Energy 196 (2020) 117117

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Emission reduction effect and carbon market efficiency of carbon emissions trading policy in China

Wei Zhang [a,1], Jing Li [b,*,1], Guoxiang Li [c], Shucen Guo [d]

[a] School of Economics and Management, China University of Geosciences, Wuhan, 430074, China
[b] College of Economics and Management, Shandong University of Science and Technology, Qingdao, 266590, China
[c] School of Public Economics and Administration, Shanghai University of Finance and Economics, Shanghai, 200433, China
[d] School of Economics and Management, Dalian University of Technology, Dalian, 116024, China

ARTICLE INFO

Article history:
Received 3 August 2019
Received in revised form
1 January 2020
Accepted 6 February 2020
Available online 7 February 2020

Keywords:
Carbon emission reduction
Carbon market efficiency
Carbon emission trading system
Difference-in-differences
Data envelopment analysis

ABSTRACT

China has implemented its carbon emission trading system (ETS) in seven pilots since 2013. Many methods have been used to evaluate the effect and efficiency of the ETS in reducing carbon emissions. Evaluating the carbon ETS to determine whether it has co-benefited the economy and environment in the seven pilots is crucial for the development of China. Moreover, different methods of measurement reveal different results on how efficient the seven carbon emission trading markets (ETMs) are. We use the difference-in-differences (DID) method to evaluate the impact of carbon emissions and economic growth following ETS implementation. Based on the data of industrial carbon emissions in 30 provinces of China from 2008 to 2016, the impact of ETS on the carbon emission reduction and economic growth of enterprises is empirically tested. Data envelopment analysis (DEA) evaluates the operating efficiency of the carbon ETMs. Based on the seven carbon emission trading pilots conducted in China in 2014–2016, the carbon ETMs differentiation system in the pilot area is taken as the input index and the ETS implementation effect is used as the output index to construct the full DEA evaluation model for gauging the operation efficiency of the carbon ETMs. The results show that the implementation of the carbon trading policy increases the economic dividend (13.6%) generated by the gross industrial output value, but significantly reduces the emission (24.2%) of industrial CO_2 in all seven carbon emission trading pilots. The average DEA efficiency of the seven carbon ETMs operations in China have increased annually.

1. Introduction

To realize the international carbon emission reduction target, the National Development and Reform Commission promulgated the Notice on Carbon Emission Rights Pilot Work in October 2011. Seven provinces and cities, including Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, Hubei, and Chongqing, were selected to conduct the pilot work of the carbon ETS. Each pilot had covered more than 20 industries and nearly 3000 key emission enterprises by the end of September 2017. The market operation has been generally stable, with an accumulated turnover of 200 Mt of CO_2. The industrial sector is the main carbon emitter. Therefore, the industrial CO_2 emissions and gross industrial output value are the key data to evaluate the effect of the carbon ETS. In addition, exploring the operating efficiency of the seven carbon ETMs is a powerful illustration of the ETS.

The effect of carbon ETS implementation and its operating efficiency at home and abroad in recent years are reported in this study. A large corpus of literature has explored the impact of the carbon ETS on economic growth and environment. P. et al. [1] used the energy-saving and emission-reduction investment data of 29 provinces and cities in China from 1996 to 2005, based on the allocation of five regional emission reduction targets, such as carbon emissions, energy consumption, population, GDP, and per capita GDP. The study found that emission reduction targets based on carbon emissions and populations are more equitable in terms of abatement cost savings across regions. Hübler et al. [2] used the computable general equilibrium model to evaluate the carbon trading policy in China. Model simulations reveal that climate policy can result in a GDP loss of around 1% in 2020 and a welfare loss of around 2% by 2030. Wang et al. [3] examined the abatement

* Corresponding author.
E-mail address: 15621450881@163.com (J. Li).
[1] These two authors contributed equally to this paper.

https://doi.org/10.1016/j.energy.2020.117117
0360-5442/

costs of the electricity, smelting, cement, and steel sectors in Guangdong under the carbon trading policy based on the Copenhagen climate target. Y. et al. [4] inspected the technology investment of Shenzhen thermal power industry for emission reduction under the carbon trading policy. K. et al. [5,6] used DEA to simulate the economic potential and emission reduction costs of 30 provinces in China during 2006–2010 under the three policies of command control, space transaction, and inter-period and space transactions. The results indicate that the market transaction policy can enhance the economic and emission reduction potential more than the command control policy can. Zhang et al. [7] used China's provincial panel data for a study revealing how ETS could reduce the carbon intensity by 20.06% under the unconstrained situation by keeping the total GDP of the country unchanged. If the rigid constraints on the total GDP of the country were relaxed and the realistic constraints on economic growth and environmental protection were imposed on various regions, the implementation of ETS could reduce the carbon intensity by 22.15%. Li et al. [8] used the industrial carbon emission data of 30 provinces in China, using DID and propensity score matching–DID (PSM-DID) methods, to investigate the impact of ETS on industrial carbon emissions and carbon intensity.

There are only a few studies that have evaluated the efficiency of ETMs operation in China. Different conclusions were reported. Milunovich and Joyeux [9] conducted an empirical test on the market efficiency of European Union Allowances futures through the holding cost pricing model. Dasklakis et al. [10] conducted an empirical study to spot the futures market data of Powernext, ECX, and Nord Pool exchanges through sequence correlation analysis, variance ratio test, and income comparison of different trading strategies. Vinokur [11] and Charles [12] conducted a routine effectiveness test on the European Union Carbon Emissions Trading System (EU ETS). Montagnoli and de Vries [13] empirically tested the effectiveness of the ETM using the variance ratio, believing that only some markets had achieved weak effectiveness in the past. Feng et al. [14] conducted research on the spot price of the EU carbon emission quota, its yield sequence neither shows the characteristics of random walk, nor meets the conditions of efficient market hypothesis. Ibikunle et al. [15] and Xing Yang et al. [16] studied the ETMs efficiency and liquidity of the European Climate Exchange. Wang et al. [17] used the C^2GS^2 model to construct a DEA model that would evaluate the management efficiency of the ETMs. Liu et al. [18] used traditional dynamic financial analysis (DFA) and sliding window DFA to study the EU carbon emission quota and certified carbon emission reduction. Wang et al. [19], using the data of Beijing's ETM, conducted an R/S test of the carbon asset return rate through the R/S test method under fractal market theory. Wang et al. [20] conducted variance ratio tests on the ETMs of Guangdong, Shanghai, and Shenzhen. None had not been effective. Zhang et al. [21] conducted a research on the efficiency of ETMs using the data of China's pilot from 2013 to 2016. They established a single index and multiple Herost indexes, and then used rolling window technology to conduct a dynamic research on the changes of multiple Herost indexes. Cheng et al. [22] constructed a DEA evaluation model based on the panel data of the ETMs from 2014 to 2015. The indexes included the weighted carbon price, price stability, trading activity, quota tightness, market participation, and other evaluation indicators. Yang et al. [23] compared the operating efficiency of ETMs for market operation efficiency, energy consumption emission control, as well as economic, social, and environmental benefits.

