Regional Industrial Economic Development Based on Social Innovation Competitiveness of Economic Cluster

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Objectives: With the rapid development of the regional economy, its growth mechanism and competitiveness have gradually attracted people's attention. Based on the social innovation competitiveness of economic clusters, the regional industrial economic development has been studied. Methods: Taking the economic growth effect and industrial agglomeration effect of industrial output value as the object of study, the industrial data is used to subdivide three matching mechanisms: factor structure and industrial association, regional or urban scale and industrial structure, market scale and industrial choice. Results: The results show that different types of industries have different response characteristics to the three matching mechanisms, and there are phenomena of industry and spatial differentiation of matching mechanisms. Conclusion: The research has a certain role in promoting the social innovation of economic clusters and the development of regional industrial economy.

Key words: economic cluster; regional industry; spatial agglomeration
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With the acceleration of China's urbanization process and the profound change of economic growth momentum during the "new normal" period, China's economic and social development is confronted with such major practical problems as the optimization of economic spatial pattern and the shaping of innovative economy, the adjustment of regional industrial structure and the formation of effective supply, the treatment of "big city disease" and the development of poor and backward areas [1]. This requires an accurate understanding of the relationship between the unbalanced distribution of factors and industrial agglomeration, and "how they affect regional economic growth? And in response to this, what kind of space is suitable for the development of what industries, the best scale? What kind of industry is suitable for the development of which space, the highest efficiency? " these realistic concerns [2]. Taking the path of industry and space matching mechanism on regional economic growth as the research object, the development of regional industrial economy based on the social innovation competitiveness of economic clusters is studied.

In terms of research methods, industrial spatial agglomeration has its inherent theoretical logic, that is, cost demand and market demand, and the agglomeration mechanism of different types of industries is different. With the upgrading of industrial structure and the optimization of economic space, the change of industrial structure is bound to promote the continuous evolution of industrial spatial agglomeration and diffusion mechanism. The matching mechanism between industry and service industry from the perspective of externalities are systematically studied such as factor agglomeration, industrial structure and urban scale, in order to provide a more detailed and comprehensive analysis of the relationship between regional economic growth and industrial choice.

Research is innovative. By defining and identifying the matching efficiency and quality of industry, the endogenous mechanism of industrial agglomeration and diffusion is revealed. In the empirical study, it clarifies the agglomeration efficiency of industries with different factor structures and services with different objects, and the boundary between market and government, which is innovative.

The research is divided into three parts. The first part is a literature review. The second part is an analysis of the regional industrial economic development based on the social innovation competitiveness of economic clusters, including the analysis of industrial types and spatial characteristics and the economic growth effect of industrial-spatial matching mechanism. The third part is the analysis of the calculation results.

In terms of industrial agglomeration and urban structure, due to the industrial structure of cities in real life, they are neither fully specialized cities nor fully diversified, but some parts of industries are co-agglomerated. Balanced cities may not be efficient in scale, but also inefficient in industrial composition. Scale and composition inefficiencies are interrelated [3]. Both urban and industrial scales have the rule of ranking at the same time [4], The Zipf criterion of industrial scale is easier to identify [5]. The level of urban population agglomeration and spatial scale do not change synchronously with the urban production efficiency. There is a positive influence mechanism. The agglomeration density has an inverted U-shaped relationship with the production efficiency. Its maximum peak value increases with the increase of urban spatial scale. Population and industrial agglomeration need to be rationally distributed in the city [6]. In terms of urban scale and urban production efficiency, China has transited from planned economy to market economy, and its industrial spatial layout is constrained by different guiding principles, which results in the mismatch between urban scale and industrial development and the low factor utilization rate [7]. At the same time, due to the inverted "U" relationship between urban scale and urban productivity, the overall scale of China's urban system is small, and there is no single optimal scale. China's urban scale also does not match economic growth and industrial agglomeration. The spillover effect of material capital is significant, while the mismatch of labor and capital hinders the optimization of industrial structure [8]. The synergistic agglomeration of secondary and tertiary industries has a positive impact on the economic growth of single-center cities and urban agglomerations. Productive services and manufacturing structure affect urban production efficiency through urban scale. Big cities should choose service-oriented economic transformation, while small and medium-sized cities should promote the development of manufacturing industry and population agglomeration [9]. He Jianwu (2015) used the industrial employment population data to further measure the industrial structure and urban scale of China's cities. It was found that the relationship between industrial development and urban scale is not single, the overall competitiveness of manufacturing industry and urban scale shows an inverted U-shaped relationship, and cities with 5 million to 10 million people show stronger manufacturing competitiveness than other cities of scale [10]. Resource-based manufacturing and intermediate input manufacturing have stronger comparative advantages in smaller cities [11]. There is no direct hierarchical correspondence between the competitiveness of the mining and power industries and the size of cities [12]. The relationship between the competitiveness of consumer goods and capital goods industries and urban scale is "inverted U-shaped" [13]. There is a weak "U-shaped" relationship between the overall competitiveness of service industry and the size of the city. Productive services, real estate and cultural entertainment industries show a strong direct hierarchical correspondence, that is, the larger the scale, the stronger the competitiveness [14].

