The Spatial Economic Effect of Industrial Credit Misallocation in China

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The cross-industry allocation of bank credit plays an important role in China’s economic development and optimizing and upgrading industrial structures. This article collects the panel data of 19 industries in China from 2007 to 2017, constructs dynamic spatial panel models, and deeply analyzes the impact of credit misallocation on industry economy. The results show that structural misallocation of bank credit exists in various industries in China. Particularly, credit deviation degree of China’s industries has gradually declined, but structural volatility remains large. A large amount of capital flows to the tertiary industry, while the capital of the primary industry and the secondary industry is relatively scarce. What is more, credit misallocation has a negative impact on industry economic growth and shows a weak acceleration effect. Therefore, in formulating economic policies, the government should actively guide the rational flow of inter industry credit funds and improve the efficiency of capital allocation. The government should continue to increase investment in manufacturing and promote independent innovation. Additionally, reasonable financial policies should be formulated to ensure the effective operation of the market and reduce the degree of credit misallocation.

1. Introduction

Over the past 40 years of reform and opening up, China has witnessed rapid economic growth and become the world’s second largest economy. However, in the past, China’s economic growth mainly relied on the advantages of high savings and investment, low-cost labor, and sought driving force from the demand side. Since 2012, the traditional mode of economic growth has been flagging. Recently, the economic growth rate has dropped below 8%, and it has remained above 6%. The reasons are as follows. Firstly, the aging of population leads to the shortage of labor supply, and the advantage of demographic dividend has been lost. Secondly, high investment is accompanied by high debt, and economic risks begin to increase. Thirdly, the contribution rate of China’s total factor productivity to economic growth keeps decreasing [1–3]. After 2015, China began to strengthen supply-side structural reform, adjust and optimize industrial structure, improve industrial quality and efficiency, and promote high-quality economic growth.

Bank credit resources have always been the main driving force of China’s economic development. The allocation of credit resources among industries plays an important role in the optimization and upgrading of China’s industrial structure [4]. The influence of credit funds on economic growth not only shows the promotion effect on scale, but also contains the adjustment effect on structure. Bank credit funds are released to different types of real enterprises, which change the economic structure of China and promote its economic growth internally [5]. For the past few years, China’s economic growth has slowed down, and there are obvious differences in economic growth among different industries. Meanwhile, the imbalance of economic structure has appeared. In 2017, the proportion of China’s three industrial structure was 8.21%, 40.21%, and 51.58%, respectively. And the deviation...
between bank credit and industrial structure reached −4.52%, −5.60%, and 10.12%, respectively.

Generally speaking, credit funds are injected into micro-economic organizations through commercial banks. Rational lending behavior of banks will lead to the optimal allocation of funds; that is, it can form the actual effective demand equal to supply in the credit market. However, the market role and operating environment of China’s commercial banks are quite special and complex. First, as the main members of China’s financial system, commercial banks play an important intermediary role in the operation of the financial market [5]. Most of the commercial banks have state-owned background. Faced with government agencies, they often hold certain rights of fund consultation and adjustment. In the face of financing enterprises in the capital chain, commercial banks have greater capital distribution rights. Even with depositors, commercial banks are in a strong position. Second, different banks are located in different administrative divisions. Local governments intervene in credit to varying degrees from the perspective of local industrial economy, which results in a partial industry misallocation in the process of credit from the top to the grassroots banks [4]. Third, since China’s reform and opening up, most commercial banks lack scientific and effective credit management. Credit support overemphasizes performance and ignores fairness. The distribution of credit funds focuses on the industries in which state-owned enterprises are located, which easily leads to credit crowding, credit discrimination, and other misallocation phenomena.

From the microlevel, improper lending of credit leads to excessive concentration of bank loans and long-term overlapping of loan objects. Commercial banks have accumulated a large number of cyclical risks, the volatility of bank performance has increased, and the efficiency of credit allocation has declined [6]. With the improvement of the openness of China’s financial industry, foreign banks are constantly pouring into the Chinese market, and domestic banks are facing more and more market competition pressure. Additionally, government and industry regulation is becoming increasingly stringent, and the adverse effects of bank credit misallocation cannot be underestimated.

From the macrolevel, credit misallocation will have adverse effects on China’s industrial structure transformation. In formulating financial policies, the government not only hopes to maintain and improve the efficiency of credit allocation and promote economic growth, but also needs to guide certain credit funds to invest in “agriculture, rural areas and farmers” and small- and medium-sized enterprises to reflect the fairness of economic development, while commercial banks tend to invest in infrastructure, energy, power, and real estate industries. Over investment of funds formed for a long time will bring a variety of risks. The existence of credit misallocation shows that the purpose of government policy implementation has not been fully realized. Simultaneously, problems, such as rigid credit flow, continuous accumulation of credit risk, inefficient operation of the old kinetic energy, and difficulty in the effective conversion of new kinetic energy, have emerged. Finally, it leads to the slowdown of industrial structure and economic growth.

The “14th Five-Year Plan” period is a crucial period for deepening reform and opening up and accelerating the transformation of the economic development pattern. It is also a “critical period” for accelerating the development of strategic and innovative industries. The 19th National Congress of the Communist Party of China (CPC) has already made it clear that the economy is facing an inadequate and unbalanced situation. In order to promote and cultivate structural economic growth points, China must implement reasonable and effective financial policies, carry out supply-side structural reform of the financial system, optimize the credit structure of commercial banks, and reduce the degree of credit misallocation. Therefore, it is not only of theoretical significance in economics but also of practical significance to study the problem of bank credit misallocation in China and realize the upgrading of economic structure and coordinated economic development by adjusting the bank credit structure.

