* scatter plots, the provinces in quadrants 1 and 3 account for the majority, which reflects that the level of technological innovation in China shows a strong positive spatial correlation. The differentiation of "high-high" and "low-low" basically conforms to the spatial pattern of China's economic development from east to west. It fully demonstrates that China's economy has obvious spatial autocorrelation and spatial heterogeneity in geographical spatial distribution. The spatial distribution of regional credit and technological innovation is similar to that of economic growth (Figures 9 and 10).

5. Spatial Econometric Analysis

5.1. Model Recognition. Traditional econometric models do not involve such spatial effects, and the estimates are biased. Upon the abovementioned analysis, we find that there are spatial autocorrelation among regional credit, technological innovation, and economic growth. This means that the geographic distance and spatial effect are both significant factors affecting regional economic growth.

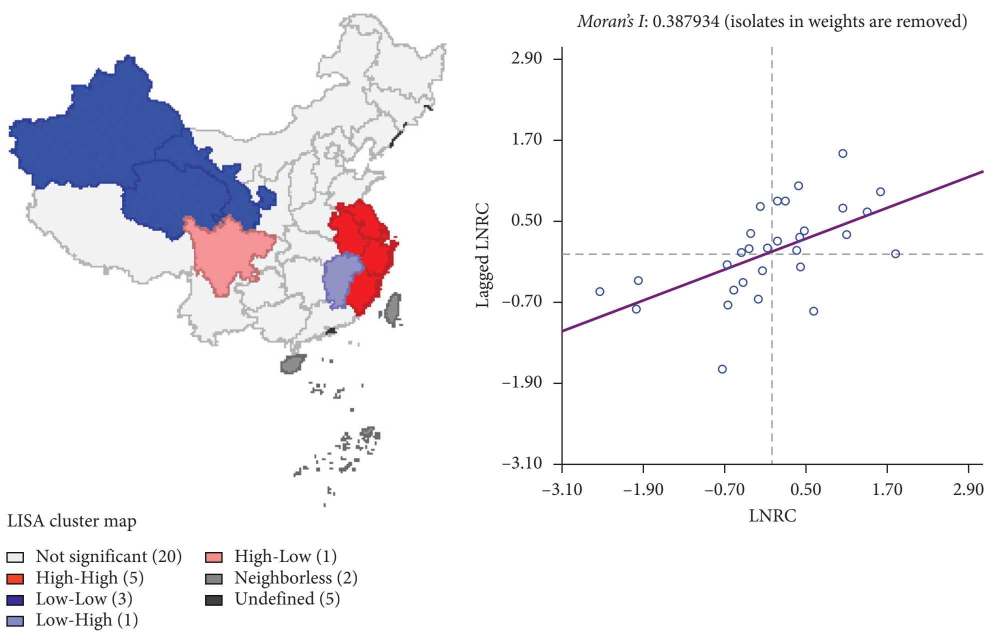
According to the model discriminant criteria of Anselin et al. [46], the SLM model and the SEM model are tested by the Lagrange multiplier (LM). LM (error) and Robust-LM (error) are used to test the spatial correlation of the residual, while LM (lag) and Robust-LM (lag) are used to test the spatial lag of the model. Table 3 shows the results. The values of LM (lag) and Robust-LM (lag) were 9.886 and 9.804, respectively, and were significant; the values of LM (error) and Robust-LM (error) were 0.105 and 0.023, respectively, and were not significant. It shows that the SAR model is better than the SEM model.

