In response to the challenges arising from global warming and climate change, the Chinese government has made a great effort to control CO2 emissions in terms of both intensity and amount. In 2015 China promised to lower its carbon intensity by 60-65% by 2030 from the 2005 level and peak its carbon emissions by approximately 2030. The power industry is of vital importance for the accomplishment of these carbon emission reduction targets. As the largest CO2 emitter among all industries, it consumes approximately 50% of China’s coal and emits more than 40% of China’s CO2 from fossil fuel combustion [1]. Given the coal-dominant energy structure in China, the situation of relying on coal-fired power plants to satisfy the growing demand for electricity can hardly be changed in the near future. Under this circumstance, it is crucial for China’s thermal power industry to promote its CO2 emission performance, not only for achieving the
national carbon emission reduction targets but also for the 
power industry’s low-carbon transition and sustainable 
development.

In the literature, several indicators have been explored 
for measuring CO₂ emission performance. Among these 
indicators, carbon productivity [2], carbon intensity [3], 
and per capita CO₂ emissions [4] are particularly attractive 
and have been successfully applied to many fields. These 
single-factor efficiency indicators are simple and easy to 
apply, but they cannot reflect the actual process of CO₂ 
being generated and neglect the influencing factors, such as 
element substitution, energy mix, and regional economic 
disparity. In recognition of the limitations of single-factor 
carbon emission performance, the total factor of carbon 
emission performance has gained popularity. Under 
the framework of environmental production technology, 
Zhou et al. (2010) [5] first proposed the concept of 
total factor carbon emissions performance (TFCP) by 
comparing the actual carbon emissions with the carbon 
emission in the frontier. Also, they constructed the 
Malmquist CO₂ emission performance index (MCPI) 
by extending the traditional Malmquist productivity 
index to examine the changes in TFCP over time. Since 
then, a large number of studies have been devoted to 
empirically measuring carbon emission performance 
and its dynamic change at various levels, including the 
national [6], regional [7-9], and even industrial levels 
[10-11]. As for the electricity generation sector, Yang and 
Pollitt (2009) [12] estimate the efficiency of the Chinese 
coal-fired power plants with data envelopment analysis 
(DEA) incorporating both undesirable outputs and uncon-
trollable variables. Related studies also can be found in 
[13-20].

From a methodological point of view, however, the 
forementioned studies mainly adopted non-parametric 
DEA to measure carbon performance. It can easily 
accommodate both multiple inputs and outputs and does 
not require a prior assumption regarding the specification 
of the production function or the distributional form of 
the error terms. However, the evaluation results from DEA 
are considered deterministic and do not consider statistical 
noise. Some studies have used the methods of bootstrap 
and order-m to overcome the shortcomings of DEA [21-22], 
while they mainly focused on the static relative efficiency 
without considering the dynamic efficiency change.

Different from DEA, the SFA method, as a parametric 
approach proposed by Aigner et al. (1997) [23], considers 
efficiency measures and stochastic noise affecting a 
frontier. It estimates the frontier production function via a 
metring method that measures efficiency and considers a 
variety of environmental factors that influence efficiency. 
Recently, SFA has also been used to estimate technical 
efficiency of electricity companies. Chen et al. (2015) 
[24] examined the technical efficiency of Chinese fossil-

fuel electricity generation companies from 1999 to 2011. 
Du et al. (2013) [25] assessed the total factor productivity 
(TFP) of Chinese fossil-fired power plants. However, 
these studies are mainly from the perspective of enterprise, 
while province-level studies using SFA are limited. 

In view of this, the main purpose of this study is to 
measure carbon emission performance and its dynamic 
variation of China’s regional thermal generation from 
2003 to 2013 using the parametric Malmquist method.

