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Article

# Dynamic Efficiency and Evolution Trends of Higher Education Resource Allocation in China: A DEA-Malmquist and Markov Chain Approach

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**Abstract:** Under the general trend of the global economy shifting to knowledge-intensive, the efficiency of higher education resource allocation has become a key factor in determining development. This study analyses the problems related to the efficiency of higher education with the help of Data Envelopment Analysis (DEA), Dynamic DEA-Malmquist Index and Markov Chain Prediction. The study shows that China's input efficiency is better overall, but regional differences are more significant, with the east being better than the west. In the Markov chain prediction of total factor productivity development trend, the total factor productivity level of higher education efficiency presents strong dynamic change characteristics, the transfer probability between states is scattered, and it is difficult to maintain in the original efficiency state for a long time. Based on this, the following suggestions are put forward: optimize resource allocation, promote technological innovation, and steadily improve the efficiency of higher education; strengthen regional collaboration, and promote the balanced development of higher education in various regions; universities and colleges to innovate the management mechanism, and inject new vitality into the development of education; and dynamically adjust the input strategy, reasonable resource allocation scheme and management measures.

**Keywords:** higher education; DEA model; DEA-Malmquist index; Markov prediction

## 1. Introduction

The global economy is gradually shifting towards a knowledge-intensive model. The knowledge economy has become the core driving force of social development, and the importance of higher education has become increasingly prominent [1]. As a key arena for talent cultivation and technological innovation, higher education bears the heavy responsibility of supplying high-quality talent to society and promoting scientific and technological progress. High-quality talents are not only inheritors of knowledge but also promoters of innovation; they can transform frontier knowledge into actual productivity, promoting industrial upgrading and economic development. Technological innovation is a core element of national competitiveness, and higher education institutions, with their rich research resources and talent reserves, have become an important source of technological innovation. To enhance competitiveness in the global economy, countries have increased their investment in higher education, striving to improve educational quality and research levels to enhance their economic competitiveness and innovation capabilities, making the cost-effectiveness of higher education input-output a subject of much attention.

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As higher education moves from elitism to massification and universalization, the demand for educational resources continues to rise. The contradiction between the limited nature of educational resources and the expansion of educational demand has become increasingly significant [2]. The level of resource allocation efficiency directly affects the quality of education and the effectiveness of social development. If resource allocation is unreasonable, it will lead to the idle waste of educational resources in some universities, while other universities cannot meet teaching and research needs due to resource shortages, seriously restricting the overall improvement of higher education quality. This makes scientific and efficient allocation of limited resources a key issue to be overcome in the education sector [3].

The rapid development of modern information technology has profoundly changed the teaching modes and research means of higher education. New educational methods such as online education and virtual laboratories are constantly emerging, providing new pathways for improving educational output; meanwhile, research cooperation is carried out more widely via network platforms, accelerating knowledge transformation and the output of innovation results. This requires a re-examination of the output effects of higher education inputs in the new technological environment, and how to further optimize the input-output relationship with the help of technological power [4]. As an important channel for social mobility, the fairness and rationality of higher education investment relate to the harmonious and stable development of society [5]. In-depth research on the efficiency of higher education resource allocation has extremely important theoretical and practical significance. The results of this study aim to provide a strong basis for government departments to formulate scientific and reasonable educational resource allocation policies, guiding resources to tilt towards regions and universities that need them more, promoting the balanced development of higher education. It also aims to help universities optimize internal resource allocation, improve operational efficiency, enhance talent training quality and technological innovation capabilities, and better serve social and economic development.

## 2. Literature Review

Investigations into fiscal education funding have identified output insufficiencies in certain institutions under given input conditions, indicating the need for optimized fund distribution systems to enhance efficiency [6]. A relatively complete cost accounting system has been constructed from the cost-benefit perspective to measure the output benefits corresponding to each input in educational resource allocation [7]. Studies on municipal education expenditure efficiency have shown that in economically underdeveloped but efficient areas, the average salary of teachers serves as an important incentive factor for improving educational efficiency [8]. The DEA model has been applied to evaluate the performance of distance education departments, revealing the impact of remote education on teaching quality. Fuzzy Data Envelopment Analysis has been employed to develop benchmark frameworks for improving institutional efficiency, with efficiency and sustainability identified as key pillars of higher education processes.

Research has examined the relationship between education funding sources and educational equity, suggesting that maintaining fiscal spending intensity and improving budget management systems are essential [9]. The critical role of process management in efficiency improvement has been emphasized, with recommendations for strengthening governmental macro-control, enhancing resource quality, and customizing resource allocation schemes based on regional contexts [10]. Comparative analysis of input-output efficiency before and after policy implementation has revealed a research gap, with abundant studies on single functions but limited research on comprehensive institutional performance [11]. Analysis of regional disparities in university efficiency has led to proposals for optimizing resource allocation models, advancing digital transformation, and establishing talent evaluation frameworks [12].

In summary, domestic and foreign studies have deeply analyzed higher education input-output issues from multiple dimensions such as cost-benefit, regional differences, and school-running performance. Existing research has laid a solid foundation for subsequent exploration, but there is still room for expansion. Future research can further excavate the deep-seated factors affecting higher education input-output efficiency and strengthen comparative research on input-output relationships under different educational environments, thereby promoting the reasonable allocation of higher education resources and the improvement of education quality.

