

Education and Innovation: The Input-Output Efficiency of Research in Chinese Universities

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Abstract: In terms of scale, China's higher education system holds a leading position globally. The nation has implemented a strategic framework that integrates higher education development with technological innovation, aiming to establish scientific hubs and innovation-driven centers. Drawing on data from 31 provincial-level regions in China, this study employs the super-efficiency Data Envelopment Analysis (DEA) model and the Malmquist Productivity Index (MPI) to systematically evaluate the research performance of Chinese universities from 2011 to 2022. The findings reveal that throughout the study period, Chinese universities maintained a relatively high level of research efficiency, demonstrating an overall upward trend. Although pure technical efficiency (PTE) remained strong, scale efficiency (SE) still leaves room for improvement. Conversely, the total factor productivity (TFP) of Chinese universities exhibited a downward trajectory, particularly after 2017, when a significant decline in the contribution of technological progress became a primary bottleneck for TFP growth. Therefore, optimizing the research efficiency of Chinese universities requires prioritizing originality-driven investments, optimizing the national layout of research resources, and reforming management mechanisms to stimulate innovative vitality.

Keywords: Research efficiency; University; Innovation; DEA; Malmquist; China

Online publication: June 9, 2026

1. Introduction

The *UNESCO Science Report: Towards 2030* outlines an ambitious blueprint for global scientific development, emphasizing the pivotal role of science and technology in driving global sustainable development and addressing societal and environmental challenges ^[1]. This report emphasizes how scientific research contributes significantly to the realization of the United Nations' 2030 Sustainable Development Goals. It asserts that Science, Technology, and Innovation are key forces in tackling global issues such as climate change, resource scarcity, energy shortages, and poverty. Furthermore, the report highlights the central role of higher education in advancing global scientific innovation and achieving sustainable development, urging countries to increase investment in university research, particularly in the fields of basic and applied sciences. The 2024 International Forum on Higher Education Annual

Conference was convened in Beijing under the theme “Scientific and Technological Innovation and Sustainable Development.” This prestigious academic gathering brought together renowned experts, academicians, scholars, and industry representatives from over 30 countries and regions. Participants engaged in rigorous scholarly dialogues examining higher education’s pivotal role in achieving sustainable development, with particular focus on generating innovative solutions to address the pressing challenges facing humanity and planetary sustainability ^[2]. Universities is becoming the core drivers of technological innovation in response to current and future global challenges.

In recent years, the scale of higher education in China has expanded rapidly, making it one of the largest higher education systems in the world, with the total number of higher education students ranking first globally. According to data from Ministry of Education of the People’s Republic of China (2024), the gross enrollment rate for higher education in China exceeded 60% in 2023, indicating that nearly two-thirds of the college-age population now has access to higher education ^[3]. Currently, China is home to more than 3,000 higher education institutions, covering a wide range of academic disciplines and offering a complete education system that includes associate, undergraduate, master’s, and doctoral programs. Through the “double world-class project” initiative, the government is committed to building world-class universities and disciplines to improve the overall quality and global impact of Chinese higher education institutions ^[4,5].

The Chinese government has proposed a strategy for the integrated, collaborative development of education, science and technology, and talent, recognizing education as a critical support for achieving the goal of “high-level scientific and technological self-reliance and strength” ^[6,7]. As crucial foundations for the nation’s scientific and technological innovation, universities lead the way in both basic science and cutting-edge technology research. University research is not only a crucial source of knowledge innovation but also directly serves the core strategic needs of the nation. By cultivating innovative talent, promoting scientific and technological independence, supporting high-quality economic development, and strengthening national comprehensive power, universities provide significant impetus for the country’s modernization efforts ^[8].

Therefore, China’s investment in higher education research funding has increased steadily, reaching levels in several research fields (such as quantum science, artificial intelligence, and 5G) that are on par with or surpass those of some developed countries ^[9]. As the importance of university research has increased steadily over the years, many key universities have undertaken major national research projects in fundamental sciences, engineering technologies, and advanced technologies, becoming core components of the national innovation system. Research has gradually become a significant indicator of the comprehensive strength of universities. At the same time, the quantity of research achievements from Chinese universities ranks among the highest globally. According to the Nature Index (2023), The global output of research papers from Chinese universities has surged, especially in disciplines like physics, engineering, chemistry, and materials science ^[10]. Chinese universities are among the top in terms of paper output, with university scholars publishing more frequently in leading journals, and the number of highly cited papers and papers in high-impact journals showing significant growth.