Compared with the extant studies, the main 
contributions of this study are as follows. Firstly, it extends 
the study concerning carbon emission performance by 
using the SFA method to China’s regional thermal power 
generation. Secondly, this study measures the carbon 
emission performance of China’s regional thermal power 
generation from both static and dynamic perspectives; 
specifically, the static TFCP is measured first by the 
SFA method considering the influential factors on the 
in efficiency term, and then MCPI is introduced to measure 
the dynamic variation of carbon emission performance. 
The decomposition for MCPI is also conducted to 
evaluate the relative contribution of efficiency change 
and technology change to the dynamic variation of MCPI. 
Thirdly, according to the average levels of TFCP and 
MCPI, the 30 provinces are divided into four categories: 
high TFCP-low MCPI, low TFCP-low MCPI, low TFCP-
high MCPI, and high TFCP-high MCPI, which can 
provide a scientific basis for policymakers to implement 
regional-oriented strategies for the improvement of both 
TFCP and MCPI.

Material and Methods

Carbon Emission Performance under 
The Framework of Environmental Production 
Technology

Assuming that there are n (n = 1, 2, ..., N) regions 
and each regional power sector employs capital stock (K), 
labor force (L), and fossil fuel (F) as inputs to generate 
electricity (E) as a desirable output and carbon emissions 
(C) as an undesirable output, this production process can 
be expressed as:

\[ S = \{(K, L, F, E, C) : (K, L, F) \text{ can produce } (E, C)\} \]

(1)

Generally, S is assumed to be a closed and bound set, 
meaning that finite inputs can only generate finite outputs. 
According to Zhou et al. (2010) [5], the inputs and desirable 
outputs are supposed to be strongly or freely disposable. 
In addition, both the weak disposability assumption and 
the null-jointness assumption need be considered. This 
means that the reduction of carbon emissions entails 
an opportunity cost and the only way to avoid carbon 
emission is to stop electricity production.

Under the framework of environmental production 
technology, according to the thoughts of Shephard’s 
distance function, CO₂ emission distance function can be 
declared as

\[ CO_2 = \frac{E}{\frac{K}{L} + \frac{F}{L}} \]
Eq. (2) can be used to define the total factor CO₂ emission performance (TFCP) as:

\[ TFCP = 1 - D_C(K, L, F, E, C) \]  

(3)

TFCP can explore the CO₂ emissions performance of the regional thermal power generation sector from the static perspective. For the purpose of inter-temporal comparisons of the dynamic change in CO₂ emissions performance, the Malmquist CO₂ emissions performance index (MCPI) can be introduced. Let \( t \) and \( t+1 \) denote two consecutive time periods, following Zhou et al. (2010) [5], the MCPI can be defined as:

\[
MCPI_{t+1} = \left[ \frac{D_1(K_t, L_t, F_t, E_t, C_t)}{D_1(K_{t+1}, L_{t+1}, F_{t+1}, E_{t+1}, C_{t+1})} \right]^{1/2}
\]

(4)

Also, MCPI can be decomposed into efficiency change (EFFCH) and technological change (TECH), as shown in Eq. (5):

\[
MCPI_{t+1} = \frac{D_{t+1}(K_{t+1}, L_{t+1}, F_{t+1}, E_{t+1}, C_{t+1})}{D_t(K_t, L_t, F_t, E_t, C_t)} \times \left[ \frac{D_1(K_t, L_t, F_t, E_t, C_t)}{D_1(K_{t+1}, L_{t+1}, F_{t+1}, E_{t+1}, C_{t+1})} \right]^{1/2} = EFFCH_{t+1} \times TECH_{t+1}
\]

(5)

SFA Model Specification

Estimating the CO₂ emission distance function with parametric SFA method needs the assumption on the form of production function. Since the trans-log function is a flexible form and less restrictive than Cobb-Douglas on production and substitution elasticity, we choose the trans-log production function as follows:

\[
\ln D_1'(K'_t, L'_t, F'_t, E'_t, C'_t) = \ln C'_t + \alpha_{K_t} \ln K'_t + \alpha_{L_t} \ln L'_t + \alpha_{F_t} \ln F'_t + \alpha_{E_t} \ln E'_t + \alpha_{C_t} \ln C'_t
\]

where \( \nu_t \) is a random variable of statistical noise and approximation error. Since the Shephard distance function is linearly homogeneous in carbon, we can get:

\[
\ln D_1(K_t, L_t, F_t, E_t, C_t) = \ln C_t + \ln D_1'(K'_t, L'_t, F'_t, E'_t, C'_t)
\]