## 3. Research Design

### *3.1. Data Sources*

The data for this paper are derived from the China Statistical Yearbook, China Educational Statistical Yearbook, and China Statistical Yearbook on Science and Technology, covering the period from 2013 to 2022.

### *3.2. Indicator Selection*

Due to the serious lack of higher education output indicators for the Tibet Autonomous Region, it was not included in the analysis model [13]. According to the requirements of the DEA model for sample selection, this paper selects 30 provinces (autonomous regions, municipalities) nationwide as research objects to comprehensively understand the differences in higher education inputs and outputs in different regions; the selected period is from 2013 to 2022, reflecting the dynamic changes and development trends of higher education in recent years.

In constructing the indicator system for higher education inputs and outputs, this study referenced the first-level indicator classification frameworks [12,14] regarding manpower, material resources, financial resources, as well as talent and technology outputs. On this basis, some second-level indicators were optimized and adjusted.

For example, regarding manpower input, compared to the indicators selected in previous frameworks [12] article, this study selects full-time teachers with senior professional titles and research personnel as key indicators. This aims to focus more precisely on key human elements in core teaching and research activities of higher education, highlighting their direct impact on education quality and research output to more effectively reflect the actual benefits of manpower input. In material input, indicators such as the number of higher education schools, higher education equipment assets, and the area of higher education schools are used to comprehensively consider dimensions like resource scale layout, teaching/research hardware foundation, and campus carrying capacity. Similarly, the selection of second-level indicators for financial resources, talent output, and technology output has been optimized based on the internal logic of higher education input-output and the specific goals of this study, thereby constructing a more targeted, explanatory, and accurate indicator system for higher education resource allocation efficiency analysis. Table 1 shows the specific input and output indicators.

**Table 1.** Input-Output Indicator System for Higher Education Development in China.

| Indicator | Level 1 Indicator | Level 2 Indicator |
|---|---|---|
| Input Indicators | Manpower Input | Full-time teachers with senior professional titles |
| | | Research personnel |
| | Financial Input | Education funds |
| | | Research funds |
| | Material Input | Number of higher education institutions |
| | | Higher education equipment assets |
| | | Higher education school area |
| Output Indicators | Talent Output | Number of degrees awarded in higher education |
| | Technology Output | Number of patent applications granted |
| | | Transaction value in technical markets |
| | | Number of research projects |

## 4. Model Construction

### *4.1. Data Envelopment Analysis (DEA)*

In 1978, renowned American operational research scientists Charnes and Cooper provided a linear programming method for evaluating the relative efficiency of decision-making units (DMUs) of the same type, calling it Data Envelopment Analysis (DEA). DEA implements efficiency measurement for selected input variables and output variables. DEA decision units can be physical entities or at a conceptual level. The selection of input and output indicators can usually be based on similar research results and personal experience according to the research direction of the article. An input-output combination with an efficiency value of 1 represents DEA optimal efficiency.

The basic principle of Data Envelopment Analysis is as follows: Assume there are n decision-making units $DMU_j\left(j = 1, 2, \cdots, n\right)$, the input vector is $X_j = \left(x_{1j}, x_{2j}, \cdots, x_{mj}\right)^T > 0$, the input weight vector is $v = \left(v_1, v_2, \cdots, v_m\right)^T$; the output vector is $Y_j = \left(y_{1j}, y_{2j}, \cdots, y_{sj}\right)^T > 0$, and the output weight vector is $u = \left(u_1, u_2, \cdots, u_s\right)^T, j = 1, 2, \cdots, n.$

Evaluating the *j*-th DMU, the efficiency score of the DMU is:

$$\theta_j = \frac{u^T Y_j}{v^T X_j} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}, (j = 1, 2, \cdots, n) \quad \left(\theta_j \le 1\right) \tag{1}$$

DEA solves for the efficiency score of decision units through analysis of two dimensions: input-oriented and output-oriented. In input-oriented DEA analysis, the focus is on maximizing output under prescribed input conditions; in output-oriented DEA analysis, the focus is on minimizing input under prescribed output conditions. Returns to scale are divided into variable and constant: constant returns to scale (CRS) means the measured efficiency value is the same regardless of orientation; while variable returns to scale (VRS) means the measured efficiency values can differ.

The input-oriented CCR model under the CRS assumption is as follows: Assume there are \$I\$ decision units, each with N inputs and M outputs. The input of the *i*-th decision unit is $x_{io}$, and the output is $y_{io}$. DEA analysis obtains the input-output efficiency of each decision unit by solving the following linear programming problem:

$$\begin{aligned} &\text{Max} \quad \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{i0}} \\ &\text{st} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, j = 1, 2, \cdots, n, \\ &\quad u_r, v_i \ge 0 \end{aligned} \tag{2}$$