In short, the current research on regional industrial economic development has been relatively rich, but the research based on the perspective of social innovation competitiveness of economic clusters and spatial matching mechanism is not enough. Therefore, the study from this perspective has innovative and practical significance.

METHODS

Industrial Types and Spatial Characteristics of Industry

The relationship between industrial agglomeration (mainly mining and manufacturing) and regional economic growth, especially the related research results of manufacturing agglomeration, can be described as vast. Due to the inconsistent production and consumption space of industrial products, industrial space agglomeration has inherent theoretical logic, namely cost and market demand, and the aggregation mechanism of different types of industries is different. With the upgrading of industrial structure and the optimization of economic space, the transformation of industrial structure will inevitably lead to the continuous evolution of industrial space agglomeration and diffusion mechanisms. The existing research mostly considers the spatial measurement and economic effect of industrial agglomeration, but does not further explain the connotation of industrial spatial agglomeration and diffusion, and less systematically studies the relationship between regional and urban industrial growth, agglomeration effect and factor structure allocation mechanism. At the same time, there are few studies on the spatial effects of factor production organization from the perspective of matching. In the face of the actual policy needs of “what industries can be diverted and transferred, and which industries are accepted” in the context of urban functional reconciliation, they often face the contradiction of different theoretical analysis conclusions. Industry mainly involves the mining industry, manufacturing industry, power, heat, gas and water production and supply industry, and construction industry. Because the basic industries such as construction industry and electric power thermal supply industry have a state that is compatible with market demand and population size, this chapter mainly takes mining industry and manufacturing industry as an example. It should be pointed out that although there is a spatial dependence of natural resources endowment in coal and petroleum mining industries, there are still resource-based areas or cities with resource exploitation as the leading industry in the region, and there are also related industries such as petroleum processing in the manufacturing industry. Therefore, both manufacturing and mining industries are covered in the study. Owing to the production characteristics of industrial products, industry can usually be divided into labor-intensive, capital-intensive and technology-intensive categories according to the input structure of factors. However, this classification is not absolute, and there are also industrial types with higher capital and technology input requirements [15]. The per capita capital of unit labor (k=K/L) is used to represent the input structure of industrial factors.

$$k_i = \frac{K_i}{L_i} = \frac{K_i^* / \sum_{i=1}^{N} K_i^*}{L_i^* / \sum_{i=1}^{N} L_i^*} \quad K_i = \frac{K_i^*}{\sum_{i=1}^{N} K_i^*} \quad L_i = \frac{L_i^*}{\sum_{i=1}^{N} L_i^*} \tag{1}$$

