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Research Article

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Research on Measurement and Improvement Path of Total-Factor Carbon Emission Efficiency in China's Power Industry: A Perspective of Technological Heterogeneity

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Abstract: Improving the total-factor carbon emission efficiency of the power industry (TCEPI) is of great significance for realizing the low-carbon development of power industry and promoting the transformation of society to green development. Considering the technological heterogeneity of different regions in China, this paper adopted the Meta-frontier Global Malmquist-Luenberger (MGML) index to measure TCEPI in 30 provinces from 2003 to 2017, and then analyzed the dynamic evolution and regional differences of TCEPI. Finally, the two-step system GMM model was used to explore the influencing factors of TCEPI. The results showed that: (1) During the survey period, the average annual growth rate of TCEPI in China was 4.2%, and average values of TCEPI in all provinces were greater than 1. The innovation effect was the key to TCEPI growth, while the catch-up effect and leading effect were not significant. (2) There was obvious technological heterogeneity in the three regions of China. TCEPI showed a decreasing trend from the western to eastern and central regions, with average annual growth rates of 5.69%, 3.66% and 2.89%, respectively, and the driving factors of each region were different. Moreover, the technology gap among the regions was constantly narrowing. (3) Both the economic development level and the R&D level had played a significant role in promoting TCEPI, while the intensity of power consumption had hindered the rise of TCEPI to a large extent. Based on the conclusions of this article, relevant policy recommendations were put forward to improve TCEPI in China.

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1. Introduction

Climate change is a huge challenge facing human society, which has attracted great attention of all countries in the world. Since the signing of the Paris Agreement, dozens of countries and regions have put forward their own carbon emission reduction targets and specific implementation plans. As a responsible country, China has been actively participating in global environmental governance for a long time and has put forward a number of carbon emission reduction policies and measures. The "Thirteenth Five-Year Plan for Controlling Greenhouse Gas Emissions" clearly stated that by 2020, carbon dioxide emissions per unit of GDP should be reduced by 18% compared with 2015. In addition, it stressed the need to strengthen the control of energy carbon emission targets and implement the dual control of total and intensity of energy consumption. In order to further enhance the national independent contribution, China proposed the "30 60" goal in September 2020, that is, to achieve a

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carbon peak by 2030 and carbon neutrality by 2060. Achieving this goal requires the joint efforts of all sectors in China, especially the power industry, which must transition to low-carbon development. The power industry is the basic support for social and economic development, but also the largest source of carbon emissions, accounting for more than 40% of China's total carbon emissions. The carbon emission reduction of the power industry has a direct impact on the progress of the overall carbon emission reduction target. Consequently, it is necessary to conduct in-depth research on carbon emission reduction of the power industry.

The process of power production has the characteristics of total factors so that the generation of carbon emissions is not a single factor, but the result of multiple factors such as economic development, energy consumption and improvement of living standards. Therefore, the key to carbon emission reduction in the power industry is to improve the total-factor carbon emission efficiency of the power industry (TCEPI). However, due to the imbalance of economic development level, technical condition and resource endowment in different regions of China, there is significant technology gap in power production, which indicates that to measure TCEPI accurately, technological heterogeneity needs be taken into account. For this reason, TCEPI of 30 provinces in China was estimated from the perspective of technological heterogeneity in this paper. Then the dynamic evolution and regional differences were analyzed, and the influencing factors were discussed. This study is conducive to providing scientific data and theoretical references for China to formulate and refine carbon emission reduction policies in the power industry, so as to explore the low-carbon development path of the power industry and promote the transformation of society to green development.

2. Literature review

In the context of low-carbon development, the evaluation of carbon emission efficiency has aroused close attention of scholars at home and abroad. The most popular method to evaluate carbon emission efficiency is total factor productivity (TFP), which can reflect the comprehensive influence of multiple factors (Ramanathan, 2002). Generally, there are two types of methods to construct the production frontier: parametric methods and non-parametric methods. Stochastic Frontier Analysis (SFA) is the most classic parameter method that measures effectiveness based on random errors (Ghosh and Kathuria, 2016). The SFA method requires dependent variables to be independent of each other, which is difficult to achieve in real life. Unlike the parameter method, Data Envelopment Analysis (DEA) model can measure efficiency in all specifications. DEA has been widely used in estimating efficiency of fossil fuel power generation (Barros and Peypoch, 2008; Sueyoshi et al., 2010; Zhou et al., 2010; Jaraite and Maria, 2010; Yan et al., 2012; Lin and Yang, 2014; Wu and Ke, 2018).

Malmquist productivity index is popular in the measurement of dynamic efficiency (Malmquist, 1953). Yan et al. (2017) employed undesirable-SBM model and Malmquist index to analyze the carbon emission efficiency of China's thermal power industry, and decomposed it into efficiency change and technology change. However, the traditional Malmquist index ignores the impact of desirable outputs, such as environmentally harmful by-products. For this reason, Chung et al. (1997) proposed the Malmquist-Luenberger (ML) index based on the direction distance function. Compared with the traditional TFP, the measurement results of ML index is more accurate. Nakano and Managi (2008) measured the Luenberger productivity indicator in Japan's steam power-generation sector. By using the ML index based on DEA, Arabi et al. (2014) calculated the performance of Iranian power plants. Due to some defects of ML index, such as non-circulation, non-transmission, and possible infeasible solutions, Oh (2010) used the sum of each period as a reference set to establish the Global Malmquist-Luenberger (GML) index, which effectively solved the above problems.

However, the GML index assumes that all of DMUs have the same or similar production technology, which is obviously inconsistent with reality. Due to differences in the internal characteristics and external environment of DMUs belonging to different groups, the technical benchmarks of different groups are generally not the same. For this reason, Oh and Lee (2010) further proposed the Meta-frontier GML (MGML) index. Unlike the GML index, in the MGML index, all DMUs are divided into different groups according to certain attributes, and the group frontier and meta frontier are constructed, fully considering the technological heterogeneity of different groups. Meta-frontier method has been widely used in the evaluation of carbon emission efficiency. Wang et al. (2017) employed the Meta-frontier ML (MML) index to calculate the environmental efficiency of G20 countries from the perspective of technological heterogeneity, Cheng et al. (2018) adopted the Meta-frontier total factor carbon productivity to measure China's inter-provincial industrial carbon emission efficiency from 2005 to 2015. In addition to national and industrial levels, studies have also been carried out on specific industries. Aiming at high energy consuming industries, Lin and Tan (2017) established the Meta-frontier Malmquist carbon emission efficiency index to measure carbon emission efficiency and divided it into three parts: efficiency change, technology change and catch-up effect. Lin and Wu (2020) studied the carbon emission efficiency of China's steel industry by using the Meta-frontier non-radial Malmquist index.

