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RESEARCH ARTICLE

What Affects the Efficiency of Science and Technology Output and Transformation in Universities?–Evidence From Chinese Universities

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ABSTRACT Using 57 universities directly under the Ministry of Education of China from 2009 to 2017 as the research samples, the overall efficiency, technology research efficiency, result transformation efficiency and efficiency influencing factors of the transformation of scientific research results in universities were explored using the leader-follower model in two-stage network Data Envelopment Analysis (DEA) and Tobit regression model, respectively. It is found that: firstly, the overall low efficiency of the scientific research results is primarily caused by the low efficiency of the transformation stage, which is on a downward trend and has lower average efficiency than the technology research stage. The efficiency of the technology research stage is on an upward trend, while the efficiency of the transformation stage is on a downward trend. Secondly, the number of universities reaching DEA effective in results transformation stage is more than that of technology R&D stage; Thirdly, the overall efficiency and result transformation efficiency of ''985'' universities are better than those of non-''985'' universities, but the efficiency of technology R&D is lower than that of non-''985'' universities; Fourthly, regional economic strength, government's financial investment, the quality of patents, the number of papers, and the other eight factors all have an impact on efficiency.

INDEX TERMS Transformation of scientific research results, university, two-stage network DEA model, Tobit, efficiency, efficiency influencing factors, China.

I. INTRODUCTION

In recent years, the high-tech industry has emerged as a dominant force in China's economic development. The government has also made efforts to enhance scientific research activities within universities. The focus has been on accelerating the conversion of scientific and technological achievements and integrating them with the market economy. This approach is crucial for building a strong nation with advanced science and technology capabilities. Moreover, it plays a significant role in enhancing enterprise innovation and China's overall competitiveness. However, despite the abundance of scientific and technological achievements in China, there exist numerous obstacles hindering their successful transformation. This leads to a substantial disparity between Chinese scientific and technological accomplishments and their practical implementation [1], [2].

China's transformation rate of scientific research results significantly lags behind that of developed countries. The conversion of scientific research outcomes is a critical area that requires improvement. Data from the Ministry of Education reveals that the general public budget allocation income for the ministry in 2022 amounted to 13.794 billion yuan. Unfortunately, the ''2022 China Patent Survey Report'' highlights that the implementation rate of invention patents in Chinese universities was a mere 16.9% in the same year,

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TABLE 1. Abbreviations.

DEA	Data Envelopment Analysis
DMU	Decision Making Units
R&D	Research and Development
MOE	Ministry of Education
CCR	A Data Envelopment Analysis(DEA) method for nonparametric mathematical planning applied to frontier surface estimation proposed by Charnes, Cooper, and Rhodes (1978). It is the most basic and important technique in DEA modeling.
985	Project 985, which was proposed in 1998 by the Chinese government, is a programme in which the Chinese government aims to create world-class and high-level universities.

significantly lower than the national average of 36.7%. These statistics serve as clear evidence of the inadequate capability to transform scientific research achievements in Chinese universities. The inefficiency is further compounded by the wastage of valuable resources.Amidst the backdrop of a new wave of industrial and technological revolutions, securing a competitive advantage in this evolving landscape necessitates a dual focus on innovation and the conversion of scientific and technological advancements into productive assets.

Within the realm of Chinese education, there exist universities directly governed by the Ministry of Education of China. These institutions, strategically dispersed across China's central, eastern, and western economic regions, spearhead pioneering initiatives and reforms in Chinese education. They serve as hubs for major scientific and technological breakthroughs and nurturing innovative talents, positioning them prominently within China's research achievement transformation framework. Consequently, these universities amass comprehensive and representative scientific research data.

Quantitatively assessing the efficiency of scientific and technological achievement transformation within higher education institutions, identifying key factors contributing to suboptimal efficiency, and proposing tailored improvement strategies constitute fundamental efforts to address the issue of inefficiency in such transformations. These endeavors hold substantial practical significance. While numerous domestic and international scholars have delved into the efficiency of research achievement transformation within universities, several limitations persist in existing research. First and foremost, many studies oversimplify the university research achievement transformation process [3], [4], [5], either reducing it to a single stage or narrowly focusing on specific phases. This approach lacks a comprehensive examination of the entire research achievement transformation process, from initial research achievement transformation to its ultimate commercialization, and fails to analyze it systematically across stages. Furthermore, it overlooks the interconnectedness and mutual constraints of different sub-stages within the transformation process, undermining the validity of the research. In reality, university research achievement transformation is a multi-faceted, multi-output, multi-stage process with multiple inputs [6], making isolated sub-stage analysis insufficient.

Regarding research methodology, the predominant approach relies on empirical methods, often utilizing stochastic frontier estimation (SFE) and data envelopment analysis (DEA) [7], [8]. DEA stands out for its ability to determine model weights, avoiding potential inaccuracies associated with subjective weight assignment. This method simultaneously assesses the relative efficiency of inputs and outputs within decision-making units. However, in current research, DEA primarily computes efficiency at the initial and final stages of the research achievement transformation chain, neglecting intermediate links' operational efficiency. Some scholars employ network DEA models to gauge the efficiency of different links, but often aggregate sub-stage efficiencies when calculating overall system efficiency. This approach fails to adequately address mutual sub-stage influences, dominant link identification, and the factors impacting sub-stage efficiency. Additionally, it encounters challenges in converting nonlinear programs to linear ones, particularly in the second stage with added inputs.

To overcome these limitations, this paper leverages the leader-follower model within a two-stage network DEA framework [9]. This innovation involves the transformation of a nonlinear program into a parametric linear program, enabling the identification of a global optimal solution. This enhancement furnishes more precise insights into research achievement transformation efficiency in Chinese universities.

To address the gaps in current research, this paper strategically selects input and output elements, establishes the leader-follower model in a two-stage network DEA, and assesses the overall efficiency of university research achievement transformation. Additionally, it incorporates considerations of the dominant stage's constraints on sub-stages, mutual influences among sub-stages, and their combined impact on overall system efficiency within the model. Subsequently, it employs the Tobit model to analyze the influencing factors on the efficiency of different sub-stages. Notably, this paper uniquely combines the leader-follower model with the Tobit model, offering a comprehensive exploration of the strengths and weaknesses of various research achievement transformation stages in Chinese universities. It delves into the factors influencing the efficiency of different sub-stages, providing data-driven insights for enhancing research achievement transformation efficiency within universities.

II. LITERATURE REVIEW

Examining the existing research on the transformation of scientific research results, the main focus lies on three aspects: enterprises, research institutions, and universities. However, early research in China primarily concentrated on the theoretical aspects of mechanisms, paths, and countermeasures [10], [11], [12], [13], [14], with few empirical studies conducted. In contrast, foreign scholars have increasingly measured research efficiency. For instance, Timothy R. Anderson [15] utilized the Data Envelopment Analysis (DEA) method to assess technology transfer efficiency in 54 colleges and universities in the U.S. Interestingly, the study found that the distinction between private and public institutions, as well as medical schools, did not affect efficiency. Similarly, SIEGEL D S [7] evaluated the technology transfer efficiency of 80 U.S. universities using the Stochastic Frontier Approach (SFA), considering the number of licenses, licensing revenue, invention disclosure, number of TTO personnel, and IP expenditure costs as variables. Another study by Chapple [8] developed a two-stage model to assess the relative performance of technology transfer in UK universities, employing DEA for initial efficiency assessment in the first stage and SFA for statistical noise analysis in the second stage.

Currently, Data Envelopment Analysis (DEA) has emerged as the predominant approach for assessing the efficacy of research outcomes conversion in universities, both domestically and internationally. Berbegal-Mirabent [16] conducted a case study examining the internal progress of 20 institutions engaged in scientific and technological outcome conversion in Italy. Johnes [17] employed DEA techniques to evaluate the teaching efficiency of universities in the United Kingdom (UK), utilizing data from the 1993 cohort of UK university economics graduates to gain insights into educational performance. Fandel [18] utilized DEA methodologies to assess the efficiency of universities participating in the funding allocation process in the region of North Rhine-Westphalia, shedding light on the effectiveness of resource allocation within this context. Moreover, Lee and Worthington [19] expanded the investigation by adopting a two-stage network DEA model to quantify the research efficiency of Australian universities. Their findings exposed notable disparities in efficiency estimations compared to traditional DEA model calculations, thus contributing to a more nuanced comprehension of research productivity in the Australian higher education milieu. Yang et al. [20] developed a directed distance framework based on a two-stage network DEA model and a network Luenberger productivity indicator to analyze the inefficiency of universities directly under the Ministry of Education and the evolution of university productivity. Interestingly, the findings indicated an increase in the average efficiency of universities during the sample period, despite a decrease in technology level and changes in the inefficiency of 985 project universities. Additionally, Shamohammadi et al. [21] evaluated the teaching and research performance trends in private universities in Korea from 2010 to 2016, employing a two-stage network DEA model. The outcomes highlighted that most universities achieved high teaching outputs, surpassing higher inputs between 2011 and 2015, while research efficiency displayed an overall diminishing trend. Numerous analogous DEA models have been utilized in various studies within the higher education domain [22], [23], [24], [25], [26].

Apart from efficiency measurement, it is vital to analyze the factors influencing efficiency. Feng [27] conducted a separate study employing DEA and the Tobit two-step method to evaluate the conversion rate of scientific and technological achievements in 24 Chinese universities. The investigation revealed several factors positively impacting the efficiency of university science and technology achievement conversion, such as internal R&D expenditure, development expenses on new products, investment in scientific and technological activities, full-time equivalent of R&D personnel, patent application quantity, and scientific papers published in core journals. Conversely, the cumulative number of relevant policies in the regions where universities are located had a negative impact on efficiency. Similarly, Yu et al. [28] conducted a study analyzing the influence of environmental factors on the innovation efficiency of Chinese universities, research institutions, and enterprises. The research employed Tobit regression and found that a more open region had a positive effect on the innovation of research institutions and front enterprises. However, the regional economic environment exhibited varying negative influences on the three major innovation entities. Moreover, the study highlighted significant disparities in the direction and significance of the influence of education investment, government support, and information infrastructure on these entities. Another study by Kounetas et al. [29] measured the output efficiency of diverse departments in Greek universities using the DEA method. The study also analyzed the degree of influence of environmental factors on efficiency using the Tobit model. The results demonstrated that departmental infrastructure, the age of the department, and the personnel situation significantly impacted the overall efficiency of each respective department.

