

Measurement and Difference Analysis of Total Factor Productivity in China Province

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Abstract:

Improving total factor productivity is a key strategy for promoting economic transformation and upgrading, and its importance is self-evident. Currently, due to differences in economic activities, the degree of factor agglomeration in various provinces and cities in China has significantly differentiated, exacerbating the gap in total factor productivity between regions. Based on this, this article uses provincial panel data from 2007 to 2019 to quantitatively evaluate total factor productivity. Research has found that: (1) the total factor productivity of 30 provinces in China has entered a stable growth track after initial fluctuations, but there are still significant differences in total factor productivity between provinces. (2) The contribution of technological progress and the performance of technological efficiency both show dynamic fluctuations, and both jointly affect total factor productivity. Based on the above conclusion and the current economic situation, this article suggests that efforts should be made to improve the total factor productivity of underdeveloped areas, strengthen investment in scientific and technological innovation and research and development, in order to effectively narrow the gap in total factor productivity between regions and promote balanced economic development.

Keywords:

Total Factor Productivity, Data Envelopment Analysis (DEA)

1. Introduction

Since the reform and opening up, after 30 years of hard work, China has achieved a leapfrog development in its economy through large-scale factor inputs. However, compared with developed countries, China still faces significant gaps in certain areas, manifested in the need to improve per capita income levels, incomplete coordination between economic growth rate and quality, and challenges such as environmental pollution and excessive resource consumption. Looking back, the reason why China's economy has achieved such rapid growth is largely due to our relatively backward economic starting point compared to developed countries. This has given our country enormous potential for latecomers and vast development space, enabling significant

results to be achieved solely through the massive investment of traditional factors (capital, labor, and land). Today, China has jumped to become the world's second largest economy and its economic level has significantly improved. This historic achievement has prompted China to shift its strategic focus of economic development from pursuing high-speed growth to paying more attention to the quality and efficiency of development. The 19th National Congress of the Communist Party of China in 2017 clearly pointed out that improving total factor productivity has immeasurable value in promoting the transformation of economic growth models and promoting high-quality economic development. In this new era, it is particularly important to conduct in-depth research on total factor productivity. Total factor productivity, as a key indicator for measuring input and output efficiency in the production process of a country or region, can intuitively reflect its production scale and efficiency status. By scientifically measuring total factor productivity, it provides powerful decision-making basis for policy makers, helps enterprises optimize production processes, improve product quality and efficiency, and thereby enhance China's competitiveness in the global economic landscape.

Therefore, based on the panel data of China's provinces (except Xizang) from 2007 to 2019, this paper systematically explores the evolution trend of total factor productivity and regional differences by using data envelopment analysis (DEA), an efficiency evaluation method, in order to contribute wisdom and strength to the high-quality development of China's economy.

2. Literature Review

2.1. Overview of DEA related principles

DEA (Data Envelopment Analysis) is a non parametric linear programming technique used to measure and evaluate the performance of units such as enterprises, organizations, government agencies, etc. The basic principle is based on an input-output model, which compares the input and output data of different units to evaluate relative efficiency and determine which unit activities are optimal [1]. Specifically, the core of the DEA method is to establish an input-output model that takes the inputs (such as labor, funds, equipment, etc.) and outputs (such as output, sales, profits, etc.) of each unit as elements of the model. Using linear programming techniques, DEA considers each unit as a producer and determines the effective frontier and efficiency score of each unit through model solving [2]. The effective frontier is a boundary composed of optimal units, where units located on this boundary are considered the most efficient, while units not located on this boundary are considered relatively inefficient. Its wide application fields include economics, management, and engineering, which are of great significance for optimizing resource allocation and improving production efficiency.

2.2. Related research on total factor productivity

Existing research mainly explores total factor productivity (TFP) from the perspectives of region and industry, aiming to evaluate the quality of economic development in various regions through accurate measurement of TFP. At the regional level, scholars [3,4,5] used diverse methods to conduct detailed calculations and analysis of TFP of enterprises and provinces across different periods. Turning to the industry level, the research focus mainly focuses on the manufacturing industry [6]

to reveal the TFP changes within the industry and their impact on production efficiency.

