Research on Innovation Efficiency Measurement of China's High Tech Industries

——Based on the three Stage DEA Malmquist Index Model

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Abstract. High tech industry as the key industries can help traditional industry transform and upgrade and optimize our industrial structure, its development degree and innovation level have become the important factor to realize the high-quality development of China. Furthermore, this paper selects the three stage DEA Malmquist index model to measure the innovation efficiency of 20 high tech subdivisions industries during the period of "11th Five Year Plan" to "13th Five Year Plan" and carry out static and dynamic research. The results show that: (1) the heterogeneity of innovation effectiveness of high tech subdivided industries increases, and the trend of innovation efficiency is that communication equipment manufacturing>computer manufacturing>pharmaceutical manufacturing, and the development focus shifts to emerging industries; (2) Talent is the core factor that determines the high quality development of high tech industries; (3) Continuing to master key core technologies is still the primary task of upgrading the innovation level of high tech industries at the presentation stage. Therefore, rational planning of industrial development pattern, improving innovative personal training mechanism and increasing scientific research investment benefits more and more significant to enhance the efficiency of target industries at presentation.

Keywords: Innovation efficiency; High tech industries; Three stage DEA - Malmquist index.

1 Introduction

Currently, China has entered the 14th Five Year Plan period. Against the background of the new development pattern of "dual circulation" and the new form of economic development, the high tech industry, as a significant industry that affects international competitiveness and China's industrial layout, has become an important lever to improve our country economic development. Its development process and level cannot be ignored. High quality development cannot be achieved without the integration of industry and technology. High tech industries conform to the concept of high-quality development. Although data shows that China's industrial added value has exceeded

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4.3 trillion US dollars, accounting for about 30% of the world's manufacturing industry and almost the sum of the United States, Japan, and Germany, there is still a considerable gap between China and the United States in chip manufacturing, Germany's automobile manufacturing, and Japan's pharmaceutical manufacturing level. That is, China's high-end manufacturing industry still needs to continue to break through high-precision and cutting-edge technology, and the layout and structure of target industries need to be further adjusted to make up for the gap with other developed countries. The report of the 20th National Congress of the Communist Party of China also come up with that innovation is the primary driving force, and we must adhere to the core position of innovation in China's modernization construction, enhance our independent innovation capabilities, enhance the overall efficiency of the national innovation system, and further reflect the important role of innovation in China's economic development and construction. To better promote economic development from factor driven to innovation driven, improving the efficiency of innovative resources in target industries has become a necessary path. Therefore, how to effectively improve the efficiency of technological innovation in China's target industries has become a hot topic of concern for scholars.

