Efficiency of Research and Development (R&D) Investment in Chinese Higher Education: A DEA-Malmquist Analysis

Haidong Sun[1*] and Xuan Zhu[2]

[1*] *Xuzhou Open University, Mainland China*

[2] *Qufu Staff Secondary Vocational School, Mainland China*

ABSTRACT

Background and Objectives: Higher education institutions (HEIs) are crucial to scientific research and technological innovation, playing a key role in both regional and national development. Despite increasing government investments in research and development (R&D), significant disparities persist in efficiency across Chinese provinces. Previous studies have been limited in scope, either focusing on single regions, covering short time spans, or lacking a dynamic perspective on efficiency changes. This study addresses these gaps by conducting a nationwide, long-term empirical analysis of HEI R&D efficiency across 31 provinces from 2018 to 2023. The objective is to evaluate efficiency variations, identify regional disparities, and provide policy recommendations for optimizing HEI R&D resource allocation.

Methodology: This study employed the Banker–Charnes–Cooper Data Envelopment Analysis (BCC-DEA) model to measure HEI R&D efficiency. It used R&D expenditure and personnel as input variables, while patents and academic publications comprised output variables. Additionally, the Malmquist index was applied to examine efficiency dynamics over time. Data was sourced from the Compilation of Higher Education Science and Technology Statistics (2018–2023) to ensure reliability. This combined approach enabled a comprehensive evaluation of both static and dynamic efficiency, providing insights into technical efficiency, scale efficiency, and the impact of technological progress on productivity changes.

Main Results: The findings indicate significant regional disparities in HEI R&D efficiency across China. Shanghai and Xinjiang consistently achieve high DEA efficiency, benefiting from strong research infrastructure and favorable policy support. In contrast, provinces such as Anhui, Jiangxi, and Guangdong demonstrate lower efficiency levels and input redundancy, highlighting inefficiencies in resource allocation. The Malmquist index decomposition reveals that

ARTICLE INFO

Article history:

Received 21 March 2025

Revised 26 July 2025

Accepted 4 August 2025

Keywords:

Higher Education Institutions, R&D Efficiency, DEA-Malmquist, Regional Disparities, Technological Progress

technological progress is the primary driver of total factor productivity (TFP) growth, yet many provinces fail to effectively translate technological advancements into productivity improvements. While some regions maximize technological innovation for efficiency gains, others struggle with weak research output commercialization and limited policy support, leading to persistent inefficiencies.

Discussions: The study underscores that economic development, policy support, and technology commercialization are key determinants of HEI R&D efficiency. Developed coastal regions benefit from better technology transfer mechanisms, research infrastructure, and financial resources, allowing them to achieve higher TFP growth. However, provinces with high R&D investment but low efficiency indicate barriers in converting research into practical applications, often due to weak industry linkages and funding inefficiencies. Policy interventions should prioritize bridging the gap between technological progress and commercialization by strengthening university-industry collaboration, optimizing R&D resource allocation, and enhancing knowledge-sharing networks. Addressing these inefficiencies is crucial for promoting balanced regional innovation and improving the overall research ecosystem.

Conclusions: To enhance HEI R&D efficiency and reduce regional disparities, targeted policies should be implemented. Financial support for underperforming regions, enhanced university-industry collaboration, and optimized technology commercialization mechanisms are key strategies. Promoting inter-regional HEI cooperation can improve resource sharing, talent mobility, and knowledge spillovers, fostering a more integrated innovation network. Policymakers should ensure that technological advancements translate into productivity gains, aligning research outputs with industry needs. Strengthening policy coordination and refining funding mechanisms will contribute to a balanced and efficient innovation system, supporting sustainable national development.

*Corresponding author
E-mail address: 2210453100002@live4.utcc.ac.th

Introduction

Higher education institutions (HEIs) are integral components of a nation's innovation system and serve as a core driving force in scientific research and development (R&D). They play an irreplaceable role in enhancing technological innovation capabilities and fostering high-quality economic and social development. The R&D activities of HEIs encompass basic research, applied research, and experimental development. Through systematic and creative scientific research and experimental development, HEIs not only expand the total stock of knowledge but also facilitate the transformation of knowledge into practical applications, thereby contributing to the sustainable development of society and the economy.

In recent years, with the continuous increase in government investment in R&D activities in Chinese HEIs, substantial progress has been made in scientific and technological innovation. However, the regional allocation and efficiency of HEI R&D resources remain critical challenges that hinder the balanced development of regional innovation capacity in China. Existing research presents limitations in terms of scope, time span, and methodological application. Hu (2023), based on statistical data from 2013 to 2021 on R&D activities in Chinese HEIs, employed bibliometric analysis and graphical methods to illustrate the latest trends in HEI R&D funding, institutional numbers, personnel development, and research output. However, the study was limited to trend and descriptive analysis, without assessing efficiency or identifying key factors contributing to regional disparities (Hu, 2023). Similarly, Chen (2024) utilized the Data Envelopment Analysis (DEA) model to examine the efficiency of R&D resource allocation in HEIs in Anhui Province, emphasizing the balance between rationality and efficiency. Nevertheless, the study was confined to Anhui Province, making it difficult to generalize the findings to HEIs nationwide (Chen, 2024). Additionally, Bu and Li (2022) analyzed the R&D data of 24 undergraduate HEIs in Shanghai from 2018 to 2019 and found that institutional efficiency was generally low, with diminishing returns to scale. However, the study was restricted to Shanghai, had a short time span, and lacked nationwide applicability (Bu & Li, 2022).

In a nationwide study, He (2023) systematically analyzed the R&D efficiency of HEIs using data from 2020 to 2021, employing a two-stage Data Envelopment Analysis–Variable Returns to Scale (DEA-VRS) model and a super-efficiency DEA model. The findings indicated that efficiency disparities were closely related to regional economic development levels and policy support (He, 2023). However, given that the study covered only a two-year period, it failed to capture the dynamic changes and long-term evolution of efficiency.

Overall, existing studies face three major challenges: (1) they are regionally constrained and disallow comparative analysis on a national scale; (2) they cover short time spans, making it difficult to reveal dynamic trends in efficiency changes; and (3) they rely on a limited set of indicators, failing to comprehensively encompass multiple input and output factors. However, few studies have simultaneously addressed all three limitations through an integrated methodological framework. Thus, a clear research gap remains in conducting a nationwide, long-term, and multi-indicator dynamic efficiency evaluation of HEI R&D performance.

To fill this gap, this study focused on the R&D activities of HEIs across 31 provinces in mainland China from 2018 to 2023. Provincial-level administrative divisions were used as decision-making units (DMUs) to empirically analyze HEI R&D input-output efficiency at the provincial level. By combining the Banker–Charnes–Cooper Data Envelopment Analysis (BCC-DEA) model with the Malmquist index, this study not only assessed static efficiency across regions but also captured intertemporal efficiency dynamics, offering new insights into both technical and scale efficiency changes over time. The primary objective was to assess efficiency metrics and dynamic changes to provide a comprehensive understanding of regional disparities and their evolutionary patterns. The findings aim to serve as a scientific basis for optimizing HEI R&D resource allocation and enhancing regional innovation capacity.