Given the significant differences in resource endowment and development conditions among different regions in China, this heterogeneity directly leads to regional differences in total factor productivity levels, thereby exacerbating regional economic imbalances. In the long run, this regional economic gap poses significant challenges to the sustained and steady development of China's economy. Therefore, in the study of regional economic disparities, scholars generally focus on the regional disparities in total factor productivity, and conduct in-depth analysis at the provincial and urban levels. Among them, the Data Envelopment Analysis (DEA) method has become a widely used measurement tool due to its unique advantages [7], which not only helps to accurately identify the shortcomings of regional economic development, but also provides important theoretical support and empirical basis for formulating regional coordinated development strategies.

3. Empirical Research

3.1. Research Methods

There are two types of data envelopment models in the measurement of total factor productivity: constant returns to scale (CCR) and variable returns to scale (BCC). In this paper, the DEA model with variable returns to scale is selected to measure total factor productivity.

The Data Envelopment Analysis method, proposed by Charnes and Cooper in 1978, is a method for evaluating the efficiency of multiple decision units with multiple inputs/outputs. The DEA model is a non parametric analysis method that can measure the efficiency of each Decision Making Unit (DMU). Its basic idea is to treat all DMUs as input and output production process systems, and provide a basis for improving the production system by comparing the efficiency of each DMU.

The DEA method covers various models, among which the BCC and CCR models are the most commonly used, targeting variable and constant returns to scale, respectively. As an optimization of the CCR model, the BCC model not only inherits its essence, but also further divides the comprehensive efficiency into technical efficiency and scale efficiency, providing a more detailed analysis perspective. Given its superiority, this article adopts the BCC model in the DEA method to accurately measure total factor productivity and deeply analyze its internal composition and changing patterns.

Assuming there are n DMUs, namely the 30 provinces in this article, each DMU has m inputs x_{ij} and s outputs y_{rj} . Let their input and output vectors be:

$$x_{ij} = (x_{1j}, x_{2j}, \dots, x_{mj})^T, i = 1, 2, \dots, m \quad (1)$$

$$y_{rj} = (y_{1j}, y_{2j}, \dots, y_{sj})^T, r = 1, 2, \dots, s \quad (2)$$

Where x_{ij} represents the input value of the i -th item in the j th province; y_{rj} represents the output value of the r -th item in the j th province. The BCC model for evaluating total factor productivity in this article is as follows:

Among them, θ is the efficiency value, λ_j is the weight variable, s^- and s^+ are the relaxation variables.

$$\left\{ \begin{array}{l} \min \theta \\ \sum_{j=1}^n \lambda x_{ij} + s^- = \theta x_{i0}, i = 1, 2, \dots, m \\ \sum_{j=1}^n \lambda x_{rj} - s^+ = y_{r0}, r = 1, 2, \dots, s \\ \sum_{j=1}^n \lambda x_{0j} = 1 \\ \Lambda_j, s^-, s^+ \geq 0, j = 1, 2, \dots, n \end{array} \right. \quad (3)$$

3.2. Indicator Selection and Data Explanation

Based on previous research and literature review, it has been found that the input indicators of total factor productivity mainly start from labor and capital, while the output indicators are mostly GDP. Therefore, this article selects the number of employed people (10000 people) as the labor input, capital stock as the capital input, and actual GDP as the output. This article uses sample data of gross domestic product, capital stock, and labor input from 30 provinces (municipalities, autonomous regions) in China from 2007 to 2019 to calculate total factor productivity. The data comes from the China Statistical Yearbook and provincial statistical yearbooks.

(1) Gross Domestic Product

The total output of each province (municipality, autonomous region) in China is measured by GDP, with a unit of billions of yuan. And using 2006 as the base year, convert the annual GDP to constant prices to eliminate the influence of price factors.

