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Analysis on the Production Efficiency of Private Industrial Enterprises in 31 Provinces of China*

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Abstract

Purpose: The purpose of this study is to understand the status quo of production efficiency in private industrial enterprises above designated scale in China's 31 provinces (including municipalities directly under the central government, autonomous regions) (hereinafter referred to as China's 31 provinces). **Research design, data and methodology:** Find out the factors affecting the development of production efficiency in private industrial enterprises, using DEA, Data Envelopment Analysis and Malmquist index analysis, build the evaluation model of production efficiency in private industrial enterprises, and analyze the data of China's 31 provinces private industrial enterprises in 2015-2019. **Results:** The research results show that the production efficiency of private industrial enterprises in China is improving on the whole. Although the total factor productivity has decreased slightly, the overall efficiency and pure technical efficiency have increased significantly. **Conclusions:** The conclusion of this study can provide reference for Chinese private industrial enterprises to improve production efficiency and make development plan. The limitation of this paper lies in the fact that the private industrial enterprises in inefficient provinces have not been given specific improvement plans.

Keywords : 31 provinces of China, Private industrial enterprises, Production efficiency, DEA Data Envelopment Analysis, Malmquist index analysis

JEL Classification Code : E44, F31, F37, G15

1. Introduction

Since the reform and opening up, especially the 1990's, the proportion of China's private industrial enterprises in the national economy has kept rising, becoming the main area of employment and entrepreneurship, the main body of technology innovation and an important source of national revenue. China's private industrial enterprises have played a positive role in the rural surplus labor transfer, the transformation of government functions and the international market development, etc. According to the statistics, in 2019, there were 243,640 private industrial enterprises above designated size in China, with a total asset of 28,282.96 billion yuan, main business income of 39,458.718 billion yuan(the arithmetic mean in the last three

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years is used as reference because some of the 2018 and 2019 data for the main business income in the China Statistical Yearbook is missing.), and total profit of 2,065.084 billion yuan, an increase of 11 times, 73 times, 82.4 times and 108.5 times, respectively, over that of 2000. As is shown in Figure 1, the number of private industrial enterprises peaked to 273,259 in 2010, and there was a significant reduction phenomenon in the number of enterprises in 2011 (only about 2/3 of that in 2010). This is mainly because since 2011 the standard for the industrial enterprises above designated size has been raised from the main business income of 5 million yuan or more to 20 million yuan or more, and several other indicators being affected as a result, but not obviously. Looking from the whole situation, the number of enterprise units, total assets, main business income and total profit of private industrial enterprises change every year, but on the whole they are still at a higher level, and show an upward trend. With the increase of the number of enterprise units and total assets of private industrial enterprises, the main business income and total profit have increased, especially the income of the main business has increased more obviously. With the increase of investment, China's private industrial enterprises have created more and more economic benefits.

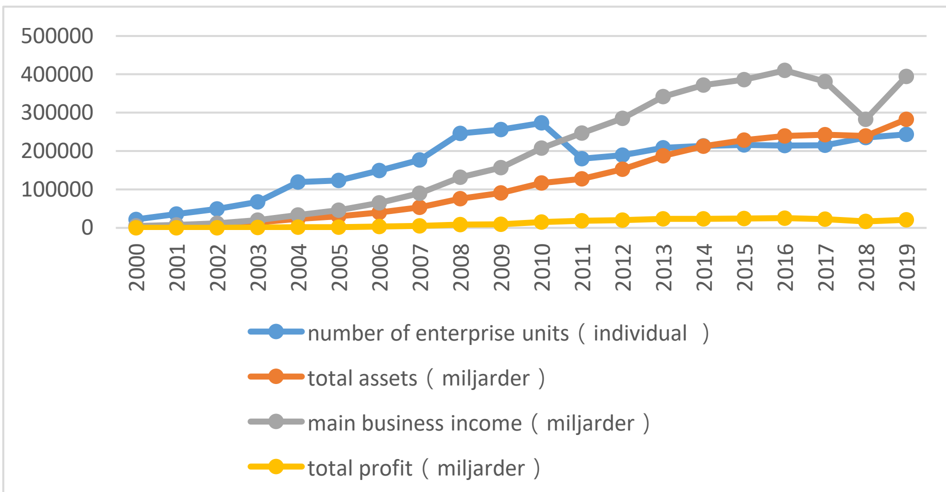

Fig 1: Growth of private industrial enterprises in China

Around 2000, the number of employees in private industrial enterprises was only about 3,464.2 million. In 2004, it was over 15,154.3 million. In 2012, it was more than 30 million, and in 2019, it reached 32,454 million. See figure 2.