In this study, R&D expenditure and the number of R&D personnel in HEIs were selected as input variables, while the number of granted patents and published academic papers were used as output variables. The BCC-DEA model was employed to calculate R&D efficiency across provinces. Additionally, time series analysis was conducted to examine the dynamic characteristics and regional distribution trends of efficiency. This methodological combination provides a more robust and comprehensive assessment compared to previous single-method or short-term studies. By undertaking this research, this study sought to deepen the theoretical understanding of HEI R&D efficiency while providing empirical support for optimizing resource allocation and enhancing institutional innovation capabilities. Furthermore, it offers policy recommendations for promoting coordinated regional development and advancing technological innovation at the national level.

Literature Review

Research Progress in Evaluating HEI R&D Efficiency

The evaluation of HEI R&D efficiency serves as a crucial metric for assessing the relationship between resource input and research output. It is also a key instrument for optimizing the allocation of research resources and enhancing innovation capacity. In recent years, the Data Envelopment Analysis (DEA) model has emerged as a dominant analytical tool in this field due to its suitability for multi-input, multi-output scenarios. While static DEA models are primarily used for efficiency analysis at a single point in time, dynamic DEA models and the Malmquist index extend the capability of efficiency assessment over time. For example, a study by Jhantasana (2019) employed the BCC-DEA model to evaluate the efficiency of social responsibility implementation across nine Rajabhat universities in Thailand, highlighting variations in input-output performance across institutions. Similarly, Um et al. (2022) used a two-stage network DEA approach to assess the efficiency of South Korea's regional innovation systems over a 16-year period, uncovering temporal disparities in R&D performance and emphasizing the importance of integrated efficiency evaluation methods (Ikcheon Um & Kwangseon, 2022).

Moreover, the Malmquist index has been applied to analyze regional differences in HEI efficiency across China, demonstrating that technological progress is the primary driver of efficiency improvement while also highlighting significant efficiency disparities among HEIs (Du & Seo, 2022). The dynamic network DEA model further refines efficiency assessments by decomposing the "black box" of the R&D process, thereby offering a more precise evaluation of both technological development and research output transformation (Bai et al., 2020).

Beyond methodological advancements, research has shown that HEI R&D efficiency is significantly influenced by external environmental factors, such as technological specialization, international collaboration, and R&D team diversity (Hung & Shiu, 2014). Studies integrating efficiency and effectiveness evaluations have widely adopted network DEA and multi-indicator comprehensive evaluation methods, revealing that many regional HEIs suffer from both low efficiency and low effectiveness, necessitating region-specific resource optimization strategies (Qin & Du, 2018). Furthermore, research on the integration of policy and practice continues to advance, with performance management systems based on priority matrices proving effective in enhancing project management efficiency (Lee et al., 2023).

Applications of DEA Models in Efficiency Evaluation

The DEA model, which does not require a predefined production function and is well-suited for multi-input, multi-output assessments, has been widely applied in efficiency evaluation. The Charnes–Cooper–Rhodes (CCR) model assumes constant returns to scale (CRS), making it appropriate for systems with minimal scale effects. It effectively assesses overall efficiency but fails to distinguish between technical and scale efficiency.

In contrast, the Banker–Charnes–Cooper (BCC) model accommodates variable returns to scale (VRS), allowing for the decomposition of technical and scale efficiency. This makes it more suitable for contexts where scale differences are significant. Moreover, an improved BCC model that incorporates cross-efficiency evaluation has been proposed to address the issue of non-unique weight allocation, thereby enhancing model stability (Wu et al., 2016).

Models based on the VRS assumption have further extended the applicability of DEA methodologies, particularly in analyzing efficiency changes in complex systems. Studies on HEI R&D efficiency have revealed varying returns to scale among different institutions—whether increasing, decreasing, or constant (Liu & Xu, 2011). The Malmquist index, which is widely used for dynamic efficiency analysis, decomposes efficiency change sources into technical efficiency changes and technological advancements. For instance, research on provincial HEIs in China using the Malmquist index has confirmed that technological progress is the primary driver of efficiency improvements while also exposing substantial regional disparities (Du & Seo, 2022). Additionally, the index has been extensively applied in other fields, such as agriculture, where it has been combined with CCR and BCC models to analyze dynamic efficiency changes and identify efficiency improvement pathways across different regions (Miao & Wang, 2023).

This study is conceptually grounded in the framework of National Innovation Systems (NIS), which views HEIs as central actors in the creation, dissemination, and application of knowledge. The NIS perspective provides a meaningful theoretical foundation for analyzing regional disparities in R&D efficiency, as it links institutional performance to broader policy and innovation ecosystem structures. This is similar to Shin and Kim's (2025) analysis of regional innovation systems in South Korea—where efficiency variations were examined through both technical and policy lenses (Shin & Kim, 2025). This study applies the NIS framework to interpret spatial differences in the performance of HEI R&D systems across Chinese provinces.

Research Methodology

Data Sources

The data used in this study were obtained from the Compilation of Higher Education Science and Technology Statistics published from 2018 to 2023. This compilation is prepared by the Department of Science, Technology, and Informatization of the Ministry of Education of the People's Republic of China. The study encompasses statistical reports continuously compiled between 2018–23, ensuring the authority and consistency of the data. This dataset provides a reliable foundation for the empirical analysis of the input-output efficiency of R&D activities in HEIs.

Model Construction

To systematically evaluate the input-output efficiency of R&D activities in Chinese HEIs, this study established a comprehensive analytical framework based on the BCC-DEA model and the Malmquist index model.

First, the BCC-DEA model was employed to conduct a cross-sectional analysis of the efficiency of HEI R&D activities in each year. This model assessed efficiency levels across different HEIs and regions, decomposed technical efficiency and scale efficiency, and identified the sources of inefficiency.

Second, the Malmquist index model was applied for dynamic analysis spanning from 2018 to 2023. By decomposing efficiency changes into technical efficiency changes and technological progress contributions, this model explored the temporal evolution of HEI R&D efficiency.

This integrated framework combined the advantages of static efficiency assessment and dynamic trend analysis, offering a comprehensive understanding of the distribution and variation characteristics of HEI R&D efficiency. The findings provide scientific insights for improving efficiency and optimizing resource allocation.

Indicator System

In accordance with the requirements of the DEA model, this study constructed a scientifically sound input-output indicator system to ensure a clear causal relationship between inputs and outputs, where input indicators directly contributed to the generation of output indicators. Specifically, the input indicators included the number of universities, the number of research institutions, the number of R&D personnel (persons), and R&D expenditure (in thousands of Renminbi), which comprehensively reflected the resource investment levels of HEIs in R&D activities. Meanwhile, the output indicators consisted of the number of research projects, the number of scientific and technological monographs, the number of scientific and technological papers, the actual revenue from technology transfer in the given year (in thousands of RMB), and the number of awarded research achievements, which were designed to measure the research output and socio-economic contributions of HEI R&D activities. The selection of input and output indicators followed international R&D evaluation standards, particularly the Organisation for Economic Co-operation and Development (OECD) Frascati Manual (OECD, 2015), which suggests using R&D personnel, R&D funding, patents, and academic publications as key metrics for assessing research efficiency.

