Received 7 March 2022
Revised 26 March 2022
Accepted 2 April 2022

Analysis of nonlinear evolution mechanism of power technology progress under the constraints of net-zero carbon dioxide emissions in China

Huaihua Zheng
Zhejiang Power Transmission and Transformation Engineering, Hangzhou, China

Abstract

Purpose – Striving to achieve the goal of carbon neutrality before 2060 indicates that China, as the most extensive power system in the world and a country based on coal power, is imperative to improve the technical level of electric power utilization. This paper aims to explore the nonlinear evolution mechanism of power technology progress under the constraints of net-zero carbon dioxide emissions in China.

Design/methodology/approach – This paper, first, based on China's provincial panel data from 2000 to 2019, uses global direction distance function to measure power technological progress. Second, the threshold regression model is used to explore the nonlinear relationship between carbon emission reduction constraints on electric power technological progress.

Findings – There is a significant inverted U-shaped relationship between China's provincial carbon emission reduction constraints and electric power technological progress. Meanwhile, the scale of regional economic development has a significant moderating effect on the relationship between carbon emission reduction constraints and power technological progress.

Research limitations/implications – This paper puts forward targeted suggestions for perfecting regional carbon emission reduction policy and improving electric power technological progress.

Originality/value – Based on the global directional distance function, this paper extracts power as a production factor in total factor productivity and calculates the total factor electric power technological progress. This paper objectively reveals the influence mechanism of carbon emission reduction constraints on electric power technology progress based on the threshold regression model.

Keywords Carbon emission, Electric power, Technological progress, Nonlinear, Threshold model

Paper type Research paper

1. Introduction

To limit global warming effectively and to avert the worst effects of global climate change, countries are supposed to take responsibility for all of their negative influences on the environment and take every possible measure to reduce them as soon as possible. To realize

International Journal of Climate Change Strategies and Management
Vol. 15 No. 2, 2023
pp. 128-140
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-03-2022-0030

the goal of not exceeding 1.5°C global temperature rise, the world needs to achieve carbon neutrality, which refers to achieving net-zero carbon dioxide emissions by balancing carbon dioxide emissions with elimination (Wang *et al.*, 2022; Dong *et al.*, 2022a, 2022b). As a significant contributor to carbon emission reduction globally, the Chinese government announced at the 75th U.N. General Assembly that it will adopt more effective policies and measures to achieve carbon peak by 2030 and carbon neutrality by 2060. Electric power resources are the cornerstone of economic and social development, and the transition path of electric power under the constraint of carbon emissions is laid out in advance to create essential prerequisites for achieving the goal of carbon neutrality and averting the worst effects of global climate change (Tan *et al.*, 2021). However, according to incomplete statistics, the carbon dioxide emission per electric power generation unit in China was about 577 g/kWh in 2019, nearly 30% higher than the global average of 450 g/kWh. To realize the low-carbon transformation of the electric power industry, government departments and scholars generally believe that adjusting the power production structure and improving the technical level of power resource utilization are effective ways (Zhang *et al.*, 2020; Zhang *et al.*, 2021; Wang *et al.*, 2019). However, due to China's energy endowment conditions, it has a strong dependence on coal and high carbon energy in the short term (Pan *et al.*, 2019a, 2019b). At the same time, the vigorous development of clean energy faces high costs and technical constraints. Therefore, compared with adjusting the electric power production structure, effectively improving the utilization technology level of electric power resources is more appropriate for alleviating the constraints of carbon emissions now (Wang and Feng, 2020). Moreover, the low-carbon transformation of electric power production is a process of cumulative change in the transformation strategy of power production subjects through matching appropriate cleaner production technology innovation under the regulation of the government's macro carbon emission reduction system (Dong *et al.*, 2022a, 2022b; Lyu *et al.*, 2020). Hence, improving the macro carbon emission reduction policy's regulation effect and guiding all kinds of cleaner production technologies to match the low-carbon transformation strategy of electric power production entities are necessary guarantees for the successful low-carbon transformation of the electric power industry (Pan *et al.*, 2019a, 2019b). That is, to achieve the "double carbon" goal proposed by the Chinese government, the technical level of electric power production and consumption in China will not only comply with the law of economic development but also be subject to the constraints of carbon emission reduction policies for a long time in the future (Zhou *et al.*, 2020). In the above realistic context, this paper takes the low-carbon transformation of local electric power production as the primary research object; focuses on the perspective of dual constraints of carbon emission reduction and micro-electric power technological progress; explains the nonlinear effect of carbon emission reduction constraints on electric power technological progress and discusses the low-carbon transformation mechanism of local electric power production; and provides a new theoretical perspective for the in-depth study of the low-carbon transformation of China's local electric power production.