In the formula, K is measured by total assets and fixed assets converted value respectively, and L is the average value converted by the number of workers, both of which are converted according to the total number of Industrial Enterprises above the current scale. K_i^* , L_i^* are the actual data values of the economic census and the Yearbook of industrial statistics (total assets or fixed assets) and the average number of workers employed by enterprises. When k > 1, it indicates that industry is capital intensive industry; when k < 1, it is labor intensive industry; when k = 1, industry emphasizes both capital and labor factors. It needs to be further explained that the net fixed assets (Nie Huihua et al., 2012; Fan Jianyong et al., 2014; Yang Rudai, 2015) have been mostly used as indicators to measure industrial capital investment. In order to compare the impact of the change of asset statistical caliber, the total fixed assets and capital (fixed assets + current assets) are calculated based on industrial data in 2015. As shown in Fig. 1, there is little difference between the two methods to measure industrial capital input. In order to unify with the existing research, net fixed assets are used to measure industrial capital input. For technology-intensive industries, according to China's "High-tech Industry (Manufacturing) Classification (2013)", the industrial technology investment level is measured by the industry's technology R&D investment expenditure as the main business income (rey). When rey>0.6, it indicates that the industrial technology investment has a large proportion and is a technology-intensive industry. The data on science and technology input comes from the "China Science and Technology Statistical Yearbook". In addition, according to the "2013 Economic Census Yearbook" issued by the State Council based on the Third National Economic Census, the factor input of the industrial industry in 2016 was supplemented and found to have little change in the structure of the elements. Therefore, the follow-up study in this chapter adopts this division. The classification of industrial industries in China is shown in Figure 2 and Table 1.

Figure 1
Differences in Factor Structure in Chinese Industry (2015)

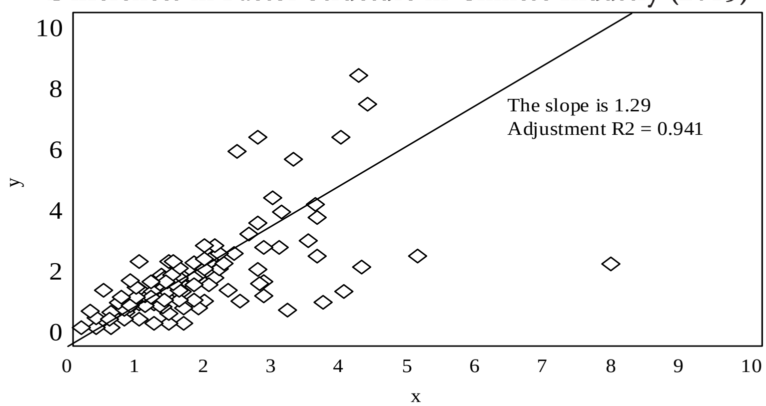
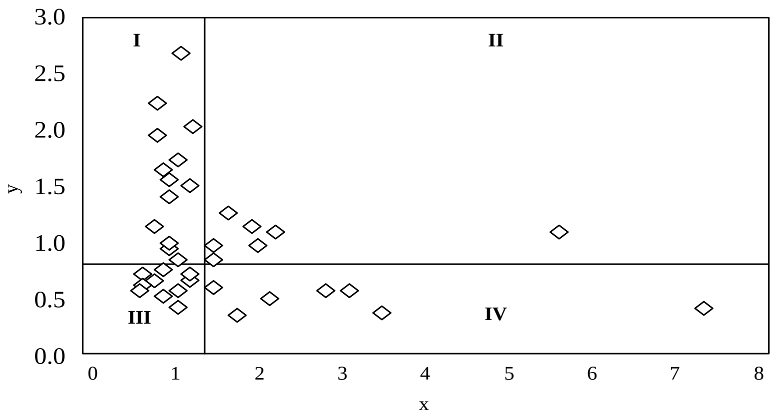


Figure 2
Industrial Classification of China (2015)



It can be seen that China's industrial industries are mainly pure labor-intensive formed industries (such as non-metallic mineral processing, agricultural and sideline food processing), pure capital-intensive industries (ferrous metal mineral processing, petroleum processing and coking, gas and power supply industries) , labor and technology intensive industries (pharmaceutical manufacturing, instrument manufacturing, automobile manufacturing, computer and communication electronic equipment manufacturing, etc.), capital and technology intensive industries (oil and gas exploitation, non-ferrous metal calendering, chemical fiber manufacturing). Through the preliminary division of the industrial factor allocation structure into follow-up industry spatial matching mechanism research laid the foundation.