Research Tools and Process

This study employed DEAP 2.1 software to standardize the dataset before applying the BCC-DEA model to measure technical efficiency, scale efficiency, and overall efficiency for each province. Based on these results, the Malmquist index analysis was further conducted to decompose efficiency changes into technical efficiency variations and technological progress, thereby assessing the dynamic efficiency evolution and technological advancement trends across provinces. The research followed these specific steps:

The first step involved determining the Decision-Making Units (DMUs). In this study, 31 provinces in mainland China served as the DMUs. Based on R&D activity data from HEIs between 2018 and 2023, an input-output indicator system was established. The input variables represented the resource factors invested in HEI R&D activities, including the number of HEIs (denoted as x_1), number of research institutions (denoted as x_2), number of R&D personnel (denoted as x_3), and R&D expenditure (denoted as x_4). The output variables reflected the research achievements and performance outcomes of HEI R&D activities, including the number of research projects (denoted as y_1), number of scientific and technological monographs (denoted as y_2), number of scientific and technological papers (denoted as y_3), technology transfer revenue (denoted as y_4), and number of awarded research achievements (denoted as y_5).

Table 1. Summary of Sample Data on HEI R&D Input and Output in Selected Provinces (2018–2023)

NO.	YEAR	DMU	X1	X2	X3	X4	Y1	Y2	Y3	Y4	Y5
1	2018	Beijing	46	741	40943	19134058	63698	573	96704	620954	424
2	2018	Tianjin	15	209	11625	4297225	14312	79	21366	27907	81
3	2018	Hebei	112	173	10882	2396970	12564	125	25934	35394	170
4	2018	Shanxi	67	109	8490	1230286	6270	120	14233	130192	63
------	------		------	------	------	------	------	------	------	------	------
------	------		------	------	------	------	------	------	------	------	------
------	------		------	------	------	------	------	------	------	------	------
182	2023	Shaanxi	70	763	20884	13673616	57797	337	60352	405603	253
183	2023	Gansu	42	269	5018	1352459	9595	71	15060	9680	108
184	2023	Qinghai	11	92	659	366918	903	17	3636	588	22
185	2023	Ningxia	13	55	2448	650626	4218	34	5897	14790	29
186	2023	Xinjiang	39	103	4279	530705	7409	101	13226	1901	63

The Second Step: Calculating the Distance Function. Using DEAP 2.1 software, the BCC-DEA model was applied to compute the efficiency values for each province across the years 2018–23. These efficiency values served as a measure of the relative efficiency of each DMU over different periods. The specific distance function formula is as follows:

$$d_t^t(x_i^t, y_i^t) = \min\{\theta | (x_i^t / \theta, y_i^t) \in P^t\}$$

$$d_{t+1}^{t+1}(x_i^{t+1}, y_i^{t+1}) = \min\{\theta | (x_i^{t+1} / \theta, y_i^{t+1}) \in P^{t+1}\}$$

The Third Step: Calculating the Malmquist Index. The Malmquist Productivity Index (MPI) was used to measure the productivity changes of DMUs between period t and t+1, providing a comprehensive reflection of the effects of efficiency change and technological progress on productivity. By calculating the Malmquist Index, this study analyzed the input-output efficiency of HEI R&D activities across 31 provinces in mainland China from 2018 to 2023, revealing the dynamic changes in productivity across regions. The calculation formula is as follows:

$$M_t^{t+1}=\sqrt{\left(\frac{d_t^t(x_i^t,y_i^t)}{d_{t+1}^t(x_i^{t+1},y_i^{t+1})}\right)\times\left(\frac{d_t^{t+1}(x_i^t,y_i^t)}{d_{t+1}^{t+1}(x_i^{t+1},y_i^{t+1})}\right)}$$

The Fourth Step: Decomposing the Malmquist Index. The Malmquist Index can be further decomposed into two key components: Technical Efficiency Change (EC) and Technical Progress Change (TC). By decomposing the Malmquist Index, this study conducted an in-depth analysis of the dynamic changes in HEI R&D efficiency across 31 provinces in mainland China, identifying the sources of productivity variation. This decomposition provides a scientific basis for regional efficiency improvement and technological progress enhancement. The specific formula is as follows:

$$TFP=EC\times TC$$

$$EC=\frac{d_{t+1}^0(x_i^{t+1},y_i^{t+1})}{d_t^0(x_i^t,y_i^t)}$$

$$TC=\left[\frac{d_t^0(x_i^t,y_i^t)}{d_t^{t+1}(x_i^t,y_i^t)}\times\frac{d_{t+1}^{t+1}(x_i^{t+1},y_i^{t+1})}{d_{t+1}^0(x_i^{t+1},y_i^{t+1})}\right]^{1/2}$$

In the Malmquist Index decomposition, Technical Progress Change (TC) measures the dynamic shift in the production possibility frontier.

When TC > 1, it indicates technological progress, whereas TC < 1 signifies technological regression.

Meanwhile, Technical Efficiency Change (EC) reflects the improvement or decline in efficiency of a Decision-Making Unit (DMU) over time.

A value of EC > 1 suggests efficiency improvement, while EC < 1 indicates efficiency deterioration.

Furthermore, Technical Efficiency Change (EC) can be further decomposed into Scale Efficiency Change (SEC) and Pure Technical Efficiency Change (PEC). SEC evaluates the impact of scale expansion or contraction, while PEC assesses the degree of improvement in resource allocation and management capabilities. This decomposition enables a more detailed examination of the sources of efficiency variation, providing insights for optimizing HEI R&D efficiency and resource utilization.

$$EC=SEC\times PEC$$

$$SEC=\frac{SEC_0^{t+1}(x_{t+1},y_{t+1})}{S_0^t(x_t,y_t)}$$

$$PEC=\frac{d_{t+1}^0(x_{t+1},y_{t+1})}{d_t^0(x_t,y_t)}$$

Results

DEA Analysis of HEI R&D Activities (2018–2023)

This study examined 31 provinces in mainland China and utilized data on HEI R&D activities from 2018 to 2023 to analyze Overall Efficiency (OE) using the BCC-DEA model. The model calculations systematically evaluated the efficiency levels of each province across different years. Additionally, the total number of years in which a province exhibited DEA strong efficiency (NDEA) over the six-year period was recorded. A comparative analysis was conducted based on regional classifications to identify efficiency disparities and patterns in HEI R&D activities across different regions. The detailed results are presented in Table 2.