The contributions of this article are as follows. Firstly, different from the traditional credit misallocation, this article links the credit structure and economic structure from a macroperspective and redefines the credit misallocation from the perspective of industries. If the current credit structure deviates from the industrial structure in proportion (i.e., credit misallocation), then the efficiency of credit resource allocation can be evaluated. Secondly, based on the industry spatial weight matrix, a dynamic spatial panel model is constructed to study the credit misallocation problem. Most of the spatial econometric studies focus on the regional perspective, and there is no research on the bank credit problem through the construction of the spatial weight matrix from the industry perspective.

2. Literature Review

According to Chacholiades [7], the misallocation of credit resources is an objective phenomenon that cannot form the optimal allocation of credit resources due to the incomplete market. Currently, the existing literature has different research perspectives on credit misallocation. Li and Liang [8] discussed interest rate liberalization and industrial structure optimization from the perspective of misallocation. They found that compared with private enterprises, state-owned enterprises occupy too much credit resources, but their inefficiency was not conducive to the upgrading of industrial structure. In the renewable energy industry, Wang et al. [6] revealed that capital inefficiency was the fundamental reason for the reduction of total factor productivity. Moreover, in different stages of renewable energy industry development, capital efficiency shows different degrees of deviation. Zhang and Li [9] studied the relationship between credit misallocation and enterprise capital allocation efficiency from the micro-enterprise level and found that credit misallocation led to inefficient investment of enterprises and inhibited the development of private enterprises. Brant et al. [10] estimated the total factor productivity loss caused by capital and labor misallocation in China’s nonagricultural economy from 1985 to 2007. They found that credit misallocations reduced nonagricultural GDP by an average of 20%. Li [4] adopted the Jorgenson growth accounting model and
confirmed the mismatch phenomenon in China’s capital market. He attributed this mainly to large capital inflows into the services sector, which offers lower returns. Zhu [11] studied the allocation of credit resources, government intervention, and bank performance. She found that the government’s intervention in credit resources was directional, and effective intervention helps to alleviate the friction in the credit market. However, the government provides tangible or intangible guarantee for inefficient enterprises, which will lead to the continuous misallocation of credit resources. Yuan [12] analyzed the spatial economic effect of the allocation of bank credit in 31 provinces of Chinese mainland from a regional perspective and confirmed the existence of bank credit misallocation.

Currently, most scholars focus on the problems of credit misallocation and overcapacity from a macro perspective, but seldom study the credit allocation of industry in China. Han et al. [13] show that credit misallocation is related to the state-owned status of Chinese enterprises. Specifically, when the presence of state-owned banks is strong, the interest costs associated with state-owned enterprises are more severely distorted. Zhang et al. [14] found that the reason of credit misallocation was the selective capital investment of bank credit constraints caused by information asymmetry. The concentration of credit funds to large enterprises will lead to overcapacity in some areas. Research group of Neijiang Central Sub-branch of the People’s Bank of China [15] also studied credit misallocation. They believed that the misallocation of credit resources was the “driving force” behind overcapacity, and the worsening quality of credit assets and the rise of nonperforming loan ratio will eventually affect regional financial stability. Zhao and Jiang [16] discussed the impact of credit resource allocation on overcapacity. They found that in the early stage of enterprise production, banks issued large amounts of cheap loans to enterprises in industries with overcapacity, resulting in over investment. When enterprises try to exit the overcapacity industry, banks and the government jointly set high exit barriers to aggravate the problem of overcapacity. Therefore, the tendentious credit rationing is the key factor for the development of industry overcapacity. Reasonable allocation of credit funds will be conducive to the development of industry economy and maintain the stability of financial development.

Generally speaking, there are two problems in the existing literature. Firstly, the existing research on credit misallocation belongs to different perspectives. For the allocation of industry credit resources, most of them stay in the field of overcapacity and credit misallocation. There are few studies on the impact of bank credit misallocation on industry economic growth. Secondly, the quantitative analysis method is seldom used in the research of credit misallocation. It is difficult to draw a clear, specific, and complete conclusion due to the insufficient application of industry credit data in China. Based on the perspective of industry credit, this article collects the panel data from 2007 to 2017 and constructs a dynamic panel model to identify the industry effect of bank credit misallocation. It can not only effectively solve the endogenous problems of explanatory variables in the model and make the analysis results more authentic and reliable, but also further expand the research depth of credit misallocation from the perspective of industry.

Credit misallocation, also known as credit deviation, refers to the deviation between the current credit structure and its best credit structure or other economic structure in different dimensions. Credit misallocations include both positive and negative misallocations. From the micro- and macro-point of view, it can be divided into credit misallocation of commercial banks and credit misallocation of macro-economy. In essence, credit misallocation is a problem of financial resource allocation. It is manifested in the loss of efficiency in the allocation of credit resources and the misallocation between credit resources and enterprise development. It is easy to cause industrial structure imbalance, economic growth quality decline, and so on. Actually, the allocation of credit structure is to keep a dynamic balance among the cost of credit, the amount of credit, and the profitability of enterprises. If there is imbalance, it will cause efficiency loss. The credit misallocation proposed in this article emphasizes the misallocation between the bank and the government’s objectives caused by the system and policy under the condition of market economy, which is a long-term nonequilibrium state. This misallocation is particularly evident in China. It is also the game between the bank and the government in different stages to the enterprise loan link and finally reflected in the change of economic growth.

Based on the above definition, two hypotheses are proposed.

Hypothesis 1. For bank credit, whether it is a positive misallocation or a negative misallocation, it will have a negative impact on the economic growth of the industry. Positive misallocation means that the scale of bank credit is relatively abundant in the industry, but the distribution in the subindustry is unreasonable. The use efficiency of enterprise funds decreases, which will have a negative impact on economic growth. Negative misallocation means that the scale of bank credit capital is relatively deficient in the industry and the distribution of it in subindustries is more unreasonable. The shortage of funds has restricted the further expansion of enterprises’ production, operation, and investment scale, which also has a negative impact on economic growth.

