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Original Research

The Impact of Environmental Information Disclosure on Carbon Efficiency

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Abstract

In China, rapid development has lead to serious environmental pollution. Excessive carbon dioxide emissions have not only caused significant damages to the environment, but also harmed people's health. Subject to carbon peaking and carbon neutrality goals, cities need to conserve energy and reduce emissions while maintaining steady economic growth, an effective measure for which is to improve carbon efficiency. Carbon efficiency is affected by environmental regulation. As a kind of environmental regulation featuring public participation, environmental information disclosure has become an important measure affecting carbon efficiency. In this paper, we estimated carbon efficiency of Chinese cities with super-efficiency DEA model, analyzed the spatial and temporal heterogeneity of carbon efficiency. Unlike previous literature, we further investigated the impact of environmental information disclosure on carbon efficiency using difference-in-differences model, tested split samples by geographical location and city size to examine the impacts of environmental information disclosure on carbon efficiency in different regions and cities of different sizes, and validated that environmental information disclosure affects carbon efficiency through technological improvements and clean industry substitution. On this basis, we proposed policy measures to improve carbon efficiency, including transforming government functions, offering inter-regional carbon compensation, and establishing a diversified carbon emissions reduction system.

Keywords: environmental information disclosure, carbon efficiency, technological improvement effect, clean industry substitution effect

Introduction

Along with continuous advancement of industrialization and urbanization, China embraces significantly improved economy and resident income, but in the meanwhile faces increasingly serious environmental pollution. Pollutants represented by CO_2 have caused serious ecological problems and greatly impacted people's physical and mental health. China's economic growth since the reform and opening up has shown that environmental protection and economic development are contradictory. Driven by the desire for maximum GDP, local governments often stressed economic growth but ignored or even sacrificed the environment. On September 22, 2020, President Xi Jinping announced at the 75th UN General Assembly

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that China would strive to peak CO_2 emissions before 2030 and achieve carbon neutrality before 2060. Subject to "dual carbon" goals, local governments have to take into account energy conservation and emission reduction while promoting economic growth. For China at current development stage, excessive emission reductions will inevitably come at the expense of economic growth. Improving carbon efficiency (CEC) is the route that it must rake towards green development.

CEC refers to achieve high economic growth with less energy consumption and fewer industrial carbon emissions. The improvement of CEC not only depends on economic growth, industrial restructuring and foreign investment, but also requires environmental intervention. Generally speaking, environmental intervention refers to imposing environmental regulation to restrict various environment polluting behaviors and thus protect the environment. Environmental regulation is divided into command-and-control regulation, market-based regulation and public participation-based regulation. Existing research mostly centered on the former two, with limited attention to the last one. However, public participation is an essential means of environmental governance. It can not only enhance the public's environmental awareness, promote enterprises to reduce emissions, but also stimulate the market and stakeholders to supervise enterprises' production. Hence, public participation-based regulation has become an increasingly important means for environmental governance.

As an important part of public participation-based regulation, environmental information disclosure (EID) is regarded as an essential means and tool for environmental management. It means governments, enterprises and other subjects of social behavior report and publicly disclose their environmental behavior in accordance with and out of respect for the public's right to know, in order to facilitate public participation and supervision. In 2007, China's State Council introduced the Regulations of the People's Republic of China on Disclosure of Government Information, and former State Environmental Protection Administration issued the Measures for Environmental Information Disclosure (Trial) (came into effect in May 2008), which marked the beginning of institutionalized EID in China.

China attaches great attention to green development. Does EID play an important role in carbon emissions reduction? Does it help reduce carbon emissions and improve CEC? Through what mechanism does it affect CEC? Figuring out answers to these questions will help us further understand the relationship between informal environmental regulation and CEC as well as the mechanism of impact on environment. This is of great significance for China to achieve peak carbon emissions and carbon neutrality, improve its multi-dimensional carbon emission governance system, and promote green development.

This paper aims to reveal the relationship between EID and CEC. Due to difficulties in accurately measuring the degree of EID and the influence of endogenous problems, we first worked out how to capture and identify the impact of EID on the environment. The Institute of Public and Environmental Affairs and the Natural Resources Defense Council jointly developed pollution information transparency index (PITI) and evaluated the disclosure of pollution information by 120 Chinese cities (mainly key cities for environmental protection). Based on China's system for EID, we designed a "quasi-natural experiment" to examine the impact of EID on CEC with difference-in-differences method. This study not only reveals the effectiveness of EID on CEC at the city level, but also provides empirical evidence and theoretical support for improving EID in the future.

Literature Review

Studies on CEC and Its Influencing Factors

CEC can be measured through single-factor test and multi-factor test. In the former approach, the definition and measurement of CEC are closely related. Kaya and Yokobori [1] defined CEC as carbon productivity, namely GDP output per unit of CO_2 (the ratio of CO_2 emissions to GDP), which has become an important criterion for evaluating a country's energy conservation and emissions reduction. Mielnik and Goldemberg [2] defined CEC as carbon emission intensity, and Ang [3] defined it as carbon emissions spent on per unit of GDP growth. How indicators were measured is actually how CEC was defined. With single-factor test, CEC is defined and measured from a single-factor perspective, which focuses on certain factors but ignores other factors that may affect carbon emissions and CEC [4-5]. In other words, it fails to fully interpret CEC. In contrast, multi-factor test takes into account the impact of capital, labor, technology and other inputs. Its result is more reasonable than that of single-factor test. Main methods for multi-factor test are stochastic frontier analysis (SFA) model (parametric method) and data envelopment analysis (DEA) model (non-parametric method). Risto et al. [6] measured CEC with the SFA model, while Ran et al. [7] used the DEA model.