At present, research on the innovation efficiency of target industries can be mainly divided into the following aspects. Firstly, to calculate the innovation efficiency of target industries in stages. Based on the temporal evolution characteristics, they analyzed that the innovation efficiency of both stages showed a development pattern of eastern>central>western; Li Tianzi and Han Yuangang (2023) [1] introduced a global innovation network perspective to empirically analyze target industries data by province based on this stage division; Fang Yingying and Liu Jiejiao et al. (2022) [15] considered the mutual influence between the two stages and innovatively constructed a two-stage shared input correlation DEA model to measure innovation efficiency. Secondly, Yuan Huiwen and Gao Bo (2022)[7] used a benchmark regression model to verify the substantive impact of the development level of the digital economy on the innovation efficiency of target industries; Cowling Marc and Liu Weixi et al.(2021)[14] study the bond market and the stock market how to respectively affect the reaction of target industries and innovative enterprise. Leng Song and Yu Liping et al. (2022) [3]take the relationship between economic growth and innovation efficiency as the research perspective, use the center of gravity model to calculate the innovation efficiency center and the economic center movement trajectory of target industries, and obtain the synchronous characteristics of high spatial overlap between the two; Dam M M , Kaya F et al.(2024)[4] made use of the ARDL estimator to analyze the relationship between technological innovation (TI), renewable energy consumption (REC), natural resource rent (NRR), and ecological footprint (EF) among seven countries .Alnafisah N ,Alsmari E et al. (2023)[9] made use of the modified innovation environment Kuznets Curve Model (ICC) theory to analyze Target countries, and the final conclusion wae that the use of innovative technologies initially increases carbon, but it can reach a tipping point after a certain threshold; Xu Yi and Li Jian et al. (2023)[2]used government subsidies as a research entry point and used a panel threshold regression model to explore whether their impact on innovation efficiency in target industries will change with changes in the scale and quality level of enterprises. Thirdly, Song Yuegang and Zhang Xin (2022) [10] used this model to calculate the innovation efficiency of China's target industries's input-output data from 2009 to 2018, and conducted empirical analysis on the regional heterogeneity and dynamic changes of its technological innovation efficiency; Walrave B ,Wal D V Net al.(2024) [10] concluded that the positive correlation between the knowledge diversity of inventors and innovation performance increases with the functional structure, but decreases with the administrative intensity based on the data of 124 pharmaceutical companies, 2815 executives and 34,203 inventors.; Chen(2020) [5] adopted the three-stage DEA model to measure the innovation efficiency of high-tech industries in western region and its influencing factors. Li(2023)[8] used the three-stage DEA to analyze the conditional configuration path that affects the improvement of innovation efficiency in high-tech industries by stages, and explored the regional differences between technology R&D and achievement transformation efficiency in high-tech industries. Yang(2022)[6]used the three-stage DEA-Tobit model to measure the innovation efficiency of China's target industries and explored the influencing factors. Meng Weizhan and Li Chunyan et al. (2019) [12]used a three-stage DEA to calculate the efficiency of 12 high-tech segmented industries in China, and compared and analyzed the results of the first and third stages of the DEA in the research and development stage and the transformation stage, respectively. They concluded that the comprehensive technical efficiency of the two stages after the impact of environmental variables was mainly based on technical efficiency.

However, most of the above studies calculate the innovation efficiency of target industries based on the inter-provincial panel data of different years,and rarely take the 15-year time span as the research time interval to measure the innovation efficiency of subdivided industries in target industries as the research object. Therefore, this paper is based on the previous studies on the innovation measurement of target industries. Taking the "11th Five-Year Plan" to "13th Five-Year Plan" as the time interval of this study, the three-stage DEA-Malmquist index is adopted to measure the innovation efficiency of 20 sub-industries in the target industries, and the reasons affecting the innovation efficiency of the target industries are deeply explored in combination with various factors such as policy and market development. Finally, the paper put forward some policy implications about how to improve the innovation efficiency of this industries.

2 The Selection of Variables

This article is based on previous research, the characteristics of target industries, and the principle of data availability. The following input, output, and environmental variables are selected. As the main output of innovation achievements, R&D activities have a direct impact on innovation efficiency through innovation investment related to R&D. Therefore, relevant indicators are selected from the perspective of R&D in the input variables. Based on the perspectives of R&D funding investment and R&D personnel investment, internal expenditure of R&D funds and full-time equivalent of R&D personnel are selected as input variable indicators. Drawing on Chen Songyi's

(2023)[13] research on this aspect, and selecting new product development expenditure as the input variable. Select the number of patent applications and the number of effective patent applications from the output variables that can effectively reflect the innovation level of the industry to measure the level of industrial innovation research and development output; At the same time, the production scale of new products is also used as an output indicator to measure the innovation level of China's high-tech segmented industries. The production scale of new products is measured by the rate of the sales revenue of new products and the main business income. The innovation efficiency of target industries is influenced by various environmental factors, and the market structure foundation of different industries will have a mediating effect on innovation efficiency. Therefore, the number of enterprises in the industry is used to measure market structure and explore the influence of this environmental variable in it; Chen Zitao and Meng Fanrong et al. (2020) [11]explored the impact of government support as the sole explanatory variable on the innovation efficiency of target industries, and concluded that government support has a dual impact on different segmented industries. Therefore, this study continues to consider government support as one of the environmental variables and measures it using government funding input/R&D internal expenditure. The specific input-output and environmental variables are shown in Table 1.

In this study, the variables are from the China Science and Technology Statistical Yearbook and the China High tech Industry Statistical Yearbook. A total of 13 sub industries are excluded from the sub industries of target industries. The study is conducted on the remaining 20 high-tech sub industries; At the same time, interpolation method is used to fill in some missing data to meet the data continuity requirements of the model.

