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# Allocation Efficiency of Higher Education Resources in China:A Three-Stage DEA Model-Based Calculation

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## Abstract

**Higher education is the foundation of national economic development, and its resource allocation efficiency has become a key factor affecting high-quality economic development. This study selects 31 provinces in China as the research object. The number of researchers, the number of computers and the expenditure of research funds are taken as input indicators, and the three types of output indicators of higher education are selected according to the logical framework of "talent cultivation-scientific and technological achievements-social services", and the environmental variables are screened from the aspects of economic development, governmental support, and social development, and degree of openness to the outside world, and the input efficiency of higher education in China was analyzed from 2019 to 2023 with the help of the three-stage DEA model. The results of the study show that China's higher education input efficiency is generally high at the initial stage, revealing that the higher education system has achieved some success in terms of resource allocation as well as management and technology. Further stochastic frontier analysis shows that the macroeconomic environment is positively related to the improvement of higher education input efficiency, while social development and opening up are negatively related to the improvement of higher education input efficiency. After removing the influence of environmental factors and stochastic disturbances, the average value of comprehensive efficiency decreases, and shows the regional difference characteristic of "the center leads, the east, the northeast follows, and the west lags behind".**

## Keywords

**Higher Education Resource Allocation; Three-Stage DEA; External Factors; Regional Allocation Efficiency.**

## 1. Introduction

At present, China's higher education has entered the stage of popularization, having already supplied a substantial number of talents to drive social and economic development and playing a pivotal role in the nation's economic progress[1][2]. According to the latest statistics, China's higher education enrollment ratio has reached 60.3% in 2023, establishing the world's largest higher education system[3]. However, there remain significant shortcomings in its capacity to support innovative economic development. Over the past 40 years of reform and opening up, China's economy has achieved remarkable accomplishments, with an average annual GDP growth rate exceeding 9%, creating a notable miracle in economic history. A critical factor contributing to China's ability to sustain long-term high growth is its economy's status as a catch-up economy, characterized by well-educated human resources capable of swiftly absorbing advanced technologies from abroad[4]. However, as China's economy approaches the threshold of high-income countries, particularly in certain emerging strategic industries, China has begun to parallel or even lead developed countries, transitioning from a catch-up economy to an innovative economy[5].

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There are fundamental differences between an innovative economy and a catching-up economy in terms of development models, dynamics, and operational mechanisms, which inevitably lead to greater disparities in the allocation of educational resources[6]. In a catch-up economy, the role of education in driving economic growth primarily manifests in expanding production factors and rapidly absorbing foreign technology[7][8]. In contrast, in an innovative economy, education contributes to economic growth mainly through enhancing total factor productivity, with innovation serving as the primary form[9]. Therefore, it is essential to re-evaluate and measure the allocation efficiency of China's higher education resources and explore a new path for higher education resources to align with the demands of an innovative economy[10][11].

Higher education resource allocation efficiency directly impacts a nation's economic development, and scholars have conducted extensive research on this topic. This paper primarily addresses two aspects of the literature. First, it examines the factors influencing higher education resource allocation efficiency. From a macro perspective, factors such as government financial support[12], economic development level[13], higher education system[14], and urbanization degree[15][16][17]affect the efficiency of higher education resource allocation. From a micro perspective, factors including the optimal education input-output ratio[18][19], university student quality[20-22], and high teacher salaries[23-25] also influence resource allocation efficiency. Second, it focuses on higher education resource efficiency evaluation. Using the DEA method, the overall efficiency of educational resources is assessed.Li et al. (2021) analyzed gender differences in primary school education resource allocation efficiency through parallel DEA[26]. You et al. (2021) employed the super-efficiency DEA-Malmquist method and Tobit model to evaluate higher education resource allocation efficiency in China[27]. Furthermore, Zhao et al. (2024) applied the DEA method to analyze and evaluate higher education resource allocation efficiency across 30 Chinese provinces from 2006 to 2020, noting significant differences between the stages of economic transformation and productivity[28]. Additionally, the DEA method was used to assess scientific research efficiency. Liu et al. (2014) measured and analyzed the efficiency of scientific research outputs between Chinese regions using the DEA-BCC method, finding that most universities exhibit inefficiencies with notable regional disparities[28]. Zhang et al. (2021) allocated scientific and technological innovation resources in Chinese universities across 31 provinces from 2015 to 2017 using the DEA method and identified output shortfalls in each province during 2017[29].

Despite the valuable references provided by previous studies, there are still some shortcomings, primarily reflected in the following aspects: Firstly, scholars used to reflect that higher education output indicators were relatively homogenous, usually focusing only on the number of scientific and technical papers[22][26][28], the number of topics[11][13], etc., and ignoring the ability of educational achievements to be transformed into practical applications.Secondly,previous studies have mostly focused on one aspect of the higher education system, such as the efficiency analysis of “double first-class” universities, higher vocational education inputs, and the development of higher education in specific regions, etc., and relatively few studies have been conducted on the overall input efficiency of higher education.Thirdly,the existing evaluation mainly adopts the traditional DEA model, which fails to eliminate the interference of environmental factors and random noise.Therefore, this paper employs the three-stage DEA analysis method to analyze and assess the efficiency of China's educational resource allocation, removing the interference of external factors to measure actual efficiency, and evaluates the results based on the same environment, yielding more realistic and reliable outcomes. This study not only enriches the theoretical research in the field of educational resource allocation efficiency but also provides new ideas and methods for practice, holding significant theoretical and practical value.