Equation (2) has infinite solutions. To prevent the appearance of infinite solutions, constraints are added to Equation (2). Using dual programming, the equivalent envelopment model for equation (2) is derived as:

$$\begin{aligned} &Min \quad \theta_o \\ &\text{st} \quad \theta_o x_{io} - \sum_{j=1}^{n} x_{ij} \lambda_j \ge 0, \quad \text{i} = 1, 2, \cdots, \text{m}. \\ &\quad \sum_{j=1}^{n} y_{rj} \lambda_j - y_{ro} \ge 0, \quad \text{r} = 1, 2, \cdots, \text{s}. \\ &\quad \lambda_j \ge 0, \text{j} = 1, 2, \cdots, \text{n}. \end{aligned} \tag{3}$$

The calculated $\theta_o$ is the efficiency value of the i-th DMU. If the efficiency value of the DMU equals 1, it is considered that the DMU is on the frontier and in a state of comprehensive technical efficiency; the closer to 1, the greater the relative efficiency value of the DMU. The CRS assumption applies only when all decision units operate at optimal scale. In reality, decision units usually operate at non-optimal scales. Therefore, the Variable Returns to Scale (VRS) assumption is widely adopted. To construct the BCC model, a convexity constraint condition $\sum_{i=1}^{n} \lambda i = 1$ needs to be added to Equation (3). In the BCC model, to deeply analyze the reasons for non-DEA effectiveness, comprehensive efficiency can be further decomposed into scale efficiency and pure technical efficiency. Through the above quantitative analysis, the efficiency level of the decision unit can be determined.

### *4.2. Dynamic DEA-Malmquist Index*

Traditional DEA models are static analyses, evaluating the efficiency of different decision units at a fixed point in time; such analysis is only suitable for cross-sectional data. However, the efficiency of higher education inputs and outputs changes dynamically. To perform dynamic efficiency analysis on different decision units over a specified time stage, the dynamic DEA-Malmquist index is chosen to analyze the efficiency of higher education inputs and outputs [15]. The dynamic DEA-Malmquist index evaluates total factor productivity (TFP) from stage t to stage $t + 1$. The model is as follows:

$$Tfpch = M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D^{t+1}\left(x^t, y^t\right)}{D^t\left(x^t, y^t\right)} \times \left[\frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)} \times \frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right] \tag{4}$$

The product of Technical Efficiency (Effch) and Technological Progress Rate (Techch) is Total Factor Productivity (Tfpch). Furthermore, under the condition of variable returns to scale, the product of Pure Technical Efficiency (Pech) and Scale Efficiency (Sech) is Technical Efficiency (Effch). From this, we know:

$$Tfpch = Effch \times Tech = Pech \times Seech \times Tech \tag{5}$$

In the formula, $x^t$ and $x^{t+1}$ represent the input indicators in period t and $t + 1$ respectively; $y^t$ and $y^{t+1}$ represent the output indicators in period $t$ and $t + 1$ respectively. $D^t\left(x^t, y^t\right)$ and $D^t\left(x^{t+1}, y^{t+1}\right)$ represent the distance functions with period t as the technical reference for period $t$ and period $t + 1$ respectively. $D^{t+1}\left(x^t, y^t\right)$ and $D^{t+1}\left(x^{t+1}, y^{t+1}\right)$ represent the distance functions with period $t + 1$ as the technical reference for period t and period $t + 1$ respectively

### *4.3. Markov Chain Prediction*

The total factor productivity of public investment in higher education in China is divided into four situations using the quartile method. By constructing a transition matrix, the transfer characteristics and laws of total factor productivity of higher education public investment under different situations within the selected time are explored. The formula used is as follows:

$$P\left\{X_\propto = j | X_{\propto-1} = i, X_{\propto-2} = i_{\propto-2}, \cdots, X_0 = i_0\right\} = P\left\{X_\propto = j | X_{\propto-1} = i,\right\} = P_{ij} \tag{6}$$

$$P_{ij} = n_{ij}/n_i \tag{7}$$

$X_\alpha$ represents the moving state, $P_{ij}$ represents the probability of the higher education input efficiency level transferring from type $i$ at moment α to type j at moment α; nij represents the sum of the number of provinces transferring from type $i$ at time t to state $j$ at time $t + 1$ within the research period; ni represents the sum of the number of provinces belonging to type i within the research period [15].

## 5. Measurement of Higher Education Input Efficiency

### *5.1. Static Analysis of Higher Education Input Efficiency*

Based on DEA Model This study selects China's higher education system in 30 provinces (autonomous regions, municipalities) in 2022 as the research scope, comprehensively considering multi-dimensional input indicators such as manpower, material resources, and financial resources, as well as talent cultivation and research result transformation output indicators, striving to fully reflect the allocation and transformation effects of higher education resources. Using DEAP2.1 software and the DEA-BCC model, the input-output data of higher education in each region were deeply mined and processed to precisely measure the output efficiency level of each province (autonomous region, municipality) under given inputs according to the four major economic zones, and then clearly present the advantages and shortcomings of higher education development in each region through horizontal comparison. The calculation and ranking results of the technical efficiency and its decomposition for higher education input-output in 30 provinces (autonomous regions, municipalities) nationwide in 2022 are shown in Table 2 below.