Hypothesis 2. Credit misallocation in adjacent industries will also have a negative impact on the economy of the industry. Due to the different degrees of cross-connection between industries, credit misallocation in adjacent industries will have a negative impact on the economic growth of the industry. The more closely connected the industry is, the greater the degree of such a knock-on impact will be. The spatial correlation between industries needs to be analyzed by the spatial econometric method. Simultaneously, in order to overcome the problem of endogeneity, the dynamic spatial panel model is used to empirically test the above hypothesis.

3. Methodology

Lin and Sun [17] believe that economic development is essentially a process of continuous industrial innovation and
Structural change. The essence of modern economic growth is the continuous upgrading of the industrial structure [18]. In order to test the relationship between the credit misallocation in the banking industry and the economic growth of the industry in recent years, a dynamic spatial panel model of credit misallocation is constructed below. Considering the availability of data, the time range of a sample interval is selected from 2007 to 2017. The main reason is that the loan data of commercial banks in different industries are mainly from the annual report of the former China Banking Regulatory Commission (CBRC), which only publishes the annual report from 2007 to 2017. After the merger of the former CBRC and the former China Insurance Regulatory Commission (CIRC) into the China Banking and Insurance Regulatory Commission (CBIRC) in 2018, the annual report of the former CBRC will no longer be disclosed. Other economic data are from China Statistical Yearbook and Local Statistical Yearbook, etc.

There are few quantitative studies on the spatial characteristics of industry economy in China. Hu and Jiao [19] used cross-sectional data to calculate the proportion of R&D investment in the total R&D investment of each industry in the oil and gas industry and 27 manufacturing industries, and simply calculated the technical distance between industries. Zhu et al. [20] conducted a more in-depth study on the spillover effect of R&D capital elements on R&D output among local industrial sectors from two dimensions of vertical spillover effect and horizontal spillover effect. Specifically, they divided the vertical spillover effects into forward spillovers and backward spillovers. Based on the spatiotemporal data of 33 industries in China from 2003 to 2011, the spatial weight matrix was constructed by using the induction coefficient and influence coefficient in the input-output matrix.

3.1. Spatial Panel Model. Spatial econometrics originated from the mutual development of regional economics and econometrics. It studies how to deal with spatial interaction and spatial structure in cross-section data and panel data. The concept of spatial econometrics was first proposed by Paelinck and Klaassen [21]; then developed by Anselin [22]; and gradually formed a relatively complete framework system. Anselin [23] classified spatial econometric models from two dimensions: the types of spatial lag variables and the scope of spatial correlation. Furthermore, he revealed the economic significance of the spatial autoregressive (SAR) model and spatial error model (SEM) to some extent. SAR shows that the dependent variables of a space unit can affect the dependent variables of other space units through the spatial conduction mechanism, while SEM shows that the spatial spillover or interaction is the result of random shock.

Scholars generally use cross-sectional data to establish spatial econometric model or combine cross-sectional spatial element with time series to establish spatial econometric model of static panel data. Cross-sectional spatial econometric model is simple and easy to operate, but there are two problems. On the one hand, it ignores the time lag between bank credit and economic growth. On the other hand, the data information is not fully utilized, which increases the contingency and randomness of the results. The static spatial panel model expands the number of observed values, makes full use of data information, and improves the accuracy of the model. However, it is still possible to ignore the impact of factors other than bank credit on economic growth. The dynamic spatial panel model can effectively solve aforementioned problems.

The basic form of the spatial econometric model can be expressed as:

$$y = \alpha + \rho (I_T \otimes W_N) y + X' \beta + \mu = \lambda (I_T \otimes M_N) \mu + \epsilon,$$

where \(y\) is the explained variable. \(X\) is the exogenous explanatory variable matrix. \(\rho\) is the spatial autoregression coefficient. \(\lambda\) is the spatial error coefficient. \(\beta\) reflects the influence of explanatory variable \(X\) on explained variable \(y\). \(I_T\) is the T-dimensional unit time matrix. \(W_N\) and \(M_N\) are the \(n\)-th order space weight matrix (\(n\) is the number of industries). \(\epsilon\) and \(\mu\) is the random error term, where \(\epsilon \sim IID(0, \sigma^2)\). Ref. [28] pointed out that the spatial Durbin model (SDM) was the general form of SAR and SEM. If one model satisfies either SAR or SEM or both, it is necessary to further investigate the more generalized SDM. The expression is as follows:

$$y = \rho (I_T \otimes W_N) y + \theta (I_T \otimes W_N) X + X' \beta + \mu,$$

where \((I_T \otimes W_N) X\) is the spatial lag term of explanatory variable and represents the influence of independent variables in adjacent industries. Elhorst and Freret [24] believed that if there were missing variables in the model and these variables were exactly related to explanatory variables, then the model could get unbiased estimation only if it included spatial lag explanatory variables. Therefore, in order to fully reflect the spatial and time lag effects of bank credit deviation, dynamic spatial Durbin model (DSDM) should be established, namely,

$$y = \gamma y_{t-1} + \rho (I_T \otimes W_N) y + \eta (I_T \otimes W_N) y_{t-1} + \theta (I_T \otimes W_N) X + X' \beta + \mu.$$

The significance of introducing DSDM lies in the following two aspects. On the one hand, spatial factors are introduced to reflect the spatial correlation and spatial effect of bank credit activities. On the other hand, the explained variables of the lag period are introduced into the model as independent variables to overcome the influence of endogenous.

3.2. Spatial Weight Matrix. Referring to the construction method of regional spatial matrix by Zhu et al. [20], this article defines different industries as spatial individuals of economic activities. According to the industry classification standard of the national bureau of statistics, 19 industry categories are selected, and the economic value of the industry is used to set the industrial economic distance matrix \((W_0)\) through the “adjacent” of the industry. Then, based on...
two spatial weight matrices are set: technical distance weight matrix \((W_1)\) and industry credit allocation weight matrix \((W_2)\). Through the introduction of \(W_1\) and \(W_2\) matrices, this article comparatively studies the impact of bank credit deviation on economic growth.

