

Analyzing Efficiency Drivers in Higher Education Systems: Integrating Dual-Frontier DEA and Regression Models

Yanan Wang, Tingting Hong

School of Finance, Shandong University of Finance and Economics, Jinan, China

Email: 20173948@sdufe.edu.cn

How to cite this paper: Wang, Y. N., & Hong, T. T. (2026). Analyzing Efficiency Drivers in Higher Education Systems: Integrating Dual-Frontier DEA and Regression Models. *Open Journal of Social Sciences*, 14, 168-187.

<https://doi.org/10.4236/jss.2026.142011>

Received: January 11, 2026

Accepted: February 6, 2026

Published: February 9, 2026

Copyright © 2026 by author(s) and Scientific Research Publishing Inc. This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

This study uses a dual-frontier data envelopment analysis model and regression analysis to evaluate the efficiency of China's higher education system, including its general education and vocational education subsystems and to analyze their driving factors. The research results show that there is significant regional disparity and structural imbalance in the overall efficiency of China's higher education system. As for the subsystems, except for a few regions showing coordinated efficiency, most provinces have a mismatched development feature of one strong and one weak subsystem. Furthermore, the regression analysis shows that the efficiency of the higher education system is synergistically driven by four dimensions: government, economy, society and universities. In summary, efforts to improve efficiency should involve establishing a multi-stakeholder governance framework led by government investment, within which universities optimize resource allocation through strategic academic resource development, and the broader economic and social environment provides an indispensable foundation for enhancement. Policy formulation should recognize the regional and subsystem differences and adopt corresponding policies.

Keywords

Dual-Frontier DEA, Higher Education System Efficiency, Regional Disparities

1. Introduction

Bringing together the best country for education lies in higher education. This vision was even more clearly articulated at the State Council executive meeting in

early 2025: “Promote coordinated reform of university education approaches, research systems, schools and governance, to form a good loop of education, science and technology, and talent cultivation. High-quality development of higher education provides strong support for China’s overall modernization.” With the gross enrollment rate of higher education in China reaching 60.2% and entering the universalization stage, improving education quality and optimizing resource allocation have become key links. The landscape of Chinese higher education is undergoing profound and continuous transformations in both scale and structure. Since the 18th CPC National Congress, China has opened up 21,000 undergraduate majors and withdrawn or suspended 12,000 undergraduate majors that are not in line with the development of economy and society. In 2024, 3343 related majors have been adjusted. In terms of adjustment strength, it is unprecedented. This comprehensive restructuring demonstrates the nation’s commitment to aligning higher education with the demands of economic and social development. Concurrently, a new wave of technological revolution and industrial transformation, driven particularly by advances in artificial intelligence and big data, is profoundly reshaping the landscape and models of higher education. Opinions on Accelerating the Rapid Development of Education Digitalization issued by nine departments including the Ministry of Education are trying to explore new spaces for development and create new competitive advantages through education digitalization. Digital technology has not only changed the production and dissemination of knowledge, but also promoted the accurate allocation of educational resources to strategic emerging industries, thereby promoting personalized learning and teaching.

Facing the dual challenges of structural transformation and technological paradigm shift, establishing a scientifically reasonable efficiency evaluation system for higher education to achieve optimal allocation of higher education resources has become particularly important. Not only does this issue directly respond to the national policies of improving the efficiency of higher education in serving high-quality development, but it is also an important link to improve the allocation of educational resources and serve the socio-economic development of regions.

In terms of research methods of evaluating higher education efficiency, parametric approach and non-parametric approach have emerged as the two mainstream paradigms. Concerning the theoretical decomposition of efficiency dimensions of higher education institutions, Lindsay (1982) first advanced theoretical basis for evaluation methods classification of higher education institutions by systematically decomposing efficiency dimensions and classifying three kinds of evaluation methods step by step: input-output ratio analysis, regression analysis and production frontier analysis. Within the parametric methods, Titus et al. (2016) advanced systematic review about application of Stochastic Frontier Analysis (SFA) in evaluating degree productivity of higher education institutions. By comparing different models, they provided a stepwise parametric analytical frame-

work for research on higher education institution efficiency. Regarding nonparametric approach, Data Envelopment Analysis (DEA) is widely employed due to its distinct advantage in handling multi-input, multi-output problems. [Yu et al. \(2024\)](#) use three-stage DEA model to measure higher education fiscal expenditure efficiency in China's 31 provinces and cities. [Chen et al. \(2021\)](#) solve the problem of evaluating the efficiency of university teaching and research resources allocation in sharing process by establishing two-stage network DEA model.

From a research perspective, the existing studies present evident tendency of gradually extending from micro level of individuals to macro level of systems and from single-tiered to multi-tiered levels. At the micro level, [Naderi \(2022\)](#) use multi-level boundary analysis method to establish a research framework and find out that the heterogeneity across three-tiered structures—departments, faculties, and colleges within universities—exerts a significant influence on efficiency evaluation. At the meso level, [Moreno-Gómez et al. \(2019\)](#) compare the efficiency of Colombia's higher education system and identify differences between public and private universities across various efficiency levels. At the macro level, [Thanassoulis et al. \(2011\)](#) use the DEA method to study UK higher education institutions. Through Malmquist index, they uncovered patterns of productivity change in universities during periods of scale expansion. [Johnes & Yu \(2008\)](#) use DEA method to study the research efficiency of China's universities. Their analysis revealed that there exists great influence of resource allocation on efficiency from two aspects of regional disparity and school type at the same time. All the above researches promote the development of diversified and systematic higher education institutions' efficiency research and lay solid foundation for later research.

The review of the existing literature shows that although some achievements have been made, there are still some limitations: Firstly, China's higher education includes general higher education (GHES) and vocational higher education (VHES). There is a lack of methodological research on constructing a comprehensive evaluation framework that can take into account the cross-subsystem heterogeneous characteristics of GHES and VHES. Secondly, research on the interaction between these two subsystems and its impact on overall system efficiency remains scarce. Thirdly, there is still a lack of systematic multidimensional integration analysis on the factors affecting the higher education efficiency.