(6)

Then technological change (TECH) can be calculated as:

\[
TECH_{t+1} = \left[ \exp(\alpha_{K_t} \ln K_{t+1} + \alpha_{L_t} \ln L_{t+1} + \alpha_{F_t} \ln F_{t+1} + \alpha_{E_t} \ln E_{t+1} + \alpha_{C_t} \ln C_{t+1}) \right] - 1
\]

(7)

To calculate efficiency change (EFFCH), re-arranging Eq. (7) we can get:

\[
EFFCH_{t+1} = \ln \left[ \frac{\exp(\alpha_{K_t} \ln K_{t+1} + \alpha_{L_t} \ln L_{t+1} + \alpha_{F_t} \ln F_{t+1} + \alpha_{E_t} \ln E_{t+1} + \alpha_{C_t} \ln C_{t+1})}{\exp(\alpha_{K_t} \ln K_{t} + \alpha_{L_t} \ln L_{t} + \alpha_{F_t} \ln F_{t} + \alpha_{E_t} \ln E_{t} + \alpha_{C_t} \ln C_{t})} \right]
\]

(8)

\[
EFFCH_{t+1} = \ln \left[ \frac{\exp(\alpha_{K_t} \ln K_{t+1} + \alpha_{L_t} \ln L_{t+1} + \alpha_{F_t} \ln F_{t+1} + \alpha_{E_t} \ln E_{t+1} + \alpha_{C_t} \ln C_{t+1})}{\exp(\alpha_{K_t} \ln K_{t} + \alpha_{L_t} \ln L_{t} + \alpha_{F_t} \ln F_{t} + \alpha_{E_t} \ln E_{t} + \alpha_{C_t} \ln C_{t})} \right]
\]

(9)

Where \( \mu_t \) is a non-negative variable representing the inefficiency when CO₂ emission performance in i region in the period of t is evaluated. Based on Eq. (11), carbon emission efficiency (EFF) and its change (EFFCH) can be estimated as:

\[
EFF_{t+1} = \exp(-\mu_{t+1})
\]

(10)

\[
EFF_{t+1} = \exp(-\mu_{t+1})
\]

(11)

It is important to note that the carbon emission efficiency measurements are also affected by other factors. Referring to existing studies [26-28], the efficiency of fuel utilization (FE), the research and development (R&D) expenditure (RD), the investment-based regulations (IR) and fee-based regulations (FR), are selected as the main influential variables. As a result, it is assumed that the stochastic term \( \nu_t \) is expressed as
\[
\mu_{it} = \lambda_0 + \lambda_1 F_{it} + \lambda_2 R_{it} + \lambda_3 I_{it} + \lambda_4 F_{it} + \omega_{it}
\]

...where \( \lambda_i \) (\( i = 0, 1, \ldots, 4 \)) represents the vector of unknown parameters to be estimated, here \( \lambda_i \) (\( i = 1, \ldots, 4 \)) are assumed to be negative; \( \omega_{it} \) follows truncated normal distribution.

Variables and Data Description

Panel data of China’s 30 provincial (Tibet, Hong Kong, Macao, and Taiwan are not included due to lack of data) thermal power generation sectors over 2003-2013 were collected from China Electric Power Yearbook, China Statistical Yearbook, China Industry Economy Statistical Yearbook, and China Energy Statistical Yearbook. The related variables are illustrated as follows:

1. Input variables. Capital (K) is measured in terms of installed thermal power generating capacity. Labor (L) in power and thermal generation and supply industry is taken as the proxy of the labor in the power generation sector since there are no separate data about it. Data on fuel (F) are collected from the physical quantity sheets balance by region in China Energy Statistical Yearbook and converted into million tons of standard coal equivalent.
2. Output variables. Electricity (E) generated from thermal power plants in each province is used as the single desirable output and CO2 emission (C) is the undesirable output. Because the official data on CO2 emissions from regional thermal power generation are not available in China, they can be obtained as Eq. (14).

