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A Comparative Study on the Efficiency of R&D Activities of Universities in China by Region Using DEA–Malmquist

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Abstract: This paper analyzes the efficiency of the input and output of R&D activity and the status of its development and management in universities in each region of China and proposes suggestions for improvement. The DEA–Malmquist model was used to analyze the static and dynamic science and technology statistics for universities in each region during 2006–2019 to reveal changes in the input and output of R&D activity. The overall efficiency of the R&D activity of universities in all regions of China was low. Among the 27 regions studied, DEA revealed effective efficiency in 20 regions in 2006, accounting for 74.07%, and in 19 regions in 2019, accounting for 70.37%. The Malmquist index was greater than 1 in 17 regions in 2006–2019, with an average value of 1.023 during 2006–2019. The technological progress of R&D activity in universities in each region plays a major role in the improvement of the overall efficiency. Conclusions: The efficiency of the R&D activity of Chinese universities in all regions is low in general, with large disparities between regions. The R&D activity of Chinese universities lacks scientific management. It is necessary to optimize the allocation of research resources, construct an evaluation system for the efficiency of R&D activity, and offer incentives for research to improve the output and promote the transformation of results in Chinese universities.

Keywords: R&D activity efficiency; DEA; data envelopment analysis; Malmquist index

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1. Introduction

Colleges and universities are the main sites of scientific and technological innovation nationally. In terms of the types of R&D (research and development) activity, funds for it in universities are divided into three categories: basic research, applied research and experimental development. Research and development, including both scientific research and experimental development in the fields of science and technology aims to increase the total amount of knowledge and the use of this knowledge to create new applications for systematic and creative activities. Research and development activity in colleges and universities has always been an important theoretical and practical issue among science and technology administrators. On the issue of improving the efficiency of R&D activity in colleges and universities, the huge investment of R&D funds in colleges and universities has brought about many scientific research achievements. However, the scientific, rational, and efficient allocation and operation of limited R&D resources remains one of the problems to be solved in China's universities. At the same time, the efficiency of R&D achievements in colleges and universities needs to be measured and evaluated. In this way, the management department can improve them more pertinently to achieve the goal of sustainable development. Thus, measurement of the efficiency of R&D activity in colleges and universities has become a concern for scholars.

There are different methods for evaluating the efficiency of R&D activity. Data envelopment analysis (DEA) is a new field of interdisciplinary research in operations research, management science and mathematical economics. It is a quantitative analysis method to evaluate the relative effectiveness of comparable units of the same type that uses linear programming based on several input and output indicators. The data envelopment analysis method is widely used because it is more objective than other efficiency evaluation methods and has advantages in measuring the relative efficiency of decision-making units (DMU) with multiple inputs and outputs. To overcome the shortcomings of the current static and dynamic analyses of the efficiency of R&D activity, this paper combines the DEA method and the Malmquist productivity index to portray the changing patterns of the efficiency of the R&D activity of universities in each region of China.

In view of this, this paper studies the efficiency of the R&D inputs and outputs of universities in each region (provinces, autonomous regions and municipalities directly under the central government) in China during 2006–2019, analyzes the patterns of changes in the efficiency of R&D activities in each region, and explores the factors that cause these changes, to provide a reference for measuring and promoting R&D activity in Chinese universities.

The remainder of this paper is structured as follows. Section 2 reviews previous literature related to the research topic and research methods. Section 3 proposes evaluation indicators and models and uses the models to assess the efficiency of universities in each region of China. The presentation and interpretation of applying the DEA-based Malmquist model to the data is illustrated in Section 4. Concluding statements are presented in Section 5.

2. Literature Review

The DEA model is an input–output analysis method based on relative efficiency, proposed by Charnes et al. in 1978 [1]. It is widely used in efficiency assessments because of its advantages in terms of not requiring a priori weights to be assigned to inputs and outputs and for its ability to measure the relative efficiency of decision units with multiple inputs and outputs.