Table 2. Summary of DEA Analysis Results for HEI R&D Activities (2018–2023)

Item	2018		2019		2020		2021		2022		2023		N	R
	OE	SRC	OE	SRC	OE	SRC	OE	SRC	OE	SRC	OE	SRC	DEA	
Beijing	1	1	1	1	0.962	1.076	0.986	1.053	1	1	1	1	4	N
Tianjin	0.873	0.511	0.938	0.509	0.873	0.721	0.878	0.684	1	1	1	1	2	N
Hebei	1	1	0.966	8.286	0.747	6.817	0.64	5.529	0.598	4.46	0.553	3.44	1	N
Shanxi	1	1	0.976	3.16	1	1	0.919	2.163	0.929	6.434	0.78	1.316	2	N
Neimenggu	1	1	0.925	0.628	0.909	0.75	0.946	0.729	1	1	1	1	3	N
Liaoning	1	1	1	1	0.972	1.161	0.977	1.159	0.94	1.004	0.984	1.206	2	NE
Jilin	1	1	0.993	0.931	0.853	0.864	0.998	0.961	0.993	0.939	1	1	2	NE
Heilongjiang	1	1	1	1	1	1	1	1	1	1	0.862	0.866	5	NE
Shanghai	1	1	1	1	1	1	1	1	1	1	1	1	6	E
Jiangsu	0.994	8.254	0.943	3.559	0.834	2.094	0.913	2.514	0.974	1.792	1	1	1	E
Zhejiang	1	1	0.969	3.043	0.856	2.525	0.906	2.356	0.862	1.114	0.858	2.191	1	E
Anhui	0.616	1.234	0.64	2.329	0.682	9.705	0.627	6.557	0.734	4.104	0.694	3.115	0	E
Fujian	0.722	1.405	0.675	2.05	0.739	4.156	0.769	3.78	0.778	3.117	0.838	2.399	0	E
Jiangxi	0.75	1.115	0.774	0.943	0.644	3.857	0.949	0.56	0.669	1.795	0.676	1.649	0	E
Shandong	1	1	0.72	2.326	0.689	1.418	0.706	1.24	0.712	1.866	0.794	1.157	1	E
Henan	1	1	1	1	0.871	1.22	0.757	1.308	0.735	1.187	0.85	0.961	2	C
Hubei	1	1	1	1	0.913	2.584	0.967	1.05	0.997	1.25	1	1	3	C
Hunan	0.836	2.084	0.774	1.723	0.794	2.578	0.85	1.157	0.838	1.046	0.793	1.564	0	C
Guangdong	0.72	1.654	0.79	1.589	0.687	1.836	0.839	1.31	0.83	1.561	0.831	2.163	0	S
Guangxi	0.824	1.362	0.829	0.894	0.861	2.208	0.942	1.91	0.948	1.571	1	1	1	S
Hainan	1	1	0.925	0.852	0.685	0.248	0.906	0.673	0.909	0.662	1	1	2	S
Chongqing	0.99	0.612	0.976	1.744	0.96	0.815	0.952	0.774	1	1	0.971	0.847	1	SW
Sichuan	0.986	3.492	1	1	0.955	1.356	1	1	0.982	1.209	1	1	3	SW
Guizhou	1	1	1	1	0.912	1.081	0.949	1.388	0.964	1.386	0.923	1.366	2	SW
Yunnan	0.988	3.591	0.893	4.65	0.811	1.248	0.802	2.613	0.902	1.799	0.69	1.843	0	SW
Tibet	1	1	1	1	0.643	0.064	0.73	0.318	0.887	0.59	0.759	0.216	2	SW
Shanxi	1	1	1	1	0.948	1.443	1	1	1	1	1	1	5	NW
Gansu	0.994	1.561	0.881	2.009	0.72	1.354	0.881	3.494	0.823	0.988	0.994	5.188	0	NW
Qinghai	1	1	1	1	0.879	0.878	1	1	0.936	0.769	1	1	4	NW
Ningxia	1	1	1	1	0.83	0.31	0.763	0.237	0.804	0.677	0.916	0.237	2	NW
Xinjiang	1	1	1	1	1	1	1	1	1	1	1	1	6	NW

Note: OE: Overall Efficiency
SRC: Scale Returns Coefficient
NDEA: Number of DEA Strongly Efficient Units
R: regionE (East)C (Central)S (South)SW (Southwest)NW (Northwest)NE(Northeast)

In Table 2, the statistical measure Overall Efficiency (OE) is defined as the product of Technical Efficiency and Scale Efficiency, representing the overall efficiency of DMUs in resource allocation (Charnes et al., 1978). Due to space limitations, this study did not present the specific data for Technical Efficiency, Scale Efficiency, and Slack Variables in full detail. However, the DEA effectiveness of a DMU can be determined based on their relationships:

If OE = 1 and both S^- (input slack) and S^+ (output slack) are 0, the DMU is classified as "DEA Strongly Efficient", indicating that both Technical Efficiency and Scale Efficiency are optimal.

If OE = 1 but either S^- or S^+ is greater than 0, the DMU is considered "DEA Weakly Efficient", meaning that some resource redundancy or insufficiency still exists.

If OE < 1, the DMU is classified as "Non-DEA Efficient", reflecting that there is significant room for improvement in resource allocation efficiency.

Additionally, the Scale Returns Coefficient (SRC) in Table 2 is used to analyze the scale efficiency status of DMUs. The value of SRC determines the state of returns to scale:

When SRC = 1, it indicates constant returns to scale (CRS), meaning that the DMU is operating at an optimal scale.

When SRC < 1, it suggests increasing returns to scale (IRS), implying that expanding the scale can further enhance efficiency.

When SRC > 1, it reflects decreasing returns to scale (DRS), suggesting that reducing the scale would optimize resource allocation efficiency.

DEA Strong Efficiency Analysis of HEI R&D Activities (2018–2023)

Over the six-year period from 2018 to 2023, a total of 63 DMUs consistently maintained DEA strong efficiency. The regional distribution of these DMUs is illustrated in Figure 1. Among them, the Northwest region had the highest number of DEA strongly efficient DMUs, totaling 17, followed by North China with 12, while South China had the fewest, with only three. For instance, Shanghai and Xinjiang remained DEA strongly efficient throughout the entire study period, with their Overall Efficiency (OE) consistently equal to one, and both input slack (S^-) and output slack (S^+) equal to zero, indicating optimal resource allocation without redundancy or insufficiency.

Additionally, Heilongjiang (Northeast China) and Shaanxi (Northwest China) achieved DEA strong efficiency in five out of six years, demonstrating a high level of efficiency stability. Beijing (North China) and Qinghai (Northwest China) achieved DEA strong efficiency in four years, exhibiting both outstanding and stable efficiency performance. Meanwhile, Inner Mongolia, Sichuan, and Hubei each had three years of strong efficiency, showcasing a certain level of regional competitiveness.

From a regional perspective, East China and North China had a relatively high proportion of strong efficiency years, reflecting the efficiency advantage of developed regions in HEI R&D activities. In contrast, the central, western, and some southern provinces had a lower proportion of strong efficiency years, highlighting regional disparities in R&D resource allocation and utilization efficiency. This uneven distribution provides a foundation for subsequent policy optimization. In particular, for the central, western, and southern provinces, further efforts should be made to enhance R&D resource allocation and management, thereby promoting the overall improvement of HEI R&D efficiency.

