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COMPARING THE EFFICIENCY OF REGIONAL KNOWLEDGE INNOVATION AND TECHNOLOGICAL INNOVATION: A CASE STUDY OF CHINA

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Abstract. The combination of knowledge innovation and technology innovation provides vitality for social science and technology innovation. China leaps into the front ranks of the world in the 2021 Global Innovation Index (GII). Therefore, this research takes China's theoretical-application innovation as the research object and empirically analyzes measure the innovation efficiency of knowledge innovation dominated by universities and technological innovation dominated by enterprises in China, as well as the gravity-center migration trajectory. The results show that the ranking of overall efficiency of theoretical innovation-application innovation is eastern region > central region > western region. Knowledge innovation presents a drag on overall efficiency, while technology innovation offers a contribution to overall efficiency. In the analysis of PIE (R&D personnel of industrial enterprises above a designated size) variables, the efficiency value is relatively low. The peak value of kernel density increases in the eastern, central and western regions, namely the concentration degree of theoretical innovation-application innovation efficiency in China has risen. The gravity center of each stage migrates to the eastern region, meaning the efficiency value of China's theoretical innovation and application innovation increases more significantly in the eastern region. From the perspective of knowledge innovation and technology innovation, this paper puts forward suggestions for China and provides some references for other developing countries.

Keywords: PEBM model, theoretical innovation stage, application innovation stage, efficiency.

JEL Classification: C44, O35, O53.

Introduction

The combination of knowledge innovation and scientific and technology innovation provides important talents and technical support for the strategic development of national enterprises and economic transformation (Cassiman & Veugelers, 2006). Under the background that innovation is a great driving force leading development (Pei et al., 2021), knowledge in-

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novation with universities as the main body and technology innovation with enterprises as the main body have formed China's theoretical innovation system and promoted the vigorous development of the nation's application innovation. What still needs to be examined is whether the efficiency of China's innovation system operations and whether the temporal and spatial differences are all significant. As the largest developing country in the world and with the reform of the national innovation system, China is gradually promoting scientific and technology innovation and transformation of said achievements closely around enterprises and universities. China ranks 12th in the 2021 Global Innovation Index (GII) 2021 and first among the 34 upper middle-income group economies. However, knowledge innovation and technology innovation simultaneously affect the process of industrial growth, and so regional differences of innovation need to be further explored. Taking China as the research object, this study investigates the efficiency evolution of a once-backward country in the process of scientific and technological innovation, providing a worthy reference for many other developing countries.

Knowledge production catalyzes and develops in the activities of people's social lives, so as to effectively transform their knowledge into social productive forces (Tsoukas, 2009). The education and knowledge production of colleges and universities provide the power of sustainable development for a country (Cai et al., 2020). During the 13th Five-Year Plan, China's higher education is promoting the construction of domestic knowledge innovation by focusing on improving quality and promoting fairness. The supporting investment of teaching and scientific research personnel and funds have brought corresponding knowledge innovation output to colleges and universities. Although knowledge innovation as a comprehensive concept is difficult to measure, some specific indicators do show the achievements of knowledge innovation in colleges and universities, such as scientific papers, international projects, and so on. In addition, industry-university research cooperation can gradually strengthen the relationship between universities and enterprises. Colleges and universities, as the main body of knowledge innovation, are increasingly cooperating with enterprises. In fact, science and technology funds of enterprises and institutions are gradually expanding, from 3.5 billion Chinese yuan (CNY) in 2015 to 4.8 billion Chinese yuan (CNY) in 2018. The knowledge innovation entrusted by enterprises to colleges and universities further promotes the vitality of enterprises' technology innovation.

Technology innovation can effectively optimize China's industrial structure and promote the reform of its technological science system (Liao et al., 2020). The effective construction of a virtuous circle within an innovation system is of great strategic significance for China's scientific and technological development. As the main part of enterprises to promote technology innovation, participating in the construction of a perfect technological innovation system is conducive to promoting the improvement and development of innovation ability. The country's State Council issued "Made in China 2025", which aims to promote its technological innovation and significantly improve its leading innovation ability and competitiveness in the manufacturing industry. As of 2019, China's full-time equivalent of R&D personnel reached 4,800,000 people, and R&D expenditure hit 1.3 trillion CNY in that year, as human capital and capital investment in technological innovation gradually increased. With the support of R&D personnel and funds, enterprises can use the achievements of technological innovation to develop new products and new patents. Such R&D achievements have further promoted the increase of China's exports and sales revenue of new products of industrial enterprises above a designated size, thus promoting the vitality of the domestic science and technology application market.

The close combination of knowledge innovation and technology innovation is an important cornerstone of China's transformation from theoretical innovation to application innovation. Under the mutual influence of knowledge innovation and technology innovation, China's theoretical innovation can be effectively transformed into social productivity – that is, application innovation. Only by closely combining the knowledge innovation of colleges and universities with the technological innovation of enterprises – that is, colleges and enterprises play an important role in one system – can we get a glimpse of the whole picture of China's theoretical innovation. On the basis of theoretical innovation, this study explores and analyzes the vitality and efficiency of China's science and technology application market. Taking its high-end manufacturing industry as an example, although the efficiency of green technology innovation in the high-end manufacturing industry is growing, it is still at a low level (Li et al., 2018a). Investigating the knowledge innovation ability of colleges and universities and considering their scientific research construction ability and economic effect, the results show that the overall level of scientific research at colleges and universities is quite different under the mode of scientific and technological innovation (Wang et al., 2022).

In view of the related literature, most scholars focus on analyzing the development of innovation ability of universities or enterprises and tend to conduct independent analysis of knowledge innovation and technology innovation, or they make a separate analysis of universities or enterprises and fail to build a connection framework between the two. Most of their methods use regression analysis or the traditional data envelopment analysis (DEA) model. In the process of social and economic production, knowledge innovation and technology innovation are parallel and interactive, and so it is difficult to discuss them separately. At the same time, in the process of education reform China's universities and enterprises are closely linked. Thus, this research proposes the PEBM model to study and evaluate the theoretical innovation and application innovation in 30 provinces (ex-Hong Kong/Macao/Taiwan/Tibet) from 2015 to 2018.

This study offers two main contributions to the literature. First, the PEBM model closely combines universities as the main body of knowledge innovation and enterprises as the main body of technological innovation to build the theoretical innovation stage. Through further use of the effective invention patents of universities and enterprises to connect with China's application innovation, this study discusses the effective construction of China's scientific and technological innovation evaluation system. Second, after calculating the efficiency of scientific and technological innovation in China, this study uses the kernel density estimation method to empirically analyze the evolution trend of the distribution characteristics of scientific and technological innovation in colleges and universities along with time and puts forward targeted suggestions on the basis of the analysis; Using the center of gravity migration model, this study calculates the center of gravity migration in each innovation stage in China and explore the change trend of its innovation space efficiency by analyzing migration direction and distance.

The remainder of this paper is organized as follows. In Section 1, this paper reviews the relevant literature of knowledge innovation and technology innovation. In Section 2, this paper introduces the mathematical details of PEBM model, kernel density estimation and gravity center migration model. In Section 3, this paper makes an empirical analysis of China's innovation efficiency and has a deeper discussion on the temporal and spatial distribution of China's innovation efficiency. In the last section, this paper gives conclusions and suggestions.

1. Literature review

Past literature has mainly focused on theoretical innovation and the influencing factors of knowledge innovation and technology innovation, followed by efficiency analysis of the technology and R&D achievements of universities or enterprises. Therefore, this paper is sorted out as follows according to the literature's various strands.

1.1. Research on knowledge innovation

For the research of technology transformation in universities, some scholars start from the results of research and development. The Poisson regression model was used to discuss whether activities related to invention patents closely relate to the academic performance of university professors in South Africa (Lubango & Pouris, 2009). By using the minimum distance method, the knowledge innovation efficiency of universities in 30 provinces of China was studied with results showing that the contribution rate of papers and performance evaluation to inefficiency has improved (Li et al., 2018b). Based on the two-stage DEA model, the efficiency of technology transfer in U.S. universities was studied, presenting findings that different innovation capabilities are needed for technology transfer (Ho et al., 2014).

By using stochastic frontier analysis and knowledge production function, the innovation system of Italy was measured, and the importance of university for innovation activities was also analyzed (Barra & Zotti, 2018). In order to investigate the efficiency level of policy for research universities and non-research universities, the innovation efficiency of two types of universities was compared (Chandran et al., 2021). The DEA model was used to discuss the research efficiency of 55 Mexican universities from 2007 to 2012 with findings showing the research efficiency of most universities is not satisfactory (Sagarra et al., 2017). The DEA model and Malmquist index were applied to discuss the research efficiency of Spanish public universities from 2006 to 2010. The results offered that the average research efficiency of most Spanish universities has significantly improved (Berbegal-Mirabent, 2018).