Strong financial support is necessary in reducing pollution, so financial development is a key factor affecting the environment [8]. Some scholars uphold that financial development allows enterprises to adopt advanced environment-friendly technologies and attract foreign investment, thereby promoting R&D and improving environmental quality. Therefore, there is a negative correlation between it and carbon emissions [9-12]. But some scholars reached an opposite conclusion [13-14]. Shen et al. [15] held that financial development increases carbon emissions, for which there may be three reasons. Firstly, financial development reduces information asymmetry and expands financing channels through low-cost capital loans, which helps expand production and increase carbon emissions. Secondly, a developed financial system brings better consumer credit services and encourages consumers to buy more goods, so carbon emissions will increase. Thirdly, upward stock market ensures economic growth. Good performance of stock market increases consumers and enterprises' confidence and promotes production and consumption. As a result, energy consumption demand and carbon emissions will rise [16].

Gao et al. [17] found that industrial structure have a positive impact on CEC in both short and long term, which indicates increasing the proportion of the tertiary industry can boost CEC. Guo et al. [18] showed that carbon emissions in Jinzhong almost doubled, mainly due to the vigorous development of local heavy chemical industry. This indicates industrial structure exerts significant impacts on carbon emissions and CEC. Lyu et al. [19] demonstrated that the digital economy affects CEC through upgrading and rationalizing industrial structure. Therefore, the government should guide high energy consuming industries, especially traditional manufacturing industries to seek transformation and upgrade by applying digital technologies represented by the Internet, and encourage intelligent upgrading in energy production, transportation, consumption, etc. to optimize industrial structure. Different from the above conclusions, Sun and Dong [20] held industrial structure does not affect CEC.

There are two hypotheses on the impact of foreign direct investment (FDI) on carbon emissions in the host country. One is pollution haven hypothesis, that is, local governments lower environmental access standards and introduce highly polluting industries to solve financial difficulties and boost economic growth, which leads to an increase of carbon emissions [21-22]. The other is pollution halo hypothesis, that is, FDI brings administrative and technical experience, which reduce carbon emissions [23-24]. Some other scholars found that population, policies and R&D also affect CEC [25-27].

Studies on the Impact of EID on Environmental Pollution

Environmental regulation means regulating behaviors polluting the environment. There are three types of such regulation: command-and-control regulation, market -based regulation, and public participation-based regulation, of which the first two are more commonly used [28-29]. Owing to increasing pressures on economic development and environmental protection, local governments usually prioritize economic growth and symbolically implement environment policies. And the central government fails to truly understand the true situation of policy implementation due to lack of effective supervision. Consequently, the limitations of the first two types of regulation become increasingly prominent. In contrast, public participation-based regulation represented by EID is gaining popularity and has created the third wave of environmental regulation [30].

EID system is based on and respects the public's right to know. Governments, enterprises and other subjects of social behavior publicly disclose their environmental performance to facilitate public participation and supervision. The public and non-governmental organizations exert pressure on polluting enterprises and local governments, thus achieving energy conservation and emission reduction [31]. As an information tool, EID can directly or indirectly regulate public behavior and change people's choices in daily life [32-33].

EID has a positive impact on the environment. It produces a "reverse force" on environmental governance, forcing enterprises to comply with environmental regulations, improve environmental standards, reduce pollution and enhance government credibility [34-39]. Bennear and Olmstead [40] studied the 1996 US Consumer Confidence Report (CCR), which included information on drinking water sources, violations of health-based drinking water regulations and procedural regulations. The implementation of EID policy reduced 30% to 44% of total violations and 40% to 57% of serious health violations in the US. In 1986, state governments required all production sites to report toxic chemical emissions to local environmental protection authority to renew the Toxics Release Inventory (TRI). According to Konar and Cohen [41], the stock price of related enterprises fell the most on the day when environmental information is disclosed, and the enterprises reduced more emissions than their peers. Although information disclosure facilitates environmental governance, the actual effect may vary by region and industry, possibly owing to inadequate report of all pollutants for TRI [42]. Scholars also found that information disclosure reduces environmental pollution in emerging economies. Powers et al. [43] used detailed factory survey data to evaluate the impact of India's Green Rating Project (GRP) on the environmental performance of pulp and paper mills. They concluded that GRP significantly reduced the mills' pollution load. García et al. [44] indicated that Indonesia's Program for Pollution Control, Evaluation and Rating (PROPER) produced a significant effect on corporate emissions reduction. Xiong et al. [45] noted that China's EID policy not only reduced local emissions, but also lowered the concentration of air pollutants in adjacent areas through spatial spillover.

In the process of policy implementation, many factors may cause information disclosure to fail to improve the environment or even bring negative effects, such as slow disclosure, limited disclosing entities, blurred boundaries between disclosure and non-disclosure [46-47], and serious information asymmetry between the public and the government in environmental management [48]. Brouhle et al. [49] concluded that EID have no impact on carbon emissions reduction, possibly because voluntary environmental regulation can not affect corporate behavior. Uchida [50] showed both binary eco-labeling and full information disclosure policy exert adverse effects on the environment and lead to greater pollution, which may because pollution from increased total product demand offsets improvements in environmental quality. Only when product quality is high enough or minimum quality standards are low enough can overall pollution be reduced through comprehensive information disclosure. It should be noted that EID creates pressure on local pollution-intensive enterprises, who may relocate to areas with weaker regulation intensity and bring negative impacts on the environment there [51-52].