Based on above research, the possible marginal application effects of this study are as follows: First, this paper uses a dual-frontier parallel data envelopment analysis model, applying it to the higher education system and then dividing it into two parallel subsystems (general higher education, vocational higher education). Second, the internal structure of the higher education system is exposed by the simultaneous efficiency analysis of both subsystems and the overall system. Third, an integrated analytical framework of four dimensions of government, economy, society, and universities is constructed, which explores the multiple driving mechanism of the higher education efficiency in a systematic way, provides a more

comprehensive theoretical basis and practical reference for the optimal allocation of higher education resources.

The structure of this paper is as follows: Chapter 2 reviews parallel system models and proposes a dual frontier model; Chapter 3 conducts a comprehensive empirical analysis of China's higher education across 31 provinces from 2021 to 2023; Chapter 4 summarizes the entire study.

2. Research Methods

Based on the theoretical framework proposed by Kao (2012), this paper comprises two parallel subsystems. Figure 1 illustrates the parallel system structure of the provincial higher education system.

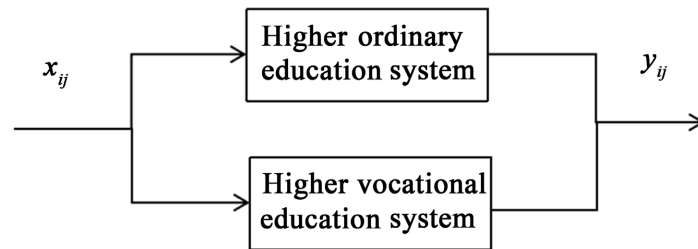


Figure 1. Two parallel systems of a higher education system.

Assume that each provincial higher education system (denoted as $DMU_j, j = 1, \dots, n$) consumes input $x_{ij}^1 (i = 1, 2, \dots, m)$ items in the first subsystem while simultaneously obtaining outputs $y_{rj}^1 (r = 1, 2, \dots, s)$ in the second subsystem, it consumes inputs $x_{ij}^2 (i = 1, 2, \dots, m)$ while simultaneously producing outputs $y_{rj}^2 (r = 1, 2, \dots, s)$.

Under constant returns to scale, the efficiency evaluation model for the two subsystems is as follows:

$$E_{1j} = \frac{\sum_{r=1}^s u_r y_{rj}^1}{\sum_{i=1}^m v_i x_{ij}^1} \quad (1)$$

$$E_{2j} = \frac{\sum_{r=1}^s u_r y_{rj}^2}{\sum_{i=1}^m v_i x_{ij}^2} \quad (2)$$

The unknown variables u_r, v_i, ω_t in the equation represent the relative weight coefficients of x_{ij}^k, y_{rj}^k .

Models (1) and (2) can employ a weighted approach to integrate the efficiencies of each subsystem into the overall system efficiency, that is,

$$E_0 = \omega_1 E_{10} + \omega_2 E_{20} \quad (3)$$

where E_{10} and E_{20} denote the efficiencies of the two subsystems, and ω_1 and ω_2 represent the relative importance weights of the two subsystems, respectively. According to the study by Chen et al. (2010), the weights are determined based on the proportion of the input share of the two subsystems relative to the total input. Therefore, weights ω_1 and ω_2 can be expressed in the following form, and

$$\omega_1 + \omega_2 = 1.$$

$$\omega_1 = \frac{\sum_{i=1}^m v_i x_{ij}^1}{\sum_{i=1}^m v_i x_{ij}^1 + \sum_{i=1}^m v_i x_{ij}^2} \tag{4}$$

$$\omega_2 = \frac{\sum_{i=1}^m v_i x_{ij}^2}{\sum_{i=1}^m v_i x_{ij}^1 + \sum_{i=1}^m v_i x_{ij}^2} \tag{5}$$

After substituting all the above formulas into model (3), model (6) for calculating the overall system efficiency can be derived:

$$E_0 = \omega_1 E_{10} + \omega_2 E_{20} = \frac{\sum_{r=1}^s u_r y_{rj}^1 + \sum_{r=1}^s u_r y_{rj}^2}{\sum_{i=1}^m v_i x_{ij}^1 + \sum_{i=1}^m v_i x_{ij}^2} \tag{6}$$

2.1. Optimistic Model

The traditional DEA model evaluates decision units from the perspective of an optimistic frontier. By defining an optimal production frontier, it assesses the relative technical efficiency of each decision unit, hence, it is also known as the “optimistic DEA model.” The optimistic efficiency value of the “optimal” decision unit is 1, positioned on the efficient frontier. A lower optimistic efficiency indicates that the unit has the greatest potential for proportionally reducing inputs relative to the optimal unit, thus being in a relatively less efficient state. Therefore, under optimistic conditions, the model is as follows:

$$\max E_0^O = \frac{\sum_{r=1}^s u_r y_{r0}^1 + \sum_{r=1}^s u_r y_{r0}^2}{\sum_{i=1}^m v_i x_{i0}^1 + \sum_{i=1}^m v_i x_{i0}^2} \tag{7}$$

$$\text{s.t. } \frac{\sum_{r=1}^s u_r y_{rj}^1}{\sum_{i=1}^m v_i x_{ij}^1} \leq 1, j = 1, \dots, n$$

$$\frac{\sum_{r=1}^s u_r y_{rj}^2}{\sum_{i=1}^m v_i x_{ij}^2} \leq 1, j = 1, \dots, n$$

$$u_r, v_i \geq 0, i = 1, \dots, m; r = 1, \dots, s.$$

E_0^O represents the optimistic efficiency value of the DMU. The DMU is optimistic efficient if and only if $E_0^O = 1$ holds. The subsystem is optimistic efficient if and only if $E_{1j}^O = 1$ (or $E_{2j}^O = 1$) holds.