To overcome the problems in the traditional DEA model, many scholars have improved it. For example, to enable further comparative analysis of efficient units, Andersen et al. proposed the super-efficiency DEA model (super-efficiency DEA) [2], which enables the comparison of efficiency between efficient decision units. To address the problem whereby traditional DEA models ignore slack adjustment and cannot further distinguish effective decision units, Tone constructed a non-radial slack measure model (SBM) [3], which incorporates all slack measures into the objective function through a scalar approach. The DEA has been widely used in the field of university performance evaluation. Athanassopoulos and Shale used the DEA method to measure the overall efficiency of 45 colleges and universities in the UK and verified the rationality of the method for evaluating the efficiency of college operations [4]. McMillan and Datta used the DEA method to assess the relative efficiency of 45 Canadian colleges and universities and found that the majority had high efficiency scores; they argued that the method provides a new way to understand the efficiency of Canadian colleges and universities [5]. Abbott and Doucouliagos used a DEA model based on a system of different input–output indicators and found that Australian universities have relatively high operational efficiency [6]. Johnes used the DEA method to analyze and evaluate the efficiency of educational resource allocation in more than 100 higher education institutions in the UK and found that the majority of institutions have high technical efficiency and scale efficiency [7]. Agasisti conducted a cross-country comparative study of the efficiency of resource allocation in higher education systems in European countries using the DEA methodology and found that the influence of the public sector has a key role in resource allocation efficiency [8]. Subsequently, many scholars have evaluated and analyzed the scientific research activities of colleges and universities from different perspectives, considering various influencing factors. Nigsch and Schenker provided an overview of the strengths and limitations of the DEA approach for higher education performance evaluation over the past 20 years [9]. Yang et al. developed a network directional distance framework based on a two-stage network DEA model to measure the inefficiencies of Chinese research universities. The empirical results showed that the average efficiencies of the 64 sampled universities increased within the examined period of 2010–2013. The productivity gains were primarily driven by improvements in efficiency. In other words, the efficiency increased on average over the examined period [10]. Based on the triple helix theory, Wang established three groups of DEA models—personnel funds versus projects, projects versus achievements and personnel funds versus achievements—and evaluated the performance of social science research in 46 universities in Jiangsu Province [11]. Duan used the super-efficiency DEA method to establish an evaluation index system for the scientific research performance of colleges and universities from the two dimensions of the scientific and technological investment of colleges and universities and the output of the scientific and technological achievements of colleges and universities, and conducted empirical research and analysis on the scientific research performance of Chinese colleges and universities [12]. The DEA is frequently used to measure the efficiency of universities, however, it can also be applied to different industries, such as ICT [13], banking [14,15], hospitals [16–18], supplier selection [19–21], energy [22–24], regional innovation evaluation [25–27] and port performance [28–31], and has many other applications [32–37].

The Swedish economist and statistician Sten Malmquist proposed the Malmquist index to analyze changes in consumption over time. On this basis, the Malmquist total factor productivity index (abbreviated as Malmquist TFP index) was first proposed by Caves, Christensen and Diewert in 1982 [38]. They used the Malmquist input or output function to define the TFP index, but it did not receive much attention at the time. It was not until 1994, when Färe et al. proposed the Malmquist productivity index using a nonparametric linear programming algorithm to examine total factor productivity growth, that the Malmquist TFP index was widely used in various fields, such as finance, public administration and research management [39]. The results of the Malmquist productivity index evaluation mainly focus on three dimensions: productivity change, efficiency change and technological change analysis. Meng et al. evaluated the efficiency of basic research in China and found that funding input was the main reason for the growth in output, while the efficiency of scientific research increased significantly from 1991 to 1996, and then gradually slowed down [40]. Hung et al. decomposed the growth rate of research papers into four components. Through the empirical study of 27 countries, they showed that the factors affecting the growth rate of output varied greatly among different countries; researchers have a greater impact on the quality of output and research funding has a greater role in the impact of citations [41]. Worthington and Lee used the Malmquist index methodology to analyze the productivity growth of 35 Australian universities over the period 1998–2003. The analysis included five inputs of full-time equivalent academic and non-academic personnel, non-labor expenditure and the number of undergraduate and postgraduate students, while the six outputs were undergraduate, postgraduate and doctoral graduates, national competitiveness and industry funding and publications [42]. Fernandez-Santos et al. used the Malmquist production index method to study the efficiency of teaching and research in Spanish public universities [43]. Wang used the Malmquist productivity index model to examine the technical efficiency, technological change and productivity performance of eight New Zealand universities over the period 2013–2018, and the results showed that the average catch-up efficiency and frontier shift efficiency of the universities were roughly in a "no change" scenario, meaning that these universities have not made any progress over the years [44]. Xue applied the three-stage data envelopment analysis (DEA) and Malmquist index method to evaluate the static and dynamic efficiency of the research output and input data of universities directly under the Ministry of Education in China from 2010 to 2017 [45]. Zhou used the DEA–Malmquist index model and constructed an evaluation index system to analyze the input–output efficiency of China's educational science and technology development from three aspects: comprehensive efficiency, pure technical efficiency and scale efficiency [46]. The Malmquist index method is also used in other areas. Chen and

Ali adopted the Malmquist productivity index to measure changes in productivity over time and used the method to empirically study Fortune Global 500 computer and office equipment companies from 1991 to 1997 [47]. Wu et al. applied data envelopment analysis (DEA) and the Malmquist index to study the energy efficiency of 30 provinces in China. The results showed that, from 2006 to 2009, the average industrial energy efficiency in the eastern region was the best, followed by the central region [48]. Wang et al. proposed a mixed data envelopment analysis (DEA) model, which combined the DEA–Malmquist method with epsilon-based measurement (EBM), to solve the performance evaluation problem of harbor terminal operators [49]. Firsova and Chernyshova adopted the Malmquist productivity index to evaluate the dynamics of regional innovation development and compare the Russian regions according to their innovation efficiency, used resources and achieved results [50]. Liu and Bai used the DEA–Malmquist index method and DEA–Tobit stochastic response model to evaluate the inter-provincial differences in regional innovation efficiency in China in terms of four aspects—technical efficiency, efficiency index changes, returns to scale and predictive analysis—to explore the impact of government funding on regional innovation efficiency [51]. Because the Malmquist index can better analyze panel data, it can better reflect the dynamic change status of relative efficiency and better measure the dynamic continuous change characteristics, to effectively analyze the reasons for efficiency changes. Therefore, this paper adopts the DEA–Malmquist index method to evaluate the efficiency of the R&D activity of universities, analyzes their input–output efficiency and further decomposes the technical change index in the measurement results to explore the management information implied by it.