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## 2. Research Design

### 2.1. Selection of Indicators

#### 2.1.1. Selection of Input-Output Indicators

Based on existing research[2][15], the input of educational resources is measured from three perspectives: human, material, and financial resources. The reason for selecting these three perspectives is that the fundamental goal of educational resource input is to achieve the maximum possible educational output with the least input of human, material, and financial resources. For the measurement of educational resource output, it is mainly measured by the research output of universities. Additionally, the selection of input-output indicators is crucial for the DEA method efficiency evaluation, and the conclusions drawn from different indicators may vary significantly. The number of indicators selected will also impact the final evaluation results. If too many indicators are chosen, it may lead to a situation where the majority of provinces receive an educational efficiency score of 1. Conversely, if too few indicators are selected, it may result in core issues being overlooked, leading to inaccurate results. The specific indicators are as follows:

**Table 1.** Input-output indicator system

| Indicator categories | One level | Two level | Variable Definition |
|---|---|---|---|
| Inputs index | human inputs | Researcher | Persons with teaching qualifications who specialize in teaching in higher education. |
| | Material inputs | Computer | Number of computers in the current period. |
| | Financial inputs | Research expenses | Refers to the costs actually spent on higher education in the budgets of the central and local finance ministries. |
| Outputs index | scientific and technical payoffs | Publication of monographs | Refers to the number of exclusive publications of higher education institutions in the current period. |
| | | patents authorized | Refers to the number of patents granted by the patent administration department to higher education institutions in the region in the current period. |
| | community service | Actual income from technology transfer | Refers to the income received by institutions of higher education from the transfer of patented technology, computer software, etc. |

#### 2.1.2. Selection of Exogenous Variables

In addition to government inputs, external environmental factors also play a significant role in the allocation efficiency of higher education. Therefore, when selecting external environment variables, the "separation hypothesis" should be adopted, and the indicator should be chosen with simultaneous consideration of its impact on inputs and outputs, while ensuring it is excluded from the controllable range of the sample. Among the numerous factors affecting the efficiency of resource allocation in education, internal factors are controllable, whereas external factors are uncontrollable. A wide range of external variables may significantly influence the assessment of the efficiency of resource allocation for education. Consequently, in the second stage of the SFA stochastic frontier regression model analysis, the impact of these external factors should be removed before calculating the allocation efficiency of educational resources in each province and city. Drawing on existing studies[8][16], four variables—

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macroeconomic environment, government support, social development, and openness to the outside world-were selected as external variables, with specific quantification as follows:

**Table 2.** Index system of external environment variables

| Indicator categories | One level | Two level | Variable Definition |
|---|---|---|---|
| Environment variables | Economic development | GDP | Refers to the final result of the production activities of all resident units in the area for the current period. |
| | Government support | Education expenditure / public budget expenditure | Refers to the proportion of local government expenditure on education services to general public budget expenditure. |
| | Social development | Urbanization rate | Refers to the rate of urbanization in the current period. |
| | Open to the outside world | Share of total imports and exports in regional GDP | Refers to the share of total imports and exports in regional GDP for the period. |

## 2.2. Data Sources

This paper selects panel data for the period 2019-2023 to analyze the efficiency of higher education resource allocation in China. All data for output indicators are sourced from the "Compendium of Science and Technology Statistics of Higher Education Institutions," compiled by the Department of Science and Technology, Ministry of Education of China. Similarly, all data for input indicators are extracted from the "China Education Statistical Yearbook." Furthermore, all data regarding student environmental variables are obtained from the EPS database.

## 2.3. Three-stage DEA model introduction

Charnes and Cooper (1978) first used the data envelopment analysis (DEA) method to solve the multiple-input multiple-output problem[30].However, this method does not exclude the effects of environmental variables and random noise, so the calculation results are not realistic. In order toTo circumvent this shortcoming, Fried et al. (2002) proposed a three-stage DEA model in 2002[31], and the logical framework is shown in Figure 1.

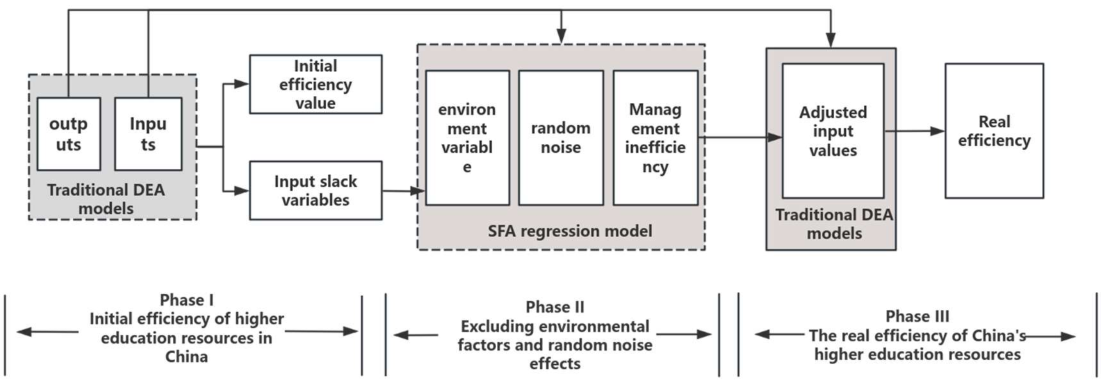


**Figure 1.** Logical framework diagram for the three-phase DEA

### 2.3.1. The First Stage

The first stage is an input-oriented BCC-DEA model for initial efficiency measurement, which can obtain the technical efficiency, pure technical efficiency, scale efficiency of decision-making units and the slack variables of each index. The specific model is as follows:

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$$\text{s.t.}\quad \begin{cases} \sum_{j=1}^{n} x_j\lambda_j + s^- \le \theta x_0 \\ \sum_{j=1}^{n} y_j\lambda_j + s^+ \le y_0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ s^- \le 0, s^+ \ge 0, \lambda_j \ge 0, j = 1,2,\ldots\ldots,n \end{cases} \qquad \text{Formula (1)}$$

where θ is the combined technical efficiency of the decision unit; x and y are the observed values of the input and output indicators, respectively. λ is the weighting coefficient; s - is the improvement in the slack of the input indicator, and s + is the improvement in the slack of the output indicator. n is the number of the decision unit; x0 and y0 denote the vector of inputs and outputs of the oth decision unit, respectively.