Furthermore, the Hausman test shows that the Hausman statistic is 183.65 and has passed the significance test of 1%, indicating that the spatial fixed effect model is more applicable. In general, the fixed effect model works better when the subject is a specific individual. Compared with the random effect model, Lee and Yu [47] believe that the fixed effect model is more robust and simpler in calculation. According to the different control of space and time effect, the model of the spatial fixed effect can be divided into the time fixed effect, space fixed effect, mixed effect (that is, no space fixed effect and no time fixed effect), and both fixed effect. This paper also estimates the four spatial econometric models and finds that the model fits better under the dual fixed effect of space and time. In fact, there are obvious regional differences in China's economic growth. Mixed effects and time effects ignore these differences. Spatial both fixed effects take into account both temporal and regional impacts and also distinguish spatial correlation from spatial heterogeneity and missing variables [48]. Therefore, both



(a) (b)

Figure 8: LISA agglomeration map and *Moran's I* scatter plot of economic growth in 2017.



(a) (b)

Figure 9: LISA agglomeration map and *Moran's I* scatter plot of regional credit in 2017.

fixed effects can more accurately reflect the actual situation of regional economic growth. Therefore, the both fixed effect model of SAR is adopted in this paper.

5.2. Estimation Results Analysis. To enhance the validity and robustness of spatial models, we simultaneously employ three kinds of weight matrices to estimate the static SAR models. The regression results are shown in the models (1), (2), and (3) in Table 4. The spatial weight matrices in static spatial panel model (1), (2), and (3) are the spatial adjacency matrix (W_1), spherical distance weight matrix (W_2), and innovation capital input weight matrix (W_3). The spatial correlation coefficient of model (1) is 0.229, which is significant at 1%, higher than that of model (2) and model (3). It shows that the economic growth of adjacent provinces affects each other, but that of nonadjacent provinces is not strong. According to the adjusted statistics of R^2, Sigma^2,

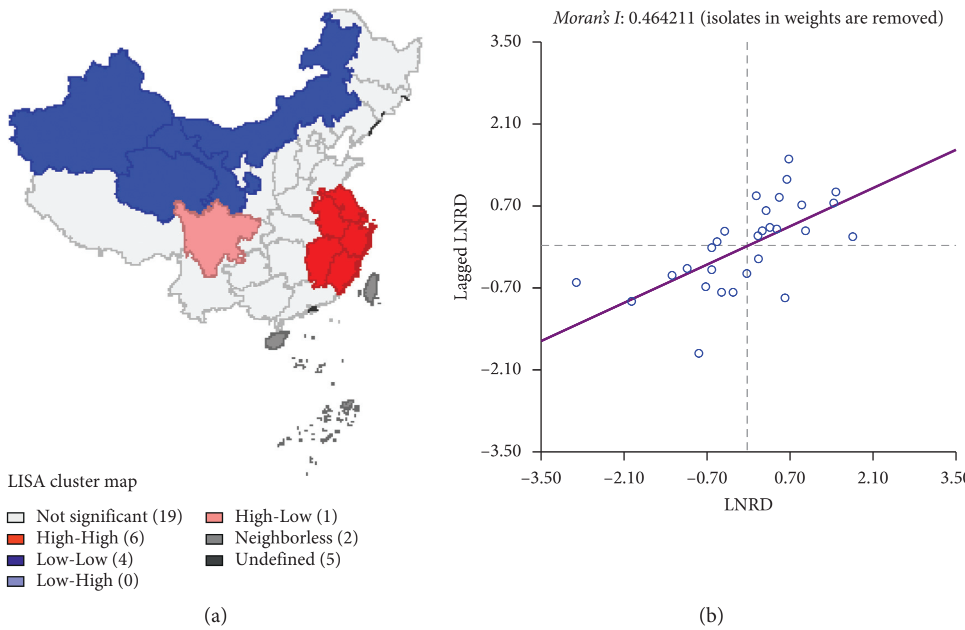


Figure 10: LISA agglomeration map and *Moran's I* scatter plot of technological innovation in 2017.

Table 3: The results of the LM test.

Test	Statistic
Lagrange multiplier (error)	0.105
Robust Lagrange multiplier (error)	0.023
Lagrange multiplier (lag)	9.886^{***}
Robust Lagrange multiplier (lag)	9.804^{***}

***, **, and *denote statistical significance levels at 1%, 5%, and 10%, respectively.

and Log-L, the models (1), (2), and (3) have goodness of fit. From the estimation results of explanatory variable coefficients in the model, there is little difference among explanatory variable coefficients and the significance test.