3. Evaluation Index System and Evaluation Analysis Model

3.1. Evaluation Index System

Based on science and technology statistics and related economic and social statistics, the indicators for measuring the allocation of scientific and technological resources and their output in universities are divided into two categories, input indicators and output indicators, which mainly included the two aspects of scientific research input and innovation output. In the existing literature on the efficiency of R&D activities in universities, inputs usually refer to indicators such as research and development personnel and funds, and outputs usually refer to research results, such as academic papers, income from patent applications and patent sales. Therefore, this paper constructs an index system for evaluating the efficiency of R&D activity in universities, dividing input into scientific and technological manpower and research funds. The manpower input index includes the number of teaching and research personnel, the number of associate professors and professors, the direct R&D personnel input, the personnel for the application of R&D results (R&D indirect personnel input). The financial input index mainly refers to R&D fund expenditure and R&D results application fund expenditure. The innovation output includes the number of papers published, the number of scientific and technical monographs published, the number of patent applications, the number of patents granted, the income from the sale of patents and the income from technology transfer (as shown in Table 1).

In this paper, the above six input variables and six output indicators were incorporated into the R&D activity efficiency analysis model to analyze the characteristics of R&D resource allocation patterns and output efficiency of universities in each region of China. The data for the statistical analysis were obtained from the compilation of the science and technology statistics of Chinese higher education institutions published in each year from 2006 to 2019, and the data did not include Hong Kong, Macao and Taiwan. The data for four regions—Tibet, Hainan, Ningxia and Qinghai—were omitted because of missing data in some years.

Table 1. R&D innovation efficiency input–output indicators of Chinese universities.

Indicator Categories	Indicators	Indicator Units
Input Indicators	No. of teaching and research staff	
	No. of associate professors and professors	
	Amount of R&D expenditure	CNY
	No. of R&D direct personnel input	
	No. of R&D results application expenditure funds	CNY
	No. of R&D results application personnel input	
Output Indicators	No. of papers published	
	No. of patent applications	
	No. of scientific and technical monographs published	Volume
	Amount of revenue from patent sales	CNY
	No. of patents granted	CNY
	Amount of technology transfer income	CNY

3.2. Data Envelopment Analysis (DEA)

The DEA model treats each evaluated unit as a decision-making unit (DMU), which is, to some extent, a convention, and consists of all decision units forming the evaluation group. Each decision unit under the same group DMU has the same input indicators and output indicators. The DEA base model includes the CCR model (denoting the three authors, A. Charnes, W. W. Cooper E. Rhodes) and the BCC model (denoting the authors, Bankerl, Chames and Cooper), in which the CCR model considers constant returns to scale and its technical efficiency contains a scale efficiency component, while the BCC model considers variable returns to scale and its technical efficiency refers to pure technical efficiency. Then R&D activities in universities have significant knowledge economy characteristics, which can perturb the diminishing marginal returns of traditional factors of production and cause uncertainty in the returns of scientific and technological activities or technology transfer. Therefore, in this paper, the BCC model (variable payoff of scale) is chosen to evaluate the efficiency of R&D activities in China's universities, and, for any decision unit, the model can be expressed as follows.

$$
\begin{gathered}
min\theta - \varepsilon\left(\hat{e}^T S^- + e^T S^+\right) \\
\text{s.t.} \begin{cases} \sum_{j=1}^{n} X_j\lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j\lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, S^-, S^+ \geq 0 \end{cases}
\end{gathered} \tag{1}
$$

where, $j = 1,\ 2, \cdots, n$ represents the decision-making unit, and X and Y are the input and output vectors, respectively; if $\theta = 1$, $S^+ = S^- = 0$, the DEA of the decision-making unit is efficient; if $\theta = 1, S^+ \neq 0$, or $S^- \neq 0$, the DEA of the decision-making unit is slightly efficient; if $\theta < 1$, the DEA of the decision-making unit is inefficient.

