Research on Total Factor Productivity Change of Industrial Sectors in Guizhou Province in China

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Abstract. To analyze the current status of industrial efficiency development in Guizhou Province, firstly, the development profile of key industries in Guizhou Province was initially screened and analyzed by using the location quotient method. And then, the development trend of the total factor productivity change rate of key industries in Guizhou Province was analyzed by using the DEA-Malmquist index method from the perspectives of the three input indexes, namely, capital, labor, and energy consumption. It is found that (1) except for the two years of 2016-2018, the total factor productivity of key industries in Guizhou Province has maintained a long-term growth trend, in which the main contribution comes from the improvement of pure technical efficiency and scale efficiency; (2) some industries like non-ferrous metals, metal products and transportation equipment show most significant total factor productivity increase in recent years, which could be further studied to learn from their good experience.

Keywords: Guizhou Province; industrial sector; total factor productivity; DEA-Malmquist

1 Introduction

With the rapid growth of China's economy, the problems of energy consumption and the environment have become more and more prominent, especially in the industrial sector, where energy consumption and emissions are the most significant. Although, as the "world factory", China produces industrial products for global supply and the end consumption of industrial products is not limited to our country, the energy consumption, greenhouse gas emissions and pollutant emissions that are directly related to production are closely related to our living environment. With the improvement of economic level and the deepening of the understanding of energy and environment, it is difficult to adapt to the rough economic development mode to meet the needs of today's social development. From national to local, society is actively exploring development path like "energy saving and emission reduction" and "industrial transformation": outside the industrial category, seeking secondary to tertiary transformation; within the industrial category, seeking high energy -consuming industries to environmentally

X. Li et al. (eds.), *Proceedings of the 2025 International Conference on Agriculture and Resource Economy (ICARE 2025)*, Advances in Biological Sciences Research 46,
https://doi.org/10.2991/978-94-6463-746-5_16

friendly high-tech industry transformation; within the high-energy-consuming and high-emission industries, new technology research and development and breakthroughs are sought to achieve the "new look" of industries.

The population of Guizhou Province accounts for about 2.7 percent of China's population, while the number of industrial enterprises accounts for only 1.1 percent and total energy consumption of industrial enterprises accounts for 1.4 percent of the country's total energy consumption. The level of industrial development is more lagging behind compared to the country, and the development of various industries and subclasses within the major categories of the industry is not balanced. In March 2023, Guizhou Province issued the "Guizhou Province Industrial Area Carbon Peak Implementation Program", which sets out eight key tasks, including promoting the transformation and upgrading of industrial industries, advancing industrial energy conservation and carbon reduction, and implementing special actions for green manufacturing and efficiency promotion.

Efficiency is the evaluation of inputs and outputs, including single-factor efficiency evaluation and multi-factor efficiency evaluation. Single-factor efficiency evaluation evaluates only one input, for example, asset utilization efficiency evaluates the relationship between asset inputs and output value, and energy utilization efficiency evaluates the relationship between energy inputs and output value. Multi-factor efficiency evaluation is used to evaluate the overall efficiency level of multiple inputs and multiple outputs, such as total factor productivity, which can be used to evaluate the development and use efficiency level of the overall resources (capital, labor, land, energy, etc.) of a production unit, and commonly used measurement methods include Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA).

Zhu et al.[1] adopted a three-stage data envelopment analysis model and the Malmquist index to assess the agricultural production efficiency of Jiangsu and Anhui Provinces from 2018 to 2022. Shobha et al.[2] conducted a two-stage analysis and uses data envelopment analysis and global Malmquist productivity index (MPI) approach in the first stage to calculate the managerial performance of a panel of 63 Indian hotels in 2019–2020. Luo[3] conducted DEA Malmquist index analysis on the dynamic changes of total factor productivity in the logistics industry at different times. Horváthová et al.[4] applied DEA model and MI method to discuss the process of the digital transformation of EU countries. Dorta et al.[5] aimed to estimate technical efficiency using a sample of 34 airline groups between 2019 and 2022, with a Malmquist-Data Envelopment Analysis methodology that includes financial, operational, and sustainability scores. Edziah et al.[6] employs an endogenous stochastic frontier analysis model using data from the Asia Pacific Energy Portal Policy database covering 23 emerging economies from 2000 to 2017 to assess how energy policies affect energy efficiency in the APAC region. Altab et al.[7] aimed to present scientific evidence for the energy efficiency through the interaction effects of AI and energy use along with other variables in the Middle East and North Africa region from 2000–2021 using the dual approaches of data envelope analysis and stochastic frontier analysis. Kallel et al.[8] followed the stochastic frontier analysis to evaluate and compare bank efficiency between the two Maghreb countries, Tunisia and Morocco, over the period 2005–2014. In industry sector, there are also other methods being adopted to discuss the efficiency development, like STIRPAT model[9], knee-point-driven multi-objective optimization[10], operation strategy considering power flow[11] and bi-level stochastic production simulation[12].