Model (7) is a fractional model. To linearize it, the following procedure is used to transform Model (7) into a linear model.

$$\max \sum_{r=1}^s u'_r y_{r0}^1 + \sum_{r=1}^s u'_r y_{r0}^2 \tag{8}$$

$$\text{s.t. } \sum_{i=1}^m v'_i x_{i0}^1 + \sum_{i=1}^m v'_i x_{i0}^2 = 1$$

$$\sum_{r=1}^s u'_r y_{rj}^1 - \sum_{i=1}^m v'_i x_{ij}^1 \leq 0, j = 1, \dots, n$$

$$\sum_{r=1}^s u'_r y_{rj}^2 - \sum_{i=1}^m v'_i x_{ij}^2 \leq 0, j = 1, \dots, n$$

$$u'_r, v'_i \geq 0, i = 1, \dots, m; r = 1, \dots, s.$$

Ultimately, solutions v_i^* and u_r^* can be derived, yielding the efficiency values for GHES and VHES as follows:

$$E_{10}^{O^*} = \frac{\sum_{r=1}^s u_r^* y_{r0}^1}{\sum_{i=1}^m v_i^* x_{i0}^1} \quad \text{and} \quad E_{20}^{O^*} = \frac{\sum_{r=1}^s u_r^* y_{r0}^2}{\sum_{i=1}^m v_i^* x_{i0}^2}$$

2.2. Pessimistic Model

Khanjarpanah et al. (2018) proposed the pessimistic efficiency model based on the classical DEA framework. The core concept of the pessimistic efficiency model mirrors that of traditional models, referring to the maximum proportional variation in inputs while maintaining constant outputs. This is compared against the “worst” decision unit and termed pessimistic efficiency. The pessimistic efficiency value of the “worst” decision unit equals 1 and locates in the inefficiency frontier. The larger the pessimistic efficiency is, the more input items can be proportionally increased in a smaller proportion compared with that of the “worst” unit and then the state of relative efficiency. Therefore, the pessimistic efficiency can be constructed by the following model:

$$\begin{aligned} \max E_0^P &= \frac{\sum_{r=1}^s u_r y_{r0}^1 + \sum_{r=1}^s u_r y_{r0}^2}{\sum_{i=1}^m v_i x_{i0}^1 + \sum_{i=1}^m v_i x_{i0}^2} & (9) \\ \text{s.t.} \quad & \frac{\sum_{r=1}^s u_r y_{rj}^1}{\sum_{i=1}^m v_i x_{ij}^1} \geq 1, j = 1, \dots, n \\ & \frac{\sum_{r=1}^s u_r y_{rj}^2}{\sum_{i=1}^m v_i x_{ij}^2} \geq 1, j = 1, \dots, n \\ & u_r, v_i \geq 0, i = 1, \dots, m; r = 1, \dots, s. \end{aligned}$$

Similar to Model (7), Model (9) can be transformed into the following linear model:

$$\begin{aligned} \max \quad & \sum_{r=1}^s u'_r y_{r0}^1 + \sum_{r=1}^s u'_r y_{r0}^2 & (10) \\ \text{s.t.} \quad & \sum_{i=1}^m v'_i x_{i0}^1 + \sum_{i=1}^m v'_i x_{i0}^2 = 1 \\ & \sum_{r=1}^s u'_r y_{rj}^1 - \sum_{i=1}^m v'_i x_{ij}^1 \geq 0, j = 1, \dots, n \\ & \sum_{r=1}^s u'_r y_{rj}^2 - \sum_{i=1}^m v'_i x_{ij}^2 \geq 0, j = 1, \dots, n \\ & u'_r, v'_i \geq 0, i = 1, \dots, m; r = 1, \dots, s. \end{aligned}$$

Ultimately, solutions v_i^* and u_r^* can be derived, yielding the efficiency values for GHES and VHES as follows:

$$E_{10}^{P^*} = \frac{\sum_{r=1}^s u_r^* y_{r0}^1}{\sum_{i=1}^m v_i^* x_{i0}^1} \quad \text{and} \quad E_{20}^{P^*} = \frac{\sum_{r=1}^s u_r^* y_{r0}^2}{\sum_{i=1}^m v_i^* x_{i0}^2}$$

2.3. Overall Efficiency

The optimistic DEA model and pessimistic DEA model evaluate the efficiency of

decision-making units based on two different frontiers, and their evaluation results may be different. These two approaches are mutually complementary; if we just use one of these two views, the evaluation results may be biased. Therefore, it is necessary to combine the optimistic DEA model and the pessimistic DEA model to construct the dual-frontier DEA model. This approach can make an effective and accurate evaluation of the decision units and get more comprehensive and realistic results, and also can improve the ranking and differentiation of decision units.

There are many methods to calculate the overall efficiency of dual-frontier DEA model. This paper chooses the method of Wang & Lan (2011) and uses the geometric mean method to combine the optimistic and pessimistic efficiencies. The geometric mean locates in the overall efficiency of dual-frontier DEA model. Its formula is shown as follows:

$$E_0^{overall} = \frac{E_0^{O^*}}{\sqrt{\sum_{j=1}^n (E_0^{O^*})^2}} + \frac{E_0^{P^*}}{\sqrt{\sum_{j=1}^n (E_0^{P^*})^2}} \quad (11)$$

where $E_0^{O^*}$ and $E_0^{P^*}$ represent the optimistic and pessimistic efficiency scores of the decision unit, respectively.

3. Empirical Study

3.1. Data Selection and Sources

This paper uses China's 31 provincial-level administrative regions from 2021 to 2023 as the research sample. Hong Kong SAR, Macao SAR, and Taiwan region were excluded owing to significant data unavailability. Considering the regional development differences, the 31 provincial-level regions are divided into four economic zones according to the regional classification principles published in the "Statistical System and Classification Standards" on the website of National Bureau of Statistics of China. These zones are the Eastern, Central, Western, and Northeast regions. The specific divisions are shown in Table 1.

Table 1. Distribution of China's 31 provincial administrative units.

Areas	Provinces/municipalities/autonomous regions
Eastern area	Beijing Shanghai Tianjin Guangdong Shandong Hainan Zhejiang Jiangsu Fujian Hebei
Central area	Jiangxi Anhui Hunan Henan Hubei Shanxi
Western area	Sichuan Inner Mongolia Ningxia Guizhou Guangxi Shaanxi Yunnan Gansu Xinjiang Qinghai Chongqing Xizang
Northeast area	Liaoning Heilongjiang Jilin

Based on relevant literature (Zhang et al., 2020; Fandel et al., 2007; Anderson et al., 2007; Wu et al., 2020), the selected indicators are listed in Table 2:

Table 2. Input-output table.