3.3. Malmquist Index Model

Both the CCR model and the BCC model are evaluations of static data, which means that efficiency can only be evaluated for multiple subjects in one period or multiple periods for one subject. The Malmquist model, on the other hand, allows for dynamic evaluation, and it can perform efficiency measurements over multiple subjects and periods. The Malmquist productivity index, used to measure productivity, is a measure of the dynamic trend of total factor productivity (tfpch) in a sector from moment t to moment $t + 1$ using a nonparametric distance function, i.e., the ratio of the distance functions before and after the two periods, and the index is expressed in the form of

$$
M_t = \frac{D^t\left(X^{t+1}, Y^{t+1}\right)}{D^t\left(X^t, Y^t\right)} \tag{2}
$$

$$M_{t+1} = \frac{D^{t+1}\left(X^{t+1}, Y^{t+1}\right)}{D^{t+1}\left(X^{t}, Y^{t}\right)} \tag{3}$$

$$M_{t,t+1} = \sqrt{\frac{D^{t}\left(X^{t+1}, Y^{t+1}\right)}{D^{t}\left(X^{t}, Y^{t}\right)} \times \frac{D^{t+1}\left(X^{t+1}, Y^{t+1}\right)}{D^{t+1}\left(X^{t}, Y^{t}\right)}} \tag{4}$$

According to Färe et al. [31], the Malmquist index can be decomposed into an index of technical efficiency change (effch) and an index of technical progress (techch) through an equivalence transformation. Furthermore, the technical efficiency change index (effch) can be decomposed into pure efficiency change (pech) and scale efficiency change (sech).

$$\begin{aligned} M_{t,t+1} &= \frac{D^{t+1}\left(X^{t+1},Y^{t+1}\right)}{D^{t}\left(X^{t},Y^{t}\right)} \times \sqrt{\frac{D^{t}\left(X^{t+1},Y^{t+1}\right)}{D^{t+1}\left(X^{t+1},Y^{t+1}\right)} \times \frac{D^{t}\left(X^{t},Y^{t}\right)}{D^{t+1}\left(X^{t},Y^{t}\right)}} \\ &= \frac{D^{t+1}\left(X^{t+1},Y^{t+1}\right)_{CRS}}{D^{t}\left(X^{t},Y^{t}\right)_{VRS}} \times \frac{\frac{D^{t+1}\left(X^{t+1},Y^{t+1}\right)_{CRS}}{D^{t+1}\left(X^{t+1},Y^{t+1}\right)_{VRS}}}{\frac{D^{t}\left(X^{t},Y^{t}\right)_{CRS}}{D^{t}\left(X^{t},Y^{t}\right)_{VRS}}} \times \sqrt{\frac{D^{t}\left(X^{t+1},Y^{t+1}\right)}{D^{t+1}\left(X^{t+1},Y^{t+1}\right)} \times \frac{D^{t}\left(X^{t},Y^{t}\right)}{D^{t+1}\left(X^{t},Y^{t}\right)}} \\ &= \frac{D^{t+1}\left(X^{t+1},Y^{t+1}\right)_{VRS}}{D^{t}\left(X^{t},Y^{t}\right)_{VRS}} \times \frac{SE^{t+1}\left(X^{t+1},Y^{t+1}\right)}{SE^{t}\left(X^{t},Y^{t}\right)} \times \sqrt{\frac{D^{t}\left(X^{t+1},Y^{t+1}\right)}{D^{t+1}\left(X^{t+1},Y^{t+1}\right)} \times \frac{D^{t}\left(X^{t},Y^{t}\right)}{D^{t+1}\left(X^{t},Y^{t}\right)}} \end{aligned} \tag{5}$$

The three factors on the right-hand side of the equation represent the change in pure technical efficiency, scale efficiency and technical progress efficiency, respectively. Thus,

$$M = effch \cdot techch \tag{6}$$

$$= pech \cdot sech \cdot techch \tag{7}$$

If $M > 1$, this means that the level of total factor productivity has increased from period t to period $t + 1$.

If $M = 1$, this means that there is no change in the total factor productivity level from period t to period $t + 1$.

If $M < 1$, this means that the total factor productivity level has decreased from period t to period $t + 1$.

4. Empirical Study

4.1. Static Analysis of DEA Model

Using DEAP2.1 software to calculate and organize the annual data of R&D activities corresponding to each index of the universities in each region of China, the overall technical efficiency of the R&D input–output status of the universities in each region and its decomposition results were obtained (see Table 2). The technical efficiency consists of two parts, namely pure technical efficiency and scale efficiency, and technical efficiency = pure technical efficiency × scale efficiency, where "irs" indicates that the decision unit is in the increasing scale payoff stage; "drs" indicates that the decision unit is in the decreasing scale payoff stage; and "-" indicates that the decision unit is in the constant scale payoff stage; crste = technical efficiency from constant returns to scale DEA(CRS DEA); vrste = technical efficiency from variable returns to scale (VRS DEA); scale = scale efficiency = crste/vrste.

Table 2. Efficiency values of R&D activities of universities in 27 regions of China in 2006 and 2019.

