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Evaluation of Regional Innovation Efficiency in China Based on Three-Stage DEA Model

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***Abstract*—This paper uses the three-stage DEA model to measure the regional innovation efficiency of 30 provinces in China from 2009 to 2016. The research shows that: (1) the innovation efficiency of most provinces in China is overestimated by environmental factors and random factors; (2) Except for Beijing and Zhejiang, most of the provinces have large room for improvement in regional innovation capability, and regional differences are significant; (3) Gini coefficient, coefficient of variation, and Theil index verify that there is a significant overall difference in regional innovation efficiency in China, but the difference is fluctuating. Based on this, further improvement of China's regional innovation capability requires strengthening inter-regional mobility, weakening regional innovation barriers, and promoting the establishment of regional innovation alliances to promote the coordinated development of regional innovation.**

Keywords—regional innovation; three-stage DEA model; regional difference

I. INTRODUCTION

With the development of the globalization of knowledge economy, national and regional economic development is highly dependent on the ability to transform innovation and knowledge [1]. From the international experience, most countries put innovation at the forefront of seeking development. For example, the United States has formulated a national innovation strategy, South Korea has proposed the 2020 Industrial Technology Innovation Strategy, and the EU has announced the 2020 Innovation Strategy. Innovation has become a key part of national development planning. On the one hand, Víctor et al. [2] and Bai et al. [3] proved that innovation has a significant positive impact on regional economic growth, on the other hand the regional innovation concept with coordination, openness and sharing as the core has been deepened. Therefore, regional innovation has gradually become the key to enhancing the capacity of independent innovation and driving regional economic growth.

Despite the new economic normality and the rapid development of regional economic integration, China's regional innovation has achieved remarkable results. However, it is undeniable that a series of problems have gradually emerged in this process. For example, the pace of regional innovation and development is inconsistent, and the level of regional interconnection is not higher. These problems not only restrict the improvement of regional innovation capability, but also become the paralysis of regional economic development. Therefore, a comprehensive assessment of China's regional innovation capability is of great significance for optimizing the allocation of regional innovation resources and exploring new models for regional innovation economic growth.

At present, the innovation ability is mainly measured by the index of innovation efficiency. Innovation efficiency is the ratio of innovation resources input and innovation achievements output in the innovation process, which measures the contribution degree of each subject's innovation input into achievements output. There are two methods for measuring innovation efficiency widely used in academia: one is the parameter method—Stochastic frontier analysis SFA [4], subjectively estimating the form of the production function by artificially limiting the production optimal boundary, such as Li et al. [5] and Zhang and Zhang [6] respectively used SFA models to measure the innovation efficiency of Chinese industrial enterprises and enterprises above designated size; the other is the non parametric method—data envelopment analysis DEA [7], the relative effectiveness of efficiency is evaluated by using input and output as the basis for evaluation. Xiao et al. [8] and Li et al. [9] respectively used the DEA model to study the innovation efficiency of Chinese industrial enterprises and urban agglomerations. In addition the three-stage DEA model [10] further incorporates the influence of environmental factors and random noise on the efficiency evaluation of decision-making units into the measurement dimension, thus greatly improving the accuracy of DEA measurement.

Considering the differences in the economic base and industrial development level of different provinces in China, this paper chooses the three-stage DEA model to measure the regional innovation efficiency of each province in China. Based on the variation coefficient, Gini coefficient and Theil index, the paper analyzes the regional innovation ability of China and grasps the characteristics of regional innovation to guide China's future regional innovation planning and practice.

II. RESEARCH METHODS

A. Three-stage DEA Model

In order to overcome the shortcomings of the traditional DEA model without considering the influence of environmental factors and random noise on the efficiency evaluation of decision-making units, Fried et al. [11] proposed a new efficiency evaluation model The-Three-Stage DEA

model, taking the input-oriented DEA model as an example. The three-stage DEA will divide the efficiency evaluation of the decision-making unit into three stages:

1) The first stage: the traditional DEA model: The traditional DEA model was originally proposed by ACharnes, WW Cooper et al. of the University of Texas in 1978. The DEA method can be further divided into a CCR model based on the principle of fixed-scale compensation and a BCC model based on the principle of variable-scale compensation.

