**The spatial effect of industrial credit mismatch in China**

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**Abstract**

The existing studies pay less attention to the positive and negative mismatch of bank credit among industries and its impact on economic growth. This paper 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 mismatch on industry economy. The results show that there are structural mismatches of bank credit in various industries in China. Recently, credit deviation degree of China's industries and industries has gradually declined, but Structural volatility remains high. A large amount of capital flows to the tertiary industry, while the capital of the primary industry and the secondary industry is relatively scarce. The existence of credit mismatch has a negative impact on industry economic growth, and shows a weak acceleration effect. In formulating economic policies, the government should actively guide the rational flow of inter industry credit funds and improve the efficiency of capital allocation. We will continue to increase investment in manufacturing and continue to promote independent innovation. Formulate reasonable financial policies to ensure the effective operation of the market and reduce the degree of credit mismatch.

*Keywords*:Credit mismatch; spatial econometric model; economic effect

1. Introduction

After four decades of rapid economic growth, China has become the second largest economy in the word. However, in the past, China's economic growth mainly relied on high savings and high investment, low cost labor advantage, 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 below 7%. 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 (Lai, 2016; Cai and Fu, 2017). 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 industrial structure. The impact of credit funds on economic growth first shows the promotion of scale, but also contains the effect of structural adjustment. Bank credit funds to different types of entity enterprises, changing the country's economic structure, internal promotion of a country's economic growth. For the past few years, China's economic growth has slowed down step by step, and the economic growth of different industries has become more and more different, and the economic structure is unbalanced. In 2017, the proportion of China's three industrial structure was 8.21%, 40.21%, 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 equals to supply in the credit market. However, the market role and operating environment of China's commercial Banks are quite special and complex. First, commercial Banks, as the main members of China's financial system, play an important intermediary role in the operation of the financial market and have always had a high market position. 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 mismatch in the process of credit from the top to the grassroots Banks. Third, since the reform and opening up, most commercial Banks lack scientific and effective credit management. Credit support emphasizes too much on performance and ignores fairness. The release of credit funds is concentrated in the industries where state-owned enterprises gather, which easily leads to credit congestion, credit discrimination and other mismatches.

From the micro level, improper credit supply leads to the over concentration of bank loan investment 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 resource allocation has declined. 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 mismatch cannot be underestimated.

From the macro level, credit mismatch 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 mismatch 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 effective conversion of new kinetic energy, have emerged. Finally, it leads to the slow down of industrial structure and economic growth.

The "14th Five-Year Plan" period in the future 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 mismatch. Therefore, it is not only of theoretical significance in economics but also of practical significance to study the problem of bank credit mismatch in China and realize the upgrading of economic structure and coordinated economic development by adjusting the bank credit structure.

二 文献综述和提出假说

According to Chacholiades (1978), the mismatch 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 mismatch. Li and Liang (2016) discussed interest rate liberalization and industrial structure optimization from the perspective of mismatch. They found that compared with private enterprises, state-owned enterprises occupy too much credit resources, but their efficiency is low, which is not conducive to the upgrading of industrial structure. Zhang and Li (2018) studied the relationship between credit mismatch and enterprise capital allocation efficiency from the micro enterprise level, and found that credit mismatch led to inefficient investment of enterprises and inhibited the development of private enterprises. Brant et al. (2013) estimated the total factor productivity loss caused by capital and labor mismatch in China's non-agricultural economy from 1985 to 2007. They found that credit mismatches reduced non-agricultural GDP by an average of 20%. Zhu (2017) studied the allocation of credit resources, government intervention and bank performance. She found that the government's intervention in credit resources is 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 mismatch of credit resources. Yuan (2018) 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 mismatch.