Guironnet and Peypoch (2018) used the DEA model to analyze the efficiency of education communication and research productivity in urban and rural areas of the United States. The research results showed that the efficiency of education communication in most areas is high, but that research efficiency fell by 7% due to the localization factor of some rural universities. The bootstrap DEA model helped explore the efficiency of Spain's higher public universities from 2002 to 2012, and the results showed that age and how to use universities' resources for the development of a university have a significant impact, but technical specialization has a negative impact (Martinez-Campillo & Fernandez-Santos, 2020). Moncayo-Martinez et al. (2020) evaluated the research efficiency of 40 public higher education institutions in Mexico from 2008 to 2016 with the DEA model. The two-stage network DEA model was used to discuss the overall efficiency of South Korean universities from 2010 to 2016, presenting results that the overall efficiency of most universities declined during the research period (Shamohammadi & Oh, 2019).

1.2. Research on technology innovation

Some investigation efforts have been made on the input of scientific and technological resources from regional innovation in China, with findings noting that the allocation efficiency of regional scientific and technological resources is low (Zhang et al., 2020). The role of tacit knowledge in the innovation process of technology-based small- and medium-size enterprises (SMEs) was analyzed (Koskinen & Vanharanta, 2002). According to the role of market subsidies and innovation subsidies in the process of technology innovation, results showed that the combination of market subsidy and technology subsidy can improve the utilization rate of subsidy funds under the action of multiple agents (Guan et al., 2019). Pearson correlation analysis was used on the relationship between corporate governance and R&D investment of marine science and technology companies, and the results showed that the size of the board of directors negatively correlates with R&D investment (Cu, 2020).

Some scholars have made an in-depth analysis of the relationship between technological innovation and economic development. The coordination between marine technological innovation and the development of ecological economy in Fujian Province has gradually improved, that is, technological innovation provides growth power for the development of ecological economy, and the development of ecological economy provides basic guarantee for marine technology (Wang et al., 2020). Shan et al. (2018) analyzed the contribution of China's technological entrepreneurship to national development by using the methods of grey absolute correlation and elasticity coefficient. The results showed that there is a high correlation between technological entrepreneurship and economic growth, and technological entrepreneurship has a significant contribution to technological progress and foreign trade. (Kihombo et al., 2021) analyzes the relationship between financial development (FD), technological innovation, economic growth and ecological footprint. The results showed that technological innovation helps to reduce the environmental footprint and promote economic growth in West Asia and the Middle East. There is an inverted U-shape between China's technological progress and economic growth, that is, reaching a turning point, and structural upgrading will stimulate economic growth (Zhou et al., 2021).

(Ding et al., 2022) discussed the relationship between technological innovation and digital economy. The results showed that technological innovation is an important communication path for the development of digital economy to high-quality economy. The impact of the process of internationalization on the innovation efficiency of emerging market firms was also explored. The results showed that R&D internationalization helps to improve the innovation efficiency of electronics manufacturing firms (Zhong et al., 2020). The influencing factors of enterprises' independent innovation performance was explored, and the results showed that the comprehensive efficiency of independent innovation is increasing (Zhou et al., 2020). Based on the financial statements of 83 listed semiconductor companies in 23 provinces of China from 2004 to 2019, the relationship between innovation space and the expansion of technology investment to promote enterprise growth was explored by using stepwise regression and backward regression methods. The results showed that innovation space, technology input, geographical area, and other factors contribute to the development of enterprises (Nam & Wang, 2020).

According to the above literature, there are two main directions for analysis. One is to analyze the efficiency of knowledge innovation, but the education problem is not considered, and the method is mainly regression and one-stage analysis. The other direction is to explore the efficiency of technology innovation, but it is not combined with knowledge innovation. In order to solve the above problems, this research uses the PEBM model to discuss problems such as knowledge and technology in the theoretical innovation stage and the transformation of the application stage.

2. Methods

The model of Network Data Envelopment Analysis (Network DEA) was put forward (Färe et al., 2007) whereby the production process is made up of many sub-production technologies. A basic type of network structure is a parallel system, in which the decision making unit (DMU) in the production process is composed of sub-units. The relationship between the low efficiency of component units and the low efficiency of the whole system is explored in depth, and the Parallel DEA model was presented to calculate the overall and component efficiencies, but the model does not maximize efficiency (Kao, 2009). Single-level and two-level hierarchical structures have been studied, where each DMU consists of contiguous parallel sub-units (Castelli et al., 2010). However, in this model, each component unit is handled independently without considering the relationship between component units. For both series and parallel network structures, a network DEA model was proposed to calculate the efficiency of the whole system and the efficiency of each section and to distribute the inefficiency of the system into the process of its composition (Chiang & Shiuh-Nan, 2010). If each DMU of different processes has the same number and each corresponding process has the same function, then the parallel structure can be considered. On this premise, teaching and research functions in a UK chemical department have been discussed in depth (Kao, 2012).

To solve the shortcomings of radial and non-radial models, Tone and Tsutsui (2010) proposed the EBM (Epsilon-based Measure) DEA model. This method can solve the weaknesses of the radial DEA model and non-radial DEA model, but it fails to deal with the problem of two stages. The Network DEA model solves the problem of multi-stages, but does not deal with the problem of radial and non-radial slacks and does not consider the problem of the function of the sub-units. Therefore, in order to solve these problems, the PEBM model is proposed by combining Tone and Tsutsui (2010)'s two-stage DEA model, Tone and Tsutsui (2010)'s EBM DEA model, and Kao (2009)'s parallel DEA model.

2.1. PEBM model

PEBM model accounts for divisional efficiencies as well as the overall efficiency in a unified framework. This means that we evaluate the total efficiency of DMUs as the main objective, which involves divisional efficiencies as their components (Tone & Tsutsui, 2010). DMUs have two internal procedures that are linked with intermediate measures. The first stage is divided into stage 1.1 (Knowledge Innovation Section) and stage 1.2 (Technology Innovation Section); The second stage is the Application Innovation Stage.

The number of teaching and research staff (TRS) and educational and research funding (ERF) respectively refer to the number of personnel engaged in teaching and scientific research in universities and the funds invested in teaching and scientific research. The acceptance of international projects in universities (AIPU), university science and technology papers (USTP), and university valid invention patents (UVIP) are all outputs in the section of knowledge innovation, and their forms include project acceptance, paper publication, and effective patent publication for Chinese universities. The R&D personnel of industrial enterprises above a designated size (PIE) and the R&D internal expenditure of industrial enterprises above a designated size (IE) respectively refer to the number of personnel and the total amount of funds invested in R&D in enterprises above a designated size. Among them, science and technology funds entrusted by enterprises and institutions (STF), as a link variable for knowledge innovation and technological innovation, mean that enterprises provide financial support for higher education due to the need of scientific research development. The number of new product projects of industrial enterprises above a designated size (NPP) and enterprise valid invention patents (EVIP) are respectively the total number of patents invented and new products developed by enterprises in the section of technological innovation. The turnover of technology market (TMT), sales revenue of new products of industrial enterprises above a designated size (SR), and export sales revenue of new products of industrial enterprises above a designated size (ESR) are respectively the outputs in the application stage, including the turnover in the technology market, total sales in the sales process of new products, and income from export sales. Figure 1 shows the process structure of the PEBM model.

Suppose that there are n DMUs denoted by $DMU_j\left(j=1,\ldots,n\right)$, with each having k divisions $\left(k=1,\ldots,K\right)$. A DMU uses m inputs $X_i\left(i=1\ldots.m\right)$ to produce r outputs $Y_r\ \left(r=1\ldots r\right)$. $X_{ijk}\in R_+\left(i=1,\ldots,m;\ j=1,\ldots,n;\ k=1,\ldots,K\right)$ refers to input i at time period t for DMU_j divi-

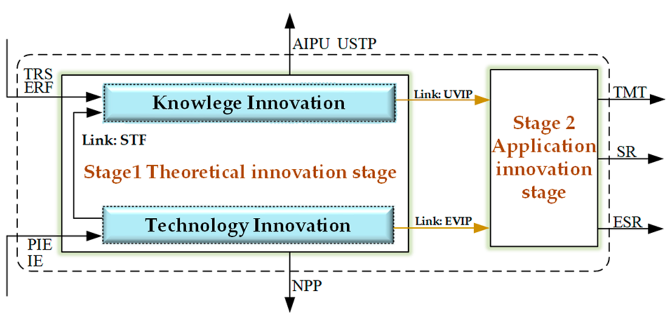


Figure 1. Flow chart of the PEBM model

sion k; X_{ijk}: In stage 1.1 (Knowledge Innovation Section), Teaching and Research Staff and R&D Internal Expenditure of Industrial Enterprises above Designated Size are its inputs. In stage 1.2 (Technology Innovation Section), R&D Personnel of Industrial Enterprises above Designated Size and R&D Internal Expenditure of Industrial Enterprises above Designated Size are its inputs.

