# A study on the innovation efficiency of high-tech listed companies in China - Analysis based on three-stage DEA with Malmquist index

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**Abstract.** In order to adapt to the changing market environment, enterprises need to continuously conduct innovative R&D activities, and innovation efficiency has become a key factor for high-tech enterprises to capture the market. This paper uses a three-stage DEA model and the Malmquist index to measure and analyze the technical efficiency of 60 high-tech enterprises in China from 2013-2021. The findings show that environmental factors have a significant impact on the technical efficiency of enterprises, pure technical efficiency is underestimated and scale efficiency is overestimated, and scale efficiency should be improved by expanding production scale; high-tech enterprises face contradictions between scale efficiency and technical efficiency, and policies drive the technical level to improve, but the comprehensive technical efficiency does not grow. Technological innovation during the epidemic has improved the technical level and utilization efficiency, but the comprehensive technical efficiency still declined. This paper is of great significance in assessing the efficiency of high-tech enterprises between technological inputs and market output, helping them to identify room for improvement and enhance innovation efficiency and competitiveness.

**Keywords:** high-tech enterprises, innovation efficiency, DEA, Malmquist index.

## 1. Introduction

Science and technology are the first productive force, innovation is the driving force for high-quality development in the new era, and scientific and technological innovation is an important force for the country's economic development. In recent years China will accelerate the construction of an innovative country and supported the construction of international and regional science and technology innovation centers in areas with the conditions, fully reflecting the main position of enterprises in innovation activities [1]. According to the 2022 National Economic and Social Development Statistical Bulletin, high-tech enterprises, as the main innovators of core and frontier technologies, have become a strategic key to enhancing national core competitiveness and promoting national economic development [2]. However, high-tech enterprises still have problems such as low overall international competitiveness, lack of sustainable growth capability, unbalanced R&D capability, and ability to transform results [3]. The 2022 Global Innovation Index released by the World Intellectual Property Organization shows that China ranks 11th globally in terms of overall innovation capacity in 2022, with institutions ranked 42nd, human capital and research 20th, and infrastructure 25th in the innovation pillar ranking. Although China's innovation capacity ranking has jumped 23 places from 2012, there is still a large gap compared to developed countries such as the UK and the US. Therefore, this paper uses a three-stage model combining DEA and SFA to eliminate the influence of environmental factors and random errors, accurately measure and objectively evaluate the innovation efficiency of 60 high-tech enterprises from 2013-2021, and analyze their constraints, which is important for promoting high-quality economic development and enhancing high-tech enterprises to continuously conduct scientific and technological research and development and transformation of technological achievements.

## 2. Review of the literature

The innovation efficiency of a high-tech enterprise is its ability to achieve a certain amount of innovative output with the minimum amount of input required, or the maximum amount of innovative output that can be produced with a given amount of input, all else being equal, according to a specified ratio of resource inputs. With variable returns to scale, innovation efficiency can be expressed as the product of pure technical efficiency and scale efficiency.

The innovation efficiency of high-tech enterprises is related to the development of regional industries and economies, and the use of scientific methods to measure the innovation efficiency of enterprises and find the optimization path is a current research hotspot. The literature review of this paper will focus on innovation efficiency measurement and DEA modeling for high-tech enterprises.

From the perspective of research, many scholars have measured the innovation efficiency of high-tech enterprises from different perspectives. Lan Fei et al. [4]. used the BC2 model of DEA to evaluate the innovation efficiency of high-tech enterprises from the perspective of heterogeneous property rights; Liu Hedong et al. [5]. deconstructed the innovation system of high-tech enterprises into two subsystems, R&D and commercialisation, based on the "black box" perspective, and used the two-stage composite network DEA evaluation method; Zhang Sen[6] used the DEA model to analyse the innovation efficiency of high-tech enterprises in the Zhongguancun demonstration zone based on the industrial perspective; Zhang Jihong[7] et al. conducted an evaluation study on the innovation performance of high-tech enterprises in Shanxi Province from the perspective of transformation development; Yin Jie[8] et al. used DEA model and Malmquist index to analyze the innovation efficiency of high-tech industry in China based on the perspective of innovation ecosystem.