For any decision unit, the input-directed dual-form BCC model [12] can be expressed as:

$$\min_{\lambda,\ \theta} \theta$$

$$\text{S.t.} \quad \begin{aligned} &\sum_{i=1}^{n} x_i\lambda_i \le \theta x_0 \\ &\sum_{i=1}^{n} y_i\lambda_i \ge y_0 \\ &\sum_{i=1}^{n} \lambda_i = 1 \\ &\lambda_i \ge 0, i = 1,2,\cdots,n, \theta \in R \end{aligned} \tag{1}$$

Where i=1, 2..., n represents the decision unit, x and y are the input and output vectors, respectively.

2) The second stage: similar SFA model: Construct the following SFA regression function (take the input orientation as an example):

$$S_{ni} = f(Z_i;\beta_n) + v_{ni} + \mu_{ni}; i = 1,2,\cdots,I; n = 1,2,\cdots,N \tag{2}$$

Among them, S_{ni} is the relaxation value of the n-th input of the i-th decision-making unit; Z_i is the environmental variable, β_n is the coefficient of the environmental variable; $v_{ni}+\mu_{ni}$ is the mixed error term, where v_{ni} represents random interference and μ_{ni} represents management inefficiency.

The main purpose of SFA regression is to eliminate the effects of environmental factors and random noise in efficiency estimates, thereby adjusting all decision units to the same external environment.

The adjustment formula is as follows:

$$\begin{aligned} &X_{ni}^{A} = X_{ni} + [\max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)] + [\max(v_{ni}) - v_{ni}]; \\ &i = 1,2\cdots,I; n = 1,2,\cdots N \end{aligned} \tag{3}$$

Among them, X_{ni}^{A} is the adjusted input; X_{ni} is adjusted input; $[\max(f(Z_i;\hat{\beta}_n)) - f(Z_i;\hat{\beta}_n)]$ is to adjust the external environmental factors; $[\max(v_{ni}) - v_{ni}]$ is to put all decision-making units to the same level of luck.

3) The third stage: the adjusted DEA model

Substituting the adjusted input data and the original output data into the BCC model, and recalculating the efficiency values of each decision unit after removing environmental factors and random noise effects.

B. Analysis of Regional Innovation Efficiency Differences

This paper will use the indicators of Theil index, coefficient of variation and Gini coefficient to measure the overall difference of regional innovation, and reflect the evolution characteristics of regional innovation ability differences through the changes of three indicators.

The Theil index is calculated as:

$$I_a = \left(\sum_{i=1}^{n} \lg \overline{X_t} / X_{it}\right) / n \tag{4}$$

The coefficient of variation is calculated as:

$$CV = \sqrt{\sum_{i=1}^{n} (X_{it} - \overline{X_t})^2 / n} / \overline{X_t} \tag{5}$$

Where $\overline{X_t}$ is the average value of regional innovation efficiency of each evaluation unit at time t; X_{it} is the innovation efficiency value of the i-th region at time t; n represents the number of regions to be evaluated, and the larger the value of the Theil index and the coefficient of variation, the more the difference in innovation level of each unit region Large; the opposite is the smaller.

The Gini coefficient is calculated as:

$$G = 1 + \frac{1}{N} - \frac{2}{N^2\overline{y}}(y_1 + 2y_2 + ... + Ny_n) \tag{6}$$

Where N is the number of units to be evaluated, $\overline{y}$ representing the average value of regional innovation efficiency, and y1, y2, ..., yn are the innovation efficiency values of each unit area arranged in descending order. The value of the Gini coefficient is in the range of 0 to 1, and the closer the G value is to 1, the greater the difference in regional innovation level; the smaller the G value, the smaller the difference between the regions.

