Productivity Decomposition of Chinese Energy Generation Enterprises: an Index Calculation Approach Embedded in the Data Envelopment Analysis Framework

Longfei Xue[1,a], Bingnan Yang[1,b], Fan Yang[2,c], and Xue Li[2,d]

[1] School of Management, Huazhong University of Science and Technology, Wuhan, Hubei, 430074, China;

[2] State Grid Beijing Procurement Company, Beijing, China;

[a] xuelongfei@hust.edu.cn, [b] yangbingnan@hust.edu.cn, [c] andysung@sohu.com,

[d] lx_3104@163.com

Abstract. To explore the development of China's energy power generation enterprises, undertake reasonable resource allocation and optimization, and promote sustainable development. We apply an index calculation approach within the data envelopment analysis framework, collecting data from 50 enterprises in 2007-2022, resulting in a total of 800 observations (16*50) for the in-depth analysis of productivity decomposition. The results highlight that during the study years, the sample enterprises experienced the following changes on average per year: an increase of 0.244% in efficiency change (effch), a decline of 0.293% in technical progress (techch), an increase of 0.119% in pure efficiency change (pech), an increase of 0.134% in scale efficiency change (sech), and a decline of 0.057% in total factor of productivity (tfpch). These findings suggest an ongoing improvement in overall efficiency, indicating that energy generators are achieving better results in terms of operations, resource utilization, and scale effects, but need to focus on research and adoption of new technologies while seeking opportunities to further enhance productivity.

Keywords: Energy generation enterprises; productivity decomposition; data envelopment analysis; SBM-Malmquist.

1. Introduction

China is a major consumer of energy, with the calculated total energy consumption reaching approximately 5.24 billion tons of standard coal in 2021, accompanied by a significant amount of carbon dioxide emissions. To advance China's industrial and energy structure transformation, and promote green and sustainable development, there is increasing emphasis on the construction and application of new and clean energy facilities. Among these, electric power is a crucial component of clean energy, and the stable supply of electricity relies on the effective operation of energy generation enterprises. Therefore, studying the productivity changes of energy generation enterprises holds paramount significance in maintaining a stable supply of electric power. However, there is currently a relatively limited amount of research on the productivity decomposition of energy generation enterprises.

Productivity analysis is an important method for studying the development of enterprises or industries. Decomposing productivity helps identify and address inefficiencies in the production process, thereby enhancing resource utilization efficiency and overall competitiveness. By understanding the trends and influencing factors of productivity, enterprises can formulate more scientific and effective development strategies. However, energy generation enterprises face numerous challenges in their development, including environmental pressures, ensuring energy security, research and development of technologies, and the integration of renewable energy. These factors significantly impact the development of enterprises and contribute to fluctuations in productivity. Therefore, this study focuses on Chinese energy generation enterprises, examining the evolution of their productivity from 2007 to 2022.

The primary reasons for selecting publicly listed companies in thermal power, hydropower, and new energy generation as our research subjects are as follows: (1) Electricity is increasing prominence within the realm of clean energy, emphasizing its vital role in steering away from a predominantly fossil fuel-based energy consumption structure and facilitating the development of energy transition. (2) There has been limited attention to the productivity of energy generation enterprises, particularly a scarcity of studies assessing their long-term productivity. (3) The data transparency of publicly listed companies enhances the reliability of our research and aligns with the prevailing trend in empirical studies.

This study aims to explore the development status and the reasons behind the low productivity of publicly listed Chinese energy generation companies from the perspective of productivity and its decomposition. Additionally, we further categorize the sample companies into those with decreasing, unchanged, and increasing productivity, investigating the proportion of companies falling into each productivity status. Utilizing balanced panel data from publicly listed Chinese energy generation companies, we calculate productivity and its decomposition by establishing the Malmquist index based on the SBM (a slack-based measure). This approach differs from previous studies that treated the SBM model and Malmquist index as independent models, conducting separate computations and analyses to determine static and dynamic efficiency. Our study embeds the index calculation approach into the data envelopment analysis framework.

Our study contributes in the following ways: (1) The research provides evidence at the level of energy generation enterprises, expanding the literature on productivity and energy generation companies. (2) This study offers a long-term dynamic analysis of productivity and its decomposition, exploring the reasons behind the decline in productivity. (3) With the results, it provides management recommendations for enterprises to promote productivity growth.

The paper is organized as follows: section 2 reviews the literature related to productivity decomposition and energy power generation enterprises. Section 3 describes the method. Section 4 provides the data collection and results analysis. Section 5 provides conclusions and implications.