In terms of research methods, Liu Van et al. [9]. a super-efficient DEA model to measure the innovation efficiency of national high-tech zones from 2013 to 2017; Mao Yunshi[10] conducted a comparative study of the M&A performance of high-tech enterprises and traditional enterprises in the post-financial crisis based on the DEA-Malmquist index model; Wang Juntao et al[11]. A study on the innovation efficiency evaluation and resource allocation of high-tech industrial technology in Shanxi Province based on CCA-DEA; Liu Wei et al. resource allocation study; Liu Wei et al. [12]. An analysis of regional differences in technological innovation efficiency of high-tech industries in China based on a three-stage DEA model with Bootstrap method; Tan Jin et al. [13]. An evaluation of Changzhou's science and technology innovation input performance in the southern Jiangsu region using CCR, BCC, and SE-DEA models.

From the above literature, most of the existing studies are the single application of traditional DEA or SFA models to examine the innovation efficiency research of high-tech enterprises, ignoring the influence of environmental factors and other factors included in the redundant variables on the efficiency level, which to some extent leads to the lack of reliability and accuracy of the research conclusions. Given this, this paper will use a three-stage model combining DEA and SFA to Given this, this paper will use a three-stage model combining DEA and SFA to measure the innovation efficiency of 60 high-tech enterprises in China from 2013 to 2021, to examine the innovation efficiency of high-tech enterprises more accurately by excluding the influence of environmental factors and random errors, and on this basis, to propose paths and directions to promote the innovation efficiency of high-tech enterprises.

# 3. Research Methodology

## 3.1. Three-stage DEA

To analyze the innovation efficiency of high-tech listed companies, this paper uses a three-stage DEA model combining the DEA and SFA models proposed by Fried et al. (2002) and eliminates the influence of environmental variables and random errors on the efficiency values to make the measurement results more accurate.

Stage 1: DEA-BCC model. In this stage, this paper uses the original input-output data for the evaluation of the initial efficiency value, the calculated efficiency value is the comprehensive technical efficiency (TE), and TE=SE*PTE, where the scale efficiency (SE) reflects the impact of the change in input scale of the high-tech listed companies on the comprehensive technical efficiency, and the pure technical efficiency reflects the technical situation of the high-tech enterprises, the model is as follows:

$$\min\theta - \varepsilon(\widehat{e}^T S^- + e^T S^+)$$
$$s.t\begin{cases} \sum_{i=1}^{n} X_i\lambda_1 + S^- = \theta X_0 \\ \sum_{i=1}^{n} Y_i\lambda_i - S^+ = Y_0 \\ \lambda_1 \geq 0, S^-, S^+ \geq 0 \end{cases} \tag{1}$$

Where i=1,2,3...,n denotes the number of decision units, i.e. 60 high-tech listed companies; $X_i$ denotes input, $Y_i$ denotes output; $S^+$ denotes slack variables, $S^-$ denotes redundant variables; $\lambda_i$ denotes weighting coefficients; θ denotes efficiency RMS.

Stage 2: SFA regression model. In the second stage, a stochastic frontier model is applied to isolate the external disturbances affecting the efficiency of the decision unit and place all study subjects in the same environment for efficiency calculations. The input-oriented class SFA regression function is as follows:

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

Where $S_{ni}$ represents the relaxation value of the ith high-tech enterprise to the nth type of investment, $Z_i$ denotes the environmental variable, $\beta_n$ denotes its coefficient; denotes the random error and μni denotes inefficiency.

The formula for adjusting the initial input values is as follows:

$$X_{ni}^A = X_{ni} + \left[\max(f(Z_i, \widehat{\beta}_n)) - f(Z_i, \widehat{\beta}_n)\right] + \left[\max(\nu_{ni} - \nu_{ni}\right] \tag{3}$$

Where denotes adjusted inputs, denotes pre-adjusted inputs, and the two middle brackets in the expression adjust the environmental factors and random disturbance terms to the same condition respectively to eliminate the effect on the efficiency values. The input variables and environmental variables calculated in the first stage were used as the explanatory and explanatory variables respectively, and the values of the input variables excluding environmental variables, random factors, etc. were obtained using Frontier 4.1 software.