**Table 2.** Calculation and Ranking of Technical Efficiency and its Decomposition for Higher Education Input-Output.

| Region | Province (City) | Technical Efficiency (Crste) | Pure Tech Efficiency (Vrste) | Scale Efficiency (Scale) | Returns to Scale | Rank |
|---|---|---|---|---|---|---|
| East | Beijing | 1 | 1 | 1 | Constant | 1 |
| | Tianjin | 1 | 1 | 1 | Constant | 1 |
| | Hebei | 1 | 1 | 1 | Constant | 1 |
| | Shanghai | 1 | 1 | 1 | Constant | 1 |
| | Jiangsu | 1 | 1 | 1 | Constant | 1 |
| | Zhejiang | 1 | 1 | 1 | Constant | 1 |
| | Fujian | 1 | 1 | 1 | Constant | 1 |
| | Shandong | 1 | 1 | 1 | Constant | 1 |
| | Guangdong | 1 | 1 | 1 | Constant | 1 |
| | Hainan | 0.913 | 1 | 0.913 | Increasing | 27 |
| Central | Shanxi | 1 | 1 | 1 | Constant | 1 |
| | Anhui | 1 | 1 | 1 | Constant | 1 |
| | Jiangxi | 1 | 1 | 1 | Constant | 1 |
| | Henan | 1 | 1 | 1 | Constant | 1 |
| | Hubei | 1 | 1 | 1 | Constant | 1 |
| | Hunan | 1 | 1 | 1 | Constant | 1 |
| West | Inner Mongolia | 1 | 1 | 1 | Constant | 1 |
| | Guangxi | 1 | 1 | 1 | Constant | 1 |
| | Chongqing | 1 | 1 | 1 | Constant | 1 |
| | Sichuan | 1 | 1 | 1 | Constant | 1 |
| | Guizhou | 1 | 1 | 1 | Constant | 1 |
| | Yunnan | 1 | 1 | 1 | Constant | 1 |
| | Shaanxi | 1 | 1 | 1 | Constant | 1 |
| | Gansu | 0.898 | 0.995 | 0.902 | Increasing | 28 |
| | Qinghai | 0.7 | 1 | 0.7 | Increasing | 30 |
| | Ningxia | 0.821 | 1 | 0.821 | Increasing | 29 |
| | Xinjiang | 0.988 | 1 | 0.988 | Increasing | 26 |
| Northeast | Liaoning | 1 | 1 | 1 | Constant | 1 |
| | Jilin | 1 | 1 | 1 | Constant | 1 |
| | Heilongjiang | 1 | 1 | 1 | Constant | 1 |
| National | Mean | 0.977 | 1 | 0.977 | | |

Through the analysis of Table 2, it is known: The mean technical efficiency of higher education input-output in China's 30 provinces (autonomous regions, municipalities) in 2022 is 0.977, the mean pure technical efficiency reached 1, and the mean scale efficiency is 0.977. The overall level is relatively high, indicating that the effectiveness of resource allocation and transformation is good, but there is still room for improvement compared to the optimal efficiency value of 1.

From the regional level, most provinces (autonomous regions, municipalities) in the Eastern region have technical efficiency, pure technical efficiency, and scale efficiency of 1, showing excellent performance. Only

Hainan is slightly lower in scale efficiency at 0.913, in a state of increasing returns to scale, with the potential to improve efficiency through moderate scale expansion.

Internal differences in the Western region are obvious. The technical efficiency of Gansu, Qinghai, Ningxia, and Xinjiang did not reach the optimum. These regions are mainly constrained by scale efficiency, with Qinghai showing the most obvious decline in scale efficiency, at only 0.7. Gansu is the only region in the country where pure technical efficiency did not reach the optimum.

The Central region and Northeast provinces performed outstandingly, with technical efficiency, pure technical efficiency, and scale efficiency all reaching the optimum.

Overall, the input-output efficiency of higher education in most provinces (autonomous regions, municipalities) in China is good, but some regions need improvement in pure technical or scale efficiency. Each region should specifically optimize higher education resource allocation according to its own situation to improve overall efficiency.

### *5.2. Dynamic Analysis of Total Factor Productivity*

Based on Dynamic DEA-Malmquist Index Within the scope of higher education input-output efficiency research, the BCC model, as a static model in efficiency analysis, cannot effectively present the dynamic trend of input-output efficiency. To more accurately depict the efficiency characteristics of input-output activities in the field of higher education, DEAP2.1 software and the dynamic DEA-Malmquist model were used to measure the Total Factor Productivity (TFP) index of higher education input-output, decomposing it into the Technical Efficiency Change index and Technological Progress Rate index. Furthermore, the Technical Efficiency index was re-decomposed into Pure Technical Efficiency index and Scale Efficiency index, aiming to deeply analyze the internal structure and dynamic evolution mechanism of higher education input-output efficiency.

#### 5.2.1. National Higher Education Total Factor Productivity 2013–2022

Based on the 7 input indicators and 4 output indicators of 30 provinces (autonomous regions, municipalities) nationwide from 2013 to 2022, using output orientation and variable scale effects, the dynamic DEA-Malmquist index was used to analyze the dynamic changes. The results of TFP changes in higher education input-output from 2014 to 2022 are shown in Table 3.