At present, as far as the research object is concerned, it can be seen that scholars have more research on the economy impact than on the environmental impact about the carbon ETS. Since China's CO_2 emissions are largely derived from industry, and the main body of carbon emissions trading is mainly in the industrial sector, and in the current literature, there is relatively little literature on the impact of China's carbon trading on the industrial sector. Therefore, we will study the real carbon emission reduction effect of the ETS and the efficiency of the carbon ETMs comprehensively. According to the relevant data of industrial carbon emissions from 30 provinces in China, DID is used to explore the impact of the ETS on CO_2 emissions and total industrial output value. DID has been chosen in this study as it can model the net impact of the carbon ETS. This study uses the carbon ETM differentiation system in the pilots as input indexes and the implementation effect of the ETS as output indexes. The operation efficiency of the seven ETMs is evaluated using DEA model. The overall diagram of this study is shown in Fig. 1.

The main contributions of this paper are as follows. First of all, using the DID model empirically test the environmental and economic effects of China's carbon emission trading policy, thus making up for the vacancy in empirical research in this field. Secondly, this paper not only examines the policy effects of the carbon ETS, but also further analyzes the efficiency of the carbon ETMs to examine the operation of the ETS. Finally, the conclusions of this

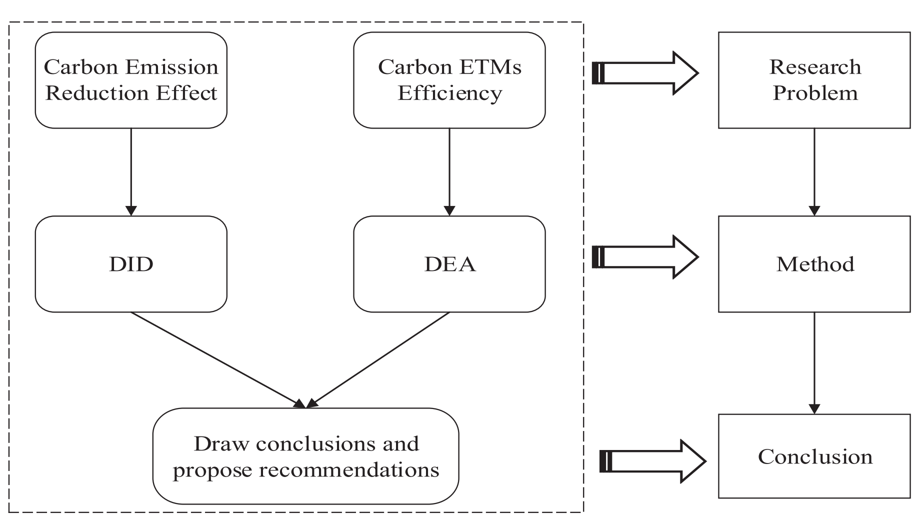

Fig. 1. The overall flow diagram for this article.

paper can provide empirical support and policy recommendations for China to improve the carbon ETS and implement the national unified carbon ETMs.

2. Methods and data

2.1. Model design

2.1.1. Evaluation of policy effect using DID model

There are many factors affecting CO_2 emissions, such as macroeconomic policies [24], climate change, resource dependency [25,26], foreign direct investment [27]. Previous scholars did not rule out these factors during the research, so the results did not reflect the net impact of carbon emission reduction of ETS in China. It is challenging to judge whether carbon emissions trading policy is successful solely based on the changes in the CO_2 emissions. The DID model could be applied to examine whether ETS inhibits the growth of CO_2 emissions. In fact, the pilot policy for industrial carbon emissions trading since 2012 can be considered a quasi-natural experiment.

To study whether the ETS reduces industrial CO_2 emissions, it is necessary to compare the changes of CO_2 emissions during the two time periods in the seven carbon ETMs in China (i.e., Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, Hubei, and Chongqing). These seven pilot provinces and cities are the treatment groups, and the remaining 24 provinces are the control group before and after the implementation of the policy. Before and after the year of 2012 are the non-pilot and pilot periods.

This work distinguishes the four sub-samples by setting the treatment and period. Treatment at 1 represents the pilot of carbon trading, treatment at 0 represents other provinces, period at 0 represents the year before the carbon trading pilot, and period at 1 represents the year after the carbon trading pilot (including that year). The DID models constructed are shown in Eq. (1) and Eq. (2).

$$\ln CE_{jt} = \beta_0 + \beta_1 treated_j + \beta_2 period_t + \beta_3 treated_j \times period_t + v_{jt} \tag{1}$$

$$\ln Y_{jt} = \beta_0 + \beta_1 tredted_j + \beta_2 period_t + \beta_3 treated_j \times period_t + v_{jt} \tag{2}$$

$\ln CE_{jt}$ and $\ln Y_{jt}$ represent the logarithmic value of industrial CO_2 emissions and logarithmic value of the gross industrial output value in the t year of province j. Taking Eq. (1) as an example, the meaning of each parameter in the DID model is shown in Table 1.

In regions where the ETS is implemented ($treated = 1$), the CO_2 emissions before and after the carbon trading pilot are $\beta_0+\beta_1$ and $\beta_0+\beta_1+\beta_2+\beta_3$, respectively. The change of CO_2 emissions before and after the pilot is $\Delta Y_0=\beta_2+\beta_3$. Among them, ΔY_0 includes the role of carbon emissions trading policies. Similarly, for other provinces ($treated = 0$), CO_2 emissions before the carbon trading pilot are β_0 and after the carbon trading pilot are $\beta_0+\beta_2$. The change of CO_2 emissions before and after the pilot not affected by carbon emissions trading policies is $\Delta Y_1 = \beta_2$, and ΔY_1 does not include the impact of carbon emissions trading policies on regional CO_2 emissions. Therefore, by subtracting ΔY_1 from ΔY_0 before and after the policy in the treatment group, the net effect of the carbon emissions trading policy on CO_2 emissions can be obtained, that is, $\Delta\Delta Y = \beta_3$. This is the focus of the current study's DID estimation. If the carbon emissions trading policy inhibits the growth of CO_2 emissions, then the β_3 coefficient should be significantly negative. After this treatment, the general factors affecting China's CO_2 emissions, such as macroeconomic policies and climate change, will be eliminated to estimate the impact of ETS more accurately.