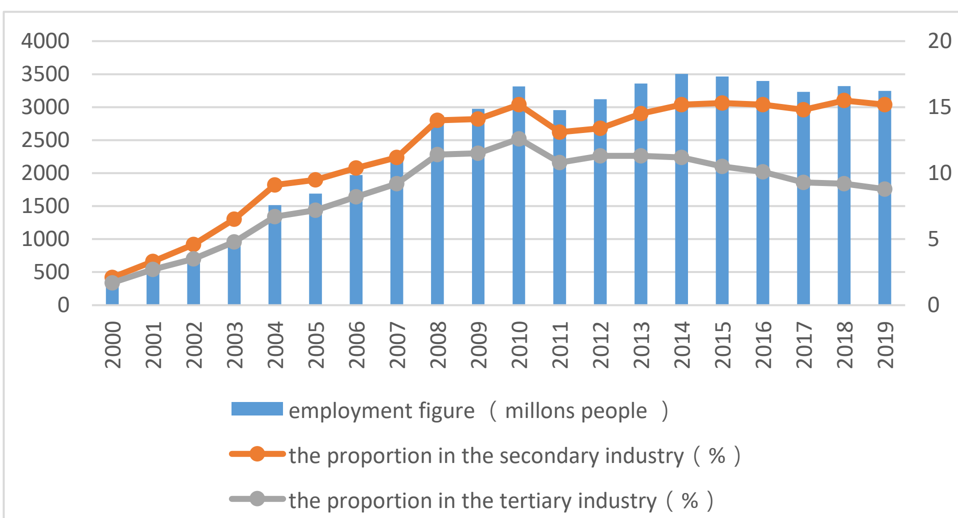

Fig 2: Employment number and employment structure of China's private industrial enterprises.

China's private industrial enterprises have experienced the sustainable development, from scratch, from small to large and from weak to strong. Statistics show that the number of private enterprises in the manufacturing sector has accounted for more than 90% and the proportion of private investment has exceeded 85%. The private enterprises in the manufacturing sector are the real "main force and commando" (Guo, 2017). Being an important part of socialist market economy, the private industrial enterprises are based on the real economy. The private industrial enterprises' improving production efficiency plays an irreplaceable role in increasing opportunities of employment, promoting economic growth, making scientific and technological innovations, improving people's well-being and social harmony and stability. It has strategic significance to promote industrial upgrading, transform the mode of economic development, promote sustained and healthy economic and social development, and to continuously improve the strategic emerging industries and the socialist market economy.

2. Research Methodology

2.1. DEA Model

The Data Envelopment Analysis (DEA) is a method to evaluate the relative efficiency of the same level decision making unit (DMU) with multi-input and multi-output, and it can be improved by evaluating the disadvantages of the DMU (Zhang, Shuang & Yuan, 2013). In 1978, Charnes and Cooper proposed CCR model with constant return to scale, which was the first DEA model. In 1984, Banker and Charnes proposed BCC model with variable return to scale (Yang, 2013). The basic idea is to think of each unit or department being evaluated as a Decision Making Unit, or DMU, consisting of DMUs, an evaluation group. Each DMU in the evaluation group has the same kind of resource consumption, that is, each DMU has the same input item index and output item index. After the index item DMUs are determined, the relative efficiency between DMUs is compared with the mathematical programming model, the input-output ratio is comprehensively analyzed, and the quantitative index value of the comprehensive efficiency of each DMU is obtained, so as to determine the DMU with the highest relative efficiency (DEA effective), and the DMUs are ranked and rated. At the same time, the gap data between DMU that is not DEA effective and DMU that is DEA effective can also be given, which can be used as the quantitative basis for adjusting the non-DEA effective DMU, making efforts toward the effective mode and adjusting the related input or output items.