### 2.3.2. The Second Stage

This stage is the core of the whole three-stage DEA model. Since the previous stage not only obtains the raw efficiency value, but also derives the slack value of the input factors, i.e. the difference between the actual inputs and the target inputs. Because of the influence of environmental factors and random errors, the actual inputs differ from the target inputs, and a more accurate result can only be obtained by eliminating the relevant influencing factors. Therefore, the regression model of input slack variables with exogenous environmental factors and random errors should be constructed through SFA stochastic frontier analysis. The specific model is as follows:

$$S_{ni} = f(Z_i; \beta_n) + \upsilon_{ni} + u_{ni} \qquad \text{Formula(2)}$$

where i = 1, 2 ..... , 1 is the decision unit, S is the slack variable of the decision unit, f(Zi; βn) represents the exogenous environmental factors, vni+uni is the mixed error term, vni represents the random disturbance, and uni represents the management inefficiency. where v~N(0, σv.), u~N*(0, σu), and v and u are independent of each other.

In separating the managerial inefficiency term, the managerial inefficiency (μ)formula deduced by Jondrow (1982) is adopted[32].

$$E\left(\mu/\varepsilon\right) = \sigma^* \left[ \frac{\phi(\lambda\frac{\varepsilon}{\sigma})}{\phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma} \right], \sigma^* = \frac{\sigma_\mu\sigma_v}{\sigma}, \sigma = \sqrt{\sigma_\mu^{\ 2} + \sigma_v^{\ 2}} \quad \lambda = \frac{\sigma_\mu}{\sigma_v} \qquad \text{formula (3)}$$

The random noise is then measured based on the separated managerial inefficiencies and is calculated as follows:

$$E\left[v_{ni} \middle| v_{ni} + \mu_{ni}\right] = S_{ni} - f(Z_i; \beta_n) - E\left[\mu_{ni} \middle| v_{ni} + \mu_{ni}\right] \qquad \text{formula(4)}$$

Finally, the adjusted new input values under homogeneous conditions. The specific formula is as follows:

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$$X_{ni}^{A} = X_{ni} + [\max(f(Z_i;\beta_n)) - f(Z_i;\beta_n)] + [\max(v_{ni}) - v_{ni}](i = 1,2....I; n = 1,2...N) \quad \text{formula(5)}$$

where XniA is the adjusted input; Xni is the pre-adjusted input; [max(f(Zi; βn))-f(Zi; βn)] is the adjustment for external environmental factors, and [max(vni)-vni] is to bring all decision-making units under the same environment

### 2.3.3. The Third Stage

In the third stage, the input values adjusted in the second stage are used to replace the original data, and the output values remain unchanged, and the BCC-DEA model is applied again for efficiency evaluation to obtain the efficiency values after excluding exogenous environmental factors and stochastic factors.

# 3. Empirical Analysis

## 3.1. The First Stage - Initial Measurement of Resource Allocation Efficiency of Higher Education in China

### 3.1.1. Comprehensive Technical Efficiency Analysis

The first stage employs an analysis based on DEAP 2.1 software, utilizing the BCC model to assess the overall technical efficiency of 31 provinces and cities in China over the five-year period from 2019 to 2023. This analysis also provides an in-depth decomposition of the overall technical efficiency into pure technical efficiency and scale efficiency for the year 2023. The efficiency ratings for the first stage are presented in Table 3.

(1) Overall analysis

We find that without considering the influence of external environmental factors and random disturbances, China's higher education resource allocation efficiency overall maintains a high level during the 2019-2023 period, with the average comprehensive technical efficiency value for each year ranging from 0.8 to 0.9. The highest efficiency value of 0.851 was recorded in 2023, which is 14.9% away from the effective production frontier, indicating room for improvement. Conversely, the lowest efficiency value of 0.812 was observed in 2018, with 18.8% room for improvement from the effective production frontier. According to the results presented in Table 3 and Figure 1, China's higher education resource allocation efficiency during these five years exhibits a smooth and gradual upward trend. However, the distance from the optimal state still requires improvement, and significant disparities exist among the provinces. Specifically, the minimum efficiency values for each year are marked by fluctuations between 0.1 and 0.3 in Tibet, while the maximum efficiency values exhibit a large gap. As shown in Table 3, among the 31 provinces, only five provinces and cities-Beijing, Hebei, Henan, Chongqing, and Shaanxi-achieve an efficiency value of 1 for five consecutive years, meaning these institutions have consistently reached DEA efficiency. These five provinces account for less than one-fifth of all decision-making units (16.13%), demonstrating that colleges and universities in these provinces are the most efficient in their allocation of higher education resources. Conversely, the majority of Chinese provinces are not fully utilizing their educational resources, leading to redundancy and waste in resource allocation.

(2) Sub-regional analysis

We can observe from Table 3 that the average comprehensive technical efficiency of higher education resource allocation across China's central, eastern, western, and northeastern regions is 0.906, 0.855, 0.627, and 0.687, respectively. This indicates that the central region has the highest comprehensive technical efficiency, followed by the eastern region, western region, and northeastern region. From Figure 2, we can also see that the central region's comprehensive technical efficiency has consistently remained above the levels of the other

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three regions, fluctuating roughly around 0.9. The eastern region experienced a declining trend from 2019 to 2021, with its efficiency value rising in 2021 but failing to reach the 2019 level of 0.865 in 2023. The northeastern region exhibits the largest fluctuations, suggesting that it has struggled to find a stable equilibrium point. On the other hand, the western region, which initially had the lowest comprehensive technical efficiency, has been gradually increasing its efficiency value over the years, with the gap between it and the eastern and northeastern regions narrowing progressively.This is mainly due to certain regional differences in the allocation, coordination and technical management of educational resources, which are significantly higher in the central and eastern regions than in the western and northeastern regions.Overall, the efficiency values reveal a gradual upward trend in the western region, while the northeastern region's instability remains a notable issue.