Higher general education system	Input	Higher Education Expenditure
		Full-time Faculty
		Number of Schools
	Output	Undergraduate Enrollment
		Graduate Student Enrollment
		Number of Invention Patents Granted
Higher vocational education system	Input	Higher Education Expenditure
		Full-time Faculty
		Number of Schools
	Output	Vocational Enrollment
		Projected Graduates
		Number of Invention Patents Granted

Note: The input and output data for each subsystem in this paper are directly sourced from provincial statistics and have been clearly categorized under either regular higher education or vocational higher education in accordance with the national higher education statistical classification standards. **Data sources:** “China Education Statistical Yearbook 2021-2023”, “China Education Expenditure Statistical Yearbook 2021-2023”, “Compilation of Science and Technology Statistics in Higher Education Institutions 2021-2023”, “Annual Report on the Quality of Higher Vocational Education”.

1) Higher Education Funding: This indicates the material foundation upon which universities conduct teaching, research, and administrative activities. It includes spending on the purchase of teaching equipment, faculty salaries, and research projects. The amount of investment has a direct impact on the quality and development potential of higher education.

2) Full-time Faculty Count: Full-time faculty members are the main bodies responsible for performing teaching functions. The number of full-time faculty members is an important indicator of a university’s faculty resources. A sufficient and high-quality full-time faculty is an important means of guaranteeing quality in teaching.

3) Number of Institutions: This reflects the scale of higher education provision. The number of institutions is closely related to the distribution of educational resources and regional access to education.

4) Undergraduate Enrollment: Undergraduate education is a basic function of general higher education. Undergraduate enrollment numbers reflect the scale of talent cultivation and serve as an important indicator of the social influence and attractiveness of an institution.

5) Graduate enrollment: Graduate education is a higher level of higher education. Enrollment numbers reflect the scale and level of an institution’s talent cul-

tivation in high-level talents. It plays an important role in promoting scientific innovation and the development of society.

6) Vocational Education Enrollment: Enrollment numbers reflect the scale of talent cultivation in vocational higher education. It reflects the societal demand for vocational education and the social attractiveness of vocational institutions.

7) Projected Graduate Numbers: Graduates directly embody vocational education's contribution to socioeconomic development. Projected graduate numbers partially reflect vocational institutions' talent cultivation efficiency and capacity to supply future labor markets.

8) Number of granted invention patents: Invention patents are important indicators of the research achievements of universities. They reflect the level of scientific innovation achieved by universities and their degree of contribution to technological development in society. Vocational higher education also focuses on research achievements and innovation. The number of granted invention patents reflects the achievements in terms of technological R&D and innovation attained by vocational institutions. It plays a positive role in enhancing the social recognition and competitiveness of vocational education.

3.2. Analysis of Provincial Higher Education Systems

3.2.1. Overall Evaluation Analysis

According to the measurement results, the mean values for China's higher education system from 2021 to 2023 are shown in **Figure 2**. Optimistic efficiency exhibits an overall upward trend, reflecting the gradual improvement in the performance of China's higher education system under ideal conditions. The increase in optimistic efficiency indicates that the efficiency level achievable under optimal conditions is continuously rising, which to some extent, reflects the overall enhancement of China's higher education system and its strengthened capacity for resource allocation. Unlike the sustained rise in optimistic efficiency, pessimistic efficiency exhibits a trend of initial increase followed by decline, reflecting that the performance of China's higher education system underwent a process of initial improvement followed by deterioration. Comprehensive efficiency is the combination of optimistic and pessimistic efficiency. Compared with optimistic efficiency and pessimistic efficiency, comprehensive efficiency has a more comprehensive and objective reflection of the actual efficiency level of the higher education system. From 2021 to 2023, the comprehensive efficiency level of the national higher education system of China increased slightly, which means that the overall situation of the higher education system has improved slightly. The comprehensive efficiency level of sustained increase in optimistic efficiency provides positive impetus for improving comprehensive efficiency. The efficiency level of initial increase and then decrease in pessimistic efficiency has a certain restraining effect on comprehensive efficiency. Overall, the upward momentum of optimistic efficiency is greater than the downward restraining effect of pessimistic efficiency, so there is a slight upward trend in overall efficiency. It is obvious that the evaluation results based on different frontiers are different.

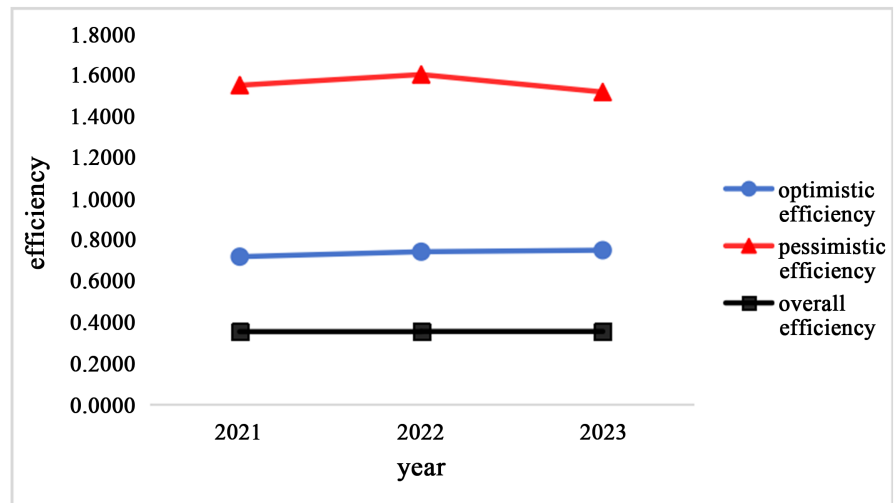


Figure 2. Average efficiency of the higher education system by year nationwide.