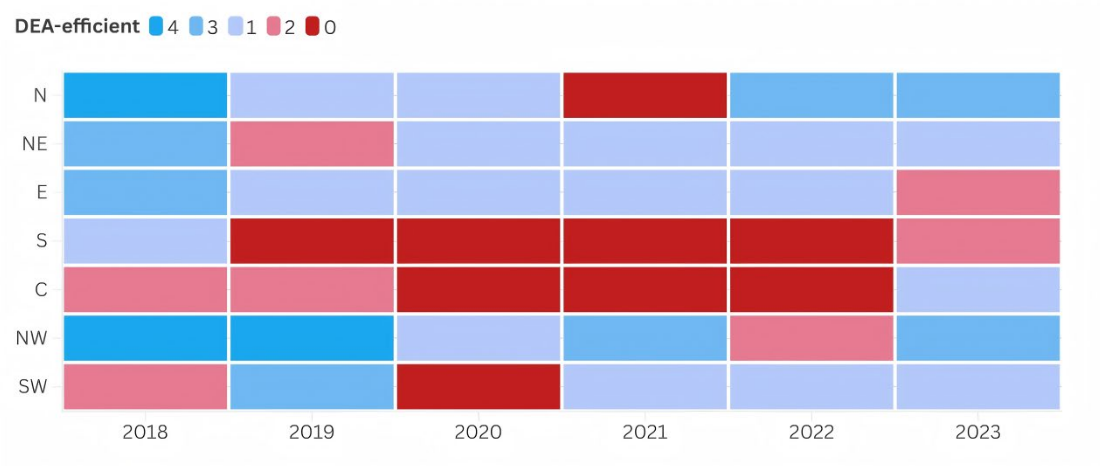

Figure 1 Regional Distribution of DEA Strongly Efficient HEI R&D Activities (2018–2023)

DEA Inefficiency Analysis of HEI R&D Activities (2018–2023)

According to the statistical results in Table 2, apart from the 63 DEA strongly efficient DMUs, there were still 123 DMUs in a DEA inefficient state between 2018 and 2023. In terms of regional distribution, the Northeast region had nine inefficient DMUs, North China had 18, East China had 33, South China had 15, Central China had 13, Northwest China had 13, and Southwest China had 22.

As shown in Figure 2, DEA inefficient DMUs are widely distributed across all regions, with East China having the highest number, highlighting the regional disparities in HEI R&D input-output efficiency.

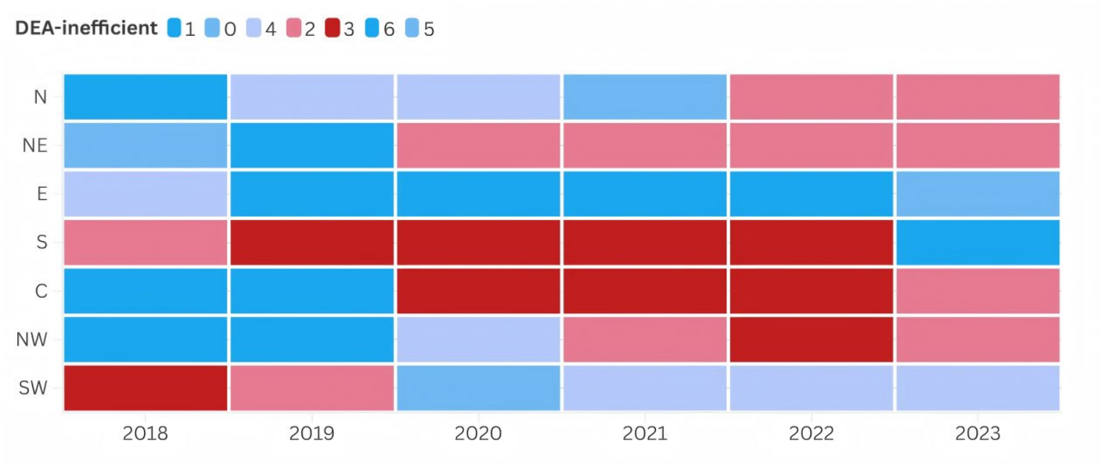

Figure 2 Regional Distribution of DEA Inefficient HEI R&D Activities (2018–2023)

Further analysis reveals that some provinces remained in a DEA inefficient state throughout the entire study period, indicating persistent issues in input-output efficiency. Specifically, seven provinces—Anhui, Fujian, and Jiangxi in East China; Guangdong in South

China; Hunan in Central China; Gansu in Northwest China; and Yunnan in Southwest China—maintained DEA inefficiency for six consecutive years (2018–2023) as detailed in Table 3.

Table 3. Summary of DEA Inefficient Provinces in HEI R&D Activities (2018–2023)

Year	Ietm	TE	SE	OE	S-	S+	SRC	R
2018	Anhui	0.623	0.989	0.616	0	36865.951	1.234	E
2018	Fujian	0.766	0.942	0.722	87.296	8360.964	1.405	E
2018	Jiangxi	0.816	0.918	0.75	61.482	897.601	1.115	E
2018	Hunan	1	0.836	0.836	9.749	15983.372	2.084	C
2018	Guangdong	0.81	0.889	0.72	142.395	190087.572	1.654	S
2018	Yunnan	1	0.988	0.988	37.227	17986.664	3.591	SW
2018	Gansu	1	0.994	0.994	0	9863.83	1.561	NW
2019	Anhui	0.658	0.973	0.64	216.794	0	2.329	E
2019	Fujian	0.753	0.897	0.675	85.746	4428.052	2.05	E
2019	Jiangxi	0.774	1	0.774	77.795	21905.101	0.943	E
2019	Hunan	0.86	0.9	0.774	28.061	4219.955	1.723	C
2019	Guangdong	0.92	0.858	0.79	201.204	164360.526	1.589	S
2019	Yunnan	0.977	0.914	0.893	0	16277.528	4.65	SW
2019	Gansu	0.903	0.976	0.881	18.493	5216.726	2.009	NW
2020	Anhui	0.754	0.905	0.682	3130.939	101330.475	9.705	E
2020	Fujian	0.828	0.892	0.739	127.869	499.016	4.156	E
2020	Jiangxi	0.666	0.968	0.644	52.528	20684.56	3.857	E
2020	Hunan	0.818	0.972	0.794	3476.101	73151.143	2.578	C
2020	Guangdong	0.795	0.863	0.687	141.933	164925.574	1.836	S
2020	Yunnan	0.872	0.931	0.811	18.128	14594.551	1.248	SW
2020	Gansu	0.722	0.997	0.72	277.079	622.871	1.354	NW
2021	Anhui	0.662	0.947	0.627	0	95937.27	6.557	E
2021	Fujian	0.916	0.839	0.769	184.137	1380.911	3.78	E
2021	Jiangxi	0.955	0.994	0.949	142.188	2407.661	0.56	E
2021	Hunan	0.882	0.964	0.85	1657.818	4129.982	1.157	C
2021	Guangdong	0.864	0.971	0.839	324.026	88973.212	1.31	S
2021	Yunnan	0.814	0.986	0.802	0	36560.372	2.613	SW
2021	Gansu	0.915	0.963	0.881	61.57	18479.317	3.494	NW
2022	Anhui	0.764	0.961	0.734	0	155428.906	4.104	E
2022	Fujian	0.88	0.884	0.778	862.631	7065.609	3.117	E
2022	Jiangxi	0.677	0.988	0.669	27.939	1493.332	1.795	E
2022	Hunan	0.85	0.986	0.838	718.393	10736.755	1.046	C
2022	Guangdong	0.942	0.881	0.83	80.145	203033.271	1.561	S
2022	Yunnan	0.92	0.98	0.902	0	46582.77	1.799	SW
2022	Gansu	0.823	1	0.823	83.364	23804.134	0.988	NW
2023	Anhui	0.763	0.91	0.694	98265.201	48027.916	3.115	E
2023	Fujian	0.926	0.904	0.838	2324.019	14470.933	2.399	E
2023	Jiangxi	0.727	0.931	0.676	25.047	4470.374	1.649	E
2023	Hunan	0.857	0.925	0.793	0	204736.224	1.564	C
2023	Guangdong	1	0.831	0.831	158.795	155394.385	2.163	S
2023	Yunnan	0.691	0.998	0.69	11.144	27996.794	1.843	SW
2023	Gansu	1	0.994	0.994	132.875	27669.821	5.188	NW

The R&D input-output efficiency of HEIs in the seven provinces listed in Table 3 varies significantly. In terms of Technical Efficiency (TE), Gansu, Guangdong, Yunnan, and Hunan exhibit relatively high technical efficiency, while Anhui and Jiangxi show lower TE values, indicating insufficient resource utilization.