Compared with other evaluation methods, DEA has distinct advantages. First, there is no need to set the index weight in advance, and the evaluation results are relatively objective. Secondly, DEA can evaluate different dimensional indexes without determining the relationship function of evaluation indexes, which makes it more efficient to process. At present, DEA is the most widely used in CCR and BCC model, among them, CCR model (also called scale constant return model) is used to study Decision Making Units (Decision Making Unit, DMU) with multiple input, especially multiple output , at the same time, it is also used to evaluate the overall effectiveness of Decision Making Units in scale and technology, and the efficiency value obtained is the technical efficiency (TE); BCC model (variable scale return model) is a model to decompose and evaluate the pure technical efficiency and scale efficiency of the decision making unit, and the efficiency value obtained is pure technical efficiency (PTE).From technical efficiency (TE), scale efficiency (SE) is decomposed to obtain pure technical efficiency (PTE), and the relationship of the three is: TE=SE×PTE (Fang, 2006). The basic theory of DEA is (Liu, 2019):

$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{i0}, i = 1,2,\cdots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, r = 1,2,\cdots,p \\ \lambda_j \ge 0, \theta \end{cases}$$

By introducing slack variables S* and S*-, the formula transformed by dual programming is the classical CCR model of DEA:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j x_j + s^- = \theta x_0 \\ \sum_{j=1}^{n} \lambda_j y_j - s^+ = y_0 \\ s^- \ge 0, s^+ \ge 0, \lambda_j \ge 0, \\ \theta \text{ is unconstrained} \end{cases}$$

2.2. Malmquist index Method

The Malmquist index was first put forward in 1953 by the Swedish economist and statistician Malmquist to analyze changes in consumption over time (Chang, Yao & Jiang, 2011).In 1994,RolfFare et al. established the Malmquist productivity index model to investigate total factor productivity growth (Pang, Li, Zhou and Sun, 2008). Hong Gyun park et al. used DEA method to calculate the technical efficiency, pure technical efficiency and scale efficiency of 14 logistics supplier enterprises in South Korea from 2007 to 2011, and then used DEA window analysis and Malmquist index method to calculate the dynamic efficiency of each enterprise from 2007 to 2011 (Park & Lee, 2015).While traditional DEA methods can only measure the efficiency of different decision-making units during the same period, Malmquist index analysis method can not only analyze the efficiency change of decision making units during different periods from the perspective of dynamics, also the index can be further decomposed into technical efficiency change index (TEch) and the technical progress index (TECHch), determine the Malmquist index value changes. In the variable scale return state, the change of technical efficiency is further decomposed into pure technical efficiency change (PEch) and scale efficiency change (SEch). Specific concepts are expressed as follows:

$$TFP = TEch \times TECHch = PEch \times SEch \times TECHch$$

In the formula, TEch represents the change of technical efficiency from t period to t+1 period. When TEch>1, it indicates that the technical efficiency has been improved; otherwise, it represents a decline. TECHch represents the influence of the technology progress index from t period to t+1 period on the change trend of efficiency. When TECHch>1, it indicates that the technology has improved and brought efficiency improvement; on the contrary, it means that the technology progress has not brought efficiency improvement (Zhang & Zhao, 2020).

From t period to t+ 1 period, the expression of the Malmquist index, which measures the growth of total factor productivity, is expressed in the form (Chen & Lv, 2019)：

$$M\left(x^{t+1}, y^{t+1}, x^t, y^{'}\right) = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^{'}\right)} \times \left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right]^{\frac{1}{2}}$$

The index of technical efficiency change is to measure the degree of each decision-making unit catching up with the productivity possibility frontier from t period to t+1 period. When Effch>1, it indicates the efficiency of technology has been improved, Otherwise, the efficiency of technology is reduced. When TECHch>1, it indicates that the technology is making progress, otherwise, retrogression. When M>1, the productivity during t+1 period is making progress compared to that of the previous phase; When M= 1, it indicates that the productivity is stable compared to that of the previous phase; When M<1, it indicates that the productivity during t+1 period has declined compared to that of the previous phase.

3. Literature Review

For the research problem of private industrial enterprise efficiency evaluation, Song and Chang (2009) take the share of state-owned and private industrial enterprises in various industries as basic indicators, using Data Envelopment Analysis (DEA) model to calculate the relative efficiency between the two kinds of enterprises in various industries, and conclude the running efficiency of private industrial enterprises in the industry as a whole is higher than that in state-owned enterprises.

Similarly, using the share of state-owned and private industrial enterprises in each industry as the basic indicator system, Tang (2008) use factor analysis method to compare their economic benefits in each industry, and conclude that private industrial enterprises have advantages in competitive and labor-intensive industries. From the overall analysis of comprehensive technical efficiency, pure technical efficiency, scale efficiency and DEA effectiveness, Ren and Ding (2013) show that the production efficiency of China's private industrial enterprises is steadily improving, and most regions are making active efforts to optimize the industrial structure to promote the development of productivity, which is specifically reflected in the increasing stage of scale returns. Ding, Jo, Wang and Yeo (2015) use DEA method to calculate the technical efficiency, pure technical efficiency and scale efficiency of 21 small and medium-sized coastal ports in China. Fan, Yu and Zhao (2015) use DEA analysis model to study the regional efficiency differences among state-owned, private and foreign-funded industrial enterprises in China. The results show that the average comprehensive efficiency of private industrial enterprises is always higher than that of state-owned industrial enterprises, and the overall comprehensive efficiency of private industrial enterprises presents an upward trend. The advantage of private industrial enterprises lies in technical efficiency and scale efficiency, while the advantage of state-owned industrial enterprises lies in low technical efficiency but significant growth trend. Existing literature studies have revealed the relationship between state-owned industrial enterprises and private industrial enterprises in various industries, which provides a strong support for the analysis method and index selection in this paper.