$Y_{rjk} \in R_+ \left(r = 1,\ldots,r_k;\ j = 1,\ldots,n;\ k = 1,\ldots,K\right)$ refers to output r for DMU_j division k. Y_{rjk}: Acceptance of International Projects in Universities and University Science and Technology Papers are outputs of stage 1.1. Number of New Product Projects of Industrial Enterprises above Designated Size is output of stage 1.2. Technology Market Turnover, Sales Revenue of New Products of Industrial Enterprises above Designated Size and Export Sales Revenue of New Products of Industrial Enterprises above Designated Size are outputs of stage 2.

$Z_{j(kh)_l} \in R_+ \left(j = 1,\ldots,n;\ l = 1,\ldots,L_{hk}\right)$ is links from DMU_j division k to division h, with L_{hk} being the number of k to h links. $Z^t_{j(kh)_l}$: Science and technology funds entrusted by enterprises and institutions are selected as the link indicator in the Knowledge Innovation Section and Technology Innovation Section and Application Innovation. University valid invention patents are selected as the link indicator in the Knowledge Innovation Section and the application innovation stage. Enterprise valid invention patents are the link indicator in the Technology Innovation Section and the application innovation stage.

Equations (1)–(5) calculate the overall efficiency and divisional efficiencies, as follows.

(a) Overall efficiency:

$$\min\theta^* = \min_{0\eta,\lambda,s^-,s^+} \frac{\sum_{k=1}^{K} W^k \left[\theta_{ijk} - \varepsilon_{ijk} \sum_{i=1}^{m_k} \frac{w^-_{ijk} s^-_{ijk}}{x_{ijk}}\right]}{\sum_{k=1}^{K} W^k \left[\eta_{rjk} + \varepsilon_{rjk} \left[\sum_{r=1}^{r_k} \frac{w^+_{rjk} s^+_{rjk}}{y_{rjk}}\right]\right.}. \tag{1}$$

Subject to:

Knowledge Innovation Stage 1.1

$$x_{ij1.1} = \sum_{j=1}^{n} X_{ij1.1}\lambda_{ij1.1} + s^-_{ij1.1},$$

$$y_{rj1.1} = \sum_{j=1}^{n} Y_{rj1.1}\lambda_{rj1.1} - s^+_{rj1.1},$$

$$\lambda_{ij1.1} \geq 0,\ \lambda_{rj1.1} \geq 0, s^-_{ij1.1} \geq 0,\ s^+_{rj1.1} \geq 0,$$

$$Z_{rj(1.1,2)} = \sum_{j=1}^{n} Z_{rj(1.1,2)_l}\lambda_{rj(1.1.,2)} - S_{rj(1.1,2).} \tag{2}$$

Technology Innovation Stage 1.2

$$x_{ij1.2} = \sum_{j=1}^{n} X_{ij1.2}\lambda_{ij1.2} + s^-_{ij1.2},$$

$$y_{rj1.2} = \sum_{j=1}^{n} Y_{rj1.2}\lambda_{rj1.2} - s^+_{rj1.2},$$

$$\lambda_{ij1.2} \geq 0,\ \lambda_{rj1.2} \geq 0,\ s^-_{ij1.2} \geq 0,\ s^+_{rj1.2} \geq 0,$$

$$Z_{rj(1.2,2)} = \sum_{j=1}^{n} Z_{rj(1.2,2)}\lambda_{rj(1.2,2)} - S_{rj(1.2,2)},$$
$$Z_{ij(1.21.1)} = \sum_{j=1}^{n} Z_{\ ij(1.2,,1.1)}\lambda_{ij(1.2,1.1)} + S_{ij(1.2,1.1)}. \quad (3)$$

Application Innovation Stage 2

$$x_{ij2} = \sum_{j=1}^{n} X_{ij2}\lambda_{ij2} + s_{ij2}^{-},$$
$$y_{rj2} = \sum_{j=1}^{n} Y_{rj2}\lambda_{rj2} - s_{rj2}^{+},$$
$$\lambda_{ij2} \geq 0,\ \lambda_{rj2} \geq 0; s_{ij2}^{-} \geq 0, s_{rj2}^{+} \geq 0,$$
$$e\lambda_k = 1\ (\forall k,). \quad (4)$$

Y – DMU output item;
X – DMU input item;
S^- – slack variables;
S^+ – excess variable;
W^- – i input weights, and $\sum W_i^- = 1\ (\forall_i\ W_i^- \geq 0)$;
W^+ – S output weights;
ε – combination of radial θ and non-radial slack;
(k, h): the link from Division k to Division h.

(b) Division efficiency

The efficiency of Division K (Theoretical Innovation Stage and Application Innovation Stage) can be calculated by:

$$\min\rho^* = \min_{0\eta,\lambda,s^-,s^+} \frac{\left[\theta_{ijk} - \varepsilon_{ijk}\sum_{i=1}^{m_k} \frac{w_{ijk}^- s_{ijk}^-}{x_{ijk}}\right]}{\left[\eta_{rjk} + \varepsilon_{rjk}\left[\sum_{i=1}^{S_k} \frac{w_{rjk}^+ s_{rjk}^+}{y_{rjk}}\right]\right.}. \quad (5)$$

For the relationship between overall efficiency and divisional efficiencies, the overall efficiency score is the weighted arithmetic mean of the divisional scores, as shown by:

$$\theta^* = \sum_{k=1}^{K} W^k \rho^{*k}. \quad (6)$$

(c) Input and output efficiency

Hu and Wang's (2006) total-factor energy efficiency index is used to overcome any possible biases in the traditional energy efficiency indicators. TRS, STF, AIPU, USTP, UVIP, PIE, IE, NPP, EVIP, STF, UVIP, TMT, SR, and ESR are the variables used. Eqs (7)–(8) calculate the efficiency of each variable:

$$\text{Input efficiency } = \frac{\text{Target input}}{\text{Actual input}}; \quad (7)$$

$$\text{Output efficiency} = \frac{\text{Actual Desirable output}}{\text{Target Desirable output}}. \quad (8)$$

2.2. Kernel density analysis

As a non-parametric estimation method, kernel density estimation is mainly used to obtain the distribution pattern of random variables by smoothing the probability density of random variables based on the kernel function, which is widely used in the analysis of regional differences. Here, n is the number of provinces of China; *X*1, *X*2..., *Xn* denote the efficiency of the provinces; and Eq. (9) is the kernel density estimation of the density function *f*(*x*) at any point *x*. Moreover, *f*(*x*) is defined as the density function, *K*(·) is the kernel function, and h is the bandwidth.

$$f_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right). \tag{9}$$

2.3. The gravity-center of efficiency

To test the spatial and temporal distributions and change characteristics of theoretical and applied innovations in China, this study selects the center of gravity analysis method to measure its spatial migration trajectory. The position of the center of gravity indicates that the knowledge innovation section, technology innovation section, and application innovation stage of the surrounding area remain relatively balanced in all directions. Within the scope of investigation, if the proportion of efficiency value in a certain area increases, then the center of gravity will move to this position and then evolve into a certain regular migration trajectory.

Assuming that 30 provinces are in a unified and homogeneous plane, and the theoretical innovation and application innovation of each province are located in its central urban area, its center of gravity can be further calculated. In the formula, $LONG_t$ and LAT_t represent the longitude and latitude of the center of gravity in $t = (2015, 2016, 2017, 2018)$; $TIAI_t^i$ represents the efficiency value of theoretical innovation – application innovation of province i in year t.

$$LONG_t = \frac{\sum_{i=1}^{30}\left(TIAI_t^i \times \mathrm{long}_i\right)}{\sum_{i=1}^{30} TIAI_t^i},$$
$$LAT_t = \frac{\sum_{i=1}^{30}\left(TIAI_t^i \times \mathrm{lat}_i\right)}{\sum_{i=1}^{30} TIAI_t^i}. \tag{10}$$

We presume that the efficiency centers of the gravity coordinates in year *t* are $\left(LONG_t{}^{\circ}, LAT_t{}^{\circ}\right)$ and the efficiency centers of gravity coordinates in year *j* are $\left(LONG_j{}^{\circ}, LAT_j{}^{\circ}\right)$. The moving distance D and direction θ of the center of gravity from year *t* to year *j* are thus:

$$D = R \times \sqrt{(LAT_t - LAT_j)^2 + (LONG_t - LONG_j)^2},$$
$$\theta_{t-j} = \frac{n\pi}{2} + \arctan\left(\frac{LAT_t - LAT_j}{LONG_t - LONG_j}\right) \quad (n = 0,1,2). \tag{11}$$

3. Empirical analysis

Based on the PEBM model, this research evaluates the theoretical innovation stage and application innovation stage of 30 provinces (excluding Hong Kong, Macao, Taiwan, and Tibet Autonomous Region) from 2015 to 2018.