(2) Capital stock

In order to pursue empirical rigor, this article uses Gold Smith's (1951) perpetual inventory method. The capital stock for period t is defined as: $K_t = I_t/P_t + (1 - \delta)K_{t-1}$.

Among them, K_t and K_{t-1} is the capital stock of the t and $t-1$ periods respectively, in 100 million yuan, I_t Indicate the total amount of fixed asset formation. P_t is the price index of fixed assets investment. δ is the depreciation rate. This article adopts Zhang's [8] setting of $\delta=9.6\%$. Regarding the initial capital stock, the earlier the initial year of the sample, the smaller the error in subsequent years affected by the basic stock of the base year. Based on the availability of data and the feasibility of operations, this article uses the capital stock calculated by Zhang [8] as the base year capital stock.

(3) Labor input

Regarding labor input, it generally refers to the quantity of labor force applied to actual social production. This article uses the year-end employment figures of the entire society in various regions to express it, with a unit of 10000 people.

As shown in Table 1.

Table 1. Input Output Indicator System.

Indicator Category	Indicator Name	Variable Name
Investment indicators	Number of employed L	Labor force (10000 people)
Output indicator	Capital K	capital stock
	Output G	Real GDP

3.3 Calculation and Analysis of Total Factor Productivity

Based on the variable index selection of total factor productivity accounting mentioned above, this paper uses DEAP2.0 software to select the DEA Malmquist index model with variable returns to scale and input orientation to calculate and decompose the TFP of 30 provinces (municipalities, autonomous regions) in China from 2007 to 2019. The results are shown in Table 2.

Table 2. TFP Calculation Results of Each Province from 2007 to 2017.

Region	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.76	1.12	0.777	0.574	0.962	1.186	2.503	0.58	0.879	0.714	1.258	1.405	0.629
Tianjin	1.347	1.099	0.698	0.566	1.084	1.207	2.165	0.631	0.902	0.679	1.223	1.529	0.578
Hebei	1.766	0.851	0.707	0.588	1.197	1.582	1.251	0.677	0.832	0.656	1.282	1.374	0.71
Shanxi	1.812	0.729	0.762	0.608	1.319	1.043	1.653	0.815	0.86	0.593	1.359	1.202	0.654
Inner Mongolia	1.79	0.746	0.781	0.569	1.833	0.582	1.828	0.832	0.844	0.597	1.371	1.701	0.634
Liaoning	1.917	0.624	0.739	0.682	1.328	0.925	1.887	0.809	0.829	0.63	1.44	1.441	0.694
Jilin	1.849	0.587	0.733	1.208	1.022	0.8	1.88	0.72	0.934	0.598	2.487	0.969	0.707
Heilongjiang	1.633	0.52	0.73	0.974	1.729	0.738	2.21	0.578	0.934	0.718	1.552	1.204	0.757
Shanghai	1.82	0.607	2.391	0.342	1.827	0.778	1.945	1.188	0.475	1.563	0.667	1.3	0.816
Jiangsu	1.848	0.6	1.778	0.438	1.845	0.805	1.622	1.186	0.513	1.196	0.818	1.435	0.754
Zhejiang	1.801	1.103	1.024	0.503	1.803	0.728	1.668	1.16	0.756	0.711	0.807	1.465	0.7
Anhui	1.629	0.803	1.319	0.615	1.681	0.666	1.603	1.263	0.512	1.244	0.781	1.38	0.654
Fujian	2.343	0.573	1.109	0.679	1.539	0.72	1.479	1.71	0.598	1.099	0.731	1.237	0.668
Jiangxi	1.691	0.743	1.326	0.577	1.482	0.795	1.442	1.088	0.823	1.28	0.647	1.047	0.754
Shandong	0.798	0.798	1.186	0.627	1.368	0.818	1.979	0.66	0.805	1.26	0.606	1.039	1.686
Henan	1.159	0.723	1.132	0.611	1.268	0.898	1.5	0.829	0.789	1.333	0.63	0.905	1.806
Hubei	1.019	0.74	1.228	0.506	1.241	1.279	0.837	1.007	0.708	1.231	0.635	1.017	1.829
Hunan	0.975	0.805	2.657	0.227	1.345	1.049	0.995	1.068	0.632	1.068	0.825	0.972	1.688
Hunan	0.789	0.949	2.439	0.271	1.65	0.972	0.947	0.932	0.685	1.104	0.783	1.27	1.173
Guangxi	0.704	1.233	1.836	0.331	1.184	1.15	1.052	0.882	0.643	2.48	0.555	0.708	1.789
Hainan	0.626	1.068	2.209	0.442	1.042	1.153	1.054	0.781	0.805	2.075	0.838	0.747	1.499
Chongqing	0.61	1.026	1.76	0.364	1.477	1.314	0.952	0.737	0.942	1.839	0.698	0.841	1.775
Sichuan	0.586	1.02	1.897	0.598	1.487	1.26	0.86	0.71	0.97	1.738	0.75	0.793	1.317