**Table 3.** Comprehensive technical efficiency of the first stage

| Province | 2019 | 2020 | 2021 | 2022 | 2023 | Mean |
|---|---|---|---|---|---|---|
| Beijing | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Tianjin | 0.524 | 0.558 | 0.569 | 0.620 | 0.687 | 0.592 |
| Hebei | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Shanxi | 0.853 | 0.889 | 0.921 | 0.894 | 0.871 | 0.886 |
| Inner Mongolia | 0.957 | 1 | 1 | 0.998 | 1 | 0.991 |
| Liaoning | 0.820 | 0.794 | 0.934 | 0.823 | 0.877 | 0.850 |
| Jilin | 0.658 | 0.698 | 0.709 | 0.789 | 0.854 | 0.742 |
| Heilongjiang | 1 | 0.869 | 0.885 | 0.751 | 0.702 | 0.841 |
| Shanghai | 0.827 | 0.785 | 0.854 | 0.850 | 0.980 | 0.859 |
| Jiangsu | 1 | 1 | 0.941 | 0.974 | 1 | 0.983 |
| Zhejiang | 1 | 1 | 1 | 0.988 | 0.994 | 0.996 |
| Anhui | 0.924 | 0.905 | 0.824 | 0.795 | 0.805 | 0.851 |
| Fujian | 0.864 | 0.795 | 0.768 | 0.805 | 0.734 | 0.793 |
| Jiangxi | 0.952 | 0.906 | 0.841 | 0.816 | 1 | 0.903 |
| Shandong | 0.936 | 0.987 | 1 | 0.854 | 0.794 | 0.914 |
| Henan | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Hubei | 0.752 | 0.798 | 0.875 | 0.888 | 0.924 | 0.847 |
| Hunan | 0.889 | 0.904 | 1 | 1 | 0.944 | 0.947 |
| Guangdong | 0.534 | 0.510 | 0.549 | 0.611 | 0.642 | 0.569 |
| Guangxi | 0.732 | 0.816 | 0.658 | 0.715 | 0.726 | 0.729 |
| Hainan | 0.965 | 0.821 | 0.659 | 1 | 0.803 | 0.850 |
| Chongqing | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Sichuan | 0.795 | 0.879 | 0.906 | 0.917 | 0.934 | 0.886 |
| Yunnan | 0.801 | 0.921 | 1 | 1 | 0.958 | 0.936 |
| Xizang | 0.125 | 0.153 | 0.158 | 0.251 | 0.268 | 0.191 |
| Gansu | 1 | 1 | 0.780 | 0.906 | 1 | 0.937 |
| Qinghai | 0.400 | 0.394 | 0.458 | 0.587 | 0.528 | 0.473 |
| Guizhou | 1 | 0.951 | 1 | 1 | 1 | 0.990 |
| Ningxia | 0.428 | 0.581 | 0.608 | 0.684 | 0.721 | 0.604 |
| Xinjiang | 0.498 | 0.714 | 0.688 | 0.697 | 0.734 | 0.666 |
| Shaanxi | 1 | 1 | 1 | 1 | 1 | 1.000 |
| National Average | 0.812 | 0.824 | 0.825 | 0.841 | 0.851 | 0.823 |
| Maximum | 1 | 1 | 1 | 1 | 1 | - |
| Minimum | 0.125 | 0.153 | 0.158 | 0.251 | 0.268 | 0.191 |
| East average | 0.865 | 0.845 | 0.834 | 0.870 | 0.863 | 0.856 |
| Northeast average | 0.803 | 0.763 | 0.837 | 0.737 | 0.778 | 0.811 |
| Central average | 0.895 | 0.900 | 0.910 | 0.899 | 0.924 | 0.906 |
| Western average | 0.728 | 0.784 | 0.771 | 0.813 | 0.822 | 0.784 |

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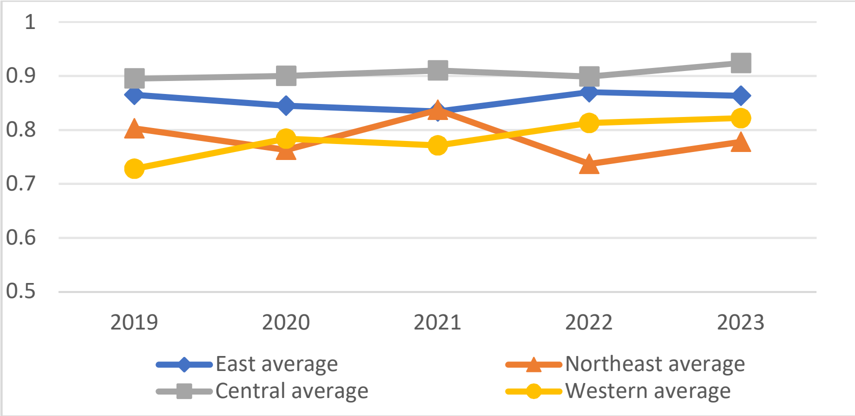


**Figure 2.** Trend Map of Regional Integrated Technical Efficiency (Phase I)

### 3.1.2. Decomposition Analysis of Comprehensive Technical Efficiency

The efficiency values for each province in 2023 reflect a more accurate representation of reality. To further analyze the reasons behind the non-DEA effectiveness of certain provinces, this study will decompose the comprehensive technical efficiency value of 2023 into pure technical efficiency and scale efficiency. Pure technical efficiency refers to the maximum output achievable by a decision-making unit under given inputs, typically resulting from management systems and poor scientific and technological capabilities. This inefficiency can be short-termily addressed by optimizing resource allocation through the deployment of existing resources to achieve efficient output. Scale efficiency, on the other hand, is influenced by the scale factors of the decision-making unit and refers to whether university education operates at the most appropriate scale. When scale efficiency is equal to 1, it indicates optimal scale . Deviations from 1 are interpreted as increments or decrements in scale efficiency.

The results from Table 4 reveal that among the 31 provinces in China, 10 provinces have effectively achieved combined technical and scale efficiency, while 15 provinces have attained pure technical efficiency, representing 32.3% and 48.4% of the total provinces, respectively. Approximately half of the provinces exhibit inefficiency across all three efficiency dimensions, indicating that a significant proportion of Chinese universities are unable to achieve efficient research output under the current allocation of research resources, highlighting room for further improvement.