Despite the significant progress made by Chinese universities in research, a gap still exists when compared to some of the world’s leading universities regarding the accumulation of basic research, the originality of research findings, and the quantity and organization of high-level researchers ^[11,12]. In the context of increasingly intense international scientific and technological competition and the growing demand for technological self-reliance, examining the research performance of Chinese universities not only

supports the enhancement of China's technological innovation capabilities and promotes the more efficient use of research resources, but also provides foundational support for international collaboration and global scientific governance. This, in turn, enables Chinese universities to play a larger role in the global research system, contributing to the achievement of the nation's "powerful nation in science and technology" strategy. Therefore, this study, incorporating the latest data and employing the super-efficiency Data Envelopment Analysis (DEA)-Malmquist method, conducts a dynamic assessment of the research efficiency of universities across 31 Chinese provinces from 2011 to 2022, with a focus on the following questions:

- (1) What is the current status and key characteristics of research efficiency in Chinese universities?
- (2) What are the dynamic trends in the TFP of research in Chinese universities, and what are the main factors influencing these changes?
- (3) How can Chinese universities effectively improve research efficiency?

2. Literature review

In higher education, studies on resource allocation efficiency primarily aim to determine the optimal distribution, management, and utilization of resources to maximize their impact, enhancing the quality and effectiveness of education while fully supporting its roles in talent development, scientific research, and societal service^[13]. At present, the integration of DEA and MPI has emerged as a crucial method for assessing and improving the efficiency of educational resource utilization^[14,15]. Applying the DEA-Malmquist approach to higher education enhances the scientific evaluation of institutional efficiency, while simultaneously equipping policymakers and university leaders with practical strategies for improvement

Researchers have consistently used the DEA-Malmquist approach to analyze the efficiency of resource distribution in higher education, achieving significant progress in areas such as multidimensional efficiency, dynamic efficiency, regional and international comparisons, and policy optimization. Avkiran utilized DEA to construct three efficiency models: overall performance, educational service provision performance, and fee-paying enrollment performance^[16]. In this study, the efficiency of Australian universities was measured by evaluating university inputs (such as teaching staff, administrative staff, etc.) and outputs (such as student enrollment numbers, international students, etc.). The research found that Australian universities generally operated with considerable technical and scale efficiency, and the three performance models effectively distinguished between efficient and inefficient institutions. The study concluded that the greatest potential for improvement lies in increasing output. Castano and Cabanda applied the DEA-Malmquist method to explore the efficiency and sources of productivity growth in state universities in the Philippines^[17]. The results showed that there were certain discrepancies in efficiency and productivity among Philippine state universities, with 83% of institutions achieving efficiency. However, less than half of the universities demonstrated growth in TFP, with the primary source of productivity growth being improvements in technical efficiency rather than innovation. Kuah and Wong employed DEA to design input-output indicators for the teaching and research dimensions, assessing the efficiency of these functions in Malaysian universities^[18]. They examined differences in resource usage efficiency across universities, providing data support for policy-making. Wolszczak-Derlacz used the DEA-Malmquist method to quantitatively evaluate the efficiency of 500 universities in the United States and Europe in teaching and research^[19]. Through common frontier and inter-group frontier comparisons, the study found that TFP in European universities generally increased, with the Netherlands and Italy showing the most significant improvements, while U.S. higher education institutions experienced a slight decline in productivity. The

study also analyzed the main factors influencing TFP changes in the U.S. and European samples. In recent years, scholars worldwide have increasingly applied the DEA method to evaluate the teaching and research efficiency of higher education institutions, providing a robust basis for higher education policymaking across different countries ^[20–23].