2. Literature review

The literature on the relationship between carbon emission and electric power production and consumption includes two main lines: the impact of power production and consumption on carbon emissions and carbon emission reduction constraints on electric power production and consumption (Mou *et al.*, 2019; Wang *et al.*, 2017). On the one hand, scholars point out that electric power production and consumption are the primary carbon emission sources. They focus on calculating electric power carbon emissions and analyzes the influencing factors based on different methods (Tao *et al.*, 2020; Mai *et al.*, 2020; Liu *et al.*, 2016). On the other hand, with the further increase of carbon emission reduction constraints, scholars believe that carbon emission reduction is an institutional constraint of electric power production and consumption. Especially in the market environment without adequate supervision, carbon emission reduction constraints are necessary to encourage economic entities to improve the utilization of electric energy (Chen *et al.*, 2021; Pan *et al.*, 2020). To confirm the constraint effect of carbon emission reduction on the utilization of electric power resources, scholars incorporate carbon emissions into the process of electric power consumption, construct an electric energy efficiency measurement model including unexpected output based on the total factor productivity framework and discuss the impact of carbon emission reduction constraints on electric power consumption (Sun *et al.*, 2020; Chen *et al.*, 2017; Li *et al.*, 2014; Zheng, 2014; Sueyoshi and Goto, 2012). Although the study focusing on calculating electric energy efficiency considers the impact of carbon emission reduction constraints on electric power consumption to a certain extent, it is difficult to reveal the influence mechanism of carbon emission reduction constraints on electric power consumption (Pan *et al.*, 2018). Considering that technological progress is the leading factor in improving electric power efficiency, parts of scholars take the carbon emission reduction as the external driving condition and discuss the impact of carbon emission reduction on electric power consumption through electric power technological progress (You *et al.*, 2022).

The relationship between carbon emission reduction institutional constraints and cleaner production technologies (renewable energy technology, clean coal technology, etc.) has been studied for a long time. First, in the case of limited resources, the increase of carbon emission reduction costs occupy cleaner production technology innovation resources to a certain extent (Cole *et al.*, 2010). At the same time, cleaner production technology innovation is a comprehensive process involving opportunity perception, resource allocation and achievement transformation. Carbon emission reduction constraints put forward specific standards and requirements to improve the difficulty and risk of innovation (Cole and Elliott, 2003). Second, with the development of cleaner production technology innovation, the marginal carbon emission reduction cost decreases, accompanied by evident innovation, which forms an incentive for cleaner production technology innovation (Hu *et al.*, 2017). In addition, cleaner production technology innovation effectively forms the competitive advantage and motivates for carrying out cleaner production technology innovation intention (Ambec *et al.*, 2013; Naso, 2017); Finally, facing the constraints of carbon emission reduction, heterogeneous regions cannot follow a consistent code of conduct because of the differences of resource endowment, capacity and other factors. Carbon emission reduction constraints are hard to form an effective innovation compensation mechanism for cleaner production technology innovation in all regions (Chakraborty and Chaterjee, 2017). Affected by the uncertain factors existing in the institutional environment and regional subject competition, there are significant differences in cleaner production technology innovation in different regions under the carbon emission reduction constraints (Daddi *et al.*, 2010).

To summarize, carbon emission constraints and technological progress are essential in coordinating energy conservation and carbon emission reduction. Most scholars pay attention to the impact of carbon emission constraints on technological progress. Considering that the technological progress of electric power resource utilization is the critical link to realize economic low-carbon transformation, this paper explores the nonlinear impact mechanism of carbon emission reduction constraints on the technological progress of electric power factor utilization. Compared with the existing literature, this paper has the following two innovations. First, considering the central position of power factors in the energy consumption system, electric power is also the primary source of carbon emissions. This paper focuses on the impact of carbon emission reduction constraints on power technology progress, which has a more substantial practical reference value. Second, from the perspective of regional endowment conditions, this paper investigates the regulatory effect of regional economic development on the relationship between carbon emission reduction constraints and electric power technological progress.

3. Model and data

3.1 Measurement of power technological progress

Data envelopment analysis (DEA) is an efficiency evaluation method proposed by Charnes *et al.* (1978). To reflect economic growth and electric power saving, that is, the electric power factor input is the smallest and the economic output index is the largest, this paper constructs a non-angle DEA model combined with the directional distance function. $P(x)$is the production set, it satisfies the input vector x_i, and economic output gdp_i can be disposed freely. The input vector of i province is $x_i = (e_i, k_i, l_i)$, e_i, k_i, l_i represents the total electric power consumption, capital stock and labor force of the i^{th} province, respectively, gdp_i is the economic output of the i^{th} province. On this basis, this paper constructs the direction vector under the dual objectives of economic growth and electric power conservation is $g = (-e, 0, 0, gdp)$:

$$D\left(e^t, k^t, l^t, g^i | CRS\right) = \max\left\{\beta : \left(e - \beta e, k, l, gdp + \beta g_{gdp}\right) \in P(x)\right\} \tag{1}$$