Eq. (1) examines the impact of carbon emissions trading policies on local industrial CO_2 emissions and Eq. (2) examines the impact of carbon emissions trading on the industrial output. The β_3 coefficient represents the net effect of the policy, that is, the impact of ETS on both the industrial CO_2 emissions and gross industrial output value. Since the pilot provinces and cities are not randomly selected, the basic requirements for quasi-natural experiments to randomly select the treatment group will not be met. Therefore, control variables need to be added.

For Eq. (1), the control variables (cv), including population size ($\ln pop$), economic scale ($\ln gdp$), living standard ($\ln pgdp$), technical level (ei), economic structure ($industry$), and the number of heavy industry enterprises ($\ln hcount$), are introduced to investigate the impact of the ETS on the gross industrial output value and CO_2 emissions. The basic model Eq. (1) is revised as Eq. (3):

$$\ln CE_{jt} = \beta_0 + \beta_1 treated_{jt} + \beta_2 period_{jt} + \beta_3 treated_{jt} \times period_{jt} + \sum_i \alpha_i cv^i_{jt} + v_{jt} \tag{3}$$

For Eq. (2), it is necessary to introduce three major production factor variables—capital (K), labor (L), and energy consumption (E). Eq. (2) becomes Eq. (4):

$$\ln Y_{jt} = \beta_0 + \beta_1 treated_{jt} + \beta_2 period_{jt} + \beta_3 treated_{jt} \times period_{jt} + \sum_i \alpha_i cv^i_{jt} + v_{jt} \tag{4}$$

2.1.2. Evaluation of ETMs efficiency using DEA model

According to the point of view of Jiayu Wang et al. [28], the DEA method can be used for efficiency evaluation of multiple inputs and multiple outputs. Previous efficiency assessment methods could only handle the individual outputs. In contrast, the DEA approach reported in this study could deal with multiple inputs and multiple outputs. This method does not need a production function to estimate the parameters. At present, the most representative DEA models are the Charnes-Cooper-Rhodes (CCR) and the Banker-Charnes-Cooper (BCC) models. The BCC model decomposes the comprehensive technical efficiency in the CCR model into pure technical efficiency (PTE) and scale efficiency (SE). It can be divided into input-oriented and output-oriented types. The input-oriented refers to minimizing resource input to improve efficiency when output is constant, while the output-oriented refers to increasing output under the condition of unchanged input factors. This study selects an input-oriented BCC model to measure the operational efficiency of ETMs.

Learn from the model of Yujiao Xian et al. [29] and Keying Wang et al. [30], suppose there are n decision making units (DMUs),

Table 1
Parameters in the DID model.

	Before becoming the carbon trading pilot ($period = 0$)	After becoming the carbon trading pilot (including that year) ($period = 1$)	Difference
Carbon trading pilot (treatment group, $treated = 1$)	$\beta_0+\beta_1$	$\beta_0+\beta_1+\beta_2+\beta_3$	$\Delta Y_0 = \beta_2+\beta_3$
Other provinces (control group, $treated = 0$)	β_0	$\beta_0+\beta_2$	$\Delta Y_1 = \beta_2$
DID			$\Delta\Delta Y = \beta_3$

where each DMU has m inputs (representing the consumption of resources) and s kinds of outputs (results of resource consumption). X_{ij} represents the ith input of the jth DMU$_j$, Y_{rj} represents the rth output of the jth DMU$_j$, and λ_j is the index weight of n DMU.

$\sum_{j=1}^{n} xij\lambda j$ indicate the inputs of the DMU after weighting and $\sum_{j=1}^{n} yij\lambda j$, the outputs of the DMU after weighting. The specific model of BCC is shown in Eq. (5).

$$\begin{cases} \min\left[\theta-\varepsilon\left(\sum_{i=1}^{m}S_i^- + \sum_{i=1}^{m}S_i^+\right)\right] \\ \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- = \theta x_{ij},\ i\in\left(1,2,\cdots,\mathrm{m}\right) \\ s\cdot t\cdot \sum_{j=1}^{n} y_{rj}\lambda_j - S_i^+ = y_{rj}, r\in\left(1,2,\cdots,\mathrm{s}\right) \\ \sum_{j=1}^{\mathrm{n}} \lambda j = 1 \\ \theta,\lambda_j,S_i^-,S_i^+ \geq 0 \\ j=1,2,\cdots,\mathrm{n} \end{cases} \tag{5}$$

θ is the relative efficiency; s_i^- and s_i^+ are the slack variables; ε is the non-Archimedean infinitesimal, generally $\varepsilon = 0.000001$. Assume that the optimal solution of the model is θ^*, s^{*+}, s^{*-}, and λ^*, where:

(1) If $\theta^* = 1$, the DMU is at least weak DEA effective.
(2) If $\theta^* = 1$ and $s^{*+} = s^{*-} = 0$, the DMU is DEA effective.
(3) If $\theta^* < 1$ or $s^{*+} \neq 0$, $s^{*-} \neq 0$, the corresponding DMU is non DEA efficient. The larger the θ^*, the higher the relative efficiency of the DMU.
(4) The optimal solution is used to analyze the corresponding status of the scale return of the DMU. If $\sum_{j=1}^{n} \lambda j = 1$, the scale returns remain unchanged; and if $\sum_{j=1}^{n} \lambda j < 1$, the scale returns are increased; and if $\sum_{j=1}^{n} \lambda j > 1$, the scale returns are decremented.

2.2. Data source and variable selection

2.2.1. Data source and selection of policy evaluation model variables

The sample data were collected from the industrial enterprises above designated size in 30 provinces and cities in China from 2008 to 2016. Because there are missing data in Tibet, this article does not use its data. The data are mainly from *China's Statistical Yearbook*, from 2008 to 2016; *China's Energy Statistical Yearbook*, from 2008 to 2016; *China's Industrial Statistical Yearbook*, from 2008 to 2016; and the 2008–2016 statistical yearbooks of 30 provinces and cities.

The ETS was officially approved in October 2011. However, the carbon emissions trading pilot project only began in June 2013. It was likely that the companies exhibited forward-looking characteristics in decision-making. Thus, they have responded accordingly to the carbon emissions trading policy in 2012. Therefore, this study uses the data from 2012 to 2016 as the post-pilot period, and the data from 2008 to 2011 as the pre-pilot period.