In this analysis, we have two primary objectives. Firstly, our aim is to construct an appropriate input-output model that effectively captures the research outcome transformation activities carried out by universities. Previous research has raised debates regarding the efficiency of research outcome transformation. One contentious issue revolves around whether the number of published papers should be considered both as outputs and inputs. Some scholars have applied the traditional DEA method to gauge the efficiency of research outcome transformation [30], [31], [32], [33], [34], [35], [36], which is founded on the assumption of production. This method treats the production process as a "black box," essentially converting inputs into outputs while disregarding any potential intermediate processes. To address this limitation, some researchers have employed two-stage network DEA models to unpack the "black box" within the scientific research results transformation process. This approach allows for the evaluation of the intermediate links and focuses on the structural relationships of subsystems within the production unit. While these two-stage network DEA models have their merits, they do not fully elucidate the mutual influence among subsystems and which subsystems exert a dominant influence, leading to variations in input-output variables.

In reality, a Decision Making Unit (DMU), such as a university, often undertakes diverse functions and can be subdivided into various components that interact intricately. This complex interplay resembles a more intricate network, where outputs from one series can become intermediate inputs for subsequent production, and subsequent processes can be influenced by prior production stages. To better capture this complex research transformation within Chinese universities, we have chosen to utilize the leader-follower model [9] within the network DEA framework. This leader-follower model helps resolve the issue of the efficiency of the results transformation stage being constrained by the efficiency of the technology development stage, jointly affecting the overall efficiency of research results transformation. The inclusion of additional inputs in the second stage necessitates a different approach, as assuming the overall efficiency as the geometric mean [37], [38] of the two stages would lead to the infeasibility of converting the nonlinear program into a linear program. Our model overcomes this challenge by converting the nonlinear program into a parametric linear program, enabling the leader-follower model to identify the global optimal solution, thereby enhancing the accuracy of our study's results.

This paper pioneers the application of this model in evaluating the efficiency of research results transformation within Chinese universities. By positioning the technology development stage as the leader and the results transformation stage as the follower, we provide a more precise assessment of efficiency.

Our second objective revolves around exploring the factors influencing the efficiency of research achievement transformation in Chinese universities, a practical issue with significant implications for future research project incubation. While the DEA method offers insights into the static efficiency of each DMU's research results transformation, it falls short in identifying the factors affecting input and output efficiency across the entire process. To bridge this gap, we employ the Tobit regression model for a two-stage, in-depth analysis of each decision-making unit.

In summary, this paper employs a two-stage network DEA and Tobit regression model approach to assess and analyze the efficiency of research results transformation and its influencing factors within different sub-stages in Chinese universities. The first stage employs the leader-follower model to evaluate overall efficiency and the efficiency of different sub-stages. In the second stage, the Tobit model is used to conduct a regression analysis on the factors influencing the efficiency of the two sub-stages, namely technology R&D and results transformation. The findings from this analysis provide valuable insights and recommendations for enhancement.

III. METHODOLOGY

A. DEA

After the introduction of the data envelopment analysis (DEA) method by Charnes [39] in 1978, scholars have made significant contributions to enriching and advancing the DEA method. Numerous models have been proposed, leading to substantial theoretical and application achievements. However, the traditional DEA method overlooks the internal structure of the decision unit and only evaluates efficiency based on initial inputs and final outputs. In reality, the production process of a decision unit is highly complex. To address this issue, Li et al. [9] developed a two-stage leader-follower DEA model based on the work of Liang et al. [37] and Kao and Hwang [38], drawing inspiration from non-cooperation models in game theory. This model assumes the presence of additional inputs in the second stage, along with the outputs from the first stage. It further decomposes the overall efficiency into the product of the efficiencies of the first and second stages. The calculation is as follows (with the first stage acting as the leader):

Firstly, calculate the specific first stage (leader) efficiency using the CCR model [39].

$$
\begin{aligned}
e_1^{0*} &= max \sum_{d=1}^{D} w_d z_{do} \\
&s.t. \quad \sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad \forall \text{j} \sum_{i=1}^{m} v_i x_{io} = 1; \\
&\qquad v_i, w_d, Q_h, u_r \geq 0, \forall \text{i, d, h, r} \qquad (1)
\end{aligned}
$$

At this point, the weights $v_i^*, i = 1, \cdots, m, w_d^*, d = 1, \cdots, D$ can be derived when the optimal efficiency value $e_1^{0*}$of the first stage is taken. Moreover, $v_i^*$and w_d^* are introduced into the second stage, the efficiency of the second stage is maximized as the objective function and the efficiency of the first stage is fixed, and the optimal value of the efficiency of the second stage is calculated, i.e., the efficiency of the first stage of DMU_0 is kept constant, and the efficiency of its second stage is optimized, and the model is shown as follows:

$$
\begin{aligned}
e_2^{0*} &= max \frac{\sum_{r=1}^{S} u_r y_{ro}}{\sum_{d=1}^{D} w_d z_{do} + \sum_{h=1}^{H} Q_h x_{ho}^2} \ \text{s.}t. \ \frac{\sum_{d=1}^{D} w_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \ \forall j; \\
&\frac{\sum_{r=1}^{S} u_r y_{rj}}{\sum_{d=1}^{D} w_d z_{dj} + \sum_{h=1}^{H} Q_h x_{hj}^2} \leq 1 \ \forall j \frac{\sum_{d=1}^{D} w_d z_{do}}{\sum_{i=1}^{m} v_i x_{io}} = e_1^{0*}; \\
&v_i, w_d, Q_h, u_r \geq 0, \forall \text{i, d, h, r} \qquad (2)
\end{aligned}
$$

$$
\begin{aligned}
e_2^{0*} &= max \sum_{r=1}^{s} u_r y_{rj_o} \ \text{s.t.} \sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \ \forall j; \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{h=1}^{H} Q_h x_{hj}^2 - \sum_{d=1}^{D} w_d z_{dj} \leq 0 \quad \forall j \\
&\sum_{h=1}^{H} Q_h x_{ho}^2 + \sum_{d=1}^{D} w_d z_{do} = 1
\end{aligned}
$$

TABLE 2. The time interval and meaning of indicators.

Indicators	Time interval	Meaning of indicators
Inputs in the technology R&D stage	2009-2016	R&D personnel Allocated fundings of R&D project
Outputs in R&D stage/ Inputs in results transformation stage	2010-2017	Number of academic papers published Number of patents granted
Additional inputs in results transformation stage	2010-2017	R&D results application and science and technology service personnel Allocated fundings of R&D results application and science and technology service
Outputs in results transformation stage	2011-2017	Number of national-level project acceptance Actual revenue from patent sales in the year Actual income from technology transfer in the year

$$\sum_{d=1}^{D} w_d z_{do} - e_1^{o*} \sum_{i=1}^{m} v_i x_{io} = 0;$$
$$v_i, w_d, Q_h, u_r \geq 0, \forall \text{i, d, h, r} \tag{3}$$

The overall efficiency of the two stages of DMU_0 can be derived from e_1^{0*} and e_2^{o*} obtained from the above arithmetic process $e^{non,1} = e_1^{0*} \times e_2^{o*}$.

The input and output of the transformation of research results in universities are divided into two stages, the first stage is the technology development stage, i.e., from the initial input to the intermediate output stage, which describes the efficiency of the input and output of the creation process of research results. The second stage is the transformation stage, i.e., the intermediate output is used as input and additional inputs are added to the transformation benefit stage, which describes the contribution of the transformation of scientific research results to the university itself, the industry and the society [40]. From this point of view, the efficiency of the second stage is constrained by the efficiency of the first stage, and the efficiency of each of the two stages jointly affects the efficiency of the final scientific research results transformation, so this paper takes the first stage as the leader.

B. TOBIT

Since the efficiency of research innovation measured by the traditional DEA model obeys a truncated distribution of [0,1], the estimation of the traditional least squares (OLS) function may lead to inaccurate analysis results. Therefore, after calculating the efficiency of university research results transformation by DEA method, Tobit regression model is used to further analyze the factors influencing the efficiency of university research results transformation. The standard Tobit model is as follows:

$$Y_i^* = X_i\delta + \varepsilon_i$$
$$Y_i = Y_i^* \quad if \ Y_i^* > 0$$
$$Y_i = 0 \quad if \ Y_i^* \leq 0 \tag{4}$$

Y_i^* is the latent dependent variable, Y_i is the observed dependent variable,X_i is the vector of independent variables, δ is the vector of correlation coefficients, and ε_i is the interference term (independent and $\varepsilon_i \ : \ N(0, \sigma)$), thus $Y_i^* : N(X_i\delta, \sigma)$ [41].

IV. DATA SOURCES, INDICATOR SELECTION AND RESEARCH MODEL

A. DATA SOURCES

The data utilized in this paper is sourced from the≪ Compilation of Science and Technology Statistics of Higher Education Institutions≫, which provides statistics on higher education institutions directly under the Ministry of Education. However, it should be noted that the latest available statistics are only updated until 2017. Out of the 76 colleges and universities under the Ministry's jurisdiction, a subset of 57 institutions was selected as the empirical study sample. This selection process involved excluding 11 institutions not covered in the compilation, 7 institutions with incomplete data, and Southwest University of Finance and Economics, which became directly affiliated with the Ministry of Education in 2017.

It is important to highlight the temporal gap between the input and output phases in both stages. For this study, a synchronized approach was adopted, assuming a fixed time lag of 1 year between the two phases. Specifically, the input and output data for the technology R&D phase, as well as the output data for the results transformation phase, were collected from years t, $t + 1$, and $t + 2$.

Detailed information regarding the corresponding years and specific indicators can be found in Table 2.

B. INDICATOR SELECTION

The evaluation of the efficiency of scientific research results transformation in this study emphasizes the assessment of inputs and outputs. In line with the chosen methodology and model, specific input and output variables from the technology research and development stage, as well as the results transformation stage, are selected for calculating DEA efficiency values. Additionally, variables that influence efficiency are identified for the subsequent Tobit regression analysis. Detailed descriptions of the selected variables and corresponding data are provided below.