Huang and Fan (2013) use DEA analysis model to analyze the production efficiency of private industrial enterprises in 12 provinces and autonomous regions in western regions. As a whole, the private industrial enterprises in western regions present the phenomenon of excessive resource input and insufficient output. The western region government should strive to expand investment and construction in infrastructure, create a good production and operating environment for the private industrial enterprises and needs to pay attention to the introduction of professional and technical personnel and provide better management and technology for the rational use of the private industrial enterprises resources in western areas (Huang & Fan, 2013). Xiao and Fan (2016) use DEA analysis on innovation efficiency of China's industrial enterprises, find out that most studies focus on economic growth and ignore the environmental and energy impact on the efficiency of enterprise innovation, put forward the thinking of the situation of shared inputs and intermediate product withdrawal, and propose the environmental effect should be brought into the research framework of innovation efficiency.

Summarize the relevant indicators in previous studies, most of the input indicators used in the research literature are: net fixed assets, number of employees, number of enterprise units and total assets (Ren & Ding, 2013); Number of employees, main business cost, net fixed assets (Huang & Fan, 2013); Total assets and number of employees (Fan & Yu & Zhao, 2013); Main business cost, administrative expenses, employee’s salary, net fixed assets (Chen & Lv, 2019); Financial expenses and administrative expenses (Liu, 2019). The output indicators used are: gross output value (Ren & Ding, 2013); Gross output value, main business income (Huang & Fan, 2013); Total output value (Fan & Yu & Zhao, 2013); Total profit and revenue of main business (Chen & Lv, 2019); Total profit (Liu, 2019).

Based on the principles of scientificility, systematiation, practicality and generality, a combination of DEA method and Malmquist index model will be used in this article, the Malmquist DEA index method will be used in the empirical analysis part, taking each province as a decision making unit, 31 provinces in China as the research object. As shown in Table 1, cost of sales of the private industrial enterprises , management fees, financial expenses, the number of enterprises, the total assets, main business cost are selected as input indicators, main business income and total profit as output indicators, to evaluate and analyze the present situation of total factor productivity in the private industrial enterprises and the situation of improvement, the corresponding countermeasures and suggestions are put forward according to the conclusions obtained.

Table 1: Input and output indicators

project	indicators	unit
input	Cost of sales	One hundred million yuan
	Management fees	One hundred million yuan
	Finance charges	One hundred million yuan
	Number of enterprise units	One
	Total assets	One hundred million yuan
	Main business cost	One hundred million yuan
output	Main business income	One hundred million yuan
	Total profit	One hundred million yuan

All the data selected in this paper are from 2015-2019 data of China Statistical Yearbook, National Bureau of Statistics (Since the 2018 and 2019 figures for the main business income and the 2018 figures for the total profits of Tibet Autonomous Region in the China Statistical Yearbook are missing, the arithmetic mean is used as a reference.). DMUs are for 31 provinces in China, according to the order of China Statistical Yearbook, Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia Autonomous Region, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi Autonomous Region, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet Autonomous Region, Shaanxi, Gansu, Qinghai, Ningxia Autonomous Region, Xinjiang Autonomous Region. The analysis was performed using the Malmquist index method.

Through referring to relevant literature, I have found out that the domestic scholars do less research on the production efficiency of Chinese private industrial enterprises, and starting later, in comparison. There're some innovations in this article: (1) The studies of the production efficiency of China's private industrial enterprises by the previous scholars are mainly confined to part of the provinces or regions, this paper is to analyze the production efficiency of all of China's private industrial enterprises; (2) In the previous studies on the production efficiency of private industrial enterprises, scholars mostly use the traditional DEA method, which belongs to static research method. In this paper, DEA and Malmquist index method are combined to analyze the production efficiency of private industrial enterprises, which is not included in the previous studies. (3) This paper studies the influence of technological efficiency changes and technological progress on total factor productivity in private industrial enterprises, which is also lacking in previous studies.