Although the application of the DEA-Malmquist method to assess the efficiency of resource allocation in Chinese universities has been relatively recent, an increasing number of researchers have begun to employ this method to evaluate various aspects of resource allocation in higher education institutions. In terms of overall resource allocation, You and Kong analyzed the efficiency of higher education resource allocation in 31 provinces of China from 2016 to 2019, using the super-efficiency DEA-Malmquist method to explore efficiency disparities between the eastern, central, and western regions ^[24]. The study found that the overall resource allocation efficiency had steadily improved, primarily driven by changes in technical efficiency, and emphasized the need for reforms in resource allocation methods and enhanced regional collaborative development to comprehensively improve the quality of higher education. Bao *et al.* analyzed the data from 58 Ministry of Education-affiliated universities from 2008 to 2017, using the super-efficiency DEA model and the MPI for evaluation ^[25]. The research revealed that there was still room for improvement in overall resource input-output efficiency, with quality-oriented output efficiency being lower than quantity-oriented output efficiency, indicating an imbalance in resource allocation. Additionally, the contribution of the three primary functions—scientific research, talent cultivation, and social service—to overall efficiency showed a gradual decline in research efficiency and an increase in talent cultivation efficiency. Zhao and Zhang proposed a comprehensive framework for studying the resource allocation process in higher education systems, divided into three dimensions: resource supply, educational growth, and societal advancement ^[26]. Using the network two-stage DEA model and Malmquist index, they examined the efficiency of higher education resource allocation in 30 Chinese provinces from 2006 to 2020. The findings indicated that resource allocation efficiency in the higher education system improved each year, but the efficiency levels in the two sub-stages—output commercialization and economic integration—varied greatly, with inefficiency in the economic integration phase being the primary obstacle to overall efficiency gains.

In the area of university research efficiency, Cha *et al.* analyzed research efficiency and its influencing factors using panel data from “double world-class project” universities between 2010 and 2019, employing the super-efficiency SBM-Malmquist and Tobit models ^[27]. The study revealed an upward trend in the TFP index of research in the sample universities. It found that regional economic development levels, human capital investment, and the proportion of government funding in research budgets significantly impacted research efficiency. The study recommended strengthening the accumulation of high-quality human capital and improving talent incentives and financial support mechanisms. Guo *et al.* categorized university technological innovation into the stages of technological output and technology commercialization ^[28]. They applied a two-stage DEA approach to evaluate efficiency over the span from 2009 to 2020. The results indicated that efficiency in the technology output stage did not show an upward trend, while the commercialization efficiency significantly improved after 2016. Li *et al.* selected data from local universities in 31 provinces between 2018 and 2021 and applied the DEA-Malmquist index to measure technological innovation efficiency ^[29]. The study found that the technological innovation efficiency of local universities developed steadily overall, though there was still room for improvement in the scale of innovation. Additionally, the study used spatial autocorrelation analysis to reveal the geographical distribution characteristics of innovation efficiency, suggesting that local universities should optimize the allocation of technological resources to enhance their innovation capacity.

Previous studies have shown that the DEA-Malmquist method is extensively used in international research on the efficiency of resource allocation in higher education. In China, research primarily focuses on

the input-output efficiency of university resources at both the inter-provincial and inter-institutional levels, emphasizing the importance of resource allocation efficiency in the reform and development of higher education [30–32]. These studies have provided empirical evidence for policy making, driving the enhancement of quality and the innovative development of Chinese higher education. Based on the previous studies, this research intends to carry out a dynamic analysis of the research efficiency of universities in 31 provinces in China over the period from 2011 to 2022, by establishing suitable evaluation indicators and incorporating the latest data. The goal is to provide effective theoretical and empirical support for the improvement of higher education resource allocation efficiency and the optimization of related policies.

3. Methodology

3.1. DEA-VRS

DEA is a non-parametric method used to evaluate relative efficiency, primarily applied in areas such as production efficiency and performance assessment of Decision-Making Units (DMUs). The DEA model was initially proposed by Charnes, Cooper, and Rhodes in 1978 constructing an efficiency frontier using linear programming techniques [33]. The model, named after its founders, is referred to as the CCR model. However, the CCR model assumes Constant Returns to Scale (CRS), meaning that efficiency remains unchanged regardless of variations in input or output scale. To address this limitation, Banker, Charnes, and Cooper introduced the BCC model, which assumes Variable Returns to Scale (VRS), making DEA more adaptable to various real-world scenarios [34].