Table 1
Classification of China's Industrial Industries

Industrial Classification	Classification criteria	Industry Name
Labor-intensive industries	k<1	10, 13, 14, 15, 17, 18, 19, 20, 21, 221, 23, 24, 30
capital-using industry	k>1	8, 9, 16, 25, 44, 45, 46
Technology-intensive industries	rey >0.6	6c, 7c, 15, 17, 22, 23, 26c, 27, 28c, 29, 31c, 32c, 33, 34, 35, 36, 37, 38, 39, 40, 41, 43

Note: ①Technology-intensive industries are classified according to the proportion of R&D expenditure in main business income (rey=Outyr/Iny) in the Classification of High-tech Industries (Manufacturing Industry) (2013). According to the actual calculation value of technology expenditure in high-tech industries, industries with Rey greater than 0.6 are selected as technology-intensive industries.②In technology-intensive industries, there are also industries with high proportion of capital investment, which should be marked by c in the upper right corner of the industrial code, such as 6c and 7c. Similarly, industries with high technical and technical requirements should be marked by 1 in the upper right corner of the industrial code, such as 221. Due to the spatial imbalance of industrial factor structure and the characteristics of industrial correlation, there are spatial differences in different types of industrial agglomeration. The spatial Gini coefficient and regional specialization index are used to compare the spatial distribution of industries and the degree of regional specialization of industries. Spatial Gini coefficients are defined in Chapter IV. Referring to Krugman (1991) and Sun Jiuwen, Yao Peng (2017) to define the level of regional specialization, regional specialization index is used to measure the degree of regional industrial structure differences. The data of the employment population of each province come from the "China Population and Employment Statistics Yearbook". The number of the employment population of each province is totaled by the employment population of state-owned units, urban collective units and other units. M is the number of regions and N is the number of industries. From the above formula, the degree of specialization in China can be gotten. This section first compares the level of regional specialization with the Gini coefficient of regional industries. From the relationship between regional specialty and regional spatial Gini coefficient, we can see that except Shanxi, the degree of specialization of other provinces and municipalities has a linear relationship with the regional industrial distribution. The higher the degree of regional specialization, the higher the regional Gini coefficient, that is, the regional industrial distribution tends to be more spatial agglomeration. The lower the degree of regional specialization is, the lower the Gini coefficient is, that is to say, the industrial distribution in the region tends to be spatially dispersed. Shanxi Province is mainly due to the centralized distribution of coal mining industry and high degree of industrial specialization. There is no inverse relationship between the degree of regional specialization and industrial spatial agglomeration in China. Secondly, from the perspective of industrial evolution, the spatial agglomeration level of mining industry has little change, such as coal mining and oil and gas mining. The spatial agglomeration of downstream manufacturing industries related to mining industry, such as petroleum processing and coking industry, has little change. In addition to computer and communication equipment manufacturing, the degree of spatial agglomeration of technology-intensive industries has changed steadily. Since 2009, the agglomeration degree of computer communication industry has gradually increased, and gradually to the eastern region, such as Jiangsu and Guangdong. Through different ranks, we can see the regional comparative advantages of different regions and industries. Taking the computer communication equipment manufacturing industry as an example, Jiangsu has the highest level of specialization, while Sichuan, Guizhou, Shanxi, Shanghai, Jilin and Shenyang have relatively high level of specialization. It is also found that there is spatial correlation between the same industries in adjacent areas, so it is necessary to carry out spatial correlation analysis. Taking the industrial added value of prefecture-level cities from 2000 to 2016 as an example to calculate the spatial correlation of industries, the global Moran's I is adopted as follows.

$$Moran' sI = \frac{\sum_{i=1}^{N}\sum_{j\neq i}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{N}\sum_{j\neq i}^{N} w_{ij}} \quad S^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \tag{2}$$

When the value of Moran's I is greater than 0, it indicates that agglomeration is dominant; when the value of Morale's I is less than 0, it means that factor agglomeration is more dispersive.