Existing studies on the manufacturing industry in Guizhou Province were carried out a long time before, and there are differences in the research methods, which have a limited role in guiding the industrial development of Guizhou Province under the new policy environment and new development mode. This study aims to analyze the development level of industries in Guizhou Province, so as to play a positive role in promoting energy conservation and emission reduction as well as industrial transformation and coordinated development in Guizhou Province.

2 Research Methodology

In this study, we firstly conducted a preliminary mapping of the development level and importance of 41 industrial sectors (7 in mining, 31 in manufacturing, and 3 in electricity, heat, gas, and water production and supply) in Guizhou Province from the perspective of location quotient, and located the key sectors for subsequent detailed analyses. Afterwards, the DEA-Malmquist index method was used to analyze the total factor productivity growth rate of key industries in Guizhou province, and to study the differences in the development of the industries.

2.1 Location Quotient

Location quotient is often used to measure the spatial distribution of a certain element or the importance of a certain region in a high-level region. In industrial analysis research, location quotient indicators are often used to analyze the status of leading industries in a region.

Taking industry n in region m as an example, its location quotient relative to the whole country is calculated as shown in formula (1).

$$LQ_{mn} = (P_{mn}/P_m)/(P_n/P) \tag{1}$$

where P_{mn} denotes the characteristic index P (e.g. output value, number of employees, energy consumption, etc.) of industry n in region m, P_m denotes the corresponding characteristic index P of all industries in region m, P_n denotes the corresponding characteristic index P of industry n in the whole country, and P denotes the corresponding characteristic index P of all industries in the whole country. Generally speaking, LQ_{mn} greater than 1 means that industry n in region m has a concentration level relative to the whole country: the higher its value, the higher the agglomeration level of region m's n industry. Bandara[13] utilized shift-share and location quotient analyses to identify the sectors driving regional employment in West Virginia and assesses their performance. Cheng[14] adopted location quotient of the logistics industry to measure the industry’s concentration degree in Korea.

2.2 DEA-Malmquist Index

Data Envelopment Analysis, a non-parametric technical efficiency analysis method, was first proposed in 1978. Since then, the theory and practical methods of DEA have developed rapidly, and the scope of application has been expanding. The commonly used basic models include Constant Returns to Scale (CRS, also known as CCR model) and Variable Returns to Scale (VRS, also known as BCC model). Both the CCR model and the BCC model are radial DEA models, whose measure of the degree of inefficiency includes only the proportion of all inputs that shrink or increase in equal proportion to their outputs, and excludes slack improvements. In order to consider the slack improvement component in the measurement of efficiency value, Slack Based Measure (SBM) was proposed as shown in equation (2).

$$
\begin{gathered}
min\ \theta = \left[\left(1 - \frac{1}{m}\sum_{i=1}^{m} s_i^-\right)/x_{ik}\right] \Big/ \left[\left(1 + \frac{1}{q}\sum_{r=1}^{q} s_r^+\right)/y_{rk}\right] \\
s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ik} \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk} \\ \lambda, s^-, s^+ \geq 0 \\ i = 1,2,\ldots,m; j = 1,2,\ldots,n; r = 1,2,\ldots,q \end{cases}
\end{gathered} \tag{2}
$$

where θ denotes the efficiency value of the decision unit, x denotes inputs, y denotes outputs, λ denotes the weight coefficient, and s^- and $s^+$are the input slack and output slack variables, respectively.

When we set resources (like, labour force, capital investment and energy consumption) as the input and industry added value as the output, the efficiency θ is also called total factor productivity (TFP). But as DEA is a non-parametric method, the number of TFP in a single year could not be computed. Only the change rate of TFP could be calculated using time-series panel data, which is called DEA-Malmquist index (MI).