4. Empirical Analysis

4.1. DEA static result analysis of production efficiency of private industrial enterprises

4.1.1. Comprehensive efficiency analysis

DEAP is used to process the sample data. By using CCR model and BCC model in DEA method, the comprehensive efficiency and pure technical efficiency of each private industrial enterprise can be measured. The value range is 0-1. When the efficiency value is 1, the DEA is effective. By using CCR model, TE of comprehensive efficiency of private industrial enterprise in 31 provinces of China is measured, and its comprehensive efficiency value is shown in Table 2.

Table 2: Comprehensive efficiency of private industrial enterprises in 31 provinces of China 2015 to 2019

DMU	2015	2016	2017	2018	2019	The mean
Beijing	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000
Hebei Province	0.986	1.000	1.000	1.000	0.981	0.993
Shanxi Province	0.915	0.946	0.989	1.000	0.942	0.958
Inner Mongolia Autonomous Region	1.000	1.000	0.982	1.000	1.000	0.996
Liaoning Province	0.949	0.909	0.972	0.957	0.953	0.948
Jilin Province	0.981	1.000	0.977	1.000	1.000	0.992
Heilongjiang Province	0.966	0.964	0.934	0.960	0.944	0.954
Shanghai	0.968	0.995	0.997	0.998	0.983	0.988
Jiangsu Province	0.976	0.976	0.986	0.983	0.980	0.980
Zhejiang Province	0.948	0.953	0.964	0.956	0.939	0.952
Anhui Province	0.973	0.974	0.976	0.965	0.978	0.973
Fujian Province	0.976	0.981	0.988	1.000	1.000	0.989
Jiangxi Province	1.000	1.000	1.000	1.000	1.000	1.000
Shandong Province	0.988	1.000	1.000	0.979	0.975	0.988
Henan Province	1.000	1.000	1.000	1.000	1.000	1.000
Hubei Province	0.974	0.977	0.989	0.965	0.973	0.976
Hunan Province	1.000	1.000	1.000	1.000	1.000	1.000
Guangdong Province,	0.987	0.988	1.000	0.996	0.982	0.991
Guangxi Autonomous Region	1.000	1.000	1.000	0.989	0.993	0.996

Hainan Province,	0.919	0.945	0.949	0.933	0.911	0.931
Chongqing	0.994	0.994	0.999	1.000	1.000	0.997
Sichuan Province	0.978	0.981	0.987	0.982	0.982	0.982
Guizhou Province	0.975	0.991	0.984	0.999	0.999	0.990
Yunnan Province,	0.922	0.937	0.962	0.943	0.935	0.940
Tibet Autonomous Region	1.000	1.000	1.000	1.000	1.000	1.000
Shaanxi Province	1.000	0.998	1.000	1.000	1.000	1.000
Gansu Province	0.929	0.921	0.956	0.941	0.944	0.938
Qinghai Province	0.953	0.920	0.947	0.926	0.944	0.938
Ningxia Autonomous Region	0.920	0.923	0.965	0.910	0.918	0.927
Xinjiang Autonomous Region	0.988	1.000	1.000	1.000	1.000	0.998

According to the analysis in Table 2, the comprehensive efficiency values of Beijing, Tianjin, Jiangxi, Henan, Hunan and Tibet were 1, that is, DEA was effective, accounting for 19.35% of the total. The comprehensive efficiency of Shaanxi Province in 2016 was 0.998, and that in other years were all 1. Inner Mongolia had a combined efficiency of 0.982 for 2017 and 1 for the rest of the year. Compared with 9 provinces in 2015, the number of DEA effective provinces in 2019 increased to 12, accounting for 38.71% of the total, indicating that there were 12 provinces in the best production efficiency state. The average comprehensive efficiency of Hebei Province, Shanxi Province, Liaoning Province, Jilin Province, Heilongjiang Province, Shanghai City, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Shandong Province, Hubei Province, Guangdong Province, Guangxi Autonomous Region, Hainan Province, Chongqing City, Sichuan Province, Guizhou Province, Yunnan Province, Gansu Province, Qinghai Province, Ningxia Autonomous Region, and Xinjiang Autonomous Region over five years were above 0.9, all in a relatively high position. The comprehensive efficiency of Shanghai in 2013 was 0.884, and that in other years were above 0.9. The total efficiency of Hainan Province in 2013 and 2014 were 0.856 and 0.892 respectively, and that in other years were above 0.9.