Currently, most scholars focus on the problems of credit mismatch and overcapacity from a macro perspective, but seldom study the credit allocation of industry in China. Zhang et. al. (2014) found that the reason of credit mismatch is 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 (2016) also studied credit mismatch. They believe that the mismatch of credit resources is the "driving force" behind overcapacity, and the worsening quality of credit assets and the rise of non-performing loan ratio will eventually affect regional financial stability. Zhao and Jiang (2014) 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 mismatch belongs to different perspectives. For the allocation of industry credit resources, most of them stay in the field of overcapacity and credit mismatch. There are few studies on the impact of bank credit mismatch on industry economic growth. Secondly, quantitative analysis method is seldom used in the research of credit mismatch. It is difficult to draw a clear, specific and complete conclusion due to insufficient application of industry credit data in China. Based on the perspective of industry credit, this paper collects the panel data from 2007 to 2017, and constructs a dynamic panel model to identify the industry effect of bank credit mismatch. It can not only effectively solve the endogenous problems of explanatory variables in the model, make the analysis results more authentic and reliable, but also further expand the research depth of credit mismatch from the perspective of industry.

Credit mismatch, 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 mismatches include both positive and negative mismatches. From the micro and macro point of view, it can be divided into credit mismatch of commercial banks and credit mismatch of macro-economy. In essence, credit mismatch is a problem of financial resource allocation. It is manifested in the loss of efficiency in the allocation of credit resources and the mismatch between credit resources and enterprise development. It is easy to cause industrial structure imbalance, economic growth quality decline and so on. 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 mismatch proposed in this paper emphasizes the mismatch between the bank and the government's objectives caused by the system and policy under the condition of market economy. It is a long-term non-equilibrium state. This mismatch is particularly evident in China. It is 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 mismatch or a negative mismatch, it will have a negative impact on the economic growth of the industry. Positive mismatch means that the scale of bank credit is relatively abundant in the industry, but the distribution in the sub-industry is unreasonable. Enterprise capital use efficiency decreases, have negative effect to economic growth. Negative mismatch means that the scale of bank credit capital is relatively deficient in the industry and the distribution of it in sub-industries 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 mismatch in this industry will also have adverse effects on neighboring industries. Due to the different degree of close and far links between industries, the credit mismatch of this industry will have a negative impact on the economic growth of other industries. The closer the industry is, the greater the degree of joint influence will be.

In this paper, the spatial panel model is used to test the above hypotheses.

**3. Methodology**

Lin (2008) believes 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 industrial structure (Su,2012). In order to test the relationship between the credit mismatch of the banking industry and the economic growth of the industry, and in consideration of the availability of data, the time range of the sample interval was selected from 2007 to 2017.

There are few quantitative studies on the spatial characteristics of industry economy in China. Scholars including Hu and Jiao (2010) 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. (2016) 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 divide the vertical spillover effects into forward spillovers and backward spillovers. Based on the spatio-temporal data of 33 industries in China from 2003 to 2011, the spatial weight matrix is constructed by using the induction coefficient and influence coefficient in the input-output matrix.

3.1 Spatial panel model

Spatial econometrics originated from 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 (1979), and then developed by Anselin (1988), and gradually formed a relatively complete framework system. Anselin (2003) classified spatial econometric models from two dimensions: the types of spatial lag variables and the scope of spatial correlation. Furthermore, he reveals the economic significance of Spatial Autoregressive Model(SAR) 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 section data to establish spatial measurement model, or combine section space element with time series to establish spatial measurement model of static panel data. Section space measurement 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 chance and randomness of the results. The static space panel model expands the number of observed values, makes full use of data information and improves the accuracy of the model, but it is still possible to ignore the impact of factors other than bank credit on economic growth. However, the dynamic space panel model can effectively solve aforementioned problems.

The basic form of spatial econometric model can be expressed as

 (1)

whereis explained variable. is the exogenous explanatory variable matrix. is the spatial autoregression coefficient. is the spatial error coefficient. reflects the influence of explanatory variable  on explained variable . is the T-dimensional unit time matrix. and are the n-th order space weight matrix (n is the number of industries). andis the random error term, where～. Le Sage and Pace(2009) pointed out that the spatial Durbin model (SDM) is 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,

 (2)

In equation (2), is the spatial lag term of explanatory variable, and represents the influence of independent variables in adjacent industries. Elhorst and Freret(2009) believe that if there are missing variables in the model and these variables are exactly related to explanatory variables, then the model can get unbiased estimation only if it includes 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,

 (3)

The significance of introducing DSDM model 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 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. (2016) and extending it, this paper sets the industrial economic distance matrix (W0). Then, based on W0, two spatial weight matrices are set: technical distance weight matrix (W1) and industry credit allocation weight matrix (W2). Through the introduction of W1 and W2 matrices, this paper comparatively studies the impact of bank credit deviation on economic growth.