1) INPUT VARIABLES SELECTION

Science and technology activities encompass various categories, including research and development (R&D) activities, R&D results application activities, and science and technology service activities. The R&D activities consist of three sub-processes: basic research, applied research, and experimental development, which contribute to the generation of commercially viable outcomes derived from scientific research knowledge. In the context of universities, their research and development activities predominantly focus on basic research, while R&D results application activities and science and technology service activities involve the transformation and application of these outcomes. Previous studies have commonly utilized human and financial resources as input indicators [18], [33], [42], [43].

Expanding on this notion, this paper primarily considers two key aspects as input indicators: human input and financial input. Specifically, within the technological R&D stage, two specific indicators are emphasized, namely the number of R&D personnel and the allocated funding for R&D projects. In the transformation stage, the input indicators encompass not only the number of R&D personnel and the allocated funding for R&D results application and science and technology service, but also the number of academic papers and patents generated during the technological R&D stage.

2) SELECTION OF OUTPUT INDICATORS

Previous studies have typically employed various output indicators such as papers, patents, and research income [31], [44], [45], [46]. In this paper, the evaluation of the technology R&D stage focuses on innovative theoretical and methodological research, thus the output indicators selected are the number of academic papers published and the number of patents granted. Academic papers represent the quantity of knowledge achievements by universities, while the number of patents granted reflects the quality of their knowledge achievements.

In contrast, the evaluation of the results transformation stage places greater emphasis on industry promotion and social recognition. As a result, the output indicators in this stage include the number of national-level project acceptances, actual income from patent sales in the given year, and income from technology transfer in the given year. The number of national project acceptances indicates the societal evaluation of university research outcomes. Additionally, the two indicators of actual income from patent sales and technology transfer income in the same year consider disciplinary differences, taking into account the alignment between input and output in natural science research at universities. These indicators primarily measure the economic and social benefits generated by university research results.

3) SELECTION OF VARIABLES OF EFFICIENCY INFLUENCING FACTORS

To investigate the factors that influence the efficiency of the technology development and results transformation stages and gain a deeper understanding of the patterns affecting efficiency in the context of scientific research transformation in universities, this study extends its analysis to external environmental and internal structural factors. Despite having the same input resources, variations in the external environment, such as the university's location, and the internal structure, including the composition of personnel and funding, can lead to diverse output results. Therefore, it is crucial to identify the factors that impact the efficiency of these two sub-stages, as this knowledge can assist universities in optimizing resource allocation and enhancing the efficiency of scientific research results transformation.

In terms of external environmental variables, two factors are selected for both the technology development stage and the results transformation stage. These variables are ''regional GDP per capita'' and ''proportion of government funding in university science and technology.'' Regional GDP per capita serves as an indicator of the economic development level of the university's location and reflects the overall economic strength of the region. On the other hand, the proportion of government funding in university science and technology represents the policy and economic support for research activities within the region.

Regarding internal structural variables, several indicators are considered. Firstly, the ''proportion of scientists and engineers among R&D personnel'' is chosen to assess the influence of researcher involvement in the technology development stage on efficiency. Similarly, the ''proportion of scientists and engineers among R&D results application and science and technology service personnel'' measures the participation of researchers in the transformation stage. The ''proportion of invention patents among granted patents'' and ''number of published academic papers'' are used to evaluate the impact of scientific research outputs in the technology development stage on the results transformation stage.

Furthermore, internal structural variables reflecting the personnel and funding structure in the two sub-stages are identified. These include indicators such as the ''proportion of graduate students enrolled in basic research,'' ''proportion of graduate students enrolled in applied research,'' ''proportion of funding allocated to basic research in the year,'' and ''proportion of funding allocated to applied research in the year.'' Additionally, the ''proportion of graduate students enrolled in R&D results'' and ''proportion of funds allocated to R&D results in the year'' are selected as influencing factors for the results transformation stage.

It is important to note that certain internal structural indicators can be inferred from others. For example, a lower investment in basic and applied research implies a higher investment in experimental development. Similarly, a higher level of human and financial investment in R&D results application suggests a lower investment in science and technology services. To address multicollinearity concerns, it is advisable to exclude these four indicators as explanatory variables when conducting Tobit regression analysis.

C. RESEARCH MODEL

Xue et al. [47] conducted a related study using a traditional DEA model to measure the efficiency of university research

TABLE 3. The influencing factors of the technology research and development stage.

	Influencing Factors	Specific indicators
External environment variables	Regional Economic Power (gdp)	Regional GDP per capita
	Government funding efforts (gov)	The proportion of government funding for science and technology in higher education
Internal structure variables	The degree of involvement of scientific researchers in R&D (hr1)	Proportion of research and development staff who are scientists and engineers
	Basic research personnel (s1)	Percentage of graduate students enrolled in basic research in research and development programs
	Applied Research personnel (s2)	Percentage of graduate students enrolled in applied research
	Investment in basic research funding efforts (f1)	Percentage of funds allocated to basic research in the year
	Applied research funding efforts (f2)	Percentage of funding allocated to applied research for the year

TABLE 4. The influencing factors of the result transformation stage.

	Influencing Factors	Specific indicators
External environment variables	Regional Economic Power (gdp)	Regional GDP per capita
	Government funding efforts (gov)	The proportion of government funding for science and technology in higher education
Internal structure variables	The degree of participation of scientific researchers in the application of results and scientific services (hr2)	Percentage of scientists and engineers among R&D results application and science and technology service personnel
	Patent Quality (patent)	Percentage of invention patents among granted patents
	Papers (paper)	Number of academic papers published
	R&D results application of scientific research personnel (s3)	Percentage of R&D results applied to graduate students in school
	R&D results application funding investment efforts (f3)	The proportion of allocated funds in the year of R&D results application

input based on initial input and final output. However, this approach fails to effectively unveil the intricacies of research activities, thus necessitating the development of an alternative approach. In this study, an additional input type two-stage network DEA model is proposed to address this issue and divide the university research results transformation activities into two stages: technology development and results transformation. To be specific, the two-stage network DEA model is constructed with additional inputs, and it encompasses the stages of technology research and development, as well as results transformation. The technology research and development stage entails universities investing specific scientific and technological resources to generate intermediate knowledge results of practical value. On the other hand, the results transformation stage represents a crucial phase where universities utilize the knowledge results obtained from the technology research and development stage, along with additional scientific and technological resources, to achieve industrialization, commercialization, and assess the economic value of the knowledge results. The two-stage process model of this study is illustrated in fig.1.

V. EMPIRICAL ANALYSIS

A. DEA ANALYSIS

A Python-based computational model utilizing a two-stage network DEA approach was developed to assess the efficiency of research results conversion in universities directly under the Ministry of Education for the period spanning 2009 to 2017.

1) MEASUREMENT AND ANALYSIS OF THE OVERALL EFFICIENCY OF THE TRANSFORMATION OF RESEARCH RESULTS IN UNIVERSITIES

The Chinese government initiated the "Project 985" in 1998, aiming to cultivate globally renowned universities. As highlighted by Yang et al. [20], the Ministry of Education (MOE) of China has committed to allocating 1% of the nation's annual revenue towards this initiative. In this study, among the 57 universities directly supervised by the MOE, 29 are affiliated with the "985 Project," while the remaining 28 universities are not part of it.

The average values of overall efficiency in the transformation of scientific research results for the MOE-affiliated universities during the sample period are presented in Table 5. The results reveal that the overall efficiency of each university during this period is below par, with an average efficiency value of only 0.085. Even Tsinghua University, one of the top universities, only achieved an average efficiency of 0.287, while the lowest efficiency value falls below 0.010. Analyzing the average efficiency values of each university, we observe that out of the five universities with an efficiency value exceeding 0.2, only Jiangnan University does not belong to the "985 Project" (0.253). Among the universities surpassing the overall average, there are 32, including 22 "985 Project" universities, accounting for 76% of the total number of "985 Project" universities in the sample. Among the remaining 7 "985 Project" universities, Chongqing University (0.074), South China University of Technology (0.070), Sun Yat-sen University (0.054), Renmin University of China (0.053), Hunan University (0.053), Jilin University (0.026), and Northwest Agriculture and Forestry University of Science and Technology (0.024) exhibit relatively lower efficiency levels. Comparing the average efficiency between the two types of universities, the "985 Project" universities (0.107) demonstrate slightly higher average efficiency than the non-"985 Project" universities (0.066). However, it is important to note that the overall efficiency of scientific research results transformation in "Project 985" universities is still relatively low, indicating ample room for improvement. This finding is consistent

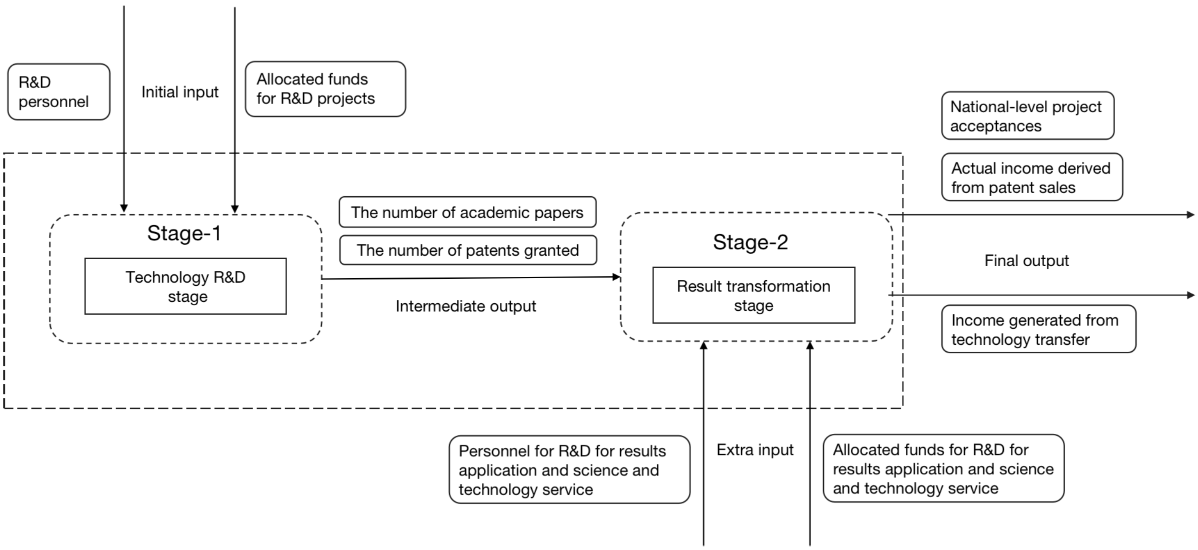

FIGURE 1. Two stage network process of universities.