Studies on Environmental Regulation and Resource Utilization Efficiency

The relationship between environmental regulation and resource utilization efficiency has always been a hot topic in environmental economics [53]. The former may exert a negative impact on the latter, possibly because it increases costs, so that enterprises do not sufficient funds to improve efficiency. These costs include both direct costs for terminal equipment, production and other costs incurred to comply with environmental regulations [54], which is known as cost hypothesis. This hypothesis suggests that environmental regulation hinders economic development by increasing corporate environmental management costs, reducing the proportion of investments in R&D and hindering the improvement of production efficiency [55]. Chen et al. [56] studied differences in water use efficiency in China and its influencing factors. They revealed that environmental regulation suppresses the improvement of industrial water use efficiency, which may because it is a potential external constraint that increases enterprises' transaction, production and management costs, and prompts enterprises to reduce spending on innovation. Xie et al. [57] demonstrated that environmental regulation exerts a negative impact on capacity utilization, so the government should improve pollutant emission standards and strictly enforce them to enhance regulation on the manufacturing industry, and introduce reasonable and feasible standards on production equipment to improve equipment utilization and capacity utilization.

Contrary to the above results, some scholars concluded that environmental regulation benefits both enterprises and the environment because it reduces costs through technological innovation, thereby improving resource utilization efficiency and product value, offsetting costs, and improving business productivity. This is the famous Porter hypothesis, also known as innovative compensation hypothesis, which asserts that environmental regulation forces enterprises to innovate technologies and compensate for additional costs caused by environmental governance with innovative compensation, thus improving the efficiency of green development. Jaffe and Palmer [58] further differentiated the Porter hypothesis into weak, strong and narrow Porter hypotheses based on whether compensation effects can offset costs of regulation. The weak Porter hypothesis suggest that appropriate environmental regulation stimulates corporate innovation. It deals with the relationship between environmental regulation and innovation. Jaffe and Palmer [58] studied the US manufacturing industry with investment in R&D and patent application as innovation indicators. They identified a positive correlation between investment in R&D and environmental regulation, but no correlation between patent application and environmental regulation. In contrast, Carrion-Flores and Innes [59], Lanoie et al. [60], Kneller and Manderson [61], Guo et al. [62], Zhou et al. [63] identified a positive correlation between patent application and environmental regulation.

The strong Porter hypothesis addresses if benefits brought by environmental regulation outweighs additional costs incurred by environmental regulation and enhances corporate competitiveness. In other words, it focuses on the relationship between environmental regulation and corporate competitiveness. Wang and Shen [64] confirmed a positive correlation between environmental regulation and productivity with industry heterogeneity, which partly validates the Porter hypothesis. Wen et al. [65] concluded that digitalization can improve corporate total factor productivity by reducing operating costs, promoting manufacturing enterprises' service-oriented transformation, and enhancing corporate investments in innovation. Environmental regulation promotes the transformation of manufacturing enterprises and improves their total factor productivity. The narrow Porter hypothesis centers on the nature of environmental regulation, arguing that flexible environmental regulation has a stronger stimulating effect than command-and-control environmental regulation. Thus, many scholars prefer to study market-based environmental regulation.

The correlation between environmental regulation and resource utilization efficiency may be non-linear. When environmental regulation is weak, the costs of regulation outweigh the benefits of innovative compensation, so enterprises would make a trade-off between them and spend money on pollutant control rather than innovation. When environmental regulation intensity reaches the inflection point, innovative compensation benefits outweigh costs of regulation, and enterprises would improve technologies to enhance resource utilization efficiency and relieve policy constraints [66]. Wang et al. [67] found a U-shaped correlation between regulation on marine environment and marine CEC. Marine regulation has a negative impact on CEC in the early stag e and a positive impact on it in later stage.

In summary, scholars have conducted extensive research on environmental regulation and energy utilization efficiency, and have drawn different conclusions. On the basis of measuring CEC, the research on the impact of EID on CEC is conducted. Compared to previous studies, the marginal contribution of this article is as follows: First, there have been few studies on CEC, and most of them have focused on measurement in the past. There have been few studies on the influencing factors of CEC, let alone the impact of EID on CEC. Second, in previous research literature on EID and resource utilization efficiency, few have considered the influencing mechanism. In this study, we consider two mechanisms: technological improvement effect and clean industry substitution effect when studying the impact of EID on CEC. Third, previous studies have mostly focused on the total sample, with little analysis of the impact of EID on resource utilization efficiency based on split sample data. We divide the total sample into two split samples and carry on regression analysis respectively.

Material and Methods

Research Methods

Super-Efficiency DEA Model

DEA (data envelopment analysis) is a relatively efficient method based on data inputs and outputs. Compared with other models, it features simple operation, no need to deimensionalize data and fewer subjective factors, being one of the most widely used methods for measuring efficiency. It is divided into the CCR-DEA model and the BCC-DEA model. The former is used to calculate efficiency statically when returns to scale remain unchanged, while the latter assumes that returns to scale are not static. In the latter model, comprehensive efficiency index represents the efficiency of resource allocation, resource utilization and scale aggregation of industrial development factors. Comprehensive efficiency is further divided into pure technical efficiency and scale efficiency. The BCC-DEA model can effectively identify whether the efficiency value of a decision-making unit (DMU) is valid, but cannot compare or thoroughly analyze simultaneously effective DMUs.