Scale Efficiency (SE) is generally high across these provinces. Gansu, Jiangxi, Yunnan, and Hunan are close to optimal, while Guangdong, Fujian, and Anhui still have room for optimization. However, Overall Efficiency (OE) remains low in most provinces, with only Gansu, Yunnan, and Hunan achieving OE values above 0.8, suggesting that overall efficiency still needs significant improvement.

Input redundancy is particularly evident in Anhui, Guangdong, and Hunan, highlighting the need for better resource allocation. The Scale Returns Coefficient (SRC) further reveals that Anhui has the highest expansion potential, while Fujian, Gansu, and Yunnan still have room for growth. In contrast, Jiangxi, Guangdong, and Hunan have limited expansion potential, meaning that efficiency improvements in these provinces must primarily rely on enhanced management and technological advancements.

Overall, high-efficiency provinces should focus on optimizing input structures, while low-efficiency provinces should emphasize improving technical and managerial capabilities while reducing input redundancy, thereby enhancing the utilization efficiency of R&D resources.

Annual Trends in DEA Efficiency of HEI R&D Activities (2018–2023)

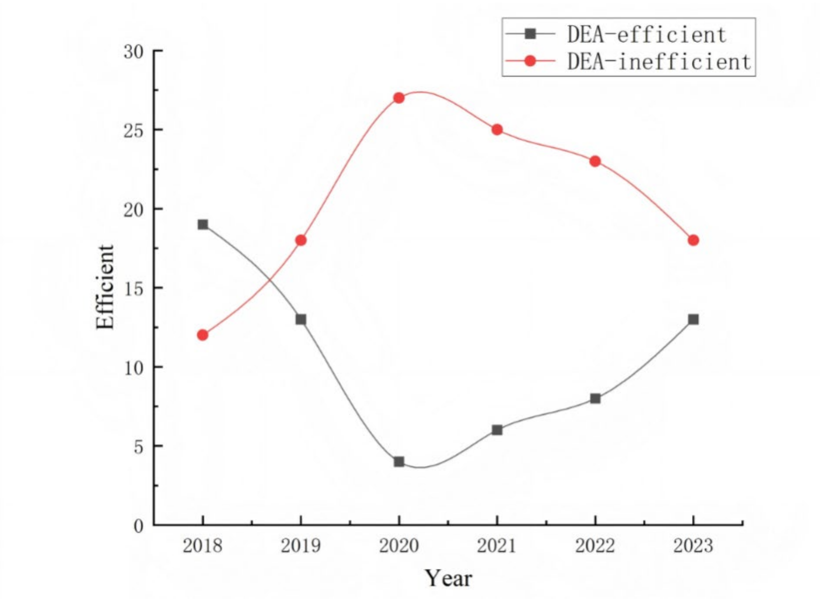

Figure 3 Trends in DEA Efficiency of HEI R&D Activities (2018–2023)

From 2018 to 2023, the number of DEA strongly efficient provinces exhibited fluctuations, but the overall trend showed improvement in the later years. 2018 was one of the strongest-performing years, with 19 provinces achieving DEA strong efficiency (OE = 1, SRC = 1). These included Beijing, Hebei, Shanxi, and Inner Mongolia in North China; Liaoning, Jilin, and Heilongjiang in Northeast China; Shanghai, Zhejiang, and Shandong in East China; Henan and Hubei in Central China; Guizhou and Tibet in Southwest China; and Shaanxi, Qinghai, Ningxia, and Xinjiang in Northwest China. This distribution reflects a high level of resource allocation efficiency in these regions. Notably, Xinjiang maintained DEA strong efficiency for six consecutive years, while Shanghai, Shaanxi, and Heilongjiang achieved strong efficiency in five of the six years, making them exemplary models for HEI R&D resource allocation in their respective regions.

Starting from 2021, the number of DEA strongly efficient provinces began to recover. In 2021, eight provinces reached strong efficiency, increasing to 11 in 2022, and peaking at 13 in 2023, the highest level within the study period. Beijing, Tianjin, Shanghai, and Xinjiang either regained or consistently maintained high efficiency in the later years. At the same time, Shaanxi, Guizhou, and Qinghai performed exceptionally well from 2021 to 2023, demonstrating high efficiency stability.

Despite these improvements, some provinces still exhibit inefficiencies in resource allocation. For example, Anhui, Jiangxi, and Guangdong performed poorly in most years, with OE values consistently below one, indicating significant room for efficiency optimization.

Periodic Dynamic Analysis of HEI R&D Efficiency (2018–2023)

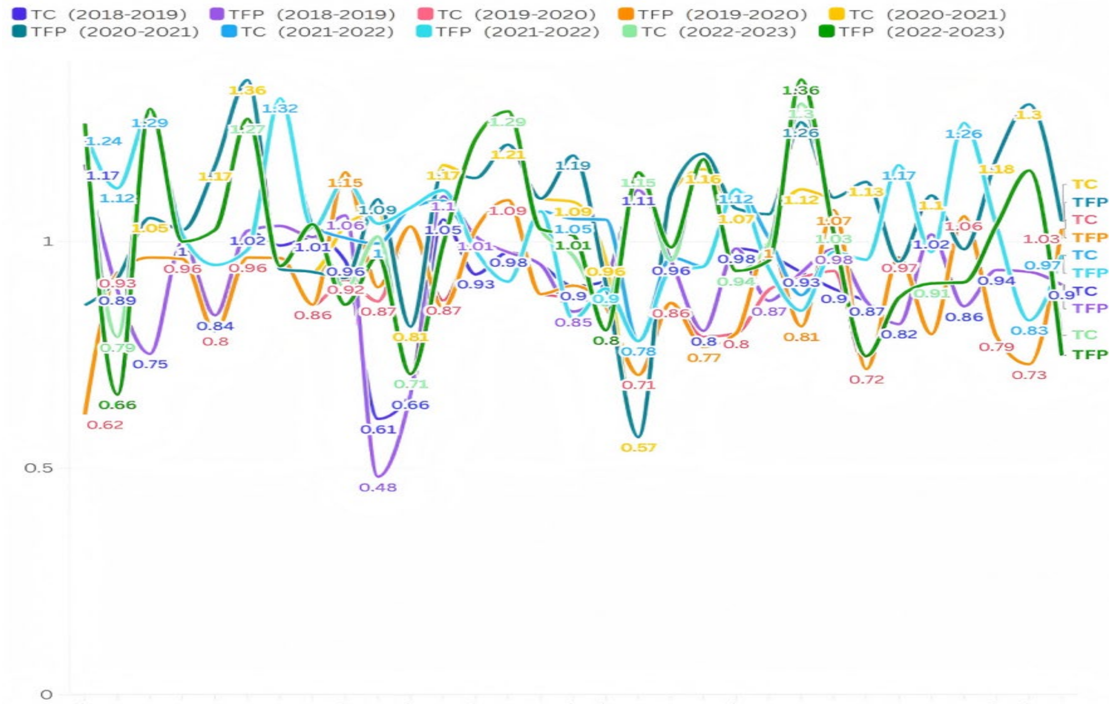

Figure 4 Periodic Dynamic Analysis of HEI R&D Efficiency (2018–2023)

From 2018 to 2023, an analysis of the Technical Change Index (TC) and Total Factor Productivity Change Index (TFP) across 31 provinces reveals notable trends in HEI R&D efficiency dynamics. The average TC value is 0.819, while the average TFP value is 0.956, indicating that most provinces' TFP growth is primarily driven by technological progress. Additionally, the correlation between TC and TFP is high (with an overall correlation coefficient close to one), further confirming that technological progress has played a key role in productivity enhancement.