\[
CO_2 = \sum_j CO_2 = \sum_j F_j \times FCU_j \times CEF_j \times COF_j \times \frac{44}{12}
\]  

(14)

...where the subscript \( j \) represents fuel type, \( F \) denotes the amount of fuel consumption, \( FCU \) is the fuel calorific value, \( CEF \) stands for carbon emission factor, \( COF \) represents the carbon oxidation factor (which is usually assumed to be one for the convenience of calculation), and 44/12 is the conversion factor from carbon to CO2. The descriptive statistics of the input and output variables are shown in Table 1.

Table 1. Descriptive statistics for inputs and outputs.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Mean (%)</th>
<th>Max (%)</th>
<th>Min (%)</th>
<th>Std. dev. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Installed capacity</td>
<td>Million KW</td>
<td>1,962.92</td>
<td>7,555</td>
<td>88.71</td>
<td>1,648.77</td>
</tr>
<tr>
<td>Fuel consumption</td>
<td>Million tons</td>
<td>28.57</td>
<td>147.59</td>
<td>1.51</td>
<td>28.45</td>
</tr>
<tr>
<td>Labor force</td>
<td>Persons</td>
<td>101,896</td>
<td>253,007</td>
<td>11,657</td>
<td>53,679.144</td>
</tr>
<tr>
<td>Generating capacity</td>
<td>Billion kWh</td>
<td>975.52</td>
<td>4,171.00</td>
<td>44.79</td>
<td>823.74</td>
</tr>
<tr>
<td>CO2 emissions</td>
<td>Million tons</td>
<td>91.45</td>
<td>390.8</td>
<td>4.11</td>
<td>74.63</td>
</tr>
</tbody>
</table>

3. Influential variables. The efficiency of fuel utilization (FE; in kWh/g) is represented by the reciprocal of the standard coal consumption for unit electricity generation. The R&D expenditure (RD) is represented by the share of investment R&D activity of large- and medium-sized industrial enterprises in gross regional production. IR is the investment-based regulations and FR stands for fee-based regulations. They are measured in million RMB and represented by the investment in the treatment of industrial pollution and the fees levied on wastes discharged at the province level, respectively.

Results and Discussion

Model Estimation Results

According to the above analysis, we employed Frontier 4.1 to estimate the coefficients of model (11), and the results are shown in Table 2. It can be seen that under a 1% significance level, the t-ratio of \( \gamma \) illustrates that the null hypothesis is rejected and the alternative hypothesis is accepted, which indicates that carbon emission inefficiency does exist and the stochastic frontier analysis is needed. It is also noted that the \( \alpha_E \) is negative and statistically significant, which means that the greater amount of electricity generated in region \( i \) generally resulted in lower efficiency loss and thus higher performance. For example, Jiangsu as the province with the largest thermal electricity generated also has the highest CO2 emission efficiency, which will be found in the following section. For the four inefficient influential factors, we place them into the model simultaneously. The results are also listed in Table 2.

It can be seen that the coefficients of all four influential factors are negative, meaning that they have positive effects on improving CO2 emission efficiency, which is consistent with the authors’ expectation. However, we noticed that only FE and IR are significant at 1% significance level, while RD and FR are insignificant even at 10% significance level.