Figure 3
Moran's I Value of China's Industrial Output

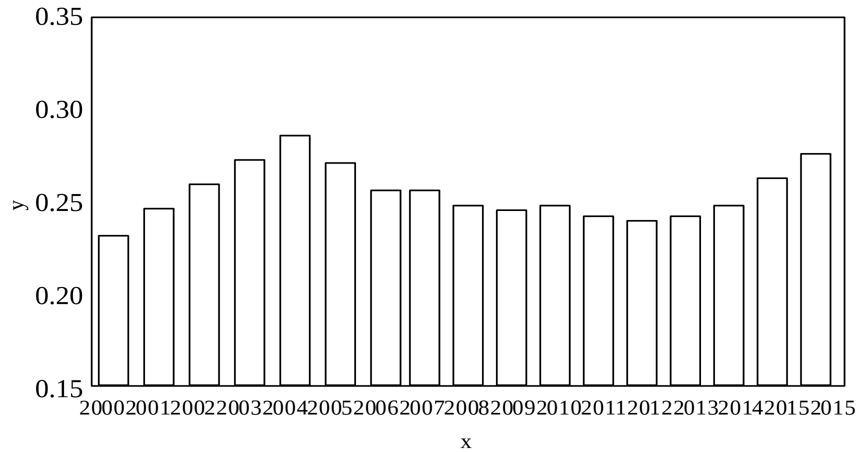


Table 2
Urban Industrial Agglomeration in China (2015)

Low Industrial Output and High Industrial Output Cities (LH)	Cities with High Industrial Output and High Industrial Output (HH)
Chengde, Langfang, Hezhou, Shaoguan and Yibin	Tianjin, Tangshan, Cangzhou, Shanghai, Suzhou, Wuxi, Changzhou, Jiaxing, Guangzhou, Dongguan, Huizhou and Shenzhen
Low Industrial Output and Low Industrial Output Cities (LL)	High Industrial Output and Low Industrial Output Cities (HL)
Datong, Lanzhou, Xining, Yinchuan, Xinjiang, Ganzi Aba Prefecture of Tibet and Sichuan, Kunming, Yunnan, Lincang, Pu'er, Baoshan and Lijiang	Chongqing and Chengdu

It can be seen that China's industrial output value has significant spatial correlation. LISA partial correlation analysis is shown in Table 2. The cities with high-high industrial output (HH) concentration are mainly concentrated in Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta. The industrial output value of most cities in the central and western regions is low-low (LL) concentration. The industrial output value of Chengdu and Chongqing is higher than that of the surrounding areas. High-low (HL) agglomeration is observed, while low-high (LH) agglomeration is observed in some cities of Chengde, northern Guangzhou and Yibin, Sichuan. The local spatial correlation of LISA in other cities is not significant.

Economic Growth Effect of Industrial-Spatial Matching Mechanism

Based on the theory of Chapter 2 and Chapter 4, this chapter uses industrial data and economic census data (2004, 2008, 2013) to make an empirical study on the economic growth effect and agglomeration effect of industrial and spatial matching mechanism. Because of the change of the caliber of industrial statistics, in order to ensure the consistency of data, the industrial data of 2007-2014 are selected for empirical study.