To address this issue, Andersen and Petersen[68] proposed super-efficiency DEA model, in which evaluated DMU is excluded from reference set. It compares evaluation units with the linear combinations of all the other evaluation units. The super-efficiency value of an efficient DMU is generally greater than 1, which is the criterion for distinguishing efficient DMUs. Assume a multi-input, multi-output evaluation system has n comparable DMUs, that is, $DMU_i(i = 1, 2, ..., n)$ and each DMU has m types of non-negative inputs, at least one of which is positive, and n types of outputs, then $x_j = (x_{1j}, x_{2j}, ..., x_{mj})^T$, where x_{tj} ($t = 1, ..., m$) is the t^{th} input of the j^{th} DMU, and $y_j = (y_{1j}, y_{2j}, ..., y_{sj})^T$, where y_{kj} ($k = 1, ..., s$) is the k^{th} output of the j^{th} DMU.

$$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$s.t.\begin{cases} \sum\limits_{\substack{j=1 \\ j\neq j_0}}^{n} \lambda_j x_j + s_i^- = \theta x_0, i = 1,2,3,...,m \\ \sum\limits_{\substack{j=1 \\ j\neq j_0}}^{n} \lambda_j y_j - s_r^+ = y_0, r = 1,2,3,...,s \\ \lambda_j \geq 0, s_i^-, s_j^+ \geq 0, j = 1,2,3,...,n \end{cases} \tag{1}$$

In this equation, θ means planned target value, ε non-Archimedean infinitesimal, λ_j planned decision variable, s^- and s^+ vectors of slack variables.

Difference-in-Differences Model

This is a quantitative research method widely used in recent years to evaluate the effects of a random test or natural experiment (such as adjustments to laws and regulations), especially to the marginal effects of a policy. Compared with other research methods, it can effectively solve endogenous problems caused by self-selection bias, and is therefore widely used in quantitative evaluation of the effects of a public policy or program. When applying this model, researchers often select data from several years before and after an experiment, divide master samples into the treatment group and the control group, and divide the sample period into before and after policy implementation.

The Institute of Public and Environmental Affairs and the Natural Resources Defense Council jointly developed pollution information transparency index (PITI) and evaluated the disclosure of pollution information in 120 Chinese cities based on indicators such as regulatory information, self-monitoring, interactive response, emission data and environmental impact assessment information. Each indicator has its own weight and is evaluated quantitatively from systematization, timeliness, completeness and user-friendliness.

Based on the above analysis, the authors built the following model:

$$\begin{aligned} dea_{it} = {} & \alpha_0 + \alpha_1 treat_{it} * post_{it} + \alpha_2 finance_{it} + \alpha_3 cundak_{it} \\ & + \alpha_4 ratio_{it} + \alpha_5 employ_{it} + \alpha_6 fdi_{it} + \theta_{it} \end{aligned} \tag{2}$$

in which i indicates the city, t the year, θ_{it} the residual, *dea* energy efficiency, *treat* grouped EID, and *post* period dummy variable. The control variables are lnfinance (level of government intervention), lncundk (level of financial development), ratio (industrial structure), employ (workforce level) and FDI (foreign direct investment).

Data Source and Variable Selection

Data Source

Indicators of EID policy come from PITI [69]. Carbon emissions in different cities come from the China Emission Accounts and Datasets [70]. Control variables are from the *China City Statistical Yearbook*, including fiscal expenditure, deposit balance, loan balance, the proportion of secondary industry output value in GDP, the proportion of tertiary industry output value in GDP, average number of employees in the city at the end of the year, regional GDP, and actually utilized FDI (missing values were calculated through interpolation and geometric mean) [71].

Variable Selection

(1) Explained variable: CEC (dea)

To estimate CEC with super-efficiency DEA model, we first selected input and output variables. Based on existing research and the characteristics of this study, we selected three input variables, i.e. capital (the proxy indicator of capital stock measured through perpetual inventory with the net value of fixed assets in each city), labor (total number of employers in each city), and energy consumption (energy input as the indicator of resource consumption measured with the entropy method by calculating the total water supply, total electricity consumption and total supply of liquefied petroleum gas of each city), and two output variables, i.e. GDP (the GDP of each province in previous years, converted with GDP deflator with 2003 as the base period), and CO_2 emissions (of each city). Input and output data are from the China City Statistical Yearbook for 2004-2019.

To save space, the average CEC of eastern, central and western China as well as the national average are listed only in Fig. 1. Except for western China, carbon efficiencies in other regions were lower than national average. Western China embraced relatively high CEC, of which Jiayuguan, Ordos and Shizuishan had the highest CEC, all exceeding 1. The three cities with the lowest CEC were Guangyuan, Deyang and Yibin, among which CEC in Guangyuan was the lowest at 0.927. CEC in central China ranked second, slightly higher than that in eastern China. Zhangjiajie and Huangshan ranked relatively high, both exceeding 1. Jiaozuo and Sanmenxia ranked relatively low, both below 0.9. CEC in eastern China was the lowest, except Haikou at 1.016. Xingtai, Binzhou and Jiaxing's carbon efficiencies were below 0.9. From 2003 to 2018, CEC in these three regions fluctuated and showed an upward trend. CEC in western China had four peaks and four valleys, with a maximum value of 0.991 in 2010 and a minimum value of 0.934 in 2018. CEC in central China, eastern China and the national average showed similar trends, all witnessing peaks in 2006, 2010, 2013, and valleys in 2008, 2012, 2015. It is worth noting that CEC in eastern China surpassed that of central China from 2016, and surpassed the national average from 2017.