The calculation of the MI by the DEA method is commonly used as a neighborhood measure, i.e., it focuses on the TFP of two neighboring periods, whose specific values cannot be calculated directly, but whose proportions can be calculated to reflect the changes in TFP. Therefore, the DEA-MI method does not calculate TFP directly, but calculates the rate of change of TFP, taking the neighborhood measure from (t-1) time to t time as an example, and its calculation logic is shown in (3).

$$
\begin{aligned}
MI(t, t-1) &= \frac{\phi_t(x_t, y_t)}{\phi_{t-1}(x_{t-1}, y_{t-1})} \\
&\times \sqrt{\frac{\phi_{t-1}(x_{t-1}, y_{t-1})}{\phi_t(x_{t-1}, y_{t-1})} \times \frac{\phi_{t-1}(x_t, y_t)}{\phi_t(x_t, y_t)}} \\
&= EC(t, t-1) \times TC(t, t-1)
\end{aligned} \tag{3}
$$

where $\phi_{t-1}(x_{t-1}, y_{t-1}) = TFP(x_{t-1}, y_{t-1})/TFP(benchmark_{t-1})$ denotes the value of DEA efficiency derived from the efficient frontier at the time of (x_{t-1}, y_{t-1}) reference (t-1). MI can be decomposed into the Technical Efficiency Change (EC) and Technical Change (TC) components. EC (the part before the multiplication sign in formula above) represents the change in the two periods relative to their respective efficient frontiers, reflecting an increase or decrease in technical efficiency, while TC (the part after the multiplication sign in formula above) represents the relative change in the efficient frontiers in the two periods, reflecting an advance or retreat in the technology itself. The combination of the CCR-Malmquist and BCC-Malmquist methods yields different EC values, which is the result of scale effect. Thus, EC can be further decomposed into Pure Technical Efficiency Change (PTEC) and Scale Efficiency Change (SEC), that is EC=PTEC×SEC, which reflects its impact on technical efficiency measures when considering the scale effect, i.e., as shown in Equation (4).

$$\begin{aligned} MI(t,t-1) &= PTEC(t,t-1) \\ &\times SEC(t,t-1) \times TC(t,t-1) \end{aligned} \tag{4}$$

3 Case Study

3.1 Data Source

For LQ analysis, the key basic data for the overall analysis of the industrial sector in Guizhou province include the number of industrial enterprises (NE), the output value of industrial enterprises (OVE) and the total energy consumption of each industrial sector (EC), while the derived data include the enterprise size (ES = OVE / NE) and the energy consumption of ten thousand yuan output value (ECY= EC / OVE). The data include province-wide data and national data for location quotient analysis. The data sources are Guizhou Statistical Yearbook and China Statistical Yearbook.

For DEA-MI analysis, it is based on the panel data of subindustries in Guizhou Province in period of 2013-2022, with the input variables being capital stock, labor force and energy consumption, and the output part being industrial output value. Among them, the labor force data are from the China Industrial Statistical Yearbook, and the remaining three data are from the Guizhou Provincial Statistical Yearbook. As the China Industrial Statistical Yearbook lacks data for 2017 and 2018, linear interpolation is used to complete the labor force panel data for these two years in order to avoid unbalanced panels affecting the model analysis

3.2 Location Quotient Analysis of Industrial Sector in Guizhou Province

Location quotient is calculated for 41 industrial sectors in Guizhou Province according to three factors (set NE, OVE and EC separately as the P in formula 1) to analyze the LQ concentration of enterprises (CEP), LQ concentration of revenue (CR) and LQ concentration of energy (CE) in every industry sector; meanwhile, the relative scale of enterprises (PEP = ES in an industry in Guizhou Province / ES in that industry in China) and the relative energy efficiency level of enterprises in the sector (EE = ECY of an industry in Guizhou Province / ECY of same industry in China), in order to analyze the position of the industry enterprises and energy efficiency level. The results are shown in Table 1.

Table 1. Location quotient analysis of industrial sector in Guizhou Province in 2022