As shown in formula (2), based on the direction vector, Chung *et al.* (1997) proposed the traditional DEA Malmquist–Luenberger index (ML), takes the input-output data of single-stage cross-sectional decision-making unit as the production technology set. It is easy to cause the discontinuity of technological progress, but make the measurement results of technological progress have the defect of false technological regression:

$$ML^{t,t+1} = \left[\frac{1 + D^t\left(e^t, k^t, l^t, gdp^t; g\right)}{1 + D^t\left(e^{t+1}, k^{t+1}, l^{t+1}, gdp^{t+1}; g\right)} * \frac{1 + D^{t+1}\left(e^t, k^t, l^t, gdp^t; g\right)}{1 + D^{t+1}\left(e^{t+1}, k^{t+1}, l^{t+1}, gdp^{t+1}; g\right)}\right] \tag{2}$$

Oh (2010) proposed the global Malmquist–Luenberger (GML) index based on the global perspective, which effectively overcomes the shortcomings of the traditional ML index mentioned above. Based on the research of Fernandez *et al.* (2018) and Ma *et al.* (2017), this paper constructs the following index model:

$$GML^{t,t+1} = \frac{1 + D^G\left(e^t, k^t, l^t, gdp^t; g\right)}{1 + D^G\left(e^{t+1}, k^{t+1}, l^{t+1}, gdp^{t+1}; g\right)} = GECH^{t,t+1} * GTCH^{t,t+1}, \tag{3}$$

$$GECH^{t,t+1} = \frac{1 + D^t\left(e^t, k^t, l^t, gdp^t; g\right)}{1 + D^{t+1}\left(e^{t+1}, k^{t+1}, l^{t+1}, gdp^{t+1}; g\right)}, \tag{4}$$

$$GTCH^{t,t+1} = \left[\frac{1 + D^G\left(e^t, k^t, l^t, gdp^t; g\right)}{1 + D^t\left(e^t, k^t, l^t, gdp^t; g\right)} \bigg/ \frac{1 + D^G\left(e^{t+1}, k^{t+1}, l^{t+1}, gdp^{t+1}; g\right)}{1 + D^{t+1}\left(e^{t+1}, k^{t+1}, l^{t+1}, gdp^{t+1}; g\right)}\right], \tag{5}$$

where $D^t\left(e^t, k^t, l^t, gdp^i, g\right)$ represents the directional distance function based on the production set of the same period. $D^G\left(e^t, k^t, l^t, gdp^i, g\right)$ is the direct distance function based on the global production set. $GTCH$ is the electric power technological progress. If $GTCH >$ 1, it means that the production frontier of the decision unit is closer to the global effective production frontier in $t+1$ than that t.

3.2 Econometric regression model

To quantitatively test the impact of carbon emission reduction constraints on electric power technological progress, this paper constructs a benchmark regression model as follows:

$$GTCH_{it} = a_0 + a_1 CE_{it} + a_2 CE_{it}^2 + \beta \sum X_{it} + \varepsilon_{it} \tag{6}$$

$GTCH_{it}$ is the electric power technological progress of i^{th} province in t year, CE_{it} is the carbon emission constraint of i province in t year. To investigate the possible nonlinear relationship between carbon emission reduction constraints and electric power technological progress, this study adds the square term of carbon emission reduction constraint variables ($CE_{it}^{\;2}$) in the benchmark effect model. X_{it} is a series of regional characteristics affecting electric power technological progress, such as regional economic development level, degree of opening, urbanization level, industrial structure and electric power price level. ε_{it} is a random disturbance term.

A group test model and cross term linear model can further analyze the nonlinear effect of carbon emission reduction constraints on electric power technological progress. However, it is hard to objectively and effectively carry out piecewise regression. Moreover, cross term linear model considers the interaction between them by establishing a linear regression model between variables, but it is difficult to estimate the regression coefficient in the form of the cross term. Following the panel threshold regression model proposed by Hansen (2000), this study constructs a basic model as follows:

$$\begin{aligned} GTCH_{it} = {} & a_0 + a_1 CE_{it} * I(CE_{it} \le r_1) + a_2 CE_{it} * I(CE_{it} > r_1) + \cdots + a_n CE_{it} * I(CE_{it} \le r_n) \\ & + \beta \sum X_{it} + \varepsilon_{it}, \end{aligned} \tag{7}$$

$$\begin{aligned} GTCH_{it} = {} & a_0 + a_1 CE_{it} * I(RGDP_{it} \le r_1) + a_2 CE_{it} * I(RGDP_{it} > r_1) + \cdots \\ & + a_n CE_{it} * I(RGDP_{it} \le r_n) + \beta \sum X_{it} + \varepsilon_{it}, \end{aligned} \tag{8}$$

where $r_i (i = 1, 2, \ldots, n - 1)$is the $n-1$ threshold value, $I(\bullet)$is the symbol function, if the threshold variable meets the conditions in parentheses, $I(\bullet)$is equal to 1 otherwise, $I(\bullet)$is equal to 0. α_n and β are the coefficients to be estimated.