Table 3
Selection of Industrial Types in Empirical Research

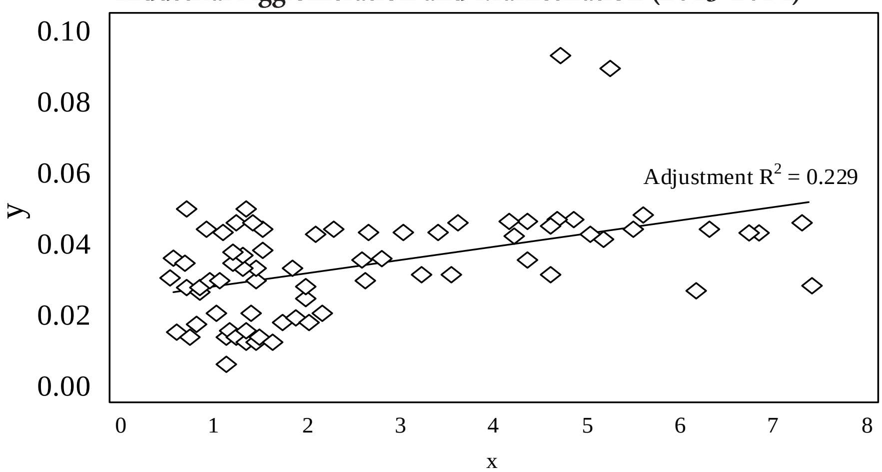
Industrial Classification	Industry Name
Labor-intensive industries	Non-metallic mining and processing industry 10, agricultural and sideline food processing industry 13, food manufacturing industry 14, wine, beverage and refined tea manufacturing industry 15, textile industry 17, paper and paper manufacturing industry 22
capital-using industry	Ferrous Metal Mining and Concentration 8, Nonferrous Metal Mining and Concentration 9, Tobacco Products 16, Petroleum Processing, Coking and Nuclear Fuel Processing 25
Technology-intensive industries	Coal mining and washing industry 6c, oil and gas mining industry 7c, chemical raw materials and chemical products manufacturing industry 26c, pharmaceutical manufacturing industry 27, chemical fiber manufacturing industry 28c, general equipment manufacturing 34, special equipment manufacturing 35, electrical machinery and equipment manufacturing 38, computer, communications and other electronic equipment manufacturing 39, instruments Instrument Manufacturing Industry 40

In order to define the spatial matching mechanism of industry, a benchmark model of matching efficiency for economic aggregate is proposed on the basis of the previous paper. Unlike the horizontal correlation of industrial input and output, the definition of industrial correlation of intra-industry matching mechanism needs to be further clarified. For a single industry, because industrial linkages involve vertical linkages between inputs and outputs (intra-industry linkages) and horizontal linkages between inputs and outputs (inter-industry linkages), the former is influenced by Marshall externalities of common technologies, while the latter benefits from Jacobs'diversity of externalities. Market size is still expressed by regional social sales. Transportation cost is still expressed by regional freight volume, and the larger the freight volume, the lower the transportation cost. Big cities agglomerate high-efficiency enterprises and industries because of their high productivity (Okubo et al, 2010; Venables , 2011 ; Behrens et al , 2014), however, previous studies have not shown whether the spatial industrial agglomeration with higher productivity is balanced or centralized. In order to clarify the effect mechanism of production efficiency on industrial agglomeration and diffusion, factor allocation efficiency J of 31 provinces and municipalities in China in 2015 was studied. In the preliminary analysis, factor allocation efficiency was measured by means of per capita capital output $y=Y/k$. In the follow-up study, TFP and per capita $y=K/L$ were used to measure factor allocation efficiency, and industrial Gini coefficient in the region was studied, as shown in Figure 4. It can be found that the higher the factor productivity of different regions, the lower the Gini coefficient of industrial space, that is, the more uniform the spatial distribution of industries in different regions. On the contrary, when the productivity of industrial factors in regional or urban space is smaller, the spatial distribution of industries in the region tends to agglomerate. Therefore, the hypothesis of the matching mechanism of industrial space is put forward. I. The higher the productivity, the faster the industrial diffusion. In the follow-up empirical research, TFP is also used to replace capital output y per capita for further research.

RESULTS

Industrial diffusion is also influenced by the degree of government-led and market-oriented (Jin Yu, Chen Zhao, Lu Ming, 2006). For the upstream and downstream manufacturing enterprises with large manufacturing share and close vertical links, trade liberalization will make them tend to agglomerate (Amiti, 2005). China has been carrying out industrial transfer since the strategy of developing the western region, trying to promote the balanced development of economic space through industrial transfer. Drawing on existing empirical research, the proportion of non-public economy is used to measure the degree of marketization, and the empirical indicators are replaced by the relative proportion of non-state-owned and collective capital investment. Further study of the impact of the degree of marketization on industrial agglomeration shows that the higher the degree of marketization (the higher the proportion of non-public economy), the larger the Gini system of industrial space, that is, the more obvious the characteristics of industrial spatial agglomeration. Therefore, hypothesis II is put forward. The higher the degree of marketization is, the more industry tends to agglomerate.