3.2.1. Technical Distance Weight Matrix \((W_1)\). Jaffe [25] defined the technology distance between enterprises based on the characteristics of R&D activities of enterprises and considered that the technology spillover effect between enterprises can be measured by the knowledge stock of other enterprises. This knowledge stock is obtained by weighting the technology distance as the weight, and the calculation method of technology distance is as follows:

\[
a_{ij} = \frac{F_i F_j}{\sqrt{([F_i F'_i][F'_j F_j])}}, \quad i, j = 1, 2, \ldots, n, \quad (4)
\]

where \(F_i\) and \(F_j\) represent the time row vectors of the share of \(i\) and \(j\) in the output of each industry, respectively, which is shown as \(F_i = (F_{i1}, F_{i2}, \ldots, F_{it})\). Therefore, \(a_{ij}\) represents the technical distance between enterprise \(i\) and enterprise \(j\) in the sample time interval, and \(0 < a_{ij} \leq 1\). The more similar the technical level, product composition or scale of enterprise \(i\) and enterprise \(j\) are, the closer \(a_{ij}\) is to 1; otherwise, the closer \(a_{ij}\) is to 0. As can be seen from the above definition, different from the vertical spillover effect by means of input-output matrix, the spillover effect of technical distance measure by Jaffe [25] did not have a specified direction and could not reflect the vertical relationship between upstream and downstream.

Xu and Deng [26] calculated the “proximity” between industries based on the structure of the direct consumption coefficient of each industry sector and constructed the technical distance weight of the industry, namely, \(W_{ij} = (\sum_k a_{ik} a_{kj})/\left(\sqrt{\sum_k a_{ik}^2 a_{kj}^2}\right)\), where \(a_{ik}\) and \(a_{kj}\) are elements at the \(k\)th position of the column vector of the direct consumption coefficient structure of the \(i\)th and \(j\)th industrial sectors, respectively. The entries on the main diagonal are 0.

3.2.2. Industry Credit Allocation Weight Matrix \((W_2)\). In order to represent the influence of industry credit deviation degree on the economic growth level of one industry and other industries, the spatial weight matrix of bank credit \((W_2)\) is established. The specific form is \(W_2 = W_1 \ast \text{diag}(\overline{c}_1/\overline{c}_2, \overline{c}_2/\overline{c}_3, \ldots, \overline{c}_m/\overline{c}_n)\), where \(\overline{c}_i = 1/t_i - t_0 + 1 \sum_{t=1}^{t_i} c_{it}\) is the average of bank credit balance in industry \(i\). \(\overline{c} = 1/n(t_1 - t_0 + 1) \sum_{i=1}^{n} \sum_{t=1}^{t_i} c_{it}\) is the average of the overall bank credit balance.

3.3. Data and Variables. The industry classification is derived from the classification method explained in the annual report of CBRC, which includes 19 sectors in total, including 1 primary industry, 4 secondary industries, and 14 tertiary industries. The classification methods are consistent with the Industry Classification for National Economic Activities GB/T4754-2017 issued by the National Bureau of Statistics of China and with the industry classification issued by the China Securities Regulatory Commission (CSRC). The primary industry refers to agriculture, forestry, animal husbandry, and fishery (excluding the service industry of agriculture, forestry, animal husbandry, and fishery). The secondary industry includes mining, manufacturing, production and supply of electricity, heat, gas and water, and construction. The tertiary industry, namely, the service industry, refers to other industries other than primary industry and secondary industry. The tertiary industry includes wholesale and retail trades, transport, storage and post, hotels and catering services, information transmission, software and information technology, financial intermediation, real estate, leasing and business services, scientific research and technical services, management of water conservancy, environment and public facilities, service to households, repair and other services, education, health and social service, culture, sports and entertainment, public management, social security and social organizations, international organizations, as well as the service industry of agriculture, forestry, animal husbandry and fishery, auxiliary activities in mining, metal products, machinery, and equipment repair in manufacturing.

The extended production function model is established by introducing credit allocation factors. The explained variable is the economic output of different industries. Explanatory variables include labor input, capital input, and credit misallocation. The control variables are mainly individual and time factors. The model is shown in the following equation:

\[
RIVA = \beta_0 + \beta_1 \ast CDD + \beta_2 \ast SCDD + \beta_3 \ast FAIR + \beta_4 \ast EPR + \beta_5 \ast RLOAN + \mu, \quad (5)
\]

where industrial economic output is measured by Growth Rate of Industry Value Added \((RIVA)\). \(RIVA\) is calculated by the Industry Value Added at current price, that is, \(RIVA = (IVA_t - IVA_{t-1})/IVA_{t-1}\). Credit misallocation is measured by credit deviation degree and credit deviation square. Credit deviation degree \((CDD)\) is equal to the difference between the proportion of commercial banks’ loans in each industry and the proportion of their industry’s added value. The data are from the annual report of China Banking Regulatory Commission and China Statistical Yearbook. As CDD has both positive and negative characteristics, square of credit deviation degree \((SCDD)\) is constructed in actual processing to describe the nonlinearity of credit misallocation. It is generally believed that when the credit deviation degree approaches the credit equilibrium point, the credit deviation square will gradually become smaller. Credit availability tends to be reasonable and economic growth rate gradually increases. There is a negative quantitative relationship between credit deviation and economic growth rate.

Fixed-asset investment ratio \((FAIR)\) is measured by fixed-asset investment in each industry in the national total investment. China Statistical yearbook published the number of urban nonprivate employment in all 19 industries, but only the number of private enterprises and individual employment in 7 industries. Therefore, employment population ratio \((EPR)\) is obtained by dividing the number of
of urban nonprivate employees in each industry by the total number of urban nonprivate employees. The data are collected according to the latest statistical yearbook of China. Table 1 is a statistical description of some variables.