Therefore, when evaluating the efficiency of higher education, we should not only focus on the single system overall situation but also consider the system's different states and contexts. Only by evaluating the optimistic efficiency and pessimistic efficiency in detail can we make a more thorough and objective judgment on the efficiency level of the higher education system.

In 2021, the efficiency of China's higher education system was the lowest in 2021-2023. This may be because 2021 was the year in which the COVID-19 pandemic had the greatest impact on higher education. The disturbance of the pandemic forced an overall adjustment of the higher education system, which may have caused a negative impact on the efficiency of the higher education system in 2021 and thus caused the efficiency level to be the lowest in that year. The efficiency peak value in 2023 may be because after the pandemic, appropriate adjustments were made in various aspects of the higher education system, and the education industry received more national investment, universities accelerated the digital transformation, online and offline teaching became more orderly and mature, educational resource allocation became more rational, and all these factors together improved the efficiency.

3.2.2. Analysis of the Higher Education Subsystem

Based on the model, we calculated the efficiency scores and rankings of China's higher education systems and subsystems in the 31 provinces, municipalities, and autonomous regions from 2021 to 2023. The results are shown in **Table 3**.

In the GHES, efficiency driving forces are different. Jiangsu (0.4541), Sichuan (0.4250), Chongqing (0.4130) rank in the top three. It can be seen that Jiangsu has built a virtuous cycle of technological innovation and high-end talent cultivation with its strong economy and dense concentration of top universities and research institutes. Sichuan and Chongqing may also take advantage of the national strategy of the Chengdu-Chongqing Economic Circle to improve the academic output of GHES by adjusting the layout of research strength and attracting talents. As for

Table 3. Three-year average efficiency values and rankings for the higher education sub-system.

Region	HES	Rank	VHES	Rank	GHES	Rank
Beijing	0.3452	20	0.1860	30	0.3835	9
Tianjin	0.3428	22	0.3697	14	0.3452	19
Hebei	0.3561	18	0.3611	18	0.3398	21
Shanxi	0.3651	13	0.3644	17	0.3670	11
Inner Mongolia	0.2833	28	0.2757	27	0.2859	28
Liaoning	0.3303	24	0.3739	11	0.3367	22
Jilin	0.3606	17	0.4230	5	0.3590	12
Heilongjiang	0.3837	9	0.3715	13	0.3984	7
Shanghai	0.3051	26	0.2897	25	0.3297	24
Jiangsu	0.4338	2	0.3982	8	0.4541	1
Zhejiang	0.3838	8	0.3686	15	0.3950	8
Anhui	0.3640	15	0.3683	16	0.3497	18
Fujian	0.3445	21	0.3459	20	0.3405	20
Jiangxi	0.3651	14	0.3531	19	0.3510	17
Shandong	0.4039	5	0.4276	4	0.3673	10
Henan	0.4158	3	0.3990	7	0.4078	5
Hubei	0.3770	12	0.4317	3	0.3552	15
Hunan	0.4049	4	0.3804	10	0.4103	4
Guangdong	0.4006	6	0.3835	9	0.4026	6
Guangxi	0.4378	1	0.4817	1	0.3562	13
Hainan	0.3218	25	0.3160	23	0.3340	23
Chongqing	0.3782	11	0.3375	22	0.4130	3
Sichuan	0.3990	7	0.3736	12	0.4250	2
Guizhou	0.3458	19	0.3425	21	0.3100	27
Yunnan	0.3790	10	0.4318	2	0.3273	25
Xizang	0.2010	31	0.1827	31	0.2249	31
Shaanxi	0.3609	16	0.4227	6	0.3521	16
Gansu	0.3026	27	0.2838	26	0.3139	26
Qinghai	0.2583	30	0.2447	29	0.2722	29
Ningxia	0.2658	29	0.2725	28	0.2704	30
Xinjiang	0.3394	23	0.3065	24	0.3558	14

the general higher education, there are also some challenges. Even for the top-ranked Beijing, its efficiency of GHES is only 0.3835 and it hasn't reached the top level (the top-ranked efficiency is 0.4541 of Jiangsu); while the efficiency of Shanghai (0.3297, 24th) is much lower than that of Beijing. It means that in the region with highly concentrated high-quality higher education resources, the simple investment in resources may also face the problem of diminishing returns. The operational costs of top research universities are extraordinarily high. If their disciplinary structures become homogenized or fail to align closely with emerging industry needs, the efficiency of translating academic achievements into practical outcomes may see limited growth. In addition, the relatively low GHES efficiency in some central and western provinces, such as Guizhou (0.3100) and Gansu (0.3139), may largely reflect their underlying problems in attracting and retaining high-caliber faculty, winning competitive research funding, and improving the quality of their degree programs.

Furthermore, the efficiency performance of the VHES has different characteristics in different regions. Guangxi (0.4817), Yunnan (0.4318), Hubei (0.4317) are ranked in the top three. Guangxi and Yunnan may also benefit from their advantageous position facing ASEAN and the local industrial development strategy. Their vocational education system can realize efficient resource conversion with accurate industry-education alignment and school-enterprise cooperation. As a province with a strong educational tradition, Hubei may leverage its robust industrial base to align vocational education with advanced manufacturing, thereby achieving high efficiency. In contrast, Beijing (0.1860, 30th place) and Shanghai (0.2897, 25th place) are ranked at the bottom of the country's efficiency of VHES. It means that in the industrial structure of megacities where knowledge-intensive services and high-tech industries are highly concentrated, the demand of society for traditional skills-based vocational education may meet relative saturation. If the vocational education system cannot quickly transition to training advanced technical skills and lifelong vocational education, it will also be detached from the market demand, so that the invested resources cannot be effectively converted into high-quality outputs. Moreover, a persistent bias in resource allocation toward general higher education in these two regions may further suppress the developmental vitality of vocational education.

