Research on the R&D Efficiency Based on the Three-Stage Dea Index-Taking the High-Tech Industry as an Example

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Abstract: With the development of economic globalization, the high-tech industry has gradually become a new growth point in my country's economic development and has attracted attention from all walks of life. Therefore, investigating and analyzing the factors affecting the innovation efficiency of my country's high-tech industry is of great significance to economic growth. Based on the data of 32 sub-industries of China's high-tech industries from 2015 to 2019, this paper analyzes the efficiency of high-tech industries based on the three-stage DEA model. The research shows that environmental factors overestimate the R&D efficiency of China's high-tech industries, and each segment is subdivided R&D efficiency losses between industries are common in the industry and there are obvious differences. The efficiency value ranges from 0.3 to 1. After excluding environmental factors and random errors, high-tech industries such as radio and television equipment manufacturing, computer parts manufacturing, The overall technical efficiency of industries such as office equipment manufacturing has dropped significantly, and scale efficiency is the main factor affecting overall technical efficiency.

Keywords: Three-stage DEA;High-tech industry; R & D efficiency; Scale efficiency

INTRODUCTION

1.1RESEARCH BACKGROUND AND RESEARCH SIGNIFICANCE

1.1.1RESEARCH BACKGROUND

With the development of the times and society, the world has entered a new economic era led by economy and technology. Starting from 2016, the China Institute of Science and Technology Information has released a report on the output of China's outstanding scientific and technological papers. According to statistics, in 2019, the total number of outstanding scientific and technological papers in China 387,300 articles, an increase of 22.6% over 2018, including 225,600 outstanding international scientific papers and 161,700 outstanding domestic scientific papers. The number of outstanding papers in clinical medicine, chemistry, biology, electronics, communication and automatic control is the largest. In addition, in terms of technology patents, according to the statistics of the Organization for Economic Cooperation and Development (OECD) in November 2020, the number of tripartite patents in China in 2018 was 5,323, accounting for 9.3% of the world’s total. This is an increase of 1 place compared with 2017, surpassing Germany’s ranking. Ranked 3rd in the world. Vigorously developing high-tech industries has become an important strategy for the country to implement innovation-driven development strategies and compete internationally.

1.1.2RESEARCH PURPOSE AND SIGNIFICANCE

The improvement of the efficiency of scientific and technological innovation is the basis for the long-term sustainable economic development. The country pays more and more attention to the development of advanced science and technology fields such as pharmaceutical manufacturing, aviation manufacturing, and electronic manufacturing. The high-tech industry is compared with traditional technology. The industry has better economic benefits, more advanced technology and stronger competitive advantages. The development of high-tech industries indirectly affects the status of countries in the world economy and trade. Many countries have begun to gradually consider and study the development potential and evaluation system in them. Although my country is constantly increasing its investment in capital and innovation in high-tech industries, there are fewer studies on how to select and measure input and output variables, and fewer studies on the separation of environmental factors.

Based on this, this article wants to conduct a research on the sub-industries of the high-tech industry through a comprehensive structural analysis, considering the comprehensive technical efficiency, pure technical efficiency, scale efficiency and other factors, and excluding the impact of environmental factors to analyze the technology industry Innovate efficiency, put forward targeted improvement measures and suggestions, and further promote the transformation and upgrading of the industry.

1.1.3RESEARCH STRUCTURE

This article is mainly divided into five parts

Chapter One Introduction. First, the research background of this article is described. It expounds the importance of high-tech industry to social and economic development, and discusses the purpose and significance of this article based on the background, and then introduces the research content and methods of this article.

The second chapter is a literature review and related theories. It mainly focuses on the themes of high-tech industry and R & D efficiency to sort out and summarize.

The third chapter is related to efficiency evaluation methods. It mainly introduces and summarizes the related concepts and theoretical basis of the innovation efficiency evaluation methods DEA, SFA, and three-stage DEA model.

Chapter 4 Analysis of the R & D efficiency of high-tech industry According to the relevant statistical data of the China Science and Technology Statistical Yearbook from 2015 to 2020, input-output variables and environmental factors are selected, and then a three-stage DEA model is established and used to eliminate the impact of environmental factors to analyze the efficiency of each sub-industry.