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Guizhou	0.68	0.849	1.049	0.952	1.49	1.28	0.78 6	0.72 3	1.09 7	1.484	0.65 7	1.058	1.276
Yunnan	0.714	1.463	0.512	1.114	1.359	1.19	0.85 9	0.68 9	1.44 3	1.083	0.72 9	0.955	1.283
Shaanxi	0.733	1.214	0.558	1.122	1.41	1.05 3	0.89 8	0.71 3	1.15 3	1.402	0.93 5	0.873	0.845
Gansu	0.948	0.672	0.647	1.08	1.306	1.00 5	1.00 2	1.56 1	0.56 9	1.479	0.95 9	0.805	0.792
Qinghai	1.072	0.763	0.687	0.973	1.302	1.04 6	1.17 2	0.95	0.70 7	1.452	0.97 1	0.997	0.398
Ningxia	0.892	0.689	0.734	0.951	1.211	1.08 8	1.77 2	0.75 3	0.74 7	1.245	1.03 4	0.912	0.805
Xinjiang	1.08	0.763	0.681	0.85	1.29	0.98 3	1.33 6	0.93 6	0.75 7	1.302	0.69 6	0.925	0.925

From Table 2, it can be seen that the overall total factor productivity shows a trend of first decreasing and then increasing. Before 2014, more than half of the regions had experienced a decline in total factor productivity, with over 70% of the regions experiencing a decline in total factor productivity from 2007 to 2009. This may be related to the economic crisis in 2008, and the data confirms this speculation. Most regions had lower TFP in 2008 than in 2007.

Secondly, among these provinces, Beijing and Shanghai have the highest level of economic development because their base period total factor productivity is relatively high. Shanxi, Hainan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang and other places have relatively low levels of economic development because their base period total factor productivity is already low and has been continuously decreasing in the early stage, so there is a lot of room for improvement. These situations are basically consistent with the facts. Furthermore, it can be seen that there are significant differences in total factor productivity among different provinces. Some developed economies such as Beijing, Shanghai, Jiangsu, Zhejiang and other provinces have relatively high total factor productivity, while some economically underdeveloped regions such as Xizang, Qinghai, Xinjiang and other provinces have relatively low total factor productivity. On the whole, the total factor productivity of China's 30 provinces shows a steady growth trend after experiencing initial fluctuations.

However, it is worth noting that several provinces suffer from excessive dependence on factors such as resources and the environment, which affect the improvement of their total factor productivity. The changes in total factor productivity are related to many factors, such as natural environment, economic measures, policy regulations, management capabilities, and so on. In addition, total factor productivity is also influenced by factors such as capital input, labor input, and technological progress. For example, regions like Beijing and Shanghai have large capital inputs and are also important technology centers in China, resulting in a significant increase in total factor productivity. But in other regions, due to the imbalance of technological level and capital investment, the level of total factor productivity growth varies. For example, provinces such as Beijing, Shanghai, and Zhejiang have relatively high total factor productivity, which is closely related to their developed economic strength, policy advantages, advanced technology, and so on. For some underdeveloped areas with low total factor productivity, it is necessary to start from multiple aspects, increase investment and reform efforts, and continuously improve the economic level and total factor productivity of weaker areas.