Stage 3: Adjusted DEA model. The adjusted input variables and the original output variables obtained in the second stage were again substituted into the DEA-BCC model, and the DEAP 2.1 software was used to measure the efficiency, which resulted in the efficiency values of each decision unit after excluding the influence of environmental and random factors.

## 3.2. Malmquist Productivity Index

The Malmquist Productivity Index was first proposed by Malmquist (1953) and is defined as the geometric mean of the distance between two indices. The formula is calculated as follows:

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = (M^t \times M^{t+1})^{\frac{1}{2}} = \left[ \frac{D_C^t(x^{t+1}, y^{t+1})}{D_C^t(x^t, y^t)} \times \frac{D_C^{t+1}(x^{t+1}, y^{t+1})}{D_C^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{4}$$

Fare et al. (1994) decompose the Malmquist index into two components, the change in technical efficiency (EFFCH), which is primarily an indication of the effectiveness of the decision unit's use of technology at the current stage, and the movement of the efficiency frontier surface, called the rate of technical change (TECHCH), with the Malmquist index = composite technical efficiency change index x technological progress index.

# 4. Data Sources and Selection of Indicators

## 4.1. Data sources

This study takes 60 high-tech enterprises in China as the research target and selects their cross-sectional data such as net fixed assets, payroll payable to employees, operating revenue, number of corporate employees, and number of invention patents for each year from 2013 to 2021 as the research data, with the main data coming from Guotaian database and company annual reports.

## 4.2. Selection of Indicators

### 4.2.1 Input/output variable selection

To evaluate the innovation efficiency of high-tech enterprises, net fixed assets and employee remuneration payable were selected as input indicators; while operating income was selected as an output indicator.

## 4.3. Environment variable selection

Environmental variables are factors that can have an impact on innovation efficiency but are not under the control of the decision-making unit, so their impact on innovation efficiency measures needs to be removed in the measurement process [14]. Concerning studies on innovation efficiency in other industries or sectors, four environmental variables were selected: macroeconomic fluctuations, government subsidies, years on the market, and the gross domestic product of the region to which they belong.

**Macroeconomic fluctuations**: Macroeconomic fluctuations refer to changes in the general level and development of national and regional economies.

**The ratio of government subsidies to operating income**: The ratio of government subsidies to operating income reflects the extent to which a company relies on government subsidies in its operations and the effectiveness of their use.

**Length of time on the market**: High-tech companies often face different business environments and market pressures after going public, and the length of time on the market may have an impact on a company's innovation efficiency.

**Gross regional product**: Gross regional product is the total economic volume of the region in which the business is located, reflecting the impact of factors such as the regional economic environment and the size of the market in which the business is located.

The selection of variables above allows for a more comprehensive examination of the innovation efficiency of high-tech enterprises, including various factors such as capital, manpower, technology, and policy, to gain insight into the current state of business and optimize business strategies.

The indicators were selected as shown in Table 1.

**Table 1.** Evaluation index system for operational efficiency of high-tech start-ups

| Category | Indicator name |
|---|---|
| Input variables | The net value of fixed assets ($) |
| | Employee remuneration payable ($) |
| Output variables | Operating income ($) |
| Environment variables | Macroeconomic volatility % |
| | Government subsidies / Operating income % |
| | Number of years on the market (years) |
| | Gross domestic product of affiliated regions (yuan) |

## 5. Analysis of empirical results

### 5.1. Phase 1: Analysis of traditional DEA model results sources

Based on the traditional DEA model, the DEAP2.1 software was applied to measure the innovation efficiency of the study sample, and the results are shown in Table 2 (some companies are shown due to space constraints).