In theory, R&D plays an important role in combating climate change. More R&D expenditure can bring the promotion of innovation capability and improvement of environmental efficiency. In our results the RD is insignificant, meaning that the impacts of RD on TFCP
of China’s regional thermal electricity generation are relatively limited. This may be related to the fact that the long-term effects of RD on CO₂ emission efficiency have not been fully revealed. As for fuel efficiency, the coefficient of FE is negative and significant, indicating that a higher FE will lead to a lower loss of efficiency, and corresponding to a higher CO₂ emission performance, which shows that the efficiency of fuel usage is one of the main drivers for CO₂ emissions performance. This result is consistent with the findings of Fan et al. (2007) [29]. It should be noted that both IR and FR are the variables standing for environmental regulation. But the coefficient of IR is significant while FR is insignificant. This reveals the complicated effects of regulation on efficiency. The classical theory argues that environmental regulation has a negative effect on efficiency. In contrast, “Porter hypothesis” considers that environmental regulation has positive effects on efficiency. Several studies have empirically investigated the impact of environmental regulation on China’s thermal power generation sector in each province. For comparison, we also estimate the corresponding TFCPs using the DEA model, which describes the maximum possible reduction CO₂ emissions while keeping other factors fixed. The results are listed as Fig. 1.

It can be seen that the values of TFSCP from DEA are lower than that from SFA, and are more volatile. The reason for this is that the DEA technique regards all deviation from frontier as inefficient, while SFA assumes deviation from efficient frontier including two parts: inefficiency and random shock. Thus, DEA may overestimate the efficiency loss, resulting in the underestimation of the TFSCP. To further investigate whether the values of TFSCP obtained from SFA are significantly different from that of DEA in a statistical sense, we conduct a Wilcoxon

Estimated Results and Discussion of TFSCP

According to the above estimation from the SFA model, we can calculate the value of TFSCP of the thermal power generation sector in each province. For comparison, we also estimate the corresponding TFCPs using the DEA model, which describes the maximum possible reduction CO₂ emissions while keeping other factors fixed. The results are listed as Fig. 1.

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<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>t-ratio</th>
<th>Variables</th>
<th>Coefficient</th>
<th>t-ratio</th>
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</thead>
<tbody>
<tr>
<td>α₀</td>
<td>3.054**</td>
<td>2.481</td>
<td>α₄</td>
<td>0.0269**</td>
<td>2.2509</td>
</tr>
<tr>
<td>α₆</td>
<td>-2.381**</td>
<td>-2.507</td>
<td>α₆₄</td>
<td>-0.049*</td>
<td>-1.652</td>
</tr>
<tr>
<td>α₇</td>
<td>-0.019</td>
<td>-0.045</td>
<td>α₆₄</td>
<td>-0.007</td>
<td>-1.147</td>
</tr>
<tr>
<td>α₈</td>
<td>0.716</td>
<td>0.882</td>
<td>α₆₄</td>
<td>0.044</td>
<td>1.463</td>
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<tr>
<td>α₉</td>
<td>-0.525**</td>
<td>-2.203</td>
<td>αₗ</td>
<td>0.037</td>
<td>0.619</td>
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<tr>
<td>α₁₀</td>
<td>0.017</td>
<td>0.093</td>
<td>αₚ</td>
<td>0.003*</td>
<td>1.696</td>
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<tr>
<td>α₁₁</td>
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<td>5.529</td>
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<tr>
<td>α₁₃</td>
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<td>λ₂</td>
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<td>-0.922</td>
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<tr>
<td>α₁₄</td>
<td>-0.107*</td>
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<td>λ₃</td>
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<td>-2.736</td>
</tr>
<tr>
<td>α₁₅</td>
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<td>λ₄</td>
<td>-0.091</td>
<td>-1.163</td>
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<tr>
<td>α₁₆</td>
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<td>-1.648</td>
<td>LR test of the one-sided error</td>
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<tr>
<td>α₁₇</td>
<td>0.411**</td>
<td>2.115</td>
<td>sigma-squared</td>
<td>0.0776***</td>
<td>6.742</td>
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<tr>
<td>α₁₈</td>
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<td>gamma</td>
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<tr>
<td>α₁₉</td>
<td>0.170</td>
<td>1.031</td>
<td>Log likelihood</td>
<td>97.64</td>
<td></td>
</tr>
</tbody>
</table>

Note: ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Fig. 1. Comparisons of TFSCP.
signed-ranks test, and the results indicate that the value of Z statistic is \(-2.934\), and the P-value is 0.003, meaning that the null hypothesis is rejected at 1% significance level. Thus, the TFCP obtained from SFA should be analyzed further and taken as the basis for measuring MCPI.