Among the 21 non-DEA efficient provinces, Qinghai, Tibet, Hunan, Hubei, and Sichuan exhibit inefficiency solely due to scale efficiency issues. This suggests that the universities in these provinces operate at non-optimal scales—either excessively large or insufficiently sized. By examining the returns to scale, it is recommended that Sichuan, Hubei, and Hunan reduce the size of their universities to eliminate diminishing returns, while Tibet and Qinghai should expand their university sizes to leverage increasing returns to scale.Shanxi demonstrates inefficiency due to pure technical efficiency issues, likely stemming from low overall education management levels and research productivity within its universities, coupled with suboptimal utilization of research resources. The remaining 15 provinces exhibit inefficiency due to a combination of pure technical and scale efficiency challenges, suggesting multifaceted issues that require targeted interventions to address both management and scale-related problems.

Since the results of the first-stage DEA include the influence of exogenous environmental variables and random factors, which cannot truly reflect the efficiency of higher education resource allocation in China's provinces, the second-stage DEA analysis is needed to further separate the interfering factors from the calculation.

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**Table 4.** Integrated technical efficiency and its decomposition in the first stage

| Province | Comprehensive technical efficiency | Pure technical efficiency | Scale efficiency | Return of scale |
|---|---|---|---|---|
| Beijing | 1 | 1 | 1 | Invariant |
| Tianjin | 0.687 | 0.558 | 0.933 | Increase progressively |
| Hebei | 1 | 1 | 1 | Invariant |
| Shanxi | 0.871 | 0.840 | 1 | Increase progressively |
| Inner Mongolia | 1 | 1 | 1 | Invariant |
| Liaoning | 0.877 | 0.871 | 0.989 | Decrease progressively |
| Jilin | 0.756 | 0.757 | 0.999 | Increase progressively |
| Heilongjiang | 0.702 | 0.724 | 0.969 | Increase progressively |
| Shanghai | 0.980 | 0.987 | 0.993 | Increase progressively |
| Jiangsu | 1 | 1 | 1 | Invariant |
| Zhejiang | 0.994 | 0.998 | 0.999 | Decrease progressively |
| Anhui | 0.805 | 0.905 | 0.969 | Increase progressively |
| Fujian | 0.734 | 0.795 | 0.979 | Increase progressively |
| Jiangxi | 1 | 1 | 1 | Invariant |
| Shandong | 0.794 | 0.871 | 0.858 | Decrease progressively |
| Henan | 1 | 1 | 1 | Invariant |
| Hubei | 0.924 | 1 | 0.875 | Decrease progressively |
| Hunan | 0.944 | 1 | 0.897 | Decrease progressively |
| Guangdong | 0.642 | 0.510 | 0.874 | Decrease progressively |
| Guangxi | 0.726 | 0.704 | 0.924 | Decrease progressively |
| Hainan | 0.803 | 0.821 | 0.987 | Increase progressively |
| Chongqing | 1 | 1 | 1 | Invariant |
| Sichuan | 0.934 | 1 | 0.906 | Decrease progressively |
| Yunnan | 0.958 | 0.921 | 0.941 | Decrease progressively |
| Xizang | 0.268 | 1 | 0.205 | Increase progressively |
| Gansu | 1 | 1 | 1 | Invariant |
| Qinghai | 0.528 | 1 | 0.528 | Increase progressively |
| Guizhou | 1 | 1 | 1 | Invariant |
| Ningxia | 0.721 | 0.687 | 0.762 | Increase progressively |
| Xainjiang | 0.734 | 0.714 | 0.688 | Increase progressively |
| Shaanxi | 1 | 1 | 1 | Invariant |
| Mean | 0.851 | 0.892 | 0.912 | - |

## 3.2. The Second Stage-analysis of External Environmental Factors Affecting the Efficiency of China's Higher Education Resource Allocation

To obtain the true efficiency values, the second stage establishes an SFA (Stochastic Frontier Analysis) regression model for adjustment and correction, eliminating the influence of exogenous environmental factors and random variables. By normalizing each province under the same environmental level, the efficiency results are more aligned with reality. The slack variables derived from the DEA measurement in the first stage-specifically, the number of

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research and development personnel, expenditure on scientific research, and the number of computers-are used as explanatory variables in the SFA model. Additionally, the four exogenous environment variables-selected as regional economic development , government support, social development degree, and openness to the outside world-are included as explanatory variables after applying a logarithmic transformation. Using Frontier-4.1 software, the regression results are presented in Table 5, providing a clearer and more accurate reflection of the true efficiency of higher education resource allocation across Chinese provinces.

The results from Table 5 reveal that the one-sided t-tests for the four exogenous variables on the three input slack variables yield values of 126.32, 18.96, and 246.39, respectively, all of which exceed the critical value of 15.68 at the 1% significance level.The γ-value of the number of researchers is 0.89, the γ-value of the number of computers is 0.56, and the γ-value of the research expenditure is 0.95, which are all greater than 0.5. Therefore, the selected environmental variables are reasonable and applicable.The regression coefficients reveal that the macroeconomic environment and the redundancy of the three input indicators are significantly negatively correlated, suggesting that improved economic development enhances educational resource efficiency. The regression coefficients for government support are significantly negative for the redundancy of the number of research and development personnel and research expenditure, but significantly positive for the number of computers, indicating that increased government support inhibits the redundancy of research personnel and expenditure while increasing the redundancy of computer numbers. The regression coefficients for the degree of social development and openness to the outside world are significantly positive for the redundancy of all three input indicators, suggesting that higher levels of social development and openness to the outside world increase the redundancy of higher education resources.

**Table 5.** Results of the second-stage SFA regression analysis

| **Envionment variables** | **Slack variable** | | |
|---|---|---|---|
| | **L1** | **L2** | **L3** |
| Economic development | -15112.62***(-45.02) | -25658.69***(-2585.65) | -4015.38***(-115.20) |
| Government support | -2052.19***(6.32) | -31529.36***(-3014.85) | 52036.84***(78.96) |
| Social development | 3698.99(7.86) | 72549.39***(18526.60) | 53687.13***(259.68) |
| Open to the outside world | 399.25***(2.30) | 94178.37***(94178.39) | 23451.98***(15.69) |
| Constant | 14987.63***(39.63) | -221586.74***(-25143.61) | 42589.67***(725.62) |
| $\sigma^2$ | 0.005***(0.005) | 0.0048****(0.0052) | 0.0036***(0.0036) |
| γ | 0.89***(49.06) | 0.56***(7.66) | 0.95***(125.63) |
| Log likelihood | -1528.32 | -2587.39 | -2158.61 |
| LP unilateral test | 126.32*** | 18.96*** | 246.39*** |

## 3.3. The Third Stage-Analysis of the Allocation Efficiency of China's Educational Resources in a Homogeneous Environment

Through the regression analysis of the stochastic frontier model in the second stage, it is found that external environmental factors significantly impact the allocation efficiency of educational resources across provinces. To ensure a consistent baseline for comparison, input indicators are adjusted to place each province under the same environmental conditions. Based on the adjusted input variables and the output values from the first stage, the BCC-DEA model is employed in the third stage to conduct efficiency measurement.