2. Literature review

In the literature on electric power energy, diverse trends are observed. Literature [1], utilizing simulation experiments, analyzes the investment strategies of Chinese electric power enterprises from conservative, neutral, and proactive perspectives, suggesting that companies should moderately increase short-term investments. Literature [2], employing a double-difference approach, investigates the impact of value-added tax preferential policies on new energy-listed enterprises, revealing the temporal nature of policy effects. Literature [3], using a life cycle assessment method, calculates the emission levels and spatial distribution of atmospheric pollutants in the Chinese electric power industry, identifying the highest emission levels and intensity in eastern cities. Literature [4], utilizing a four-stage Data Envelopment Analysis (DEA) model, calculates the technical efficiency of Chinese wind power listed companies and concludes that there is a phenomenon of scale inefficiency in China's wind power industry.

The literature on productivity, as the research theme, encompasses various aspects of productivity. Literature [5], employing the Olley-Pakes and Levinsohn-Petrin methods, calculates the productivity of energy-intensive industries and studies the impact of differential electricity pricing policies. It suggests that implementing such policies may have significant short-term adverse effects but positive long-term effects. Literature [6] establishes a dynamic macroeconomic model to study the long-term impact of power outages on productivity, emphasizing the elimination of power outages as a crucial goal for developing countries. Literature [7] investigates the effects of power shortages on enterprise development, asserting that power shortages can seriously damage revenue and labor output, and reliable power supply significantly enhances productivity.

Based on the review of the literature, it is evident that there is a considerable amount of research related to energy generation enterprises, covering various aspects. However, the focus has predominantly been on investigating the impacts of policies, energy consumption, and carbon emissions. Exploring the changes in productivity can equally contribute to the sustainable development of this industry, an area where current research is lacking. Additionally, existing studies employ diverse models for calculating the productivity of energy generation enterprises, but they often lack an assessment from the perspective of data envelopment analysis. Therefore, this study incorporates the framework of data envelopment analysis into the Malmquist index model, providing a valuable contribution to the existing body of research in this field.

3. Methods

The Malmquist index is a method of index calculation, which has been incorporated into DEA with the development of DEA theory. The SBM-Malmquist model utilized in this study adopts the SBM as its foundational model for calculations. The approach involves embedding SBM efficiency into the computation of the Malmquist index, rather than treating SBM and Malmquist models independently and analyzing their results separately. Therefore, our study differs from many current literature. We will further elaborate on these two modeling methods in the following sections.

3.1. The SBM model

DEA is an effective method that considers multiple input and output indicators. In contrast to traditional DEA models, Tone's SBM model possesses non-radial and non-oriented characteristics [8]. Throughout the computation process, it provides slack values for variables, facilitating the study of resource utilization efficiency. Simultaneously, the SBM model incorporates variable slacks into the objective function, yielding more favorable efficiency results compared to traditional models. Additionally, it encompasses undesired outputs into the model through the inclusion of constraint conditions. The strengths and distinctive features of this model are the reasons we chose to incorporate it into our research. Formula (1) elucidates the specific details of this model.

$$\begin{gathered} min\,\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{q_1}\sum_{r=1}^{q_1}\frac{s_r^g}{y_{r0}^g}} \\ s.t.\ \sum_{j=1}^{n}\lambda_j x_{ij} \le x_{i0} \\ \sum_{j=1}^{n}\lambda_j y_{rj}^g \ge y_{r0}^g, r = 1,2\ldots, q_1 \\ \sum_{j=1}^{n}\lambda_j = 1 \\ s_i^-, s_r^g, \lambda \ge 0;\ i = 1,2,\ldots,m;\ j = 1,2\ldots,n; \end{gathered} \tag{1}$$

It's worth noting that our research does not involve undesired outputs; therefore, Formula (1) does not mention relevant constraints. In the formula, ρ represents the efficiency value corresponding to the research topic, s_i^- and s_r^g denote the redundancies of input and desired output variables, x_{ij} represents the *i*-th input of the *j*-th DMU, y_{rj}^g represents the r-th desired output of the *j*-th DMU, and λ_j represents the weights of the *j*-th DMU. When the model result is less than 1, it indicates the presence of resource redundancies, rendering the DMU inefficient. When the model result equals 1, it signifies zero resource redundancy, indicating DMU efficiency.