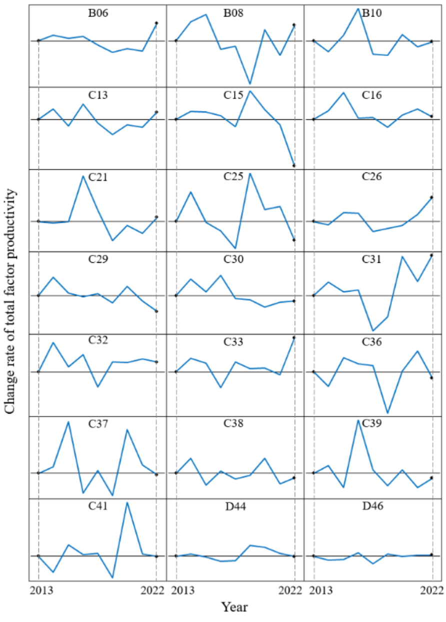
Industry Index[a]	CEP	CR	CE	PEP	EE
B06	7.21	2.88	4.53	0.27	3.01
B07	-[b]	-	-	-	-
B08	1.30	0.17	0.50	0.09	5.70
B09	2.60	1.21	0.93	0.31	1.47
B10	4.25	3.45	1.76	0.54	0.97
B11	-	-	-	-	-
B12	-	-	-	-	-
C13	1.49	0.59	0.64	0.26	2.10
C14	1.15	0.75	0.54	0.43	1.37
C15	6.68	11.51	3.70	1.15	0.62
C16	2.01	5.16	3.55	1.71	1.31
C17	0.16	0.14	0.12	0.58	1.62
C18	0.38	0.22	0.25	0.39	2.18
C19	0.55	0.34	0.24	0.42	1.36
C20	0.84	0.51	0.85	0.40	3.18
C21	0.49	0.14	0.85	0.19	12.08
C22	1.21	0.90	0.63	0.49	1.34
C23	0.83	0.88	0.44	0.71	0.94
C24	0.28	0.11	0.34	0.25	6.09
C25	0.77	0.28	0.19	0.24	1.30
C26	0.83	0.88	0.70	0.70	1.51
C27	1.36	1.16	0.57	0.57	0.94
C28	-	-	-	-	-
C29	0.68	0.73	0.60	0.71	1.58
C30	1.89	1.18	1.42	0.42	2.31
C31	1.45	0.59	0.61	0.27	1.99
C32	1.19	1.40	2.74	0.78	3.75
C33	0.57	0.38	0.46	0.44	2.31
C34	0.27	0.24	0.19	0.59	1.52
C35	0.32	0.20	0.22	0.43	2.04
C36	0.29	0.27	0.15	0.63	1.08
C37	0.82	2.15	1.20	1.75	1.07
C38	0.52	0.51	1.71	0.65	6.45
C39	0.53	0.70	0.30	0.88	0.81
C40	0.24	0.14	0.59	0.39	7.99
C41	0.74	1.10	1.25	0.99	2.17
C42	1.01	0.35	1.37	0.23	7.47
C43	-	-	-	-	-
D44	2.02	2.30	1.35	0.76	1.13
D45	1.57	0.99	0.27	0.42	0.51
D46	2.84	1.93	1.76	0.45	1.74

a. Index from GB/T 4754-2017 Industrial Classification for National Economic Activities.
b. "-" indicates missing data.

From the results of the initial screening of industry location quotients, it can be seen that the following 21 sub-industries have higher concentration in Guizhou Province, are more closely related to the development of Guizhou's industrial economy and the vision of energy saving and carbon reduction: B06 mining and washing of coal, B08 mining and processing of ferrous metal ores, B10 mining and processing of nonmetal ores, C13 processing of food from agriculture products, C15 manufacture of alcohol beverages and refined tea, C16 manufacture of tobacco, C21 manufacture of furniture, C25 processing of petroleum coking and nuclear fuel, C26 manufacture of chemical raw materials and chemical products, C29 manufacture of rubber and plastics, C30 manufacture of non-metallic mineral products, C31 smelting and processing of ferrous metals, C32 smelting and processing of non-ferrous metals, C33 manufacture of metal products, C36 manufacture of automobiles, C37 manufacture of railway ships aerospace and other transportation equipment, C38 manufacture of electrical machinery and equipment, C39 manufacture of computers communication and other electronic equipment, C41 other manufacturing, D44 production and distribution of electric power and heat power, D46 production and distribution of tap water. Among them, B06, C15, C30, C32, and D44 are the most notable ones, with a large number of enterprises, high output value, and a large share of energy consumption, which play a pivotal role in the green development of Guizhou's industry. The following analysis of total factor productivity in industrial industries will only focus on the 21 key industries initially screened out in this study.

3.3 Analysis of Total Factor Productivity in Industrial Sectors

The DEA-MI method is used to analyze the total factor productivity growth rate of the above 21 key industrial industries in Guizhou Province from 2013 to 2022, and to study the differences in industry development. The results of the analysis of each industry are shown in Figure 1.



*For every sparkline diagram in the graph, the black solid line indicates the change rate as 1 (no change). Higher than the black solid line means total factor productivity increase, and vice versa.