From the analysis of comprehensive efficiency, the comprehensive efficiency of China's 31 provinces in the past five years and their means were above 0.9, which indicates that the comprehensive efficiency of private industrial enterprises in China was at a high level. Due to the economic development of Shanghai and the rich diversity of other economies, the private industrial enterprises have been impacted, and the overall efficiency value of Shanghai was 0.884 in 2013. Because Hainan Province is an island province with a small population, the comprehensive efficiency value in 2013 and 2014 appeared lower values of 0.856 and 0.892 respectively. The overall efficiency of Qinghai Province also showed a lower value of 0.896 in 2013 due to its large land area and sparse population. Overall, in 2019 there were 21 provinces with combined efficiency greater than or equal to that in 2015, accounting for 67.74 per cent of the total. During the five years, the overall efficiency of China's private industrial enterprises remained high, and at the same time, it grew slowly, with little fluctuation.

4.1.2. Pure technical efficiency analysis

In order to further study the efficiency of private industrial enterprises in 31 provinces of China, BCC model based on variable scale return is used to measure the pure technical efficiency value of private industrial enterprises, and the pure technical efficiency value of private industrial enterprises is analyzed, and its pure technical efficiency is shown in Table 3.

Table 3: Pure technical efficiency of private industrial enterprises in 31 provinces of China 2015 to 2019

DMU	2015	2016	2017	2018	2019	Means
Beijing	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000
Hebei Province	1.000	1.000	1.000	1.000	0.986	0.997
Shanxi Province	0.923	0.951	0.990	1.000	0.951	0.963
Inner Mongolia Autonomous Region	1.000	1.000	0.983	1.000	1.000	0.997
Liaoning Province	0.966	0.948	0.972	0.961	0.956	0.961
Jilin Province	0.981	1.000	0.978	1.000	1.000	0.992
Heilongjiang Province	0.967	0.964	0.936	0.960	0.952	0.956
Shanghai	0.990	1.000	1.000	1.000	1.000	0.998
Jiangsu Province	1.000	1.000	1.000	1.000	1.000	1.000

Zhejiang Province	0.992	0.992	0.992	0.980	0.991	0.989
Anhui Province	0.974	0.975	0.987	0.978	0.989	0.981
Fujian Province	0.978	0.981	1.000	1.000	1.000	0.992
Jiangxi Province	1.000	1.000	1.000	1.000	1.000	1.000
Shandong Province	1.000	1.000	1.000	1.000	1.000	1.000
Henan Province	1.000	1.000	1.000	1.000	1.000	1.000
Hubei Province	0.975	0.978	0.998	0.976	0.974	0.980
Hunan Province	1.000	1.000	1.000	1.000	1.000	1.000
Guangdong Province,	1.000	1.000	1.000	1.000	1.000	1.000
Guangxi Autonomous Region	1.000	1.000	1.000	0.989	0.996	0.997
Hainan Province,	0.919	0.979	1.000	0.976	0.931	0.961
Chongqing	0.999	0.997	1.000	1.000	1.000	0.999
Sichuan Province	0.978	0.981	0.987	0.993	0.989	0.986
Guizhou Province	0.987	0.997	0.984	0.999	1.000	0.993
Yunnan Province,	0.945	0.959	0.964	0.950	0.951	0.954
Tibet Autonomous Region	1.000	1.000	1.000	1.000	1.000	1.000
Shaanxi Province	1.000	1.000	1.000	1.000	1.000	1.000
Gansu Province	0.944	0.937	0.957	0.948	0.953	0.948
Qinghai Province	0.955	0.926	0.951	0.934	0.945	0.942
Ningxia Autonomous Region	0.929	0.932	0.966	0.921	0.926	0.935
Xinjiang Autonomous Region	1.000	1.000	1.000	1.000	1.000	1.000

Based on Table 3, the pure technical efficiency of 11 provinces, including Beijing, Tianjin, Jiangsu, Jiangxi, Shandong, Henan, Hunan, Guangdong, Tibet, Shaanxi and Xinjiang, were 1, that is DEA was effective, the net technical efficiency of

Hainan Province was 0.870 in 2013, and the net technical efficiency of other provinces were above 0.9 in five years, accounting for 35.48% of the total. The comprehensive efficiency of 31 provinces during the five years and their means were above 0.9. In 2019, there were 23 provinces with pure technical efficiency greater than or equal to that of 2015,

accounting for 74.20% of the total. The pure technical efficiency also showed an increasing trend in the past five years, which showed that the investment of private industrial enterprises in technology increased year by year, and the collocation of production factors became more reasonable. Although this progress was slow in terms of data, its impact was far-reaching, indicating that with the encouragement and support of national policies, private industrial enterprises were steadily developing to achieve the goal of promoting production efficiency through science and technology.