3.1. The Malmquist index model

The Malmquist index, initially proposed by the Swedish economist Sten Malmquist in 1953, underwent significant development when Fare, Grosskopf, Lindergren, and Roos incorporated the strengths of both the Malmquist index and DEA theory [9]. This integration transformed the Malmquist productivity index from a theoretical concept into an empirical metric. They further decomposed the index results into components representing technical efficiency change, technological progress, and scale efficiency change. This approach has gained widespread recognition. With the ongoing advancement of DEA theory, the calculation of the Malmquist index now allows for the use of any DEA model as the foundational model. This expansion has broadened the research prospects within the field of DEA. Formulas (2) and (3) respectively illustrate the computational logic and decomposition process of the Malmquist index.

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = (M_t \times M_{t+1})^{1/2} = \left[\frac{D_c^t(x^{t+1},y^{t+1})}{D_c^t(x^t,y^t)} \times \frac{D_c^{t+1}(x^{t+1},y^{t+1})}{D_c^{t+1}(x^t,y^t)}\right]^{1/2} \tag{2}$$

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_v^{t+1}(x^{t+1},y^{t+1})}{D_v^t(x^t,y^t)} \times \left[\frac{D_c^t(x^t,y^t)}{D_c^{t+1}(x^t,y^t)} \times \frac{D_c^t(x^{t+1},y^{t+1})}{D_c^{t+1}(x^{t+1},y^{t+1})}\right]^{1/2} \times \frac{D_c^t(x^{t+1},y^{t+1})/D_v^{t+1}(x^{t+1},y^{t+1})}{D_c^t(x^t,y^t)/D_v^t(x^t,y^t)} = Pech \times Techch \times Sech \tag{3}$$

For the Malmquist and its decomposition results, a value greater than 1 indicates an improvement in the metric from period t to t+1, a value equal to 1 signifies that the metric remains unchanged from period t to t+1, and a value less than 1 indicates a decrease in the metric from period t to t+1.

Our study employs a model that integrates the strengths of both the SBM and Malmquist models. The foundation model for our calculations is the SBM, and the index results are calculated with the Malmquist model after obtaining the efficiency results. This approach differs from many current studies that conduct separate calculations for the SBM model and the Malmquist index, obtaining the efficiency results and index results, respectively.

4. Data and results

This section describes the sources of data, descriptive statistics, and model results. To assess productivity changes in the sample data in the time dimension, we construct 16 years of balanced panel data to obtain a longer time horizon and more objective model results for productivity and its decomposition.

4.1. Data

To measure the productivity of Chinese energy generation firms and its decomposition from the perspective of operations management, we obtained data from the Resset database for 50 relevant firms for the period 2007-2022, totaling 800 observations. We measure the productivity of these firms based on the SBM-Malmquist index, and the input variables are chosen to be the firm's fixed assets (FA), total operating costs (TOC), and employee compensation expenditures (ECE), and the total operating revenues (TOR) are set as the only desirable output variable. To eliminate the possible effect of data magnitude on the results, we logged the variables selected and excluded ST firms and firms with missing data. Table 1 below shows the statistical description of the data after logging.

Table1. Descriptive statistics of the data in 2007-2022.

Variables	Inputs			Output
	FA	TOC	ECE	TOR
Min	11.618	18.557	15.980	18.061
Max	26.391	26.275	23.570	26.232
Mean	22.682	22.156	19.725	22.212
St.d	1.697	1.492	1.316	1.517

4.2. Results

Our study measures the productivity of the selected 50 sample firms for the years 2007-2022 based on the global reference SBM-Malmquist index model. Table 2 demonstrates the geometric mean of the productivity of the sample firms.

Table 2. Average productivity results for the 50 enterprises in 2007-2022

DMU	tfpch	DMU	tfpch	DMU	tfpch
000027	0.996	000993	1.002	600642	0.995
000037	0.996	001896	1.000	600644	0.998
000155	1.005	002015	0.997	600674	0.995
000531	0.997	002039	1.005	600726	1.000
000539	0.999	600011	0.998	600744	0.999
000543	1.002	600021	1.000	600780	0.999
000600	0.996	600027	0.999	600795	0.999
000601	0.999	600098	0.998	600821	1.002
000690	0.995	600101	1.000	600863	1.002
000722	1.001	600116	1.001	600868	1.001
000767	0.999	600157	0.993	600886	0.999
000791	0.999	600236	1.003	600900	0.997
000862	1.000	600310	1.002	600969	0.997
000875	1.001	600396	0.997	600979	1.000
000883	0.998	600452	1.002	600995	1.002
000899	1.002	600483	1.002	601991	0.996
000966	0.999	600505	0.999		

The findings reveal that the average productivity of the sampled firms ranges from 0.993 to 1.005, showing a difference of 0.012. Furthermore, among these firms, 28 have a productivity below 1, 6 have a productivity equal to 1, and 16 have a productivity greater than 1. Generally, this suggests that the majority of the firms witnessed a decrease in productivity year by year during the examination period, constituting 56%, while 12% of the firms maintained a consistent level of productivity, and 32% experienced an annual increase in productivity. Therefore, energy power generation companies should address the issue of declining productivity to minimize resource waste and underutilization.