(2) Control variables

finance (level of government intervention) is measured with the ratio of fiscal expenditure to GDP, *cundk* (level of financial development) with the ratio of deposit and loan balances in each city to GDP, *ratio* (industrial structure) with the ratio of the output value of the tertiary industry to that of the secondary industry, *employ* (workforce level) with the average number of employees in each city at the end of the year in the logarithmic form, and FDI (*fdi*) with total FDI in the logarithmic form.

Table 1 presents the results of descriptive statistics analysis on 3,215 samples in total. Except for *treat*post* and *fdi*, the mean values of all other variables are greater than the standard error. The mean of *treat*post* is 0.345 and its standard error is 0.475. The mean of *fdi* is also slightly smaller than its standard error. This suggests these two sample groups have certain discreteness. However, since there are more than 30 samples, regression results are not be affected. This table shows maximum and minimum values of each variable, with *employ* having the biggest minimum value, *finance* having the smallest minimum value, *employ* having the biggest maximum value and *fdi* having the smallest maximum value. *cundak* shows the biggest gap between

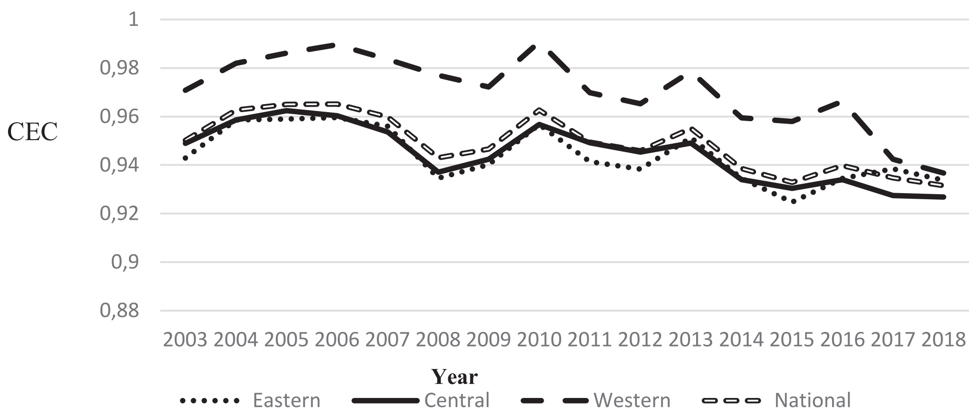

Fig. 1. Regional average carbon efficiency.

maximum and minimum values (6.110), while *fdi* shows the smallest gap between maximum and minimum values (0.112).

Highly correlated data will lead to distorted regression results or inaccurate estimations. Therefore, we tested whether there is serious multicollinearity among data before conducting empirical analysis. Table 2 reports the results of correlation analysis on panel data. According to it, the highest correlation coefficient is 0.454 between *lnemploy* and *treat*post*, and the lowest is -0.319 between *lncundak* and *dea*. Therefore, there is no serious multicollinearity among data, and empirical analysis can be performed.

Results and Discussion

Test for Parallel Trends

An important premise of empirical analysis with difference-in-differences method is that the parallel trend assumption must be valid, which means the CEC of experimental and control cities should show similar trend in the absence of policy interference. We adopted the event study methodology to conduct parallel trend test, results for which are shown in Fig. 2. In Fig. 2, *current* is the year of policy implementation, namely 2008; *pre1, pre3* and *pre5* the 1st, 3rd and 5th year before policy implementation, and *post1, post3* and *post7* the 1st, 3rd and 7th year after policy implementation.

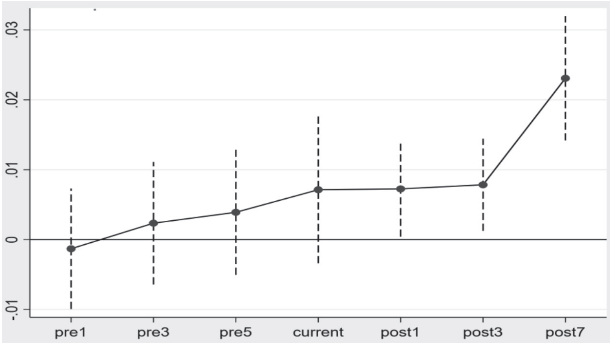

Fig. 2. Parallel trend test.

There was no significant differences in CEC between the treatment group and the control group before the implementation of information disclosure policy. After the policy was implemented, such difference became increasingly larger, which indicates that the CEC of experimental and control cities met the conditions for parallel trend test. Therefore, the difference-in-differences method can be used.

Analysis of the Impact of EID on Carbon Efficiency

To avoid the impact of sample selection bias on estimation results, we used difference-in-differences model to empirically analyze the impact of EID

Table 1. Descriptive statistical analysis.

Variable	obs	Mean	Std.dev.	Min	Max
dea	3215	0.949	0.047	0.811	1.604
*treat*post*	3215	0.345	0.475	0.000	1.000
finance	3215	-1.568	0.432	-3.047	1.082
cundak	3215	1.544	0.554	-2.139	3.971
ratio	3215	0.865	0.428	0.129	4.347
employ	3215	3.695	0.811	1.398	6.898
fdi	3215	0.008	0.009	0.001	0.113

Table 2. Results of the correlation analysis.