Region	2006				2019			
	Crste	Vrste	Scale		Crste	Vrste	Scale	
Beijing	1	1	1	-	1	1	1	-
Tianjin	1	1	1	-	1	1	1	-
Hebei	0.958	0.963	0.995	irs	0.863	1	0.863	drs
Shanxi	0.927	0.996	0.93	irs	1	1	1	-

Table 2. *Cont.*

Region	2006				2019			
	Crste	Vrste	Scale		Crste	Vrste	Scale	
Inner Mongolia	1	1	1	-	1	1	1	-
Liaoning	0.732	0.737	0.994	irs	0.901	0.91	0.99	drs
Jilin	0.877	0.89	0.986	irs	1	1	1	-
Heilongjiang	0.717	0.719	0.996	irs	0.869	0.878	0.99	irs
Shanghai	1	1	1	-	1	1	1	-
Jiangsu	1	1	1	-	1	1	1	-
Zhejiang	1	1	1	-	1	1	1	-
Anhui	1	1	1	-	1	1	1	-
Fujian	0.78	0.886	0.881	irs	0.866	0.877	0.987	irs
Jiangxi	1	1	1	-	0.877	0.904	0.97	irs
Shandong	1	1	1	-	0.973	1	0.973	drs
Henan	1	1	1	-	1	1	1	-
Hubei	1	1	1	-	0.946	0.966	0.979	drs
Hunan	0.927	0.931	0.995	drs	1	1	1	-
Guangdong	1	1	1	-	1	1	1	-
Guangxi	1	1	1	-	0.986	0.996	0.99	drs
Chongqing	1	1	1	-	1	1	1	-
Sichuan	1	1	1	-	1	1	1	-
Guizhou	1	1	1	-	1	1	1	-
Yunnan	1	1	1	-	1	1	1	-
Shaanxi	1	1	1	-	1	1	1	-
Gansu	1	1	1	-	1	1	1	-
Xinjiang	1	1	1	-	1	1	1	-
Mean	0.96	0.967	0.992		0.973	0.983	0.99	

(1) The comprehensive technical efficiency index (crste) obtained by DEA showed that R&D in 2006 and 2019, with values of 0.96 and 0.973, respectively, while having an overall increasing trend, revealed efficiency was still not very high. From the regional perspective, there were still some disparities in the R&D innovation efficiency of universities in different regions, among which the comprehensive efficiency of Shanxi, Liaoning, Jilin, Heilongjiang, Fujian, and Hunan increased, and the comprehensive efficiency of Hebei, Jiangxi, Shandong, Hubei, and Guangxi decreased. The regions with combined efficiency values of less than 1 in both 2006 and 2019 were Hebei, Liaoning, Heilongjiang and Fujian, accounting for 14.81%. Twenty regions reached the production frontier surface in 2006, accounting for 74.07%, and nineteen regions reached the production frontier surface in 2019, accounting for 70.37%. Beijing, Tianjin, Inner Mongolia, Shanghai, Jiangsu, Zhejiang, Anhui, Henan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, and Xinjiang were DEA effective in both study periods, accounting for 55.56%, indicating that the innovation efficiency of the universities in these regions achieves optimal allocation, a reasonable investment structure and optimal inputs and outputs under different combinations.

(2) The pure technical efficiency (vrste) of R&D activities in colleges and universities shows an increasing trend. In 2019, the pure technical efficiency of R&D activities in colleges and universities across the country was 0.983, which indicated a 0.017 difference from the production frontier, reflecting that there is room for improvement at the management level. The scale efficiency of R&D activities in colleges and universities was greater than the pure technical efficiency, indicating that the management and technical level were the main factors restricting the efficiency of scientific and technological innovation in Chinese colleges and universities. The number of purely technically efficient provinces was 20 and 21 in 2006 and 2019, respectively, and the number of scale-efficient provinces was 20 and 19, respectively, while the number of purely technically efficient regions was more than the number of scale-efficient

regions, indicating that these regions were more advanced in terms of management and technology, etc., and the established inputs maximize output. The pure technical efficiency values of Hebei, Liaoning, Jilin, Heilongjiang, Fujian, and Hunan were low, at 0.963, 0.737, 0.89, 0.719, 0.886 and 0.931, respectively, in 2006, accounting for 22.22%, except for Hebei and Hunan, whose values were much lower than the national average of 0.967 in the same year. There is a need to further improve the management and technical level of university science and technology innovation in these regions. The pure technical efficiency of Liaoning, Heilongjiang, Fujian, Jiangxi, and Hubei in 2019 was lower than the national average of 0.983 in the same year, accounting for 18.52%. Among them, Hebei, Liaoning, Heilongjiang, and Fujian had lower pure technical efficiency than the national average in the same year in both study periods, accounting for 14.81%.

(3) The scale efficiency of the R&D activities of universities can reflect whether the supply of science and technology innovation infrastructure of universities in each region is at the optimal scale. From Table 2, it can be concluded that the scale efficiency declined from 0.992 in 2006 to 0.99 in 2019, and the number of scale-optimal regions lowered from 20 to 19. Regions with increasing returns to scale should reasonably increase their investments in university infrastructure, while regions with decreasing returns to scale have obvious efficiency loss problems because the funds are not effectively used, and special attention should be paid to improving the efficiency of the use of funds. In 2006 and 2019, the scale efficiency reached the production frontier surface in 20 and 19 regions, accounting for 74.07% and 70.37%, respectively. The scale efficiency did not reach the production frontier surface in seven regions (Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Fujian, and Hunan) and eight regions (Hebei, Liaoning, Heilongjiang, Fujian, Jiangxi, Shandong, Hubei and Guangxi), respectively, accounting for 25.93% and 29.63%. Among them, Hebei, Liaoning, Heilongjiang, and Fujian did not reach the front line of efficiency in both study periods, accounting for 14.81%.