Table 1. Innovation Efficiency Index System for High tech Segmented Industries

Variable type	Variable Name	Measurement indicators
Input variables	Internal R&D expenditure/10000 yuan	
	R&D activity personnel full-time equivalent/person year	
	New product development expenditure/10000 yuan	
Output variables	Production scale of new products	
	The number of patent applications/piece	
	The number of valid invention patents/piece	
environment variable	Government support	Government funding/R&D internal expenditure
	market structure	Number of enterprises
	Industry quality	Number of R&D personnel/average number of industry practitioners
	Innovative atmosphere	Number of R&D institutions/number of enterprises

3 Empirical Analysis

3.1 Empirical Analysis of Three Stage DEA

3.1.1.Empirical Analysis of the first Stage DEA-BCC Model.

In the first stage of DEA, DEAP2.1 software was used to calculate the relevant data of input-output variables in the innovation efficiency index system of 20 high-tech segmented industries in China. The calculation results of the overall changes during the period from the 11th Five Year Plan to the 13th Five Year Plan are shown in Table 2.

According to Table 2, target industries has achieved significant improvements in these three efficiency from 2006 to 2015; the development of 20 high-tech sub sectors in China has also maintained a stable level, and the level of innovation has remained basically unchanged from 2011 to 2020. The value of the electronic computer manufacturing industry has increased from 0.619 to 0.896, which is due to the significant increase in scale and efficiency supported by national policies. The scale efficiency of the broadcasting and television equipment manufacturing industry has decreased from 0.702 to 0.662. The reason for this is that China is actively promoting the change and sustainably achieve the development by upgrading these industries, and actively promoting the integration of broadcasting digital technology and television digital technology. The future orientation of development of the television equipment manufacturing and broadcasting industry has shifted towards a more qualitative leap, resulting in a decline in its industrial scale during this period.

Table 2. Comparison of results between the first and third stages of high-tech segmented industry DEA

industry	During the 11th Five Year Plan period (average from 2006 to 2010)						During the 12th Five Year Plan period (average from 2011 to 2015)						During the 13th Five Year Plan period (average from 2016 to 2020)					
	TE		PTE		SE		TE		PTE		SE		TE		PTE		SE	
	Stage1	Stage3	Stage1	Stage3	Stage1	Stage3	Stage1	Stage 3	Stage 1	Stage 3	Stage 1	Stage3	Stage 1	Stage 3	Stage 1	Stage 3	Stage 1	Stage3
Chemical pharmaceutical manufacturing industry	0.353	0.514	0.363	0.994	0.973	0.518	0.507	0.54	0.52	0.559	0.974	0.966	0.43	0.472	0.43	0.485	1	0.972
Traditional Chinese patent medicines and simple preparations manufacturing industry	1	0.959	1	1	1	0.959	1	1	1	1	1	1	0.825	0.764	0.832	0.8	0.992	0.955
Biological and biochemical product manufacturing industry	1	1	1	1	1	1	0.462	0.488	0.478	0.679	0.966	0.719	0.479	0.551	0.483	0.582	0.99	0.946
Communication equipment manufacturing industry	0.952	1	1	1	0.952	1	0.967	1	1	1	0.967	1	1	1	1	1	1	1
Communication transmission equipment manufacturing industry	0.626	0.549	0.652	0.996	0.96	0.551	1	1	1	1	1	1	1	1	1	1	1	1
Communication exchange	1	1	1	1	1	1	0.938	1	1	1	0.938	1	1	1	1	1	1	1

equipment manufacturing industry																		
Communication terminal equipment manufacturing industry	0.851	0.351	0.899	1	0.946	0.351	0.796	0.949	1	1	0.796	0.949	1	1	1	1	1	1
Radar and supporting equipment manufacturing industry	0.847	0.493	1	1	0.847	0.493	0.697	1	1	1	0.697	1	0.884	1	0.912	1	0.969	1
Broadcasting and television equipment manufacturing industry	1	0.395	1	1	1	0.395	0.601	0.844	0.857	0.858	0.702	0.984	0.662	0.85	1	1	0.662	0.85
Electronic device manufacturing industry	0.682	0.473	0.684	0.996	0.996	0.475	0.705	0.827	0.834	0.83	0.846	0.995	0.718	0.774	0.781	0.807	0.92	0.96
Electronic vacuum device manufacturing industry	0.633	0.175	0.94	1	0.674	0.175	1	1	1	1	1	1	1	0.993	1	0.997	1	0.996
Semiconductor discrete device manufacturing industry	0.281	0.1	0.622	1	0.451	0.1	0.716	0.73	0.721	1	0.994	0.73	0.782	0.618	0.853	0.785	0.917	0.786