3.1. Data description and statistical analysis

This study uses panel data from 30 provinces in China from 2015 to 2018. The variables in this study help interpret and statistically analyze the data. The year 2015 is a connecting time between China's 12^{th} Five-Year Plan and the 13^{th} Five-Year plan. As an investigation year, it can help us to effectively investigate the efficiency level of China's theoretical application innovation in the 12^{th} Five-Year Plan, further analyze the changes of theoretical application innovation level in the 13^{th} Five-Year plan, and measure it as a whole. The delayed impacts of macroeconomic data collection and COVID-19 hinder the development of statistical work. Up to the end of this paper, the years 2019–2020 and their statistical data have not been released. Therefore, this paper controls the data from 2015 to 2018.

3.1.1. Explanation of variables

After literature collation and analysis, this paper selects the input and output indices for evaluating the efficiency of theoretical and application innovations at the provincial level in China as follows. All the data used in this study are from China Statistical Yearbook and local statistical yearbooks from 2016 to 2019. Table 1 lists the data.

3.1.2. Geographical division

This study takes 30 provinces in China as the research object. Due to the lack of data in Tibet, Hong Kong, Taiwan, and Macao, they were not included in the scope of this investigation. Moreover, the division of the eastern, central, and western regions is decided by the 7^{th} Five-Year Plan adopted at the Fourth Session of the Sixth National People's Congress. Due to the problem of economic development planning, Inner Mongolia and Guangxi are also divided into the western region in the western development. Table 2 lists the details.

3.2. Statistical analysis of inputs and outputs

This paper selects the theoretical and application innovation input-output data of 30 provinces in China from 2015 to 2018 to measure the mean value, maximum value, minimum value, and standard deviation of TRS, STF, ERF, AIPU, UVIP, PIE, IE, EVP, TMT, NPP, SR, and ESR. Please refer to Table 3 for details.

Table 1. Input and output variables

Stage		Variable	Unit
Theoretical Innovation Stage	Knowledge Innovation Section	Inputs	
		Teaching and research staff	Person
	(Link)	Science and technology funds entrusted by enterprises and institutions	1,000 CNY
		Education and research funding	1,000 CNY
		Outputs	
		Acceptance of international projects in universities	Project
		University science and technology papers	Article
	(Link)	University valid invention patents	Item
	Technology Innovation Section	Inputs	
		R&D personnel of industrial enterprises above a designated size	Person
		R&D internal expenditure of industrial enterprises above a designated size	10,000 CNY
		Outputs	
		Number of new product projects of industrial enterprises above a designated size	Project
	(Link)	Enterprise valid invention patent	Item
Application Innovation Stage		Outputs	
		Technology market turnover	100 million CNY
		Sales revenue of new products of industrial enterprises above a designated size	100 million CNY
		Export sales revenue of new products of industrial enterprises above a designated size	100 million CNY

Table 2. Areas in China

Region	Provinces and Municipalities
Eastern	Beijing, Tianjin, Shanghai, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan
Central	Heilongjiang, Jilin, Henan, Shanxi, Anhui, Hubei, Hunan, and Jiangxi
Western	Gansu, Guizhou, Ningxia, Qinghai, Shaanxi, Yunnan, Xinjiang, Sichuan, Chongqing, Guangxi, and Inner Mongolia

Table 3. Descriptive statistics of inputs and outputs

Variable	TRS	STF	ERF	USTP	AIPU	UVIP	PIE
Mean	35336.09	1378293.39	33873697.32	43182.12	133.97	9224.94	131819.50
Median	31037.50	655290.00	27060430.00	35211.50	49.50	5586.00	73681.00
SD	20711.36	1719776.34	24027170.43	31314.18	218.31	10786.96	167101.19
Min	3437.00	11407.00	2572832.00	2261.00	0.00	48.00	2065.00
Max	79973.00	8575476.00	122100103.00	131706.00	1198.00	52806.00	806431.00

End of Table 3

Variable	IE	EVIP	TMT	NPP	SR	ESR
Mean	3827044.59	28095.16	419.64	14618.53	59506869.20	11079278.88
Median	2419719.60	12448.00	148.24	7930.00	35447974.00	2817349.00
SD	4807264.11	51251.70	786.28	22137.13	79727365.10	20960003.43
Min	65029.00	271.00	2.19	121.00	228191.00	760.00
Max	21072031.40	328467.00	4957.82	121523.00	393760563.00	110517202.00

3.3. Results and analysis

3.3.1. Overall efficiency analysis

The two stages of the theoretical and application innovation PEBM model show that the overall efficiencies of Beijing, Guangdong, Jiangsu, Qinghai, and Zhejiang are relatively optimal from 2015 to 2018. An efficiency value of 1 indicates that the input and output of the DMU are located on the production frontier and shows a relatively optimal level among the provinces investigated. Therefore, under the existing linear constrained programming, we see that the theoretical innovation-application innovation efficiency level of a DMU is the best within the scope of this investigation – that is, the input-output structure allocation of the DMU is the best. The overall efficiencies of most provinces present an upward trend during 2015–2018. However, the overall efficiencies of Anhui, Gansu, Hainan, Hebei, Henan, Ningxia, and Chongqing have a downward trend during 2015–2018. Overall, most overall efficiency values are between 0.65 and 0.80.

The overall efficiency of Jiangxi in 2017 and 2018 is 1. Compared with its innovation efficiency value of 0.6–0.7 in the previous two years, the efficiency of theoretical innovation-application innovation has greatly improved. On the contrary, the efficiency value of Ningxia is 1 during 2015–2016 and drops to about 0.7 during 2017–2018. It shows that the efficiency of theoretical innovation-application innovation in Ningxia fell from 2017 to 2018.

Table 4 shows the overall efficiency of theoretical and application innovations in 30 provinces of China from 2015 to 2018. See Table 4 for details.

In order to effectively present the theoretical and application efficiencies in different regions of China, this paper summarizes the mean innovation efficiency of knowledge and technology by using a bitmap. As can be seen from the chart, there are three provinces with an efficiency level between 0 and 0.5: Xinjiang, Shanxi, and Yunnan. See Figure 2 for details.

The peak of kernel density overall increases – namely, the concentration of theoretical and application innovation efficiency also increases. However, the peak value in 2017 shows a significant decline, and the concentration of theoretical and application innovation efficiency also presents a significant decline.

From the eastern region, the concentration of theoretical and application innovation efficiency shows a trend of increasing year by year, the peak value gradually moves to the right, and the efficiency value increases gradually. In 2018 the kurtosis increases significantly, indicating a rise in concentration and polarization. In the central region, there is a bimodal pattern in 2016, indicating a trend of regional differentiation. In the following years, it changes to a unimodal pattern again, and the peak shows an upward trend. Compared with

Table 4. Theoretical and application innovation efficiency in each province

DMU	Mean	2015	2016	2017	2018	DMU	Mean	2015	2016	2017	2018
Anhui	0.91	0.90	0.92	0.93	0.88	Jiangxi	0.86	0.63	0.81	1.00	1.00
Beijing	1.00	1.00	1.00	1.00	1.00	Liaoning	0.67	0.63	0.67	0.65	0.74
Fujian	0.60	0.55	0.59	0.62	0.65	Inner Mongolia	0.55	0.57	0.52	0.53	0.57
Gansu	0.69	0.76	0.64	0.67	0.69	Ningxia	0.90	1.00	1.00	0.82	0.79
Guangdong	1.00	1.00	1.00	1.00	1.00	Qinghai	1.00	1.00	1.00	1.00	1.00
Guangxi	0.65	0.58	0.64	0.66	0.71	Shandong	0.78	0.73	0.81	0.78	0.78
Guizhou	0.59	0.53	0.58	0.61	0.64	Shanxi	0.48	0.38	0.40	0.50	0.62
Hainan	0.53	0.57	0.55	0.51	0.50	Shaanxi	0.60	0.64	0.53	0.49	0.72
Hebei	0.71	0.71	0.62	0.69	0.82	Shanghai	0.83	0.82	0.81	0.82	0.86
Henan	0.75	0.84	0.69	0.70	0.76	Sichuan	0.63	0.60	0.55	0.59	0.80
Heilongjiang	0.54	0.51	0.44	0.48	0.72	Tianjin	0.85	0.85	0.85	0.83	0.89
Hubei	0.75	0.74	0.74	0.75	0.77	Xinjiang	0.41	0.39	0.45	0.41	0.40
Hunan	0.65	0.66	0.63	0.64	0.68	Yunnan	0.45	0.36	0.46	0.52	0.44
Jilin	0.84	0.80	0.79	0.81	0.95	Zhejiang	1.00	1.00	1.00	1.00	1.00
Jiangsu	1.00	1.00	1.00	1.00	1.00	Chongqing	0.83	0.86	0.88	0.81	0.77