3.2.1 Technical distance weight matrix W1

Jaffe (1986) 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



Where, andrespectively represent the time row vectors of the share of i and j in the output of each industry, as shown below. Therefore, represents the technical distance between enterprise i and enterprise j in the sample time interval, and 0≤≤1. The more similar the technical level, product composition or scale of enterprise i and Enterprise j are, the closeris to 1. Otherwise, the closeris 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 (1986) did not have a specified direction and could not reflect the vertical relationship between upstream and downstream.

Xu and Deng (2016) calculated the "proximity" between industries based on the structure of direct consumption coefficient of each industry sector, and constructed the technical distance weight of the industry, namely, . Where, andare elements at the kth position of the column vector of the direct consumption coefficient structure of the ith and jth industrial sectors, respectively. The entries on the main diagonal are 0.

3.2.2 Industry credit allocation weight matrix W2

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 (W2) is established. The specific form is . Where, is the mean of bank credit balance in industry i. 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 China Banking Regulatory Commission(CBRC), which includes 19 sectors in total, including 1 primary industry, 4 secondary industry and 14 tertiary industry. 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 mismatch. The control variables are mainly individual and time factors. The model is shown in Equation (4).

**,**  (4)

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, i.e. RIVA =(IVAt-IVAt-1)/IVAt-1. Credit mismatch 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 non-linearity of Credit mismatch. 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 non-private 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 urban non-private employees in each industry by the total number of urban non-private employees. The data are collected according to the latest Statistical yearbook of China. Table 1 is a statistical description of some variables.

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 |

1. Descriptive analysis
   1. Descriptive analysis(产业维度)

As can be seen from Figure 1, commercial bank credit in three industries are increasing year by year. The growth rate of bank credit in the secondary and tertiary industry are relatively stable, while the growth rate of bank credit in the primary industry fluctuates greatly from 2008 to 2012, and then gradually declines. As shown in Figure 2, commercial bank credit are mainly concentrated in the secondary industry and the tertiary industry. The proportion of the primary industry is growing very slowly, accounting for 3.70% in 2017. The proportion of tertiary industry has always been higher than that of secondary industry. With the implementation of the economic stimulus plan in 2008, the credit of major commercial banks are increased by a third in 2009 (Wong, 2011). Meanwhile, the gap between tertiary industry and secondary industry is gradually widening. This indicates that more credit funds are transferred from the secondary industry to the tertiary industry. After 2012, the credit growth rate of the secondary industry slow down, and the credit proportion gradually decreases. The credit growth rate of the tertiary industry first decreases and then increases, and the proportion of credit gradually increases. 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%.

Data sources: Calculated according to the annual report of CBRC.

**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

* 1. Sector dimensions

From the perspective of sector distribution, as shown in Figure 3, from 2007 to 2017, the proportion of manufacturing credit has been the highest. Although the country 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. From 2007 to 2014, the proportion of wholesale and retail trades has been gradually increasing, reaching 17.84% in 2014, and declining year by year after 2015, and 15.52% in 2017. It has been the second largest sector in terms of bank lending. The third is transport, storage and post, 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 change 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 were transferred from the secondary industry to the tertiary industry, and 2.41% to the primary industry. Manufacturing and production and supply of electricity, heat, gas and water decreased, while mining and construction increased. The secondary industry presents the characteristics of "two declines and two rises". Among them, the proportion of manufacturing decreased from 30.85% in 2007 to 20.14% in 2017, with a decrease of 10.71% and the largest decline. The proportion of construction increased from 4.03% in 2007 to 6.00% in 2015, with an increase of 1.97 %. The proportion of production and supply of electricity, heat, gas and water decreased from 10.57% in 2007 to 5.65% in 2014, with a decrease of 4.92 %. Mining accounted for 2.83% in 2014, up 0.33% from 2.50% in 2007. In the tertiary industry, wholesale and retail trades increased by 5.65 % from 9.87% in 2007 to 15.52% in 2015, with the largest increase. The share of transport, storage and post was 11.14 percent in 2007, the same as in 2015. The proportion of real estate decreased by 1.10 % from 11.02% in 2007 to 9.92% in 2015. The leasing and business services increased from 4.55% in 2007 to 9.66% in 2014, up by 5.11%, with a large 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.