**Table 3.** Changes in National Higher Education Total Factor Productivity and its Composition 2013–2022.

| Period | Technical Efficiency (effch) | Tech. Progress (techch) | Pure Tech. Efficiency (pech) | Scale Efficiency (sech) | Total Factor Productivity (tfpch) |
|---|---|---|---|---|---|
| 2013–2014 | 1.001 | 1.119 | 0.998 | 1.003 | 1.12 |
| 2014–2015 | 0.999 | 1.046 | 1.003 | 0.996 | 1.044 |
| 2015–2016 | 1.003 | 0.961 | 1 | 1.002 | 0.964 |
| 2016–2017 | 1.003 | 0.944 | 1 | 1.003 | 0.947 |
| 2017–2018 | 0.989 | 1.537 | 0.999 | 0.991 | 1.521 |
| 2018–2019 | 0.983 | 0.87 | 0.996 | 0.987 | 0.856 |
| 2019–2020 | 0.994 | 1.629 | 1.002 | 0.992 | 1.62 |
| 2020–2021 | 1.005 | 0.886 | 1 | 1.005 | 0.89 |
| 2021–2022 | 1.004 | 1.096 | 1.002 | 1.002 | 1.1 |
| Mean | 0.998 | 1.094 | 1 | 0.998 | 1.092 |

Through the analysis of Table 3, it is known: From 2013 to 2021, China's higher education total factor productivity showed a fluctuating trend. In the period 2019 – 2020, TFP reached a maximum of 1.62, and dropped to a minimum of 0.98 in the subsequent 2020–2021 period. Overall, from 2013 to 2022, TFP increased by an average of 9.2% annually. From the decomposition of TFP, technical efficiency decreased by an average of 0.2% annually, hindering TFP growth, while the technological progress rate increased by an average of 9.4% annually, promoting TFP growth; from the decomposition of technical efficiency, pure technical efficiency basically remained at 1, and scale efficiency decreased by an average of 0.2% annually, having very little impact on technical efficiency.

Broken down by time, periods where China's higher education TFP showed positive growth were 2013–2015, 2017–2018, 2019–2020, and 2021–2022; periods showing negative growth were 2015–2017, 2018–2019, and 2020–2021.

In periods where TFP showed positive growth, technical efficiency only promoted TFP growth in 2013–2014 and 2021–2022; in other periods it hindered growth. The technological progress rate promoted TFP growth in all these periods, and its promoting effect was greater than that of technical efficiency.

In periods where TFP showed negative growth, technical efficiency only hindered TFP growth in 2018–2019; in other periods it promoted growth. The technological progress rate hindered TFP growth in all these periods, and its hindering effect was greater than that of technical efficiency.

From the Figures 1–3, it is known that between 2013 and 2017, the fluctuation of TFP was relatively gentle, while after this time, the fluctuation was large. From the decomposition of TFP, the fluctuation of TFP is mainly related to the fluctuation of the technological progress rate, while technical efficiency remained around 1 with basically no fluctuation. In the decomposition of technical efficiency, pure technical efficiency and scale efficiency also remained around 1 with no fluctuation.