In terms of the power industry, Zhang and Choi (2013) introduced the metafrontier method and developed metafrontier non-radial Malmquist CO_2 emission performance index (MNMCPI) to evaluate the carbon performance of China's power plants. The principle fundings showed that total-factor CO_2 performance grew at a rate of 0.38% during the sample period. Munisamy et al. (2015) also considered the technical heterogeneity and constructed the MML index to measure the eco-efficiency of Iranian power plants. They found that the eco-efficiency of all the three types of the thermal power plants had improved significantly. Yan et al. (2017) estimated the carbon emission efficiency of China's power industry based on the global Malmquist index, but they didn't considered the technology gap in different regions in China.

By combing the existing literature, we can find that the Meta-frontier method was widely used in carbon emission efficiency, but there are few studies specifically aimed at the power industry. Zhang and Choi (2013) only took some power plants as research objects, not the entire power industry. Munisamy et al. (2014) considered the overall eco-efficiency, not the individual carbon emission efficiency. Yan et al. (2017) ignored the technological heterogeneity. Accordingly, the existing studies still have some defects.

As China's regional development is extremely unbalanced, the power industry shows significant technological heterogeneity in different regions. If we ignore the technological heterogeneity, the conclusion will be biased, as a result of which, it is difficult to find the real reason for the gap, finally misleading the policy-making. For this reason, the technological heterogeneity was considered in this paper.

Possible contributions of this study are as follows. (1) Carbon emission for the power industry was treated as the undesirable output to measure total-factor carbon emission efficiency of the power industry (TCEPI) in China, which enriched the research content of related fields. (2) Under the technological heterogeneity of different regions in China, the Meta-frontier Global Malmquist-Luenberger (MGML) index was established to measure TCEPI in all of the China provinces, which would be more comprehensive and accurate. The MGML index was decomposed into the efficiency change (EC) index, the best-practice gap change (BPC) index, and the technology gap change (TGC) index, so as to reveal in-depth the sources of TCEPI growth, and then we analyzed the dynamic evolution and regional differences of TCEPI. (3) Considering the possible path effect of TCEPI growth, the two-step system GMM model was employed to explore the influencing factors of TCEPI. Based on the conclusions of this article, relevant policy recommendations were provided for the improvement of TCEPI in China.

The rest of this paper is arranged as follows. The "Methodology and data" introduces the MGML index and the GMM model, as well as the data details. Main results are reported and discussed in section "Results and discussion". In section "Conclusions and recommendations", we present our conclusions and policy recommendations.

3. Methodology and data

3.1 Meta-frontier Global Malmquist-Luenberger（MGML） index

The core of the Meta-frontier approach is to construct group frontier and meta frontier separately, which can better reflect the technology gap of different groups. This paper established MGML index based on Meta-frontier method to measure TCEPI in China.

Supposing there are N DMUs (30 provinces), which are divided into J groups (this paper refers to the eastern,central and western regions in China) with technological heterogeneity. Each DMU has m inputs, r_1 desirable outputs, and r_2 undesirable outputs. The input and output variables for each DMU are $X=(x_1,...,x_m)\in R_+^m$, the desirable output set is $Y=(y_1,...,y_{r_1})\in R_+^{r_1}$, and the set of undesired outputs is $B=(b_1,...,b_{r_2})\in R_+^{r_2}$, respectively. In order to calculate the MGML index, three benchmark technology sets need to be introduced: the contemporaneous, the intertemporal, and the global benchmark technology set. The contemporaneous benchmark technology can be defined as $P_{R_j}^t=\left\{(x^t,y^t,b^t)\,|\,x^t \text{ can produce } (y^t,b^t)\right\}$, where $t=1,...,T$, which represents the set of production possibilities for the group j at time t. The intertemporal benchmark technology can be defined as $P_{R_j}^I=P_{R_j}^1\cup P_{R_j}^2\cup ...P_{R_j}^T$, indicating the set of production possibilities for the group j over the entire period (T). The global benchmark technology can be defined as $P^G=P_{R_1}^I\cup P_{R_2}^I\cup ...P_{R_j}^I$, which indicates the set of production possibilities for all groups (J) over the entire period (T). The relationship between the three is shown in Fig. 1.

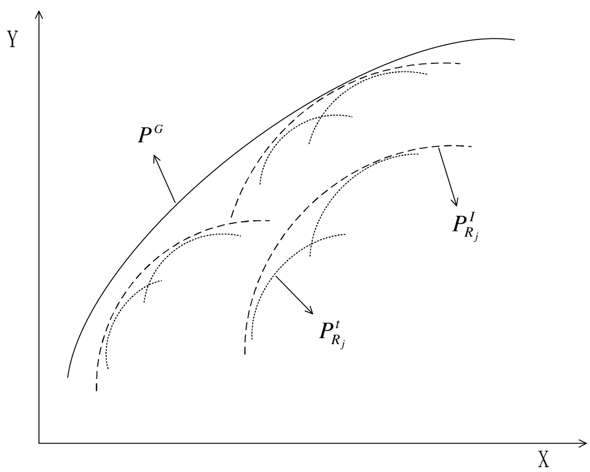

Fig. 1 Diagram of the MGML index

Under the Meta-frontier method, MGML index is used to measure TCEPI in this study, which can be defined and decomposed as:

$$
\begin{aligned}
&MGML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) \\
&= \frac{D^G(x^{t+1}, y^{t+1}, b^{t+1})}{D^G(x^t, y^t, b^t)} = \frac{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D^t(x^t, y^t, b^t)} \\
&\times \left[\frac{D^G(x^{t+1}, y^{t+1}, b^{t+1}) / D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D^G(x^t, y^t, b^t) / D^t(x^t, y^t, b^t)} \right] \\
&= \frac{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D^t(x^t, y^t, b^t)} \times \frac{D^I(x^{t+1}, y^{t+1}, b^{t+1}) / D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D^I(x^t, y^t, b^t) / D^t(x^t, y^t, b^t)} \\
&\times \frac{D^G(x^{t+1}, y^{t+1}, b^{t+1}) / D^I(x^{t+1}, y^{t+1}, b^{t+1})}{D^G(x^t, y^t, b^t) / D^I(x^t, y^t, b^t)} \\
&= \frac{TE^{t+1}}{TE^t} \times \frac{BPG^{t+1}}{BPG^t} \times \frac{TGR^{t+1}}{TGR^t} \\
&= EC \times BPC \times TGC
\end{aligned} \tag{1}
$$

Where $D^s(x, y, b)$, *s=t, t+1* represents the contemporaneous directional distance function; $D^I(x, y, b)$ represents the intertemporal directional distance function; and $D^G(x, y, b)$ represents the global directional distance function.