For model (3), the regional GDP (ln*gdp*), per capita GDP (ln*pgdp*), and gross industrial output value of each province (ln*Y*) are reduced by the regional GDP index, per capita GDP index, and producer ex-factory price index in 2008 (*China's Statistical Yearbook*, 2009). The CO_2 emissions factor (*CE*) is calculated using Eq. (6) (Intergovernmental Panel on Climate Change or IPCC Carbon Emissions Calculation Guide, 2009) [31].

$$CE = \sum_{i=1}^{17} E_i \times C_i \tag{6}$$

E_i is the energy i consumption, based on standard coal. C_i is the energy i carbon emission coefficient, where i is a type of energy from 17 categories (mainly including raw coal, refined coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery dry gas, other petroleum products, other coking products, heat, electricity, coke oven gas, other gas, and natural gas).

The carbon emission factor of the main energy consumption is derived from the default value of the IPCC Carbon Emissions Calculation Guide, and the original data is in standard units of J. To be consistent with the statistics, the energy units need to be converted to standard coal. The value refers to the carbon emission coefficient of various energy sources calculated by Zhao et al. [32].

For model (4), the net value of the industrial fixed assets is *K*. The average annual number of employees in the industry is *L* and the industrial energy consumption in the sub-region is taken as *E*.

2.2.2. Data source and selection of ETMs efficiency evaluation model variables

Carbon trading policy, as an important governance tool for the government to deal with environmental issues such as global warming, is mainly achieved through system design and policy promulgation. It affects by establishing a carbon trading market first, and then by administrative intervention. Governments participating in the operation of the market mechanism make behavioral decisions to achieve control of regional carbon emissions and thus achieve regional emission reduction targets. Refer to indicators used by Yongwei Cheng et al. [22] to evaluate the operating efficiency of the carbon ETMs, this research collect policy documents issued by the pilots (including the implementation rules of carbon emission quota management and implementation plan of the pilot work). Therefore, the ETMs differentiation system design in the pilots is the input index and the implementation effect of the ETS (i.e., transaction results, economic benefits, and environmental benefits) comprise the output indicators to construct the ETMs efficiency evaluation index system. Specific input and output indicators are shown in Table 2. The data are taken from the relevant transaction data published by *The World Bank Report: Current Situation and Trend of Carbon Market, China's Carbon Market Survey Report* from 2015 to 2017, China's Carbon Emission Trading Network and the seven pilots of the Carbon Emission Trading Network. Part of the data is calculated according to the data collected on the Internet.

3. Analysis of empirical results

3.1. Estimation of policy effect results

3.1.1. Applicability test of the DID

The hypothesis of the DID application is that the differences between the treatment group and the control group are fixed. According to the statistics, the trend of the average CO_2 emissions and average gross industrial output value of the treatment and control groups from 2008 to 2016 are shown in Figs. 1 and 2. The treatment and control groups follow a similar trend before the year of 2012. The average CO_2 emission of the control group is higher than that of the treatment group between the year of 2008 and 2016 (Fig. 2). The average gross industrial output value of the treatment group

Table 2
The efficiency rating indicator system for the ETS operation market.

	Primary indicator	Secondary indicators	Indicator interpretation
Input indicator	Distribution system	Total quota: X_1 (10^2 Mt)	Consists of initial and reserve quotas
	Controlled coverage	Number of controlled enterprises: X_2	Disclosure data of official trading platform of each transaction
	Reporting and verification system	Number of verification agencies: X_3	Disclosure data of official trading platform of each transaction
	Legal System	Number of policy documents: X_4	Disclosure data of official trading platform of each transaction
Output indicator	Trading situation	Total trading volume: Y_1 (10^4 t)	Carbon Emissions Trading Online Data Calculation
	Economic benefit	Regional industrial production growth rate: Y_2 (%)	Organized by *China'S Statistical Yearbook* and regional statistical yearbooks
	Environmental benefits	Rate of decline in energy consumption per unit of GDP: Y_3 (%)	Organized by *China'S Energy Statistics Yearbook* and regional statistical yearbooks

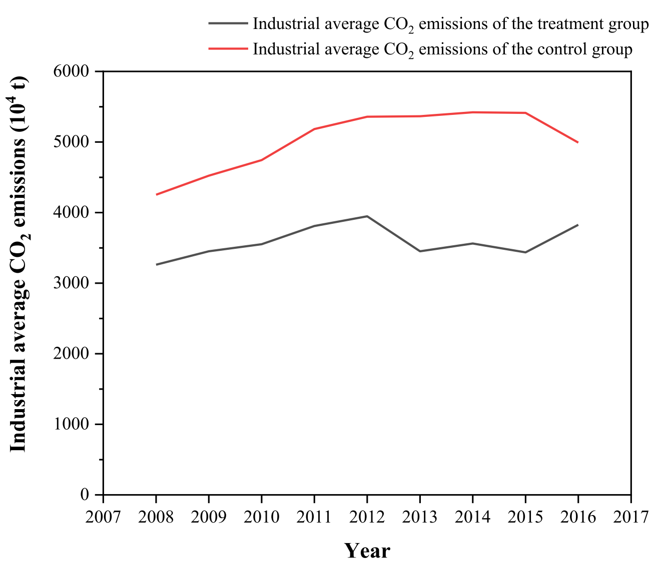

Fig. 2. Trends in CO_2 emissions from treatment and control groups in 2008–2016.

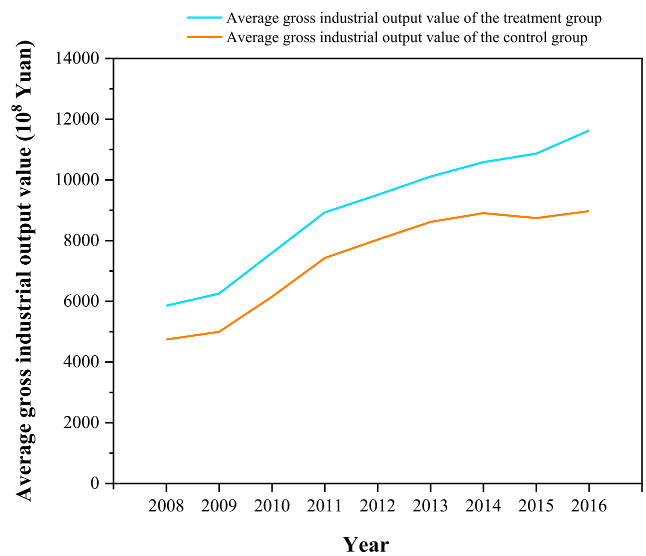

Fig. 3. Trends in the average gross industrial output value of the treatment and control groups in 2008–2016.

over the years is higher than that of the control group (Fig. 3). These results validate the use of the DID method.

3.1.2. Statistical analysis of main variables

Supplementary Information (Table S1) lists the results of the descriptive statistical analysis. The logarithm of the industrial CO_2 emissions in 30 provinces is 8.14 and the standard deviation is 0.80. The average value of the gross industrial output value of 30 provinces is 8.56 and the standard deviation is 0.99. Thus, there is no significant difference between the CO_2 emissions and gross industrial output value in each province.