Variable	*dea*	*treat*post*	*finance*	*cundak*	*ratio*	*employ*	*fdi*
dea	1.000						
*treat*post*	-0.048	1.000					
finance	-0.191	0.092	1.000				
cundak	-0.319	-0.105	0.297	1.000			
ratio	0.092	0.146	0.191	0.182	1.000		
employ	-0.139	0.454	0.016	0.086	0.262	1.000	
fdi	-0.178	-0.079	0.037	0.289	-0.113	0.037	1.000

Table 3. Impact of environmental information disclosure on CEC.

Explained variable	*dea*			
*treat*post*	-0.004***	-0.007**	-0.007**	-0.007**
	(0.002)	(0.003)	(0.004)	(0.003)
finance		-0.011***	-0.012***	-0.012***
		(0.002)	(0.002)	(0.002)
cundak		-0.027***	-0.025***	-0.023***
		(0.002)	(0.002)	(0.002)
ratio		0.021***	0.024***	0.022***
		(0.002)	(0.002)	(0.002)
employ			-0.011***	-0.011***
			(0.002)	(0.002)
fdi				-0.346***
				(0.071)
_cons	0.951***	0.964***	0.987***	0.988***
	(0.001)	(0.007)	(0.009)	(0.009)
Obs		3215		3215
R^2	0.102	0.154	0.175	0.181

Note: *** , **, and * indicate significant levels at 1%, 5%, and 10%, respectively; the data in parenthesis are standard errors.

on CEC. Results are shown in Table 3. Whether control variables were included, the coefficient of the interaction term of policy effect was significantly negative, which shows EID leads to carbon emission increases and hinders CEC improvement. The reason is that EID is essentially public participation-based regulation, which means increasing the public's access to environmental pollution information to let them engage in environmental governance. Currently, China's environmental regulation is dominated by command-and-control mode and supplemented by market-based mode. Public participation-based regulation can not fully leverage the supervisory function of the entire society. It works by putting great pressure on enterprises in terms of reducing energy consumption and emissions, and forcing those with high pollution and energy consumption to reduce environmental pollution. Although some enterprises may take measures to reduce carbon emissions under pressure from the public, due to enormous pollution control costs, they shift their production lines to regions with lower environmental regulation intensity to gain greater marginal benefits. On the other hand, local governments, confronted with a dilemma between economic benefits and environmental protection, often prioritize the former. Such a development mode leads to selective disclosure of environmental information, distorts the effect of EID on reducing local environmental pollution, increases regional carbon emissions, and hinders CEC improvements.

Regarding control variables, *lnemploy* (workforce level) and *lncundk* (level of financial development) have negative effects on CEC, which indicates under current economic conditions, neither human resources nor financial resources can well absorb or digest EID policy. Therefore, in response to coordinated development of the ecology and the economy, when there is less economic pressure and stronger human capital, environmental assessment will be prioritized to force high polluting and high energy-consuming enterprises to reduce their environmental pollution. The influence coefficient of *lnfinance* (level of government intervention) on CEC is significantly negative, which means excessive government intervention hinders improvements in CEC. Ecological improvement and sustainable economic growth are contradictory. In the face of fiscal decentralization and economic assessment indicators, the government intervenes more in GDP growth, which leads to increased carbon emissions and reduced CEC. *Ratio* (industrial structure) has a significantly positive impact on CEC, which indicates an advanced, rational industrial structure can reduce corporate carbon emissions and improve CEC. *FDI* is significantly negative at the 1% level, which demonstrates that FDI is more about manufacturing cheap goods with China's resources and labor force, rather than bringing advanced production technologies which can improve local environment. That is, FDI transfers pollution to China and confirms the existence of a pollution haven in China.

Table 4. Robustness test.

Explained variable	dea		
	Lag 1	Lag 2	Lag 3
*treat*post*	-0.004	-0.003	-0.001
	(0.004)	(0.005)	(0.006)
_cons	1.018***	1.021***	1.020***
	(0.009)	(0.009)	(0.010)
Control variable	Yes	Yes	Yes
Obs	3215	3215	3215
R^2	0.173	0.168	0.166

Note: *** , **, and * indicate significant levels at 1%, 5%, and 10%, respectively; the data in parenthesis are standard errors.

Robustness Analysis

Changing the Time of Policy Shocks

To test whether new regression results are consistent with the above results when some parameters are changed, we conducted robustness tests. There are generally three methods for robustness test, i.e. variable replacement, method replacement and sample size change. For this study, method replacement was adopted. According to previous analysis, EID has a significant negative impact on CEC, but this may be caused by other policies or reasons. To prove the robustness of this conclusion, we adopted counterfactual analysis to examine whether core explaining variables are still significant before EID policy was implemented. If they are significant, other policies or reasons that have not been observed reduce CEC. If not, the negative impact of EID on CEC is stable and reliable. We advanced the year of implementing EID policy by 1 year (Lag1), 2 years (Lag2) and 3 years (Lag3). Table 4 presents the results of counterfactual analysis. It shows the impact of EID policy on CEC is not significant in these three years. That is, the negative impact of EID on CEC is stable and reliable.