Figure 4
Industrial Agglomeration and Marketization (2013-2014)



In order to further define the degree of government intervention in the economy, the government's role in the transfer of industrial space is measured by the proportion of government expenditures to GDP. Because the industrial output value is measured by the industrial sales output value, the industrial output value in different years and regions needs to be reduced by price index. The price index chooses the industrial producer ex-factory price index in China Statistical Yearbook and converts it into 2007 as the base period. In summary, the following models can be obtained for metrological testing:

$$\ln Y_{it} = \beta_0 + \beta_1\eta_{it} + \beta_2 \ln k_{it} + \beta_3\eta_{it} \times \ln k_{it} + \beta_4\eta_{it} \times \ln N_{it} + \beta_5 \ln(Q_{it} \times \tau_{it}) + \beta_6 mar_{it} + \beta_7 gov_{it} + \beta_8 tech_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

In the formula, mar is the degree of marketization; gov is the role of the government, tech is the regional technical level, and the relative amount of patent acceptance in each region is used to measure the technical input ratio to measure the technical level of factor input, and the corresponding coefficient to measur e the matching relationship between regional technology reserves and technology input in industry. u_i is a fixed effect and ε_{it} is an error term. Coefficients β_3, β_4 and β_4 indicate the first matching mechanism of factor structure and industry correlation, the second matching mechanism of city scale and industry structure, and the third matching mechanism of market scale and industry choice respectively. When the coefficient is greater than 0, the matching efficiency of this matching mechanism is effective. Variable definitions and descriptive statistical indicators are detailed in Table 4. Because there are many types of industrial industries, only computer and communication equipment manufacturing industries in coal mining and fine separation industries and manufacturing industries are taken as examples to illustrate the industrial correlation ^ as shown in Fig. 5 and Fig. 6. It can be seen that the former increases more in industrial relevance, and the increase in output value of this kind of industry depends on industrial correlation and factor input; while the latter does not change much in industrial correlation, and output value depends more on other factors, such as technological progress to improve total factor productivity.

Table 4
Definition of Variables and Descriptive Statistics in Industrial Matching Mechanism Model

Variable Symbols	index	Maximum	minimum value	mean value	standard deviation	Coefficient of variation
InYit	Industrial output value of industry	8.72	-0.95	4.991	2.383	0.477
Inkit	Industrial per capita capital K/L	1.929	-2.120	-0.278	0.695	- 2.499
η1it	Intra-industry linkages	0.331	0.000	0.0539	0.0707	1.311
η2it	Inter-industry linkages	0.910	0.482	0.691	0.0898	0.124
InNit	Regional or urban population size	9.27	5.67	8.089	0.856	0.106
Inφit	Regional or urban market size	10.14	3.72	8.107	1.110	0.137
Inτit	Transportation cost	12.97	5.915	11.187	1.132	0.101
marit	Marketization Degree	0.829	0.257	0.656	0.111	0.169
govit	The role of government	1.291	0.0874	0.242	0.184	0.749
techit	Regional or urban technology input	0.247	0.0009	0.0315	0.0465	1.379