The average value of ln*hcount* is 8.46 and the standard deviation is 1.23, revealing that the number of heavy industry enterprises varies from province to province, and there is a large gap. The carbon trading pilot provinces accounted for 20%, indicating that they are too small compared with the total provinces in China. The period of carbon trading policy implementation accounts for 50%, indicating that it is just in the middle of the sample period.

3.1.3. Regression results and analyses

The results of the regression on models (3) and (4) are shown in Table 3.

ln*CE* (column 1) and ln*Y* (column 2) in Table 4 examine the impact of the ETS on carbon emissions and economic growth, respectively. Column (1) shows that the coefficient of *treated*period* is −0.24, which is significant at the 1% level. Thus, the ETS has evident carbon inhibition. Column (2) shows that the coefficient of *treated*period* is 0.14, which is significant at the 5% level. Thus, the ETS has a positive effect on economic growth. The results indicate that the ETS significantly achieves the effects of economic growth along with energy conservation and emission reduction. The results of this study are similar to those of Guangming Li et al. [8]. They have empirically tested that carbon ETS can significantly suppress the increase in carbon emissions and increase the total industrial

Table 3
The regression results of ETS on CO_2 emissions and economic growth.

Variable	$\ln CE_{it}$ (1)	$\ln Y$ (2)
*treated*period*	−0.24*** (0.08)	0.14** (0.07)
treated	−0.03 (0.06)	−0.18*** (0.06)
period	0.08* (0.04)	0.05 (0.07)
ln*pgdp*	−0.09 (0.33)	
ln*pop*	0.19 (0.34)	
ln*gdp*	0.80** (0.34)	
industry	1.66*** (0.26)	
ln*hcount*	0.03 (0.03)	
ei	0.72*** (0.04)	
ln*K*		0.58*** (0.11)
ln*L*		0.52*** (0.04)
ln*E*		−0.01 (0.10)
_cons	−0.80 (3.10)	0.90*** (0.36)
N	270	270
R-squared	0.92	0.89

Note: The parentheses are the standard error of the regression coefficient. ***,**, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 4
Input and output data after treatment in the carbon pilots in 2014–2016.

Year	DMU	Input indicator		Output indicator
		F_1	F_2	P_1
Year 2014	Beijing	0.82	0.87	0.19
	Tianjin	0.25	0.37	0.13
	Shanghai	0.41	0.73	0.10
	Hubei	0.1	0.1	1
	Guangdong	0.29	0.41	0.17
	Chongqing	0.50	1	0.64
	Shenzhen	1	0.91	0.92
Year 2015	Beijing	0.89	0.11	0.58
	Tianjin	0.25	0.15	0.10
	Shanghai	0.51	1	0.35
	Hubei	0.10	0.20	1
	Guangdong	0.35	0.57	0.60
	Chongqing	0.51	0.40	0.57
	Shenzhen	1	0.1	0.95
Year 2016	Beijing	1	0.49	0.62
	Tianjin	0.24	0.35	0.10
	Shanghai	0.32	1	0.66
	Hubei	0.10	0.19	0.73
	Guangdong	0.12	0.18	0.97
	Chongqing	0.42	0.21	0.50
	Shenzhen	0.93	0.10	1

output value.

The regression results of the *CV* (Table 3) indicate that economic scale (ln*gdp*), industrial structure (*industry*), and energy intensity (*ei*) in column (1) have a significant positive impact on carbon emissions. The results show that China is a society with high energy consumption and the increase of regional GDP will inevitably lead to an increase in CO_2 emissions. As Pan, X. et al. [33–36] advocate, China should improve energy efficiency. Capital (ln*K*) and labor (ln*L*) in column (2) have a positive impact on the significance level of the gross industrial output value at 1%, while energy consumption (ln*E*) has no obvious effect on the gross industrial output value (ln*Y*), but may even reduce it.

3.2. Analysis of operational efficiency in the ETMs

3.2.1. Principal component analysis

The number of DEA evaluation units should be more than twice the input and output indicators. To solve this problem, this study first uses the factor analysis method (FAM) to compress the input and output indicators separately.

After SPSS 23.0 analysis, the KMO value of the input index is 0.53 (>0.5) and of the output index is 0.51 (>0.5). The significant probability of the Cartesian statistical value of the Bartlett test is 0.00. The value of each input index in the indicator system is correlated, in line with the requirements for the FAM for data analyses.

FAM is applied to four input indicators and three output indicators, respectively, and the analysis results are shown in *Supplementary Information* (Table S2). According to the principle that the cumulative contribution rate of principal component is $\geq$ 70% and the eigenvalue is $\geq$ 1, two principal components and one principal component are respectively extracted for the input and output indices. The maximum variance method rotates each index to obtain the rotated factor load matrix. This matrix shows that, in the input index, the common factor F_1 has a greater influence on the indicators X_1, X_2, and X_3, defined as the quota allocation, control, and verification factors. The common factor F_2 has a greater impact on indicator X_4, defined as the legal system factor. The output indicator only proposes one component, so it cannot be rotated. It is named the trading, environmental benefit, and economic benefit factor.

According to the input and output index component score coefficient matrix, the score of each sample on each principal component from 2014 to 2016 is calculated. To smoothen the data and meet the input and output data requirements of the DEA model, the input and output factor scores calculated herein are processed forward with the maximum standard model as follows:

Assume that F_{ij} and F'_{ij} are the principal component values before and after the transformation, and max F_{ij} and min F_{ij} are the maximum and minimum values in each index. Eq. (7) is used to change the data to a positive value:

$$F'_{ij} = 0.1 + 0.9*(F_{ij} - \min F_{ij})/(\max F_{ij} - \min F_{ij}) \tag{7}$$

The transformation of data can make the transformed data all in [0.1, 1], without changing the original relationship. After the dimensionless processing, the DEA model data with two input indicators and one output indicator are obtained. The specific data are shown in Table 4.

3.2.2. Analysis of the DEA results

DEAP 2.1 software is used as the analysis tool, a range of efficiency coefficients, comprehensive technical efficiency (crste), pure technical efficiency (vrste), and scale efficiency (scale) of the seven ETMs in China from 2014 to 2016 were computed and shown in Supplementary Information (Table S3) and Figs. 4–7.