4.2. Dynamic Analysis of the Malmquist Index

The Malmquist index can dynamically reflect the trend of the R&D innovation efficiency of universities in each region. Therefore, the DEAP2.1 software was used to analyze the R&D input and output data of 27 regions in China from 2006 to 2019, and then examine the dynamic changes and heterogeneity of total factor productivity; the results of the analysis are shown in Tables 3–5 (effch: efficiency change, techch: technology change, pech: pure efficiency change, sech: scale efficiency change, tfpch: total factor productivity change).

Table 3. Malmquist index summary of annual means.

Year	Effch	Techch	Pech	Sech	Tfpch
2	1.007	0.992	1.016	0.991	0.999
3	1.013	1.056	1.002	1.011	1.069
4	1.002	1.153	0.997	1.005	1.155
5	1	1.1	1.016	0.984	1.1
6	1.006	0.862	0.998	1.008	0.867
7	0.995	1.109	0.995	1	1.103
8	0.993	1.045	0.994	0.999	1.037
9	1.001	1.055	1.003	0.998	1.056
10	1.012	1.128	1.013	0.999	1.142
11	1.013	1.008	1	1.014	1.021
12	0.976	1.058	0.992	0.984	1.032
13	1.009	0.905	1	1.009	0.914
14	0.991	0.868	0.993	0.999	0.861
Mean	1.001	1.022	1.001	1	1.023
>1	8	9	5	5	9
>Mean	6	8	4	5	8

Table 4. Malmquist index summary of region means.

Region	Effch	Techch	Pech	Sech	Tfpch
Beijing	1	1.031	1	1	1.031
Tianjin	1	1.045	1	1	1.045
Hebei	0.992	1.004	1.003	0.989	0.996
Shanxi	1.006	0.958	1	1.006	0.963
Inner Mongolia	1	0.985	1	1	0.985
Liaoning	1.016	1.007	1.016	1	1.023
Jilin	1.01	1.039	1.009	1.001	1.049
Heilongjiang	1.015	1.038	1.015	0.999	1.054
Shanghai	1	1.03	1	1	1.03
Jiangsu	1	1.056	1	1	1.056
Zhejiang	1	1.103	1	1	1.103
Anhui	1	1.063	1	1	1.063
Fujian	1.008	0.98	0.999	1.009	0.988
Jiangxi	0.99	1.044	0.992	0.998	1.033
Shandong	0.998	0.996	1	0.998	0.994
Henan	1	0.935	1	1	0.935
Hubei	0.996	0.992	0.997	0.998	0.988
Hunan	1.006	0.991	1.006	1	0.997
Guangdong	1	0.997	1	1	0.997
Guangxi	0.999	1.046	1	0.999	1.045
Chongqing	1	1.012	1	1	1.012
Sichuan	1	1.026	1	1	1.026
Guizhou	1	1.107	1	1	1.107
Yunnan	1	1.082	1	1	1.082
Shaanxi	1	1.017	1	1	1.017
Gansu	1	1.075	1	1	1.075
Xinjiang	1	0.955	1	1	0.955
Mean	1.001	1.022	1.001	1	1.023

Table 5. Malmquist index of efficiency of R&D activities in universities in 27 regions of China during 2006–2019.