C. Indicator Selection and Data Source

According to the research of Tan et al. [13], combined with the evaluation reality of regional innovation efficiency in China, the following input-output variables for DEA model are selected.

The evaluation variables are composed of regional innovation input and regional innovation output. Among them, the innovation investment selects R&D personnel full-time equivalent and R&D expenditure internal expenditure respectively represents regional innovation capital investment and human input; innovation output adopts patent application authorization number and the technical market contract turnover which mainly depends on innovation to achieve. The selected variables are shown in Table I.

In addition, drawing on the research by Simar and Wilson [14], the environmental variables should satisfy the "separation hypothesis", that is, those factors that have an impact on the innovation efficiency of each province and city but are not subjectively controlled by the sample. Taking into account the development characteristics of various provinces and cities in China, this paper proposes environmental variables that affect

the innovation efficiency of each region from two aspects: macroeconomic environment and government policy support. Among them, macroeconomic environment variables select per capita GDP to reflect the economic development level of different provinces; government policy support selects government funds expenditure in R&D funds as indicators of regional innovation support for each province.

Due to the serious lack of data in Tibet, Hong Kong, Macao and Taiwan, this paper rejects them, with the remaining 30 provinces and cities in China as the research object. The research interval is from 2009 to 2016, and the sample data is from the 2010-2017 China Science and Technology Statistical Yearbook.

III. China's Regional Innovation Efficiency Measurement And Analysis

A. *Regional Innovation Efficiency Calculation Results Based on Three-stage DEA Model*

According to the regional innovation data of 30 provinces and cities from 2009 to 2016, the software DEAP2.1 was used to realize the measurement of regional innovation efficiency in the first and third stages of 2009-2016. Among them, the input value after the third stage adjustment comes from the regression result of the second stage; the second stage takes the slack variable as the dependent variable in the output result of the first stage, and the environmental variable as the independent variable, the second stage is realized by Frontier4.1 software. The empirical results are shown in Table II and Table III.

By comparing the results of the innovation efficiency of the first stage and the third stage, it can be found that except for the provinces of Beijing and Zhejiang, which are always at the frontier of efficiency, the innovation efficiency values of other provinces have changed. After eliminating environmental factors and random error interference, the innovation efficiency values of Tianjin, Jiangsu and Guangdong provinces increased slightly, while the innovation efficiency values of other provinces declined to varying degrees. Among them, the innovation efficiency values of Hainan, Guizhou, Gansu and Qinghai have dropped significantly, with the declines exceeding 60%. This result indicates that the regional innovation efficiency of most provinces and cities in China is overestimated by environmental and random factors. Therefore, the calculation of efficiency values based on the three-stage DEA model improves the accuracy of the results.

TABLE I. China's Regional Innovation Efficiency Evaluation Variables

Variable type	Variable parition	variable
Regional innovation input	Human input	R&D personnel full-time equivalent（human year）
	Capital input	Internal expenditure of R&D fund（Ten thousand yuan）
Regional innovation output	Non-economic output	Number of patent applications（Piece）
	Economic output	Technical market contract turnover（Ten thousand yuan）

TABLE II. Results Of The First Stage Of Regional Innovation Efficiency In China's 30 Provinces From 2009 To 2016