In terms of the TFCP obtained from SFA, the average TFCP increased from 0.795 in 2003 to 0.881 in 2013, while regional CO2 emission efficiency is of obvious difference. The average values of TFCP for eastern, central, and western areas\(^1\) are 0.910, 0.905, and 0.833, respectively, which means that the eastern area has the highest TFCP, followed by central and the western areas with the lowest TFCPs. Furthermore, CO2 emission efficiency scores show great variations across provinces. All eastern provinces except Hainan witnessed higher than 0.90 in terms of TFCP on average. This means that in general the provinces in the eastern area are more efficient than those in other areas, which is the same with the finding of Lam and Shiu (2001) \([26]\). In order to further investigate the difference of TFCP among provinces, Fig. 2 provides the changes in standard deviation (Std dev) of efficiency values from 2003 to 2013. It can be seen that the difference in TFCP among provinces is significant before 2005 with the standard deviation fluctuating around 0.18. However, the standard deviation in 2011 is around 0.06 – two times lower than before 2005, meaning that the differences among different regions are gradually being reduced.

Estimated Results and Discussion of MCPI

Table 3 presents the results of MCPI in China’s regional thermal power generation sector, which describes the dynamic change of carbon emission performance.

It can be seen from Table 3 that the average MCPI of the whole sample is 1.031, indicating that for 30 regions in China as a whole they experienced a 3.1% improvement in MCPI per year. But this improvement trend is full of great fluctuation, of which the MCPI experienced the highest improvement in 2006. The reason for this is related to the emission reduction policy. It is well known that during the “11th Five-Year Plan” the Chinese government announced a mandatory target of reducing energy intensity by 20% by 2010 compared with the 2005 level. Under this target, the thermal power generation sector implemented a range of policy measures, such as “upgrading the large and suspending the small” and promoting large-capacity high-efficiency units, as well as implementing the project of replacing coal-fired power plants in big cities with gas-fired plants. Under these policies, China has closed down small thermal power plants with total power-generating capacity of 76.83 million kilowatts during the period 2006-2010, accounting for roughly 10.9% of the total thermal power generation capacity, which makes great contribution to the improvement of MCPI.

Table 3 further presents the two ingredients of MCPI to help identify the contributors to MCPI growth in China’s thermal power generation sector. TECH indicates the extent to which MCPI growth is due to the shift in the production frontier over time, hence it represents the capacity of the thermal power industry to improve its production process in an innovative way. It can be found from Table 3 that at the national level the average score of TECH for the whole sample is quite close to unit (1.006), indicating that the annual technological progress in carbon emission reduction is very trivial. EFFCH, on the other hand, reflects the degree to which MCPI growth is caused by the endeavor made by a province’s thermal power industry to catch up with a more efficient thermal power sector in other provinces. Table 3 indicates that the average value of EFFCH at the national level is 1.025, accounting for most of the MCPI growth. Therefore, MCPI growth observed for the thermal power industry during the sample period is almost exclusively driven by efficiency change, while the effect of technological innovation is little.

Table 3 also shows the results of MCPI and its decomposing components for three areas. It can be seen that the similar growth pattern of MCPI in different areas and the value of MCPI of the western area is 1.034, higher than that of eastern and central areas. However the situations at the provincial level are quite different. All provinces except Tianjin, Shanghai, and Chongqing registered a positive shift in MCPI. In order to illustrate the CO2 emission performance and its dynamic change of thermal power generation sector in China’s province more clearly, according to the average levels of TFCP and MCPI, we divide the 30 provinces into four basic categories: high TFCP-low MCPI (category 1), low TFCP-low MCPI (category 2), low TFCP-high MCPI (category 3), and high TFCP-high MCPI (category 4), as shown in Fig. 3.

It can be seen from Fig. 3 that most provinces in the eastern area except Hainan and Guangdong are grouped into category 1. These provinces are leaders in TFCP.