### 4. Descriptive Analysis

#### 4.1. Descriptive Analysis

As can be seen from Figure 1, commercial bank credit in three industries is increasing. Specifically, the growth rate of bank credit in the secondary and tertiary industry is relatively stable, while in the primary industry, it fluctuates greatly. As shown in Figure 2, commercial bank credit is mainly concentrated in the secondary industry and the tertiary industry. The proportion of the primary industry is growing very slowly. With the implementation of the economic stimulus plan in 2008, the credit of major commercial banks is increased by a third in 2009 [27]. Simultaneously, the proportion of tertiary industry has always been higher than that of secondary industry, and the gap between them is gradually widening. This indicates that more credit funds are transferred from the secondary industry to the tertiary industry. In 2017, the proportion of credit to the secondary industry drops to 34.61% and the tertiary industry drops to 61.69%, with a gap of 27.08%.

#### 4.2. Sector Dimensions

From the perspective of sector distribution, as shown in Figure 3, the proportion of manufacturing credit has been the highest. Although China has been committed to economic restructuring and the proportion of manufacturing credit has been declining year by year, it still accounted for about a quarter of total credit in 2017. The proportion of wholesale and retail trades has been gradually increasing, reaching 17.84% in 2014, but declining

### Table 1: Statistical description of variables (unit: %).

| Variables | Definition                                      | Mean  | Std. Dev. | Min    | Max    |
|-----------|------------------------------------------------|-------|-----------|--------|--------|
| RIVA      | Growth rate of industry value added             | 14.114| 9.639     | −18.416| 87.350 |
| CDD       | Credit deviation degree                         | 0.000 | 4.211     | −9.949 | 8.934  |
| SCDD      | Square of credit deviation degree               | 17.645| 21.602    | 0.012  | 98.983 |
| FAIR      | Fixed-asset investment ratio                    | 5.263 | 8.402     | 0.129  | 34.097 |
| EPR       | Employment population ratio                     | 5.263 | 6.408     | 0.400  | 29.053 |
| RLOAN     | Growth rate of industry credit loan             | 15.925| 22.871    | −78.586| 109.379|

**Figure 1:** Industrial credit and its growth of China from 2007 to 2017. Data sources: Calculated according to the Annual Report of CBRC.

**Figure 2:** The proportion of industrial credit to total credit of China from 2007 to 2017. Data sources: Calculated according to the Annual Report of CBRC.

**Figure 3:** The proportion of sector credit to total credit of China from 2007 to 2017. Data sources: Calculated according to the Annual Report of CBRC.
after 2015, and has been the second largest industry in the share of bank loans. The third is transport, storage, and post, and real estate ranked fourth. The two sectors have only a small difference in the proportion of loans, both around 10% to 11%. The proportion and variation tendency of transport, storage, and post are similar to that of real estate.

The results show that during this period, 10.93% of the credit funds are transferred from the secondary industry to the tertiary industry and 2.41% to the primary industry. Specifically, the secondary industry presents the characteristics of “two declines and two rises” (manufacturing and production and supply of electricity, heat, gas, and water decreased, while mining and construction increased). Among them, the proportion of manufacturing decreased the largest, 10.71%. The proportion of construction increased from 4.03% in 2007 to 6.00% in 2015, with an increase of 1.97%. In the tertiary industry, wholesale and retail trades increased by 3.65% from 9.87% in 2007 to 15.52% in 2015, with the largest increase. By the end of 2017, in the credit structure of commercial banks, the proportion of industrial loans was still the highest in the manufacturing of the secondary industry, followed by the wholesale and retail trades, transport, storage and post, and real estate of the tertiary industry.

4.3. Growth Rate of Industry Value-Added (RIVA). Figures 4 and 5 show the distribution of RIVA of various industries. In Figure 4, the red line represents the RIVA of 19 sectors in 2017. The green line represents the average of RIVA of 19 sectors from 2007 to 2017. As can be seen, the average of RIVA of financial intermediation ranks the first...
(22.42%), followed by scientific research and technical services (18.02%), health and social service (17.77%), leasing and business services (17.51%), real estate (16.46%), and so on. The lowest three were agriculture, forestry, animal husbandry and fishery (10.07%), production and supply of electricity, heat, gas and water (7.49%), and mining (5.25%).

In Figure 5, RIVA generally shows a downward trend of fluctuation. The average growth rate of the primary industry value-added was 10.07%, that of the secondary industry 9.88%, and that of the tertiary industry 15.61%. After 2015, the secondary industry has a sustained and rapid rising trend. The tertiary industry is slowly rising, while the primary industry is declining.

From the red line in Figure 4, in 2017, the top three RIVA are information transmission, software, and information technology (25.36%); service to households, repair, and other services (20.32%); and public management, social security, and social organizations (17.51%). The majority above the mean (11.96%) belong to the tertiary industry. Other sectors are below average, with mining at the bottom (−1.50%). In 2017, the RIVA of the primary industry is 3.08%, the secondary industry 11.89%, and the tertiary industry 12.37%.

4.4. Proportion of Industry Value-Added to GDP. Composition of GDP by the three strata of the industry refers to the proportion of the value-added of each industry to GDP. It is calculated at current prices. Figure 6 shows the variation of the composition of GDP by China’s three strata of the industry from 2007 to 2017, and Figure 7 shows the variation of the composition of GDP by China’s 19 sectors from 2007 to 2017. From the perspective of the industry, the proportion of value-added of the primary industry and the secondary industry decrease, while that of the tertiary industry increases. The proportion of value-added of the secondary industry decreases from 46.85% in 2007 to 40.21% in 2017. The proportion of value-added of the tertiary industry increases from 42.50% in 2007 to 51.58% in 2017.

6.64% of the contribution is transferred from the secondary industry to the tertiary industry and 2.44% from the primary industry to the tertiary industry.