Area	2009	2010	2011	2012	2013	2014	2015	2016	Mean
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.548	0.524	0.482	0.481	0.518	0.537	0.583	0.626	0.537
Hebei	0.305	0.333	0.300	0.307	0.326	0.365	0.444	0.477	0.357
Shanxi	0.277	0.305	0.271	0.283	0.328	0.351	0.403	0.419	0.330
Inner Mongolia	0.263	0.319	0.223	0.485	0.237	0.210	0.234	0.243	0.277
Liaoning	0.505	0.512	0.534	0.516	0.440	0.427	0.546	0.537	0.502
Jilin	0.298	0.342	0.359	0.280	0.299	0.304	0.299	0.463	0.331
Heilongjiang	0.420	0.411	0.609	0.757	0.673	0.665	0.619	0.695	0.606
Shanghai	0.960	0.944	0.772	0.694	0.611	0.660	0.656	0.635	0.742
Jiangsu	0.759	0.900	1.000	1.000	0.838	0.752	0.773	0.705	0.841
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Anhui	0.414	0.535	0.798	0.675	0.677	0.712	0.722	0.769	0.663
Fujian	0.467	0.522	0.494	0.480	0.513	0.531	0.761	0.845	0.577
Jiangxi	0.238	0.318	0.392	0.383	0.399	0.608	0.839	1.000	0.522
Shandong	0.518	0.559	0.452	0.450	0.451	0.483	0.537	0.523	0.497
Henan	0.374	0.376	0.377	0.363	0.361	0.420	0.478	0.511	0.408
Hubei	0.412	0.417	0.414	0.417	0.546	0.592	0.636	0.655	0.511
Hunan	0.383	0.409	0.369	0.360	0.396	0.474	0.483	0.469	0.418
Guangdong	0.727	0.729	0.643	0.563	0.582	0.661	0.778	0.822	0.688
Guangxi	0.286	0.265	0.265	0.233	0.308	0.434	0.553	0.667	0.376
Hainan	0.552	0.617	0.456	0.308	0.436	0.455	0.529	0.466	0.477
Chongqing	0.660	0.835	0.766	0.692	0.804	0.837	1.000	1.000	0.824
Sichuan	0.596	0.786	0.612	0.675	0.708	0.760	0.926	0.816	0.735
Guizhou	0.399	0.532	0.558	0.617	0.784	0.958	1.000	0.748	0.700
Yunnan	0.492	0.460	0.411	0.549	0.506	0.606	0.515	0.526	0.508
shaanxi	0.317	0.393	0.551	0.607	0.750	0.803	0.814	1.000	0.654
Gansu	0.594	0.627	0.650	0.654	0.769	0.747	0.621	0.700	0.670
Qinghai	0.735	0.606	0.724	0.673	0.812	0.822	1.000	1.000	0.797
Ningxia	0.446	0.421	0.278	0.227	0.249	0.318	0.329	0.498	0.346
Xinjiang	0.427	0.466	0.403	0.367	0.489	0.601	0.802	0.702	0.532

From the perspective of regional innovation efficiency trends in various provinces from 2009 to 2016, except for the fluctuations in a few provinces, the value of regional innovation efficiency in most provinces is increasing year by year, and the difference between different provinces is gradually decreasing, indicating that in recent years China's regional innovation capability has been continuously improved. Overall, China's regional innovation has shown a good development trend.