Fig. 1. Rates of change in total factor productivity in key industrial sectors in Guizhou Province in period of 2013-2022

It can be found from the growth rate of total factor productivity in key industries that the development pattern is mainly divided into the following three types: U-type, L-type, W-type. U-type mainly includes B06, C13, C16, C21, C26, C31, C32, C33, C37, D44, the overall form of early productivity gains, the middle period declines, and in recent years, productivity returns to the growth trend; L-type includes C15 and C30, with overall performance of the early production efficiency maintaining growth for a long time, but in recent years performing a decline in efficiency; W-type including B08, B10, C25, C29, C36, C38, C39, C41, D46, the overall performance of the industry's production efficiency fluctuates in the neighboring years of efficiency with gains and declines occurring repeatedly. The two leading industries in Guizhou Province, namely "B06 Mining and Washing of Coal" and "C15 Manufacture of Alcohol Beverages and Refined Tea", are selected as examples for analysis to illustrate that the growth rate of total factor productivity of the industry is closely related to the development trajectory of the industry itself.

The coal industry is greatly affected by economic development and policies. With the capital expansion under the "Four Trillion" plan, the coal industry has gradually become overcapacity, and entered the supply-side reform stage in about 2016, followed by more stringent environmental protection and safety policies in 2019, which led to the tightening of supply, and ultimately the price of coal was reduced in 2021 under the dual influence of strong demand and supply constraints. From the coal index annual K chart can also be seen, the index from 2014-2017 rose in successive years, 2018-2020 fell after the low-level shock, 2021 quickly rebounded and rose, and its trend and B06 total factor productivity curve pattern have a high degree of consistency.

Chinese Baijiu is a pillar industry in Guizhou Province, and "C15 Manufacture of Alcohol Beverages and Refined Tea" is the manufacturing industry with the highest output value in Guizhou Province. The liquor industry has obvious cross-cyclical attributes, and the industry has developed steadily over a long period of time. During the period 2009-2012, the industry's development was hindered at a stage due to the increase in taxes and fees, the restriction of public consumption and the plasticizer incident, etc. Subsequently, the market share of famous liquor enterprises steadily increased, and the concentration of the industry improved. Since Moutai's sales reached top in 2013, it has gradually led to the "Jiang-flavor Baijiu fever", which has helped the output value of Guizhou's liquor industry to grow year after year until 2020. By the baijiu index annual K chart can also be seen, the index from 2014-2020 (except 2018) rose in successive years, 2021 fell from the peak, and its trend and C15 total factor productivity curve shape also have a high degree of consistency.

By decomposing the TFP growth rate into factors as TC, PTEC and SEC, the relevant factor decomposition for each key industry is calculated as shown in Table 2.

Table 2. Decomposition of total factor productivity growth rate of key industrial sectors in Guizhou Province in 2022

Industry Index	**EC**	**TC**	**PTEC**	**SEC**	**TFP**
B06	1.042	0.948	1.000	1.042	0.987
B08	0.996	0.949	1.041	0.957	0.945
B10	1.011	0.969	0.980	1.032	0.980

C13	1.038	0.953	1.000	1.038	0.989
C15	0.972	0.999	1.000	0.972	0.971
C16	1.000	1.061	1.000	1.000	1.061
C21	1.030	0.988	1.000	1.030	1.018
C25	1.045	0.994	1.041	1.004	1.039
C26	1.037	0.995	1.011	1.026	1.032
C29	1.055	0.948	1.023	1.032	1.000
C30	1.042	0.967	1.014	1.028	1.008
C31	1.078	0.968	1.000	1.078	1.043
C32	1.104	0.997	1.062	1.039	1.101
C33	1.110	0.960	1.100	1.009	1.065
C36	1.013	0.943	1.035	0.979	0.955
C37	1.071	0.991	1.093	0.980	1.062
C38	0.952	1.017	0.959	0.993	0.969
C39	0.992	0.988	1.000	0.992	0.980
C41	1.001	0.981	0.940	1.065	0.982
D44	1.020	1.024	1.000	1.020	1.044
D46	0.977	1.001	0.936	1.044	0.978
Average	1.027	0.983	1.010	1.017	1.009