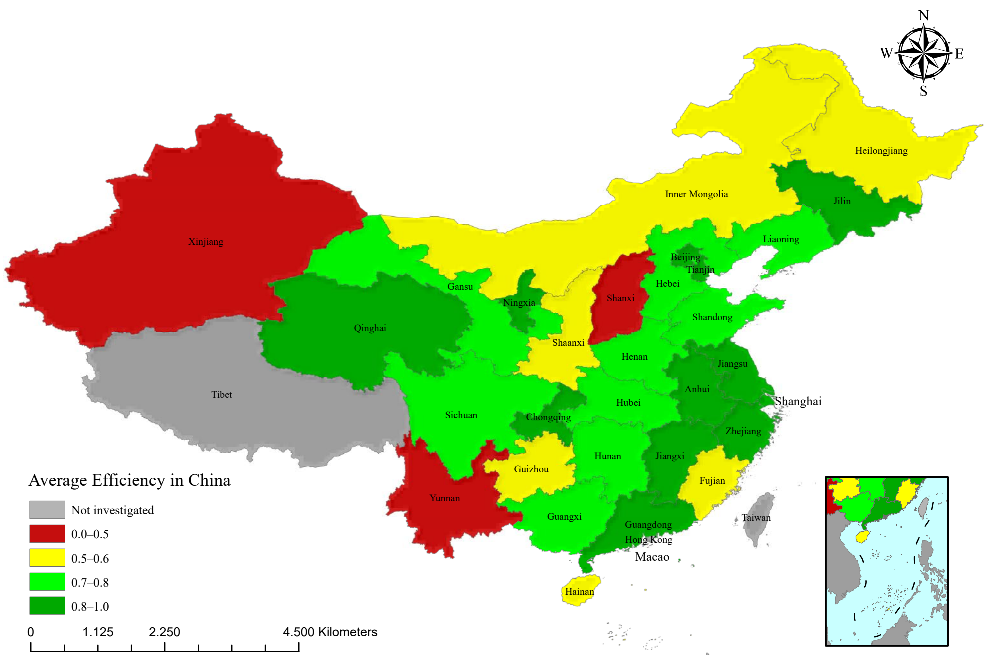


Figure 2. Mean theoretical and application innovation efficiency

the eastern and central regions, the peak value in the western region decreased significantly in 2017, but rose to the maximum value in 2018. We see that the concentration of theoretical innovation-application innovation in the western region fluctuates in a "V" shape. See Figure 3 for details.

From the table the overall efficiency value in the eastern region is always the largest, while that in the western region is always the lowest. From 2015 to 2018, the overall efficiency values in the eastern and central regions all show an upward trend. The overall efficiency value of the eastern region has been above 0.8 in the past 4 years. The central region is about 0.7, while the western region is between 0.6–0.7, but never exceeds 0.7. Table 5 shows the average overall efficiency values of the eastern, central, and western regions in China from 2015 to 2018.

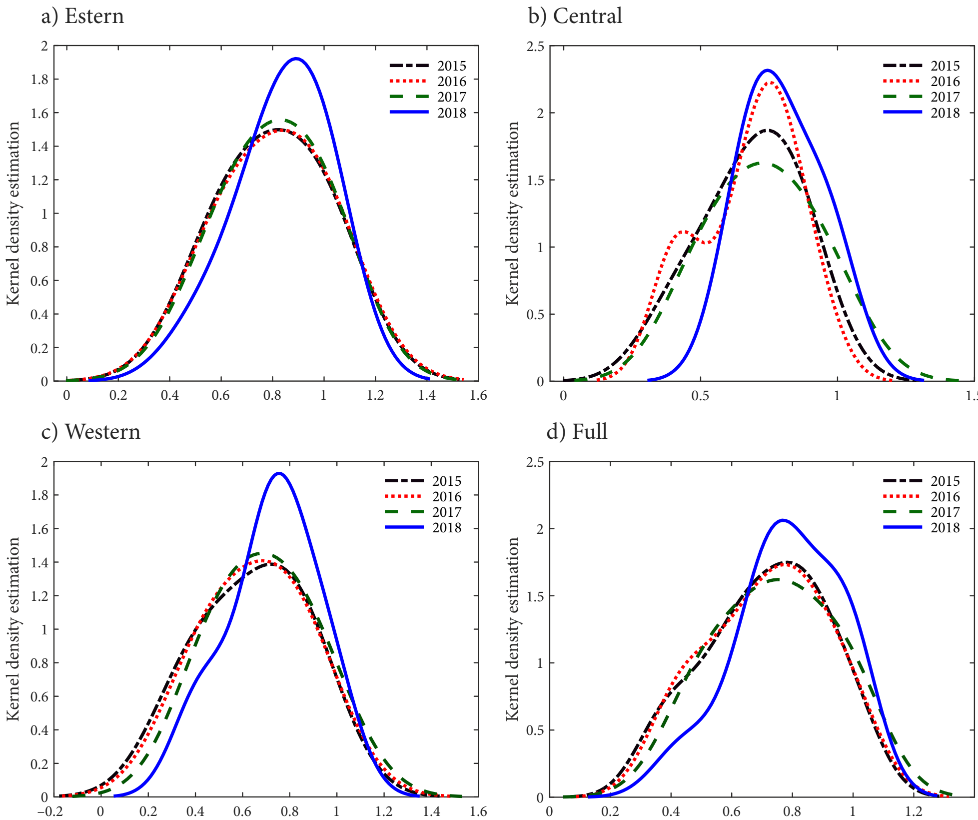


Figure 3. Kernel density curve of national, Eastern, Central, and Western Regions

Table 5. Overall efficiency from 2015 to 2018 of the Eastern, Central, and Western regions

Region	2015	2016	2017	2018
Eastern	0.804	0.809	0.810	0.840
Central	0.685	0.676	0.729	0.797
Western	0.663	0.660	0.648	0.683

3.3.2. Efficiency analysis of the theoretical innovation stage

This section explores the efficiency levels of theoretical innovation and application innovation in different regions of China.

3.3.2.1. Efficiency analysis of knowledge innovation

The innovation efficiency of the eastern region is higher than that of the central and western regions, while the innovation efficiency of the western region is the lowest. Among them, the knowledge innovation efficiencies in Beijing and Guangdong are 1 from 2015 to 2018. After a sharp decrease by half from 2015 (0.67) to 2016 (0.31), the efficiency value of Jiangxi rose to 1 in 2017–2018.

From the perspective of the eastern region, except for provinces with an efficiency value of 1, knowledge innovation in most regions is between 0.55 and 0.80. According to the analysis, the efficiency of Shandong began to decline after reaching a peak in 2016 (0.68) and is basically flat in 2018 (0.61) with that of 2015 (0.62).

From the perspective of the central region, except for provinces with an efficiency value of 1, the knowledge innovation efficiency of most provinces is also on the rise from 2015 to 2018. The innovation efficiencies of most provinces are between 0.4 and 0.6.

From the perspective of the western region, except for provinces with an efficiency value of 1, the overall innovation efficiency of most provinces is in a downward trend in the past four years. Knowledge innovation in most provinces is between 0.30 and 0.55.

For knowledge innovation, the western provinces show a lower level of efficiency than the eastern and central provinces. In order to further analyze the variable factors that drag down the provinces in the western region in this innovation, further analysis will be carried out in the variables' efficiency. See Table 6 for details.

Table 6. Knowledge innovation efficiency from 2015 to 2018

Region	DMU	2015	2016	2017	2018	Region	DMU	2015	2016	2017	2018
Eastern	Beijing	1.00	1.00	1.00	1.00	Central	Hunan	0.48	0.40	0.47	0.58
	Fujian	0.58	0.44	0.63	0.66		Jilin	0.59	0.42	0.61	0.89
	Guangdong	1.00	1.00	1.00	1.00		Jiangxi	0.67	0.31	1.00	1.00
	Hainan	1.00	0.55	1.00	1.00		Shanxi	0.41	0.42	0.43	0.50
	Hebei	0.49	0.49	0.50	0.62	Western	Gansu	0.55	0.39	0.46	0.49
	Jiangsu	1.00	0.56	1.00	1.00		Guangxi	0.82	0.42	0.71	0.68
	Liaoning	0.53	0.59	0.65	0.71		Guizhou	0.64	0.39	0.62	0.61
	Shandong	0.62	0.68	0.60	0.61		Inner Mongolia	0.27	0.44	0.31	0.37
	Shanghai	0.92	1.00	0.86	0.93		Ningxia	1.00	1.00	1.00	0.57
	Tianjin	0.67	1.00	0.82	0.88		Qinghai	1.00	0.57	1.00	1.00
	Zhejiang	1.00	0.49	1.00	1.00		Shaanxi	0.49	0.44	0.50	0.63
Central	Anhui	1.00	0.35	0.97	0.96		Sichuan	0.57	0.36	0.71	0.73
	Henan	0.67	0.42	0.42	0.52		Xinjiang	0.70	0.40	0.55	0.47
	Heilongjiang	0.56	0.59	0.66	0.87		Yunnan	0.76	0.36	0.79	0.64
	Hubei	0.48	0.40	0.51	0.55		Chongqing	0.81	0.42	0.77	0.77

3.3.2.2. Efficiency analysis of technology innovation

The three regions in China generally have high technology innovation efficiency. The technological innovation efficiency of Jiangsu, Zhejiang, and Henan in 2015–2018 is 1.