The operation efficiency of ETMs in 2014–2016 are analyzed year by year below. In Figs. 4–6 and Supplementary Information (Table S3), only Hubei is DEA efficient in 2014. That means the crste, the vrste, and the scale are all 1, and the relaxation variables are 0. In addition, the scale returns remain unchanged. Except for Hubei, the scale returns of all other ETMs (Beijing, Tianjin, Shanghai, Guangdong, Chongqing, and Shenzhen) decreased in 2014. This shows that in these places' economic development, there are extensive production methods that rely on expanding input of production factors to increase economic output. Thus, the Beijing, Tianjin, Shanghai, Guangdong, Chongqing, and Shenzhen pilots can optimize the operation efficiency of the ETMs by increasing the output or reducing the input factors. Hubei and Shenzhen's ETMs were DEA efficient in 2015. Although the crste in Tianjin did not reach the effective value, its pure technical efficiency value was 1 and the scale returns increased in 2015, indicating that the level of the technical input was too rigid. The scale of Tianjin should thus be enlarged to make it effective. Guangdong and Shenzhen's ETMs

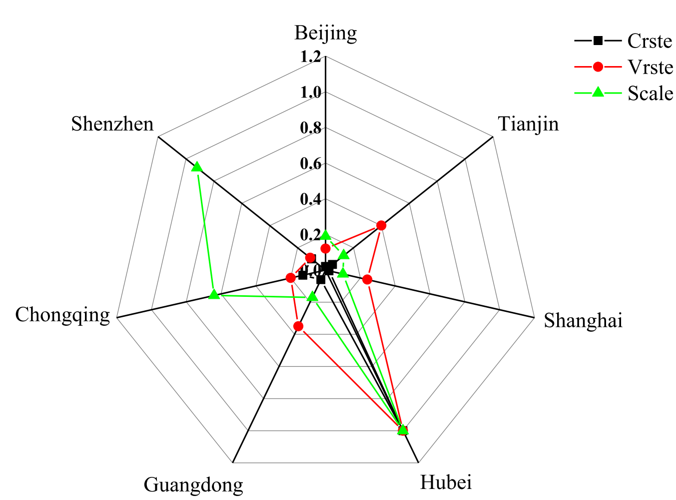

Fig. 4. The DEA evaluation value of the carbon ETMs efficiency in 2014.

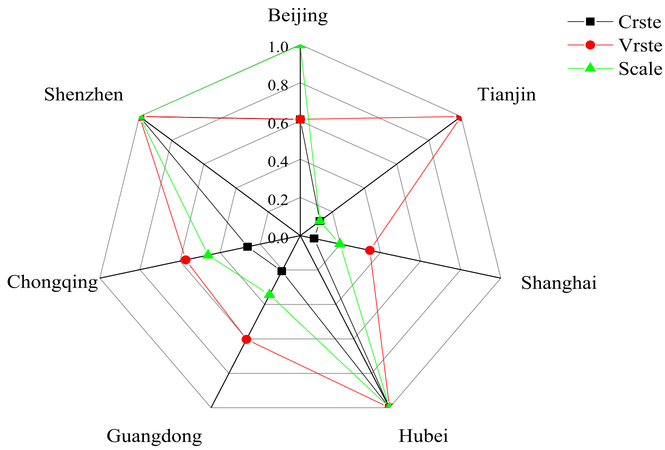

Fig. 5. The DEA evaluation value of the carbon ETMs efficiency in 2015.

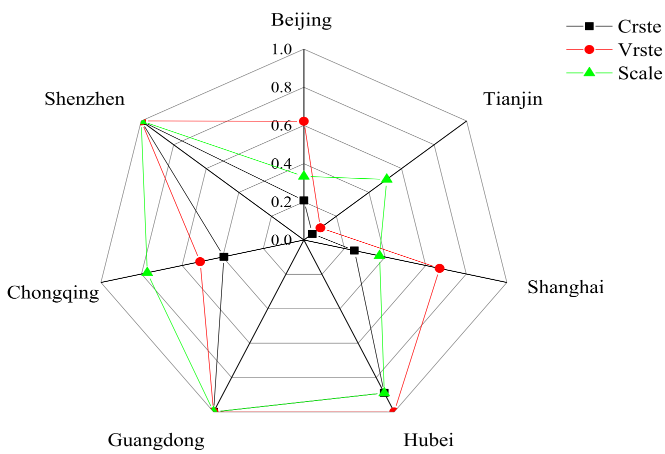

Fig. 6. The DEA evaluation value of the carbon ETMs efficiency in 2016.

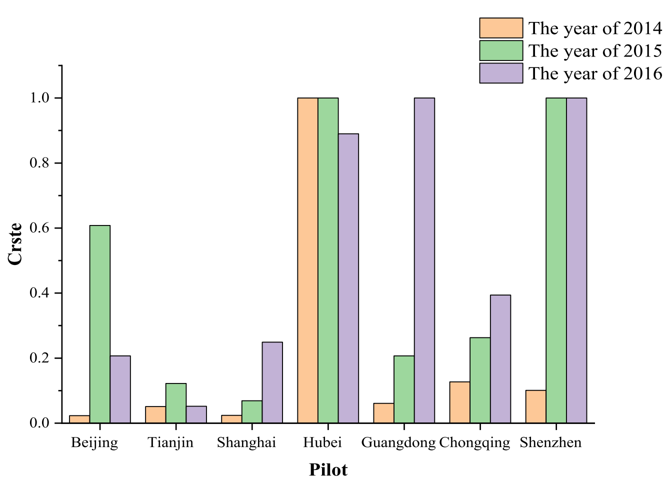

Fig. 7. Trends in the comprehensive technical efficiency of the carbon ETMs in 2014–2016.

were DEA efficient in 2016. Hubei's vrste value was 1, but it was not DEA efficient in 2016, indicating that its ETM should also be expanded in scale. It is worth mentioning that compared to the year of 2014 and 2015, the changes in the ETM in Hubei Province are related to changes in the entry threshold of the carbon trading. It can be seen that the changes in Hubei's policy have a greater impact on ETM efficiency.

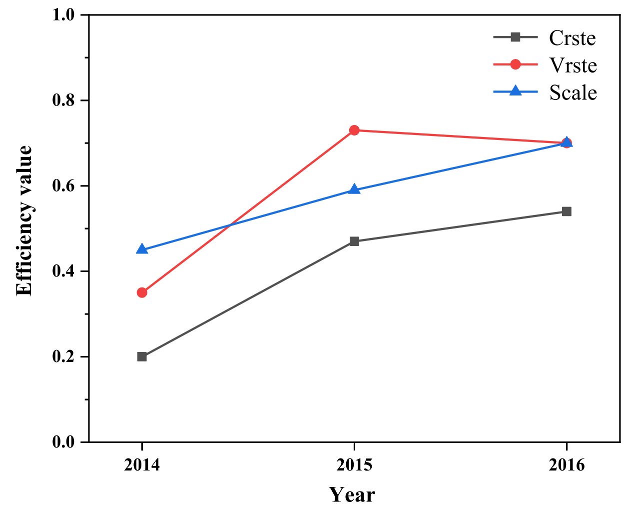

Fig. 8. China's carbon ETMs efficiency and its decomposition.