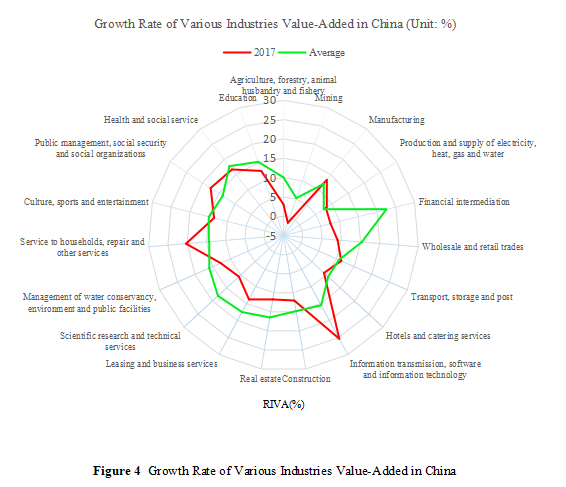
Data sources: Calculated according to the Annual Report of CBRC.

**Figure 3** The Proportion of Sector Credit to Total Credit of China from 2007 to 2017

4.3 Growth rate of industry value-added (RIVA)

Figure 4 and Figure 5 shows the distribution of RIVA of various industries in China. 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 from Figure 4, 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, the growth rate of added value of each industry generally decreases in volatility. The average growth rate of added value of the primary industry 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 growth rates of added value of the industry 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 value-added growth rate of the primary industry is 3.08%, the secondary industry 11.89%, and the tertiary industry 12.37%.



Data sources: the Annual Report of CBRC and China Statistical Yearbook.

Data sources: the Annual Report of CBRC and China Statistical Yearbook.

**Figure 5** Growth Rate of Industry Value-Added in China from 2007 to 2017

4.4 Proportion of Industry Value-added to GDP

Composition of GDP by the three strata of industry refers to the proportion of the value-added of each industry to GDP. It is calculated at current prices. Figure 6 shows the changing trend of the composition of GDP by China's three strata of industry from 2007 to 2017, and Figure 7 shows the changing trend of the composition of GDP by China's 19 sectors from 2007 to 2017. From the perspective of industry, from 2007 to 2017, the proportion of value-added of the primary industry and the secondary industry decrease year by year, while the proportion of value-added of the tertiary industry increases year by year. 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, decreasing year by year, from 32.56% in 2007 to 28.82% in 2016, and slightly increasing to 29.31% in 2017. 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. 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 6** Proportion of Industry Value-added to GDP in China from 2007 to 2017

Data sources: China Statistical Yearbook.

**Figure 7** Proportion of Sector Value-added to GDP in China from 2007 to 2017

4.5 Credit Deviation Degree (CDD) and Square of Credit Deviation Degree(SCDD)

Figure 8 and figure 10 show the change trend of credit deviation degree of various industries from 2007 to 2017. Figure 9 and Figure 11 show the change trend of square of credit deviation degree from 2007 to 2017. There are also structural differences in the degree of industry credit deviation of domestic banks in China. From 2007 to 2017, the degree of credit deviation of the primary industry has been negative, increasing year by year. The degree of credit deviation in the secondary industry has changed from positive to negative in 2009, basically unchanged. The credit deviation degree of the tertiary industry has been positive and has been decreasing year by year since 2010. Correspondingly, the square of credit deviation degree of the primary industry gradually becomes smaller, indicating that the degree of deviation is declining. The square of credit deviation degree of secondary industry remained basically unchanged, and increased suddenly in 2017. The square of credit deviation degree of the tertiary industry first rose and then decreased, and then rose suddenly in 2017. Generally speaking, the degree of credit deviation was the highest in 2009 and 2010, and then the credit deviation began to improve.