From the perspective of the eastern region, except for provinces whose technology innovation efficiency value is 1 in the past four years, the other provinces are on the rise in the same period. Shandong began to decline after reaching a peak value of 1 in 2016, while its overall efficiency of technology innovation efficiency is increasing. On the contrary, the technology innovation efficiency of Shanghai in the past 4 years is in a downward trend. Its efficiency value in the previous three years is 1, and in 2018 it dropped to about 0.9.

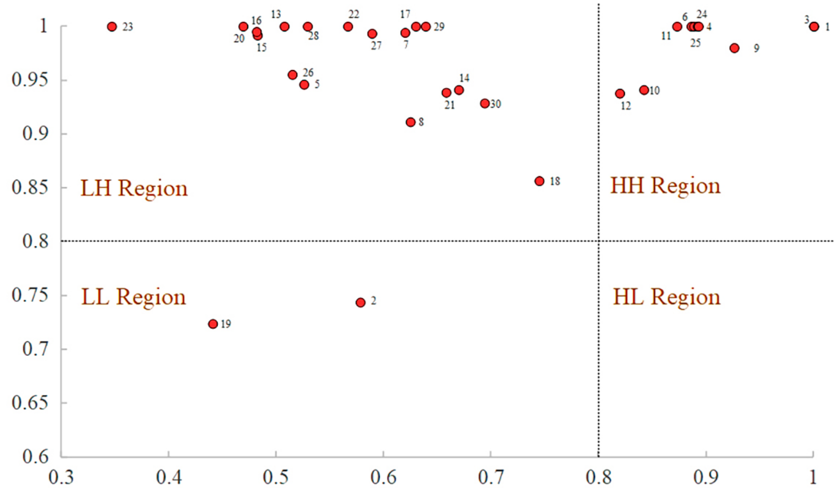
For the central region, except for the provinces whose technology innovation efficiency value is 1 in the past four years, the other provinces are on the rise in the past four years as a whole. The exception is Anhui, which is in a downward trend as a whole, and its efficiency began to decline after reaching 1 in 2016 and 2017. Hunan's efficiency value is 0.97 in 2016 and 1 in other years.

From the perspective of the western region, the value of technology innovation efficiency in most provinces is 1 and is on the rise. In Sichuan, the rate is 0.97 in 2016 and 1 in other years. See Table 7 above for details.

Based on the average innovation efficiency of knowledge and technology, this study takes 0.8 as the boundary value and divides provinces into low-low, low-high, high-high, and high-low (four parts). Most provinces are distributed in low-high areas. The efficiency level of Shanxi and Fujian is low-low, meaning the efficiency level of these two provinces is relatively low in the two stages. None of the provinces are distributed in the high-low range.

Table 7. Technology innovation efficiency from 2015 to 2018

Region	DMU	2015	2016	2017	2018	Region	DMU	2015	2016	2017	2018
Eastern	Beijing	1.00	1.00	1.00	1.00	Central	Hunan	1.00	0.98	1.00	1.00
	Fujian	0.65	0.79	0.76	0.77		Jilin	1.00	1.00	1.00	1.00
	Guangdong	1.00	1.00	1.00	1.00		Jiangxi	0.69	0.74	1.00	1.00
	Hainan	1.00	1.00	1.00	1.00		Shanxi	0.60	0.67	0.76	0.86
	Hebei	0.91	0.87	1.00	1.00	Western	Gansu	1.00	1.00	1.00	1.00
	Jiangsu	1.00	1.00	1.00	1.00		Guangxi	1.00	0.83	1.00	0.92
	Liaoning	0.98	1.00	1.00	1.00		Guizhou	1.00	1.00	1.00	1.00
	Shandong	0.78	1.00	0.94	0.94		Inner Mongolia	1.00	1.00	1.00	1.00
	Shanghai	1.00	1.00	1.00	0.92		Ningxia	1.00	1.00	1.00	1.00
	Tianjin	1.00	0.98	0.79	1.00		Qinghai	1.00	1.00	1.00	1.00
	Zhejiang	1.00	1.00	1.00	1.00		Shaanxi	0.91	0.93	1.00	0.98
Central	Anhui	0.91	1.00	1.00	0.84		Sichuan	1.00	0.97	1.00	1.00
	Henan	1.00	1.00	1.00	1.00		Xinjiang	1.00	1.00	1.00	1.00
	Heilongjiang	0.96	0.87	0.95	0.99		Yunnan	1.00	1.00	1.00	1.00
	Hubei	1.00	1.00	1.00	0.97		Chongqing	0.87	0.93	0.94	0.98



Note: The provinces represented by the numbers in the figure are as follows: 1 Beijing; 2 Fujian; 3 Guangdong; 4 Hainan; 5 Hebei; 6 Jiangsu; 7 Liaoning; 8 Shandong; 9 Shanghai; 10 Tianjin; 11 Zhejiang; 12 Anhui; 13 Henan; 14 Heilongjiang; 15 Hubei; 16 Hunan; 17 Jilin; 18 Jiangxi; 19 Shanxi; 20 Gansu; 21 Guangxi; 22 Guizhou; 23 Inner Mongolia; 24 Ningxia; 25 Qinghai; 26 Shaanxi; 27 Sichuan; 28 Xinjiang; 29 Yunnan; and 30 Chongqing.

Figure 4. Distribution of average efficiency of knowledge and technology stages

It can be seen that the innovation efficiency of knowledge in most provinces is low, while the innovation efficiency of technology is high. Figure 4 summarizes the distribution interval of knowledge and technology innovation efficiency levels.

3.3.3. Efficiency analysis of application innovation stage

From the perspective of efficiency in the application innovation stage, we see that eastern > central > western. Among the provinces, the application innovation efficiency values of Beijing, Guangdong, Jiangsu, Zhejiang, Henan, Hubei, Jilin, and Qinghai from 2015 to 2018 are 1. After effectively undertaking the theoretical innovation achievements of universities and enterprises – that is, effective invention patents – the above provinces have obtained excellent application innovation output.

From the perspective of the eastern region, except for provinces whose efficiency value is 1 in the past four years, Fujian, Liaoning and Shanghai are in an overall upward trend in the same period. In 2015 and 2018 the efficiency of Hebei is 1, and in 2016–2017 its efficiency is 0.75. The overall efficiency trend for the 4 years shows an inverted trapezoidal shape.

For the central region, except for the provinces whose efficiency value is 1 in the past four years, the other provinces are on the rise in the same period. Among them, the efficiency value of Heilongjiang in the past four years is between 0.3 and 0.5.

From the perspective of the western region, except for the provinces whose efficiency value is 1 in the past four years, the other provinces are in an overall upward trend in the same period. However, the efficiency value of Chongqing is 1 in 2015–2016, dropped to about 0.8 in 2017, and continued to drop to about 0.7 in 2018. See Table 8 for detailed data.

The efficiency of application innovation in different provinces of China presents a differentiated distribution. The application innovation levels of Beijing, Guangdong, Jiangsu, and some other provinces from 2015 to 2018 are 1, reaching the optimal DEA, and their efficiency level maintains a good trend. The average application innovation level of Xinjiang, Yunnan, Hainan, and some other provinces is 0.2–0.4, and so their efficiency level is low. Figure 5 summarizes the average application innovation efficiency.