Chapter 5 Research conclusions and suggestions. Summarize the current situation of the R & D efficiency of my country's high-tech industry, and put forward corresponding suggestions and improvements based on the conclusion.

RELATED THEORIES AND LITERATURE REVIEW

2.1RESEARCH ON HIGH-TECH INDUSTRIES

Since the 1960s, the United States first put forward the concept of high technology, believing that high technology is the science and technology of producing or using cutting-edge equipment or high-end equipment. Since then, high technology has attracted attention from all walks of life. Hippel (1988) believes that high technology is a dynamically changing technology group, and its connotations are different at different stages of development. The definition of high-efficiency technology is based on the stage of development[1]. At present, according to the 2018 ``Administrative Measures for the Recognition of High-tech Enterprises" issued by the

Ministry of Science and Technology of China, it defines pharmaceutical manufacturing, aerospace aircraft and equipment manufacturing, electronic and communication equipment, computer and office equipment manufacturing, medical instrument equipment and instrument watch manufacturing, and information chemistry Six major categories, such as product manufacturing, are areas that China needs to focus on in terms of high technology in the future. Compared with traditional industries, high-tech industries are characterized by high technology and knowledge innovation. They are emerging industries based on the latest scientific and cutting-edge technologies, and have played an important role in economic development.

Douglass (2008) believes that the high-tech industries in the United States refer to various sectors that use advanced science and engineering technology for production and services[2]. Chen (2008) believes that in developed countries and geographic regions, countries or regions dominate the performance of high-tech industries. The UK refers to the industrial clusters composed of information technology, biotechnology and other technologies at the forefront of science or technology as high-tech industries[3] . Xue (2013) summarized and analyzed the planning and response strategies of major western developed economies in the high-tech industry, and put forward suggestions based on the actual situation in China, and believed that a sound high-tech industry system framework and market environment are important foundations[4]. Hao (2017) summarized and analyzed the U.S. national-level policies on the development of high-tech industries, and put forward solutions and suggestions for the problems in the development of China's high-tech industries[5]. Lu (2018) starts from the high-tech industry itself, and builds a collaborative cooperation plan within and between industries by analyzing the synergistic development and related aggregation effects between industries[6]. At present, according to the 2018 ``Administrative Measures for the Recognition of High-tech Enterprises'' issued by the Ministry of Science and Technology of China, high-tech enterprises are mainly measured by methods such as intellectual property rights, the number of scientific and technological personnel, the number of R&D expenditures in the past three years, and the proportion of high-tech product income. Identified.

2.2RESEARCH ON R&D EFFICIENCY OF HIGH-TECH INDUSTRY

Farrell (1957) began to measure empirical technical efficiency. Under the premise of keeping output unchanged, he measured the maximum value of all inputs that could be reduced, and based on research, he divided enterprise efficiency into two parts: technical efficiency and configuration efficiency. The first part of technical efficiency refers to the ability of an enterprise to maximize output under certain input conditions, and technical efficiency can be subdivided into pure technical efficiency and scale efficiency, while the second part of configuration efficiency refers to the production technology And when the price of input factors remains unchanged, the company's ability to utilize inputs in an optimal proportion[7]. Huang (2015) used the Malmquist index decomposition method based on the DEA model to analyze the R&D efficiency of China's high-tech industries, and found that pure technical efficiency and knowledge innovation efficiency have gradually become the main factors affecting the growth rate of TFP[8]. Guan (2010) uses the two-stage DEA model method to conduct empirical research on the output efficiency of Chinese high-tech enterprises across regions, and proposes to focus on the research and development performance of the downstream industry economic output efficiency[9]. Chen, S (2017) takes the high-tech industries of 31 provinces and regions in China as a research sample, uses the DEA-Malmquist index method to conduct an empirical study on the efficiency of high-tech R&D from a regional perspective, and analyzes the rate of change of China's high-tech industries through index decomposition. And the rate of resource change in the process of technology research and development[10]. Li, L. B (2017) focused on the efficiency evaluation of China's regional high-tech industries, established a new framework for the dynamic DEA model, and found that in terms of technical efficiency and scale efficiency scores, the eastern region has always been in the leading position, while the central and western regions are obviously behind[11]. Liu (2015) used the three-stage DEA model to measure the R&D efficiency of China's high-tech industries based on the control of environmental factors. Research shows that the scale efficiency is high before excluding environmental factors such as government support, market structure, enterprise scale, and ownership structure. Estimated that pure technical efficiency is underestimated[12].