industry	During the 11th Five Year Plan period (average from 2006 to 2010)						During the 12th Five Year Plan period (average from 2011 to 2015)						During the 13th Five Year Plan period (average from 2016 to 2020)					
	TE		PTE		SE				TE		PTE		SE				TE	
	Stage1	Stage3	Stage1		Stage1	Stage3	Stage1		Stage1	Stage3	Stage1		Stage1	Stage3	Stage1		Stage1	Stage3
Integrated Circuit Manufacturing Industry	0.857	0.424	0.861	0.998	0.996	0.425	0.716	0.749	0.792	0.78	0.903	0.96	0.698	0.745	0.721	0.786	0.968	0.949
Electronic component manufacturing industry	0.347	0.498	0.377	0.997	0.921	0.5	0.509	0.708	0.654	0.73	0.778	0.97	0.843	1	1	1	0.843	1
Other electronic equipment manufacturing industry	0.463	0.176	0.615	1	0.752	0.176	0.729	0.855	0.854	0.859	0.854	0.995	0.746	0.743	0.862	0.781	0.865	0.951
Electronic Computer Manufacturing Industry	0.828	0.573	0.833	0.996	0.994	0.576	0.619	0.84	0.875	0.847	0.708	0.992	0.896	0.833	0.896	0.861	1	0.967
Manufacturing of Electronic Computer External Equipment	0.625	0.541	0.694	0.995	0.9	0.543	0.888	1	0.983	1	0.904	1	1	0.899	1	0.934	1	0.963
Office equipment manufacturing industry	0.277	0.031	1	1	0.277	0.031	0.606	0.622	0.611	0.961	0.992	0.647	1	0.637	1	0.72	1	0.884
Medical equipment and device manufacturing industry	0.878	0.295	0.878	1	0.999	0.295	0.99	0.992	1	1	0.99	0.992	1	1	1	1	1	1
Instrument and meter manufacturing industry	0.56	0.576	0.629	1	0.89	0.576	0.776	1	1	1	0.776	1	0.937	1	1	1	0.937	1
mean value	0.703	0.506	0.802	0.999	0.877	0.507	0.761	0.857	0.859	0.905	0.889	0.945	0.845	0.844	0.889	0.877	0.953	0.959

Note: 1) TE represents comprehensive technical efficiency, PTE represents pure technical efficiency, and SE represents scale technical efficiency; 2) Stage 1 represents the first stage, and Stage 3 represents the third stage.

From Table 2, it can be seen that the industries with comprehensive efficiency and scale efficiency showed a V-shaped development from 2006 to 2020, while the industries with technical efficiency showed a linear upward trend. From 2006 to 2015, the number of effective industries with comprehensive efficiency in China's target industries decreased from 4 to 3, of which only traditional Chinese patent medicines and simple preparations manufacturing industry was effective during this period; The biological and biochemical product manufacturing industry, as well as the broadcasting and television equipment manufacturing industry, have gone from being effective to ineffective. The reason for the ineffectiveness of the broadcasting and television equipment manufacturing industry is that the scale efficiency has regressed from 1 to 0.662. As mentioned in the above analysis, the scale of the broadcasting and television equipment manufacturing industry has decreased due to industrial transformation, so it will not be further elaborated. The manufacturing of communication transmission equipment and electronic vacuum devices has shifted from being ineffective to being effective.

Although the overall comprehensive efficiency has been improved from 2006 to 2020, only 10 target industries had a comprehensive efficiency higher than the average from 2006 to 2010, while only 9 industries had a comprehensive efficiency higher than the average from 2011 to 2015. Although the number of these industries increased to 11 from 2016 to 2020, overall, only half of the target industries were above the average from 2006 to 2020, indicating that the development of high-tech sub sectors is characterized by non-equilibrium, and there are significant differences in the level of industrial development.