---

\(^1\) According to geographical location and economic condition, China’s 30 provinces are divided into three areas: the eastern area includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central area includes Anhui, Jilin, Heilongjiang, Shanxi, Henan, Hubei, Hunan, and Jiangxi; and the western area includes Shaanxi, Mongolia, Guangxi, Yunnan, Guizhou, Chongqing, Xinjiang, Qinghai, Sichuan, Ningxia, and Gansu.
while with relative lower EFFCH, since the TECH is not high enough to compensate for the lower EFFCH, thus leading to MCPI lower than the national average level. These regions should pay more attention to investing more resources in sophisticated equipment, personnel training, and technological innovation for the improvement of their MCPI. On the contrary, category 3 includes the majority of western provinces. These provinces with lower TFCP, due to the catch-up effect, obtained a relatively higher EFFCH, which makes for a great contribution to the improvement of their MCPI. Taking Qinghai as an example, the TFCP of Qinghai is the lowest with an average value of 0.534, but due to the largest EFFCH of 1.09, so even with the TECH lower than unit, it can also witness the higher MCPI, which provides a typical example to illustrate the contributions of EFFCH to the growth of MCPI.

Different from what was mentioned above, Guangxi, Xinjiang, and Jiangxi are grouped into category 2. They have both lower TFCP and lower MCPI, and these regions should pay attention to not only technological advancement but also management improvement. It should be noted that category 4 includes 4 regions, of which the situation of Anhui and Inner Mongolia is similar to category 4. While Guangdong and Henan show different situations, the TFCP of Guangdong ranks fourth, only after Shandong, Jiangsu, and Zhejiang provinces, and also with a relatively lower EFFCH, but the value of TECH is the largest among all provinces, thus the improvement of MCPI is mainly driven from the component of TFCH. Henan shares this common feature with Guangdong.

**Conclusions**

A trans-log stochastic frontier analysis method was employed to measure the carbon emission performance in China’s thermal power generation industry over the period 2003-2013. On this basis, a carbon emission performance Malmquist index was further applied to measure its dynamic change. The empirical results show that the TFCP of China’s thermal power industry has increased as a whole, and some environmental factors such as the efficiency of fuel utilization, investment-based regulations, and so on, have a positive effect on the improvement of TFCP. With regard to the dynamic change of carbon emission performance, the value of MCPI indicates that the carbon emission performance of China’s provincial thermal power industry grew by 3.1% annually, and this was mainly driven by the efficiency change component. The similar growth pattern of MCPI also exists in the eastern, central, and western areas. However, significant difference can be found in MCPI among China’s different provinces. These results can have several policy implications.

First, since the growth of MCPI is mainly from the contribution of the EFFCH while the contribution of TECH is minor, improving power generation-related technologies is at the core of promoting CO₂ emissions performance of thermal power industry in China. In this regard, the application of coal-fired generating units...
with large-scale, high-efficiency, and low emissions instead of the small ones with poor efficiency and high emissions would be a feasible choice for policymakers. Some clean coal power generation technologies, such as CCS (carbon capture and storage) should be taken as long-term strategies for China’s power industry to promote its carbon emission performance [30]. At the same time, it is critical to strengthen R&D for innovating and improving equipment and technology.

Second, considering the differences in carbon emission performance and its dynamic variation among regions, region-specific policies should be put forward by considering local conditions in terms of both technological feasibility and environmental bearing capacity. For provinces with higher TFCP and higher MCPI, policymakers should encourage them to play a leading role continuously. It will be necessary for the provinces with lower TFCP and lower MCPI to change the development mode of “pollute first and treat later”. In this regard, better management is very helpful for saving energy and reducing CO₂ emissions of thermal electricity generation.

Admittedly, there still exist some limitations in this study. For example, in the SFA model we only consider four variables and do not consider the effects of fuel prices and other factors on CO₂ emission inefficiency. In addition, CO₂ emissions are measured from the perspective of electricity generation without considering the interregional electricity trade. These limitations will be taken into account in future research.

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