CORRELATION EFFICIENCY EVALUATION METHOD

3.1ONE-STAGE DEA METHOD

Data envelopment analysis was first proposed by Charnes, Coopor and Rhodes in 1978. DEA is an important non-parametric method for evaluating production efficiency. The core principle of data envelopment analysis is a systematic analysis method for evaluating the relative benefits or effectiveness of the same type of decision making units (DMU) based on multi-index input and output. Construct a relatively effective production frontier with the help of mathematical programming and data statistics, and then evaluate the effectiveness of the decision-making unit by comparing the projections of each decision unit on the production frontier and the degree of deviation from the frontier.

The advantage of data envelopment analysis is that it is more suitable for comprehensive evaluation of multi-output and multi-input effectiveness, and there is no need to set any proportional weight assumptions and function assumptions between any variables, but the actual data input and output by the decision-making unit The weight is obtained, and the influence of most subjective factors is avoided, and the objectivity is relatively strong.

3.2.1CCR MODEL

The CCR model was first proposed by Charnes et al in 1978. This model is used to calculate and measure technical efficiency under the assumption of constant returns to scale. Taking the efficiency index of the first decision-making unit as the goal, and taking the efficiency of all decision-making units as the constraint, we can get the following model. The specific model is as follows:

Assuming n decision-making units (j=1,2,3,...,n), these n DMUs are all comparable, and each DMU has m inputs and s outputs. The following linear programming can be used to express the efficiency of DUM:

$$\max \frac{u^T y_0}{v^T x_0}$$

$$\frac{u^T y_j}{v^T x_j} \leq 1,\ j = 1,2,\cdots,n$$

$$u \geq 0, v \geq 0, u \neq 0, v \neq 0$$

Where xj and yj are the commissioning and output vectors of the decision-making unit, respectively, $u = (u_1, u_2, \cdots, u_s)^T, v = (v_1, v_2, \cdots, v_m)^T$ are the weight coefficients of m types of input and s types of output, respectively, using Charnes-Cooper transform for fractional programming.Let $t = \frac{1}{v^T x_0} > 0,\quad \omega = t \cdot v, \mu = t \cdot u$,The fractional situation model (CCR) becomes the following linear programming model:

$$\max \mu^T y_0 = h^0$$
$$\omega^T x_j - \mu^T y_j \geq 0,\ j = 1,2,\cdots,n$$
$$\omega^T x_0 = 1$$
$$\omega \geq 0, \mu \geq 0$$

Introduce slack variable S^- and residual variable S^+ in the above plan,The slack variable represents the amount of input that needs to be reduced to achieve the optimal configuration, and the remaining variable represents the amount of output that needs to be increased to achieve the optimal configuration. Converted into dual form, the model can be simplified to:

$$\min \theta$$
$$\sum_{j=1}^{n} x_{ij}\lambda_j + S_r^+ = \theta x_0$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j - S_r^- = y_0$$
$$S^+, S^-,\ \lambda_j \geq 0,\ j = 1,2,\cdots,n$$

Use the CCR model to determine whether the technology is valid and the scale is valid at the same time:

1.If $\theta = 1 且 S^+ = S^- = 0$, the decision-making unit is DEA effective, and the economic activities of the decision-making unit are both technically effective and scale-effective;

2.If $\theta = 1$, at least one of $S^+ 和 S^-$ input or output is greater than 0, the decision-making unit is weak DEA effective, and the economic activities of the decision-making unit are not both technically effective and scale-effective;

3.If $\theta < 1$ is satisfied, the decision-making unit is not DEA effective, and economic activities are neither technically effective nor scale effective.

3.2.2BCC model

In order to evaluate technical effectiveness more objectively, the BCC model obtained under the assumption of variable returns to scale is used to separate scale efficiency. Calculate the efficiency of each decision-making unit DUM and the input redundancy of each DMU through the BCC model.