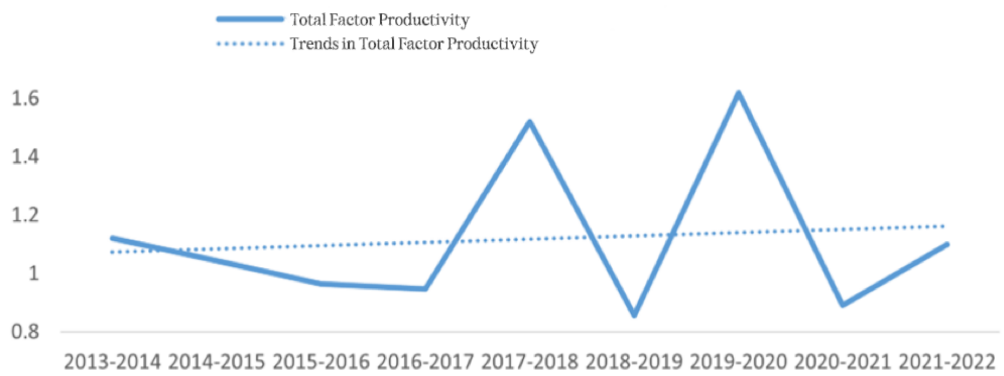


**Figure 1.** Fluctuation of Total Factor Productivity (tfpch).

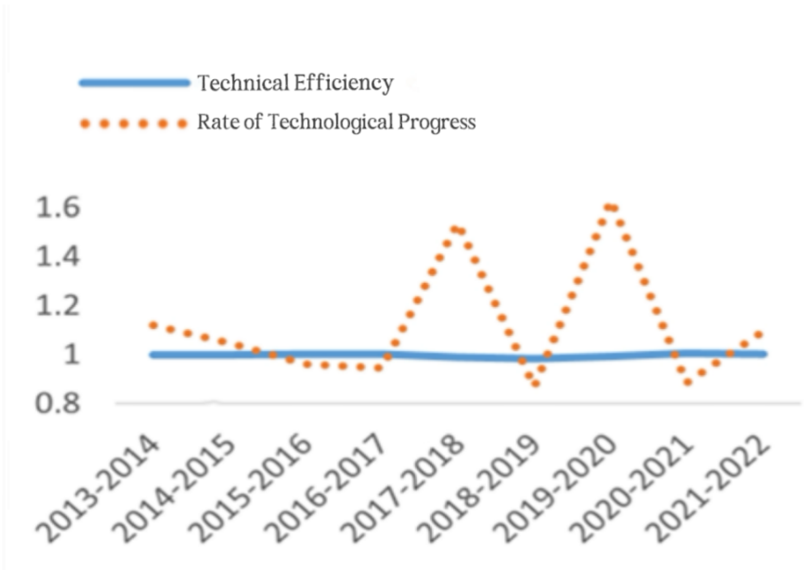


**Figure 2.** Fluctuation of Technical Efficiency (effch) and Technological Progress Rate (techch).

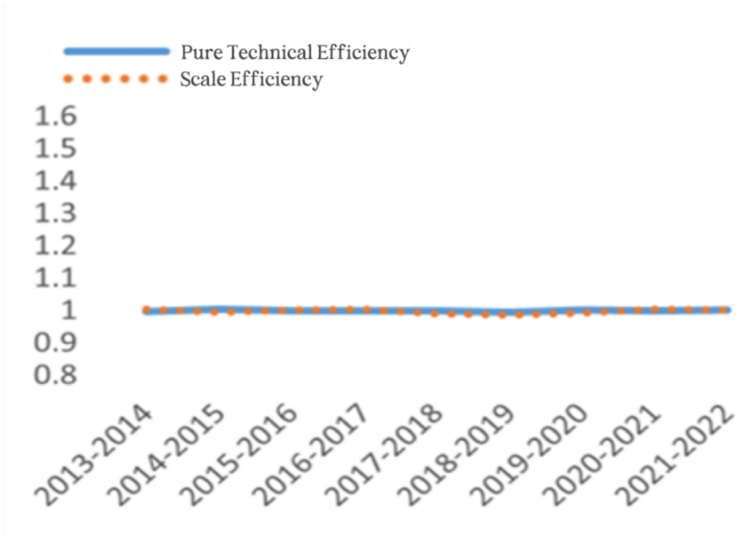


**Figure 3.** Fluctuation of Pure Technical Efficiency (pech) and Scale Efficiency (sech).

5.2.2. Higher Education Total Factor Productivity by Province (Region, City)

To deeply understand the dynamic changes, the dynamic DEA-Malmquist index was used to analyze the 30 provinces. Results are shown in Table 4.

**Table 4.** Changes in Higher Education Total Factor Productivity and its Composition by Province.

| Region | Province (City) | Technical Efficiency (Effch) | Tech. Progress (Techch) | Pure Tech. Efficiency (Pech) | Scale Efficiency (Sech) | Total Factor Productivity (Tfpch) |
|---|---|---|---|---|---|---|
| East | Beijing | 1 | 1.227 | 1 | 1 | 1.227 |
| | Tianjin | 1.007 | 1.124 | 1.003 | 1.004 | 1.132 |
| | Hebei | 1 | 1.077 | 1 | 1 | 1.077 |
| | Shanghai | 1 | 1.165 | 1 | 1 | 1.165 |
| | Jiangsu | 1 | 1.137 | 1 | 1 | 1.137 |
| | Zhejiang | 1 | 1.133 | 1 | 1 | 1.133 |
| | Fujian | 1 | 1.12 | 1 | 1 | 1.12 |
| | Shandong | 1 | 1.197 | 1 | 1 | 1.197 |
| | Guangdong | 1 | 1.194 | 1 | 1 | 1.194 |
| | Hainan | 0.99 | 1.003 | 1 | 0.99 | 0.993 |
| Central | Shanxi | 1 | 1.119 | 1 | 1 | 1.119 |
| | Anhui | 1 | 1.204 | 1 | 1 | 1.204 |
| | Jiangxi | 1.002 | 1.101 | 1.001 | 1.001 | 1.103 |
| | Henan | 1 | 1.166 | 1 | 1 | 1.166 |
| | Hubei | 1 | 1.169 | 1 | 1 | 1.169 |
| | Hunan | 1 | 1.144 | 1 | 1 | 1.144 |
| West | Inner Mongolia | 1 | 1.068 | 1 | 1 | 1.068 |
| | Guangxi | 1 | 1.083 | 1 | 1 | 1.083 |
| | Chongqing | 1.001 | 1.059 | 1 | 1.001 | 1.06 |
| | Sichuan | 1 | 1.118 | 1 | 1 | 1.118 |
| | Guizhou | 1 | 1.004 | 1 | 1 | 1.004 |
| | Yunnan | 1 | 0.989 | 1 | 1 | 0.989 |

**Table 4. Cont.**

| Region | Province (City) | Technical Efficiency (Effch) | Tech. Progress (Techch) | Pure Tech. Efficiency (Pech) | Scale Efficiency (Sech) | Total Factor Productivity (Tfpch) |
|---|---|---|---|---|---|---|
| | Shaanxi | 1 | 1.018 | 1 | 1 | 1.018 |
| | Gansu | 0.988 | 1.021 | 0.999 | 0.989 | 1.009 |
| | Qinghai | 0.961 | 1.003 | 1 | 0.961 | 0.964 |
| | Ningxia | 0.991 | 0.993 | 1 | 0.991 | 0.984 |
| | Xinjiang | 0.999 | 1.031 | 1 | 0.999 | 1.029 |
| Northeast | Liaoning | 1 | 1.055 | 1 | 1 | 1.055 |
| | Jilin | 1 | 1.096 | 1 | 1 | 1.096 |
| | Heilongjiang | 1.001 | 1.068 | 1 | 1.001 | 1.069 |
| National | Mean | 0.998 | 1.094 | 1 | 0.998 | 1.092 |