**Table 2** Innovation efficiency of listed Chinese high-tech companies in stages 1 and 3, 2013-2021

| Listed Companies | Integrated technical efficiency | | Pure technical efficiency | | Scale efficiency | |
|---|---|---|---|---|---|---|
| | Before | After | Before | After | Before | After |
| Hangzhou Huaxing | 0.497 | 0.032 | 0.878 | 0.606 | 0.538 | 0.088 |
| Midea Group | 0.246 | 0.736 | 1.000 | 1.000 | 0.246 | 0.736 |
| Yihua Chemical | 0.346 | 0.340 | 0.632 | 0.475 | 0.639 | 0.722 |
| Xugong Group | 0.372 | 0.669 | 0.450 | 0.725 | 0.862 | 0.914 |
| Guangxi Liugong | 0.284 | 0.324 | 0.317 | 0.688 | 0.919 | 0.499 |
| Genesis Technology | 0.207 | 0.209 | 0.303 | 0.780 | 0.681 | 0.297 |
| Wanxiang Qianchao | 0.091 | 0.176 | 0.101 | 0.482 | 0.885 | 0.438 |
| Shaanxi Beacon | 0.123 | 0.029 | 0.295 | 0.630 | 0.493 | 0.107 |
| Seahorse | 0.274 | 0.202 | 0.354 | 0.580 | 0.694 | 0.356 |
| Qingdao Double Star | 0.141 | 0.150 | 0.169 | 0.662 | 0.816 | 0.282 |
| Jilin Oodong | 0.051 | 0.096 | 0.094 | 0.771 | 0.542 | 0.181 |
| Tonglingnon-ferrous metals | 0.564 | 0.898 | 0.991 | 0.989 | 0.566 | 0.907 |
| Guangdong Fenghua | 0.077 | 0.091 | 0.109 | 0.606 | 0.686 | 0.221 |
| Renhe Pharmaceutical | 0.497 | 0.101 | 0.628 | 0.714 | 0.795 | 0.202 |
| Zhuhai Gree | 0.213 | 0.729 | 0.909 | 0.940 | 0.230 | 0.760 |
| Changchun High-Tech | 0.096 | 0.105 | 0.135 | 0.615 | 0.766 | 0.240 |
| Oriental Electronics | 0.119 | 0.068 | 0.179 | 0.644 | 0.696 | 0.188 |
| Xiamen Cinda | 1.000 | 0.993 | 1.000 | 1.000 | 1.000 | 0.993 |
| BOE Technology | 0.073 | 0.208 | 0.274 | 0.342 | 0.452 | 0.731 |
| China Zhenhua | 0.534 | 0.121 | 0.605 | 0.648 | 0.807 | 0.252 |
| Shenzhen Konka | 0.358 | 0.475 | 0.365 | 0.633 | 0.976 | 0.766 |
| Synergy Pharmaceuticals | 0.160 | 0.056 | 0.263 | 0.612 | 0.600 | 0.158 |
| ...... | ...... | ...... | ...... | ...... | ...... | ...... |
| Average | 0.245 | 0.196 | 0.414 | 0.612 | 0.638 | 0.349 |

Without excluding the interference of external factors, the three efficiencies of the 60 high-tech listed companies in 2013-2021 are 0.245, 0.414, and 0.638 respectively, all three of which are lower, indicating that both the technological development and scale efficiency of high-tech listed companies possess greater room for improvement, compared to the higher average value of scale efficiency and the lower overall technical efficiency, from which it can be concluded that The reason for the lower innovation efficiency of high-tech listed companies is due to the low management level and insufficient technology level of enterprises.

### 5.2. Phase 2: SFA-based stochastic frontier analysis

In the second stage, the SFA-like regression model was applied with the input slack variables obtained in the first stage as the explanatory variables. Macroeconomic fluctuations, the ratio of government subsidies to operating income, the number of years on the market, and the external environmental variables of the gross regional product were used as explanatory variables. The SFA-like regression analysis was conducted using Frontier 4.1 software, and cross-sectional data were analysed for the years 2013-2021. The regression results are shown in Table 3: (The regression results are presented for the year 2021).