TABLE 5. Results of efficiency.

School Name	Overall efficiency	School Name	Overall efficiency
"985 Project" University		Non-"Project 985" universities	
Peking University	0.2279	Beijing Jiaotong University	0.0486
Renmin University of China	0.0532	University of Science and Technology Beijing	0.0968
Tsinghua University	0.2867	Beijing University of Chemical Technology	0.1169
China Agricultural University	0.0869	Beijing University of Posts and Telecommunications	0.1609
Nankai University	0.2106	Beijing Forestry University	0.0861
Tianjin University	0.1462	Beijing University of Chinese Medicine	0.1057
Dalian University of Technology	0.1266	North China University of Electric Power	0.0402
Northeastern University	0.1169	China University of Mining and Technology (Beijing)	0.0505
Jilin University	0.026	China University of Petroleum (Beijing)	0.0558
Fudan University	0.1493	China University of Geosciences (Beijing)	0.0582
Tongji University	0.1472	Northeast Normal University	0.0096
Shanghai Jiao Tong University	0.2308	Northeast Forestry University	0.1467
East China Normal University	0.1132	Tung Wah University	0.0793
Nanjing University	0.0927	China University of Mining and Technology	0.0257
Southeastern University	0.1091	Hohai University	0.0385
Zhejiang University	0.1136	Jiangnan University	0.2532
Xiamen University	0.1228	Nanjing Agricultural University	0.0822
Shandong University	0.1287	China University of Pharmaceutical Sciences	0.0606
Ocean University of China	0.144	China University of Petroleum (East China)	0.0394
Wuhan University	0.0952	China University of Geosciences (Wuhan)	0.0203
Huazhong University of Science and Technology	0.1062	Wuhan University of Technology	0.0978
Hunan University	0.0529	Huazhong Agricultural University	0.0834
Central South University	0.176	Huazhong Normal University	0.1522
Sun Yat-sen University	0.0541	Southwestern University	0.0592
South China University of Technology	0.0699	Southwest Jiaotong University	0.0402
Chongqing University	0.0741	Xidian University	0.0764
Sichuan University	0.1116	Chang'an University	0.0778
Xi'an Jiaotong University	0.1769	Shaanxi Normal University	0.0973
Northwest Agriculture and Forestry University of Science and Technology	0.024	Average efficiency of non-985 universities	0.0663
Average efficiency of 985 universities	0.1068	MEAN	0.0845

with the research conducted by Lee and Worthington [19], which suggests that inefficiency changes in "Project 985" universities are more favorable compared to non-"Project 985" universities.

Jiangnan University, while not part of the 985 Project, has made substantial strides in the field of food science. The university has championed the integration of industry, academia, and research, particularly in the period

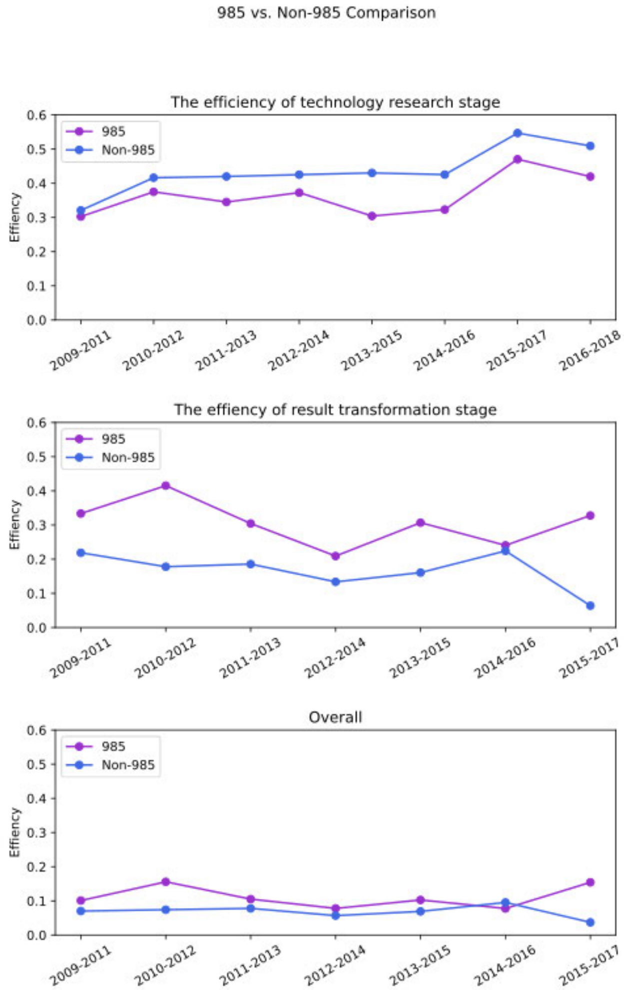

FIGURE 2. Trend of "985 project" and non-"985 project" universities' average efficiency.

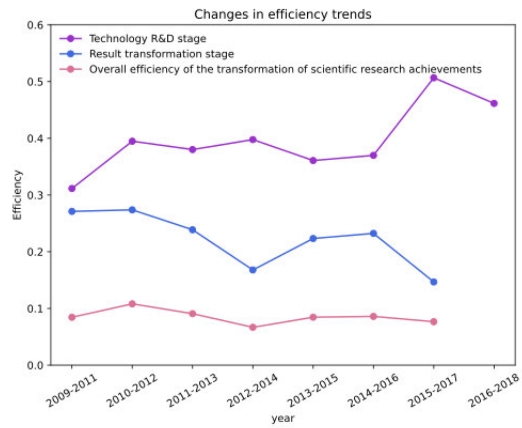

FIGURE 3. Trend of all universities' average efficiency.

from 2016 to 2020 when it successfully transferred over 1,300 scientific and technological achievements in the food sector. Key initiatives include establishing national key laboratories, decentralizing control over scientific and technological achievements, and improving incentives for researchers involved in results transformation. Moreover, Jiangnan University provides comprehensive support to enterprises, including technical assistance and branding initiatives. Collaborative efforts with brands, such as the establishment of academician workstations, have created a dynamic synergy between the university and enterprises, strengthening the university's role in the "double high" field of output and transformation.

Through a detailed examination of efficiency patterns among the two categories of universities, as depicted in Fig. 2, we observe a slight upward trend in the average efficiency value of "Project 985" universities. In contrast, there is a clear fluctuating downward trend in the average efficiency value of non-"Project 985" universities. Notably, this decline is primarily attributed to a significant decrease in the efficiency of non-"Project 985" universities during the transformation stage within the 2015-2017 period. As a result, the overall performance of the scientific research outcome transformation process has been deemed unsatisfactory.

Based on the aforementioned measurement results, it is evident that there is a noticeable disparity in performance between "985 Project" universities and non-"985 Project" universities. However, it is not immediately evident how this disparity specifically impacts the overall efficiency across the different sub-stages.

2) MEASUREMENT AND EFFICIENCY ANALYSIS OF TECHNOLOGY RESEARCH STAGE

When analyzing the temporal aspect (see Fig. 3), the average efficiency of the technology research and development (R&D) stage in universities directly supervised by the Ministry of Education exhibits a general fluctuating and increasing trend between 2009 and 2018. It is noteworthy that during the latter years of the scientific research results transformation process, the mean efficiency demonstrates relatively consistent changes from 2011 to 2016. However, from 2016 to 2017, there is a slight decline in the mean efficiency of the technology R&D stage, although it still exceeds the efficiency levels observed prior to 2017. Interestingly, 2017 emerges as the year with the highest number of universities achieving validity under the Data Envelopment Analysis (DEA) framework during the sample period. Specifically, six universities attained DEA validity in the technology R&D stage. The notable improvements in average efficiency values in both 2012 and 2017 can be attributed to their alignment with the new national "Five-Year Plan." Furthermore, in 2017, China introduced a comprehensive plan for establishing "double first-class" universities, urging each institution to actively respond to the call for fostering innovation and talent, leading to continuous enhancements in fundamental scientific research capabilities and notable advancements in input-output performance. The specific calculated values are presented in the Appendix A.

From an individual university perspective, Jiangnan University has consistently demonstrated effective DEA in the technology R&D stage from 2010 to 2017. Despite not being a "985 Project" university, Jiangnan University ranks highly in terms of patent grants throughout the sample period, particularly in 2012. This highlights the university's significant strength in creating scientific research knowledge. Following closely is Shaanxi Normal University, which achieved DEA validity for five consecutive years from 2010 to 2014. Several other universities, including Beijing University of Traditional Chinese Medicine, North China University of Electric Power, China University of Mining and Technology, Hohai University, China Ocean University, Chongqing University, Southwest Jiaotong University, and Chang'an University, also achieved DEA validity in different years. Based on the classification criteria of Xu Min et al. (reference [48]), the efficiency levels of the sample universities were categorized as follows: good efficiency (0.8-0.1), better efficiency (mean efficiency [0.394] to 0.8), average efficiency (0.3 to mean efficiency), and less good efficiency (0-0.3). From the mean value of technological R&D efficiency of each university in the sample period, only Jiangnan University and Shaanxi Normal University showcased outstanding performance with efficiency values over 0.8. Out of the 30 universities with average efficiency values exceeding the overall average, only 14 are "985" universities, less than half of them. Furthermore, the average efficiency value of "985" universities in the technology R&D stage (0.360) is lower than that of "non-985" universities (0.432). It is worth noting that only China Ocean University and Chongqing University, both "985 Project" universities, achieved DEA effectiveness. Therefore, it can be observed that the performance of non-985 universities outperforms that of 985 universities in the technology development stage. Nevertheless, the graph clearly illustrates that the efficiency of both types of universities is moving in a positive direction.