3.3 Variables description

This paper takes 30 provinces, autonomous regions and municipalities in the Chinese mainland from 2000 to 2019 as the research object. Tibet is not included due to the lack of data, and Hong Kong, Macao and Taiwan are not included due to institutional differences and data availability. The data is mainly collected from the Compilation of Statistical Data of 60 years of new China, *China Energy Statistical Yearbook*, *China Statistical Yearbook*, *China Labor Statistical Yearbook* and regional statistical yearbooks. The indexes related to price are adjusted to actual prices based on 2000.

- Electric power technological progress (*GTCH*) is expressed by the global direction distance function. Since the index is the change rate of electric power technological progress, this paper takes 2000 as the base period for cumulative multiplication. In measuring electric power technological progress, it is necessary to clarify the input-output data. In this paper, each province's capital stock, total labor force and electric power consumption are taken as input variables, and the output variables are the actual GDP of each province. Capital stock (*K*) is calculated by the method of perpetual inventory. $K_{i,t} = (1 - \delta_{i,t})K_{i,t-1} + I_{i,t}$, $K_{i,t}$ is the capital stock of i^{th} province in t year, $I_{i,t}$ is the capital investment of i^{th} province in t year and $\delta_{i,t}$ is the depreciation rate of i^{th} province in t year. Labor (*L*) is expressed by the number of employed persons at the end of each year. Each province's total annual electric power consumption (E) is expressed by total electric power consumption. *GDP* is expressed in the real GDP of each province.
- Carbon emission reduction constraint (*CE*) is expressed in economic output value per unit of carbon emission. Since no official or authoritative organization has published the annual carbon emissions of China's provinces and regions, this paper calculates the carbon emissions of energy-related activities in China's provinces and regions according to the IPCC national greenhouse gas guidelines prepared by IPCC in 2006, as shown in formula (9):

$$EC = \sum_{i=1}^{7} EC_i = \sum_{i=1}^{7} (E_i - RME_i \times CFR_i) \times CF_i \times CC_i \times COF_i \times 3.67, \tag{9}$$

- where *EC r*epresents the total carbon emissions, and *i* represents the types of energy consumption, including coal, coke, gasoline, kerosene, diesel, fuel oil and natural gas. *EI* is the total energy consumption of the i^{th} type in each province, *RME* is the energy consumption used as raw materials and materials, *CFR* is the carbon sequestration rate, *CF* is the calorific value, *CC* is the carbon content and *COF* is the oxidation factor.
- Control variables (*X*): economic development level (*RGDP)* is the per capita real GDP of each province, the degree of opening (*OPEN*) is measured by the ratio of the total import and export trade of each province to the regional GDP. Urbanization level (*CSH*) is expressed as the ratio of nonagricultural population to the total population of the region. Industrial structure (*STR*) is expressed by the ratio of the added value of the tertiary industry to that of secondary industry. Actual electric power price (*PRICE*) is measured by the actual electricity price of each province according to the consumer price index. The statistical description results of each variable are shown in Table 1.

4. Results analysis

4.1 Nonlinear influence effect test

To avoid the existence of pseudo regression in the model and ensure the accuracy of the regression coefficient, as shown in Table 2, this study carries out the stability test on the panel data. The analysis results based on LLC, IPS, Fisher-ADF and Fisher-PP test standards show that all variables have no unit root at the original sequence level, that is, I (0) stationary.

The Hausman test results indicate that we can reject the random effect model at the significance level of 1%. At the same time, considering that the primary purpose of this paper is to study the individual relationship among different provinces in China, the fixed effect model provides a better interpretation effect. Therefore, the nonlinear effect of carbon emission reduction constraints on electric power technological progress will be analyzed based on the fixed effect panel model. To further verify the robustness of the analysis results, control variables are added to the model one by one, and the specific regression results are shown in Table 3. It can be seen from the analysis results that the coefficients of the primary and secondary terms of carbon emission reduction constraints are positive and negative, respectively; that is, there is a significant inverted U-shaped nonlinear relationship between carbon emission reduction constraints and electric power technological progress. In the primary stage of the improvement of carbon emission reduction constraints, it plays a positive role in promoting electric power technological progress. However, further improvement of carbon emission reduction constraints has a compliance cost effect on electric power technological progress. The above results are also highly consistent with the existing research. Under the constraints of net-zero carbon dioxide emissions, different subjects' technological innovation and production transformation often show inconsistent effects. Even if facing similar external constraints, different subjects will still choose differentiated environmental governance strategies based on weighing economic interests and environmental effects (Wang *et al.*, 2020; Nagy *et al.*, 2021).