	06–07	07–08	08–09	09–10	10–11	11–12	12–13	13–14	14–15	15–16	16–17	17–18	18–19
Beijing	1.082	1.749	1.148	2.696	0.325	1.073	0.936	0.942	1.052	0.918	1.03	1.041	0.798
Tianjin	1.005	0.866	1.131	2.145	0.487	0.998	1.632	0.91	1.114	1.092	0.794	1.134	1.063
Hebei	0.9	1.022	1.085	1.077	1.068	0.908	1.025	0.938	1.194	1.103	0.796	1.081	0.834
Shanxi	1.079	1.009	1.149	0.811	0.854	0.999	0.863	1.232	1.195	0.744	1.388	0.595	0.91
Inner Mongolia	0.596	1.773	0.966	0.647	1.272	1.113	0.976	1.157	1.243	1.296	0.812	0.778	0.762
Liaoning	1.305	0.903	1.469	1.261	0.883	1.047	0.888	0.975	0.948	1.148	0.965	0.866	0.846
Jilin	0.851	1.292	0.987	1.332	0.82	1.24	1.094	0.963	1.376	1.103	0.97	0.783	1.048
Heilongjiang	1.362	1.024	0.989	1.623	0.8	1.181	0.973	0.974	1.172	0.97	0.938	0.948	0.974
Shanghai	1.007	1.131	1.129	1.15	1.012	0.984	0.919	1.013	1.027	1.088	1	1.157	0.831
Jiangsu	1.019	1.116	1.227	1.029	1.175	1.146	1.037	0.954	1.058	1.045	1.061	1.051	0.857
Zhejiang	1.235	1.122	1.368	1.33	0.795	1.45	1.109	0.824	1.457	1.074	1.019	1.013	0.839
Anhui	1.311	0.911	1.322	1.304	0.665	1.803	1.146	0.997	0.869	0.749	1.245	0.966	1.002
Fujian	1.054	1.044	2.236	0.375	1.071	1.307	0.957	1.18	0.77	1.126	0.973	0.77	0.901
Jiangxi	1.205	0.723	1.129	1.126	0.923	1.097	1.014	1.016	1.055	1.12	1.452	0.891	0.87
Shandong	0.866	0.875	1.148	0.942	1.17	0.925	1.126	1.09	1.14	1.031	1.393	0.529	0.979
Henan	0.895	0.949	1.076	0.631	0.899	0.959	0.973	1.128	1.075	1	1.142	0.809	0.768
Hubei	1.014	0.972	1.023	1.212	0.928	0.96	0.959	1.034	1.021	1.033	0.985	1.025	0.741
Hunan	1.045	0.973	1.071	0.998	0.919	1.052	0.896	1.011	1.136	0.999	1.164	0.937	0.814
Guangdong	0.933	0.874	1.102	1.098	0.859	1.02	0.908	0.96	1.075	1.221	0.964	1.197	0.842
Guangxi	0.897	1.161	1.064	0.995	0.991	1.188	1.004	1.311	1.263	0.9	0.837	1.006	1.077
Chongqing	1.243	1.063	1.099	0.993	0.917	0.879	0.943	1.023	1.1	1.28	0.906	0.817	0.994
Sichuan	1.041	0.962	1.22	1.215	0.905	0.814	1.028	1.008	1.034	0.975	1.038	0.986	1.193
Guizhou	0.737	1.203	1.97	1.649	0.463	1.244	1.618	2.123	4.352	0.605	1.208	0.647	0.318
Yunnan	0.71	2.004	0.863	1.051	1.05	1.319	1.272	1.119	0.98	1.027	1.044	1.113	0.94
Shaanxi	1.081	1.05	0.973	1.074	0.997	1.022	0.911	1.079	1.181	1.043	1.15	0.926	0.799
Gansu	0.803	1.039	1.236	1.186	1.032	1.846	1.221	0.909	0.948	1.277	0.882	1.008	0.924
Xinjiang	1.19	0.886	0.799	0.816	1.001	0.849	0.969	1.121	0.971	0.969	1.069	1.047	0.821
mean	0.999	1.069	1.155	1.1	0.867	1.103	1.037	1.056	1.142	1.021	1.032	0.914	0.861
M > 1	17	16	21	18	9	17	13	16	21	17	14	12	5

(1) Analysis of overall efficiency changes. Table 3 shows that during the period 2006–2019, regarding the current year compared to the previous year, effch (efficiency change) was greater than 1 for eight years, techch (technology change) was greater than 1 for nine years, pech (pure efficiency change) was greater than 1 for five years, and sech

(scale efficiency change) was greater than 1 for five years. As can be seen from Table 4, tfpch (total factor productivity change) varied annually during the period 2006–2019, with an average tfpch greater than 1 in nine years (69.23%) and less than 1 in four years (30.77%), with eight years having a Malmquist index greater than the average for the entire study period (1.023). From Tables 3 and 4, it can be concluded that, from 2006 to 2019, the average Malmquist index of scientific and technological innovation in universities in China was 1.023, showing an overall upward trend. The total factor productivity index of each year during the study period was greater than 1, indicating that the total factor productivity of universities in each region was in an increasing stage. The mean values of the technical efficiency change index, technical progress change index, pure technical efficiency change index and scale efficiency change index were 1.001, 1.022, 1.001, 1 and 1.023, respectively. tfpch = effch × techch (1.023 = 1.001 × 1.022). The average value for technical efficiency increased by 0.1%, the average value of technological progress increased by 2.2%, and the average value of scale efficiency did not change. These results show that the technological progress of scientific and technological innovation in colleges and universities in various regions plays a major role in the improvement of comprehensive efficiency, and there is still significant room for improvement regarding the efficiency of scientific and technological innovation in colleges and universities by improving the management level and resource utilization efficiency.