4.2. Malmquist index calculation results

The DEA method is used to analyze the efficiency of private industrial enterprises(in a certain year). In other words, to analyze the dynamic changes of efficiency of private industrial enterprises in the sample period. Only static comparison can be made, but dynamic comparison cannot be made. In this case, the Malmquist index method is introduced.

DEAP is used to measure the efficiency changes of private industrial enterprises in 31 provinces of China in four periods, namely 2015-2016, 2016-2017, 2017-2018 and 2018-2019.See Table 4 for details.

Table 4: Total factor efficiency of private industrial enterprises in 31 provinces of China 2015 to 2019

Evaluation period	TECI	TCI	MPI (Total Factor Productivity)
2015-2016	1.004	1.003	1.007
2016-2017	1.008	0.937	0.945
2017-2018	0.996	1.063	1.058
2018-2019	0.996	0.996	0.992

Malmquist index (MPI) represents total factor productivity, which is greater than or equal to 1, indicating effectiveness. Total factor productivity can be divided into technical efficiency change (TECI) and technical change (TCI). MPI is influenced by both TECI and TCI.

According to Table 4, the average value of dynamic change of total factor productivity (MPI) of private industrial enterprises in 31 provinces of China in 2016-2017 was 0.945, going down by 5.5%. In 2015-2016 and 2017-2018, it was 1.007 and 1.058 respectively, indicating that the total factor productivity of private industrial enterprises in 31 provinces of China increased by 0.7% and5.8% during these two evaluation periods. But from 2018 to 2019, the average value of dynamic change of total factor productivity (MPI) was 0.992, going down by 0.8%.

Further analysis shows that from 2015 to 2016, the technical efficiency change TECI was 1.004, the improvement was 0.4%, the technical change TCI was 1.003, the improvement was 0.3%, the technical change and the technical efficiency change were both rising, which led to the increase of total factor productivity MPI by 0.7%. From 2016 to 2017, the technical efficiency change TECI was 1.008, the improvement was 0.8%, the technical change TCI was 0.937, the decrease was 6.3%, the decrease of technical change was larger than the increase of technical efficiency change, which results in a 5.5% decrease of total factor productivity MPI. From 2017 to 2018, the technical efficiency change TECI averaged 0.996, going down 0.4%, and the technical efficiency change TCI averaged 1.063, going up 6.3%, leading to a 5.8% increase in the total factor productivity MPI. From 2018 to 2019, the technical efficiency change TECI averaged 0.996, going down 0.4% , the mean value of technical change TCI was 0.996, which decreased by 0.4% . The technical Change and technical efficiency change both decreased, which resulted in a 0.8% decrease in total factor productivity MPI.

Thus, it can be seen that the mean value of TECI for technical efficiency change and TCI for technical change were both greater than or equal to 1, that is, the two values were in the rising state, the total factor productivity MPI was also in the rising state. When the mean decline of TCI was larger than the mean rise of TECI, total factor productivity (MPI) declined. When the increase of technical change TCI mean was more than the decrease of technical efficiency change TECI mean, the total factor productivity of MPI increased. When the technical efficiency change TECI mean and technical change TCI mean were both less than 1, that is, when they decreased, the total factor productivity of MPI was also falling. The reason is that the excessive accumulation of private capital and labor exceed the tolerance range of the technology stock, resulting in the technical deterioration, and thus leading to the decline of total factor productivity (MPI), as shown in figure 3.