3) MEASUREMENT AND EFFICIENCY ANALYSIS OF RESULT TRANSFORMATION STAGE

Examining the temporal dimension, an analysis of the results transformation stage in universities directly under the Ministry of Education in China reveals inadequate performance, with a noticeable decreasing trend observed in the average efficiency value throughout the sample years. The average efficiency value for the transformation stage across seven years is 0.217, which falls below the average efficiency value for the technology R&D stage (0.394). The figure illustrates that the overall efficiency trend of research results transformation in the sample universities aligns with the efficiency trend of the sub-stage of results transformation. Consequently, the inefficiency in the results transformation stage strongly impacts the subpar performance of research results transformation in the Ministry of Education's universities. Therefore, it is imperative for universities to implement relevant measures and allocate resources effectively to address the current inefficiency in results transformation. The specific calculated values are presented in the Appendix B.

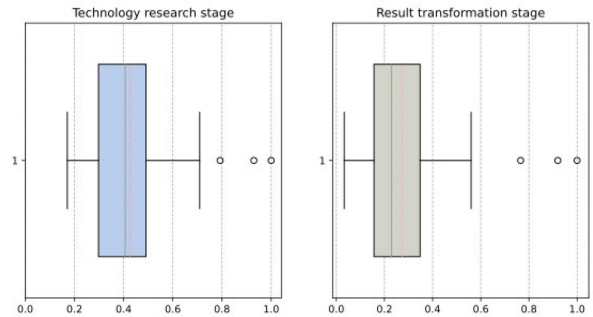

FIGURE 4. Boxplot of the distribution of university efficiency values.

When examining individual university dimensions, among the 30 universities with above-average efficiency in results transformation, only Tsinghua University achieved an average efficiency value that reached DEA validity. Nankai University closely followed, falling short of DEA validity in only one year but achieving an average efficiency value of 0.920, indicating close proximity to DEA validity. Eighteen universities, including Peking University, Huazhong Normal University, East China Normal University, Tianjin University, Sichuan University, Central South University, Fudan University, Dalian University of Technology, Xiamen University, Wuhan University of Technology, Beijing Jiaotong University, China University of Petroleum (Beijing), Renmin University of China, Southwest University, Beijing University of Traditional Chinese Medicine, Xi'an University of Electronic Science and Technology, China University of Mining and Technology (Beijing), and Shaanxi Normal University, achieved DEA validity in different years.

Overall, although more universities achieved DEA effectiveness in the results transformation stage compared to the technology development stage, the efficiency values of most universities in the results transformation stage ranged from 0.15 to 0.35, while those in the technology development stage ranged from 0.3 to 0.5 (see Fig. 4). This indicates that even if some universities achieve DEA effectiveness in the results transformation stage, the overall performance of universities remains inferior to that in the technology development stage. Therefore, universities need to identify and address the internal factors contributing to this disparity.

From the perspective of university type, among the 30 universities with above-average efficiency, 21 belong to the "Project 985" category. The average efficiency value of "Project 985" universities in the results transformation stage (0.297) surpasses that of non-"Project 985" universities (0.157). Additionally, among the 20 universities that achieved effective DEA, 11 belong to the "Project 985" category. Hence, the efficiency performance of "Project 985" universities outperforms that of non-"Project 985" universities. "Project 985" universities exhibited fluctuating efficiency levels but did not experience a significant decline. In contrast, non-"Project 985" universities attained their highest efficiency value in the sample period in 2016 and the lowest value in 2017. Furthermore, the average efficiency values in each year failed to surpass those of "Project 985" universities.

Tsinghua University's exceptional performance in scientific research results transformation efficiency can be attributed to its well-structured policy framework and technology transfer system. In recent years, Tsinghua University has consistently introduced policies aimed at fostering scientific research achievement transformation. These policies include defining revenue shares for individuals and teams contributing to technological advancements and increasing incentives for scientific and technological personnel involved in such transformations. Furthermore, Tsinghua University established a comprehensive technology transfer system ahead of many other Chinese universities. This system includes key components like the Office of Technology Licensing (OTL), the University-Land Cooperation Research Institute, the Research Institute, and Tsinghua Holdings. These entities provide a robust platform and vital support for the effective transformation of scientific research achievements.

Nankai University has also demonstrated commitment to scientific research results transformation by enhancing its system for facilitating such transformations. The university has actively promoted high-level collaboration between academia and industry, as well as between the university, land-based industry, research institutions, and results transformation platforms. This concerted effort has significantly boosted enthusiasm for the transformation of scientific research results.

4) SUB-STAGE EFFICIENCY DIMENSION ANALYSIS

In order to understand the developmental trajectory of sub-stage efficiency in the transformation of scientific research outcomes among Chinese universities, a comparative investigation was conducted between "Project 985" and non-"Project 985" institutions, as shown in Figure 5. Building upon the findings of Xu Min et al. [48], this study classified the efficiency relationship between the two stages of scientific research result transformation into four distinct modes: high output high transformation, high output low transformation, low output high transformation, and low output low transformation. Moreover, efficiency levels were categorized as either low, falling below the average value, or high, surpassing it. The distribution outcomes of these results are presented in Fig.5.

The mode of high output and high conversion encompasses nine universities affiliated with the "985 Project," including Shanghai Jiaotong University and Fudan University, as well as four non-"985 Project" universities such as Jiangnan University. Notably, the "985 Project" universities hold a competitive advantage in this category, with most of these institutions demonstrating excellence in science and technology. The high output and low conversion model applies to 17 universities, among them Nanjing University and Chongqing University. Additionally, the high output low conversion model is represented by 17 universities, with five belonging to the "985 Project" category, such as Nanjing University and Chongqing University, while the remaining 12 universities are non-"985 Project" institutions, including Southwest Jiaotong University and Donghua University. This pattern highlights the lower output exhibited by non-"985 Project" universities. The low output high conversion model comprises 17 universities, of which 11 are "985 Project" universities like Tsinghua University, Peking University, and Nankai University, while the remaining six universities are non-"985 Project" institutions like Beijing Jiaotong University and Nanjing Agricultural University. Finally, the low output and low conversion model encompasses four "985 Project" universities such as Renmin University of China and Jilin University, and six non-"985 Project" universities such as East China Normal University and Southwest University.

Examining the output and conversion dimensions from a single perspective, non-"Project 985" universities hold a slight advantage over "Project 985" universities with two more universities in the high output mode. However, in the high conversion mode, the number of "Project 985" universities significantly surpasses that of non-"985 Project" universities.

"Project 985" universities typically enjoy more substantial resource support, talent advantages, academic environments, and policy assistance. For instance, in 2023, Tsinghua University had a budget of 41.1 billion, followed by Shanghai Jiao Tong University, Zhejiang University, Peking University, Sun Yat-sen University, and Shandong University. Out of these, only Shanghai Jiao Tong University and Zhejiang University have achieved the "double-high" model. This can be attributed to the fact that the output of scientific research results does not grow exponentially with input. While abundant resources do improve research environments and research teams, the production of innovative scientific research results takes time, and the output of research does not occur at the same rate as the inflow of resources. Consequently, the efficiency is lower compared to colleges without a "985 Project" that make fewer resource investments. Additionally, some universities have recently prioritized the development of humanities and social sciences, as well as diversified development. This has led to a homogeneous pattern of scientific research and an average allocation of scientific and technological resources, rather than a centralized allocation. As a result, support for superior disciplines decreases, negatively impacting the effectiveness of technological R&D in universities.

In terms of technology transfer, several "985 Project" universities have made significant contributions to enhancing scientific research results transformation efficiency. Tsinghua University, for instance, has taken measures to break down institutional barriers by establishing a diverse range of science and technology transformation organizations. These

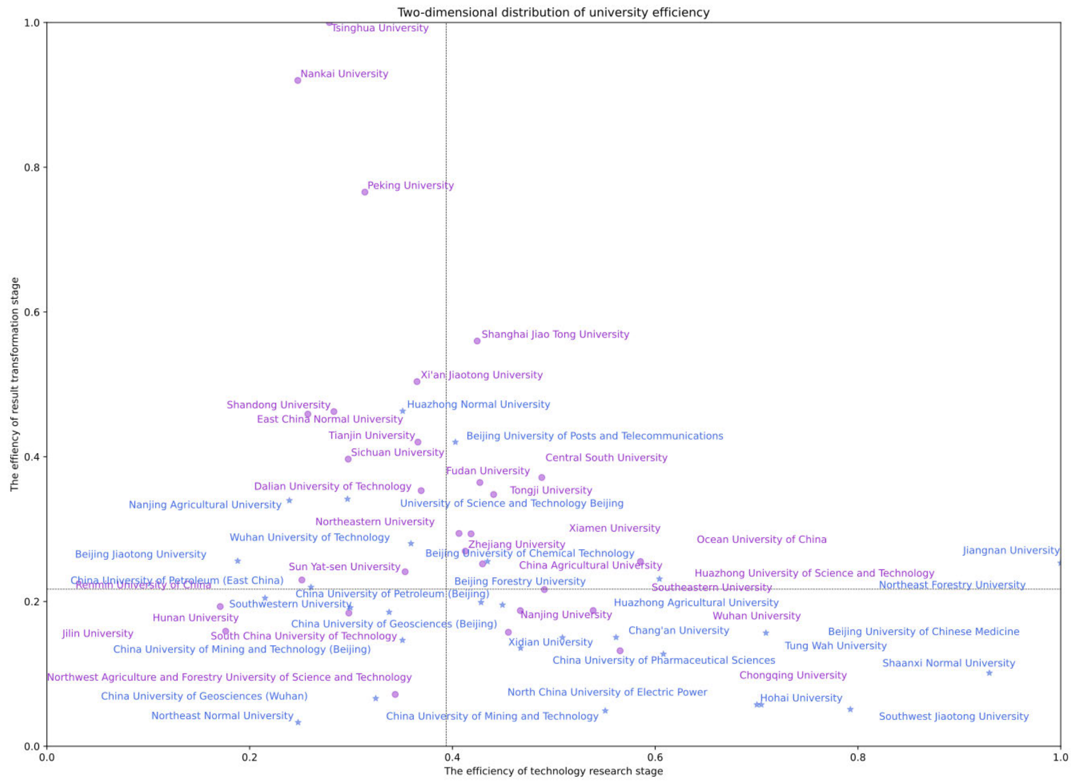

FIGURE 5. **Two-dimensional distribution of efficiency values in universities. Purple markers represent 985 universities, blue markers represent non-985 universities.**

organizations, including the Office of Achievement and Intellectual Property Management (OTL), the Institute of Technology Transfer (OTT), and others, collectively form a comprehensive system for managing, transferring, and legally safeguarding scientific and technological achievements. OTT, within this framework, focuses on national strategic priorities and cutting-edge academic issues, facilitating synergistic collaborations between universities and industries. Notably, among the global TOP50 university Technology Transfer Offices (TTOs), five mainland Chinese universities are listed, namely Peking University, Tsinghua University, Fudan University, Zhejiang University, and Shanghai Jiaotong University. These institutions adopt a ''high transformation'' approach, emphasizing quality over quantity in their technology transfer teams. Team members possess the ability to independently evaluate and select optimal solutions for diverse projects, prioritizing precision over scale.