(2) Comparison of changes in efficiency in each region. From Tables 4 and 5, it can be concluded that the value of total factor productivity was less than 1 for 10 regions, Hebei, Shanxi, Inner Mongolia, Fujian, Shandong, Henan, Hubei, Hunan, Guangdong, and Xinjiang, from 2006 to 2019. The total factor productivity indices of the other 17 regions were all greater than 1, accounting for 62.96%, indicating that total factor productivity in most of China's regions was increasing and the development trend was good. Nine regions, Shanxi, Inner Mongolia, Fujian, Shandong, Henan, Hubei, Hunan, Guangdong, and Xinjiang had a technological progress index of less than 1, accounting for 33.33%. There were 18 regions (66.67%) where the improvement in the scientific research and innovation efficiency of colleges and universities can be attributed to the improvements in technological progress and pure technical efficiency. Throughout the whole study cycle, Jiangsu experienced 11 years with a Malmquist index greater than 1; Zhejiang experienced 10 years with a Malmquist index greater than 1, indicating that it was a fast-growing region; Shanghai, Jiangxi and Yunnan experienced 9 years with a Malmquist index greater than 1; Beijing, Tianjin, Hebei, Guangxi, Sichuan, Guizhou, Shaanxi and Gansu had a Malmquist index greater than 1 for 8 years; Jilin, Anhui, Fujian, Shandong and Hubei had a Malmquist index greater than 1 for 7 years; Shanxi, Inner Mongolia, Hunan, Guangdong and Chongqing had Malmquist indices greater than 1 for 6 years; Liaoning, Heilongjiang and Xinjiang had Malmquist indices greater than 1 for 5 years, and Henan had a Malmquist index greater than 1 for 4 years. The improvement in the scientific research and innovation efficiency of universities in various regions of China mainly depends on technological progress and pure technical efficiency improvement. This shows that increasing scientific research investment has had little effect on improving scientific research efficiency. At present, Chinese universities should mainly improve their innovation efficiency through technological progress and scientific research management.

(3) Analysis of influencing factors from Malmquist. The tfpch is composed of effch and techch, where effch is composed of pech and sech, which are related as tfpch = effch × techch = pech × sech × techch. From Table 4, the average value of tfpch (total factor productivity change) during 2006–2019 was 1.023, the average value of effch (efficiency change) was 1.001, the average value of techch (technology change) was 1.022, the average value of pech (pure efficiency change) was 1.001, and the mean value of sech (scale efficiency change) was 1, where the 2.3% average growth in tfpch consisted of 0.1% of the average growth in effch and 2.2% of the growth in techch,

and the 0.1% average growth in effch consisted of 0.1% of the average growth in pech, where sech did not grow on average, i.e., it did not contribute to growth. During the study period, 17 regions (Beijing, Tianjin, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, and Gansu) had an average tfpch greater than 1, accounting for 62.96%, and these regions were in the growth period. Six regions (Shanxi, Liaoning, Jilin, Heilongjiang, Fujian, and Hunan) had an average effch greater than 1, accounting for 22.22%, indicating that the R&D efficiency in these regions was increasing. There were 18 regions (Beijing, Tianjin, Hebei, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, and Gansu) with an average techch greater than 1, accounting for 66.67% of the total, and the technological progress in these regions was faster. The average pech of five regions (Hebei, Liaoning, Jilin, Heilongjiang, and Hunan) was greater than 1, accounting for 18.52%, which indicates that the pure technical efficiency of these regions was increasing. There were three regions with an average sech greater than 1 (Shanxi, Jilin, and Fujian), accounting for 11.11%, indicating that the scale efficiency of these regions was increasing. The improvement in pure technical efficiency focuses on the appropriate structuring of research personnel, research funds and the improvement in the management system. The improvement in scale efficiency depends on the scale stage in which it is located: if it is at the stage of increasing returns to scale, the scale of research investment needs to be increased. If it is in the stage of diminishing returns to scale, this means that the scientific research of universities in the region has exceeded a certain scale, resulting in diseconomies of scale, which is likely to be related to redundant scientific researchers, institutions and funds, and the research structure needs to be adjusted reasonably.

5. Conclusions

This paper draws the following conclusions from an empirical study of R&D innovation efficiency in universities in 27 regions of China from 2006 to 2019.

Based on the calculations of the DEA model, the comprehensive efficiency of R&D innovation in universities in all regions of China did not reach DEA effectiveness in 2006 and 2019.

The R&D innovation efficiency of colleges and universities in different regions varies widely and there is room for the improvement of pure technical efficiency and scale efficiency in most provinces. Regions should focus on improving the management level of R&D innovation in universities, designing a reasonable incentive system, and moderately expanding investment to reach the optimal scale. A dynamic analysis based on the Malmquist index shows that the average value of the total factor productivity index of the R&D innovation efficiency of universities in each region of China from 2006 to 2019 was 1.023, which indicates that the overall trend of R&D innovation efficiency was increasing. Changes in technological progress in the efficiency of R&D innovation at universities in each region of China play a major role in the improvement of the overall efficiency, with changes in technical efficiency playing a secondary role as a driver. From the perspective of spatial distribution, the changes in the R&D innovation efficiency of colleges and universities in different regions are quite different. Moreover, it shows fluctuations at different times; each region should take strong measures according to the constraints in a targeted manner, to effectively improve the efficiency of R&D innovation in universities. Only in this way can the sustainable development of R&D activities in colleges and universities be realized.

The R&D activity requires higher intellectual resources, and colleges and universities are complex organizations. Limited by the availability of data, this study only uses a few representative indicators to study the R&D activity in colleges and universities; in particular, we find that the indicators that characterize people's abilities are not prominent enough. In future research, we will strengthen the analysis of the indicators and choose indicators that are more representative and influential and can better represent R&D activities and achievements.

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