As shown in Figure 7, the proportion of value-added of manufacturing has been the highest. The proportion of value-added of agriculture, forestry, animal husbandry, and
Fishery has been declining, from 10.65% in 2007 to 8.21% in 2016, ranking third. The proportion of value-added of mining decreased rapidly, from 5.00% in 2007 to 2.17% in 2017. Other industries are basically in a steady or rising trend. Among them, the proportion of value-added of wholesale and retail trades has gradually increased to 9.40% in 2017, ranking second. Financial intermediation increased rapidly, from 5.65% in 2007 to 7.94% in 2016, ranking fourth. Construction and real estate industry ranked fifth and sixth, respectively.

4.5. Credit Deviation Degree (CDD) and Square of Credit Deviation Degree (SCDD). Figures 8 and 9 show the variation of credit deviation degree of various industries from 2007 to 2017. Among them, the proportion of value-added of wholesale and retail trades has gradually increased to 9.40% in 2017, ranking second. The proportion of value-added of financial intermediation increased rapidly, from 5.65% in 2007 to 7.94% in 2016, ranking fourth. Construction and real estate industry ranked fifth and sixth, respectively.

Figure 8: Credit deviation degree of industry in China from 2007 to 2017. Data sources: the Annual Report of CBRC and China Statistical Yearbook.

Figure 9: Square of credit deviation degree of industry in China from 2007 to 2017. Data sources: the Annual Report of CBRC and China Statistical Yearbook.

Figure 10: Credit deviation degree of sectors in China from 2007 to 2017. Data sources: the Annual Report of CBRC and China Statistical Yearbook.

Fishery has been declining, from 10.65% in 2007 to 8.21% in 2016, ranking third. The proportion of value-added of mining decreased rapidly, from 5.00% in 2007 to 2.17% in 2017. Other industries are basically in a steady or rising trend. Among them, the proportion of value-added of wholesale and retail trades has gradually increased to 9.40% in 2017, ranking second. The proportion of value-added of financial intermediation increased rapidly, from 5.65% in 2007 to 7.94% in 2016, ranking fourth. Construction and real estate industry ranked fifth and sixth, respectively.

From positive to negative in 2009. CDD of the tertiary industry has been positive and has been decreasing since 2010. Correspondingly, SCDD of the primary industry gradually becomes smaller, indicating that CDD is declining. SCDD of the secondary industry remained basically unchanged and increased suddenly in 2017. SCDD of the tertiary industry first rose and then decreased, and then rose suddenly in 2017. Generally speaking, CDD was the highest in 2009 and 2010, and then began to improve.

Specifically for 19 sectors, the credit misallocation has been negative for agriculture, forestry, animal husbandry, and fishery in the primary industry. That is, compared with the contribution of economic growth, the credit of agriculture, forestry, animal husbandry, and fishery is obviously
credit misallocation is more serious and has a greater adverse impact on economic growth [12].

As shown in Figure 11, industries with positive credit deviation are production and supply of electricity, heat, gas and water, management of water conservancy, environment and public facilities, transport, storage and post, real estate, leasing and business services, and wholesale and retail trades. Mining has changed from negative deviation to positive deviation, while other industries have negative deviation. The negative deviation of credit is more serious in agriculture, forestry, animal husbandry and fishery, financial intermediation, and manufacturing.

Comparing the above figures, it can be found that the proportion of industrial credit to total credit, CDD, and economic growth rate of different industries show different characteristics. In 2017, most of the credit funds of China’s commercial banks went to the tertiary industry such as management of water conservancy, environment and public facilities, transport, storage and post, real estate, leasing and business services, and wholesale and retail trades. The credit funds of production and supply of electricity, heat, gas and water, and mining in the secondary industry are relatively abundant, while the credit funds of manufacturing and construction are insufficient. It is generally believed that if the bank’s credit support for an industry is greater, the industry’s added value will grow faster. However, it seems that such a conclusion cannot be drawn from the figure. The growth rate of added value of industries with high positive deviation and abundant credit funds is not necessarily high. So, how can we understand and explain this phenomenon more objectively? In the new economic environment, does this phenomenon contain some regular economic significance? Is there an equilibrium in credit support? Is it helpful to restore and improve economic growth by adjusting industry credit deviation and correcting credit misallocation? In view of these problems, the empirical research on industry spatial econometric model is further carried out.

5. Results and Discussion

5.1. Spatial Correlation Test. Based on the spatial panel method introduced in Section 3, the SAR and SEM are firstly interpreted and selected, which are usually completed by the robust LM test. The judgment criteria of the robust LM test are as follows. The model with more significant LM statistics is the more desirable model. If the LM statistics of the two models have the same significance, the setting form of the model needs to be determined by the significance of the robust LM statistics [28]. This article adopts the methods of LM error test [29], robust LM error test [30], LM lag test (Anselin, 1988), and robust LM lag test [30]. Three different spatial weight matrices are used for the regression estimation of equation (5). The mean value is only taken from 2007 to 2017, and the spatial correlation test results of the cross-sectional mean equation are reported, as shown in Table 2. The spatial correlation test results show that the industry variables are spatially dependent. It is necessary to establish a spatial econometric analysis model to study the essential relationship between bank credit deviation degree and insufficient. In the secondary industry, it is worth noting that the credit misallocation of manufacturing has been rising, reaching −9.18% in 2017, which is the highest in the negative misallocation. According to the data in 2017, most sectors of the tertiary industry are positive misallocation, such as wholesale and retail trades, transport, storage and post, leasing and business services, and management of water conservancy, environment, and public facilities, which are all above 6%, and the highest value of management of water conservancy, environment, and public facilities is 8.51%. CDD in the negative misallocation is smaller, the smallest is public management, social security, and social organizations (except financial intermediation), and CDD is −3.16%. Compared with regional credit misallocation, industrial
industrial economic growth from the perspective of spatial econometric analysis. It is found from Table 2 that both \( W_1 \) and \( W_2 \), the robust LM test values of SEM and SAR, are significant at 1% or 5%. Therefore, the SDM is preferred in the static spatial panel model, and its estimation results are reported and discussed.