The difference between the BCC model and the CCR model lies in the assumption that the return to scale is variable. The CCR model assumes that the return to scale of each decision-making unit remains unchanged. The premise is to ensure that the production scale is optimal, but in actual production, the enterprise may not be in In the optimal state, therefore, the BCC model separates the factor of scale efficiency from technical efficiency, thereby stripping off the influence of scale on technical efficiency. It constitutes the following BCC model:

$$\max \mu^T y_0 + \mu_0$$
$$\omega^T x_0 = 1$$
$$\omega x_j - u y_j + u_0 e \geq 0,\ j = 1,2,\cdots,n$$
$$\omega \geq 0, \mu$$

3.3TWO-STAGE STOCHASTIC FRONTIER ANALYSIS

In this stage, the purpose is to analyze the slack variables calculated in the first stage. The stochastic frontier model was first proposed by Aigner, Lovell, and Schmidt (1977), and has been widely used in the empirical field. Fried (2002) believes that the values of input slack variables and output slack variables obtained in the first stage are affected by management invalidation, environmental factors and statistical noise. Establish the following SFA model:

$$S_{ni} = f\left(Z_i : \beta_n\right) + \nu_{ni} + \mu_{ni}; i = 1,2,\cdots,I; n = 1,2,\cdots,N$$

Among them, S_{ni} is the slack value of the nth input in the i decision-making units, Z_i is the selected environmental variable, β_n is the coefficient corresponding to the environmental variable, $\nu_{ni} + \mu_{ni}$ is the error mixing term, ν_{ni} is the statistical noise term, and μ_{ni} is the management invalid item.

Then the influence of random factors is stripped from the mixed error estimated by similar SFA regression. Establish the following separation formula:

$$E(\nu_{ni} \mid \nu_{ni} + \mu_{ni}) = S_{ni} - f\left(z_i; \beta_n\right) - E(\mu_{ni} \mid \nu_{ni} + \mu_{ni})$$

3.3THREE-STAGE DEA METHOD

Based on the second-stage SFA model regression results and related calculations, the adjusted input value and output value data are obtained, and then brought into the first-stage BBC model for calculations to obtain the actual efficiency value excluding environmental factors and random errors.

ANALYSIS ON THE R&D EFFICIENCY OF HIGH-TECH INDUSTRY

4.1DATA SOURCES AND VARIABLES

According to the principles of objectivity and authority of the data, this article uses the relevant data on the high-tech industry sector from the 2015-2019 China Statistical Yearbook of Science and Technology. In order to be systematic and scientific, and consider from a comprehensive perspective, construct an input-output indicator system for the evaluation of the R&D efficiency of my country's high-tech industries, as shown in Table 1.

Table 1 New technology industry R&D efficiency evaluation input-output index system

Variable category	Variable name	unit	Variable description
Input	R&DFull-time equivalent of personnel	Mean-year	Evaluation and measurement of science and technology human resources input indicators
Input	R&DInternal expenditure	Ten thousand yuan	Evaluation and measurement of funding

Input	New product development expenditure	Ten thousand yuan	Evaluate the investment in new product development process
output	Number of patent applications	Unit	Number of applications for the results of scientific and technological research and development projects
output	Number of invention patents	Unit	Number of authorized invention patents
output	New product sales revenue	Ten thousand yuan	Evaluate the market benefits brought by new technology products Economic value

The environmental factor variables to be eliminated in the second stage of the DEA model are also called external influencing factors variables. Comprehensive consideration is given to the three key indicators of technical support, market structure, and government support level to investigate the impact of factors on high-tech industries.

4.2ONE-STAGE DEA

The BCC model in the traditional DEA is used to calculate the R&D efficiency of 32 sub-sectors of my country's high-tech industry from 2015 to 2019 with the help of DEAP2.1 software. The detailed results are shown in Table 2.