Non-''985 Project'' institutions face a lack of platforms for supporting the transformation of findings, as well as limited social recognition. Moreover, they struggle with a shortage of top researchers and research teams who have established a broad reputation and impact in their respective fields of study. This gap becomes evident when comparing these institutions to those involved in the ''985 Project.'' Surprisingly, the efficiency of the transformation of findings in non-''985 Project'' universities is not as remarkable as that of their ''985 Project'' counterparts. This discrepancy can be attributed to the fact that universities often evaluate the success of scientific research based on publications and patents, while neglecting the crucial aspect of transforming scientific research results.

B. TOBIT ANALYSIS

Based on the empirical findings presented earlier, it is evident that the efficiency of transforming scientific research results varies among universities directly under the Ministry of Education. To comprehensively investigate the factors influencing this efficiency, this study explores both external environmental factors and internal structural factors.

In terms of external factors, the regional economic strength and government funding are considered as key variables. Meanwhile, the internal structure is examined by assessing the degree of research workers' involvement in research and development, the presence of basic research talents, the availability of applied research talents, and the presence of talents in experimental development.

For the technological research and development stage, the explanatory variables include the degree of scientific researchers' engagement in research and development, the presence of research talents in basic research, the availability of research talents in applied research, and the presence of research talents in experimental development. On the other hand, the transformation stage incorporates variables such as the degree of scientific researchers' involvement in result application and scientific and technological services, the quality of patents and theses, the availability of research talents in result application, and the presence of research talents in scientific and technological services.

Considering that the calculated efficiency of university research results transformation falls within the range of 0 to 1, the explanatory variables are observed under certain restrictions. Therefore, this paper employs the Tobit model for regression analysis, as suggested by previous studies [49]. The following expressions outline the application of the Tobit model:

$$Y_{it}^1 = \alpha_0 + \alpha_1 lngdp_{it} + \alpha_2 gov_{it} + \alpha_3 hr1_{it} + \alpha_4 s1_{it} + \alpha_5 s2_{it} + \alpha_6 f1_{it} + \alpha_7 f2_{it} + \sigma_{it} \quad (5)$$

$$Y_{it}^2 = \beta_0 + \beta_1 lngdp_{it} + \beta_2 gov_{it} + \beta_3 hr2_{it} + \beta_4 s3_{it} + \beta_5 f3_{it} + \beta_6 patent_{it} + \beta_7 lnpaper_{it} + \sigma_{it} \quad (6)$$

In Equation 5 and Equation 6, $Y^1$and Y^2 represent the efficiency values of technology R&D stage and results transformation stage of 57 universities form 2009-2017, respectively. α and β are parameters to be estimated, σ is a random disturbance term, i and t denote university i and year t. Stata16.0 software was used to calculate the empirical results of Tobit model are shown in Table 6. The specific analysis is as follows:

1) ANALYSIS OF THE EMPIRICAL RESULTS OF TECHNOLOGY R&D STAGE

First and foremost, the results reveal a significant positive relationship between the economic strength of the regions and the efficiency of technological research and development (R&D) in the universities included in the sample. This indicates that the level of economic development in the regions where the universities are situated influences the initial R&D stage in the transformation of scientific research achievements. A higher level of regional economic development facilitates the assimilation of advanced technology and enhances the efficiency of transforming scientific research achievements, ultimately improving the overall research efficiency in universities. Economic development forms the foundation for scientific research innovation in higher education institutions.

Secondly, a noteworthy negative correlation at the 10% significance level is observed between the magnitude of government funding investment and the efficiency of technological R&D in universities. This suggests that greater government financial investment in universities directly under the Ministry of Education hinders the improvement of technological R&D efficiency in the sampled universities. While these universities benefit from abundant research resources and occupy a prominent position in the domestic university landscape, excessive research funding results in additional administrative burdens such as project application, approval, and evaluation. Consequently, research funding exhibits an inverted "U"-shaped inhibitory effect on technology research and development efficiency. Overreliance on government funding can lead to a crowding-out effect, negatively impacting research output supported by government funds. Increased government intervention has also been observed to reduce the effectiveness of technology research and development, particularly in collaborative innovation endeavors involving high-tech industries, universities, and research institutions. This exacerbates inefficiencies in fund management and research activities, thereby impeding the effectiveness of enterprises engaged in high-tech R&D and technology transfers.

Third, the level of researchers' participation exhibits a significant positive relationship with technological R&D efficiency in universities at the 10% level. A higher percentage of scientists and engineers among the personnel involved in research and development projects leads to increased technological R&D efficiency. Researchers with strong scientific research capabilities contribute to the efficiency of technology R&D. However, it is important to control the evaluation of full-time teachers' titles within universities to prevent talent redundancy and promote technology innovation efficiency. Recent investigations have revealed a negative correlation between the presence of scientists and engineers in the academic community and research productivity. Therefore, while universities should absorb more scientific researchers, they should also focus on maintaining strict controls over the evaluation of full-time teachers' titles to avoid the redundancy of talent and ensure efficient technology innovation.

Fourthly, basic research talents show a negative, albeit not significant, correlation with technological R&D efficiency in universities, while applied research talents exhibit a significant negative correlation at the 5% level. This indicates that an increase in the number of master's and doctoral students invested by universities may hinder the efficiency of scientific research output to some extent. Currently, the number of postgraduates in Chinese universities is growing annually; however, the depth of professional knowledge among most postgraduates is insufficient, leading to a lack of fruitful research outcomes. To improve research input and output efficiency, universities should focus on controlling the quality of graduate students rather than blindly expanding research programs.

Fifth, the intensity of funding for basic research and applied research is positively correlated with the efficiency of technological R&D in universities at the 1% significant level. This implies that increased investment by universities in basic and applied research contributes to improved scientific research output efficiency. Funding serves as the foundation for research work, and limited funding for basic and applied research can lead to outdated infrastructure and research equipment, restricting research output. Therefore, universities should prioritize research funding to achieve greater scientific and technological innovation results.

TABLE 6. Results of efficiency.

	Efficiency of technology development stage	Efficiency of results transformation stage
gdp	0.097***	0.030
	(0.029)	(0.046)
gov	-0.122*	0.144
	(0.072)	(0.122)
hr1	0.500*	
	(0.264)	
hr2		-0.597***
		(0.165)
s1	-0.098	
	(0.135)	
s2	-0.316**	
	(0.135)	
s3		0.179**
		(0.083)
f1	0.511***	
	-0.116	
f2	0.355***	
	(0.105)	
f3		-0.134
		(0.090)
patent		0.333***
		(0.096)
paper		-0.018
		(0.031)
_cons	-1.184***	0.401
	(0.412)	(0.568)
Wald chi2	76.07	34.41
Prob> chi2	0.000	0.000

Str.Err in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2) ANALYSIS OF EMPIRICAL RESULTS AT THE STAGE OF TRANSFORMATION OF RESULTS

Firstly, the empirical regression findings indicate a non-significant positive association between external environmental variables and the efficiency of results transformation in universities. This suggests that external environmental factors have minimal direct influence on the efficiency of results transformation, whereas the efficiency is primarily driven by basic science and technology research and development (R&D) activities. This disparity may be attributed to the distinct nature of the two sub-stages involved in the process of scientific research results transformation.

The variables of per capita GDP and government funding serve as indicators of regional economic development and the availability of research funds, which play a vital role in supporting basic scientific research. Advanced technology R&D and innovation, in particular, require a strong industrial foundation, sophisticated equipment, and substantial research funding. As the regional economy develops, the industrial level and financial investment also increase, leading to more fruitful outcomes in basic scientific research. On the other hand, results transformation encompasses the application and extension of existing research findings to relevant industries. While it is influenced by regional economic conditions to some extent, its sensitivity is not as pronounced as that of the technology R&D stage. Nevertheless, the regional economic environment and government support do have a positive impact on the efficiency of results transformation.

Hence, local governments should prioritize the transformation of scientific research results within universities located in their respective regions. They should provide preferential policy support and allocate moderate research funding to facilitate collaboration between universities, governments, and enterprises. This collaborative approach will facilitate the timely transformation and utilization of research outcomes, ultimately enhancing the efficiency of results transformation.

Secondly, the degree of participation of scientific researchers in result application and scientific services exhibits a significant negative correlation with the efficiency of the results transformation stage at a 1% level of significance. Scientists and engineers play a pivotal role in basic scientific research. However, if an excessive number of researchers are engaged in result application work, it can lead to redundancy and wastage of educational resources, negatively impacting the efficiency of results transformation in the sample universities.

Thirdly, there is a positive correlation at the 5% level of significance between the involvement of applied scientific research talents in R&D results and the efficiency of the results transformation stage. This indicates that a higher number of applied postgraduates is associated with increased efficiency in results transformation. Cultivating applied postgraduates is a crucial factor in enhancing the efficiency of results transformation. Due to the current postgraduate training mechanism in China, many postgraduates focus solely on the output of thesis results without considering their practical application value. This leads to a shortage of application-oriented talents. In their investigation into the dissemination and translation of research outcomes across different regional higher education institutions, Liu (reference) observed that the inclusion of research talent from universities positively influences research performance. Therefore, universities should actively attract and incorporate application-oriented research talents to foster a mutually beneficial relationship between research output and application.