Placebo Test

In order to further eliminate the interference of unknown factors on selected cities and avoid estimation errors, we conducted a placebo test on randomly selected cities that disclosed environmental information. Specifically, we randomly selected 120 out of 210 cities as the fake treatment group, while the rest cities formed the fake control group. The random sampling was conducted 500 times, and results are shown in Fig. 3, which displays the distribution of the estimated regression coefficients of explaining variables. The horizontal axis displays estimated coefficients, and

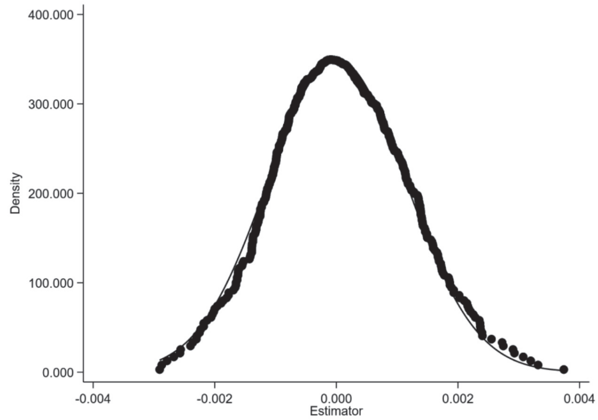

Fig. 3. Placebo test.

the vertical axis displays the distribution. We can see that the regression coefficients are mainly distributed around zero, so sample combination after random sampling does not affect CEC. Therefore, the placebo test verifies the conclusion that the impact of EID policy on CEC is not affected by unknown factors.

Split Sample Test

Split Sample Test by Geographical Location

China is a vast country, where economic development, carbon emissions and environmental pollution controls in different regions vary greatly. Therefore, there are spatial differences in EID. Sample cities were divided into eastern cities and mid-western cities based on their geographical location to study the impact of EID on their CEC separately. Specific results are shown in Table 5. EID has a negative impact on both eastern and mid-western cities, but the impact in eastern cities is significant and in mid-western cities insignificant. The coefficient in the eastern region is larger. Due to convenient land and sea transportation and outstanding geographical location, eastern China boasts high economic openness, a strong economic foundation, and a relatively advanced industrial structure. Its economic development is inseparable from massive energy consumption. In the short-term, energy consumption will offset positive effects brought by EID, increase carbon emissions, and reduce CEC. On the other hand, eastern China emphasizes economic development, which has a negative effect on energy policy, causing the public to overlook supervision over environmental pollution and a decline of CEC. Mid-western China has a vast area with a sparse population and a backward economy, where energy is mainly consumed by resource-based industries which implement strict environmental protection standards. Therefore, the impact of EID on CEC in mid-western China is weaker than that in eastern China.

Table 5. Results of split sample test.

Explained variable	*dea*			
	East cities	Central and western cities	Large and medium-sized cities	Small cities
*treat*post*	-0.010***	-0.001	-0.007**	-0.002
	(0.003)	(0.007)	(0.003)	(0.006)
_cons	0.979***	1.050***	0.962***	1.150***
	(0.005)	(0.017)	(0.004)	(0.024)
Control variable	Yes	Yes	Yes	Yes
Obs	1711	1504	1680	1535
R^2	0.290	0.168	0.314	0.286

Note: *** , **, and * indicate significant levels at 1%, 5%, and 10%, respectively; the data in parenthesis are standard errors.

Split Sample Test by City Size

Big and small cities differ in economic foundation, industrial structure, openness, financial development and environmental governance. According to the New List of Chinese Cities published by Cities Beyond DRTR in 2021, we grouped first-tier cities, new first-tier cities, second-tier cities and third-tier cities among sample cities into large and medium-sized cities, and the others into small cities to conduct regression analysis. Results are shown in Table 7, which shows EID has a negative effect on CEC in both large and medium-sized cities and small cities, but the coefficient of the former is significant while that of the latter is not significant. Besides, such a negative effect on large and medium-sized cities is greater than than on small ones. The reason is that large and medium-sized cities have relatively dense transportation facilities, well-functioning industrial structures, and mature environmental governance standards. They can improve the environment through command-and-control environmental regulation and market-based environmental regulation, so the impact of public participation-based regulation on carbon emissions is weaker. In the case of priority over economic development and information asymmetry between the government and the public, such impact may even be negative. Small cities have a weak economic foundation, incomplete industrial structure, low population density and poor transportation facilities, so the impact of EID on carbon emissions and CEC there is relatively small.

Test of Influencing Mechanism

Model Setting

The above empirical test shows that EID hinders CEC improvement, but there is heterogeneity in different regions and cities of different sizes. Through which channels does EID reduce CEC? Further research is required to answer this question. According to existing studies, EID affects a city's technology readiness level through technological improvement, or affects its clean transformation of industrial structure through clean industry substitution effect, thus affecting CEC. Therefore, we examined the influence of EID on CEC from technological improvement effect and clean industry substitution effect. The model of mediation effect is as follows:

$$dea_{it} = \beta_0 + \beta_1 treat_{it} * post_{it} + \beta_2 medium_{it} + \beta_3 finance_{it} + \beta_4 cundak_{it} + \beta_5 ratio_{it} + \beta_6 employ_{it} + \beta_7 fdi_{it} + \varepsilon_{it} \quad (3)$$

$$medium_{it} = \gamma_0 + \gamma_1 treat_{it} * post_{it} + \gamma_2 finance_{it} + \gamma_3 cundak_{it} + \gamma_4 ratio_{it} + \gamma_5 employ_{it} + \gamma_6 fdi_{it} + \tau_{it} \quad (4)$$

In this equation, i represents the province, t the year, $\beta_i (i = 0, 1, ..., 7)$ and $\gamma_i (i = 0, 1, ..., 6)$ regression coefficients, ε_{it} and τ_{it} are residuals, *dea* is CEC, *medium* is the mediating variable (*technology, clean*), and *finance, cundak, ratio, employ* and *FDI* control variables. Mediating variables refer to technological improvement effect (the proportion of highly educated population to total population in each city) and clean industry substitution effect (the proportion of tertiary industry output value to GDP). All data come from the *China City Statistical Yearbook* during 2004 and 2019.