Table 2 2015-2019 my country's high-tech industry efficiency average

Industry	Crste	Vrste	Scale
Chemical manufacturing	0.346	0.354	0.978
Chinese patent medicine production	0.452	0.462	0.979
Biopharmaceutical products manufacturing	0.405	0.448	0.907
Manufacturing of special equipment for the electronics industry	0.824	0.907	0.907
Fiber optic cable and lithium ion battery manufacturing	0.749	0.763	0.982
Lithium-ion battery manufacturing	0.762	0.785	0.972
Manufacturing of communication equipment, radar and ancillary equipment	0.674	1.000	0.674
Communication system equipment manufacturing	0.631	0.912	0.694
Communication terminal equipment manufacturing	1.000	1.000	1.000
Radar and ancillary equipment manufacturing	0.638	0.900	0.731
Broadcasting and television equipment manufacturing	0.843	0.869	0.967
Non-professional audio-visual equipment manufacturing	0.798	0.805	0.991
Electronic device manufacturing	0.849	0.991	0.855
Electronic vacuum device manufacturing	0.746	0.995	0.749
Semiconductor discrete device manufacturing	0.778	0.894	0.863
Integrated circuit manufacturing	0.703	0.728	0.960
Optoelectronic device manufacturing	0.737	0.810	0.911

Manufacturing of electronic components and electronic special materials	0.779	1.000	0.779
Manufacturing of resistance, capacitance and inductance components	0.615	0.655	0.941
Electronic circuit manufacturing	1.000	1.000	1.000
Electronic special materials manufacturing	0.612	0.706	0.867
Smart consumer equipment manufacturing	0.791	0.817	0.969
Other electronic equipment manufacturing	0.804	0.833	0.964
Computer manufacturing	1.000	1.000	1.000
Computer parts manufacturing	0.731	0.784	0.925
Computer peripheral equipment manufacturing	0.818	0.872	0.943
Office equipment manufacturing	0.871	0.993	0.877
Medical equipment and equipment manufacturing	0.911	0.918	0.991
Manufacturing of medical diagnosis, monitoring and treatment equipment	0.850	0.961	0.883
Medical, surgical and veterinary equipment manufacturing	0.743	0.920	0.810
General instrument and meter manufacturing	0.851	0.927	0.920
Special instrument and meter manufacturing	0.740	0.805	0.919
mean	0.751	0.838	0.903

It can be seen from Table 2 that, without considering random influencing factors and external environmental variables, the average R&D efficiency of China's high-tech industry from 2015 to 2019 was 0.751. The R&D efficiency is low and needs to be further improved. The average value of technical efficiency and scale efficiency are 0.838 and 0.903 respectively. The average value of pure technical efficiency is lower than the average value of scale efficiency. Pure technical efficiency reflects the decision-making ability and management level, indicating that the decision-making ability and management level is not good and is affecting China High-tech An important factor in the technology industry. Although the scale efficiency is relatively high, it has not yet reached the economies of scale. Therefore, the efficiency level can be improved by appropriately improving the scale of operation.

On the other hand, it can be seen that the efficiency of various industries in high-tech industries is uneven, and the efficiency levels of some industries are quite different. Among them, the research and development efficiency of communication terminal equipment manufacturing, electronic circuit manufacturing, and computer manufacturing are at the forefront of production. On the other hand, the other sub-industries are not on the frontier, but under the frontier of efficiency, there is much room for improvement.

4.3TWO-STAGE SFA REGRESSION ANALYSIS

The efficiency obtained by the classical DEA model analysis in the first stage does not take environmental factors into consideration, so the slack variable obtained in the first stage is used as the explained variable, and environmental variables such as technical support, market structure, and government support level are used as the explanatory variable. Establish the SFA model and use Frontier4.1 software to calculate. The test results are shown in Table 3.

Table 3 SFA regression results in the second stage

	R&DFull-time equivalent of personnel	R&DInternal expenditure	New product development expenditure
constant	-3945.7991***	-297766.16***	-396796.23***
Technical Support	13.204462***	2285.9176***	1077.6543***
market structure	-6.3623633***	-1025.2484***	-473.99527***
Government support level	-0.025520993***	-27.093794***	-2.3295314***
σ^2	8.18E+07	4.30797E+11	6.08891E+11
γ	1.00E+00	1.00E+00	1.00E+00
log	-320.188	-455.534	-457.925
LR	8.543***	10.235***	14.084***

Note：***、**and*are respectively at the significance level of 1%, 5%, and 10%

In Table 3, the γ ,σ^2, LR, and log values have all passed the significance test, indicating that relative to random errors, environmental factors play a major role in R&D efficiency. On the other hand, the parameter estimates of most environmental factors have reached a certain level of significance, which further illustrates that environmental factors have a significant impact on the slack variables obtained from the input of high-tech industries.