5.2. Spatial Panel Estimation. \( W_1 \) and \( W_2 \) are used to estimate the static and dynamic spatial panel models. In the static spatial panel model, the MLE method is used to estimate the SDM. Additionally, the GMM estimation method with the initial matrix as the weight is used to test the robustness of the model (it is verified that the GMM model with partial weighted matrix and full weighted matrix as weight is basically consistent with the GMM model with initial matrix as weight. Tables 3 and 4 only report GMM model estimation results with initial matrix as weight).

In empirical studies, endogenous bias exists in the results due to the omission of explanatory variables or reverse causality. Endogeneity is the key and difficult point of causal recognition. The dynamic spatial panel can effectively reduce the endogenous problems. In the dynamic spatial panel model, the SDM model is selected as the basic model. Based on the Han Philips method of the dynamic spatial panel model proposed by Shehata and Xtreqghp [31], the estimation is carried out. In addition, row standardization is not applied to the weight matrix of reciprocal distance (because the sample of spatial application research is basically the whole population, most of them adopt the fixed-effect model. Although a few literature studies have involved the spatial random effect model with spatial error autocorrelation is much more complex and difficult to control than other types of the spatial panel model [36], Whether the random effect model is suitable for spatial research is still controversial in academic circles [32]).

5.3. Static Spatial Panel Models. In Table 3, Model 1 is the panel model estimation of fixed effects. Model 2 is the SDM estimation of fixed effects of technical distance weight matrix \( (W_1) \). Simultaneously, Model 3 is estimated by SDM with fixed effects of economic distance weight matrix \( (W_2) \). Furthermore, the Huasman test results of Model 2 and Model 3 indicate that the fixed-effect model should be selected. The estimation results of the random effects model are omitted here. Specifically, bidirectional fixed effects including individual and time are used in fixed-effect model estimation.

5.4. Dynamic Spatial Panel Models. Since spatial lag correlation and spatial error correlation may exist at the same time, it will lead to the error of coefficient estimation if they are segmented. Based on Ref. [28], a dynamic spatial Durbin (DSD) model is further constructed to capture externalities and spillover effects produced by different sources, while taking into account the inertia characteristics of economic variables. The models in Table 4 are dynamic panel models with fixed effects, where Model 4 is an ordinary dynamic
model (SYS-GMM), Model 5 is a DSD model based on the $W_1$ matrix, and Model 6 is a DSD model based on the $W_2$ matrix. It can be seen from the estimated results in the table that the credit deviation degree of other industries has a significant negative impact on the economic growth rate of the industry. Firstly, from the perspective of the first-order lag term (L.RIVA) of the growth rate of industry added value to the industry. Firstly, from the perspective of the first-order

described in the manufacturing sector as an example. In 2017, the proportion of credit in the manufacturing sector was the highest, and the credit deviation was also the highest, while the economic growth rate of the industry was relatively high. Since 2013, with the increase in the income of micro-entities, China’s economy has begun to transform from investment-led to consumption-led [33], and consumption has replaced capital formation as the main driving force of China’s economic growth [34]. Bank loans flow from the secondary industry represented by the manufacturing industry to the tertiary industry, to the emerging industry, and to the industry related to the national economy and people’s livelihood. The manufacturing industry has always been the pillar industry of the country, and the economic growth has a high inertia, resulting in a high degree of negative deviation and a high economic growth rate.

Thirdly, the spatial effect coefficients of SCDD are significantly negative, which indicates that there is an inverted U-shaped economic effect in the SCDD of the industry. Factually, if the credit of similar industries deviates from 1%, the economic growth rate of this industry will drop by

Table 4: Estimation results of dynamic panel models.

| Variables     | Model 4 Panel model       | Model 5 Spatial panel ($W_1$) | Model 6 Spatial panel ($W_2$) |
|---------------|---------------------------|-------------------------------|-------------------------------|
| Cons         | 8.664*** (0.000)         | 0.434 (0.934)                  | -5.287 (0.476)                 |
| L.RIVA       | 0.123* (0.054)           | 1.023*** (0.000)               | 0.951*** (0.000)               |
| CDD          | -0.085 (0.540)           | -4.292*** (0.001)              | -4.762*** (0.001)              |
| SCDD         | -0.048* (0.057)          | -0.0004 (0.996)                | -0.034 (0.689)                 |
| FAIR         | 0.041 (0.623)            | 1.338 (0.384)                  | 2.492* (0.091)                 |
| EPR          | -0.115 (0.315)           | -0.594 (0.765)                 | -0.039 (0.983)                 |
| RLOAN        | 0.029 (0.229)            | 0.014 (0.622)                  | 0.015 (0.558)                  |
| $W^*$CDD      |                          | -47.003 (0.276)                | -20.036 (0.392)                |
| $W^*$SCDD    |                          | -9.356*** (0.000)              | -6.178*** (0.003)              |
| $W^*$FAIR    |                          | -86.128 (0.473)                | -109.183* (0.051)              |
| $W^*$EPR     |                          | -107.493 (0.571)               | -22.612 (0.776)                |
| $W^*$RLOAN   |                          | -1.071 (0.292)                 | -0.503 (0.656)                 |
| Time         | Control                  | Control                        | Control                        |
| ar(1) AB test| -4.96*** (0.000)         | —                             | —                             |
| ar(2) AB test| -0.91 (0.361)            | —                             | —                             |
| Sargan test  | 83.18 (0.505)            | —                             | —                             |
| Wald test    |                          | 160.322*** (0.000)             | 158.201*** (0.000)             |
| F-test       | 5.15*** (0.000)          | 5.937*** (0.000)               | 5.859*** (0.000)               |
| AIC          | —                        | 331.592                       | 331.737                       |
| SC           | —                        | 563.227                       | 563.474                       |
| GLOBALMoran MI|                          | -0.095*** (0.009)             | 0.558 9*** (0.000)             |
| LM error (Burrige) |                          | 5.046*** (0.024)              | 121.911 9*** (0.000)           |
| LM error (robust) |                          | 1.419 (0.233)                 | 303.649 9*** (0.000)           |
| LM lag (Anselin) |                          | 7.683*** (0.006)              | 6.416*** (0.011)               |
| LM lag (robust) |                          | 4.055** (0.044)               | 188.155*** (0.000)             |
| LOGL         | —                        | -789.969                      | -790.011                      |