The static spatial panel model ignores the influence of other factors (institutional factors and open conditions) other than explanatory variables on the explained variables. Therefore, this paper uses the first-order lag of regional economic growth to represent other potential influencing factors of regional economic growth and establishes a dynamic spatial econometric model of SAR. The models (4), (5), and (6) in Table 4 give the estimation results of the dynamic spatial panel model established based on the weight matrices W_1, W_2, W_3. It can be seen from Table 4 that, in the dynamic spatial panel model, the spatial correlation coefficients of the three models are 0.001, 0.379, and 0.001, respectively, and all of them are significant at the level of 5%. The spatial correlation coefficient of spatial model (4) is lower than that of the static panel. The spatial correlation coefficients of dynamic model (5) and (6) are significantly positive, which is not consistent with the estimation of the spatial correlation in the static model. Compared with the spatial correlation coefficient of model (4) and model (5), the spatial correlation coefficient of model (6) is relatively higher, which explains to some extent that the economic growth of one region depends on other regions, not only because of the adjacent and adjacent geographical locations of the two regions. In the dynamic space panel, expressed in the dependent variable of first-order lag other potential factors and other potential factors impact on regional economic growth from the separated space structure factors, spatial correlation changed, regional economic growth as a dynamic, continuous economic system, and the potential factors of its influence is very important. Therefore, it is necessary to establish a dynamic spatial panel model. The regression coefficients of dynamic factors in models (4), (5), and (6) are, respectively, 0.897, 0.879, and 0.897, which are all significant at the level of 1%, further verifying the positive influence of other factors on regional economic growth.

In the dynamic spatial panel model, Sargan statistic, Log-L, and other statistics all have good fitness. From the estimation results of explanatory variable coefficients in the model, the estimation results of model (6) have passed the significance test, which is obviously superior to the estimation results of other models. Therefore, this paper chooses the estimation results of model (6) for discussion. The regional credit regression coefficient is 0.011, and the technological innovation regression coefficient is 0.052, which is significant at the level of 1%. That is to say, if the provincial credit level and technological innovation increase by one unit, the provincial economic growth level will increase by 1.1% and 5.2%, respectively. Therefore, the regional credit level and technological innovation have significant positive effects on provincial economic growth. In the recent years, with the gradual rise of China's financial market, the market system is becoming increasingly sound, the scale is expanding, the structure is becoming more reasonable, and the role of financial credit level in promoting economic growth is becoming increasingly obvious. People's

Table 4: Regression results of SAR.

Type	Static spatial panel model			Dynamic spatial panel model		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
lnRC	0.024**	0.022**	0.022**	0.005	0.001	0.011***
lnRD	0.026	0.028	0.027	0.053***	0.046***	0.052***
lnRC × lnRD	−0.001	−0.001	−0.001	−0.004***	−0.004***	−0.005***
lnK	0.061***	0.073***	0.069***	0.001*	0.008**	0.006**
lnL	0.074***	0.071***	0.070**	0.073***	0.057***	0.065**
lnC	0.347***	0.416***	0.400***	0.029**	0.062***	0.032***
T (dynamic factors)				0.897***	0.879***	0.897***
ρ (spatial factors)	0.229***	−0.540	−0.092	0.001**	0.379***	0.001***
Cons				0.157***	0.144***	0.125***
Sigma^2	0.001***	0.001***	0.001***			
Adj-R^2	0.898	0.981	0.993			
Obs.	341	341	341	310	310	310
Log-L	719.601	742.055	736.742	871.341	886.382	884.562
Sargan statistic				777.308***	761.571***	776.856***

***, **, and *denote statistical significance levels at 1%, 5%, and 10%, respectively. This paper makes a comparative analysis of the spatial models with "lnRC × lnRD" and without "lnRC × lnRD" and finds that the estimation results of models are robust. Limited to the length of the paper, the experimental results are omitted. Interested readers can obtain it from the authors.

understanding of technological innovation is deepening gradually, R&D funds are increasing everywhere, patent authorization is increasing day by day, and the level of technological innovation plays an increasingly important role in stimulating the economy.