The impact of technical support on the slack variables of full-time equivalent of personnel, internal expenditures and expenditures for new product development are all positive and significant, which means that the increase in the number of R&D institutions will increase the full-time equivalent of personnel, internal expenditures and new product development expenditures. Redundancy of product development expenditures. Although the increase in the number of R&D institutions reflects the improvement of the industry's technological innovation capabilities, it will also lead to problems such as poor cooperation. In the increased institutions, there are differences in factors such as technology, configuration, and management, and there are imperfect phenomena, which in turn leads to resources such as capital and labor. The repeated configuration of the company has increased the waste of indicators such as the average annual number of employees, internal and expenditure of the enterprise, and is not conducive to the improvement of research and development efficiency.

The influence of market structure on the slack variables of personnel equivalent full-time equivalent, internal expenditures and new product development expenditures are all negative and significant, indicating that the increase in the number of enterprises in the industry will effectively reduce personnel equivalent full-time equivalent, internal expenditures and new product development expenditures. The redundancy of product development expenditures has improved the efficiency of research and development. The increase in the number of enterprises in the market structure has intensified competition in the market, but appropriate competition will encourage enterprises to invest in research and development, promote the improvement of enterprises in research and development, and make more concentrated and reasonable use of research and development resources, which is conducive to the improvement of research and development efficiency.

The level of government support has a negative but insignificant effect on the slack variables of the full-time equivalent of personnel, internal expenditures and new product development expenditures. In order to encourage and support the R&D and innovation of enterprises, it is implemented through investment in R&D and supporting policies. However, it can be seen that government support has not brought about a large R&D improvement, indicating that the management of support funds is imperfect and The allocation is unreasonable, and part of the research and development funds are not used rationally and was wasted, making the government support to improve the efficiency of research and development relatively small.

4.4THREE-STAGE DEA

Based on the regression results of the SFA model in the second stage and related calculations, the adjusted data after excluding environmental and random interference factors are obtained, and the BCC model is executed again with the help of DEAP2.1 software, and compared with the results of the first stage, as shown in Table 4.

Table 4 Comparison of the results of the third stage and the first stage of the efficiency of my country's high-tech industry in 2015-2019

Industry	The first stage of DEA results			The third stage of DEA results		
	Crste	Vrste	Scale	Crste	Vrste	Scale
Chemical manufacturing	0.346	0.354	0.978	0.451	0.546	0.832
Chinese patent medicine production	0.452	0.462	0.979	0.354	0.622	0.566
Biopharmaceutical products manufacturing	0.405	0.448	0.907	0.357	0.690	0.525
Manufacturing of special equipment for the electronics industry	0.824	0.907	0.907	0.620	0.952	0.649
Fiber optic cable and lithium ion battery manufacturing	0.749	0.763	0.982	0.795	0.897	0.888
Lithium-ion battery manufacturing	0.762	0.785	0.972	0.738	0.886	0.835
Manufacturing of communication equipment, radar and ancillary equipment	0.674	1.000	0.674	0.823	1.000	0.823
Communication system equipment manufacturing	0.631	0.912	0.694	0.733	0.907	0.808
Communication terminal equipment manufacturing	1.000	1.000	1.000	1.000	1.000	1.000
Radar and ancillary equipment manufacturing	0.638	0.900	0.731	0.229	0.994	0.230
Broadcasting and television equipment manufacturing	0.843	0.869	0.967	0.568	0.952	0.591
Non-professional audio-visual equipment manufacturing	0.798	0.805	0.991	0.766	0.872	0.878
Electronic device manufacturing	0.849	0.991	0.855	0.954	1.000	0.954
Electronic vacuum device manufacturing	0.746	0.995	0.749	0.207	0.960	0.215
Semiconductor discrete device manufacturing	0.778	0.894	0.863	0.364	0.958	0.378
Integrated circuit manufacturing	0.703	0.728	0.960	0.651	0.815	0.796
Optoelectronic device manufacturing	0.737	0.810	0.911	0.714	0.791	0.919
Manufacturing of electronic components and electronic special materials	0.779	1.000	0.779	0.899	1.000	0.899
Manufacturing of resistance, capacitance and inductance components	0.615	0.655	0.941	0.372	0.715	0.518
Electronic circuit manufacturing	1.000	1.000	1.000	1.000	1.000	1.000