Traditional DEA-CCR and DEA-BCC models evaluate the relative efficiency of DMUs with results typically ranging between 0 and 1. DMUs with an efficiency score of 1 are considered efficient. However, when multiple units achieve the same high efficiency, the DEA model cannot distinguish their relative performance. To resolve this issue, the super-efficiency DEA model was proposed by Charnes *et al.* in 1996, allowing efficiency scores greater than 1, thereby enabling comparisons among efficient units [35].

This study employs an input-oriented, variable returns-to-scale super-efficiency DEA model to measure the research efficiency of universities across 31 provinces in China (excluding Hong Kong, Macau, and Taiwan). Assuming there are n DMUs, each operating under m input variables and s output variables, the efficiency formula is expressed as follows:

$$\begin{aligned}
 & \min \theta_h \\
 & s.t. \left\{ \begin{array}{l} \sum_{\substack{j=1 \\ j \neq h}}^n \lambda_j x_{ij} + S_i^- = \theta_h x_{i0} \\ \sum_{\substack{j=1 \\ j \neq h}}^n \lambda_j y_{rj} - S_r^+ = y_{r0} \\ \sum_{j \neq 0} \lambda_j = 1 \\ \lambda_j, S_i^-, S_r^+ \geq 0 \end{array} \right. \quad (1)
 \end{aligned}$$

In formula (1), x_{ij} represents the i -th (where $i=1,2,\dots,m$) input of university j , and y_{rj} represents the r -th (where $r=1,2,\dots,s$) output of university j . θ_h denotes the efficiency value of university h . λ_j is the weight assigned to decision-making units that form an efficient combination relative to university h . x_{i0} and y_{r0} are the i -th input and r -th output of the decision-making unit being evaluated, and S_i^- and S_r^+ are the slack variables.

3.2. Malmquist productivity index

DEA models can only measure the static efficiency of DMUs and cannot evaluate changes in efficiency over time. The MPI is a widely used measure of productivity change over time, initially introduced by Swedish economist Sten Malmquist in 1953 and later developed by Fare et al. for broader applications in efficiency analysis [36–38]. This study utilizes the DEA-Malmquist index to further examine the dynamic changes in research efficiency among universities in different provinces. The index is defined as follows:

$$M_t^{t+1} = \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}} \quad (2)$$

$$MEFFCH_t^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \quad (3)$$

$$MTECH_t^{t+1} = \sqrt{\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}} \quad (4)$$

In the formulas, D represents the distance function, t represents the time period, x represents the input vector, and y represents the output vector. Formula (2) represents the total Malmquist index, which is used to measure the productivity change from time t to time $t+1$. A value greater than 1 reflects an improvement in productivity, while a value less than 1 indicates a decline or no change in productivity. Formula (3) is used to measure the efficiency change from time t to time $t+1$, which reflects the efficiency performance of the decision-making unit relative to the production frontier. Formula (4) measures the movement of the production frontier. That is the degree of technological change, reflecting the change in productivity due to technological advancement or regression.

3.3. Data sources and variable selection

In 1928, mathematician Charles Cobb and economist Paul Douglas proposed the Cobb-Douglas Production Function, which reflects the interrelationship between different production factors in economic activities and their contribution to productivity [39]. This function is used to describe the relationship between inputs and outputs in the production process, indicating that the total output of a production unit is jointly determined by labor input, capital input, and technological level. Accordingly, this study selects the full-time equivalent (FTE) of R&D personnel, internal R&D expenditure, and the number of R&D institutions as input indicators representing three dimensions: human, financial, and material resources. For research outputs, the number of papers, books, and patents are selected as quantitative indicators, while awards and income from technology transfer are chosen as qualitative indicators, as shown in **Table 1**. It should be noted that Hong Kong, Macau, and Taiwan are excluded from this study due to data availability.