3.1.2.SFA Regression Results and Empirical Analysis in the Second Stage.

Due to the fact that the DEA calculation results in the first stage did not exclude external factors such as government support, market structure, industry quality, and innovation atmosphere, the efficiency values calculated were not objective. Therefore, the SFA model was further adjusted in the second stage, and the Table 3 show the newest result. From table 3, if the coefficient is positive, it indicates a positive correlation between environmental variables and slack variables, it indicates that the increase in environmental variables is not conducive to improve the target industries efficiency; On the contrary, if the coefficient is negative, it indicates a negative correlation between environmental variables and slack variables, it indicates that an increase in environmental variables is good for improving the target industries efficiency. The analysis of the impact of four environmental variables on input slack variables are as follow:

Table 3. The regression model result of the Second stage SFA

variable	Relaxation variables		
	Internal R&D expenditure/10000 yuan	R&D activity personnel full-time equivalent/person year	New product development expenditure/10000 yuan
Constant term	-393866.32*** (-393866.67)	-8642.98*** (-8641.77)	-561937.08*** (-560963.36)
Government support (government funding	3299248.80***	-3533.16***	2016392.90***

input/R&D internal expenditure)	(-3299248.8)	(-3533.16)	(2016388.9)
Market structure (number of enterprises)	71.68***	0.93***	74.723498
	(272.91)	(67)	(0.96)
Industry quality (number of R&D personnel/average number of industry practitioners)	-1642900.6***	-91235.64***	-1593035.10***
	(-1642553.9)	5836.49	(410.723)
Innovation atmosphere (number of R&D institutions/number of enterprises)	-707470.75***	5664.15***	-192579.00***
	(-707471.07)	-468.31	(-192498.4)
σ^2	520325660000.00***	106410600.00***	522086110000.00***
	(520325660000.00)	-106410600	(522086110000)
γ	1.00***	1.00***	1.00***
	(5713950.9)	(2252615.1)	(1617459)
Log function value	-282.91341	-198.28399	-282.97715
LR unilateral test	11.918441	11.279178	11.858499

Note: 1) The values in parentheses represent the corresponding coefficients of t; 2) "* * *", "* *", and "*" respectively indicate significance at the 1%, 5%, and 10% significance levels. Same below.

On the one hand, this result indicates that due to the crowding out effect, the continuous expansion of government funds to support R&D expenditures and new product development expenditures will result in redundancy, given a fixed total social wealth. On the other hand, it may be due to the negligence of relevant departments in management or the lack of a reasonable fund allocation system, which results in the government funds not being used reasonably among industries and having low efficiency. The market structure and three input slack variables all have a significant positive impact. This result indicates that the number of high-tech enterprises will increase the input redundancy of the three input variables, which means that an increase in the number of enterprises does not necessarily improve the efficiency of these industries. Although enterprises gradually increase can provide more employment opportunities for the market and increase the employment of related industries, the improvement of innovation efficiency requires more core technical talents to break through technological bottlenecks. Expanding the employment base will cause redundancy in the full-time equivalent of R&D activity personnel. In addition, an increase in the number of enterprises will inevitably increase the total internal R&D expenditure and new product development expenditure of the industry. However, the support of both will not necessarily output effective innovation results. Therefore, market structure will cause internal R&D expenditure and new product development expenditure. The investment is redundant. From this, it can be seen that the allocation of resources within enterprises and high-quality resources such as high-tech talents are the core elements that determine the development of these industries.

The regression coefficients of industry quality and three input variables are both negative and significant at the 1% level. This result indicates that industry quality can reduce the investment redundancy of the three, fully utilize R&D funds and new product development funds, improve the work efficiency of R&D activity personnel, and have a positive effect on the innovation efficiency of target industries. The innovation ability of R&D personnel within the industry, as a direct influencing factor on the output of innovative achievements in scientific research activities, plays an important role in the development of intelligence intensive and knowledge intensive target industries. Therefore, the improvement of innovation efficiency in target industries cannot be separated from the continuous introduction of innovative talents and the cultivation of opportunities to enhance the industrial innovation ability of R&D personnel in the later stage.