Table 8. Application stage efficiency from 2015 to 2018

Region	DMU	2015	2016	2017	2018	Region	DMU	2015	2016	2017	2018
Eastern	Beijing	1.00	1.00	1.00	1.00	Central	Hunan	0.73	0.71	0.69	0.64
	Fujian	0.59	0.59	0.63	0.66		Jilin	1.00	1.00	1.00	1.00
	Guangdong	1.00	1.00	1.00	1.00		Jiangxi	0.70	1.00	1.00	1.00
	Hainan	0.30	0.29	0.26	0.25		Shanxi	0.40	0.41	0.55	0.69
	Hebei	1.00	0.73	0.78	1.00	Western	Gansu	0.94	0.65	0.77	0.78
	Jiangsu	1.00	1.00	1.00	1.00		Guangxi	0.36	0.51	0.51	0.68
	Liaoning	0.61	0.57	0.53	0.65		Guizhou	0.36	0.40	0.48	0.52
	Shandong	1.00	1.00	1.00	0.98		Inner Mongolia	0.83	0.66	0.62	0.61
	Shanghai	0.65	0.64	0.70	0.80		Ningxia	1.00	1.00	0.61	1.00
	Tianjin	1.00	1.00	1.00	0.83		Qinghai	1.00	1.00	1.00	1.00
	Zhejiang	1.00	1.00	1.00	1.00		Shaanxi	0.73	0.46	0.36	0.70
Central	Anhui	0.84	0.79	0.84	0.90		Sichuan	0.49	0.40	0.41	0.76
	Henan	1.00	1.00	1.00	1.00		Xinjiang	0.21	0.26	0.25	0.27
	Heilongjiang	0.38	0.31	0.31	0.52		Yunnan	0.18	0.24	0.30	0.26
	Hubei	1.00	1.00	1.00	1.00		Chongqing	1.00	1.00	0.81	0.67

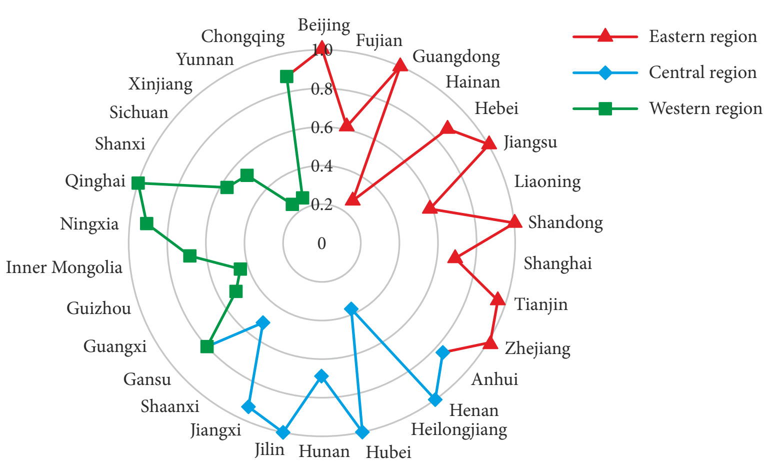


Figure 5. Average efficiency of application stage

3.3.4. Input variables' efficiency analysis

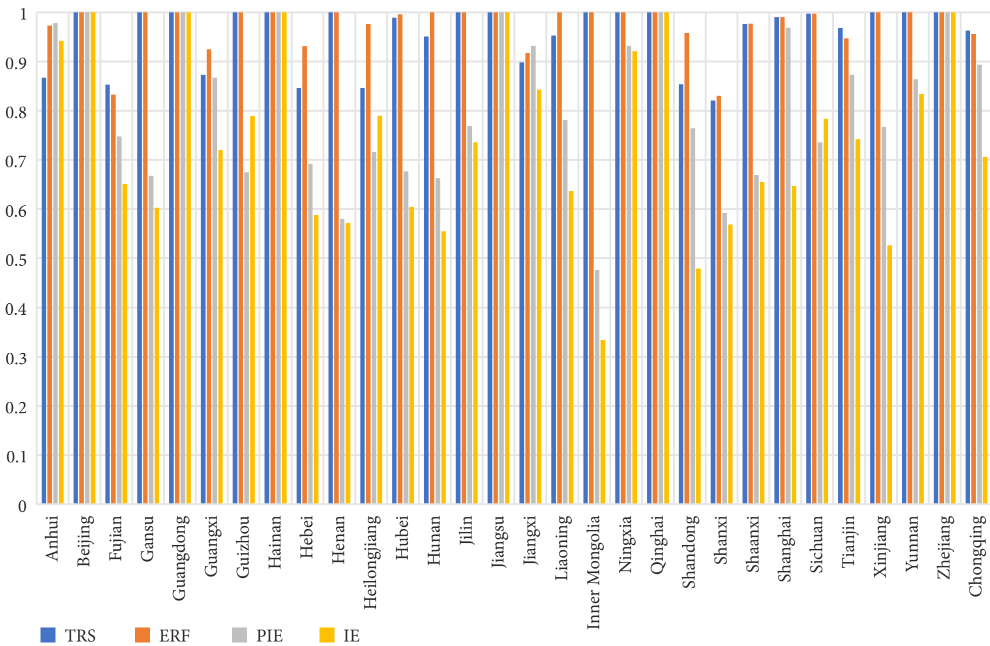
Because the input variables relative to the output variables are easier to control in theoretical innovation and application innovation, the input variables of each stage are thus selected for analysis. From the PEBM model, the efficiency values of the innovation input index of knowledge and technology in Beijing, Guangdong, Hainan, Jiangsu, Qinghai, and Zhejiang are all 1, indicating high utilization efficiency of various variables and full and effective utilization of all resources.

From the perspective of the two stages of parallel DEA model, the efficiency value of the input index for teaching and research staff is generally high, ranging from 0.85–1. Driven by the national innovation theory of industry-education-research, universities and colleges actively introduce advanced scientific researchers, and the scientific research technology level of Chinese universities is relatively advanced. In terms of the input index of ERF, the efficiency value of most provinces is above 0.9. To introduce talents through innovation, colleges and universities can further promote their own efficiency of theoretical innovation.

From the perspective of technology innovation in the two stages of parallel DEA, the efficiency of R&D personnel of industrial enterprises above a designated size is mostly between 0.6–0.8, which indicates that there is certain room for improvement in the R&D personnel efficiency of technology. In Henan, Inner Mongolia, Shaanxi, and some other provinces, their values of personnel efficiency are lower than 0.6. As can be seen from Table 7, the efficiency value of R&D personnel of industrial enterprises above a designated size in eastern China is generally higher than that in central and western China. The government should take corresponding measures to support talent introduction policies in the central and western regions and narrow the regional innovation gap. From the perspective of R&D internal expenditure of industrial enterprises above a designated size, the efficiency value of most provinces is above 0.7. However, the efficiency values of Fujian, Gansu, Hebei, Henan, Hubei, Hunan, Inner Mongolia, Shandong, Shaanxi, and Xinjiang are below 0.6. See Figure 6 for details.**3.3.5. The gravity-center of efficiency analysis**

According to Section 2.3, this paper calculates the migration path of gravity centers of theoretical innovation, application innovation efficiency and overall efficiency in China. In knowledge innovation, from 2015 to 2016 the efficiency values of Shandong and Inner Mongolia increased by 0.06 and 0.17, respectively, thus promoting the center of gravity to move to the northeast. In 2016–2017, the center of gravity shifted back to the southwest, as the efficiency of Jiangsu and Jiangxi increased by 0.44 and 0.69, respectively. From 2017 to 2018, the efficiencies values of Jilin and Heilongjiang increased by 0.28 and 0.21, respectively, promoting the center of gravity to move to the northeast. Overall, knowledge innovation moves to the northeast.

In technology innovation, from 2015 to 2016 Anhui increased by 0.09, while Jiangsu, Shanghai, and other provinces kept their efficiency value at 1, which promoted the center of gravity to move eastward. From 2016 to 2017, the efficiency value of Guangxi increased by 0.17, while that of Tianjin decreased by 0.19, promoting the southward shift of the center of



Note: TRS refers to Teaching and Research Staff; ERF refers to Education and Research Funding; PIE refers to R&D Personnel of Industrial Enterprises above a Designated Size; and IE refers to R&D Internal Expenditure of Industrial Enterprises above a Designated Size.

Figure 6. Average input efficiency by province

gravity. In 2017–2018, Tianjin's efficiency value increased by 0.21, promoting the northward shift of the center of gravity. In general, the center of gravity moves to the northeast.

In the application innovation stage, from 2015 to 2016 the efficiency value of Guangxi increased by 0.15, while the efficiency value of Hebei and Inner Mongolia decreased by 0.27 and 0.17, respectively, which promoted the center of gravity to move to the southeast. From 2016 to 2017, the efficiency value of Ningxia and Chongqing decreased by 0.39 and 0.19, respectively, continuing to push the center of gravity to the southeast. From 2017 to 2018, the efficiency of Shaanxi and Ningxia increased by 0.34 and 0.39, respectively, promoting the shift of the center of gravity to the northwest. All in all, the center of gravity in the application innovation stage shifted significantly to the south and slightly to the east.

In terms of overall efficiency, the efficiency value of Jiangxi increased by 0.18 from 2015 to 2016, which promoted the shift of the center of gravity to the southwest. In 2016–2017 the efficiency value of Jiangxi increased by 0.19, while that of Ningxia decreased by 0.18, driving the center of gravity to continue to move to the southwest. From 2017 to 2018 the efficiency values of Heilongjiang and Hebei increased by 0.24 and 0.13, respectively, pushing the center of gravity to the northeast. In general, the center of gravity shifted significantly eastward and slightly northward. See Figure 7 for details.