As shown in the results, the total factor productivity of key industrial industries in Guizhou Province increased slightly during the study year, by about 0.9% on average, mainly due to the increase in pure technical efficiency (+1%) and scale efficiency (+1.7%), while the technical level (-1.7%) declined slightly. For sub-industry, the three types of mining industry （B06, B08, B10） total factor productivity have shown a decline (-2% ~ -5.5%), of which by the most obvious reduction in the level of technology (-3.1% ~ -5.2%). As for the 16 types of manufacturing industries, total factor productivity decline in C13, C15, C36, C38, and C39. The most significant decrease in efficiency is in the C36 automobile manufacturing industry, mainly due to the decline in the level of technology (-5.7%). Among the two types of electricity, heat, gas and water supply industries (D44, D46), total factor productivity increased in the electricity and heat production and supply industry while it decreased in the water production and supply industry, mainly due to the decline in purely technical efficiency (-6.4%). Among the industries that improved their total factor productivity, the most significant improvement was in the C32 non-ferrous metal smelting and rolling industry (+10.1%), where the main drivers of progress were the increase in pure technical efficiency (+6.2%) and the rise in scale efficiency (+3.9%). In addition, significant improvements in total factor productivity were also recorded in C33 (+6.5%), C37 (+6.2%) and C16 (+6.1 %).

On a year-by-year basis (see Figure 2), total factor productivity in key industries increased in 2013-2016, with 2013-2014 mainly due to improvements in scale efficiency, 2014-2015 mainly due to improvements in pure technical efficiency, and 2015-2016 mainly due to improvements in scale efficiency and technological advances. In 2016-2018, total factor productivity showed a downward trend. In 2016-2017, it was mainly due to a decline in pure technical efficiency and scale efficiency, while in 2017-2018 it was mainly due to a regression in the level of technology and a decline in scale efficiency. There may be a correlation between the two years, when scale efficiency became a major drag on total factor productivity, and the period of supply-side structural reform, when total factor productivity fluctuated up and down after 2018, when scale efficiency regained its positive contribution, but the level of technology and pure technological efficiency failed to improve significantly during the same period, dragging down the increase in total factor productivity.

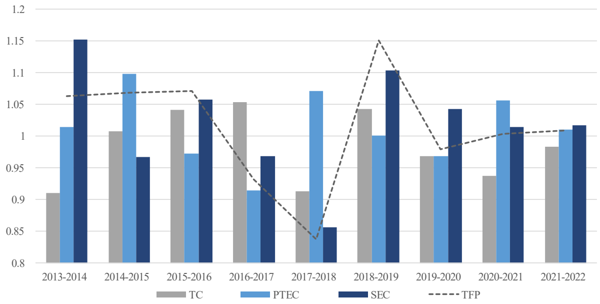


Fig. 2. Rates of change in average total factor productivity of key industrial sectors in Guizhou Province in 2013-2022

4 Conclusion

In this study, the location quotient method was first used to conduct preliminary analyses of industrial industries in Guizhou Province, and 21 key industries with greater impacts on Guizhou Province's economic development and energy consumption were screened out for subsequent studies.

For the key industries, the total factor productivity growth rate curves of various industries mainly show U, L and W shaped patterns, reflecting three types of industrial development trajectories: increase-decrease-increase, increase-decrease and long-term fluctuation. The total factor productivity growth rates from 2013-2022 were analyzed using the DEA-Malmquist index method. It can be found from the results that, except for the two years of 2016-2018, the total factor productivity of key industrial industries in Guizhou Province has maintained a long-term growth trend, with an average annual growth rate of 0.9%. Among them, the main contribution to growth comes from the improvement of pure technical efficiency and scale efficiency, while the development of technology level has not seen a positive driving effect. Among the key industries, all three mining industries showed a trend of decreasing total factor productivity, while among the manufacturing industries, the C32 smelting and processing of non-ferrous metals industry, the C33 manufacture of metal products, the C37 manufacture of railway ships aerospace and other transportation equipment, and the C16 manufacture of tobacco showed the most significant growth in total factor productivity.

Based on the results of the analysis, the following recommendations are made: (1) more attention and investment should be paid to the progress of technology itself rather than just the optimization of production efficiency or scale, because, taken together, the level of technology is the main factor dragging down the level of total factor productivity in the industrial sector in Guizhou Province; (2) more attention should be paid to the development of industries with a reduced level of total factor productivity, such as the mining industry, the alcohol manufacturing industry, the automobile manufacturing industry and the electrical manufacturing industry, and deploy different development strategies according to their different stages of development and visions; (3) Strengthen inter-industry communications and exchanges, especially among product-related industries, to complement each other's strengths and weaknesses in order to promote the common improvement of TFP in all industries, and ultimately realize the ultimate goal of green, low-carbon, high-quality development.

Acknowledgment

This work was supported by the Science and Technology Project of China Southern Power Grid Company Limited (GZKJXM20222127/GZKJXM20222133).

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