The innovation atmosphere is negatively correlated with the relaxation variables of internal R&D expenditure and new product development expenditure, and positively correlated with the full-time equivalent relaxation variables of R&D activity personnel, both of which are significant at the 1% level. This result indicates that the stronger the innovation atmosphere, that is, the greater the proportion of R&D institutions in the number of enterprises, the inevitable increase in R&D personnel engaged in related scientific research activities, thereby increasing the redundancy of full-time equivalent investment in R&D personnel.

3.1.3.Results and Empirical Analysis of the DEA-BCC Model in the Third Stage.

The latest input variable data and original output data adjusted by the SFA regression model in the second stage will be calculated using the BCC model to gain more exact efficiency values for high-tech segmented industries. The calculation results are still shown in Table 1. The following will analyze target industries that have undergone effective changes. From the trend of comprehensive technological efficiency changes in the three periods, its basic situation is basically consistent with the first stage: the efficiency of 20 high-tech sub sectors has significantly improved from 2006 to 2015, and most target industries have achieved comprehensive technological efficiency that is basically consistent with some industries experiencing slight increases or decreases from 2016 to 2020.

From 2006 to 2020, the effective industries of comprehensive efficiency and scale efficiency completely overlap and develop, while the effective industries of technical efficiency show a slight linear downward trend. From 2006 to 2015, the number of target industries with effective comprehensive efficiency increased from 3 to 8. Among them, the biological and biochemical product manufacturing industry, due to the decline in pure technical efficiency from 1 to 0.679, changed from effective to ineffective. The reason is that there are duplicate research and development in this industry, and the slow industrial process leads to a lag in China's biotechnology innovation; The manufacturing of electronic vacuum devices, communication transmission equipment, electronic computer external equipment, and instruments and meters have all become effective due to significant improvements in scale efficiency. The number of industries with pure technological efficiency has decreased from 13 to 11, while the manufacturing of biological and biochemical products and other electronic equipment has regressed from being effective to being ineffective. The manufacturing of communication and transmission equipment and external electronic computer equipment has progressed from being ineffective to being effective.

From 2011 to 2020, the efficiency values of the three technologies remained basically consistent, with individual industries fluctuating up and down no more than 0.2. The number of effective industries decreased from 11 to 9 for pure technical efficiency, while the number of effective industries for the other two indices remained unchanged. The pure technical efficiency of the semiconductor discrete device manufacturing industry has decreased from 1 to 0.785, with a significant decline. The lack of funds and talents has not yet broken through the traditional constraints of industrial research and development, and technological innovation ability has become a bottleneck and obstacle that restricts the comprehensive efficiency improvement of target industries.

To accurately understand the innovation efficiency of various high-tech sub industries, 20 sub industries were classified according to the efficiency values of the third stage of DEA from 2016 to 2020. The table 4 indicated the classification results.

Table 4. Classification of Chinese High tech Segmented Industries

type	Classification criteria	High tech segmented industries
Efficient and high-quality type	Crste&vrste&scale=1	Communication equipment manufacturing, communication transmission equipment manufacturing, communication exchange equipment manufacturing, communication terminal equipment manufacturing, radar and supporting equipment manufacturing, electronic component manufacturing, medical equipment and device manufacturing, and instrument manufacturing
Efficiency potential type	0.9<scale<1	Traditional Chinese patent medicines and simple preparations manufacturing industry, electronic device manufacturing industry, electronic vacuum device manufacturing industry, computer complete machine manufacturing industry, computer peripheral equipment manufacturing industry
	0.8<vrste<1	
Efficiency improvement type	0.7<scale<1	Chemical and pharmaceutical manufacturing, biological and biochemical product manufacturing, semiconductor discrete device manufacturing, integrated circuit manufacturing, office equipment manufacturing, broadcasting and television equipment manufacturing, and other electronic equipment manufacturing industries
	0.4<vrste<0.8	