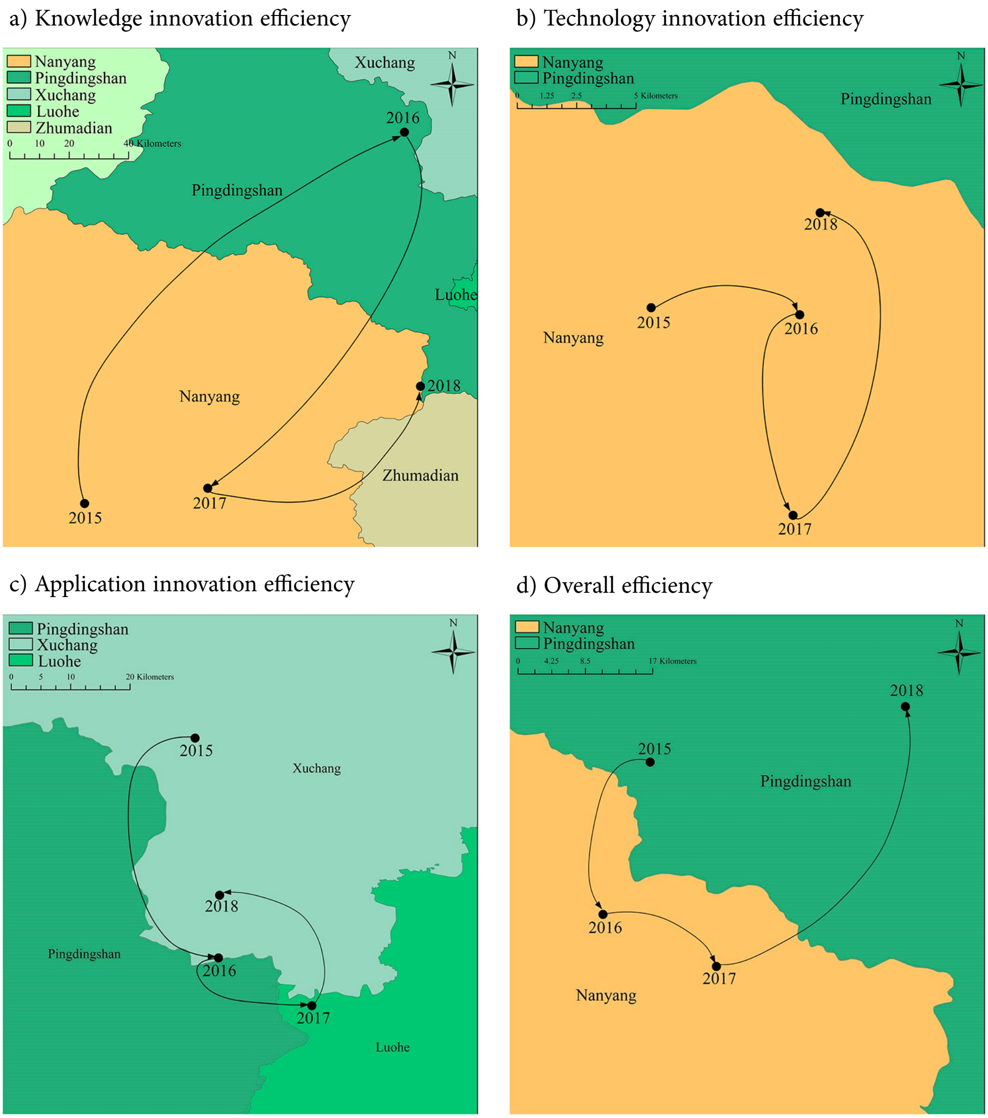


Figure 7. Migration path of gravity-center position for 30 provinces from 2015 to 2018

Conclusions and suggestions

Conclusions

(1) The theoretical-application innovation efficiency shows that the overall efficiency ranking among regions is eastern region > central region > western region. From 2015 to 2018 the overall efficiency values in the eastern and central regions all present an upward trend. The central region is about 0.7, while the western region is between 0.6–0.7, but never exceeds 0.7, indicating that the innovation efficiency of the two regions still has some deficiencies. Under China's policy inclination and geographical

advantages, the theoretical innovation in the eastern region can be effectively transformed into application innovation, and with the attenuation of radiation effect, the overall efficiency of the western region is lower than eastern region.

(2) From the results of kernel density estimation, the concentration of theoretical innovation-application innovation in the eastern and central regions of China has increased year by year. The peak value in the western region dropped significantly downward in 2017. Except for the western region, the peak value in the eastern and central regions has shifted slightly to the right – that is, the efficiency level of theoretical innovation-application innovation in these regions has improved. It can be seen that there are differences in efficiency among the eastern, central and western regions, but generally speaking, the peak value of the above regions increases, indicating that the regional differences in China are reduced. Driven by outline of the national strategy of innovation driven development, the innovation relationship between Chinese enterprises and universities has been further clarified, and its regional differences have been reduced under macro-control.

(3) The knowledge innovation efficiency in the western region is the lowest. It is worth noting that the efficiency level of Ningxia and Qinghai in the western region is relatively high. That is, the knowledge innovation with colleges and universities as the main body. Under the background of lack of college resources, most provinces in the western region have failed to make full use of the existing resources to promote the development of its knowledge innovation. The value of technology innovation efficiency in the three major regions of China is generally high. Jiangxi and Shaanxi in the central region fail to show a high efficiency level in the process of technological innovation. Compared with the eastern and western provinces, there is still an urgent need for improvement. Based on the two stages of parallel DEA, knowledge innovation is a drag on the overall output efficiency value, while technology innovation offers great contribution to the overall efficiency value. PIE is mostly between 0.6–0.8. In Henan, Inner Mongolia, and Shaanxi their value of personnel efficiency is lower than 0.6. During China's 13th Five-Year Plan, R&D personality of industrial enterprises above a designed size failed to play a full role in China's theoretical innovation -application innovation, and the deep-seated system and mechanism obstacles of industrial innovators still exist. From the perspective of application innovation efficiency, Beijing, Guangdong, Jiangsu, Zhejiang, and other provinces are in a relatively optimal state, Fujian and Shanghai in the eastern region, Anhui and Shanxi in the central region, and Guangxi and Sichuan in the western region are all on the rise. During China's 13th Five-Year Plan, on the premise of actively undertaking the achievements of theoretical innovation, most of provinces strengthened the R&D, transformation and application of technologies.

(4) In the analysis of gravity shift, China's knowledge innovation and technology innovation move to the northeast. In other words, the knowledge innovation and technology innovation undertaken by Chinese universities and enterprises perform well in the theoretical innovation in northeast provinces. In Liaoning, Jilin, Heilongjiang,

and other northeastern regions, China put forward proposals to build new competitive edges for the innovation and entrepreneurship development of the old industrial bases in 2015, invigorating theoretical innovation there. However, the center of applied innovation shifted to the southeast – that is, in the process of industrial growth the southeastern provinces undertook theoretical innovation much better. In general, the efficiency value of theoretical innovation-applied innovation in eastern China accounts for a higher proportion, and it is better among the 30 provinces, which has led to a significant shift of the overall efficiency center to the east.

Suggestions

Based on the above conclusions, the theoretical and application innovation efficiencies and overall efficiency in various provinces still need to be improved. Therefore, the following countermeasures and suggestions are proposed.

(1) In the two stages of parallel DEA, the differences among various regions in China are very significant. Among them, the eastern region with a more developed economy has higher efficiency of knowledge innovation, while the central and western regions have lower efficiency. According to this situation, the government should use financial means to support colleges and universities with the characteristics of the central and western regions, on this basis improve the knowledge innovation ability of the region, and cultivate talent centers with regional characteristics.

(2) From the perspective of technology innovation, with the improvement and development of society, isolated and closed forms of innovation are no longer suitable for modern enterprise management systems. Therefore, as the basis of technological innovation, enterprises should build effective communication media with local colleges and universities or scientific research institutions, closely integrate with external innovation institutions, and make use of the knowledge innovation content produced by colleges and universities to promote the transformation from theoretical innovation to application innovation – that is, more effective productivity.

(3) The government should focus on promoting innovation and development. The virtuous circle from theoretical innovation to application innovation is an important driving force to accelerate local economic development and promote the transformation of scientific and technological achievements. During this process the government should build an effective communication platform closely around the two organizations of universities and enterprises, so as to promote the effective transformation of knowledge innovation and technology innovation into application innovation. The government should also pay more attention to the problem of balanced regional development. It should promote its spread from the eastern region to the inland regions and fully build a support system to push for a more balanced regional development.

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