TABLE III. RESULTS OF THE THIRD STAGE OF REGIONAL INNOVATION EFFICIENCY IN CHINA'S 30 PROVINCES FROM 2009 TO 2016

Area	2009	2010	2011	2012	2013	2014	2015	2016	Mean
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	0.433	0.523	0.506	0.513	0.564	0.569	0.627	0.709	0.556
Hebei	0.293	0.327	0.226	0.224	0.253	0.300	0.388	0.394	0.301
Shanxi	0.228	0.222	0.161	0.161	0.202	0.225	0.278	0.226	0.213
Inner Mongolia	0.198	0.242	0.158	0.322	0.161	0.162	0.193	0.178	0.202
Liaoning	0.479	0.507	0.481	0.435	0.384	0.383	0.492	0.433	0.449
Jilin	0.248	0.233	0.199	0.155	0.158	0.187	0.229	0.263	0.209
Heilongjiang	0.365	0.312	0.377	0.444	0.387	0.368	0.448	0.379	0.385
Shanghai	0.867	0.945	0.782	0.690	0.615	0.661	0.659	0.691	0.739
Jiangsu	0.782	0.901	1.000	1.000	0.859	0.768	0.782	0.774	0.858
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Anhui	0.394	0.523	0.579	0.506	0.543	0.602	0.644	0.651	0.555
Fujian	0.425	0.481	0.412	0.398	0.435	0.469	0.720	0.795	0.517
Jiangxi	0.218	0.280	0.211	0.197	0.232	0.382	0.611	0.658	0.349
Shandong	0.523	0.558	0.439	0.427	0.439	0.473	0.528	0.570	0.495
Henan	0.347	0.329	0.294	0.278	0.263	0.334	0.431	0.441	0.340
Hubei	0.389	0.409	0.344	0.340	0.432	0.482	0.583	0.583	0.445
Hunan	0.364	0.402	0.280	0.278	0.317	0.395	0.429	0.412	0.360
Guangdong	0.749	0.731	0.650	0.568	0.594	0.664	0.779	0.888	0.703
Guangxi	0.206	0.205	0.131	0.117	0.168	0.260	0.374	0.347	0.226
Hainan	0.158	0.252	0.066	0.041	0.059	0.088	0.131	0.082	0.110
Chongqing	0.542	0.768	0.545	0.433	0.547	0.629	0.826	0.815	0.638
Sichuan	0.637	0.774	0.490	0.494	0.546	0.622	0.803	0.697	0.633
Guizhou	0.339	0.385	0.175	0.157	0.213	0.348	0.519	0.293	0.304
Yunnan	0.341	0.337	0.168	0.187	0.196	0.271	0.328	0.273	0.263
shaanxi	0.329	0.370	0.415	0.448	0.528	0.573	0.674	0.796	0.517
Gansu	0.380	0.303	0.203	0.201	0.208	0.236	0.311	0.259	0.263
Qinghai	0.197	0.223	0.104	0.068	0.069	0.080	0.160	0.103	0.126
Ningxia	0.168	0.272	0.056	0.036	0.051	0.080	0.117	0.114	0.112
Xinjiang	0.250	0.331	0.141	0.109	0.169	0.236	0.399	0.236	0.234

According to Fig. 1, the results of regional innovation efficiency means in China, it can be seen that there are significant regional differences in the regional innovation efficiency values of various provinces in China. Among them, Zhejiang Province and Beijing have the highest efficiency value 1 among the 30 provinces and cities in the country. The final rankings are Ningxia, Qinghai and Hainan, and the regional innovation efficiency values are all below 0.2. From the comparison of the mean values, we can find that the regional innovation efficiency is different in China, and the regional development is inconsistent. At the same time, the average efficiency of innovation in most provinces and cities in the central and western regions still falls in the middle and low range, it shows that there is still room for improvement in the regional innovation capability of most provinces in China.

B. Analysis of the Differences in Regional Innovation Efficiency in China

In order to further understand the difference of regional innovation capability in China, based on the regional innovation efficiency value obtained above, the coefficient of variation, Gini coefficient and Theil index value of regional innovation in China from 2009 to 2016 are calculated according to the formula. The results are shown in Table IV.

Fig. 2, shows the time series of the three coefficients of coefficient of variation, Gini coefficient and Theil index. First of all, the Gini coefficient and coefficient of variation of regional innovation in China are at a relatively high level, further verifying the regional innovation efficiency in China. There are significant regional differences. Secondly, the variation of Gini coefficient and coefficient of variation can be roughly divided into three stages: the rising trend in 2009-2011, indicating that the difference in regional innovation capability in China is expanding at this stage; the steady trend in 2011-2013 indicates that regional innovation differences are relatively stable; the gradual downward trend in 2013-2016 indicates that the overall difference in regional innovation in China has been gradually narrowing in recent years. The value of the Theil index also showed similar fluctuations and gradually stabilized in recent years, which also confirmed the above conclusions.

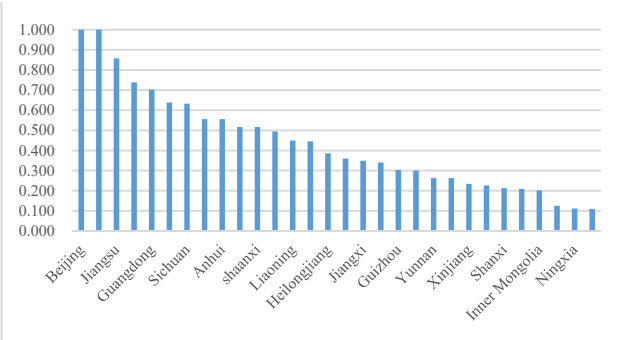

Fig. 1. Comparison of regional innovation efficiency means in 30 provinces in China.