Specifically for 19 sectors, the credit mismatch 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 insufficient. In the secondary industry, it is worth noting that the credit mismatch of manufacturing has been rising in recent years, reaching -9.18% in 2017, which is the highest in the negative mismatch in 2017. According to the data in 2017, most of the tertiary industry industries are positive mismatches, 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%. The industry mismatch degree in the negative mismatch is smaller, the smallest is public management, social security and social organizations (except financial intermediation), and the industry mismatch degree is -3.16%. Compared with regional credit mismatch, industrial credit mismatch is more serious and has a greater adverse impact on economic growth (Yuan, 2018).

Data sources: the Annual Report of CBRC and China Statistical Yearbook.

**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

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, 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.

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.

**Figure 11** Square of Credit Deviation Degree of Sectors in China from 2007 to 2017

Comparing the above figures, it can be found that proportion of industrial credit to total credit, credit deviation degree 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, 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 can not 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 mismatch? In view of these problems, the empirical research on industry spatial econometric model is further carried out.

1. Results and discussion

### 5.1 Spatial correlation test

Based on the spatial panel method introduced in the section 3, the SAR and SEM are firstly interpreted and selected, which are usually completed by Robust LM test. The judgment criteria of 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 (LeSage and Pace,2009). This paper adopt the methods oftest(Burridge,1980), Robust test(Bera and Yoon,1992), test(Anselin,1988) and Robust test(Bera and Yoon,1992). Three different spatial weight matrices are used for regression estimation of equation(4). 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 spatial econometric analysis model to study the essential relationship between bank credit deviation degree and industrial economic growth from the perspective of spatial econometric analysis. It is found from Table 2 that both W1 and W2, 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.

Table 2 LM test of spatial autocorrelation for cross section mean equation

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Spatial weight matrix | Spatial error test | | Spatial lag test | |
| LM | Robust LM | LM | Robust LM |
| W1 | 26.011\*\*\*  (0.000) | 21.668\*\*\*  (0.000) | 14.908\*\*\*  (0.000) | 10.564\*\*\*  (0.001) |
| W2 | 8.956\*\*\*  (0.000) | 6.175\*\*  (0.013) | 12.003\*\*\*  (0.001) | 9.222\*\*\*  (0.002) |

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

And the adjoint probability is shown in brackets. (similarly, hereinafter)

### 5.2 Spatial panel estimation

W1 and W2 are used to estimate the static and dynamic spatial panel models. In the static space panel model, 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[[1]](#footnote-0).

In empirical studies, endogenous bias exists in the results due to 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, SDM model is selected as the basic model. Based on the Han Philips method of dynamic spatial panel model proposed by Shehata (2012), the estimation is carried out. In addition, row standardization is not applied to the weight matrix of reciprocal distance[[2]](#footnote-1).

#### 5.3 Static spatial panel models

In Table 3, Model 1 is the panel model estimation of fixed effects. Model 2 is SDM estimation of fixed effects of technical distance weight matrix (W1). Simultaneously, model 3 is estimated by SDM with fixed effects of economic distance weight matrix (W2). 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 effects model estimation.

In model 2 and model 3, CDD passes the significance test and the symbols are consistent. The results of other variables in the fixed effect SDM model are not significant. Simultaneously, the spatial error parametersof the model show that there are significant positive spatial correlation features in model 2 and model 3. The estimated coefficient of CDD is significantly negative. If CDD deviates from 1%, the economic growth rate of the industry will decrease by 0.225%-0.239%. Although the estimation coefficient of SCDD is negative, it is not significant. The credit deviation degree of the industry has an adverse impact on the growth rate of the industry's added value. The spatial error parametersof the model show that there are significant negative spatial correlation characteristics in the model. It shows that the credit mismatch of this industry will also have adverse interaction effects on the economic growth of related industries. In other words, the economic growth of this industry will be negatively affected by credit mismatch factors in other industries.