The operation efficiency of ETMs in 2014–2016 are analyzed market by market below. In Fig. 7 and Supplementary Information (Table S3), the crste value of Shanghai, Guangdong, Chongqing, and Shenzhen gradually rose from 2013 to 2016. The crste value of Guangdong in 2016 and Shenzhen in 2015–2016 was 1, indicating that Guangdong and Shenzhen's ETMs have gradually developed and matured in recent years. Shenzhen, as the provincial municipality that took the lead in implementing carbon trading policy, is advancing with Guangdong in ETS implementation. Although the crste of Shanghai and Chongqing's ETMs have improved yearly, the efficiency value is generally low. Chongqing, as a municipality directly under the jurisdiction of the latest carbon trading pilot, has great potential in the development of the ETMs. The crste value of Hubei's ETM in 2014–2015 was 1. Although its crste value in 2016 did not reach 1, it was higher than other pilots, indicating that its ETM development momentum is stronger despite the pilot implementing later than other pilots did. The ETMs efficiency of Beijing and Tianjin were relatively low, indicating room for improvement. Generally speaking, the average annual value of ETMs in China rose annually from 2014 to 2016, indicating improving operation efficiency.

Use the average method to conduct an overall assessment of the carbon ETMs. As can be seen from Fig. 8, the characteristics of the vrste and the crste of the carbon ETMs are basically the same, and have the same inflection point, showing a significant correlation. The change trend of the scale is slightly the same as the change trend of the crste, but the fluctuation range is quite different. In general, the scale score > the vrste score > crste score. It can be seen that the level of the vrste score has a greater impact on the crste score. The results of this research are further discussed on the basis of the research of Yongwei Cheng, Yang Ye et al. [22,23]. It is empirically tested that vrste is the main factor affecting the operation efficiency of the carbon ETMs.

4. Conclusions and policy implications

This study used carbon ETS as a quasi-natural experiment in China. The DID method tested the impact of the implementation of the ETS on the carbon emission reduction at industrial scale. Then, according to the actual operation of the seven ETMs in China, the distribution system as well as coverage, reporting, and verification system evaluation indicators were constructed using the BCC–DEA method for evaluating the efficiency of ETMs. The main conclusions are as follows:

The implementation of ETS can reduce the carbon emissions (24.2%) of the pilot provinces and increase the gross industrial output value (13.6%). The ETS is still important for achieving carbon emission reduction. The economic scale, industrial structure, and energy intensity have a significant positive impact on the industrial CO_2 emissions. China is still a high energy consumption society, the increase of GDP will inevitably lead to the greater CO_2 emissions. If the proportion of high energy consumption industries and demand for energy consumption are too high, CO_2 emissions will increase. Meanwhile, the overall efficiency of the ETMs increased annually in the seven ETMs of China from 2014 to 2016. In 2014, only the ETM in Hubei was DEA efficient. In 2015 and 2016, the carbon markets in Guangdong and Shenzhen also gradually matured, with a crste value of 1. Although the crste values of Shanghai and Chongqing did not reach DEA efficiency, their carbon markets efficiency gradually increased every year. The efficiency of Beijing and Tianjin carbon markets were not high, which reflected the lack of activity of carbon trading markets. The level of the vrste score has a greater impact on the crste score.

On the basis of the research, this paper puts forward the following suggestions. Firstly, China should establish a national unified ETMs, so that the markets play a leading role in carbon emission reduction. Through the experimental results, we can clearly see that carbon trading policy can well inhibit carbon emissions, while improving the total industrial output value. So it is necessary to unify the systems and rules of ETS, and then build nationwide registration, trading, clearing, and settlement systems to develop a technical foundation for the national unified carbon market. Moreover, China should optimize the energy structure. Based on the above results, it can be seen that industrial institutions and energy structure have a significant positive impact on industrial CO_2 emissions. Therefore, various industries should strive to improve energy efficiency, reduce coal consumption, and develop new clean energy sources, such as solar energy and wind energy, so as to reduce the proportion of coal consumption in energy consumption. The government should also vigorously support the development of new energy sources and provide more subsidies for research funding and related supporting measures. Finally, China should change the mode of economic development. Among the factors examined above for the efficiency of the carbon ETMs, the vrste factor has a greater ability to restrict the final result than the scale factor. Therefore, to improve the efficiency score of the carbon ETMs, under the condition that both economic development and environmental benefits must be considered, it is possible to consider changing the economic development mode by changing production technologies and optimizing the production process. Ultimately improve resource utilization and reduce carbon dioxide emissions. China should activate the carbon markets by fostering an intermediary structure and strengthening financial innovation. In order to develop the carbon markets, China must vigorously cultivate intermediaries, including commercial banks, carbon emission rights valuation agencies, carbon asset management institutions, etc. They can provide financing services to both parties to the transaction. At present, it is necessary to guide commercial banks to develop carbon financial derivatives, such as carbon funds, carbon mortgages, carbon trusts, etc., which can not only provide opportunities for financial institutions to open up markets, but also facilitate the participation of related companies in carbon trading.

However, there are still some shortcomings in the research of this paper. First, it only considers the impact of carbon trading policies on the industrial sector. In the future, we should consider the impact of carbon trading policies on all sectors in order to get more convincing conclusions, such as household carbon emissions [37]. Then, when evaluating the efficiency of the carbon markets, other input indicators, such as carbon price researched by Qiang Ji ea al. [38], can be added to see if the changes in the input indicators will affect the operational efficiency of each carbon market.

Acknowledgment

This work was supported by the Humanities and Social Sciences Research Foundation, Ministry of Education of China (Grant No. 15YJAZH110) and supported by Major Project of National Social Science Fund of China (Grant No. 15ZDB163).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2020.117117.