Observing the regression coefficient of each control variable, economic development, urbanization level and electricity price level is beneficial to the improvement of electric power technological progress level in varying degrees; the effect of opening and industrial structure on the improvement of electric power technological progress level do not pass the

Variables	Symbol	Mean	Standard error	Minimum	Maximum
Electric power technological progress	*GTCH*	1.00	0.03	0.94	1.12
Carbon dioxide emission constraint	*CE*	0.35	0.20	0.04	1.38
Square term of carbon emission reduction constraint	CE^2	0.16	0.20	0.01	1.91
Economic development level	*RGDP*	2.43	0.23	1.34	3.17
Opening	*OPEN*	0.32	0.41	0.03	2.05
Urbanization level	*CSH*	0.33	0.16	0.14	0.89
Industrial structure	*STR*	0.40	0.07	0.28	0.76
Actual electric power price	*PRICE*	1.79	0.04	1.66	1.87

Table 1.
Statistical description results

Variables	*LLC*	*IPS*	*Fisher-ADF*	*Fisher-PP*
GTCH	0.000 (−15.706)	0.000 (−12.418)	0.000 (251.852)	0.000 (288.402)
CE	0.000 (−15.458)	0.000 (−11.083)	0.000 (243.135)	0.000 (306.106)
CE^2	0.000 (−13.307)	0.000 (−9.499)	0.000 (228.519)	0.000 (294.422)
RGDP	0.000 (−16.171)	0.000 (−13.368)	0.000 (266.487)	0.000 (301.047)
OPEN	0.000 (−19.117)	0.000 (−16.210)	0.000 (325.207)	0.000 (260.767)
CSH	0.000 (−20.733)	0.000 (−17.007)	0.000 (340.015)	0.000 (410.638)
STR	0.000 (−14.847)	0.000 (−12.804)	0.000 (253.966)	0.000 (280.707)
PRICE	0.000 (−10.094)	0.000 (−11.998)	0.000 (244.391)	0.000 (728.458)

Notes: The unit cell is the adjoint probability under each method, and the bracket is its t statistical value

Table 2.
Unit root test results

Table 3. Benchmark effect of carbon emission constraints on electric power technological progress

Variables	(1)	(2)	(3)	(4)	(5)	(6)
CE	0.099*** (5.32)	0.082*** (4.50)	0.056*** (3.22)	0.080*** (4.84)	0.084*** (4.99)	0.057*** (2.92)
CE^2	−0.062*** (−3.29)	−0.045** (−2.43)	−0.056*** (−3.22)	−0.070*** (−4.32)	−0.077*** (−4.50)	−0.061*** (−3.40)
RGDP		0.029*** (5.76)	0.024*** (4.96)	0.019*** (4.34)	0.020*** (4.49)	0.020*** (4.51)
OPEN			0.029*** (8.39)	0.002 (0.49)	0.001 (0.24)	−0.001 (−0.18)
CSH				0.082*** (8.46)	0.078*** (7.37)	0.071*** (6.60)
STR					0.027 (1.24)	0.029 (1.34)
PRICE						0.113*** (2.61)
Cons	0.975*** (248.87)	0.907*** (73.42)	0.922*** (78.83)	0.907*** (82.02)	0.896*** (62.20)	0.703*** (9.38)
R^2	0.109	0.165	0.270	0.364	0.366	0.375
Adjusted R^2	0.105	0.160	0.265	0.357	0.358	0.366

Notes: *** and **, respectively, mean passing the 1% and 5% significance test, and *t* statistical values are in parentheses significance test. First, electric power resources support economic development, but a better structure will improve electric power utilization technology. However, adjusting the economic development structure overemphasizes the proportion of different industries and ignores the regional endowment conditions, which will reduce the promoting effect on electric power utilization technology. Second, under the background of the market economy, the reforming of the electric power market corrects the distortion of price, thus optimizing resource allocation and improving electric power technological progress. Third, the gradual expansion of the scope and degree of opening makes it possible for China to introduce advanced technology, experience and equipment continuously. However, the imbalance of absorption capacity, investment attraction and cultivation environment may make the loss of the effectiveness of opening.

4.2 Nonlinear influence mechanism of carbon emission constraint on electric power technological progress

To further prove the nonlinear effect of carbon emission reduction constraints on electric power technological progress, this paper first takes carbon emission reduction constraints as a threshold variable to investigate the heterogeneity effect on electric power technological progress. The threshold model can prove the robustness of the results obtained based on the panel fixed effect model and objectively identify the threshold value of the curve between carbon emission reduction constraints and electric power technological progress. Second, with the improvement of carbon emission reduction constraints, the severe problem of regional economy and development is the increase of carbon emission reduction costs to occupy the original resources for technological innovation to a certain extent. However, for economically developed regions facing the constraints of carbon emission reduction, local governments, enterprises and other subjects have relatively abundant resources for technological innovation (Zhang, 2021). Therefore, compared with backward regions, developed regions show a more vital willingness to innovate. Hence, this study takes the per capita GDP as one of the indicators to measure the comprehensive level of regional economic development and measures the differential impact of carbon emission reduction constraints on electric power technological progress at different economic development levels.