To further explore the sources of total factor productivity growth, this article decomposes TFP into technical efficiency (EC) and technological progress (TC), with specific values shown in Table 3 and Table 4.

Table 3. EC values of each province from 2007 to 2019.

Region	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.712	1.336	0.59	1.382	0.652	1.132	1.746	0.76	1.295	0.501	1.523	1.322	0.77
Tianjin	1.208	1.318	0.527	1.357	0.735	1.147	1.611	0.762	1.351	0.47	1.48	1.439	0.708
Hebei	1.554	1.054	0.518	1.416	0.827	1.646	1.002	0.772	1.265	0.45	1.551	1.303	0.756
Shanxi	1.551	0.895	0.563	1.477	0.915	1.04	1.251	0.908	1.323	0.402	1.644	1.132	0.638
Inner Mongolia	1.507	0.936	0.563	1.423	1.466	0.628	1.326	0.899	1.311	0.402	1.66	1.527	0.677
Liaoning	1.602	0.861	0.516	1.686	0.851	0.95	1.382	0.855	1.282	0.427	1.744	1.309	0.688
Jilin	1.585	0.828	0.509	2.301	0.826	0.789	1.371	0.745	1.457	0.4	2.657	0.921	0.682
Heilongjiang	1.389	0.701	0.528	2.359	1.175	0.707	1.566	0.6	1.435	0.487	1.853	1.074	0.724
Shanghai	1.524	0.799	1.581	0.732	1.233	0.732	1.398	1.082	0.817	1.224	0.716	1.167	0.763
Jiangsu	1.557	0.774	1.392	0.912	1.29	0.748	1.181	1.1	0.854	0.853	0.977	1.301	0.699
Zhejiang	1.511	1.369	0.745	1.033	1.274	0.675	1.214	1.09	1.143	0.65	0.969	1.341	0.646
Anhui	1.364	0.941	1.1	1.24	1.2	0.615	1.182	1.18	0.762	1.012	0.941	1.269	0.603
Fujian	2.083	0.69	0.913	1.358	1.115	0.663	1.1	1.438	0.852	0.814	0.886	1.141	0.616
Jiangxi	1.337	0.871	1.077	1.189	1.075	0.73	1.082	1.054	1.16	0.915	0.788	0.969	0.697
Shandong	0.726	0.942	0.954	1.311	1.003	0.752	1.542	0.77	1.148	0.883	0.739	0.964	1.806
Henan	0.94	0.861	0.898	1.326	0.94	0.828	1.068	1.071	1.138	0.916	0.773	0.845	1.937
Hubei	0.841	0.883	0.953	1.2	0.924	1.275	0.671	1.251	1.036	0.842	0.78	0.949	1.846
Hunan	0.821	0.964	1.299	0.88	1.006	1.009	0.697	1.3	0.925	0.756	1.009	0.908	1.67
Hunan	0.666	1.135	1.247	1.003	1.101	1	0.702	1.101	1.012	0.762	0.96	1.243	1.252
Guangxi	0.602	1.483	0.948	1.183	0.839	1.121	0.794	1.018	0.952	1.382	0.691	0.647	1.798
Hainan	0.54	1.284	1.151	1.252	0.852	1.093	0.807	0.896	1.199	1.187	0.917	0.706	1.46
Chongqing	0.547	1.233	0.925	1.261	1.013	1.207	0.735	0.851	1.403	1.108	0.849	0.752	1.671
Sichuan	0.551	1.226	1.328	0.973	1.016	1.133	0.671	0.833	1.435	1.284	0.905	0.722	1.237
Guizhou	0.642	1.019	0.735	1.895	1.048	1.128	0.616	0.847	1.627	1.052	0.79	0.97	1.193
Yunnan	0.665	1.653	0.389	2.335	0.973	1.048	0.675	0.802	1.992	0.871	0.883	0.888	1.229
Shaanxi	0.684	1.448	0.448	2.327	1.01	0.927	0.704	0.833	1.642	1.033	1.144	0.841	0.902
Gansu	1	0.794	0.532	2.217	0.948	0.892	0.782	1.615	0.799	1.056	1.178	0.771	0.894
Qinghai	1.154	0.91	0.557	1.998	0.939	0.938	0.913	1.126	1.01	1.025	1.193	0.957	0.428