TABLE IV. CHINA REGIONAL INNOVATION COEFFICIENT OF VARIATION, GINI COEFFICIENT, THEIL INDEX VALUE FROM 2009 TO 2016

	2009	2010	2011	2012	2013	2014	2015	2016
Gini coefficient	0.862	0.821	0.905	0.916	0.901	0.864	0.776	0.796
Coefficient of variation	0.557	0.531	0.715	0.723	0.666	0.570	0.475	0.546
Theil index	0.058	0.053	0.114	0.128	0.108	0.082	0.060	0.083

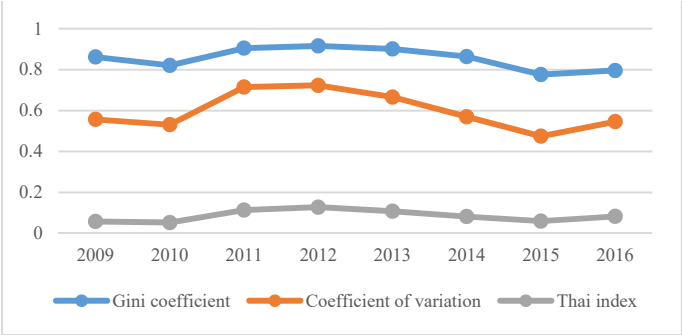

Fig. 2. China's regional innovation coefficient of variation, Gini coefficient, Theil index time value.

IV. Conclusion

Based on the panel data of 30 provinces and cities in China from 2009 to 2016, this paper uses the three-stage DEA model to measure the regional innovation efficiency of each subject. The results show that: (1) Compare DEA calculating the results of the first and third stages, the innovation efficiency values of most provinces in China have declined, indicating that the regional innovation efficiency of these provinces is overestimated by environmental factors and random factors, so the three-stage DEA model improves the accuracy of the calculation; (2) Except for Beijing and Zhejiang, which are at the forefront of efficiency, there is still room for improvement in the regional innovation capacity of most provinces in China. Most of the central and western provinces are in the low-value areas of innovation efficiency, while the eastern provinces are mostly in areas with high innovation efficiency. That is to say the regional differences in innovation are significant; (3) The calculation results of Gini coefficient, coefficient of variation and Theil index further verify that there is a significant overall difference in regional innovation efficiency in China, but the trend change of the three variables indicates that the regional innovation efficiency difference in China has fluctuated downward in recent years. The findings are consistent with previous work, such as Yu and Liu [15] and Zhao ea al. [16], these scholars have also verified the changes and differences of regional innovation efficiency in China. In contrast, this paper uses the three-stage DEA model to more clearly compare the efficiency changes before and after eliminating the influence of environmental factors and random noise. In addition, the elaboration based on the three coefficients also shows the changes of regional innovation differences more intuitively.

Based on the above research conclusions, combined with the status quo of regional innovation in China, the following suggestions are proposed: (1) Most of the provinces in the central and eastern regions are still in low-innovation efficiency areas. Compared with the eastern regions, the corresponding provinces have lower regional innovation input and conversion capacity. For these provinces, it is necessary to focus on adjusting the state of resource allocation, further promoting the inter-regional flow of factors to achieve the balance and rationalization of innovation investment, and at the same time, increase government support and strengthen the transformation of innovation results; (2) China's regional innovation capability shows significant regional differences. In the future process of regional integration development, China should build regional innovation alliances with Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta as templates. Based on this, we will further break the institutional barriers and geographical barriers that restrict the allocation of innovation resources, change the isolated pattern of regional innovation and development, and achieve coordinated development of regional innovation.

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