Before the panel threshold regression test, the threshold value γ needs to be obtained based on the threshold model, which can be arbitrarily selected within the range of the threshold variable. Carry out linear regression between variables according to the selected threshold value, and calculate the sum of squares of regression residuals $S_1(\gamma)$. Set the threshold value γ from small to large and get the sum of squares of residuals of each regression equation and finally get the threshold value γ^*, which make the sum of squares of residuals smallest, i.e. $\gamma^* = \mathrm{argmin} S_1(\gamma)$. Meanwhile, Hansen (2000) suggests that the bootstrap method is suitable for constructing the *p*-value, determining the confidence interval and testing the robustness of regression results. According to the above method, this paper uses Stata 16.0 software to estimate the threshold value of carbon emission reduction constraint and per capita GDP.

According to the threshold value determination in Table 4, this study sets up a piecewise linear regression. As shown in Table 5, when the constraint intensity of carbon emission

Table 4.
Threshold test results

Threshold variables	Original hypothesis	Bootstrap value	*P*-value
CE	No threshold	22.790	0.012
RGDP	No threshold	32.399	0.000

reduction is less than 0.75 and the per capita GDP is higher than 2.37, the regression result of carbon emission reduction constraint is positive and within the 95% confidence interval. When the carbon emission reduction constraint is less than 0.75, the electric power technological progress will increase by 0.2% if it improves by 1%. Electric power technological progress hurts when the carbon emission reduction constraint is more significant than 0.75. If per capita GDP is lower than 2.37, the effect of carbon emission reduction constraints electric power technological progress is negative. Otherwise, the effect is positive. With improved carbon emission reduction constraints for developed regions, regions can provide sufficient power technology innovation resources. At the same time, the more progressive power market reform has effectively improved the allocation efficiency of power resource elements. For backward areas, economic development and resource allocation efficiency are relatively backward. Carbon emission reduction constraints increase carbon emission reduction cost, and squeeze resources for electric power technology innovation so that carbon emission reduction constraint has a significant inhibitory effect on the progress of power technology.

5. Conclusion and policy recommendations

Based on China's provincial panel data from 2000 to 2019, this paper uses the global directional distance function to calculate the level of electric power technological progress. This paper uses the panel fixed effect and threshold regression model to test the nonlinear impact effect of carbon emission reduction constraints on electric power technological progress. The results show that, first, there is a significant inverted U-shaped nonlinear relationship between carbon emission reduction constraints and electric power technological progress. The regression results based on the threshold variable further confirm the robustness of the above conclusions. Second, due to the significant differences in the scale and quality of economic development for different regions, the impact of carbon emission reduction constraints on electric power technological progress is also different. Based on the above conclusions, this paper points out that:

- Moderately improve the government's carbon emission reduction constraints, punish the provinces with negative environmental protection attitudes and cross the threshold value of the subject's willingness to innovate. However, blindly improving the constraint intensity of carbon emission is not suitable. Differentiated low-carbon policies should be formulated according to the regions' actual economic development basis. The innovation compensation effect of carbon emission reduction constraints on electric power technological progress always exists. Backward regions such as the central and western regions should abandon the concept of "pollution before treatment" and introduce high-quality industries in developed regions to comprehensively improve the technical level of power utilization.

Table 5. Analysis results of nonlinear mechanism of carbon emission reduction constraints on power technological progress

Variables	Estimated value	Standard error	95% confidence interval	R^2
CE $\leq$ 0.75	0.002	0.010	[−0.227, 0.021]	0.371
CE $>$ 0.75	−0.073	0.031	[−0.167, −0.010]	0.542
RGDP $\leq$ 2.37	−0.294	0.013	[−0.055, −0.001]	0.397
RGDP $>$ 2.37	0.013	0.011	[−0.010, 0.036]	0.336

- For economically developed regions, actively implementing carbon emission reduction, obtaining advanced power technology and realizing the innovation compensation effect. Moreover, they should strengthen long-term exchanges with the backward areas, build large-scale innovative equipment and share advanced electric power technology. Backward areas should adjust the regional human capital structure, improve the absorption capacity of advanced electric power technology and optimize the regional electric power technology cultivation environment. At the same time, considering the availability of carbon emission reduction systems among different regions, local governments should strengthen the exchange and learning of advanced policies and systems through e-commerce and other platforms to effectively reduce the cost of carbon emission reduction policies.

References

Ambec, S., Cohen, M.A., Elgie, S., *et al.* (2013), "The porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness?", *Review of Environmental Economics and Policy*, Vol. 7 No. 1, pp. 2-22.