### 3.3.1. Adjusted Consolidated Technical Efficiency Analysis

(1) Overall analysis

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The results from Table 6 indicate that the average comprehensive technical efficiency value for the period 2019-2023 in the third stage falls within the range of 0.7 to 0.8. Compared to the first stage, these values have decreased significantly, with the highest efficiency value dropping from 0.851 to 0.768 and the lowest efficiency value decreasing from 0.812 to 0.715. The distance from the effective production frontier has increased to 28.5%, reflecting a notable gap in efficiency. The trend of China's higher education resource allocation efficiency remains upward, although the results from the third stage reveal that there is still substantial room for improvement and that provincial disparities are larger than those observed in the first stage.

As can be seen from Table 6 and Figure 3, the number of provinces with effective DEA has increased from five provinces (Beijing, Hebei, Henan, Chongqing, and Shaanxi) to six provinces (Beijing, Hebei, Henan, Jiangsu, Shaanxi, and Shandong). Chongqing has transitioned from DEA efficiency to inefficiency, with its comprehensive technical efficiency decreasing from 1 to 0.837. Additionally, Tianjin, Shanxi, Inner Mongolia, Liaoning, Heilongjiang, Zhejiang, Anhui, Fujian, Guangxi, Hainan, Jiangxi, Yunnan, Ningxia, Qinghai, Guizhou, Gansu, Tibet, and Xinjiang exhibit overestimated comprehensive technical efficiency, suggesting that external and random factors have positively influenced the efficiency of educational resource allocation in these provinces. On the other hand, the rising efficiency values of Shanghai, Jiangsu, Shandong, Hubei, Hunan, Guangdong, and Sichuan, which were previously underestimated, indicate that these provinces are efficient in allocating resources to education within a homogeneous environment stripped of environmental factors and random disturbances. Their lower efficiency values were not due to poor technical management but rather to less favorable environmental conditions.

(2) Sub-regional analysis

Compared with the first stage, the third-stage analysis reveals that the average comprehensive technical efficiency of higher education resource allocation across the four regions-Eastern, Central, Western and Northeastern-has declined, dropping from 0.856, 0.906, 0.784 and 0.811 to 0.823, 0.839, 0.612, and 0.687, respectively. The Western region exhibits the largest decline, indicating a significant drop in efficiency. The main reason is that higher education in the western region is more affected by external factors, and when the interference of external factors is removed, the efficiency of its educational resource allocation will show a significant decline.The Central region's efficiency remains comparable to the first stage, maintaining a position above the other regions.In terms of the overall trend of change, after removing exogenous environmental variables and random factors, the four major regions are changing steadily, suggesting that the level of management and research technology in the education industry in each region has not improved much in the past five years.

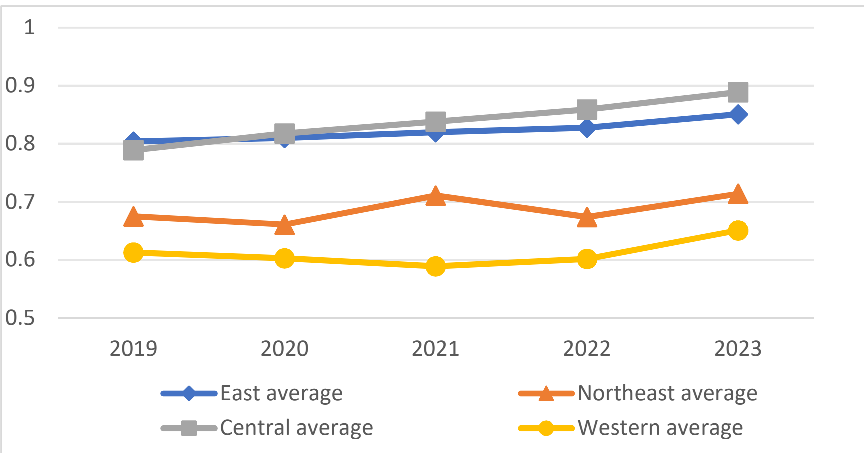


**Figure 3.** Trend Map of Regional Integrated Technical Efficiency (Phase III)

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**Table 6.** Comprehensive technical efficiency of all provinces and cities in the third stage