Equation (1) reveals the three factors of TCEPI change. The efficiency change (EC) index represents the change rate of technical efficiency in the group during two periods, which indicates the closeness of the DMU to contemporaneous frontier of the group, and it can be regarded as the "catch-up effect". EC>1 indicates an increase in technical efficiency, and on the contrary, it decreases. The best-practice gap change (BPC) index represents the change rate of technological progress in the group during two periods, reflecting the closeness of the intertemporal frontier of the group, which can be regarded as the "innovation effect". BPC>1 means technological progress, otherwise, it is regressive. The technology gap change (TGC) index indicates the technology gap ratio change, reflecting the change of the gap between the intertemporal frontier and the global frontier of the group during two periods, which can be regarded as "leading "Effect". TGC>1 means that the gap between the intertemporal frontier and the global intertemporal frontier is narrowed, and vice versa.

3.2 Econometric model

Considering the inertia of TCEPI growth, that is, the growth of this period may be affected by the growth of the previous period, this paper employed a dynamic panel regression model (generalized method of moments, GMM) to analyse the influencing factors of TCEPI. Commonly used dynamic panel data models include difference GMM and system GMM. Compared with the difference GMM, the system GMM has smaller deviations and higher efficiency, which can significantly improve the robustness of the estimation results. System GMM is further divided into one-step GMM and two-step GMM. Generally, two-step GMM can more effectively alleviate the problems of sequence autocorrelation and heteroscedasticity, especially when there are large regional differences. In addition, when estimating the influencing factors of TCEPI, it is very likely that missing variables or autocorrelation between independent variables and random disturbance items may cause endogeneity problems. Therefore, this paper selected the two-step system GMM method.

According to the characteristics of the power production process and the availability of data, the independent variables selected in this study are economic development level, R&D level, power generation structure, power consumption intensity, and environmental regulation. The model is constructed as follows:

$$\ln MGML_{i,t}^{a} = \beta_0 + \beta_1 \ln MGML_{i,t-1}^{a} + +\beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon_{i,t} \qquad (2)$$

In the formula, *ln* is the natural logarithm, *i* is the province, and *t* is the year. *MGML* is the index of TCEPI, $lnMGML_{i,t-1}$ is the lagging first order of the dependent variable, and *a* is the cumulative value. β_0 is the constant term, X_j $(j=1,...,6)$ is the independent variable, and β_j represents corresponding coefficient. $\varepsilon_{i,t}$ is a random disturbance term.

The specific explanations of these variables are as follows. (1) Economic development level (GDP), we used 2003 as the base period to calculate the actual GDP per capita (yuan/person) and took the logarithm. Compared with the total GDP, the GDP per capita can better reflect the overall level of wealth in a region. Rapid economic development is accompanied by a large increase in electricity. (3) R&D level (RD), measured by the number of patents granted in each province, affects the improvement of clean production and energy saving and emission reduction technologies in the power industry. (3) Power generation structure (EPS), measured by the ratio of thermal power generation to total power generation. At present, China's power structure is dominated by thermal power generation, with nuclear power, hydropower, and new energy sources accounting for a relatively small proportion. Thermal power generation is the main source of carbon emissions in the power industry. (4) Power consumption intensity (ECI), measured by the ratio of power consumption to GDP (kWh/yuan), reflects the degree of economic development's dependence on the power industry. (5) Environmental regulation (EGI), expressed in terms of the ratio of total investment in environmental governance to GDP. The new Environmental Protection Law has raised environmental regulation to a higher level, indicating that the role of environmental regulation in carbon emission reduction tasks should be paid attention to.

3.3 Input-output variables and data

The power generation process requires input elements such as energy, capital, and labor, and then generates the power resources we need. At the same time, a large amount of carbon dioxide are emitted, causing serious environmental pollution. The efficiency in this paper refers to the use of as little input as possible to maximize power generation and minimize carbon emissions. Thus, this study adopted installed capacity, energy consumption and labor force as input variables, power generation as the desirable output, carbon emissions as the undesirable output. To be clear, since there is no separate statistics on the number of employment in the power industry, this article used the number of employment in the power and heat production and supply industries, which are similar to the power industry.

For the calculation of carbon emissions in the power industry, this study adopted the method proposed by the IPCC (Intergovernmental Panel on Climate Change), and the formula is as follows:

$$\mathrm{CO_2} = \sum_{i=1} \mathrm{CO_{2i}} = \sum_{i=1} \mathrm{E_i} \times \mathrm{EF_i} = \sum_{i=1} \mathrm{E_i} \times \mathrm{NCV_i} \times \mathrm{CEF_i} \times \mathrm{COF_i} \times 44/12 \qquad (3)$$

Here, CO_2 represents the carbon dioxide emissions of the power industry; *i* is the type of fossil energy; E_i is the energy consumption; EF_i is the carbon emission coefficient; NCV_i represents the average low calorific value; CEF_i is the carbon content of the average calorific value; COF_i represents the carbon oxidation rate; and *44/12* is the molecular weight ratio of carbon dioxide. The eight main energy sources consumed by power generation include coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas.

MaxDEA8.0 software was used to calculate TCEPI of 30 provinces in China (in view of the availability of data，except Hong Kong, Macao, Taiwan, and Tibet). All the above data were obtained from the the 2003-2017 "China Statistical Yearbook", "China Electric Power Yearbook", "China Energy Statistical Yearbook", "China Labor Statistical Yearbook", "China Environmental Statistics Yearbook".

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4. Empirical analysis

4.1 Descriptive analysis of input-output indicators

The descriptive statistics of the input-output variables are detailed in Table 1. According to the coefficient of variation, the dispersion of each variable was relatively similar (all around 0.8), with only the labor force showing a small fluctuation, at 0.561. Table 1 is just a descriptive analysis of the absolute value of input-output variables. Since this study used panel data, further descriptive statistical analysis of the relative value is needed. In the light of data from the National Bureau of Statistics, the provinces in China are divided into eastern, central, and western regions with different production technology levels. The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan. The central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan. The western region includes Lnner Monglia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

As Table 2 shows, the growth rates of input-output variables in each region were quite different. Due to the unbalanced development of each region, the power production has obvious technical heterogeneity, so it is necessary to analyze all provinces in groups. In terms of input, the growth rates of installed capacity across the country and the three regions were higher than energy consumption and labor force, and the growth rate of each input variable in the western region was higher than that in other regions. From the perspective of output variables, the growth rates of power generation in the country and the three regions were higher than that of carbon emissions. The rapid growth of power generation in the western region was accompanied by a large increase in carbon emissions, but its total carbon emissions accounted for the lowest proportion.

In conclusion, due to the variation in economic development level and resource endowments in different regions, the growth rates of input-output variables are unbalanced, resulting large differences in production technology and production frontiers in the regions. Therefore, it is necessary to take regional technology gap into account to measure TCEPI more accurately.