From a regional perspective, the standard deviation of TFP (0.064) is slightly higher than that of TC (0.050), suggesting that TFP exhibits greater variation across different provinces. This fluctuation reflects the overall impact of technological progress on efficiency improvements while also highlighting disparities among provinces in R&D resource allocation and technology commercialization.

Although technological progress has generally contributed to TFP growth, significant discrepancies between TC and TFP persist in certain provinces. For example, Shandong has an average TC of 0.760 but a TFP of 0.873, indicating that technological advancements have not been fully translated into productivity gains. Similarly, in Jiangxi, the TC value is 0.817, whereas TFP reaches 0.933, reflecting a comparable pattern. Moreover, provinces such as Guangdong (TC = 0.858, TFP = 1.012), Henan (TC = 0.720, TFP = 0.840), and Gansu (TC = 0.857, TFP = 1.012) also demonstrate an incomplete alignment between technological change and productivity growth, underscoring potential inefficiencies in technology adoption and application.

Discussion

The Impact of Economic Development, Policy Support, and Technology Conversion Efficiency

The efficiency of HEI R&D resource allocation exhibits significant regional disparities. Based on the DEA analysis of 186 DMUs, regions such as East China (e.g., Shanghai) and Northwest China (e.g., Xinjiang) have consistently maintained high resource allocation efficiency, while the central and western regions (e.g., Henan, Guizhou) and certain southern provinces (e.g., Anhui, Jiangxi, Guangdong) have had a lower proportion of DEA strongly efficient years, with some provinces failing to reach DEA efficiency in certain years. The high efficiency of economically developed regions (e.g., Shanghai) is primarily attributed to sufficient financial support and well-established research infrastructure, whereas the relative advantage of western regions (e.g., Xinjiang) is largely due to preferential national policies (Ma et al., 2023).

These disparities may also be attributed to structural differences in regional innovation systems. As highlighted by Han et al. (2017), regions with more advanced industrial linkages, stronger institutional capacity, and better integration between universities and enterprises tend to achieve higher R&D efficiency.

Additionally, regional differences in technology conversion efficiency significantly impact the effectiveness of HEI R&D activities. The study reveals that eastern regions, due to their strong technology commercialization capabilities, demonstrate better Total Factor Productivity (TFP) performance. However, in provinces such as Anhui and Jiangxi, technological advancements have not been effectively translated into actual productivity, resulting in weak TFP growth (Tian & Yu, 2012). Although technological progress remains the key driver of TFP growth, a disconnect between technological change and productivity enhancement persists across different provinces. This phenomenon is likely attributed to variations in research resource allocation, technology commercialization capacity, and policy support. A low TC value may indicate weaker technological innovation capabilities in certain provinces, whereas higher TFP levels in other regions could result from more efficient resource allocation and stronger industrial application of research outputs. Conversely, in some provinces, even with higher TC values, low technology conversion efficiency can still limit improvements in TFP. This aligns with the regional innovation systems perspective, which emphasizes how institutional connectivity and systemic interactions influence innovation efficiency (Shin & Kim, 2025).

Regional Disparities in Resource Allocation Efficiency and Technology Commercialization

Beyond economic development and policy support, differences in technical efficiency and scale efficiency are also crucial factors influencing regional resource allocation efficiency. Research findings indicate that East China performs well in technical efficiency, demonstrating more effective utilization of R&D investments and stronger innovation capabilities, whereas West China relies more on scale advantages to improve overall efficiency. However, Central China does not exhibit competitive advantages in either aspect, leading to relatively lower HEI R&D resource utilization rates.

Furthermore, the uneven spatial distribution of HEIs and research institutions further exacerbates regional disparities in resource allocation efficiency. Coastal developed regions, which host a large number of national-level research projects and key universities, benefit from a significant regional agglomeration effect, thereby enhancing R&D efficiency in East China. In contrast, HEIs in Central and Western China face greater constraints in resource access, resulting in lower DEA efficiency and limited research investment and technology commercialization capacity (Han et al., 2017).

From a regional perspective, provinces such as Guangdong, where TFP is significantly higher than TC, may benefit from a well-established technology commercialization system and a mature market mechanism, enabling technological advancements to be rapidly translated into productivity. In contrast, provinces such as Shandong and Jiangxi, despite experiencing relatively rapid technological progress, have relatively lower TFP growth, which may be linked to lower efficiency in converting research outputs into real-world applications. Additionally, some central and western provinces, such as Henan and Gansu, have low TC and TFP values, likely reflecting weaknesses in technological innovation, talent attraction, and research funding investment.

Given these findings, policy interventions should focus not only on promoting technological innovation but also on enhancing technology commercialization efficiency and optimizing the regional allocation of research resources. For regions with rapid technological progress but limited TFP growth, policies should prioritize strengthening university-industry collaboration, accelerating the marketization of research outputs, and maximizing the contribution of technological advancements to productivity. Meanwhile, for provinces with both low TC and TFP, government support should focus on improving fundamental research capabilities, attracting high-caliber talent, and optimizing funding allocation to narrow regional development gaps and promote a more balanced national HEI R&D resource distribution.

Limitations

This study focuses on quantitative indicators and does not incorporate contextual or qualitative variables such as institutional governance quality or regional policy design. Future research could expand on this by integrating environmental and institutional factors for a more comprehensive understanding of R&D efficiency.

Conclusion

Regional Disparities in HEI R&D Resource Allocation and Optimization Strategies

This study reveals significant regional disparities in the efficiency of HEI R&D resource allocation, primarily influenced by economic development levels, financial support, and the quality of research infrastructure. Coastal regions such as Shanghai and Guangdong consistently maintained high resource allocation efficiency throughout the study period due to stable financial support, concentrated research resources, and well-developed market mechanisms. In contrast, central, western, and some southern provinces (e.g., Anhui, Jiangxi, Henan, and Guizhou) had fewer DEA strongly efficient years, with some provinces failing to achieve DEA efficiency in certain years. This reflects relative disadvantages in research resource acquisition, talent attraction, and technology commercialization in these regions.