| Province | 2019 | 2020 | 2021 | 2022 | 2023 | Mean |
|---|---|---|---|---|---|---|
| Beijing | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Tianjin | 0.428 | 0.495 | 0.520 | 0.547 | 0.589 | 0.516 |
| Hebei | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Shanxi | 0.503 | 0.605 | 0.742 | 0.752 | 0.785 | 0.677 |
| Inner Mongolia | 0.820 | 0.752 | 0.792 | 0.814 | 0.884 | 0.812 |
| Liaoning | 0.621 | 0.524 | 0.558 | 0.638 | 0.704 | 0.609 |
| Jilin | 0.589 | 0.625 | 0.692 | 0.638 | 0.756 | 0.660 |
| Heilongjiang | 0.814 | 0.835 | 0.884 | 0.746 | 0.681 | 0.792 |
| Shanghai | 0.836 | 0.884 | 0.905 | 0.941 | 0.967 | 0.907 |
| Jiangsu | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Zhejiang | 0.902 | 0.857 | 0.816 | 0.796 | 0.804 | 0.835 |
| Anhui | 0.841 | 0.806 | 0.792 | 0.754 | 0.769 | 0.792 |
| Fujian | 0.547 | 0.584 | 0.594 | 0.551 | 0.605 | 0.576 |
| Jiangxi | 0.584 | 0.624 | 0.589 | 0.687 | 0.805 | 0.658 |
| Shandong | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Henan | 1 | 1 | 1 | 1 | 1 | 1.000 |
| Hubei | 0.858 | 0.905 | 0.947 | 0.968 | 0.987 | 0.933 |
| Hunan | 0.95 | 0.97 | 0.96 | 0.99 | 0.99 | 0.972 |
| Guangdong | 0.802 | 0.847 | 0.9 | 0.912 | 0.928 | 0.878 |
| Guangxi | 0.754 | 0.652 | 0.574 | 0.558 | 0.608 | 0.629 |
| Hainan | 0.524 | 0.428 | 0.468 | 0.534 | 0.620 | 0.515 |
| Chongqing | 0.854 | 0.884 | 0.806 | 0.795 | 0.845 | 0.837 |
| Sichuan | 0.857 | 0.954 | 0.962 | 0.987 | 0.992 | 0.950 |
| Yunnan | 0.684 | 0.705 | 0.741 | 0.735 | 0.804 | 0.734 |
| Xizang | 0.125 | 0.153 | 0.158 | 0.251 | 0.268 | 0.191 |
| Gansu | 0.805 | 0.741 | 0.674 | 0.745 | 0.808 | 0.755 |
| Qinghai | 0.052 | 0.105 | 0.101 | 0.112 | 0.085 | 0.091 |
| Guizhou | 0.884 | 0.854 | 0.815 | 0.752 | 0.871 | 0.835 |
| Ningxia | 0.205 | 0.152 | 0.115 | 0.096 | 0.247 | 0.163 |
| Xainjiang | 0.320 | 0.287 | 0.335 | 0.378 | 0.405 | 0.345 |
| Shaanxi | 1 | 1 | 1 | 1 | 1 | 1.000 |
| National Average | 0.715 | 0.717 | 0.724 | 0.732 | 0.768 | 0.731 |
| Maximum | 1 | 1 | 1 | 1 | 1 | - |
| Minimum | 0.125 | 0.105 | 0.101 | 0.096 | 0.085 | - |
| East average | 0.804 | 0.810 | 0.820 | 0.828 | 0.851 | 0.823 |
| Northeast average | 0.675 | 0.661 | 0.711 | 0.674 | 0.714 | 0.687 |
| Central average | 0.789 | 0.818 | 0.838 | 0.859 | 0.889 | 0.839 |
| Western average | 0.613 | 0.603 | 0.589 | 0.602 | 0.651 | 0.612 |

### 3.3.2. Comprehensive Technical Efficiency Decomposition Analysis

The results from Table 7 indicate that, in 2023, out of the 31 provinces in China, 6 provinces achieved both combined technical efficiency and scale efficiency effectively, while 22 provinces attained pure technical efficiency effectively. These proportions account for 19.4% and 71.0% of the total provinces, respectively. As can be seen in Figure 4 , the proportion of provinces realizing combined technical efficiency decreased and the proportion of provinces realizing pure technical efficiency increased compared to the first stage. This suggests that the inefficiency identified in the first stage, attributed to pure technical inefficiency, was

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underestimated, whereas the inefficiency due to scale factors was overestimated.The improvement of pure technical efficiency indicates that the level of soft power of China's education industry is low, and the inadequacy of external factors such as the level of economic development, the modernization of society, the management mode, and the level of educational innovation seriously restricts the improvement of its level of development.The significant reduction in scale efficiency indicates that exogenous environmental and stochastic factors have had a large positive impact on the scale efficiency of higher education and have accelerated its development, but that the low value of the actual scale efficiency deserves great attention.

**Table 7.** Integrated technical efficiency and its decomposition in the first stage

| Province | Comprehensive technical efficiency | Pure technical efficiency | Scale efficiency | Return of scale |
|---|---|---|---|---|
| Beijing | 1 | 1 | 1 | Invariant |
| Tianjin | 0.589 | 0.857 | 0.625 | Increase progressively |
| Hebei | 1 | 1 | 1 | Invariant |
| Shanxi | 0.785 | 0.952 | 0.748 | Increase progressively |
| Inner Mongolia | 0.884 | 1 | 0.683 | Increase progressively |
| Liaoning | 0.704 | 0.805 | 0.796 | Increase progressively |
| Jilin | 0.756 | 0.682 | 0.784 | Invariant |
| Heilongjiang | 0.681 | 0.99 | 0.851 | Increase progressively |
| Shanghai | 0.967 | 1 | 0.852 | Increase progressively |
| Jiangsu | 1 | 1 | 1 | Invariant |
| Zhejiang | 0.804 | 1 | 0.999 | Increase progressively |
| Anhui | 0.769 | 0.802 | 0.874 | Increase progressively |
| Fujian | 0.605 | 0.952 | 0.748 | Increase progressively |
| Jiangxi | 0.805 | 1 | 0.804 | Increase progressively |
| Shandong | 1 | 1 | 1 | Invariant |
| Henan | 1 | 1 | 1 | Invariant |
| Hubei | 0.987 | 1 | 0.908 | Increase progressively |
| Hunan | 0.99 | 1 | 0.897 | Increase progressively |
| Guangdong | 0.928 | 0.510 | 0.99 | Increase progressively |
| Guangxi | 0.608 | 1 | 0.687 | Increase progressively |
| Hainan | 0.620 | 1 | 0.620 | Increase progressively |
| Chongqing | 0.845 | 1 | 0.871 | Increase progressively |
| Sichuan | 0.992 | 0.954 | 0.904 | Increase progressively |
| Yunnan | 0.804 | 1 | 0.941 | Increase progressively |
| Xizang | 0.268 | 1 | 0.268 | Increase progressively |
| Gansu | 0.808 | 1 | 0.808 | Increase progressively |
| Qinghai | 0.085 | 1 | 0.085 | Increase progressively |
| Guizhou | 0.871 | 1 | 0.952 | Increase progressively |
| Ningxia | 0.247 | 1 | 0.247 | Increase progressively |
| Xainjiang | 0.405 | 1 | 0.405 | Increase progressively |
| Shaanxi | 1 | 1 | 1 | Invariant |
| Mean | 0.768 | 0.952 | 0.785 | - |