Note: the time effect is controlled by the model, and the time effect is significant in most years, and the specific results are omitted.
6.178%–9.356%. This shows that credit misallocation will lead to a decline in the level of economic growth of the industry and has a negative impact on the economic growth of adjacent industries. The economic effect between industries is nonlinear. When the degree of credit mismatch decreases, the economic effect of credit mismatch will decrease regardless of the positive or negative mismatch. This reduces the joint economic effect within the industry system to a certain extent.

From the two spatial weight matrices, the estimated symbols of CDD, SCDD, FAIR, EPR, and RLOAN are consistent in the two fixed-effect DSD models, as are the coefficients of spatial effect. The spatial effect coefficients of SCDD are significantly negative, while the spatial effect coefficients of FAIR, EPR, and RLOAN are not significant at the significance level of 5%.

Comparing the estimation results of static and dynamic spatial panel models, it is found that the estimation coefficients of CDD in the static spatial panel model are significantly negative. It is consistent with the estimation symbol of the dynamic spatial panel model. The estimation coefficients of other variables are not significant, but they are consistent with the estimation symbols of the dynamic spatial panel model.

6. Conclusion and Policy Implications

6.1. Conclusion. Bank credit is an important booster of economic growth. The economic development of various industries in China is inseparable from the support of bank credit. Based on the panel data of 19 industries from 2007 to 2017, this article constructs a dynamic panel model to analyze the influencing factors of industry economic growth. The results show that although the CDD of China’s various industries has gradually decreased, the structural fluctuation is still very large. A large amount of capital flows to the tertiary industry, while the capital of the primary industry and the secondary industry is relatively scarce. Credit misallocation has a negative impact on industry economic growth and shows a weak acceleration effect. However, if the credit misallocation persists or deepens gradually, the acceleration effect will be amplified and eventually pose a serious threat to economic growth of industry.

6.2. Policy Implications. Based on the above conclusions, the following suggestions are proposed.

Firstly, the government should actively guide the rational flow of interindustry credit funds and improve the efficiency of capital allocation. When making credit policy, the government should consider heterogeneity and dynamic equilibrium of interindustry credit, so as to eliminate the obstacles of interindustry credit flow. The gap between the credit funds of the secondary industry and the tertiary industry is getting wider and wider, and the industrial structure adjustment policy has played a great guiding role. When formulating and issuing various economic policies, the government can consider continuing to moderately stabilize or reduce the growth rate of credit in the tertiary industry, appropriately guide the flow of credit funds to strategic emerging industries and national key support industries, gradually reduce the credit mismatch of industries, and improve the allocation efficiency of credit funds.

Secondly, the government should continue to increase investment in manufacturing and encourage independent innovation. The secondary industry, especially the manufacturing, has been the pillar industry of national economic development. Due to the high credit risk and long loan term of manufacturing, loan funds are often limited. However, the trade disputes between China and United States in 2019 made China soberly aware that technological progress ultimately depended on independent innovation rather than technology import. To become a technological power, a country also needs continuous innovation and development in manufacturing. Without mastering the core technology, China cannot easily turn industrial structure to relying on the tertiary industry to support economic growth. This is an important strategic development stage that China is in and cannot be crossed. China should consider giving sufficient financial support, including bank credit, to manufacturing enterprises with innovative spirit and Frontier technology development potential. CBIRC may adjust its capital adequacy ratio appropriately under the circumstances of controllable risks. Meanwhile, banks need to adjust credit structure within the secondary industry loan enterprises, reduce their nonperforming loan ratio, and promote their innovative development.

Thirdly, China should formulate reasonable financial policies to ensure the effective operation of the market and reduce the degree of credit misallocation. On the one hand, the central government should break down the credit flow barrier and form a credit distribution mechanism. When the degree of credit marketization is low, factors outside the market will hinder the interindustry credit flow. The government should encourage credit market information sharing and gradually form a credit allocation mechanism. The purpose of this allocation mechanism is to (1) gradually reduce the capital investment in industries with large credit surplus; (2) warn them to re-examine the importance and rationality of credit investment; and (3) avoid the scale waste and structural imbalance of credit capital. This allocation mechanism gradually transfers part of the surplus credit resources to the industries that are short of credit in an orderly way to stimulate their economic growth potential. On the other hand, the credit misallocation cannot be reduced only by the self-correction of commercial banks. The misallocation of credit is not only related to the profit-seeking characteristics of commercial banks, but also related to the credit policy orientation of the government. The government should make rational use of interest rate policy, reserve ratio policy, and capital supervision policy to effectively guide the behavior of credit structure adjustment.

6.3. The Limitations. There are some limitations that will be addressed in future research. Firstly, the spatial weight matrix in the study is based on the data of 19 industries, which can be further subdivided. Secondly, more diversified
methods will be used to study credit mismatches in future work.

Data Availability
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest
The authors have declared no conflicts of interest.

Authors’ Contributions
QY came up with the idea and drafted the manuscript. HZ collected the data and references and participated in validation and empirical analysis. Both authors wrote aspects of the main body of the article. All authors read and approved the final manuscript.

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