To optimize R&D resource allocation efficiency across regions, greater financial support should be directed toward central and western provinces with lower efficiency, along with improvements in research infrastructure and the academic environment in HEIs. Additionally, cross-regional research collaboration should be promoted, encouraging eastern universities to establish joint research platforms with institutions in central and western China. By fostering resource sharing, joint talent training, and research cooperation, the research capacity and resource utilization efficiency of HEIs in underperforming regions can be improved. Strengthening technological innovation and research commercialization capabilities in these regions will contribute to a more balanced and efficient allocation of HEI R&D resources nationwide.

The Impact of Technological Progress on TFP Growth and Optimization Pathways

Technological progress is the primary driver of Total Factor Productivity (TFP) growth, yet significant regional differences exist in technology conversion efficiency. On average, the Technical Change Index (TC) is 0.819, while TFP is 0.956, indicating that most provinces' TFP growth is primarily driven by technological progress. However, in some regions, technological advancements have not been effectively translated into productivity gains. For example, Shandong and Jiangxi exhibit relatively fast technological progress, yet TFP growth remains lower, suggesting inefficiencies in technology commercialization and industrial application, which limits the practical value of scientific research outputs.

To enhance the contribution of technological progress to TFP growth, it is essential to strengthen university-industry-research collaboration, fostering closer integration between enterprises, universities, and research institutions to establish a more cohesive innovation ecosystem. This will accelerate the commercialization of scientific and technological achievements. Additionally, regional technology transfer centers should be established to improve the alignment between research and industry needs, enhance the maturity of technology markets, and ensure that research innovations are efficiently converted into productive applications, ultimately leading to higher overall TFP levels.

Balanced Development and Optimization of HEI R&D Resource Allocation

This study further reveals that regional disparities in R&D resource allocation efficiency are not only influenced by economic development and financial support but are also closely related to technical efficiency, scale efficiency, and the spatial distribution of HEIs and research institutions. While HEIs in East China demonstrate high technical efficiency, HEIs in West

China rely more on scale advantages to enhance research output. Central China, however, lacks competitiveness in both aspects, resulting in relatively lower R&D resource utilization rates. Furthermore, coastal developed regions benefit from a high concentration of national-level research projects and key universities, forming regional agglomeration effects that significantly enhance R&D efficiency in East China. In contrast, central and western provinces, due to limited access to resources, face lower DEA efficiency, constraining both research investment and technology commercialization efficiency.

To narrow these regional disparities, eastern provinces should leverage technology spillover effects by establishing long-term research collaborations with HEIs in central and western regions, promoting scientific resource sharing. Additionally, regional technology incubation systems should be developed to optimize the mechanisms for research commercialization, facilitating the movement of high-level research talent to central and western provinces to strengthen regional research capacity coordination. Through these measures, national HEI R&D resource utilization efficiency can be enhanced, fostering a more balanced innovation landscape and promoting the high-quality development of the higher education research system.

References

Bai, X.-J., Li, Z.-Y., & Zeng, J. (2020). Performance evaluation of China's innovation during the industry-university-research collaboration process—an analysis basis on the dynamic network slacks-based measurement model. *Technology in Society, 62*, 101310. https://doi.org/10.1016/j.techsoc.2020.101310

Bu, D., & Li, H. (2022). Research on the efficiency of R&D input and output in Shanghai Universities based on data envelopment analysis. *Research on Science and Technology Innovation and Development Strategy, 6*(05), 1-9.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, X. (2024). Dynamic analysis and prediction of R&D resource allocation in Universities of Anhui Province. *Journal of Panzhihua University, 41(S1)*, 70-74.

Du, Y., & Seo, W. (2022). A comparative study on the efficiency of R&D activities of universities in China by region using DEA–Malmquist. Sustainability, 14(16), 10433. https://doi.org/10.3390/su141610433

Han, C., Thomas, S. R., Yang, M., Ieromonachou, P., & Zhang, H. (2017). Evaluating R&D investment efficiency in China's high-tech industry. *The Journal of High Technology Management Research, 28*(1), 93-109.

He, X. (2023). Empirical Study on the Efficiency of R&D Input and Output in Universities: Analysis Based on the Two-Stage DEA-VRS Model and Super-Efficiency Model. *Journal of Wuhan University of Technology (Social Science Edition), 36*(05), 136-145.

Hu, T. (2023). Research on the R&D Activities of Chinese Universities: Statistical Analysis Based on Data from 2013 to 2021. *Henan Science and Technology, 42*(22), 153-158.

Hung, C., & Shiu, P. (2014). Evaluating project performance by removing external effects: Implications to the efficiency of research and development resource allocation. *Research Evaluation, 23*, 366-380. https://doi.org/10.1093/RESEVAL/RVU022

Ikcheon Um, S. C., & Kwangseon, H. (2022). Efficiency and Its Determinants in Regional Innovation Systems in South Korea 1999-2014: The Network Data Envelope Analysis. *Korea Observer, 53*(1), 75-104. https://doi.org/10.29152/KOIKS.2022.53.1.75

Jhantasana, C. (2019). The Efficiency of Social Responsibility of Rajabhat University. *Journal of Chandrakasem Rajabhat University, 14*(1), 152-165.

Lee, J. Y., Park, J. H., & Lee, I. H. (2023). The effect of teacher influence relative to principal influence in school decision-making on teacher job attitudes. *Educational Studies, 49*(3), 529-546. https://doi.org/10.1080/03055698.2023.2174799

Liu, J., & Xu, C. (2011). Assessing the innovation efficiency of Chinese Domestic-funded Enterprises. In Bob, W. (Ed.), *2011 International Conference on Information Management, Innovation Management and Industrial Engineering* (pp.370-373). IEEE. https://doi.org/10.1109/ICIII.2011.94

Ma, T., Cao, X., & Zhao, H. (2023). Development zone policy and high-quality economic growth: quasi-natural experimental evidence from China. *Regional Studies, 57*(3), 590-605. https://doi.org/10.1080/00343404.2022.2093342

Miao, Y., & Wang, J. (2023). Application of DEA model in agricultural production efficiency evaluation. In *2023 IEEE International Conference on Electrical, Automation and Computer Engineering (ICEACE)* (pp. 46-50). IEEE. https://doi.org/10.1109/ICEACE60673.2023.10442153

OECD. (2015). *Frascati manual 2015: Guidelines for collecting and reporting data on research and experimental development*. OECD Publishing. https://doi.org/10.1787/9789264239012-en

Qin, X., & Du, D. (2018). Measuring universities' R&D performance in China's provinces: a multistage efficiency and effectiveness perspective. *Technology Analysis & Strategic Management, 30*(12), 1392-1408. https://doi.org/10.1080/09537325.2018.1473849

Shin, D. J., & Kim, B. H. S. (2025). Analyzing the Dynamic Efficiency and Critical Factors of the Regional Innovation System: A Case Study of Korea. *International Regional Science Review*, 01600176251313752. https://doi.org/10.1177/01600176251313752

Tian, X., & Yu, X. (2012). The enigmas of TFP in China: A meta-analysis. *China Economic Review, 23*(2), 396-414. https://doi.org/10.1016/j.chieco.2012.02.007

Wu, J., Chu, J., Zhu, Q., Yin, P., & Liang, L. (2016). DEA cross-efficiency evaluation based on satisfaction degree: an application to technology selection. *International Journal of Production Research, 54*, 5990-6007. https://doi.org/10.1080/00207543.2016.1148278