**Table 3** Summary of SFA model regression results

| Variable | Fixed asset net value slack variable | Payable worker pay slack variable |
|---|---|---|
| Constant term | -1477294.20 | -21822.49 |
| Macroeconomic fluctuations | -8095149.3 | -160013.3 |
| Government subsidies as a percentage of operating revenue | 323482.26 | -20798.209 |
| Number of years on the market | 5903.9445 | -209.35662 |
| GDP of the region to which you belong | -12903.768 | 2066.2502 |
| $\sigma^2$ | 16759119000000.00 | 5236365400.00 |
| $\gamma$ | 1.00 | 1.00 |

#### 5.2.1 Macroeconomic fluctuations

The regression coefficients of macroeconomic volatility and the slack variables of net fixed assets and compensation payable to employees are significantly negative. When macroeconomic volatility is high, companies face more market uncertainty and competitive pressure. To cope with this situation, companies need to focus more on efficiency and resource utilization to avoid wasting resources and unnecessary cost expenditures. Under such circumstances, firms may cut unnecessary expenditure and waste, including reducing non-essential investment in fixed assets and lowering payroll expenses payable to employees, thereby increasing efficiency and reducing the creation of redundancies.

#### 5.2.2 Ratio of government subsidies to operating revenue

An increase in the ratio of government subsidies to operating income implies an increase in the proportion of government subsidies received by the enterprise as a percentage of operating income. The regression coefficient of the ratio of government subsidies to operating income and the slack variable of net fixed assets is significantly positive. The increase in government subsidies may make enterprises rely too much on government financial support and neglect their operating efficiency and profitability. Firms may adopt unnecessary investment in fixed assets and blindly expand their production scale, and the increase in government subsidies may also cause market imbalance and distortion. Enterprises may engage in price wars or other unnecessary market behaviors, which may lead to excessive competition and waste of resources, and increase the redundancy of net fixed assets. The regression coefficient of the ratio of government subsidies to operating income and the slack variable of payables to employees is significantly negative, and an increase in government subsidies may lead to an increase in the productivity of the firm. Government subsidies may be used for technological innovation, equipment upgrading, etc., intensifying competition within the industry, and firms pursuing more rational planning of corporate capital operations, which will help reduce the generation of redundancy in firms' payables to employees.

### 5.2.3 Number of years on the market

The regression coefficients of the years on market and net fixed asset value redundancy variables are significantly positive. On the one hand, net fixed asset redundancy refers to the difference between the value of an enterprise's fixed assets and the value of the assets required for its actual production, which is a kind of reserve in production that can be used to cope with economic instability or changes in production and operation risks rather a kind of guarantee for the stability and risk resistance of an enterprise's operation. On the other hand, specifically, enterprises in the process of business will continue to invest in various fixed assets, such as land, plant, machinery, and equipment, etc., with the growth of business time, for the larger and larger fixed assets, enterprises inevitably have poor management, resources cannot be reasonably used will lead to high redundancy of net fixed assets, which is considered a waste, and ultimately lead to redundancy of net fixed assets This is seen as a waste and ultimately leads to an increase in net fixed asset redundancy. The regression coefficient of the length of time on the market and the slack variable of employee compensation payable is significantly negative, as the maturity of listed enterprises and the accumulation of management experience, enterprises can more effectively manage human resources in a more targeted manner and reduce the redundancy of employee compensation. Therefore, an increase in the number of years a high-tech company has been listed will significantly reduce the redundancy of employee compensation payable.

### 5.2.4 GDP of the region to which it belongs

The regression coefficient of the gross regional product of affiliation and the net fixed assets slack variable is significantly negative, when the higher the gross regional product of affiliation of a high-tech enterprise, the better the local production and operation activities, and the market competition may be intensified. Under such circumstances, enterprises need to be more flexible in adjusting their production and operation strategies to meet changing market demands, reducing the possibility of redundancy in net fixed assets. The regression coefficient on the slack variable of the gross product of the region to which a high-tech company belongs is significantly positive. When the gross product of the region in which a high-tech company is located increases, it usually also means that the economic level of the region has improved, and employment opportunities and average wage compensation will also increase. This may lead to higher compensation packages for companies seeking highly qualified and skilled employees and retaining key people in the company, which will lead to higher payroll expenses and increased redundancy in the company's payroll payable.