Analysis of the Result of Mechanism Test

(1) Technological improvement effect

Columns (2) and (3) in Table 8 present the mechanism of technological improvement effect. They manifest that EID has a positive and significant impact on technological improvement, and that technology readiness level has a positive and significant impact on CEC. Table 5 shows that when technology readiness level is not considered, the coefficient of impact of EID on CEC is -0.007. Table 8 shows when technology readiness level is taken into account, the coefficient is -0.008. This suggests that EID directly affects

Table 6. Results of influencing mechanism test.

Explained variable	*technology*	*dea*	*clean*	*dea*
*treat*post*	0.003***	-0.008**	-0.031***	-0.006**
	(0.001)	(0.005)	(0.010)	(0.003)
technology		0.395***		
		(0.041)		
clean				-0.027**
				(0.011)
_cons	-0.029***	1.028***	3.024***	1.101***
	(0.002)	(0.009)	(0.019)	(0.041)
Control variable	Yes	Yes	Yes	Yes
Obs	3215	3215	3215	3215
R^2	0.403	0.199	0.703	0.182

Note: *** , **, and * indicate significant levels at 1%, 5%, and 10%, respectively; the data in parenthesis are standard errors

CEC and intensifies its negative impact on CEC by affecting technology readiness level, and that improving technology readiness is an effective way to reduce CEC through EID.

(2) Clean industry substitution effect

Columns (4) and (5) in Table 6 show the mechanism of clean industry substitution effect (the proportion of tertiary industry output value to GDP). The tertiary industry features less energy consumption, low environmental pollution, and produces lower carbon emissions than the secondary industry. The coefficient of *treat*post* is significantly negative, which means EID hinders the clean transformation of industrial structure. Clean industry substitution effect has a negative impact on CEC. That is, a low degree of cleanness in urban industrial structure hinders CEC improvement. Table 5 shows when clean industry substitution is not considered, the coefficient of impact of EID policy on CEC is -0.007. Table 8 shows when clean industry substitution is taken into account, the coefficient of impact of EID on CEC is -0.006. This signifies EID directly affects CEC and reduces negative impact on CEC by affecting clean industry substitution. That is, clean industry substitution is an effective channel to reduce CEC through EID.

Conclusions

We measured the CEC of Chinese cities with super-efficiency DEA model and found regional heterogeneity in it, namely the carbon efficiencies of almost all cities were lower than the national average, except those in western China. CEC in eastern, central and western China fluctuated and showed an overall upward trend over the years. On this basis, we adopted the difference-in-differences model to empirically test the impact of EID on CEC, and found that EID increased carbon emissions and had a negative impact on CEC. Mechanism test confirmed that EID affects CEC through technological improvement effect and clean industry substitution effect. We also conducted split sample tests based on geographical location and city size to explore the heterogeneity of EID on CEC.

Based on above conclusions, we proposed several policy recommendations:

First, the government should incorporate green development index to improve assessment system, and make it an important basis for assessing, evaluating, rewarding and punishing officials. Information disclosure, as an effective way to improve the environment, can be used as an indicator for assessing the performance of local governments. The government should establish a special fund for information disclosure, broaden the scope of environmental information to be disclosed, ensure the high frequency and accuracy of disclosed contents; improve the quality and efficiency of EID to ensure sound implementation of environmental protection policies and practically promote energy conservation and emission reduction; strengthen service awareness, build a communication platform among the government, enterprises, the media and the public. These measures can improve existing EID system and effectively enhance regional CEC.

Second, cities should create carbon emission and transfer accounts, accurately measure the income and expenditure of these accounts, and quicken steps to build carbon emission measurement and assessment systems. Efforts should be made to improve the assessment of inter-regional carbon offset quota measurement system. Based on the principles of payment made by those who benefit, differentiation, fairness and sustainable development, standards for compensation by the area from which polluting enterprises move out and the area to which polluting enterprises move in should be determined through carbon compensation adjustment coefficient and shadow pricing. Consideration should also be given to different resource endowments, populations and economic strength in different regions to improve carbon emission compensation model. In addition, cities should promote inter-regional cooperation in managing carbon emissions and the environment to jointly reduce pollution and improve CEC.

Thirdly, integrated use of environmental regulation tools should be optimized and a diverse carbon reduction system should be developed. Cities should combine the advantages of command-and-control regulation, market-based regulation and public participation-based regulation to effectively reduce carbon emissions and improve CEC. An environmental governance system led by the government, mainly joined by enterprises and participated by social organizations and the public should be established to form a coordinated, complementary and incentive-compatible community of shared environmental interest. Existing EID system should be improved by including mandatory command-and-control regulation, incentive market-based regulation and supervisory public participation-based regulation to raise CEC.

This study is a more in-depth research on the impact of EID on CEC, but there are still deficiencies and limitations. We suggest that future research can focus on the following directions: First, alternative estimation methods can be used to to study the relationship between EID and CEC, For example, nonlinear regression or quantile regression can be used to verify whether future results support empirical research with different panel data. Second, theoretical models can be established in the EKC framework to study the relationship between environmental pollution and economic development in China in the current stage, which is of great significance for China to formulate appropriate carbon emission policies under the dual carbon target policy. These analyses should be more fruitful and helpful.

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Conflict of Interest

The authors declare no conflict of interest.

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