Chakraborty, P. and Chaterjee, C. (2017), "Does environmental regulation indirectly induce upstream innovation? New evidence from India", *Research Policy*, Vol. 46 No. 5, pp. 939-955.

Charnes, A., Copper, W.W. and Rhodes, E. (1978), "Measuring the efficiency of decision making units", *European Journal of Operational Research*, Vol. 2 No. 6, pp. 429-444.

Chen, W., Zhou, K.L. and Yang, S.L. (2017), "Evaluation of China's electric energy efficiency under environmental constraints: a DEA cross efficiency model based on game relationship", *Journal of Cleaner Production*, Vol. 164, pp. 38-44.

Chen, W., Ma, Y.K. and Bai, C.G. (2021), "The impact of carbon emission quota allocation regulations on the investment of low-carbon technology in the electric power industry under peak-valley price policy", *IEEE Transactions on Engineering Management*, doi: 10.1109/TEM.2021.3121002

Chung, Y.H., Fare, R. and Grosskopf, S. (1997), "Productivity and undesirable outputs: a directional distance function approach", *Journal of Environmental Management*, Vol. 51 No. 3, pp. 229-240.

Cole, M. and Elliott, R. (2003), "Determining the trade-environment composition effect: the role of capital, labor and environmental regulation", *Journal of Environmental Economics and Management*, Vol. 46 No. 3, pp. 363-383.

Cole, M., Elliott, R. and Okubo, T. (2010), "Environmental regulation and industrial mobility: an industry level study of Japan", *Ecological Economics*, Vol. 69 No. 10, pp. 1995-2002.

Daddi, T., Testa, F. and Iraldo, F. (2010), "A cluster-based approach as an effective way to implement the ECAP: evidence from some good practices", *Local Environment*, Vol. 15 No. 1, pp. 73-82.

Dong, F., Li, Y.F., Gao, Y.J., *et al.* (2022a), "Energy transition and carbon neutrality: exploring the nonlinear impact of renewable energy development on carbon emission efficiency in developed countries", *Resources Conservation and Recycling*, Vol. 177, p. 106002.

Dong, F., Zhu, J., Li, Y.F., *et al.* (2022b), "How green technology innovation affects carbon emission efficiency: evidence from developed countries proposing carbon neutrality targets", *Environmental Science and Pollution Research*, Vol. 29 No. 24, pp. 35780-35799, doi: 10.1007/s11356-022-18581-9.

Fernandez, D., Pozo, C., Folgado, R., *et al.* (2018), "Productivity and energy efficiency assessment of existing industrial gases facilities via data envelopment analysis and the Malmquist index", *Applied Energy*, Vol. 212, pp. 1563-1577.

Hansen, B.E. (2000), "Sample splitting and threshold estimation", *Econometrica*, Vol. 68 No. 3, pp. 575-603.

Hu, D., Wang, Y.D. and Li, Y. (2017), "How does open innovation modify the relationship between environmental regulation and productivity?", *Business Strategy and the Environment*, Vol. 26 No. 8, pp. 1132-1143.

Li, J.C., Li, J.Y. and Zheng, F.T. (2014), "Unified efficiency measurement of electric power supply companies in China", *Sustainability*, Vol. 6 No. 2, pp. 779-793.

Liu, L.W., Sun, X.R., Chen, C.X., *et al.* (2016), "How will auctioning impact on the carbon emission abatement cost of electric power generation sector in China?", *Applied Energy*, Vol. 168, pp. 584-609.

Lyu, X.H., Shi, A.N. and Wang, X. (2020), "Research on the impact of carbon emission trading system on low-carbon technology innovation", *Carbon Management*, Vol. 11 No. 2, pp. 183-193.

Ma, X.J., Liu, Y., Wei, X.X., *et al.* (2017), "Measure and decomposition of energy efficiency of northeast China based on super efficiency DEA model and Malmquist index", *Environmental Science and Pollution Research*, Vol. 24 No. 24, pp. 19859-19873.

Mai, L.N., Ran, Q.Y. and Wu, H.T. (2020), "A LMDI decomposition analysis of carbon dioxide emissions from the electric power sector in northwest China", *Natural Resource Modeling*, Vol. 33 No. 4, p. e12284.

Mou, X.L., Zhang, Y.J., Jiang, J., *et al.* (2019), "Achieving low carbon emission for dynamically charging electric vehicles through renewable energy integration", *IEEE Access*, Vol. 7, pp. 118876-118888.

Nagy, R.L.G., Hagspiel, V. and Kort, P.M. (2021), "Green capacity investment under subsidy withdrawal risk", *Energy Economics*, Vol. 98, p. 105259.

Naso, P. (2017), "The porter hypothesis goes to china: spatial development, environmental regulation and productivity", *CIES Research Paper*, Vol. 10 No. 2, pp. 124-135.