## 5.3. Phase 3: Analysis of DEA model results after removal of environmental variables

The input and output values excluding environmental variables were again measured for innovation efficiency through DEAP 2.1 software and collated with the Phase 1 results as shown in Table 1

According to Table 1, after excluding environmental factors, the average values of integrated technical efficiency, pure technical efficiency and scale efficiency of 60 Chinese high-tech listed companies in 2013-2021 all changed to different degrees, with integrated technical efficiency decreasing by 20%, pure technical efficiency increasing by 47.8% and scale efficiency decreasing by 45.3%. This indicates that environmental factors have a significant impact on the innovation efficiency of high-tech enterprises.

For integrated technical efficiency, after excluding environmental factors, only one company, Xiamen Xinda, is close to 1, basically on the front side of production and can be used as an industry benchmark. Midea Group, Tongling Non-ferrous Metals Group, and Zhuhai Gree Group rose more sharply, from 0.246, 0.564, and 0.213 to 0.736, 0.898, and 0.729 respectively. This suggests that environmental factors have caused these three groups to be severely undervalued. In addition, 75% of the companies have a combined technical efficiency of no more than 0.5, indicating that the vast majority of high-tech companies have a low level of innovation efficiency and have much room for improvement.

For pure technical efficiency, after excluding environmental factors, the pure technical efficiency of Midea Group and Xiamen Cinda 2 remained unchanged and on the frontier side. The Tongling Non-ferrous Metals Group and Zhuhai Gree remain above 0.9, indicating that these two companies have a high technical efficiency but still have room for improvement. The technical efficiency of the other companies is mostly above 0.5 and the difference between them is small. This indicates that the pure technology utilization rate of high-tech enterprises is generally relatively high.

For scale efficiency, after excluding environmental factors, only three enterprises, namely XCMG, Tongling Nonferrous Metals, and Xiamen Xinda, are above 0.9, while most other enterprises are generally less efficient after adjusting for scale. According to the results of the change in scale payoff, Xiamen Xinda has reached the optimal production scale; Midea Group, Tongling Non-ferrous Metals Group, Zhuhai Gree, and Weichai Power need to reduce their production scale; the rest of the enterprises should expand their production scale to improve their production efficiency.

### 5.4. Efficiency analysis based on the Malmquist Index

The different production frontiers selected for the three-stage DEA analysis result in static results, which do not allow for the observation of efficiency trends by comparing changes from year to year. Therefore, this paper calculates the Malmquist index and its decomposition indicators for the years 2013-2021 to overcome this limitation. The results are shown in Table 4.

**Table 4** Malmquist Index and its decomposition indicators for high-tech enterprises in China, 2013-2021

| YEAR | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| 2013-2014 | 1.062 | 0.707 | 0.873 | 1.217 | 0.751 |
| 2014-2015 | 0.915 | 0.759 | 1.204 | 0.759 | 0.694 |
| 2015-2016 | 1.219 | 0.707 | 1.051 | 1.16 | 0.862 |
| 2016-2017 | 1.065 | 1.001 | 1.299 | 0.82 | 1.067 |
| 2017-2018 | 0.836 | 1.198 | 0.575 | 1.454 | 1.002 |
| 2018-2019 | 0.682 | 1.393 | 1.545 | 0.441 | 0.949 |
| 2019-2020 | 0.987 | 1.063 | 0.148 | 6.684 | 1.049 |
| 2020-2021 | 0.953 | 1.726 | 5.366 | 0.178 | 1.646 |

According to the Technological Progress Change Index (TECHCH) of Chinese high-tech enterprises in Table 4, the technological progress of Chinese high-tech enterprises showed a trend of decreasing and then increasing before the epidemic (2013-2019). In the period 2014-2016, the index was consistently less than 1, and from 2017 it was greater than 1 and reached its highest value in 2019 at 1.393. This indicates that the technological level of Chinese high-tech enterprises started to increase in 2017 and the increase was the largest in 2019. This may be related to the policies related to promoting the innovation-driven strategy issued by China's State Council in 2017, which promoted high-tech enterprises' investment in innovation and thus led to technological progress.