Table 1 Descriptive statistics of input-output variables (2003-2017)

Type	Variable	Unit	Sample size	Mean	Standard deviation	Minimum	Maximum	variation coefficient
Input	Installed capacity	ten thousand kW	450	2411.003	2015.125	88.98	11209.04	0.836
	Labor force	ten thousand people	450	89285.97	50129.42	10346	312727	0.561
	Energy consumption	ten thousand tons	450	340675.7	286879.6	15721.33	1401300	0.842
Output	Power generation	hundred million kWh	450	1091.229	951.365	44.79011	4671	0.872
	Carbon emissions	ten thousand tons	450	9289.284	7884.538	195.2397	40951.07	0.849

Table 2 2003-2017 growth rate of variables and share of carbon emissions(%)

Region	Average growth rate					Share of carbon emissions
	Capital	Labor	Energy	Generating capacity	carbon emissions	
Eastern	12.791	2.760	5.314	6.849	4.859	41.140
Central	9.395	2.326	5.847	7.624	5.953	33.601

Western	14.847	3.672	7.938	9.748	8.754	25.259
National	12.639	2.979	6.418	8.119	6.579	100

4.2 The evolution and decomposition of TCEPI in China

Fig. 2 illustrates the dynamic evolution trend of the MGML index and its decomposition over the entire country from 2003 to 2017. At the national level, the MGML index fluctuated greatly, and the emergence of troughs and crests caused W-shaped growth during the sample period. The largest increase was between 2003 and 2004, reaching 21.11%, during which the government put forward the scientific development concept and promulgated a series of policies and measures to protect resources and the environment, prompting the power industry to attach great importance to carbon emission reduction. The first valley appeared in 2004-2005. During this period, China's electricity demand grew rapidly, the contradiction between supply and demand continued to intensify, and the power system was overwhelmed, resulting in a sharp decline in the TCEPI. Thus in 2005, the government accelerated the construction of power system, and soon completed a large number of power supply and power grid projects. In addition, management was strengthened in terms of ensuring supply, safe production, energy saving, and consumption reduction. Subsequently, the carbon emission efficiency tended to be stable. The MGML values were less than 1 from 2011 to 2016, and reached the second valley in 2016, indicating that TCEPI continued to decline during this period. To alleviate the situation, during the 13th Five-Year Plan period, the government attached great importance to carbon emission reduction in the power industry. The "Opinions on Further Deepening the Reform of Electric Power System" issued in 2015 prompted a new round of reform path exploration, emphasizing that the country should pay attention to the dual effects of management and operation. Moreover, the "Thirteenth Five-Year Plan for Electric Power Development (2016-2020)" also put forward strict requirements on the total carbon emission, intensity, installed capacity structure and other indicators of the power industry, which made TCEPI return to positive growth in 2016-2017.

From the perspective of the decomposition effect, EC, BPC and TGC showed various change trends. The EC index showed an upward trend of volatility, which indicates that the technical efficiency had improved, that is, the areas with backward production technology had achieved a certain catch-up with the advanced areas. The BPC index fluctuated the most, because technological reforms in the power industry were often phased. In general, the average growth rate of BPC was far ahead in the three decomposition indexes, showing that the innovation effect was extremely significant. By comparing the evolution trends of the EC and BPC, the catch-up effect and innovation effect had not been achieved at the same time, and even the trends of increase and decrease were almost deviated from each other. One of the reasons leading to this phenomenon may be that the low-carbon development of power industry mainly relied on capital and technological investment, while the improvement of resource allocation efficiency was usually ignored. There were many defects, such as power price distortion, financial system defect, backward management mode and low level of human capital, which led to low efficiency of resource allocation. Therefore, in practice, we should attach importance to the coordinated and benign development of the two, so that they can jointly promote the improvement of the TCEPI. Unlike the large fluctuations of the EC and BPC, the TGC index changed very steadily. Except for the negative growth rate during 2003-2004, all other years had experienced steady growth, showing that the technology gap in power production between regions in China was steadily narrowing, in other words, there was a convergence phenomenon in TCEPI across the country. In recent years, the central and western regions had continuously learnt the advanced technologies of the eastern region and gave full play to the advantages of energy resources, so that the TCEPI had been significantly improved, and gradually approached the national production frontier.

In a word, MGML index fluctuated greatly and showed W-shaped growth in the sample period. The change trends of MGML and BPC were almost the same, which indicates that TCEPI had a strong correlation with technological progress. That is to say, the innovation effect was the key to improve TCEPI.

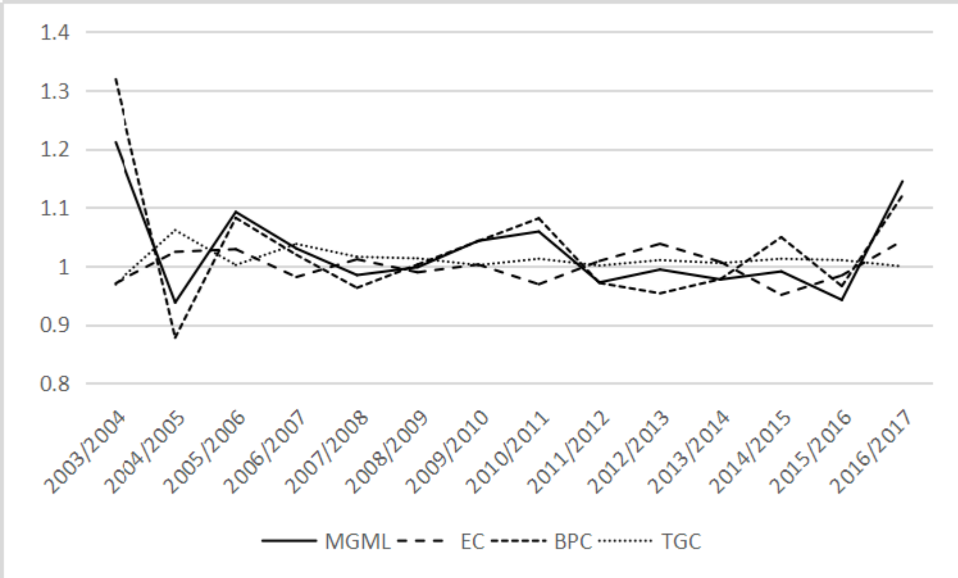

Fig.2 Dynamic trend of MGML index and its decomposition at the national level

4.3 Spatial characteristics of TCEPI in three regions of China

The MGML index and its decomposition in the three regions of China were calculated for each year of the survey period (Table 3).