References

[1] Zhou P, Zhang L, Zhou DQ, Xia WJ. Modeling economic performance of interprovincial CO2 emission reduction quota trading in China. Appl Energy 2013;112:1518–28.
[2] Hübler Michael, Voigt Sebastian, Löschel Andreas. Designing an emissions trading scheme for China- an up-to-date climate policy assessment. Energy Pol 2014;75:57–72.
[3] Wang Peng, Dai Han-cheng, Ren Song-yan, Zhao Dai-qing, Masui T. Achieving copenhagen target through carbon emission trading: economic impacts assessment in Guangdong province of China. Energy 2015;79:212–27.
[4] Huang Y, Liu L, Ma XM, Pan XF. Abatement technology investment and emissions trading system: a case of coal-fired power industry of shenzhen, China. Clean Technol Environ Policy 2015;17:811–7.
[5] Wang K, Wei YM, Huang ZM. Potential gains from carbon emissions trading in China: a DEA based estimation on abatement cost savings. Omega 2016;63:48–59.
[6] Wang K, Xian YJ, Zhang JM, Li Y, Che LN. Potential carbon emission abatement cost recovery from carbon emission trading in China: an estimation of industry sector. J Model Manag 2016;11:842–54.
[7] Zhang Cheng, Shi Dan, Li Pengfei. The potential effect of China's implementation of inter-provincial carbon emissions trading. Finance Trade Econ 2017;38:93–108 [in Chinese].
[8] Li Guangming, Zhang Weijie. Research on industrial carbon emission and emission reduction mechanism under China's carbon trading. China Popul. Res. Environ. 2017;27:141–8 [in Chinese].
[9] Milunovich G, Joyeux R. Testing market efficiency and price discovery in European carbon markets. Department of Economics. Macquarie Economics Research Papers; 2007.
[10] Daskalakis George, Markellos Raphael N. Are the European carbon markets efficient? Soc Sci Electron Pub 2008;17:103–28.
[11] Vinokur L. Disposition in the carbon market and institutional constraints. University of London. Working Paper; 2009.
[12] Charles A, Darne O, Fouilloux J. Testing the martingale difference hypothesis in CO2 emission allowances. Econ Model 2011;28:27–35.
[13] Montagnoli Alberto, Frans P, de Vries. Carbon trading thickness and market efficiency. Energy Econ 2010;32:1331–6.
[14] Feng M, Ge W, Luo S, Shevlin T. Why do CFOs become involved in material accounting manipulations. J Account Econ 2011;51:21–36.
[15] Gbenga Ibikunle, Gregoriou Andros, Andreas G, Hoepner F, Rhodes Mark. Liquidity and market efficiency in the world's largest carbon market. Br Account Rev 2016;48:431–47.
[16] Yang Xing, Liao Hanfeng, Feng Xiaoying, Yao Xingcai. Analysis and tests on weak-form efficiency of the EU carbon emission trading market. Low Carbon Econ 2018;9:1–17.
[17] Wang Wenjun, Fu Chonghui, Luo Yuejun, Xie Pengcheng, Zhao Daiqing. ETS management efficiency evaluation in China's carbon emission trading mechanism pilot area. Chinese Environ Sci 2014;34:1614–21 [in Chinese].
[18] Liu Jing, Wang Chenxi. Research on carbon market effectiveness based on sliding window DFA analysis. Green Tech 2014;5(10):271–4 [in Chinese].
[19] Wang Yanglei, Du Li. Research on the validity of China's carbon financial trading market-based on the analysis of fractal theory of beijing carbon trading market. Manag World 2015;31(12):174–5 [in Chinese].
[20] Wang Wenxie, Zhou Wanyun, Jin Li, Huang Yu. Research on the spillover effect of China's carbon market. China popul Resour Environ 2016;28(12):63–9 [in Chinese].
[21] Zhang Yuejun, Yao Ting, Lin Yuepeng. Research on the efficiency measurement of China's carbon quota trading market. J Nanjing Univ Aeronaut Astronaut 2016;18(2):1–9 [in Chinese].
[22] Cheng Yongwei, Dong Mu. Research on evaluation of operation efficiency of pilot carbon market in China. Sci Tech Manage Res 2017;37(4):96–100 [in

Chinese].
[23] Yang Xun, Qian Chongbin, Zhang Rongguang. Comparative analysis of operational efficiency of pilot carbon trading market. Land Resour Tech Manag 2017;34:19–29 [in Chinese].
[24] Pan X, Pan X, Li C, Song J, Zhang J. Int J Clim Change Strategies Manag 2018;11:326–40.
[25] Wang Keying, Meng Wua, Suna Yongping, Shi Xunpeng, Sun Ao, Zhang Ping. Resource abundance, industrial structure, and regional carbon emissions efficiency in China. Resour Pol 2019;60:203–14.
[26] Li Zhi, Shao Shuai, Shi Xunpeng, Sun Yongping, Zhang Xiaoling. Structural transformation of manufacturing, natural resource dependence, and carbon emissions reduction: evidence of a threshold effect from China. J Clean Prod 2019;206:920–7.
[27] Pan X, Zhang J, Li C, Quan R, Li B. Exploring dynamic impact of foreign direct investment on China's CO2 emissions using Markov-Switching vector error correction model. Comput Econ 2018;54:1139–51.
[28] Wang Jiayu, Wang Ke, Shi Xunpeng, Wei Yi-Ming. Spatial heterogeneity and driving forces of environmental productivity growth in China: would it help to switch pollutant discharge fees to environmental taxes? J Clean Prod 2019;223:36–44.
[29] Xian Yujiao, Wang Ke, Shi Xunpeng, Zhang Chi, Wei Yi-Ming, Huang Zhimin. Carbon emissions intensity reduction target for China's power industry: an efficiency and productivity perspective. J Clean Prod 2018;197:1022–34.
[30] Wang Keying, Meng Wua, Suna Yongping, Shi Xunpeng, Sun Ao, Zhang Ping. Resource abundance, industrial structure, and regional carbon emissions efficiency in China. Resour Pol 2019;60:203–14.
[31] Intergovernmental Panel on Climate Change. IPCC guidelines for national greenhouse gas inventories. 2008. http://www.ipcc-nggip.iges.or.jp/.
[32] Zhao Min, Zhang Weiguo, Yu Lizhong. Analysis of carbon emissions from energy consumption in shanghai. Environ Sci Res 2009;22:984–9 [in Chinese].
[33] Pan X, Ai B, Li C, Pan X, Yan Y. Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China. Technol Forecast Soc Change 2019;144:428–35.
[34] Pan X, Zhang J, Li C, Pan X, Song J. Analysis of China's regional wind power generation efficiency and its influencing factors. Energy Environ 2019;30:254–71.
[35] Pan X, Pan X, Ming Y, Zhang J. The effect of regional mitigation of carbon dioxide emission on energy efficiency in China, based on a spatial econometrics approach. Carbon Manag 2018;9:665–76.
[36] Pan X, Liu Q, Peng X. Spatial club convergence of regional energy efficiency in China. Ecol Indicat 2015;51:25–30.
[37] Li Jun, Zhang Dayong, Su Bin. The impact of social awareness and lifestyles on household carbon emissions in China. Ecol Econ 2019;160:145–55.
[38] Ji Qiang, Xia Tongshui, Fan Liu, Xu Jin-Hua. The information spillover between carbon price and power sector returns: evidence from the major European electricity companies. J Clean Prod 2019;208:1178–87.