Conclusions and recommendations of the study during the epidemic (2020-2021), high-tech companies face many challenges. At the beginning of the epidemic, the pure technical efficiency of companies declined significantly, by 86.2% compared to 2019. This indicates that the epidemic has had a significant impact on the operations of high-tech companies, preventing them from fully and efficiently utilizing their available resources for production. This could be attributed to plant shutdowns and supply chain disruptions, resulting in significant disruptions to the production activities of enterprises. Despite the policy and financial support provided by the Chinese government during this period, which allowed companies to expand their production scale and increase their economies of scale by 660% compared to 2019, the impact of the epidemic was not offset and the overall technical efficiency of high-tech companies decreased by 1.3% compared to 2019.

However, high-tech companies have accelerated their technological innovation and digital transformation in response to the challenge, optimizing their resource allocation and resulting in a huge increase in pure technological efficiency in the second year of the epidemic. Compared to 2020, Chinese high-tech firms saw a 530% increase in pure technical efficiency in 2021, and overall technological progress, with the Technological Progress Change Index reaching 1.726 in 2021. this indicates that firms invested significant effort in technology to survive, resulting in the optimization and adjustment of resource use. However, firms also ignore economies of scale as a result, resulting in the overall technical efficiency of high-tech firms remaining down during the epidemic. The contradiction between economies of scale and pure technical efficiency remains.

## 6. Conclusions and Recommendations of the Study

This article presents a dynamic and static analysis of the production of 60 listed high-tech companies in China for the period 2013-2021 using a three-stage DEA analysis and a Malmquist Index analysis and draws the following conclusions:

The static analysis illustrates that after excluding environmental factors, the overall technical efficiency, pure technical efficiency, and scale efficiency of high-tech enterprises change significantly. between 2013 and 2021, the overall efficiency, as well as scale efficiency, are overestimated, while pure technical efficiency is underestimated, indicating that environmental factors have a strong influence on the technical efficiency of high-tech enterprises. In addition, most firms show increasing returns to scale, suggesting that scale efficiency should be improved by expanding the scale of production.

The dynamic analysis illustrates that before the epidemic, Chinese high-tech enterprises faced the contradiction between scale efficiency and technical efficiency. Although the technological level of enterprises improved under the policy, the overall technical efficiency of enterprises did not improve due to the imbalance between scale efficiency and technical efficiency. And during the epidemic period, enterprises accelerated their technological innovation and improved their technological level and efficiency of technological utilization, but still due to the failure to coordinate the relationship between scale efficiency and pure technical efficiency, resulting in overall technical efficiency is on a downward trend.

Based on these findings, the following recommendations are made.

(1). Accelerate the digital transformation of enterprises. As digital technologies continue to emerge in the wake of the epidemic, the government should encourage enterprises to undergo digital transformation, such as using advanced information technology and cloud computing, to improve the efficiency of resource utilization and overall technical efficiency. At the same time, enterprises should make deeper use of new digital technologies and tap the full potential of technology.

(2). Appropriate expansion of production scale. According to the incremental payoff of scale, enterprises should appropriately expand the scale of production to increase the benefits of scale and should allocate resources appropriately to improve resource utilization. In addition, enterprises should seize the opportunity of government policy support to expand the scale of production by reducing operating costs.

(3). Improve the level of internal management. Enterprises should improve their management level and optimize the allocation of resources so that all resources are fully utilized. In addition, enterprises should find the best combination of inputs and operation modes through refined management to achieve a synergistic improvement of technological progress and scale expansion to improve their overall technical efficiency.

## 7. Limitations

This article also has several limitations. Firstly, this article only analyses 60 high-tech listed companies, the sample size is not large enough, which may lead to the inaccuracy of the research results. Secondly, the DEA analysis and Malmquist index analysis used in this article rely on some assumptions, which may not be consistent with the real situation, resulting in the analysis results differing from the real situation. Thirdly, the input and output indicators chosen in the article are not comprehensive, and some of them may not reflect the real innovation efficiency of enterprises well. In future studies, it is recommended to augment the sample size to encompass a larger and more diverse set of companies. Additionally, employing a wider array of analysis methods that better simulate real-world scenarios can help mitigate the limitations inherent in the current research. Lastly, selecting more comprehensive input and output indicators that effectively capture the nuances of innovation efficiency will contribute to a more holistic assessment of enterprise innovation.

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