From the regional level, there were significant technological heterogeneity in three regions of China. In the eastern region, the average annual growth rates of MGML and its decomposition EC, BPC and TGC were 3.66%, 0.34%, 1.77%, and 1.51%, respectively, indicating that the catch-up effect, the innovation effect and the leading effect had jointly promoted the growth of TCEPI in the eastern region. During the sample period, the eastern region had made comprehensive progress in system construction, technological innovation and internal management of power plants. The average annual growth rate of the MGML and the EC, BPC, and TGC in the central region were 2.89%, -0.23%, 2.09%, and 1.01%, respectively, which means that the growth of TCEPI in the central region was mainly derived from innovation effect and the leading effect was also significant, but the catch-up effect showed a negative impact. Similar to the central region, the MGML, EC, BPC and TGC in the western region increased by 5.69%, -0.01%, 4.98% and 0.68%, respectively. The innovation effect was also the main source of TCEPI growth in the western region, the leading effect was not significant, and the catching-up effect had a restraining effect on its growth.

To illustrate the differences among the three regions, we further compared the TCEPI of each region. The western region had the highest TCEPI, followed by the eastern region, and the central region the lowest. Due to the early reform and opening up of the eastern, the starting point in the eastern region was relatively higher and its power production technology was already at the leading level in the country, so there is little room for growth. Significant improvement in the western region primarily occurred because of the large room for improvement caused by the low historical efficiency. In recent years, the western region had learned from the technical experience of the eastern developed regions and fully utilized the advantages of energy resources to develop clean energy power generation. TCEPI in the Central region was lower than that in the eastern and western regions, because the central region had no obvious advantages in economic development and resource endowment.

Furthermore, the comparison of decomposition effect is as follows. (1) The EC index in the eastern region was greater than 1 in most years and the changes were relatively stable, indicating that the eastern region was continuously optimizing the management efficiency and institutional arrangements. The EC values in central and western regions were all less than 1, which demonstrates that technical efficiency was the bottleneck factor restricting the improvement of TCEPI in central and western regions. Because of the remote geographical location and inconvenient transportation, software and hardware conditions did not keep up, and it is difficult to introduce high-quality talents and advanced management experience, resulting in inefficient resource allocation. (2) The BPC values of the three regions were greater than 1 and greater than their respective EC and TGC values, which fully demonstrates that the innovation effect was the dominant force in the growth of TCEPI in the three regions. China had continuously promoted the reform and innovation of energy conservation and emission reduction technologies, and the power industry had achieved remarkable results in carbon emission reduction. For example, supercritical units, ultra-supercritical units and other large capacity units were developed and small thermal power units were closed, in order to reduce power generation coal consumption. There were also vigorous development of clean power generation methods such as hydropower, wind power, and solar power, which had significantly adjusted and optimized the power generation structure. What’s more, continuously strengthening the construction of smart grids had significantly improved the operating efficiency of the power system bringing greater room for carbon emission reduction. In addition, the application and innovation of low-carbon technologies such as clean coal power generation technology and carbon dioxide capture and storage technology (CCS) had also promoted the growth of TCEPI. (3) The TGC index is the most important indicator in the decomposition of MGML, which reflects the dynamic status of the regional gap change. The growth rate of TGC in the eastern region was higher than that in the central and western regions, which means that the eastern region had a very significant "leading effect" and represented the best low-carbon power production level in the country. The TGC index of the central and western regions were all greater than 1, showing that the technology gap between the three regions was narrowing.

On the whole, the TCEPI of the three regions showed a growth trend and the growth rate was decreasing from the western to eastern and central regions. The sources of TCEPI growth in the three regions were different. The catch-up effect, innovation effect, and lead effect had jointly driven the growth of TCEPI in the eastern region, while the central and western regions mainly relied on the innovation effect, the contribution of the lead effect was relatively small, and the catch-up effect hindered the growth of TCEPI.

Table 3 MGML index and its decomposition in China's three regions

Year	Eastern region				Central region				Western region			
	MGML	EC	BPC	TGC	MGML	EC	BPC	TGC	MGML	EC	BPC	TGC
2003-2004	1.1211	1.0056	1.1224	0.9932	1.2214	1.0075	1.2415	0.9764	1.3395	0.9088	1.5704	0.9385
2004-2005	0.9694	0.9950	0.9430	1.0331	0.9051	0.9657	0.8899	1.0532	0.9646	1.0960	0.8037	1.0951
2005-2006	1.0315	1.0193	0.9757	1.0373	1.1417	1.0588	1.0442	1.0327	1.1667	1.0162	1.2163	0.9439
2006-2007	1.0871	0.9996	1.0666	1.0196	1.0046	0.9875	1.0228	0.9947	1.0095	0.9583	0.9691	1.0870
2007-2008	0.9589	1.0216	0.9378	1.0009	1.0057	0.9846	0.9835	1.0387	1.0071	1.0211	0.9727	1.0139
2008-2009	0.9943	0.9660	1.0179	1.0112	0.9877	0.9971	0.9920	0.9985	1.0276	1.0070	0.9949	1.0256
2009-2010	1.0827	1.0149	1.0684	0.9986	1.0189	1.0109	1.0146	0.9934	1.0310	0.9842	1.0368	1.0104
2010-2011	1.0932	0.9986	1.0693	1.0239	1.0678	0.9671	1.0865	1.0162	1.0232	0.9405	1.0898	0.9983
2011-2012	0.9739	0.9773	1.0021	0.9945	0.9793	0.9748	0.9969	1.0077	0.9829	1.0644	0.9216	1.0020
2012-2013	1.0129	1.0380	0.9612	1.0151	0.9892	1.0220	0.9528	1.0158	0.9937	1.0492	0.9460	1.0011
2013-2014	0.9800	0.9870	0.9817	1.0113	1.0044	1.0524	0.9493	1.0054	0.9871	0.9940	0.9945	0.9986
2014-2015	1.0699	1.0184	1.0174	1.0326	0.9596	0.9644	0.9842	1.0111	0.9788	0.8735	1.1282	0.9932
2015-2016	0.9618	1.0041	0.9399	1.0191	0.9548	0.9686	0.9885	0.9973	0.9608	0.9752	0.9750	1.0105
2016-2017	1.1706	1.0022	1.1448	1.0203	1.1542	1.0070	1.1456	1.0006	1.1701	1.1104	1.0780	0.9775
Average	1.0366	1.0034	1.0177	1.0151	1.0289	0.9977	1.0209	1.0101	1.0569	0.9999	1.0498	1.0068

4.4 TCEPI and its decomposition of all provinces in China

Table 4 shows the MGML index and its decomposition effect of all provinces in China. The average value of national MGML was 1.0420, that is, TCEPI in China had grown at an average annual rate of 4.2% during the sample period. Furthermore, the average values of the MGML in all provinces were greater than 1, indicating that all provinces in China had achieved significant results in energy conservation and emission reduction in the power industry. The early economic development of China was dominated by heavy industries with high pollution and high energy consumption, causing the power industry to emit a large amount of carbon dioxide. With the transformation of China's economic growth mode and the optimization of the industrial structure, the TCEPI had been significantly improved.