From the perspective of the higher education system as a whole, the average HES efficiency is relatively low (0.355), indicating significant room for improvement in the overall utilization efficiency of resource inputs. In terms of HES efficiency, Guangxi (0.4378) ranks first, followed by Jiangsu (0.4338) and Henan (0.4158), which share the common feature of successfully coordinating the development of the two types of educational subsystems. Guangxi's efficiency score for vocational higher education (ranking first nationally at 0.4817) is the primary driver behind the high overall score for its higher education system. This may be attributed to the strong policy support from both the national and provincial levels, as well as the fact that vocational education in Guangxi is tightly connected

with distinctive industries in this province, thus forming a high input-output ratio. In contrast, Xizang (0.2010) and Qinghai (0.2583) rank at the bottom of HES efficiency, which, together with other western regions, have relatively low HES efficiency due to their weak economic foundation, limited financial input per student, and geographic and demographic factors. Notably, as two of the wealthiest cities in China, Beijing (0.3452, 20th) and Shanghai (0.3051, 26th) rank relatively low in HES efficiency, which suggests that the level of economic development is not the decisive factor for high efficiency. The reasons for relatively low efficiency in these two cities may be that their operational costs may be high, there may be administrative surplus, or the marginal return of resource input may decline relative to the increment in scale, which may hinder these two cities from performing better than some central and western provinces with more accurate resource allocation and clearer policies.

Furthermore, the model assumptions in this paper are closely aligned with provincial efficiency scores. This study adopts the constant returns to scale (CRS) assumption, which is more suitable for evaluating systems in linear expansion phases. However, for higher education systems in economically developed regions that have reached massive scale and diversified functions, this approach may introduce evaluation biases. The “inefficiency” scores in these regions partly reflect challenges from diseconomies of scale, the burden of diversified high-end output tasks, and the nonlinear relationship between resource inputs and complex outputs. In contrast, central and western provinces, characterized by smaller investment scales and a focus on distinctive areas of strength, predominantly operate within the economies of scale range. Their input-output relationships align more closely with the CRS assumption, leading to more prominent efficiency scores.

In summary, our findings clearly reveal that the efficiency of China’s higher education system is not only affected by macroeconomic factors such as the level of regional development, but also by deeper factors such as structural optimization of resource allocation, alignment of education policies with regional industrial strategies, and effective coordination and functional complementarity between the two subsystems.

3.3. Regional Analysis

Taking the four major regions into consideration, the efficiency values of HES, VHES and GHES are analyzed respectively. The results show that the regional structural characteristics of the allocation efficiency of China’s higher education resources are obvious as shown in **Figure 3**.

From the perspective of the whole, the most prominent central region, the efficiency of HES, VHES and GHES is 0.3820, 0.3828 and 0.3735, respectively. It means that the higher education in the central region is developed very coordinatively and harmoniously. One of the reasons for this achievement is that the central region is an important area connecting the eastern and western regions, and can effectively absorb the overflow of the eastern region’s resources. Another rea-

son is that the manufacturing industry in the central region is very strong, which provides a wide range of industrial demands for vocational education, and there are a large number of universities founded before in the central region, which lays a solid foundation for the general higher education. These two aspects promote the highly effective conversion of resources.

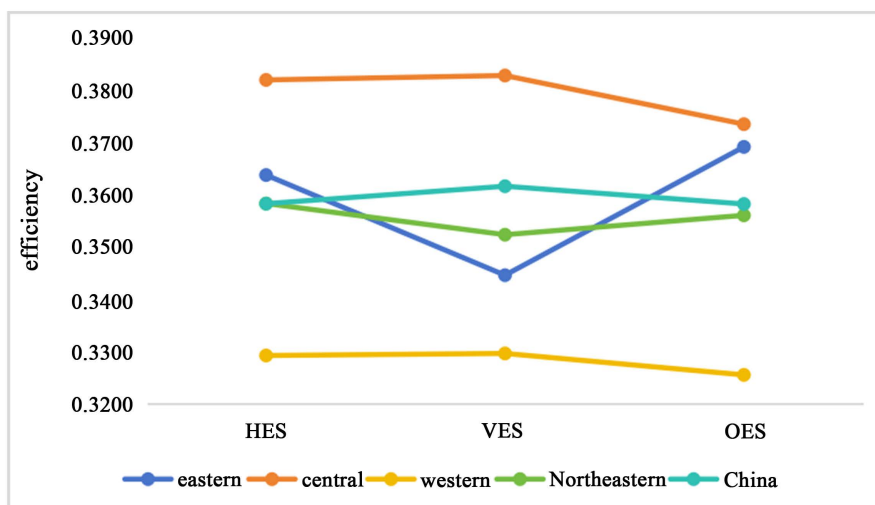


Figure 3. Average efficiency of higher education systems by region, 2021-2023.

Although the efficiency of HES (0.3638) and VHES (0.3446) in the eastern region ranks second only to the central region, the efficiency of GHES is 0.3692, which is below the national average. It shows that the characteristics of “structural imbalance” are very obvious. It is profoundly reflected that although the economic strength of the Eastern Region is strong and the research resources supporting the vigorous development of General Higher Education are abundant, the industrial structure of the Eastern Region has already shifted from a resource-based industry to a knowledge-based industry and a service industry. The vocational education system (VHES) that mainly cultivates traditional middle-level and technical talents has become “out of touch” with the demands of the vocational education market. A large amount of investment converted into efficiency cannot be transferred into corresponding efficiency output, which drags down the total efficiency (HES).

The efficiency of higher education in Northeast China presents a “stability but unexciting” feature. The HES (0.3583), VHES (0.3524) and GHES (0.3561) efficiency values of the region are very close to the national average value. This may mean that when facing the challenge of transformation of old industrial bases, the higher education system (GHES) and vocational education system (VHES) in Northeast China could still maintain a basic level of efficiency. And without breakthroughs in growth, the overall development of higher education has reached a plateau.

While compared with other regions, the western region is lagging behind in all three efficiency indicators. This shows that the western region is an overall stag-

nant area, which is limited by its relatively weak economic foundation, influence of external forces such as brain drain, and government fiscal investment. Although some preferential national policies may have alleviated the decline of vocational education investment, these policies are not enough to bridge the absolute gap with eastern and central regions in terms of scientific research innovation and faculty quality. As a result, the two subsystems are faced with bottlenecks in improving efficiency.