Ningxia	0.849	0.825	0.594	1.947	0.883	0.98 5	1.42	0.77 2	1.08 7	0.86 7	1.273	0.877	0.935
Xinjiang	0.904	0.919	0.548	1.745	0.932	0.89 6	0.98 8	1.12 6	1.10 7	0.91 8	1.486	0.678	1.057

Table 4. *TC values of each province from 2007 to 2019.*

Region	2007	2008	2009	2010	2011	201 2	201 3	201 4	201 5	2016	2017	2018	2019
Beijing	1.067	0.839	1.318	0.415	1.475	1.04 7	1.43 3	0.76 3	0.67 9	1.42 4	0.82 6	1.062	0.817
Tianjin	1.115	0.834	1.324	0.417	1.474	1.05 2	1.34 4	0.82 8	0.66 8	1.44 6	0.82 7	1.063	0.816
Hebei	1.137	0.808	1.366	0.415	1.446	0.96 1	1.24 8	0.87 6	0.65 8	1.45 8	0.82 6	1.054	0.939
Shanxi	1.168	0.814	1.353	0.412	1.441	1.00 3	1.32 2	0.89 8	0.65	1.47 4	0.82 7	1.062	1.025
Inner Mongolia	1.188	0.797	1.388	0.4	1.251	0.92 7	1.37 9	0.92 6	0.64 4	1.48 4	0.82 6	1.114	0.937
Liaoning	1.197	0.724	1.433	0.405	1.561	0.97 4	1.36 5	0.94 7	0.64 7	1.47 5	0.82 6	1.101	1.01
Jilin	1.167	0.709	1.44	0.525	1.238	1.01 3	1.37 2	0.96 6	0.64 1	1.49 6	0.93 6	1.052	1.038
Heilongji ang	1.175	0.741	1.383	0.413	1.471	1.04 4	1.41 1	0.96 3	0.65	1.47 5	0.83 7	1.12	1.046
Shanghai	1.194	0.76	1.513	0.468	1.481	1.06 3	1.39 1	1.09 7	0.58 2	1.27 7	0.93 1	1.114	1.069
Jiangsu	1.187	0.775	1.277	0.48	1.43	1.07 6	1.37 4	1.07 8	0.60 1	1.40 2	0.83 8	1.103	1.08
Zhejiang	1.191	0.806	1.374	0.487	1.415	1.07 9	1.37 4	1.06 4	0.66 1	1.09 4	0.83 3	1.093	1.084
Anhui	1.194	0.853	1.198	0.496	1.401	1.08 2	1.35 6	1.07 1	0.67 2	1.22 9	0.83	1.088	1.085
Fujian	1.124	0.831	1.214	0.5	1.38	1.08 7	1.34 4	1.18 9	0.70 1	1.35	0.82 5	1.084	1.085
Jiangxi	1.264	0.854	1.231	0.485	1.379	1.08 9	1.33 3	1.03 2	0.70 9	1.39 9	0.82 1	1.08	1.082
Shandon g	1.099	0.847	1.244	0.478	1.363	1.08 7	1.28 3	0.85 7	0.70 1	1.42 7	0.81 9	1.078	0.934
Henan	1.233	0.84	1.261	0.46	1.349	1.08 4	1.40 5	0.77 4	0.69 3	1.45 5	0.81 5	1.071	0.932
Hubei	1.212	0.838	1.289	0.422	1.344	1.00 4	1.24 8	0.80 5	0.68 4	1.46 2	0.81 5	1.072	0.991
Hunan	1.188	0.835	2.045	0.258	1.337	1.04	1.42 7	0.82 2	0.68 4	1.41 2	0.81 8	1.07	1.011
Hunan	1.184	0.836	1.955	0.271	1.499	0.97 2	1.34 9	0.84 7	0.67 6	1.44 9	0.81 5	1.022	0.937
Guangxi	1.17	0.832	1.936	0.28	1.411	1.02 6	1.32 5	0.86 6	0.67 5	1.79 4	0.80 3	1.093	0.995
Hainan	1.159	0.831	1.919	0.353	1.223	1.05 5	1.30 6	0.87 2	0.67 2	1.74 8	0.91 4	1.058	1.027
Chongqi ng	1.115	0.832	1.903	0.289	1.458	1.08 8	1.29 5	0.86 5	0.67 1	1.66	0.82 2	1.118	1.062
Sichuan	1.065	0.832	1.429	0.614	1.463	1.11 5	1.28 7	0.85 5	0.67 6	1.35 4	0.83 6	1.098	1.065
Guizhou	1.059	0.833	1.427	0.502	1.422	1.13 5	1.27 6	0.85 4	0.67 4	1.41	0.83 2	1.09	1.069
Yunnan	1.074	0.885	1.315	0.477	1.397	1.13 6	1.27 3	0.85 9	0.72 4	1.24 4	0.82 6	1.075	1.044
Shaanxi	1.071	0.839	1.244	0.482	1.395	1.13 6	1.27 6	0.85 6	0.70 2	1.35 7	0.81 8	1.038	0.937
Gansu	0.948	0.846	1.217	0.487	1.378	1.12 7	1.28 1	0.96 6	0.71 3	1.4	0.81 4	1.044	0.887
Qinghai	0.928	0.838	1.234	0.487	1.386	1.11 5	1.28 3	0.84 3	0.7	1.41 6	0.81 3	1.043	0.931
Ningxia	1.05	0.836	1.236	0.488	1.372	1.10	1.24	0.97	0.68	1.43	0.81	1.04	0.861