However, the growth rate varied greatly among provinces. For instance, the average annual growth rate in Yunnan was as high as 9.2%, and Hainan was only 0.15%. Accordingly, it is necessary to further analyze the reasons for the difference in TCEPI in various provinces. The average values of national EC, BPC and TGC increased by 0.6%, 3.03%, and 1.07%, respectively, showing that the catch-up effect, innovation effect and leading effect had jointly promoted the improvement of TCEPI in all provinces across the country, and the innovation effect was the dominant force. The EC index in 23 provinces were all greater than 1, reflecting that the efficiency of resource allocation in the power industry in most provinces had improved, and management models and institutional arrangements had also been optimized. However, there was still a lot of room for improvement in some areas, such as Shanxi, Heilongjiang, Hunan and other provinces, where the catch-up effect was negative. These provinces are mainly located in the central and western regions, where economic development is relatively backward and environmental protection is inadequate. The BPC values of all provinces in the country were greater than 1, showing that over time, the actual power production technology has gradually tended to the potential optimal technology level in each region, and the innovation effect was very significant. The TGC values of 27 provinces across the country were greater than 1, which indicates that the technological gap between the provinces in the most provinces had continued to shrink. However, the TGC values of Shaanxi, Qinghai, and Xinjiang were still less than 1, and the gap with the national production frontier continued to widen. Therefore, we must pay attention to the carbon emission reduction work of the power industry in these provinces.

In summary, the TCEPI in China had increased by 4.2% annually, and the TCEPI values of all provinces in the country were greater than 1. The growth of the TCEPI was mainly derived from the innovation effect, while the catch-up effect and the lead effect contributed less. The growth of most provinces was relatively similar and the gap was narrowing.

Table 4 MGML index and its decomposition effect in China's provinces(2003-2017)

Province	MGML	EC	BPC	TGC	Province	MGML	EC	BPC	TGC
Beijing	1.0319	1.0000	1.0015	1.0303	Hubei	1.0308	1.0041	1.0237	1.0028
Tianjin	1.0375	1.0000	1.0203	1.0168	Hunan	1.0209	0.9932	1.0260	1.0019
Hebei	1.0331	1.0110	1.0020	1.0199	Guangdong	1.0764	1.0025	1.0576	1.0152
Shanxi	1.0208	0.9873	1.0159	1.0177	Guangxi	1.0318	1.0000	1.0102	1.0214
Lnner Mongolia	1.0875	1.0000	1.0796	1.0073	Hainan	1.0015	1.0000	1.0014	1.0001
Liaoning	1.0523	1.0239	1.0187	1.0089	Chongqing	1.0220	0.9828	1.0381	1.0017
Jilin	1.0501	1.0000	1.0354	1.0142	Sichuan	1.0879	0.9644	1.1176	1.0093
Heilongjiang	1.0159	0.9960	1.0141	1.0059	Guizhou	1.0250	0.9683	1.0565	1.0020
Shanghai	1.0225	1.0000	1.0078	1.0145	Yunnan	1.0920	1.0645	1.0140	1.0117
Jiangsu	1.0260	1.0000	1.0056	1.0203	Shaanxi	1.0361	1.0138	1.0234	0.9986
Zhejiang	1.0435	1.0000	1.0158	1.0273	Gansu	1.0720	0.9801	1.0673	1.0248
Anhui	1.0385	1.0000	1.0025	1.0358	Qinghai	1.0534	1.0000	1.0561	0.9975
Fujian	1.0305	1.0000	1.0251	1.0053	Ningxia	1.0491	1.0000	1.0438	1.0050

Jiangxi	1.0263	1.0000	1.0251	1.0012	Xinjiang	1.0628	1.0252	1.0411	0.9958
Shandong	1.0463	1.0000	1.0391	1.0069	Average	1.0420	1.0006	1.0303	1.0107
Henan	1.0272	1.0011	1.0244	1.0015					

4.5 Analysis of the influencing factors of TCEPI

In order to further clarify the mechanism of TCEPI growth, the dynamic panel regression model was employed to test the influencing factors of TCEPI. lnMGML was treated as the dependent variable, L.lnMGML, lnGDP, lnEPS, lnRD, lnEPS, lnECI, and lnEGI were treated as the independent variables, and Stata 16 software was used for regression. The descriptive statistical results of the variables are shown in Table 5.

Table 5 Descriptive statistics of variables

Variable	Sample size	Mean	Standard deviation	Minimum	Maximum
lnMGML	420	0.1995	0.1864	-0.3187	0.8051
L.lnMGML	390	0.1949	0.1805	-0.3187	0.8051
lnGDP	420	10.0641	0.7111	8.2978	11.9945
lnRD	420	3.9585	0.2159	3.2221	4.9855
lnEPS	420	-0.3246	0.4339	-2.5116	0.0004
lnECI	420	2.1839	0.6887	0.5048	4.2946
lnEGI	420	0.2431	0.4778	-0.9377	1.5314

Firstly, the mixed OLS and fixed effect were adopted to estimate the parameter and the results are shown in model (1) and model (2) in Table 6. Then the two-step system GMM model was used to estimate equation (2) and the results are shown in model (3). Since the GMM model of the system requires that the instrumental variables are exogenous variables, and that the disturbance term does not have autocorrelation and the disturbance term after difference does not have second-order autocorrelation, sargan instrumental variable validity and Arellano bond sequence correlation test were carried out in this paper. The results demonstrate that the p value of AR (1) was less than 0.1, which significantly rejected the original hypothesis and the p value of AR (2) was greater than 0.1, which accepted the original hypothesis, indicating that there was no second-order sequence correlation in the error terms. The sargan test value was greater than 0.05, which means that the selected instrumental variables were effective and there was no over identification problem. All the above shows that the model setting was reasonable.

In the dynamic panel regression model, the coefficient of L.lnMGML was between the mixed OLS estimator and the fixed effect estimator, which also shows that the establishment of the model was reasonable. The coefficient of L.lnMGML was positive and had passed the 1% significance test, which indicates that the growth of TCEPI was affected by the previous period, that is, there was path dependence or inertia effect.