After analyzing the average productivity of each firm, we proceed to decompose productivity and analyze the changes in productivity and its decomposition results over time. Table 3 shows the results.

Table 3. Productivity decomposition results for the enterprises in 2007-2022

Period	pech	sech	effch	techch	tfpch
2007-2008	0.989	0.998	0.988	1.002	0.990
2008-2009	1.002	1.002	1.004	1.000	1.004
2009-2010	1.004	1.001	1.005	0.998	1.002
2010-2011	1.013	1.022	1.035	0.964	0.998
2011-2012	1.003	1.003	1.006	0.996	1.002
2012-2013	0.996	0.995	0.991	1.009	1.000

Period	pech	sech	effch	techch	tfpch
2013-2014	1.004	1.001	1.006	0.993	0.999
2014-2015	0.994	1.002	0.997	1.001	0.997
2015-2016	0.962	0.982	0.945	1.060	1.000
2016-2017	1.022	1.005	1.027	0.969	0.995
2017-2018	1.009	1.008	1.016	0.984	1.000
2018-2019	1.005	0.987	0.991	1.012	1.004
2019-2020	1.006	1.007	1.013	0.989	1.002
2020-2021	1.008	1.003	1.011	0.979	0.990
2021-2022	1.001	1.004	1.005	1.003	1.009
Min	0.962	0.982	0.945	0.964	0.990
Max	1.022	1.022	1.035	1.060	1.009
Mean	1.001	1.001	1.003	0.997	0.999
St.d	0.013	0.009	0.021	0.022	0.005

Note: *tfpch=effch×techch=pech×sech×techch*

Moreover, due to the fact that effch is the product of pech and sech, to enhance the clarity in the graphical representation, we have chosen to display only the line charts for effch, techchch, and tfpch, avoiding potential confusion caused by an excessive number of lines.