The intersection of regional credit and technological innovation (lnRC ∗ lnRD) is –0.005 at the level of 1%. That is to say, the interaction between regional credit and technological innovation will reduce regional economic growth by 0.5% for each additional unit. This shows that, in the process of development, financial credit has a significant delayed effect on the support of technological innovation and inhibits the current economic growth. On the one hand, under the incentive of regional innovation policies, some innovation-oriented enterprises exaggerate their economic effects and implement blind expansion in order to raise funds. This will lead enterprises into a vicious circle of "borrowing new debt to repay old debt," which will eventually lead to the bankruptcy of enterprises and increase the nonperforming loan ratio of credit institutions. On the other hand, due to the serious information asymmetry between credit institutions and innovative enterprises, it is difficult for credit institutions to grasp the core production technology and market competitiveness of enterprises in a timely and complete manner. As a result, credit institutions are unable to accurately assess the business performance and market prospects of enterprises, leading to the mismatch of credit resources, thus increasing the potential risk of credit funds. In a word, the integration degree of financial credit to technological innovation in China is not enough. There are still many problems in technological finance to the economic growth of provinces.

In terms of control variables, the capital investment, labor input, and consumption level of every province are significantly positive in six models, which shows that the material capital, labor input, and consumption level of every province have a significant positive effect on provincial economic growth during the survey period. The higher the consumption level of each province, the stronger the consumption capacity of the province and the faster the economic growth. Capital investment and labor input are one of the important input factors of regional economic growth. The amount of capital investment and labor input directly affects the production of economic sectors. Speeding up the construction of regional human capital and education level plays an important role in regional economic growth.

6. Conclusions

Using panel data of 31 provinces in China from 2007 to 2017, this paper establishes static spatial panel models and dynamic spatial panel models based on transcendental logarithmic production function and empirically analyses the impact of regional credit and technological innovation on regional economic growth in China. The kernel density function and Moran index are introduced for spatial statistical analysis. Spatial weight matrices are constructed from two aspects of geographical characteristics and innovative capital input characteristics. Through spatial statistical analysis and spatial econometric analysis, the following conclusions are drawn: (1) There are spatial heterogeneity and spatial correlation in economic growth, regional credit, and technological innovation of China's provinces and regions. When studying the impact of regional credit and technological innovation on economic growth, we should not neglect the influence of geographical factors and spatial effects. (2) Regional credit and technological innovation have significant positive effects on provincial economic growth. (3) Regional credit has a significant delayed effect on the support of technological innovation and inhibits regional economic growth. In the process of increasing the level of financial credit and technological innovation, they lack more and deeper integration and interaction. Regional credit and technological innovation have not yet achieved coordinated development.

Based on the abovementioned conclusions, this paper provides policy recommendations for China heading for a sustainable economic growth. (1) China government departments should strengthen the free flow of credit between regions, which is conducive to the rational and optimal allocation of financial credit funds in multilevel regions. Accelerating the strategic layout of the multilevel regional financial credit center and regional credit cooperation is conducive to the integration of financial credit market and promoting the long-term stable growth of regional economy. (2) For regions with better economic development, the Chinese government has relaxed financial control, which is conducive to the integration of financial credit capital into technological innovation and the reduction of financing costs for technological innovation of enterprises. This is the institutional guarantee for innovative enterprises to build a sound financial environment. (3) Exploring the integration mode of technological innovation and regional credit is beneficial to improving the depth and breadth of technological innovation and financial credit integration and realizing the coordinated development of technological innovation and regional credit.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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