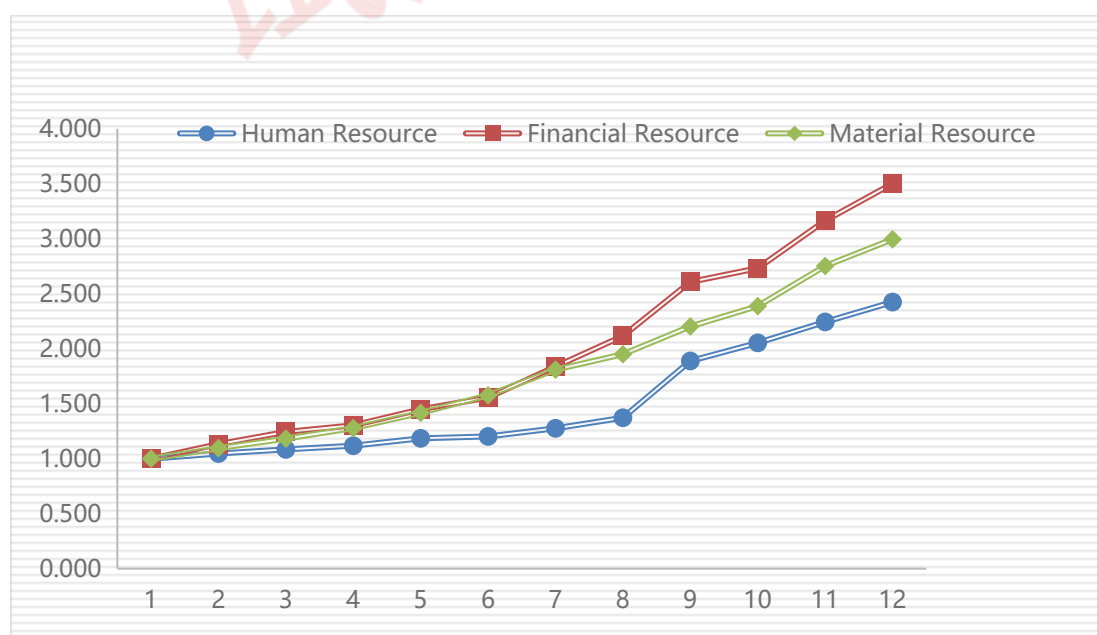
Table 1. Research input and output indicators

Primary indicator	Secondary indicator	Unit
Input	Full-time Equivalent R&D Personnel	Person-years
	Internal R&D Expenditure	10000 yuan
	R&D Institutions	Number
	Published Papers	Article
Output	Books	Volume
	Patents	Number
	Award-Winning Achievements	Item
	Technology Transfer Revenue	1000 yuan

4. Results and discussion

4.1. Descriptive statistical analysis of research input and output in universities across 31 Chinese provinces

Using 2011 as the base year (indexed to 1), we analyzed the trends in research input and output indices for universities across 31 Chinese provinces from 2011 to 2022 (**Figures 1 and 2**). In terms of research input, all indicators showed a steady annual increase throughout the study period, with a significant acceleration after 2018. Among them, funding input exhibited the most substantial growth, while human resource input increased at a relatively slower pace. Nevertheless, by 2022, human resource input had doubled compared to 2011.