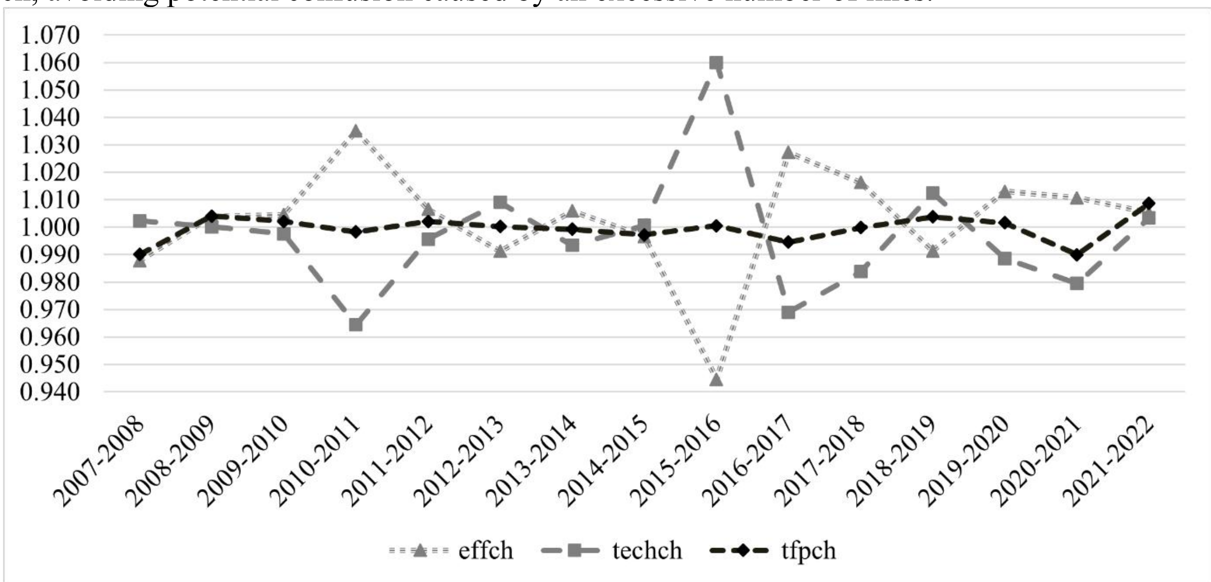

Fig. 1 Line graphs of effch, techch, and tfpch

Combined with the results of the above analysis, it can be observed that the magnitude of productivity fluctuation (with a standard deviation of 0.005) is relatively stable, while the efficiency changes and technical progress (with a standard deviation of 0.021 and 0.022, respectively) exhibit fluctuations around the productivity trends. The primary factor contributing to productivity being below 1 is the insufficient level of technological progress. Therefore, enterprises should consider encouraging research and innovation and promoting the introduction and application of new technologies. Moreover, the firm can benefit from referring to the experience of the same industry or other successful enterprises to learn from their effective management and production practices, incorporating the best practices suitable for their specific situation.

5. Conclusions

This study aims to explore the productivity decomposition of Chinese energy power generation enterprises, considering the incorporation of the data envelopment analysis framework into the calculation of the Malmquist index. Based on balanced panel data from 50 energy power generation enterprises in China in 2007-2022, we computed pech, sech, effch, techch, and tfpch, investigating the reasons for productivity loss and the current status of enterprise productivity development. The study contributes to the field in the following ways: (1) Enriching productivity calculation and decomposition research by incorporating the framework of the SBM model into Malmquist index calculation. (2) Analyzing the causes of productivity loss with a sample of 50 enterprises, providing insights for enhancing productivity in the energy power generation sector. (3) Examining the dynamic changes in productivity of Chinese energy power generation enterprises in 2007-2022, offering a more representative perspective due to the extended research timeframe.

Based on the research findings on productivity and its decomposition in energy generation enterprises, we find the following implications for achieving a steady improvement in productivity:

(1) Enterprises should gradually expand their market to steadily increase market demand. Avoiding significant fluctuations in market demand helps prevent wastage of resources. The stable growth of market demand makes it easier to manage production planning and resource allocation, consequently sustaining a steady improvement in productivity.

(2) Enterprises should enhance innovation-driven elements, and prioritize the research and application of new technologies to remain at the forefront of technological development, thereby contributing to long-term competitive advantages. Additionally, enterprises should emphasize training and development programs for employees to ensure they possess the skills required for utilizing new technologies and work methods.

(3) Disadvantaged enterprises should draw lessons from their more advantaged counterparts, establish benchmarks, and gain insights into the key factors and successful strategies of advantaged enterprises. This will aid them in their efforts to improve and adapt to the dynamics of the market.

Acknowledgment

The authors would like to thank the Science and Technology Project of State Grid Corporation of China under Grant No.5108-202218280A-2-187-XG, named "Research on Key Technologies for Improving the Resilience of Grid Material Supply Chain under the Novel Power System" for the support in this research.

References

[1] Yu X, Wu Z, Wang Q, et al. Exploring the investment strategy of power enterprises under the nationwide carbon emissions trading mechanism: A scenario-based system dynamics approach[J]. Energy Policy, 2020, 140: 111409.
[2] Sun C, Zhan Y, Du G. Can value-added tax incentives of new energy industry increase firm's profitability? Evidence from financial data of China's listed companies[J]. Energy economics, 2020, 86: 104654.
[3] Wang M, Yao M, Wang S, et al. Study of the emissions and spatial distributions of various power-generation technologies in China[J]. Journal of Environmental Management, 2021, 278: 111401.
[4] Xin-gang Z, Zhen W. The technical efficiency of China's wind power list enterprises: An estimation based on DEA method and micro-data[J]. Renewable Energy, 2019, 133: 470-479.
[5] Zheng X, Wu C, He S. Impacts of China's differential electricity pricing on the productivity of energy-intensive industries[J]. Energy Economics, 2021, 94: 105050.
[6] Fried S, Lagakos D. Electricity and firm productivity: A general-equilibrium approach[J]. American Economic Journal: Macroeconomics, 2023, 15(4): 67-103.

[7] Grainger C A, Zhang F. Electricity shortages and manufacturing productivity in Pakistan[J]. Energy Policy, 2019, 132: 1000-1008.
[8] Tone K. Dealing with undesirable outputs in DEA: A slacks-based measure (SBM) approach[J]. Presentation At NAPW III, Toronto, 2004: 44-45.
[9] Fare R, Grosskopf S, Lindgren B, Roos P. Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach[J]. Journal of Productivity Analysis, 1992, 3: 85-101.