As shown in Table 4, firstly, the three efficiency values of efficient and high-quality target industries are all in an effective state. Under the macro background of China's emphasis on 5G development, the scale and technological level of the communication equipment related industries have significantly improved; The medical equipment and instrument manufacturing industry, as a key emerging industry of national attention, is also at a stable and effective level of innovation with the support of national policies and funding. Secondly, due to the national industrial layout adjustment, the manufacturing industry of traditional Chinese patent medicines and simple preparations has regressed from an efficient and high-quality industry from 2006 to 2010 to an efficient and potential industry from 2016 to 2020, while electronic information related industries, such as electronic vacuum device manufacturing, have gradually received national attention in recent years, which has gradually expanded its industrial scale and significantly improved its technological innovation level, but there is still much room to become an efficient and high-quality industry; Finally, the chemical and pharmaceutical manufacturing industry, biological and biochemical product manufacturing industry, as well as the development of semiconductor discrete device manufacturing industry, are gradually lagging behind due to the reduction in scale and technological level.

Although the semiconductor discrete device manufacturing industry is highly valued by the state, there is still significant room for improvement due to the difficulty in breaking through technological bottlenecks.

4 The Dynamic Results and Empirical Analysis

This paper make use of a combination of static and dynamic analysis in these industries and the Malmquist productivity index to discuss the annual changes through these industries in fifteen years. Therefore, the new input variables and initial output variables were brought back to DEAP2.1 software for calculation. The table 5 indicated the classification results.

Table 5. Malmquist Index and Decomposition of High tech Segmented Industries in fifteen years

Industry	EFFCH	TECH	PECH	SECH	TFPCH
Chemical pharmaceutical manufacturing industry	0.957	2.026	0.699	1.37	1.94
Traditional Chinese patent medicines and simple preparations manufacturing industry	0.893	1.996	0.894	0.998	1.782
Biological and biochemical product manufacturing industry	0.742	2.283	0.763	0.973	1.694
Communication equipment manufacturing industry	1	2.122	1	1	2.122
Communication transmission equipment manufacturing industry	1.349	2.442	1.002	1.347	3.295
Communication exchange equipment manufacturing industry	1	1.81	1	1	1.81
Communication terminal equipment manufacturing industry	1.689	2.515	1	1.689	4.248
Radar and supporting equipment manufacturing industry	1.424	2.257	1	1.424	3.213
Broadcasting and television equipment manufacturing industry	1.467	2.121	1	1.467	3.111
Electronic device	1.28	1.902	0.9	1.422	2.434

Industry	EFFCH	TECH	PECH	SECH	TFPCH
manufacturing industry					
Electronic vacuum device manufacturing industry	0.957	2.026	0.699	1.37	1.94
Semiconductor discrete device manufacturing industry	0.893	1.996	0.894	0.998	1.782
Integrated Circuit Manufacturing Industry	1.326	1.979	0.887	1.494	2.624
Electronic component manufacturing industry	1.416	1.915	1.001	1.415	2.712
Other electronic equipment manufacturing industry	2.055	1.795	0.884	2.326	3.689
Electronic Computer Manufacturing Industry	1.205	2.079	0.93	1.296	2.505
Manufacturing of Electronic Computer External Equipment	1.29	1.885	0.969	1.331	2.431
Office equipment manufacturing industry	4.519	1.618	0.849	5.325	7.312
Medical equipment and device manufacturing industry	1.842	1.729	1	1.842	3.185
Instrument and meter manufacturing industry	1.318	1.727	1	1.318	2.276
mean value	1.442	2.009	0.929	1.552	2.897

Note: TFPCH represents total factor productivity, EFFCH represents changes in technological efficiency, TECH represents changes in technological progress, PECH represents pure technological efficiency, and SECH represents scale efficiency.

From Table 5, it can be seen that the total factor productivity of the 20 target industries is greater than one, but the values vary to varying degrees, indicating that the target industries studied have all achieved effectiveness from 2006 to 2020, but there are differences in the degree of effectiveness. The most developed target industries among them is the office equipment manufacturing industry, with a TFPCH value of 7.312. The driving effect of scale efficiency is stronger than that of technological progress. Under the policy guidance of actively encouraging mass entrepreneurship by the country, the increase in the number of enterprises drives the development of the office equipment manufacturing industry, leading to the continuous expansion of the industry scale. The more effective industries are semiconductor discrete device manufacturing, electronic vacuum device manufacturing, and communication terminal equipment manufacturing. Among them, the innovation efficiency rate of semiconductor discrete device manufacturing reaches 5.237, and the difference between technical efficiency and technological progress value is small, indicating that the balanced development of the two promotes the industry to reach its current level of effectiveness; The effectiveness of its EFFCH value is mainly due to the effective compensation of scale efficiency for the inefficiency of pure technical efficiency, indicating that the semiconductor discrete device manufacturing industry, as a national key supported industry, has seen continuous growth in market demand with the development of 5G and new energy vehicles.