**Figure 1.** Research input indicators

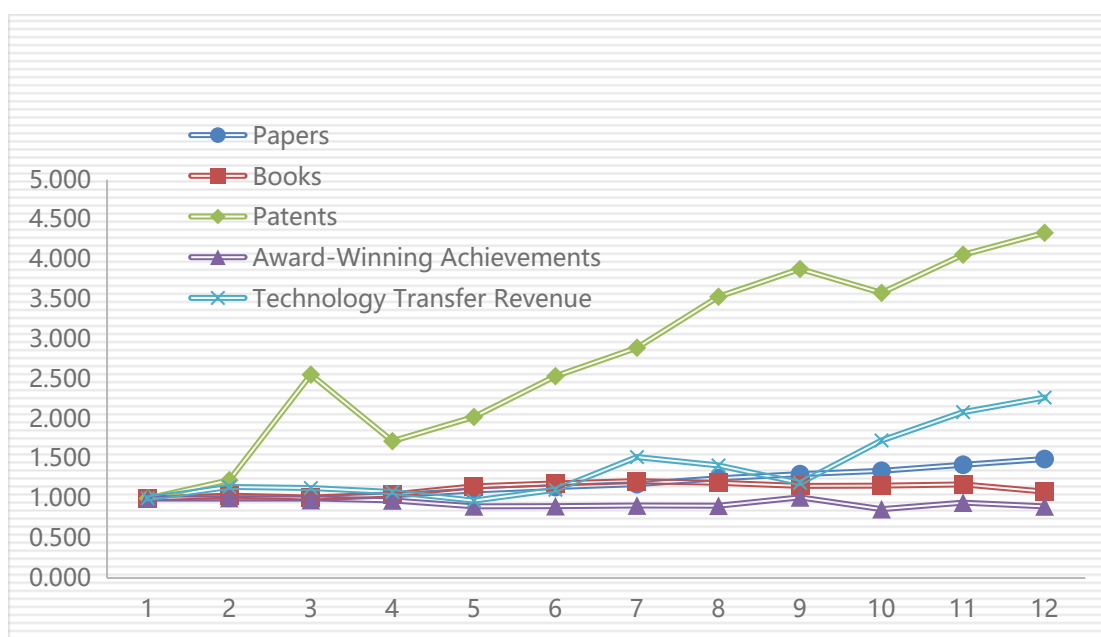


Figure 2. Research output indicators

Regarding research output, all indicators, except for the number of awarded scientific achievements, demonstrated an overall upward trend. While the total number of awarded scientific achievements stabilized at the national level, considerable variations remained across provinces. The number of authorized invention patents exhibited the fastest growth, reaching 4.3 times its 2011 level by 2022. Over the study period, the total revenue from technology transfer doubled, while the number of published books and papers increased at a relatively modest rate.

4.2. Analysis of super-efficiency DEA model results

This study employs an input-oriented, variable returns-to-scale (VRS) super-efficiency DEA model, using DEARUN 3.2.0.5 software to measure the comprehensive efficiency (TE) of research input-output for universities across 31 provinces from 2011 to 2022. TE reflects the relative efficiency of decision-making units (DMUs) in utilizing input resources for production, in comparison to the optimal efficiency frontier. The DEA-VRS model further decomposes TE into pure technical efficiency (PTE) and scale efficiency (SE), following the equation:

$$TE = PTE \times SETE = PTE \times SE$$

Since each province in each year is treated as an independent DMU, the study includes a total of 372 DMUs. Due to space constraints, only the annual average efficiency values are presented in **Table 2**.

As shown in **Table 2**, the overall trend of university research efficiency indicates an upward trajectory. Except for 2011 and 2014, the research efficiency of universities across China generally reached an effective level. The number of provinces with $TE \geq 1$ fluctuated but increased from 11 to 16, although this accounts for just over half of the total, indicating room for further improvement.

Table 2. Average values of university research efficiency and its decomposition components from 2011 to 2022 (by year)

Year	TE	PTE	SE	Effective regions	Increasing	Decreasing
2011	0.9208	1.0895	0.8451	11	14	17
2012	1.0188	1.1317	0.9003	15	10	20
2013	1.0024	1.1332	0.8846	13	10	21
2014	0.9777	1.1123	0.8790	11	11	19
2015	1.0610	1.1605	0.9143	20	13	18
2016	1.0554	1.1807	0.8938	17	11	19
2017	1.0026	1.0879	0.9215	15	9	22
2018	1.0032	1.0916	0.9190	17	9	21
2019	1.0140	1.1392	0.8900	16	8	22
2020	1.0467	1.1942	0.8765	18	9	22
2021	1.0459	1.1826	0.8845	15	6	25
2022	1.0482	1.1902	0.8806	16	9	22
Average	1.0156	1.1405	0.8905	—	—	—

Note: The average values in the table are all geometric averages.

The decomposition of TE reveals that pure technical efficiency remained relatively stable and consistently above 1 throughout the study period. Since PTE reflects efficiency differences arising purely from management and technology—excluding scale effects—this suggests that the overall research management level in universities remained high during the study period. SE, averaging around 0.9, remained stable, peaking at 0.9215 in 2017 before experiencing a gradual decline. Analysis of scale returns trends indicates that many provinces operate under decreasing returns to scale, suggesting inefficiencies in resource allocation. Enhancing scale efficiency requires optimizing resource allocation based on the scale stage of each province^[40].