Oh, D.H. (2010), "A global Malmquist-Luenberger productivity index", *Journal of Productivity Analysis*, Vol. 34 No. 3, pp. 183-197.

Pan, X.F., Pan, X.Y., Ming, Y., *et al.* (2018), "The effect of regional mitigation of carbon dioxide emission on energy efficiency in China, based on a spatial econometric approach", *Carbon Management*, Vol. 9 No. 6, pp. 665-676.

Pan, X.F., Pan, X.Y., Jiao, Z.M., *et al.* (2019a), "Stage characteristics and driving forces of China's energy efficiency convergence- an empirical analysis", *Energy Efficiency*, Vol. 12 No. 8, pp. 2147-2159.

Pan, X.F., Pan, X.Y., Li, C.Y., *et al.* (2019b), "Effects of China's environmental policy on carbon emission efficiency", *International Journal of Climate Change Strategies and Management*, Vol. 11 No. 3, pp. 326-340.

Pan, X.X., Liu, H., Huan, J.J., *et al.* (2020), "Allocation model of carbon emission permits for the electric power industry with a combination subjective and objective weighting approach", *Energies*, Vol. 13 No. 3, p. 706.

Sueyoshi, T. and Goto, M. (2012), "Efficiency-based rank assessment for electric power industry: a combined use of data envelopment analysis (DEA) and DEA-Discriminant analysis (DA)", *Energy Economics*, Vol. 34 No. 3, pp. 634-644.

Sun, X.X., Zhou, X.L., Chen, Z.W., *et al.* (2020), "Environmental efficiency of electric power industry, market segmentation and technological innovation: empirical evidence from China", *Science of the Total Environment*, Vol. 706, p. 135749.

Tan, X.D., Liu, J., Xu, Z.C., *et al.* (2021), "Power supply and demand balance during the 14^{th} Five-Year plan period under the goal emission peak and carbon neutrality", *Electric Power*, [In Chinese], Vol. 54 No. 5, pp. 1-6.

Tao, Y.H., Liang, H.M. and Celia, M.A. (2020), "Electric power development associated with the belt and road initiative and its carbon emissions implications", *Applied Energy*, Vol. 267, p. 114784.

Wang, B.J., Zhao, J.L. and Wei, Y.X. (2019), "Carbon emission quota allocating on coal and electric power enterprises under carbon trading pilot in China: mathematical formulation and solution technique", *Journal of Cleaner Production*, Vol. 239, p. 118104.

Wang, M. and Feng, C. (2020), "The impacts of technological gap and scale economy on the low-carbon development of China's industries: an extended decomposition analysis", *Technological Forecasting and Social Change*, Vol. 157, p. 120050.

Wang, Q., Jiang, X.T. and Li, R.R. (2017), "Comparative developing analysis of energy-related carbon emission from electric output of electricity sector in Shandong province", *China. Energy*, Vol. 127, pp. 78-88.

Wang, Y.L., Lei, X.D., Long, R.Y., *et al.* (2020), "Green credit, financial constraint, and capital investment: evidence from China's energy intensive enterprises", *Environmental Management*, Vol. 66 No. 6, pp. 1059-1071.

Wang, X.X., Huang, J.L. and Liu, H.D. (2022), "Can China's trading policy help achieve carbon neutrality? - a study of policy effects from the five-sphere integrated plan perspective", *Journal of Environmental Management*, Vol. 305, p. 114357.

You, C.D., Khattak, S.I. and Ahmad, M. (2022), "Impact of innovation in renewable energy generation, transmission, or distribution-related technologies on carbon dioxide emission in the USA", *Environmental Science and Pollution Research*, Vol. 29 No. 20, pp. 29756-29777, doi: 10.1007/s11356-021-17938-w.

Zhang, H. (2021), "Technology innovation, economic growth and carbon emissions in the context of carbon neutrality: evidence from BRICS", *Sustainability*, Vol. 13 No. 20, p. 11138.

Zhang, Y.Y., Wang, J.Q., Zhang, L.M., *et al.* (2020), "Optimization of China's electric power sector targeting water stress and carbon emissions", *Applied Energy*, Vol. 271 No. 115221.

Zhang, Y.S., Dong, D., Xiao, Y., *et al.* (2021), "Current status and trends in energy production, consumption, and storage under carbon neutrality conditions in China", *Chinese Science Bulletin*, Vol. 66 No. 34, pp. 4466-4476.

Zhou, Q.L., Cui, X.Y., Ni, H.F., *et al.* (2020), "The impact of environmental regulation policy on firms' energy-saving behavior: a quasi-natural experiment based on China's low-carbon pilot city policy", *Resources Policy*, Vol. 76, p. 102538.

Corresponding author
Huaihua Zheng can be contacted at: zett_110@163.com