As can be seen in Table 7 and Figure 4,the higher education resource allocation performance values obtained in 2023 for all provinces of China in a homogeneous environment show that

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the overall development of higher education resource allocation performance in China has changed from a high level to an average level .The comprehensive technical efficiency value has decreased from 0.851 to 0.768, indicating that the efficiency values of most provinces were overestimated. This overestimation is primarily attributed to the interplay of pure technical inefficiency and scale inefficiency. Specifically, the average value of pure technical efficiency has shifted from being slightly lower than the average value of scale efficiency to being significantly higher, suggesting that scale inefficiency has emerged as the primary constraint in higher education resource allocation efficiency. From the point of view of scale remuneration, the provinces with decreasing scale remuneration become increasing scale remuneration, and the provinces with constant scale remuneration drop from 10 to 6, with the majority of provinces with increasing scale efficiency, so the vast majority of provinces in our country do not meet the demand for school running, and need to expand the scale of higher education in order to achieve the optimal performance of resource allocation. However, the rapid expansion of higher education scales, as previously analyzed, poses risks of imbalances between educational input and output. Therefore, it is imperative to scale education expansions based on local development levels. If higher education output does not increase substantially in the short term while resources are consumed through scale expansions, it will inevitably lead to a significant reduction in the efficiency of resource allocation for higher education.

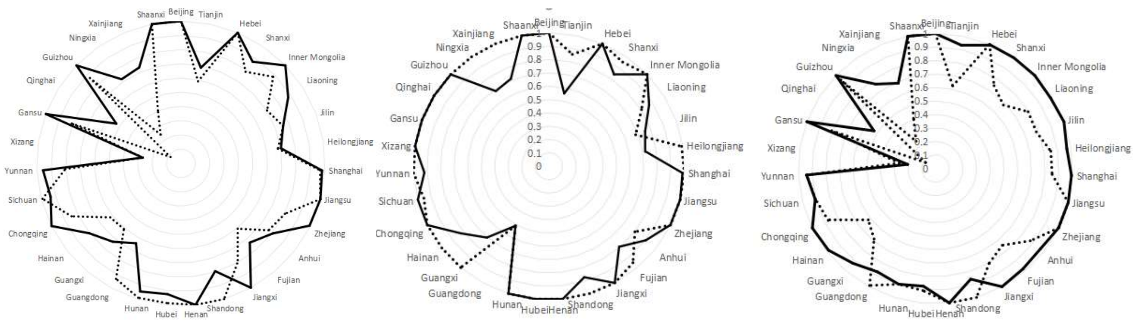

**Figure 4.** Efficiency of provinces before and after removing environmental variables and random noise from higher education

Note: The solid line is the efficiency before removing environmental variables and random noise, and the dashed line is the efficiency after. Comprehensive technical efficiency(first from the left), pure technical efficiency (second from the left), and scale efficiency (third from the left).

# 4. Conclusion and Recommendations

## 4.1. Conclusion

Based on the panel data of 31 provinces in China from 2019 to 2023, this paper employs a three-stage BCC-DEA model to analyze the temporal allocation efficiency of China's higher education resources. The specific findings are as follows: Firstly, the overall efficiency of higher education resources in China is generally at an average level. Compared to the first stage, the comprehensive efficiency of higher education resource allocation in the third stage (2019-2023) declined from 0.851 to 0.731, indicating that the efficiency value remains in the upper-middle range. However, only 19.35% of the provinces achieve DEA efficiency, while the vast majority of provinces have yet to achieve optimal resource allocation, with significant room for improvement and substantial disparities among provinces. Secondly, the allocation efficiency of higher education resources in China is influenced by external factors. After removing the impact of these external factors and random disturbances in the second stage, the re-measured comprehensive technical efficiency has declined, suggesting that higher education resources in

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most provinces are generally overestimated under the interference of external factors. Therefore, provinces should fully leverage favorable external environments to enhance the efficiency of higher education resource allocation across multiple dimensions. Thirdly, the efficiency of higher education resource allocation varies significantly across regions. The highest efficiency is observed in the central region, while the lowest efficiency is found in the western region, with a relatively large gap between the two. Through further decomposition of the comprehensive technical efficiency, it is revealed that some provinces fail to achieve optimal comprehensive efficiency due to pure technical inefficiency, while others fall short due to scale inefficiency. Therefore, each province should optimize higher education resource allocation based on its specific circumstances.

### 4.2. Recommendations

(1) The government needs to tailor differentiated development strategies for each region to ensure the balanced development of higher education. The eastern region, which is rich in educational resources, should promote the development of higher education clusters based on its geographical advantages and strengthen inter-university cooperation and resource sharing, so as to enhance the efficiency of social transformation of higher education achievements. For the relatively resource-poor western region, the transformation and upgrading of the higher education system should be driven by focusing on the construction of higher education infrastructures and formulating policies for the introduction and cultivation of talents.

(2) Expanding the diversity of educational resource sources is crucial for sustainable educational development. The study reveals that the strength of government support significantly enhances the efficiency of educational resource allocation. However, colleges and universities cannot solely rely on government funding to achieve long-term educational development; they should also actively explore additional sources of education funding and strengthen their own financial independence. To this end, institutions should first focus on optimizing asset utilization by developing idle assets and idle teaching and research equipment for reasonable configuration, thereby promoting resource sharing between universities and colleges and enhancing asset utilization efficiency. Additionally, universities and colleges should adjust their tuition policies to improve the cost-sharing mechanism and implement a tiered fee policy tailored to different levels of education, ultimately achieving better resource allocation efficiency.

(3) Build a scientific efficiency evaluation system. While focusing on the quantity of scientific research results, gradually shift the focus of assessment to the quality of scientific research. The frequency of assessment of researchers should not be too fast, and researchers should be given enough academic space and research time to promote the output of high-quality results. Colleges and universities can identify their own problems based on the evaluation results and actively take corresponding countermeasures to improve the quality of higher education.

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