Table 3 Estimation results of static panel

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | Model 1 | Model 2 | Model 3 |
| Panel model | Spatial panel(W1) | Spatial panel(W2) |
| FE | FE+SDM | FE+SDM |
| Cons | 25.977\*\*\*  (0.000) | 24.184\*\*\*  (0.000) | 26.057\*\*\*  (0.000) |
| CDD | -1.031\*\*  (0.032) | -0.225\*  (0.076) | -0.239\*  (0.072) |
| SCDD | -0.035  (0.422) | -0.007  (0.743) | -0.013  (0.580) |
| FAIR | 0.068  (0.927) | 0.046  (0.529) | 0.044  (0.552) |
| EPR | -0.312  (0.636) | -0.079  (0.416) | -0.098  (0.326) |
| RLOAN | 0.022  (0.399) | 0.006  (0.755) | 0.001  (0.955) |
| Time | Control | Control | Control |
|  | / | -3.211\*\*\*  (0.000) | -3.623\*\*\* (0.001) |
| LOGL | / | 7.674 | 7.674 |

Note: The time effect is controlled in all models, and the time effect is significant in most years, and the specific results are omitted.

#### 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 Le Sage and Pace(2009), 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. 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 of the explained variables, they all reach the significance level of 1%, indicating that there is a significant dynamic effect of economic growth.

Secondly, three fixed effect DSD models are compared. Specifically, the estimation results of the two spatial weight models show similar spatial correlation characteristics. Compared with the DSD model of W1 and W2, the estimated coefficients of CDD are significantly negative. It shows that the credit deviation degree of this industry has negative economic effect. Moreover, the positive deviation of CDD is 1%, and the economic growth rate of the industry will decrease by 4.292% - 4.762%. Synchronously, the time lag coefficientof the model is significant. It shows that economic growth has a certain inertia, which further shows the rationality of building the DSD model. The spatial effect coefficients of SCDD are significantly negative, which indicates that there is an inverted U-shaped economic effect in SCDD of the industry. Factually, if the credit of similar industries deviates from 1%, the economic growth rate of this industry will drop by 6.178%-9.356%. This shows that credit mismatch 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.

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 static spatial panel model are significantly negative. It is consistent with the estimation symbol of dynamic spatial panel model. The estimation coefficients of other variables are not significant, but they are consistent with the estimation symbols of dynamic spatial panel model.

Table 4 Estimation results of dynamic spatial panel

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | Model 1 | Model 2 | Model 3 |
| Panel model | Spatial panel(W1) | Spatial panel(W2) |
| SYS-GMM | SDM | SDM |
| 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 tes | -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 |
| GLOBAL  Moran MI | / | -0.095\*\*\*  (0.009) | 0.558 9\*\*\*  (0.000) |
| LM Error  (Burridge) | / | 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 Conclusion and policy implications

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 paper constructs a dynamic panel model to analyze the influencing factors of industry economic growth. The results show that although the degree of credit deviation of China's industries and industries has gradually decreased in recent years, 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. The existence of credit mismatch has a negative impact on industry economic growth, and the credit mismatch shows a weak acceleration effect. However, if credit mismatch exists or deepens all the time, the acceleration effect will be amplified and will eventually pose a serious threat to the economic growth of the industry. Based on the above conclusions, the following Suggestions are proposed.

Firstly, China should actively guide the rational flow of inter industry credit funds and improve the efficiency of capital allocation. When making credit policy, the government should consider not only the heterogeneity of inter industry credit, but also the dynamic equilibrium of inter industry credit, so as to remove the obstacles of inter industry credit flow. Currently, the gap between the second industry and the third industry is growing. The government's industrial structure adjustment policy has played a great guiding role. It is also closely related to the magnetic attraction and crowding out effect of environmental governance background and market activity. This paper holds that if there is too much credit fund in a certain industry, the promotion of local economic growth and national macro-economic growth is not necessarily the most efficient. If the capital is invested in the relatively scarce industries, its marginal effect will be higher. Therefore, combined with the national strategic planning objectives of stable growth and structural adjustment, China can consider continuing to moderately stabilize and reduce the growth rate of credit in the tertiary industry. At the national level, when formulating and issuing various economic policies, China moderately guides the flow of credit funds to strategic emerging industries of the primary industry and the secondary industry and key industries supported by the state. Gradually reduce the credit mismatch degree of the industry and improve the allocation efficiency of credit funds.