Fourthly, although not statistically significant, there is a negative relationship between the intensity of investment in R&D results application and the efficiency of scientific research results transformation. This indicates that continued investment in research funds for R&D results application starts to hinder the efficiency of results transformation. Excessive research funding can lead to a marginal decrease in results transformation efficiency in universities, highlighting the need to address the issue of capital crowding in result application.

Fifthly, the quality of patents demonstrates a significant positive correlation with the efficiency of scientific research results transformation at a 1% level of significance, whereas the number of published papers exhibits a non-significant negative correlation with the efficiency of the results transformation stage. This suggests that enterprises prioritize the quality rather than the quantity of scientific research output when evaluating the research results of universities. The greater the number of invention patents, the higher the efficiency of results transformation. Currently, the number of scientific and technological papers produced by universities has reached saturation, revealing an inverted "U" shape in the efficiency of scientific research results transformation. Therefore, efforts should be made to enhance the efficiency of transformation.

VI. CONCLUSION AND IMPLICATIONS

A. CONCLUSION

This research paper focuses on investigating the efficiency of research results conversion in Chinese universities directly under the Ministry of Education during the period from 2009 to 2017. To explore the intricate process of research results conversion, a two-stage network DEA model is employed, enabling a detailed examination of the underlying mechanisms. Additionally, a Tobit model is applied to analyze the factors influencing the efficiency of research results conversion. The study yields several noteworthy findings, as follows:

Firstly, the average overall efficiency of research results transformation in the sampled universities is alarmingly low, with an average efficiency value below 0.1. None of the universities achieve DEA effectiveness in both stages of the conversion process. The technology research and development stage exhibits a fluctuating upward trend, with an average efficiency value of 0.394 among the sampled universities, peaking in 2017. Conversely, the research results transformation stage demonstrates a fluctuating downward trend, with an average efficiency value of 0.217. Notably, the efficiency of the overall research results transformation depends on the combined efficiencies of both stages. It is worth mentioning that the efficiency of the technology R&D stage surpasses that of the results transformation stage in each university, indicating that the primary factor contributing to the low efficiency and significant disparities among universities lies in the results transformation stage, thus emphasizing the importance of enhancing its efficiency.

Secondly, a higher number of colleges and universities achieve DEA effectiveness in the results transformation stage compared to the technology R&D stage. Most colleges and universities exhibit efficiency values concentrated between 0.15 and 0.35 in the results transformation stage, while efficiency values in the technology R&D stage are concentrated between 0.3 and 0.5. Consequently, the overall performance of the results transformation stage falls behind that of the technology R&D stage.

Thirdly, universities participating in the "985 Project" generally outperform non-"985 Project" universities in both scientific research and results transformation stages. However, the average efficiency value of the technology R&D stage is lower for "985 Project" universities compared to non-"985 Project" universities. Nonetheless, the average efficiency value in the technology research and development stage remains lower for "985 Project" universities.

Lastly, the efficiency of scientific research results transformation in Chinese universities is influenced by external environmental factors and internal structural factors. External factors encompass regional economic strength and governmental financial investment. Different sub-stages exhibit distinct internal structural influencing factors. The efficiency of the technology research and development stage demonstrates significant positive correlations with regional economic strength, research workers' involvement in research and development, funding for technical research, and funding for applied research. Conversely, it exhibits negative correlations with government funding, applied research talents (although not statistically significant), and basic research talents. On the other hand, the efficiency of the transformation stage lacks significant positive correlations with external environmental variables. However, it exhibits non-significant positive correlations with both external environmental variables, significant positive correlations with R&D application research talents and patent quality, significant negative correlations with researcher participation in result application and science and technology services, and negative (but non-significant) correlations with investment in R&D results and the number of published papers.

B. IMPLICATIONS

Based on the aforementioned findings, this paper presents the following recommendations for optimization:

Firstly, enhance research management and improve the allocation structure of research funds. For universities that have not achieved DEA effectiveness, they should avoid

TABLE 7. Appendix A: Efficiency of the technology development stage at various universities.

School name	2010	2011	2012	2013	2014	2015	2016	2017	MEAN
Peking University	0.1162	0.329	0.3221	0.3699	0.2993	0.2889	0.5256	0.4523	0.3136
Renmin University of China	0.2388	0.371	0.3167	0.3384	0.0648	0.0859	0.1492	0.0926	0.171
Tsinghua University	0.3968	0.3758	0.2362	0.2655	0.2173	0.2494	0.3145	0.2276	0.2786
Beijing Jiaotong University	0.2254	0.2175	0.153	0.2944	0.1332	0.1598	0.1891	0.1774	0.1882
University of Science and Technology Beijing	0.3476	0.2891	0.2674	0.2846	0.1976	0.2252	0.4327	0.4056	0.2965
Beijing University of Chemical Technology	0.5339	0.4304	0.5532	0.4474	0.437	0.4375	0.3868	0.3028	0.4346
Beijing University of Posts and Telecommunications	0.3707	0.4598	0.3183	0.372	0.3079	0.3365	0.5762	0.5765	0.4029
China Agricultural University	0.4842	0.3837	0.3603	0.4592	0.2536	0.3212	0.3148	0.3081	0.3533
Beijing Forestry University	0.1737	0.3593	0.3333	0.901	0.5126	0.4857	0.6108	0.3967	0.4282
Beijing University of Chinese Medicine	0.1838	1	0.9298	0.9277	0.7113	0.5675	1	1	0.7092
North China University of Electric Power	0.4638	1	1	1	0.7671	0.4699	0.5045	0.6863	0.7004
China University of Mining and Technology (Beijing)	0.1743	0.2489	0.3717	0.2682	0.2961	0.4503	0.7077	0.5615	0.3507
China University of Petroleum (Beijing)	0.2697	0.3305	0.2294	0.1646	0.2266	0.2726	0.3276	0.3112	0.2605
China University of Geosciences (Beijing)	0.208	0.3804	0.2985	0.2026	0.2753	0.3923	0.5833	0.5598	0.3376
Nankai University	0.1153	0.2236	0.2559	0.2483	0.2128	0.2221	0.4253	0.4273	0.2475
Tianjin University	0.2898	0.2875	0.273	0.3541	0.3911	0.3297	0.5954	0.5202	0.366
Dalian University of Technology	0.3756	0.2753	0.3289	0.4274	0.3492	0.325	0.4604	0.4543	0.3692
Northeastern University	0.2441	0.2997	0.3683	0.6938	0.386	0.3278	0.667	0.4723	0.4065
Jilin University	0.1169	0.1429	0.1332	0.1134	0.1605	0.2563	0.3031	0.2973	0.1764
Northeast Normal University	0.1801	0.1834	0.3427	0.2834	0.2502	0.2248	0.257	0.3063	0.2478
Northeast Forestry University	0.4931	0.6033	0.861	0.7999	0.7102	0.6425	0.4429	0.429	0.6042
Fudan University	0.2201	0.3751	0.4021	0.4596	0.411	0.4142	0.7473	0.5699	0.4271
Tongji University	0.4528	0.486	0.4575	0.4574	0.309	0.3698	0.462	0.5843	0.4406
Shanghai Jiao Tong University	0.3745	0.4185	0.4225	0.429	0.3177	0.3813	0.5874	0.5209	0.4244
Tung Wah University	0.5367	0.6641	0.4325	0.5092	0.7245	0.9637	0.6648	0.5131	0.6081
East China Normal University	0.1729	0.3307	0.3042	0.2501	0.2223	0.1907	0.3014	0.3467	0.2574
Nanjing University	0.4039	0.5645	0.5203	0.4988	0.4044	0.4024	0.7539	0.3114	0.467
Southeastern University	0.8472	0.5429	0.4536	0.3849	0.3372	0.561	0.5433	0.4073	0.4907
China University of Mining and Technology	0.2716	0.422	0.401	0.3106	0.7658	1	1	0.7742	0.5507
Hohai University	0.2107	0.5806	0.8076	0.6148	1	1	1	1	0.7046
Jiangnan University	1	1	1	1	1	1	1	1	1
Nanjing Agricultural University	0.1831	0.0961	0.0916	0.3214	0.5209	0.3619	0.4979	0.22	0.2392
China University of Pharmaceutical Sciences	0.5322	0.8552	0.2301	0.5505	0.6417	0.2465	0.3882	0.6415	0.4672
Zhejiang University	0.6511	0.4992	0.3013	0.4508	0.3326	0.3819	0.4213	0.356	0.4127
Xiamen University	0.3788	0.3986	0.3623	0.4567	0.5059	0.3981	0.447	0.4173	0.4184
Shandong University	0.2483	0.2845	0.3118	0.2445	0.265	0.2691	0.3378	0.3182	0.2831
Ocean University of China	0.2938	0.5087	0.3113	0.485	0.8103	0.9964	1	0.7574	0.5854
China University of Petroleum (East China)	0.1239	0.1809	0.2104	0.137	0.1517	0.2771	0.3577	0.4731	0.2152
Wuhan University	0.4951	0.592	0.4172	0.4561	0.4101	0.4098	0.9287	0.8162	0.5388
Huazhong University of Science and Technology	0.5055	0.5772	0.5111	0.3992	0.2319	0.3192	0.5351	0.4928	0.4297
China University of Geosciences (Wuhan)	0.2196	0.2426	0.3378	0.4221	0.3112	0.244	0.4457	0.4768	0.3244
Wuhan University of Technology	0.3234	0.2972	0.3505	0.3701	0.3497	0.3061	0.4731	0.4384	0.3591
Huazhong Agricultural University	0.5094	0.4799	0.5674	0.2918	0.2028	0.4407	0.7192	0.6394	0.4494
Huazhong Normal University	0.2288	0.4415	0.4759	0.2508	0.3241	0.2429	0.4361	0.5563	0.351
Hunan University	0.4203	0.4262	0.2792	0.2687	0.1857	0.1904	0.3413	0.3815	0.2978
Central South University	0.3482	0.5626	0.4137	0.4145	0.4951	0.4272	0.7541	0.6014	0.4881
Sun Yat-sen University	0.1348	0.2564	0.365	0.3102	0.308	0.1736	0.1907	0.4015	0.2515
South China University of Technology	0.3795	0.4216	0.4781	0.4076	0.3176	0.5771	0.5975	0.5397	0.4552
Chongqing University	0.3873	0.5064	0.4534	1	0.5445	0.5491	0.6621	0.5929	0.5654
Southwestern University	0.2219	0.2005	0.3351	0.387	0.3732	0.3225	0.3898	0.2379	0.2993
Sichuan University	0.2019	0.3038	0.2853	0.2795	0.2704	0.2202	0.4783	0.4371	0.2972
Southwest Jiaotong University	1	0.8212	0.7276	0.6965	1	0.5136	0.8931	0.8151	0.7925
Xi'an Jiaotong University	0.3038	0.3932	0.4493	0.3402	0.2532	0.3161	0.4509	0.4787	0.3651
Xidian University	0.3604	0.6709	0.6376	0.651	0.4595	0.3693	0.5194	0.5055	0.5085
Chang'an University	0.3064	0.3507	0.5452	0.3583	0.4993	0.9411	1	1	0.5614
Northwest Agriculture and Forestry University of Science and Technology	0.2636	0.2802	0.2798	0.3208	0.382	0.3547	0.5258	0.4109	0.3435
Shaanxi Normal University	1	1	1	1	1	0.7782	0.9757	0.7346	0.9296
Mean	0.3115	0.3948	0.3801	0.3977	0.3608	0.3699	0.5067	0.4615	