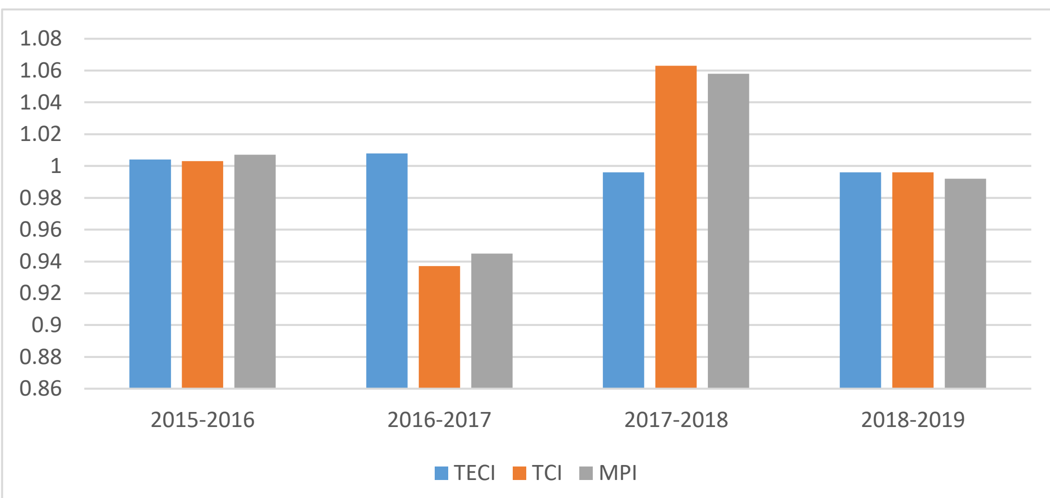

Fig 3: Mean changes of TECI, TCI and MPI of private industrial enterprises in 31 provinces of China 2015 to 2019

5. Conclusions and Suggestions

5.1. Research Conclusions

In this paper, the production data of private industrial enterprises above designated scale in 31 provinces of China from 2015 to 2019 have been evaluated by using DEA and Malmquist index analysis, and analytical conclusions have been drawn.

First, from the overall perspective of comprehensive efficiency, pure technical efficiency and total factor productivity, the production efficiency of private industrial enterprises in China's 31 provinces has been steadily improved. Most provinces are making active efforts to optimize the industrial structure to promote the development of productivity, which is specifically reflected in the fact that the overall efficiency and pure technical efficiency of private industrial enterprises above designated scale in 31 provinces in China from 2015 to 2019 were greater than 0.9.

Second, the private industrial enterprises above designated scale in 31 provinces of China have certain anti-risk ability and have maintained their competitiveness in the unfavorable economic environment. As can be seen from the analysis, the production efficiency of private industrial enterprises in most provinces shows a trend of continuous improvement, which is reflected in the data. Although private industrial enterprises declined by 0.8% in total factor productivity from2018-2019, in 2019, the number of provinces with technical inefficiency decreased by 3 compared which that in 2015, and there were 21 provinces with overall efficiency greater than or equal to that in 2015, accounting for 67.74% of the total. Most provincial private industrial enterprises were moving towards optimal scale of production efficiency. This shows that China's private industrial enterprises themselves were also actively seeking progress and development, so as to enhance their competitiveness. It is necessary to encourage and guide private industrial enterprises to participate in the reform of the state-owned and collective economy in the form of purchase, lease and contract, learn from the successful experience of state-owned, collective and foreign-invested enterprises, reform themselves in the enterprise system and management, enhance their technological development capacity and move towards a modern enterprise system.

Third, as a dynamic mainstream economy, China's private industrial enterprises continue to make more contributions to society, which have effectively promoted the establishment and improvement of the socialist system with Chinese characteristics and the socialist market economic system, and have far-reaching impact and great significance on the healthy development of national economy.

5.2. Suggestions

Based on the above analysis, in order to further improve the production efficiency of China's private industrial enterprises, the following suggestions are put forward: the state and the government should do as follows: Timely apply the industrial technological achievements to the production process of private industrial enterprises, so that private industrial enterprises can become an important driving force for scientific and technological progress. Do a good job in top-level design, advance reform to streamline the government, delegate power and improve government services, and improve the business environment for private industrial enterprises. Deepen supply-side structural reform to increase access for private industrial enterprises and reduce costs. Innovate systems and mechanisms to ensure the supply of development factors for private industrial enterprises. Encourage private industrial enterprises to "go global", and to actively participate in the implementation of national development strategies and plans such as "the Belt and Road", and provide more policy support. Private industrial enterprises should also pay attention to establishing close cooperative relations with state-owned enterprises and international industrial capacity cooperation alliances, make full use of the latter's advantages in resources and information, improve the success rate of industrial capacity cooperation, form joint efforts to jointly develop the international market, realize the optimal allocation of resources, and better promote the sustained and healthy development of China's private industrial enterprises.

Using DEA and Malmquist analysis method, this paper has analyzed the efficiency of input and output of private industrial enterprises in China's 31 provinces, studied the influence of technical progress and technical efficiency change on total factor productivity. The meaning is that the paper has found the efficient and inefficient provinces of private industrial enterprises, and put forward suggestions for improvement, and it is hoped to expand this article research results to other types of industrial enterprises. However, this study is limited by the availability of data, failing to provide detailed and specific improvement plans for private industrial enterprises in inefficient provinces. AHP and other methods can be used for further research in the future.

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