						4	8	5	7	6	3		
Xinjiang	1.194	0.831	1.244	0.487	1.385	1.09 7	1.35 3	0.83 1	0.68 4	1.41 9	0.83 4	1.027	0.876

Note: The data is calculated and organized according to DEAP2.1

Table 3 and Table 4 show the EC and TC values of 30 provinces in China from 2007 to 2019, respectively. Among them, EC value represents technical efficiency, and TC value represents technological progress. The EC value reflects the ratio of input to output in the production process, while the TC value reflects the improvement of production efficiency in the production process. From Tables 3 and 4, it can be seen that the technological progress and efficiency values from 2007 to 2019 were constantly fluctuating, while the technological efficiency showed a continuous decline, both of which jointly affect total factor productivity.

Firstly, from the perspective of technical efficiency, there are significant differences in EC values among provinces. In 2007, the EC value in Fujian was the highest, reaching 2.083. Subsequently, from 2012 to 2016, the EC values of various provinces generally showed a downward trend, indicating that the competition pressure in the entire economic environment continued to increase, and technological progress was not fully applied. This indicates that the overall growth of productivity in China is slow, and the efficiency of technology and resource utilization has deteriorated. The reasons for the decline in EC values may also include resource waste, technological backwardness, environmental pollution, lack of innovation ability, etc. in the production process. In 2017 and 2019, the EC values of most provinces have increased, which may indicate that the economy is gradually recovering and the application and innovation of technology are gradually strengthening.