Through the analysis of Table 4, it is known: Only Hainan, Yunnan, Qinghai, and Ningxia had a higher education input-output TFP of less than 1 from 2013 to 2022. Hainan and Qinghai share the same situation, where technical efficiency promoted TFP growth, but the technological progress rate hindered it; Yunnan is different, where technical efficiency hindered TFP growth while technological progress promoted it; for Ningxia, both technical efficiency and technological progress rate hindered TFP development.

In Tianjin, Jiangxi, Chongqing, and Heilongjiang, technical efficiency and technological progress rate jointly promoted TFP growth.

From the four major economic zones, the Eastern region is clearly the region with the highest TFP growth. Although Hainan showed negative growth, the decline was only 0.07%; the Central and Northeast regions developed well; in the Western region, Gansu, Qinghai, Ningxia, and Xinjiang had negative technical efficiency growth, and Yunnan and Ningxia had negative technological progress rates. There is significant room for improvement in higher education development in the Western region.

From Figure 4, nationally, although the TFP of higher education input-output varies greatly across regions, due to the basic balance of technical efficiency, the development of TFP is mainly influenced by the technological progress rate.

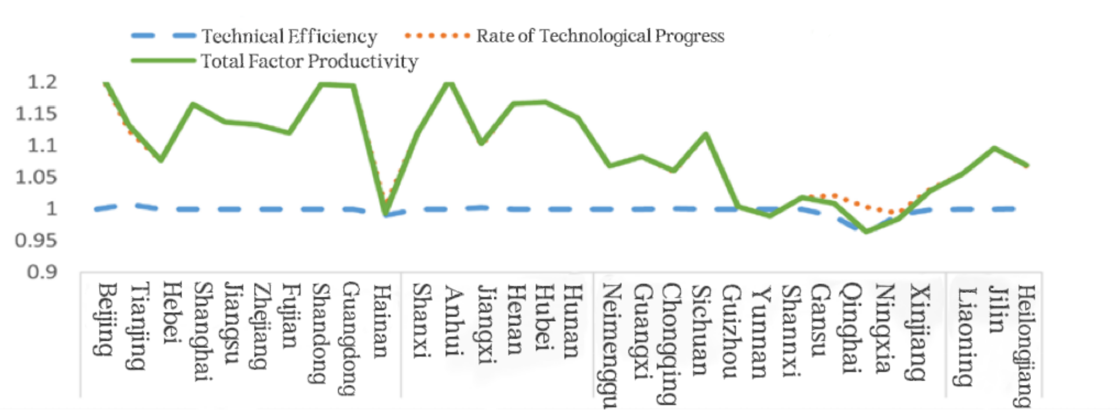


**Figure 4.** Visualization of Technical Efficiency, Technological Progress Rate, and Total Factor Productivity by Region in China.

*5.3. Markov Chain Prediction*

Using the Markov chain transition matrix to predict the TFP development trend, the TFP of each province from 2013 to 2022 was divided into four quartiles using the quartile method. The three partition points are 0.944, 1.0275, and 1.217. Accordingly, the TFP levels are divided into four items: Low Efficiency (A), Medium-

Low Efficiency (B), Medium-High Efficiency (C), and High Efficiency (D). The Markov chain prediction results are shown in Table 5.

**Table 5.** Markov Chain Prediction.

| Type | A (Low) | B (Med-Low) | C (Med-High) | D (High) | Observations |
|---|---|---|---|---|---|
| A | 0.0794 | 0.2222 | 0.2381 | 0.4603 | 63 |
| B | 0.1905 | 0.3016 | 0.2857 | 0.2222 | 63 |
| C | 0.2593 | 0.3148 | 0.2963 | 0.1296 | 54 |
| D | 0.5667 | 0.1667 | 0.1167 | 0.15 | 60 |

Through the analysis of Table 5, it is known: In the Low Efficiency (A) state, the probability of remaining in the low efficiency state is only 0.0794. This means the probability of staying in a low efficiency state in the next period is relatively low, and it is easier to shift to a higher efficiency state. Among them, the probability of shifting to the High Efficiency state is the largest, reaching 0.4603, while probabilities of shifting to Medium-Low or Medium-High are around 0.2.

In the Medium-Low Efficiency (B) state, the probability of remaining in this state is highest at 0.3016, followed by shifting to Medium-High or High states, with the lowest being shifting to Low Efficiency.

In the Medium-High Efficiency (C) state, the probability of remaining is 0.2963, slightly lower than the probability of shifting to Medium-Low, followed by shifting to Low Efficiency, while the probability of rising to High Efficiency is the lowest.

In the High Efficiency (D) state, the probability of maintaining this state is only 0.1500. The probabilities of shifting to Medium-Low or Medium-High are relatively low, while the probability of dropping to Low Efficiency is as high as 0.5667.