Secondly, China should continue to increase investment in manufacturing, encourage independent innovation and promote economic growth. The secondary industry, especially the manufacturing, has been the pillar industry of national economic development. If commercial banks increase the proportion of credit to the secondary industry, it will be beneficial to improve their business performance. Currently, due to the upgrading of industrial structure in the process of economic development, the proportion of loans in the manufacturing has been decreasing year by year. Simultaneity, due to the high credit risk of manufacturing and the relatively long term of loan, loan funds are often restricted. 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. If a country wants to become a technological power, it still needs continuous innovation and development of manufacturing. Without mastering the core technology, China can not easily turn the industrial structure to relying on the tertiary industry to support economic growth. This is an important strategic development stage that China is in and can not be crossed. China needs a healthy secondary industry to support economic growth, not a shrinking secondary industry. China should consider giving sufficient financial support, including bank credit, to manufacturing enterprises with innovative spirit and cutting-edge technology development potential. The China Banking and Insurance Regulatory Commission may adjust its capital adequacy ratio appropriately under the circumstances of controllable risks. This is conducive to increasing the proportion of credit investment in the secondary industry and reducing loans in industries with high credit mismatch in the tertiary industry. Meanwhile, banks need to adjust the credit structure in the secondary industry, including manufacturing loan enterprises, to reduce the non-performing loan rate of the secondary industry. Promote the innovation and development of manufacturing industry and actively promote economic growth.

Thirdly, China should formulate reasonable financial policies to ensure the effective operation of the market and reduce the degree of credit mismatch. On the one hand, the central government should break down the credit flow barrier and realize the market efficiency. For one reason or another, local governments often act as an umbrella for local sunset enterprises. In some cases, local governments have intervened in the opposite direction of national policies, leaving some restricted industries and even zombie enterprises still able to obtain loan support. When the degree of credit marketization is low, factors outside the market will constantly interfere in the credit supply activities. The credit flow between industries is blocked or countercurrent, the credit mismatch phenomenon is prominent. The government should guard against improper intervention by local governments and encourage and promote the free and full flow of funds in the credit market of the industry. In addition, the government should establish a credit market for information sharing and gradually form a credit allocation mechanism corresponding to the level of economic growth. The purpose of this allocation mechanism is: (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; (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 and improve their economic growth.

On the other hand, the credit mismatch cannot be reduced only by the self-correction of commercial Banks. On the one hand, the credit mismatch is caused by commercial Banks' pursuit of profits, and on the other hand, it is related to the government's credit policy orientation. The current interest rate liberalization environment and capital adequacy requirements of China's banking sector make banks more willing to lend to mature enterprises. The government should make rational use of interest rate policy and reserve ratio policy. Governments should try to introduce and implement policies that affect not only the scale of bank credit, but also the structure of credit. The government needs to continue to make full use of capital supervision policies to effectively guide the bank's credit structure adjustment in line with the national macroeconomic policy objectives. For example, when the government formulates policies, commercial banks that can increase capital investment in credit shortage industries should have lower requirements on reserve ratio and capital adequacy ratio. In this way, it can improve the enthusiasm of the Banks to implement the industry credit tilt, ensure that the commercial banks can accept and implement the intention of the policy, adjust the credit structure on the track of the policy, and realize the credit correction.

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1. 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. Table 3 and Table 4 only report GMM model estimation results with initial matrix as weight. [↑](#footnote-ref-0)
2. Because the sample of spatial application research is basically the whole population, most of them adopt fixed effect model. Although a few literatures have involved spatial random effect model (Case,1991), the estimation of random effect model with spatial error autocorrelation is much more complex and difficult to control than other types of spatial panel model (Elhorst,2015). Whether the random effect model is suitable for spatial research is still controversial in academic circles (Ji et. al., 2011). [↑](#footnote-ref-1)