Electronic special materials manufacturing	0.612	0.706	0.867	0.476	0.785	0.608
Smart consumer equipment manufacturing	0.791	0.817	0.969	0.711	0.888	0.804
Other electronic equipment manufacturing	0.804	0.833	0.964	0.674	0.857	0.783
Computer manufacturing	1.000	1.000	1.000	0.944	0.983	0.959
Computer parts manufacturing	0.731	0.784	0.925	0.374	0.831	0.446
Computer peripheral equipment manufacturing	0.818	0.872	0.943	0.473	0.930	0.507
Office equipment manufacturing	0.871	0.993	0.877	0.320	0.990	0.323
Medical equipment and equipment manufacturing	0.911	0.918	0.991	0.783	0.924	0.849
Manufacturing of medical diagnosis, monitoring and treatment equipment	0.850	0.961	0.883	0.632	0.973	0.648
Medical, surgical and veterinary equipment manufacturing	0.743	0.920	0.810	0.404	0.930	0.434
General instrument and meter manufacturing	0.851	0.927	0.920	0.945	0.973	0.970
Special instrument and meter manufacturing	0.740	0.805	0.919	0.543	0.948	0.571
mean	0.751	0.838	0.903	0.621	0.893	0.694

It can be seen from Table 4 that the R&D efficiency value before and after the adjustment has changed significantly. Environmental factors have affected and improved the efficiency of R&D. From the perspective of 2015-2019 as a whole, in terms of comprehensive technical efficiency, it was 0.751 before adjustment and 0.621 after adjustment, which was significantly lower than before adjustment, indicating that environmental factors have caused The R&D efficiency of China's high-tech industry is falsely high. In terms of pure technical efficiency, it was 0.838 before adjustment and 0.893 after adjustment, which was an improvement compared to before adjustment. In terms of scale efficiency, it was 0.903 before adjustment and 0.694 after adjustment. Compared with the pre-adjustment period, there is a significant drop and a significant decline, indicating that the low efficiency of industrial scale is the main reason that restricts the improvement of high-tech industry R&D efficiency.

The effect of environmental factors on each sub-industry is also different. Comparing the results of various industries, it can be found that after removing environmental factors and random errors, the overall technical efficiency of seven industries including chemical drug manufacturing, communication system equipment manufacturing, and electronic device manufacturing has increased, indicating that these industries are in a more unfavorable environment The policy also affects technical efficiency, not caused by its own low level of management.

CONCLUSIONS

This paper summarizes the relevant concepts and theories of the high-tech industry, collects panel data from 2015 to 2019 in 32 high-tech industries in my country, and uses the three-stage DEA model to conduct in-depth analysis of the R&D efficiency of my country's high-tech industry and draw conclusions and conclusions. Suggest.

After adjusting for environmental factors and random errors, the R&D efficiency of most of the high-tech industries in my country has been significantly reduced, and low scale efficiency is the main restricting factor. The overall technical efficiency of various industries differs greatly, and there are some industries with lower efficiency. Three environmental variables have a significant impact on the R&D efficiency of high-tech industries. Among them, technical support affects the improvement of R&D efficiency, while the market structure reduces R&D efficiency.

For these existing problems, China's high-tech industry first needs to make full use of resources to effectively improve research efficiency through the regulation of the market structure, the rational expansion of enterprise scale, and the establishment of an effective system of government support policies and funds in accordance with the environment. The efficiency characteristics of each sub-industry are significantly different, so each sub-industry should take corresponding measures according to its own specific conditions. For example, the low level of pure technical efficiency caused by the low internal management level of the chemical drug manufacturing industry requires the use of advanced and scientific management systems. To improve the management system. For industries with low scale efficiency, it is necessary to expand the scale of the industry to continuously improve the scale efficiency of the entire industry.

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