The distribution of transfer probabilities between efficiency states is relatively dispersed, and every state has the opportunity to change to other different efficiency states. This fully demonstrates that the TFP level of higher education input-output efficiency has strong dynamic change characteristics. In actual higher education operations, internal and external factors such as teaching resource input, faculty construction, and education policy changes will cause efficiency levels to fluctuate constantly and not remain fixed in a given efficiency state for a long time.

## 6. Conclusions and Suggestions

Through the static analysis of higher education input-output data of 30 provinces (autonomous regions, municipalities) in China in 2022, it is known that China's higher education input-output efficiency is overall at a relatively high level, but certain differences exist between regions. From the national mean, technical efficiency is 0.977, pure technical efficiency is 1, and scale efficiency is 0.977, indicating that the overall effect in converting manpower, material, and financial inputs into talent training and research output is good, but has not yet reached a completely optimal state.

From 2013–2022, national higher education TFP fluctuated, increasing by an average of 9.2% annually. The technological progress rate increased by 9.4% annually, promoting growth, while technical efficiency decreased by 0.2% annually, hindering it. The fluctuation is mainly due to the technological progress rate. At the provincial level, only Hainan, Yunnan, Qinghai, and Ningxia had TFP less than 1. The Eastern region leads in growth, while some Western provinces need improvement; Central and Northeast regions show good trends.

In the Markov chain prediction, the TFP level presents strong dynamic change characteristics. The probability of maintaining a low efficiency state is low, making it easier to shift to high efficiency; the probability of retaining medium-low efficiency is highest; the probability of maintaining high efficiency is only 0.15, with a high probability (0.5667) of dropping to low efficiency. The dispersed transfer probabilities indicate that influenced by various factors, higher education efficiency levels will not be fixed in one state for a long time.

To improve higher education efficiency, we can start from the following aspects:

1. Optimize resource allocation, promote technological innovation, and steadily improve higher education efficiency. Improving total factor productivity is the core task of optimizing the resource allocation structure. For provinces where resources have not reached optimal efficiency, based on input-output analysis, precisely adjust the layout of manpower, material, and financial resources at the input stage. Simultaneously, dynamically allocate resources according to disciplinary and professional differences to enhance overall competitiveness. Analyze input-output data deeply to achieve reasonable resource allocation and eliminate waste. For example, in Western regions with low scale efficiency, prudently plan university expansion and improve per-student resource possession and utilization efficiency. To promote technological innovation, universities should strengthen research innovation capabilities, establish special research funds, encourage teachers and researchers to engage in frontier research, and actively promote educational research technology innovation. Fully utilize AI, big data, and other technologies to strengthen information construction, optimize teaching modes using online education to reduce costs, or integrate them into teaching quality evaluation systems; they can also be applied to research project management. Additionally, build collaborative innovation platforms for industry-academia-research to accelerate the conversion of research results into actual productivity.

2. Strengthen regional collaboration and promote balanced development of higher education in various regions. Facing regional differences, establishing a sound regional collaboration mechanism is urgent. Central and local governments should coordinate regional higher education resources, establish university pairing assistance mechanisms, and encourage cross-regional cooperative schooling. Universities in the developed Eastern region can leverage their advantages to carry out comprehensive cooperation with universities in the Central, Western, and Northeast regions through faculty exchanges and joint research projects. In terms of policy and funding, tilt towards the West and regions with weak higher education to narrow the gap. Special funds for regional higher education development can be set up to support provinces with low TFP like Hainan, Yunnan, Qinghai, and Ningxia. Funds should be used to improve infrastructure and enhance faculty quality. Regularly hold regional development forums to provide a platform for exchange and explore development models suitable for different regions.

3. Innovate management mechanisms to inject new vitality into education development. Universities need to carry out comprehensive reform and innovation from internal management mechanisms. Grant secondary colleges more autonomy, optimize management processes, reduce cumbersome management levels, and improve decision-making efficiency. Construct a scientific performance evaluation system, such as improving teacher evaluation and incentive mechanisms, abandoning the single research-result-oriented mode, and building a diversified evaluation system that includes teaching quality and social service. Modern enterprise management concepts can be introduced to strengthen cost and performance management. Meanwhile, encourage universities to carry out educational reform and innovation, exploring diversified talent training models such as cross-disciplinary training and innovation-entrepreneurship education.

4. Dynamically adjust input strategies and optimize resource allocation schemes and management measures. Facing efficiency fluctuations, higher education efficiency is always in dynamic change due to various factors. Therefore, establishing a dynamic monitoring and evaluation system is crucial. Universities and management departments can establish efficiency monitoring mechanisms to analyze reasons for changes and adjust input strategies and management measures in a timely manner. Through real-time tracking of data and socioeconomic demands, scientific bases for decision-making are provided. For example, when social demand for a discipline increases, quickly increase faculty and facility inputs in that field. Simultaneously, precisely allocate resources to low-efficiency regions and promote cooperation; high-efficiency regions should continue to innovate and improve risk warning systems to reduce the risk of decline. Establish flexible resource allocation mechanisms to ensure rapid and effective adjustment in the face of changes.

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### Conflicts of Interest

The authors declare no conflict of interest.

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