In summary, the efficiency of China's higher education system in different regions shows that the central region is good, the eastern region is unbalanced, the northeastern region is stable, and the western region is behind. This result clearly shows that the efficiency level of different regions is not merely determined by economic development, but the comprehensive result of the mutual fitting degree of industrial structure, policy orientation, resource endowment and development model of the education subsystem.

3.4. Analysis of Influencing Factors

The development and evolution of higher education are closely related to its socio-economic context. In order to choose core indicators in four dimensions of government, economy, society and universities to systematically study the influencing factors of the efficiency of higher education system, this study employs geometric mean overall efficiency as the dependent variable, with national education expenditure, regional gross domestic product, per capita education expenditure, and total volume of literature resources serving as core indicators. Data sourced from the China Statistical Yearbook. The indicators are explained as follows:

First, in terms of economic dimension variables, per capita regional GDP is used as a proxy variable. Regional economic development is the material basis and overall environment for the development of higher education. It affects the ability of local governments to invest in education, families' willingness to pay for higher education, and the demand for highly educated talents in the labor market. Per capita GDP is a comprehensive indicator of the economic situation. It can better eliminate the impact of population size and better reflect the actual level of economic development region, so as to measure the possible supporting role or limiting role that the economic foundation plays in the resource allocation efficiency of the higher education system.

Second, in terms of government level variables, the fiscal education expenditure of the country is used as a proxy variable. As the main provider and financier of higher education, the allocation of government's material resources directly determines the scale and bottom quality of the higher education system. State education expenditure refers to the total amount of government education expenditure in all levels of education. Its scale serves as an indicator of the government's commitment to allocating resources across all educational levels and its strategic prioritization of education within national planning. As an important observation basis for observing the performance of government education, it directly affects

the amount of available resources for universities to develop faculty, update facilities and promote scientific research innovation.

Third, in terms of social dimension variables, the average years of education in the region is used as a proxy variable. The overall level of human capital and cultural environment of society play the role of the foundation of higher education development. The average years of education in the region reflect the level of human capital accumulation in the region over a long period of time. It not only serves as the quality foundation for the enrollment of higher education, but also determines the recognition degree of society and the demand for higher education. The larger the human capital stock, the more favorable the social environment for the development of higher education, the more lifelong learning individuals involved, and the tighter the industry-academy-research chain. All these provide continuous impetus for improving the efficiency of higher education in society.

Fourth, at the university level, the variable is measured by the total volume of literature resources held by the institution, specifically the combined total of physical and electronic resources, serving as a substitute indicator. The institutional conditions of universities themselves are intrinsic determinants of their resource conversion capacity. Library collections and electronic resources are the most basic components of a university's knowledge infrastructure. Their quantity and quality not only support teaching and research on the part of faculty members but also serve as important academic resources that help ensure quality in talent cultivation and encourage output in the realm of research. This indicator gauges the material capacity of universities to support their roles in knowledge accumulation, information provision, and digital infrastructure building. It provides an important objective basis for assessing the academic support system of a university and the level of learning and research environment.

Based on the selected data, this study employs a two-way fixed-effects model to calculate the results, as shown in **Table 4**.

Table 4. Regression analysis results of factors affecting the efficiency of the higher education system.

	Average years of schooling	Fiscal expenditure	Literature resources	GDP per capita
Efficiency	0.0273*** (2.8064)	0.0825*** (2.6636)	0.0354*** (3.7306)	0.0381** (2.0742)

Note: Numbers in parentheses indicate standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The regression coefficients for all four explanatory variables are positive and significant at the 5% or 1% level. The regression results indicate that the four selected dimensional factors significantly and positively affect the efficiency of the higher education system. This result verifies the rationality of analytical framework constructed in this paper.

In particular, the coefficient of government level, state-sponsored education ex-

penditure is the largest (0.0825, significant at the 1% level). This indicates that government financial investment is the most crucial factor in promoting the enhancement of higher education system efficiency. This research result strongly confirms that the government plays a decisive role in the allocation of higher education resources. Stable financial input provides basic guarantee for faculty development and upgrade of universities, and plays the core role of material basis in promoting the development of scientific research innovation.

The total literature resource coefficient is 0.0354, significantly positive at the 1% level. This indicates that the richness and accessibility of the comprehensive literature resource base—comprising both physical collections and digital resources—directly promotes the efficiency of knowledge acquisition and scientific research innovation. Therefore, universities should systematically consolidate and expand their overall academic resource reserves. While maintaining and optimizing physical resources, they should actively strengthen the development of digital infrastructure such as digital books and electronic journals. Only through the coordinated development of both can internal resource allocation be more effectively optimized, thereby comprehensively enhancing the overall strength of teaching and research.

In addition, the economic and social factors also have a significant influence. The coefficient of per capita GDP in the economic dimension is 0.0381 and is significantly positive at the 5% level. Thus, regional economic development enhances the operational efficiency of the higher education system by supplying more local matching funds, activating the industry-academy-research market, and elevating talent demand. The coefficient of the average years of education per capita in the social dimension is 0.0273 and is significantly positive at the 1% level. That is to say, the accumulation of overall social human capital creates a good foundation for the development of higher education. A higher-quality labor force not only provides the higher education system with a larger pool of potential talent to select from but also fosters a more supportive socio-cultural environment for educational development.

This regression analysis shows that the driving factors of the development of efficiency in the higher education system are multi-dimensional and integrated drivers. Among them, the fiscal investment from the government has the strongest driving effect and plays the role of the first and most important guarantee for the development of efficiency. The self-development of comprehensive literature resources by universities serves as a crucial aspect in improving the development efficiency of internal university resources. In addition, a healthy regional economic environment and strong foundation of social human capital play an indispensable role in providing the external environment and social support for the development of efficiency in the higher education system. Therefore, the higher education system should form a systematic development pattern of “government investment guarantee, university development optimization, and coordinated regional and social support” and enhance the overall efficiency of the development of China’s higher education system.

4. Conclusion and Policy Implications

4.1. Conclusion

This study uses a dual-frontier DEA model combined with a regression analysis framework to systematically study the efficiency pattern and cause analysis of China's higher education system. The main conclusions are as follows.