blindly pursuing additional research resources. Instead, they should conduct research activities in an organized manner, utilizing existing resources to improve achievement transformation efficiency before focusing on technology development efficiency.

Secondly, leverage regional advantages to enhance the efficiency of scientific research results transformation. Classify the sample universities into three tiers (''high, middle, and low'') based on the degree of economic development. Universities in the high tier can serve as drivers for those in the middle and low tiers. Pay attention to the coordinated allocation of research resources across different tiers to prevent resource redundancy and waste, thereby effectively improving the overall transformation of scientific research results

TABLE 8. Appendix B: Efficiency of the transformation stage at various universities.

School name	2011	2012	2013	2014	2015	2016	2017	MEAN
Peking University	1	1	0.6067	0.4863	1	0.5228	1	0.7657
Renmin University of China	1	1	1	0.1874	0.0001	1	0.5324	0.193
Tsinghua University	1	1	1	1	1	1	1	1
Beijing Jiaotong University	0.0909	0.2593	0.4022	0.084	0.0904	1	1	0.256
University of Science and Technology Beijing	0.2359	0.7866	0.3368	0.5369	0.5099	0.2358	0.1343	0.3415
Beijing University of Chemical Technology	0.405	0.174	0.2709	0.36	0.1958	0.1157	0.4548	0.2554
Beijing University of Posts and Telecommunications	0.5617	0.6786	0.5985	0.1421	0.6856	0.3859	0.2698	0.4202
China Agricultural University	0.6332	0.2393	0.2356	0.2782	0.2283	0.0638	0.3273	0.2411
Beijing Forestry University	0.8442	0.072	0.1122	0.1328	0.1519	0.5367	0.166	0.1988
Beijing University of Chinese Medicine	0.3169	0.3555	0.0829	0.0387	0.081	1	0.0787	0.1565
North China University of Electric Power	0.0453	0.0167	0.0685	0.0521	0.1265	0.795	0.0076	0.0575
China University of Mining and Technology (Beijing)	1	0.7971	1	0.2394	0.3213	0.2358	0.0001	0.1465
China University of Petroleum (Beijing)	0.249	0.2626	0.1679	1	0.3341	0.0657	0.1026	0.2197
China University of Geosciences (Beijing)	0.2117	0.698	0.1495	0.4879	0.4306	0.0932	0.0173	0.1853
Nankai University	1	1	1	1	0.5575	1	1	0.9199
Tianjin University	1	0.867	0.3156	0.2008	1	0.1594	0.2643	0.4202
Dalian University of Technology	0.278	1	0.4415	0.1334	0.6864	0.3346	0.1822	0.3532
Northeastern University	0.1809	0.3376	0.8308	0.0448	0.4837	0.3006	0.575	0.2941
Jilin University	0.2306	0.3845	0.2727	0.0747	0.2307	0.0841	0.0731	0.1589
Northeast Normal University	0.0805	0.1882	0.0421	0.0654	0.0703	0.1421	0.0001	0.0329
Northeast Forestry University	0.1237	0.0986	0.248	0.3599	0.6389	0.4373	0.1158	0.2311
Fudan University	0.3832	0.5159	0.1653	0.4	0.363	0.18	1	0.3644
Tongji University	0.4012	0.8062	0.3287	0.1441	0.6578	0.317	0.1929	0.3478
Shanghai Jiao Tong University	0.359	0.7451	0.7834	0.399	0.8302	0.9817	0.2531	0.5599
Tung Wah University	0.0623	0.0973	0.1489	0.1693	0.1396	0.3089	0.0823	0.1273
East China Normal University	0.2782	0.2058	0.217	1	1	0.6463	0.534	0.4589
Nanjing University	0.2017	0.1557	0.0903	0.2804	0.2426	0.0877	0.4801	0.1874
Southeastern University	0.1155	0.5297	0.3719	0.4559	0.3867	0.0278	0.1998	0.2165
China University of Mining and Technology	0.0843	0.1222	0.092	0.0613	0.0292	0.0121	0.0329	0.049
Hohai University	0.0441	0.0573	0.091	0.0229	0.1685	0.0623	0.0372	0.0574
Jiangnan University	0.2753	0.2622	0.125	0.4002	0.3449	0.3596	0.1488	0.2532
Nanjing Agricultural University	0.638	0.5519	0.8347	0.1796	0.1278	0.3635	0.212	0.3395
China University of Pharmaceutical Sciences	0.0525	0.1951	0.0885	0.5196	0.1499	0.7113	0.0168	0.1356
Zhejiang University	0.2743	0.4306	0.3889	0.1119	0.2069	0.192	0.5063	0.2696
Xiamen University	0.3407	0.5361	0.1825	0.1757	1	0.1584	0.2022	0.2935
Shandong University	0.1926	0.5103	0.2573	0.389	0.8862	0.6223	0.8336	0.4624
Ocean University of China	0.3341	0.6016	0.1413	0.3719	0.1107	0.2741	0.2199	0.2552
China University of Petroleum (East China)	0.2767	0.6642	0.6786	0.3076	0.0429	0.0845	0.1082	0.2047
Wuhan University	0.1576	0.1936	0.1333	0.0923	0.4229	0.2631	0.1954	0.1875
Huazhong University of Science and Technology	0.1651	0.1814	0.2544	0.1381	0.5056	0.41	0.2956	0.252
China University of Geosciences (Wuhan)	0.1419	0.314	0.0867	0.0108	0.0429	0.0468	0.0659	0.0661
Wuhan University of Technology	0.3457	0.3031	1	0.3332	0.1218	0.263	0.1209	0.2801
Huazhong Agricultural University	0.4554	0.1416	0.0964	0.2877	0.0426	0.4148	0.3413	0.1952
Huazhong Normal University	0.5755	0.0773	1	0.4508	1	1	0.2278	0.4631
Hunan University	0.1982	0.2804	0.2042	0.1608	0.2505	0.1069	0.1464	0.1841
Central South University	0.5424	0.5527	0.4198	1	0.4574	0.1235	0.1368	0.3713
Sun Yat-sen University	0.1237	0.5902	0.355	0.0378	0.2172	0.4117	0.3857	0.2298
South China University of Technology	0.1081	0.1172	0.1651	0.128	0.2331	0.0565	0.6806	0.1575
Chongqing University	0.1081	0.231	0.0809	0.1699	0.0945	0.168	0.1276	0.1319
Southwestern University	1	0.1665	0.2122	0.0373	0.2868	0.638	0.0392	0.1915
Sichuan University	0.8874	0.2278	1	0.164	0.4511	0.3472	0.2979	0.3967
Southwest Jiaotong University	0.0561	0.0706	0.0488	0.0149	0.045	0.0504	0.1359	0.0509
Xi'an Jiaotong University	0.7322	0.8572	0.4445	0.2956	0.8862	0.2595	0.4344	0.5038
Xidian University	0.5715	0.0623	0.1303	0.0173	0.0381	0.5599	1	0.1501
Chang'an University	0.4597	0.2789	0.1382	0.2017	0.137	0.0239	0.149	0.1505
Northwest Agriculture and Forestry University of Science and Technology	0.3594	0.05	0.0472	0.0126	0.0765	0.1088	0.1085	0.0716
Shaanxi Normal University	0.0945	0.0134	0.0745	0.0807	1	0.4041	0.0355	0.1013
Mean	0.2711	0.2738	0.2387	0.1678	0.2233	0.2323	0.1467	

in China. This approach is crucial to enhancing the overall efficiency of scientific research results transformation in the country.

Thirdly, enhance policy support for the transformation of research achievements at the government level. Create a liaison platform between universities and enterprises, accompanied by corresponding preferential policies to facilitate the transformation and application of research achievements. Optimize the structure of government capital investment by increasing investment in education during the achievement transformation stage. At the same time, moderately reduce capital investment during the technology research and development stage to prevent government appropriation from inhibiting technology research, development, and scientific innovation.

Fourthly, prioritize talent development and cultivation. Increase the proportion of professional scientific researchers during the technology R&D stage and promote the involvement of postgraduates in the achievement transformation stage. Emphasize strict quality control of postgraduates' research results, shifting the focus from quantity-oriented scientific papers. Optimize the title structure of scientific researchers within universities and strengthen the cultivation of high-level scientific talents at the university level, while avoiding talent redundancy. By implementing these suggestions, the efficiency of scientific research results transformation can be effectively improved in China.

APPENDIX A

See Table 7.

APPENDIX B

See Table 8.

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