4.3. Analysis of MPI results

MPI is a productivity measurement tool based on the DEA method, which evaluates the change in TFP of decision-making units between two time points by comparing the technological efficiency and technological progress of different periods. This study uses DEARUN3.2.0.5 software to calculate the MPI for research input-output of universities in 31 provinces from 2011 to 2022, along with its decomposition components: the Technological Efficiency Change Index (TEC) and the Technological Progress Index (TC). The relationship is as follows: $MPI = TEC \times TC$. Additionally, the TEC can be further decomposed into the Pure Technical Efficiency Change Index (PTEC) and the Scale Efficiency Change Index (SEC), with the following relationship: $TEC = PTEC \times SEC$.

From 2011 to 2022, the annual change in the TFP of research efficiency in Chinese universities showed a declining trend. As shown in **Table 3**, the average value of the change in TFP for university research efficiency across 31 provinces is 0.9495, indicating that the annual TFP of university research decreased by 5.1% during the 2011–2022 period. Further analysis of its decomposition components reveals that during the study period, the average value of the dynamic change in technological efficiency was 1.0119,

indicating an average annual growth of 1.2%, with pure technical efficiency increasing by 0.8% annually and scale efficiency increasing by 0.4% annually. Meanwhile, the average value of the dynamic change in technological progress was 0.9384, reflecting an average annual decline of 6.2%.

Table 3. The average values of university research MPI and its decomposition components from 2011 to 2022 (by year)

Year	TEC	TC	PTEC	SEC	MPI
2011–2012	1.1064	0.9196	1.0387	1.0652	1.0175
2012–2013	0.9839	1.1014	1.0013	0.9826	1.0837
2013–2014	0.9754	0.9203	0.9816	0.9937	0.8976
2014–2015	1.0852	0.8656	1.0433	1.0402	0.9394
2015–2016	0.9947	1.0216	1.0175	0.9776	1.0161
2016–2017	0.9500	1.0061	0.9214	1.0310	0.9558
2017–2018	1.0006	0.8849	1.0034	0.9972	0.8854
2018–2019	1.0107	0.8306	1.0437	0.9685	0.8395
2019–2020	1.0323	0.9513	1.0482	0.9848	0.9820
2020–2021	0.9993	0.9538	0.9903	1.0091	0.9531
2021–2022	1.0022	0.8982	1.0065	0.9957	0.9002
Average	1.0119	0.9384	1.0081	1.0037	0.9495

Note: The average values in the table are all geometric averages.

Figure 3 highlights that, except for a few years, the primary driver of TFP decline was the decreasing contribution of TC. Since 2017, the contribution of technological progress to university research productivity has weakened, resulting in persistent negative TFP growth. This suggests that the decline in China’s university research TFP is primarily driven by technological stagnation.