This study proves that the efficiency distribution pattern of three dimensions is widespread and complex. The overall low efficiency exists everywhere, which reflects the overall problem of resource allocation at a macro level. At the regional level, the pattern of "central equilibrium, eastern imbalance and western lag" is presented. In addition, the "efficiency mismatch" in most provinces between the two major subsystems of GHES and VHES is exposed.

The regression analysis results are obviously a multi-driver theoretical framework. Government fiscal investment plays the role of the engine of efficiency improvement and provides the basis of available resources; the economic environment and social human capital together build an important external support system; the expansion of a university's total literature resources reflects its capacity for optimizing the allocation of its endogenous resource system. The cross interaction among these four dimensions collectively determines the final output efficiency of the higher education system.

4.2. Policy Implications

Policy formulation should be guided by the heterogeneous characteristics of each region. In the developed eastern region, we should focus on solving the structural problem of low input-output efficiency in vocational education, promoting the deep integration of its cultivation system and needs of a knowledge-based economy. In the central region, we should focus on maintaining the synergistic advantages of balanced development between general education and vocational education, and institutionalizing and promoting successful experience. In the western and northeastern region, the central government should increase financial support and capacity building in these regions, solidifying their developmental foundation through the development of infrastructure.

The government must maintain and enhance its leading role in fiscal investment. Building upon this, further encourage and support the involvement of social and economic resources in the development of higher education. Implementing tax incentives would be an effective measure to stimulate participation and investment from market entities. Higher education institutions should prioritize the optimization of their internal resources, strengthen cooperation and sharing in the development of resources and knowledge infrastructure, and enhance the efficiency of resource utilization.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- Anderson, T. R., Daim, T. U., & Lavoie, F. F. (2007). Measuring the Efficiency of University Technology Transfer. *Technovation*, 27, 306-318. <https://doi.org/10.1016/j.technovation.2006.10.003>
- Chen, Y., Du, J., David Sherman, H., & Zhu, J. (2010). DEA Model with Shared Resources and Efficiency Decomposition. *European Journal of Operational Research*, 207, 339-349. <https://doi.org/10.1016/j.ejor.2010.03.031>
- Chen, Y., Ma, X., Yan, P., & Wang, M. (2021). Operating Efficiency in Chinese Universities: An Extended Two-Stage Network DEA Approach. *Journal of Management Science and Engineering*, 6, 482-498. <https://doi.org/10.1016/j.jmse.2021.08.005>
- Fandel, G. (2007). On the Performance of Universities in North Rhine-Westphalia, Germany: Government's Redistribution of Funds Judged Using DEA Efficiency Measures. *European Journal of Operational Research*, 176, 521-533. <https://doi.org/10.1016/j.ejor.2005.06.043>
- Johnes, J., & Yu, L. (2008). Measuring the Research Performance of Chinese Higher Education Institutions Using Data Envelopment Analysis. *China Economic Review*, 19, 679-696. <https://doi.org/10.1016/j.chieco.2008.08.004>
- Kao, C. (2012). Efficiency Decomposition for Parallel Production Systems. *Journal of the Operational Research Society*, 63, 64-71. <https://doi.org/10.1057/jors.2011.16>
- Khanjarpanah, H., Jabbarzadeh, A., & Seyedhosseini, S. M. (2018). A Novel Multi-Period Double Frontier Network DEA to Sustainable Location Optimization of Hybrid Wind-photovoltaic Power Plant with Real Application. *Energy Conversion and Management*, 159, 175-188. <https://doi.org/10.1016/j.enconman.2018.01.013>
- Lindsay, A. W. (1982). Institutional Performance in Higher Education: The Efficiency Dimension. *Review of Educational Research*, 52, 175-199. <https://doi.org/10.3102/00346543052002175>
- Moreno-Gómez, J., Calleja-Blanco, J., & Moreno-Gómez, G. (2019). Measuring the Efficiency of the Colombian Higher Education System: A Two-Stage Approach. *International Journal of Educational Management*, 34, 794-804. <https://doi.org/10.1108/ijem-07-2019-0236>
- Naderi, A. (2022). Efficiency Measurement of Higher Education Units Using Multilevel Frontier Analysis. *Journal of Productivity Analysis*, 57, 79-92. <https://doi.org/10.1007/s11123-021-00621-0>
- Thanassoulis, E., Kortelainen, M., Johnes, G., & Johnes, J. (2011). Costs and Efficiency of Higher Education Institutions in England: A DEA Analysis. *Journal of the Operational Research Society*, 62, 1282-1297. <https://doi.org/10.1057/jors.2010.68>
- Titus, M. A., & Eagan, K. (2016). Examining Production Efficiency in Higher Education: The Utility of Stochastic Frontier Analysis. In M. B. Paulsen (Ed.), *Higher Education: Handbook of Theory and Research* (pp. 441-512). Springer International Publishing. https://doi.org/10.1007/978-3-319-26829-3_9
- Wang, Y., & Lan, Y. (2011). Measuring Malmquist Productivity Index: A New Approach Based on Double Frontiers Data Envelopment Analysis. *Mathematical and Computer Modelling*, 54, 2760-2771. <https://doi.org/10.1016/j.mcm.2011.06.064>
- Wu, J., Zhang, G., Zhu, Q., & Zhou, Z. (2020). An Efficiency Analysis of Higher Education Institutions in China from a Regional Perspective Considering the External Environmental Impact. *Scientometrics*, 122, 57-70. <https://doi.org/10.1007/s11192-019-03296-5>
- Yu, Y., Yin, T., Li, R., & Wang, X. (2024). Effectiveness of Higher Education Financing: DEA and SFA Modelling. *Business Ethics and Leadership*, 8, 172-189.

[https://doi.org/10.61093/bel.8\(1\).172-189.2024](https://doi.org/10.61093/bel.8(1).172-189.2024)

Zhang, G., Wu, J., & Zhu, Q. (2020). Performance Evaluation and Enrollment Quota Allocation for Higher Education Institutions in China. *Evaluation and Program Planning*, 81, Article 101821. <https://doi.org/10.1016/j.evalprogplan.2020.101821>