The regression analysis of each influencing factor is as follows. (1) The economic development level (lnGDP) had a significant positive impact on the improvement of TCEPI. With the improvement of the level of economic development, the economic development model will be more scientific, and the economic growth mode and industrial structure will be continuously optimized. It will also drive the development of the power industry and promote the further reform of the power industry. At the same time, people's awareness of environmental protection will increase. (2) The coefficient of corporate R&D level was also significantly positive, indicating that for every 1% increased in R&D level, TCEPI will increase by 7.72%. The development of low-carbon power production mainly relied on R&D investment and technological innovation to improve resource utilization efficiency, thereby promoting the improvement of TCEPI. (3) Although the coefficient of lnEPS was positive but not significant, showing that the power generation structure did not have much impact on TCEPI. The power generation structure in China is still dominated by thermal power generation, and clean energy power generation accounts for a small proportion, so its impact of the TCEPI was not significant. (4) The coefficient of lnECI was significantly negative, which indicates that the reduction of power consumption intensity was conducive to the improvement of TCEPI. The reduction of power consumption intensity means the improvement of technology progress and terminal energy efficiency, the power energy consumption per unit GDP output is less, and the carbon emission efficiency will be consequently improved. (5) The coefficient of lnEGI was positive but not significant, indicating that increasing environmental regulation had a weak impact on improving the TCEPI. Although strengthening environmental regulation can protect the environment and reduce carbon emissions to a certain extent, it will also hit the enthusiasm of power enterprises and limit the development of the power industry. Therefore, environmental regulation should be relaxed appropriately.

Table 6 Analysis on influencing factors of TCEPI

Variable	Mixed OLS	Fixed effect	GMM
	(1)	(2)	(3)
L.lnMGML	0.780***	0.368***	0.584***
	(23.17)	(8.25)	(3.53)
lnGDP	0.0488***	0.205***	0.0545***
	(4.56)	(9.08)	(3.22)
lnRD	0.0468*	0.0512**	0.0772**
	(1.95)	(1.99)	(2.27)
lnEPS	0.0334***	0.315***	0.0159
	(2.64)	(9.72)	(0.71)
lnECI	-0.0543***	-0.246***	-0.0672***
	(-4.61)	(-7.18)	(-3.54)
lnEGI	-0.0158	-0.0667***	0.0224
	(-1.27)	(-4.30)	(0.52)
Const.	-0.495***	-1.488***	-0.622***
	(-3.85)	(-7.97)	(-3.17)
AR(1)			0.008
AR(2)			0.158
Sargan			0.478
N	390	390	390

Note: ***, **, and * indicate statistical significances at the level of 1%, 5%, and 10%, respectively; standard deviation is in the bracket.

5. Conclusions and recommendations

5.1 Conclusions

The unevenness of regional development in China leads to obvious technological heterogeneity in the power industry. Under the assumption of technological heterogeneity, this study treated the carbon emissions as the undesirable output and measured TCEPI in China from 2003 to 2017 based on MGML index, which can be decomposed into EC, BPC and TGC to reveal the source of TCEPI growth. On this basis, we analyzed the dynamic evolution and regional differences of TCEPI. Finally, the two-step system GMM model was used to explore the influencing factors of TCEPI. The main conclusions are as follows.

(1) China's TCEPI was growing at an average annual rate of 4.2% in the survey period, and TCEPI in all provinces was showing a cumulative positive growth. The innovation effect was the key to promote the growth of TCEPI, while the catch-up effect and the leadership effect were not significant.

（2）There was obvious technological heterogeneity in the three regions of China. The growth rate of TCEPI showed a decreasing trend form the western to eastern and central regions, which were 5.69%, 3.66% and 2.89%, respectively. The driving factors of each region were different. The innovation effect, catch-up effect, and leading effect in the eastern region had jointly promote the growth of TCEPI, while the central and western regions mainly relied on the innovation effect, and the catch-up effect had played a certain role in hindering.

(3) The growth of TCEPI would be affected by the previous period, that is, there was path dependence or inertia effect. The economic development level and R&D level had a significant positive impact on the improvement of TCEPI, while the intensity of power consumption played a major obstacle, and the impact of power generation structure and environmental regulation was not significant.

5.2 Recommendations

Based on the results and conclusions, the following policy recommendations are provided to improve TCEPI in China.

(1) The power industry should give full play to the driving role of the innovation effect on TCEPI by continuously promoting technological progress. The enthusiasm of power enterprises should be mobilized to increase R&D investment, optimize the structure of power units, and promote the application and innovation of clean power generation technologies such as solar energy and wind energy, and low-carbon technologies such as CCS. In addition, the power industry should improve management efficiency and optimize resource allocation. The reduction of technical efficiency has seriously hindered the TCEPI, so when promoting technological innovation, the improvement of resource allocation efficiency should also be paid attention to. The government ought to further deepen the reform of China's power system, improve the marketization level of the power industry, cultivate high-quality talents, and improve management methods, to make the catch-up effect and innovation effect jointly promote the growth of TCEPI.

(2) Technological heterogeneity needs to be fully considered in different regions and reasonable carbon emission reduction policies for the power industry should be adopted according to the characteristics of each region. Each region must adapt to local conditions and takes a path of differentiated development. As a leader in low-carbon power production in the eastern region, while strengthening independent innovation, it should continue to expand foreign exchanges, advanced technology and management experience, and give play to its leadership demonstration effect. The central and western regions are supposed to make full use of their advantages in energy resources. At the same time, At the same time, a multilateral or bilateral regular exchange mechanism can be established to strengthen economic and technological exchanges in different regions and guide the transfer of capital, technology, and labor from the eastern region to the central and western regions, so as to promote coordinated regional development in the power industry.

(3) Based on the analysis of the influencing factors of TCEPI, the following measures can be taken: While the economic development level is improving, it is necessary to pay attention to the transformation of economic growth mode and the optimization of industrial structure to explore scientific development models and sustainable development path; The power industry should increase R&D investment, establish low-carbon technology incubators, and increase the promotion of energy-saving emission reduction and low-carbon technology; The government should advocate green and low-carbon, energy-saving and emission reduction lifestyle and consumption mode in order to improve the terminal energy utilization efficiency.

Availability of data and materials The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