Secondly, from the perspective of technological progress, there are significant differences in TC values among provinces, and the total factor productivity of each province shows a continuous fluctuation trend with increasing years. Subsequently, from 2011 to 2013, the TC values of various provinces generally showed a downward trend, indicating that the competition pressure in the entire economic environment continued to increase, and technological progress was not fully applied. Since 2014, the TC values of most provinces have increased, which may indicate that the application and innovation of technology are gradually strengthening. The reasons for the changes in TC values may include technological innovation, human capital accumulation, etc. Compared to other regions, Beijing, Shanghai, Guangdong, Shandong, and other places have relatively high levels of technological progress and efficiency in the country. Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang have relatively low rankings in the country. It is necessary to optimize resource allocation efficiency to improve technological efficiency, continue to rely on policies to attract talents and enterprises, strengthen innovation and technology introduction, and thus increase the value of technological progress.

Based on comprehensive analysis, we can conclude that the trends in technological efficiency and progress are influenced by various factors such as economic environment, competitive pressure, and investment in technological innovation. For example, during periods of economic slowdown, technological innovation and application will face greater difficulties.

4. Conclusions

This paper uses the statistical data of 30 provinces (except Xizang) in China from 2007 to 2019, based on the DEA efficiency evaluation method, calculates the TFP of each province in China by constructing an input-output index system, analyzes the differences and change trends of total factor productivity in each province, and also explores the underlying reasons. Based on the entire text, the main conclusions are as follows:

(1) The total factor productivity of 30 provinces in China has shown a steady growth trend after experiencing initial fluctuations. In addition, there are significant differences in total factor productivity among different provinces. Some developed economies such as Beijing, Shanghai, Jiangsu, Zhejiang and other provinces have relatively high total factor productivity, while some economically underdeveloped regions such as Xizang, Qinghai, Xinjiang and other provinces have relatively low total factor productivity. However, it is worth noting that, in addition to the impact of capital input, labor force input, technological progress and other factors, changes in total factor productivity are related to many factors, such as natural environment, economic measures, policies and regulations, management capacity and so on.

(2) From 2007 to 2019, both the technological progress value and the technological efficiency value were constantly fluctuating, while the technological efficiency showed a continuous decline, both of which jointly affect total factor productivity. In addition, there are significant differences in EC and TC values among provinces, and the trend of technological efficiency and progress may be influenced by various factors such as economic environment, competitive pressure, and technological innovation investment.

Based on the above analysis, there is a significant gap in total factor productivity among different regions in China, and the existence of this gap has a significant impact on the economic disparities between regions. Therefore, in order to improve the total factor productivity level in underdeveloped areas, alleviate the total factor productivity gap between regions in China, and promote high-quality development of the overall Chinese economy, combined with the empirical results of this article and the current economic environment, the main policy recommendations are proposed as follows.

Firstly, strengthen investment in technological innovation and research and development. Invest more resources and funds to promote the research and application of new technologies and processes, improve production efficiency and quality, and increase R&D and manpower investment. Strengthen cooperation between universities, research institutions, and enterprises to improve APLR (Per Capita Labor Productivity).

Secondly, focus on improving domestic human capital and enhancing technological efficiency. We need to increase the cultivation of high-quality talents, increase investment in education, and improve the domestic knowledge and technology innovation capabilities and human capital level. To meet the development needs of enterprises in an open economic environment, it is necessary to further strengthen school enterprise cooperation, provide targeted and practical talents to enterprises, help schools' scientific research achievements be transformed into actual production of enterprises, improve the professional competence and technical level of enterprise

human capital, and give full play to the use of high-quality talents in enterprise research and innovation.

Thirdly, each province should formulate policies tailored to local conditions and provide differentiated guidance for the economic development of each district. The government can attract the flow of innovative factors and guide the rational aggregation of factors through a series of incentive policies. When the market fails, we should actively play a strong guiding role, adjust factor ratios, optimize resource allocation, leverage the positive effects of technological factors, improve technological efficiency, promote technological progress, and decisively upgrade industries when necessary, thereby improving total factor productivity.

Fourthly, strengthen management and supervision, and governments at all levels should formulate comprehensive plans and policies. Strengthen the management and supervision of enterprises, and promote the coordinated development of the industrial chain. At the same time, a scientific assessment system should be established, and corresponding measures should be taken for industries and enterprises with low productivity to promote the improvement of productivity.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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