However, the key technological level in the core areas still needs to be further improved to improve the overall innovation level of the industry. The target industries with weak development is divided into three sub industries under the pharmaceutical manufacturing industry: chemical medicine manufacturing industry, traditional Chinese patent medicines and simple preparations manufacturing industry, and biological and biochemical products manufacturing industry. The effective reason for the TFPCH value is the increase of the change index of technological progress. The decomposition results of Technical Efficiency (EFFCH) show that, except for the pharmaceutical manufacturing industry, all other target industries have achieved effectiveness. However, it is worth noting that the pure technical efficiency of the electronic computer whole machine manufacturing industry, integrated circuit manufacturing industry, and electronic computer external equipment manufacturing industry has not reached an effective level. The development of their industries mainly comes from the progress of scale efficiency, which indirectly reflects the need to further improve the overall innovation level of the above industries in terms of technological research and development capabilities.

5 Conclusion

The article combines static and dynamic analysis to study the development and changes of efficiency in 20 high-tech segmented industries in China from 2006 to 2020. Then these conclusions are drawn: (1) The heterogeneity of innovation efficiency in high-tech segmented industries has improved, it has been adjusted through industrial layout, showing the development trend of communication equipment manufacturing>electronic computer manufacturing>pharmaceutical manufacturing, with the focus of development shifting towards emerging industries. The efficiency results of the first and third stages of DEA both show that the innovation efficiency of 20 high-tech sub industries in China has been improved to varying degrees. However, after removing the influence of environmental variables and random noise, the results show that the comprehensive efficiency of the 12th Five Year Plan is underestimated, the comprehensive efficiency of the 11th Five Year Plan and the 13th Five Year Plan is overestimated, and the scale efficiency of the 11th Five Year Plan is overestimated, while the scale efficiency of the 12th Five Year Plan and the 13th Five Year Plan is underestimated. This indicates that the scale of target industries in the later stage has significantly increased and the industrial layout has been adjusted because of national policies' support. Among them, the communication transmission equipment manufacturing industry, as an emerging industry, has received key attention from the state for its development. However, there are significant efficiency differences among some industries, and there is still room for improvement in the balanced development of industries. (2) Talents are the core element that determines the high-quality development of target industries. The second stage SFA regression results show that an increase in market structure, i.e. the number of enterprises, will increase the redundancy of input variables, while industry quality can reduce the redundancy of input variables, indicating that the market size of the industry is not positively correlated with innovation efficiency. The continuous increase in the number of enterprises does not necessarily mean the continuous output of innovation achievements, but innovation efficiency depends on the research and development frequency and output of scientific research activities. As a key component of R&D activities, the scale and comprehensive quality of R&D personnel in the industry play a crucial role in improving the innovation efficiency of target industries. (3) Continuously mastering key core technologies remains the primary task for improving the innovation level of target industries at this stage. In the results of the third stage of DEA, it is shown that the pure technological efficiency of both the 12th and 13th Five Year Plans is overestimated. The dynamic analysis of the Malmquist index also shows that some industries have ineffective technological efficiency due to the influence of pure technological efficiency.

Both indicate that the innovation capability of technology in the core areas of the industry is a key factor in curbing the improvement of innovation efficiency in target industries at present. The shortcomings of this study are twofold: firstly, due to the limitations of data acquisition, it is not possible to conduct a comprehensive study on the innovation efficiency of all segmented industries under target industries, and secondly, linear interpolation method is used to fill in the missing values of the target industries studied, which to some extent affects the authenticity of the research results; Secondly, this article only removes the influence of government support and other factors, while innovation efficiency is still influenced by multiple environmental variables. In the future, we can enrich the types of environmental variables based on this research and further explore their impact mechanism on this kind of efficiency of target industries by join in other elements such as degree of openness.

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