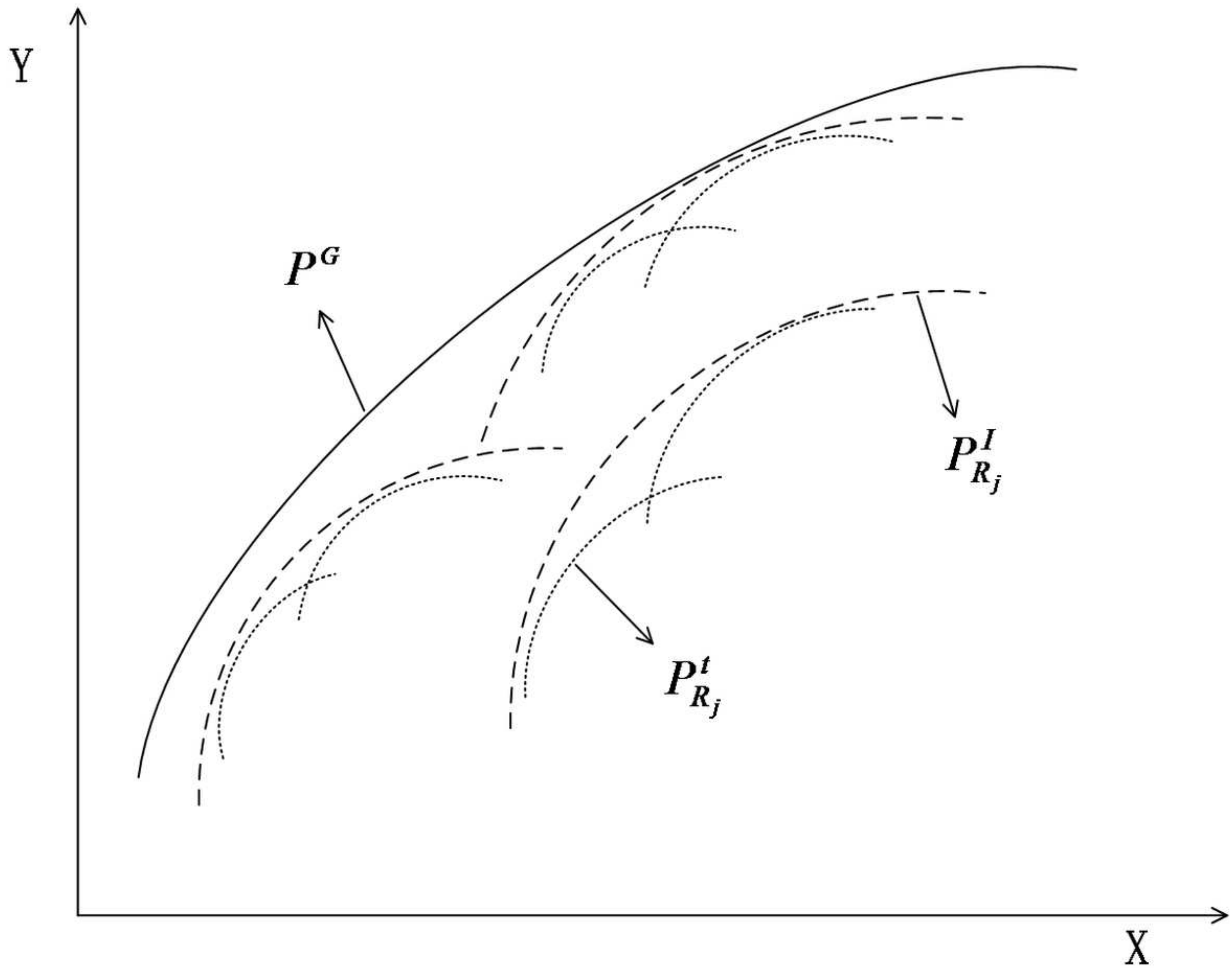

Figure 1

Diagram of the MGML index

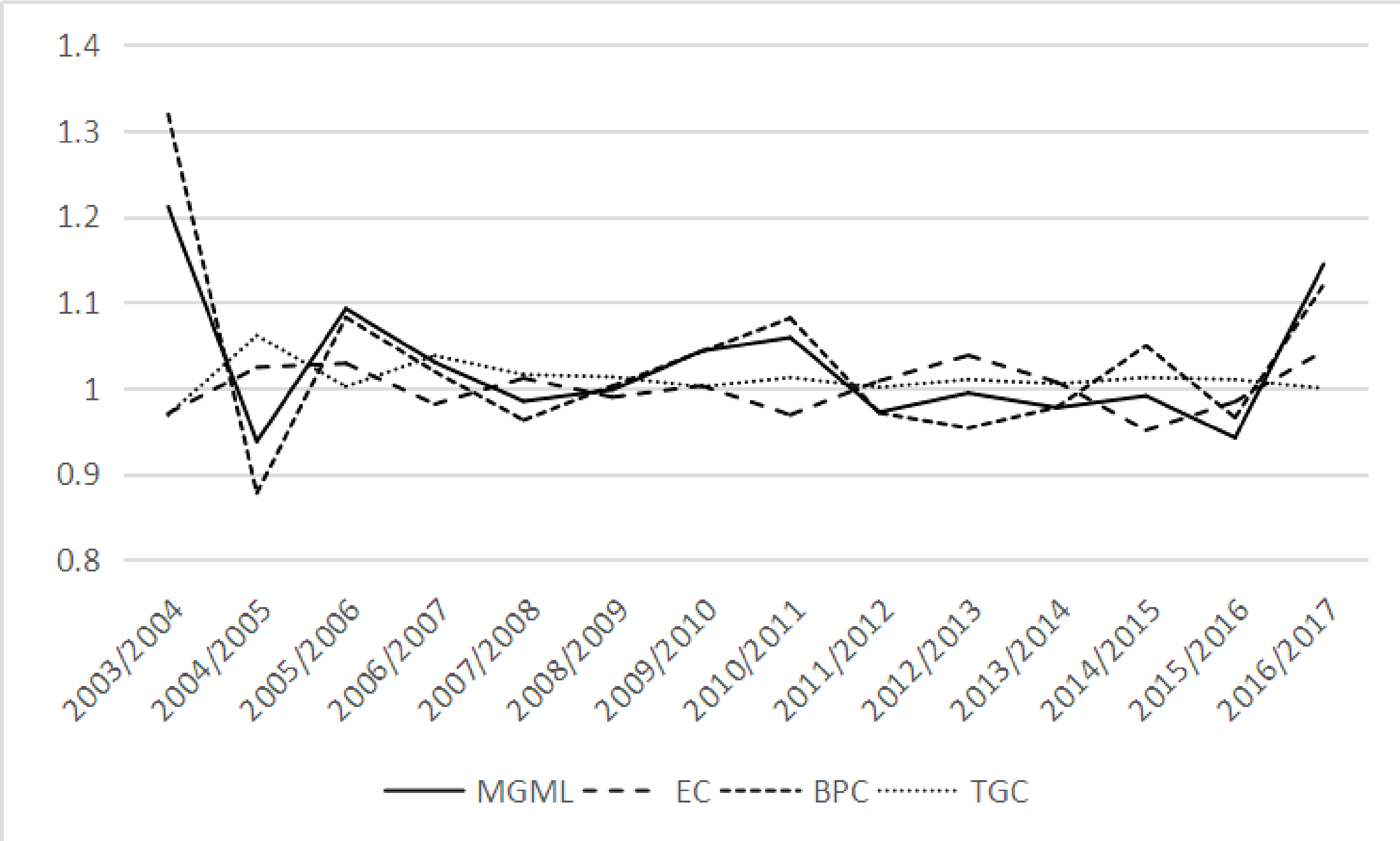

Figure 2

Dynamic trend of MGML index and its decomposition at the national level