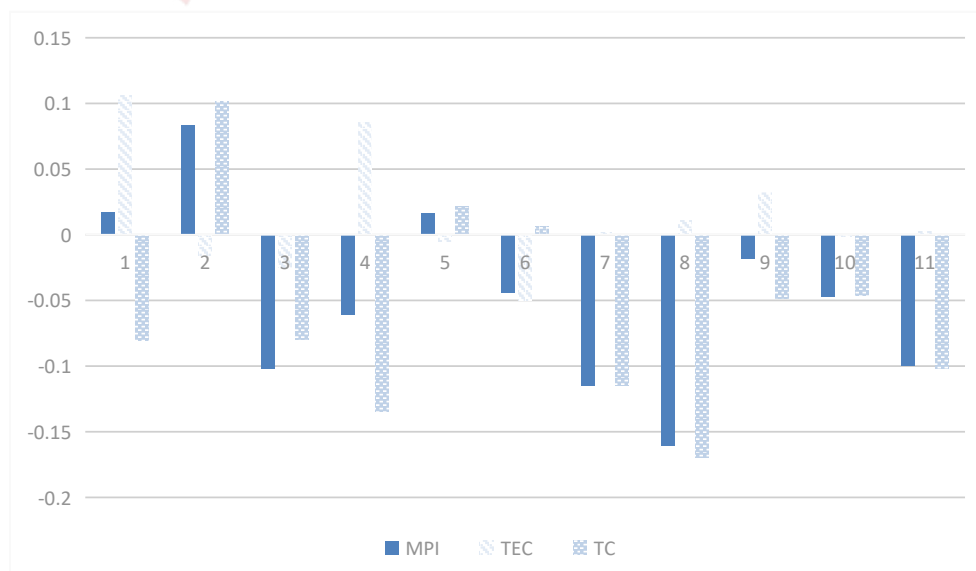


Figure 3. Contribution of TEC and TC in university research from 2011 to 2022

While technical efficiency improvements indicate that universities have optimized research management and resource utilization, the decline in TC suggests insufficient progress in technological innovation and frontier expansion. To enhance China's university research performance, future efforts should focus on fostering more original and breakthrough research while maintaining efficiency optimization strategies ^[41,42].

5. Conclusion and implications

Q1: What is the current status and characteristics of research efficiency in Chinese universities?

Research efficiency in Chinese universities remained relatively high throughout the study period, exhibiting a general upward trend. In most years, the national comprehensive research efficiency reached an efficient level, primarily driven by high PTE. This suggests that these universities possess strong capabilities in research management and technological application. However, the relatively lower SE indicates that the utilization of resource scale has not been fully optimized, leaving significant room for further improvement.

Q2: What are the dynamic trends in the TFP of research in Chinese universities and the main influencing factors?

From a dynamic perspective, the TFP of university research has shown a declining trend from 2011 to 2022. Although improvements in pure technical efficiency and scale efficiency have contributed to an overall increase in technical efficiency, the TC has shown a noticeable annual decline, particularly after 2017, where the contribution of technological progress continued to decrease, leading to a sustained negative growth in TFP. On the whole, greater emphasis should be placed on enhancing technological innovation and frontier expansion in Chinese universities.

Q3: How can research efficiency in Chinese universities be improved?

First, implement an "originality-oriented" national research investment strategy to overcome the bottleneck of technological progress. In response to the current decline in TC, the state should adjust its research evaluation and funding systems, transitioning comprehensively from a "quantity-oriented" approach to a "quality and originality-oriented" paradigm. Long-term investment in basic research and cutting-edge interdisciplinary fields should be increased, encouraging universities to explore uncharted scientific territories. By establishing a fault-tolerant mechanism, long-cycle and high-risk research projects should be supported to advance the technological frontier and reverse the downward trend of the technological progress index.

Second, optimize the national layout of research resources to improve scale efficiency. To address the deficiency in SE, the overall planning and optimization of research resources must be strengthened at the national level. It is essential to avoid low-level, redundant construction of research infrastructure and to promote the cross-institutional and cross-regional sharing of large-scale research equipment and platforms. Universities should be guided to pursue differentiated development based on their unique strengths and positioning. By establishing national or regional research alliances, knowledge diffusion and technology transfer can be accelerated, thereby maximizing the economies of scale for research outputs.

Third, promote deep-seated reforms in research management mechanisms to stimulate systemic innovation vitality. Universities should further optimize their internal research governance. On the one hand, through precise administrative empowerment, they should improve long-term incentive mechanisms for researchers, and enhance the autonomy of research teams. On the other hand, they must actively explore innovative research models, such as strengthening the deep integration of industry, academia,

research, and application, and deepening international research cooperation. By fostering a more open and collaborative research ecosystem, universities can elevate their voice in global scientific governance, thereby comprehensively enhancing the overall research competitiveness of the national higher education system.

6. Limitations and suggestions for future studies

While this study investigated the evolutionary trends of research efficiency in Chinese universities using national macro-level data, future research could explore efficiency disparities across different types of higher education institutions and incorporate multi-dimensional qualitative metrics. Furthermore, given that scientific research is a universal mission of higher education, subsequent studies could conduct cross-national comparisons to identify comparative advantages and challenges, thereby providing a broader global perspective.

Funding

This work was supported by the Scientific Research Fund of Hunan Provincial Education Department under Grant 24B1203.

Disclosure statement

The author declares no conflict of interest.

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