Figure 5
Industrial Linkages between Coal Mining and Fine Separation Industry

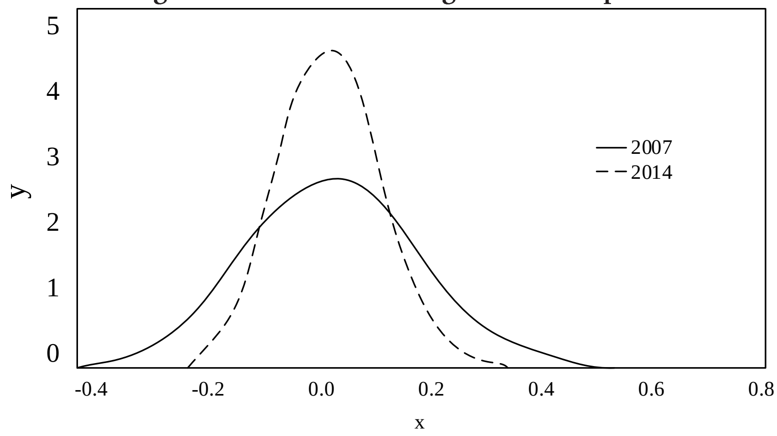
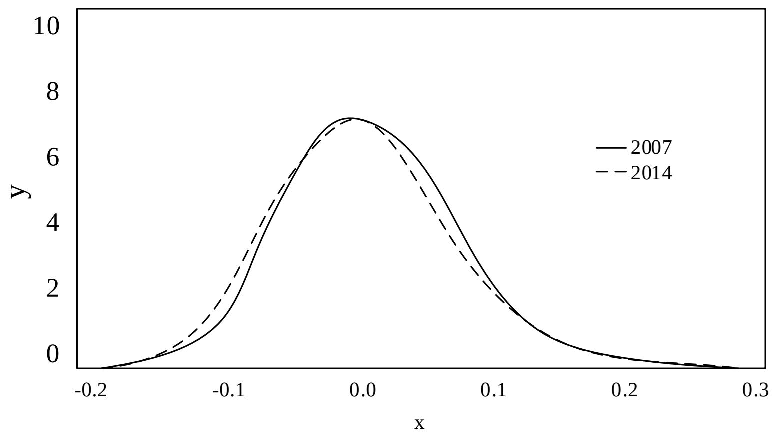


Figure 6
Industrial Linkages between Computer and Communication Equipment Manufacturing



Using Nie Huihua et al. (2011) and Yang Rudai (2015) for reference, capital input K is still measured by net fixed capital, labor L is measured by the average number of workers in enterprises, and intermediate input is measured by the main business cost. The relevant data are derived from the Yearbook of Industrial Statistics of China over the years. The ex-factory price index of industrial products is used to reduce the price of industrial sales and intermediate input. The price index comes from China Statistical Yearbook. The TFP value can be obtained by regression analysis. Due to space control, only the nuclear density estimates of TFP values in coal mining and washing industry, food manufacturing industry, pharmaceutical manufacturing industry, computer and communication equipment manufacturing industry in 2007 and 2014 are listed. It can be seen that the TFP of coal mining and fine separation industry has little change and the improvement of technology is relatively slow; the distribution of food manufacturing industry is gradually balanced; the efficiency of pharmaceutical manufacturing industry is gradually increasing, and the high-efficiency areas in the industry are gradually increasing; the TFP of computer and communication equipment manufacturing industry has improved significantly, and the efficiency has been greatly improved compared with 2007.

DISCUSSION

Based on the economic innovation competitiveness of economic clusters, the regional industrial economic development has been studied. From the perspective of industrial output growth, the effectiveness of the spatial matching mechanism of industry and service industry on the economic growth effect is industrially different. With the increase of industrial output value, in general, the effectiveness of the matching mechanism in labor-intensive industries in industry mainly depends on the matching mechanism of "market size and industry choice". However, as the value of production increases, the effectiveness of the matching mechanism decreases, such as food manufacturing, while the effectiveness of the matching mechanism of capital-intensive and technology-intensive industries increases with the output value, and the higher the level of significance. For the service industry, the direct economic growth effect of different service industry categories benefits from different matching mechanisms. For the regions with higher urbanization degree, the contribution of technological innovation to industrial transformation and upgrading is more economic value by improving inter-industry correlation, especially by actively promoting technological innovation. There are still some limitations in the study, which provides a general theoretical and empirical basis for urban and industrial growth. However, more detailed geographical space and targeted regional studies are one of the more realistic challenges in the future, such as the specific industrial layout of Beijing-Tianjin-Hebei urban agglomeration and Yangtze River Delta urban agglomeration.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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