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Evaluating the CO$_2$ abatement effects of low-carbon city policy in China: a quasi-natural experiment

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Abstract

The formulation and implementation of Low-Carbon City Policy (LCCP) is an essential initiative for China to build its low-carbon society. Based on the panel data of 282 prefecture-level cities in China from 2003 to 2016, this study evaluates the effects of LCCP implementation on pilot cities' carbon emission performance using difference-in-differences method, and then the mechanism has also been examined with a mediating effect model. The results show that: first, the LCCP implementation has increased the carbon emission performance of the pilot cities significantly, indicating that it is an effective way to promote the low-carbon transformation of Chinese cities. Second, the positive effects in CO$_2$ performance resulting from LCCP demonstrate significant heterogeneity: in general, the cities in east China, with higher economic development level and in a larger size, achieve more significant CO$_2$ emission reduction than their respective counterparts. The results on the mechanism test imply that the LCCP helps improve pilot cities' carbon emission performance in three ways, including reducing energy consumption, updating the industrial structure, and promoting technological progress. Finally, some useful policy recommendations are put forward to promote China's low-carbon city construction.

Keywords: Low-carbon city, Carbon emission performance, Mechanism analysis, Difference-in-differences method

Introduction

Global climate change caused by the excessive consumption of fossil energy has attracted more and more attention from the international community (Cole et al. 2013; Lemoine and Rudik 2017; Gökgöz and Güvercin 2018). As the chief criminal of global climate change, the rapid increase in greenhouse gas emission causes not only global warming, rising sea level, extreme weather, but also significant negative impact on human health and economic development (Zhang et al. 2017; Tang et al. 2018a; Karlsson and Ziebarth 2018). Therefore, it is imperative to reduce greenhouse gas emission and promote low-carbon economic development. Cities, as regional or even national centers in political, economic, social, and cultural development, make

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significant contributions to regional economic development; at the same time, they are also significant consumers of local resource and are the primary sources of greenhouse gas emission (Khanna et al. 2014). Thus, the key to reducing global greenhouse gas emission lies in cities (Sudmant et al. 2016); and the development of low-carbon cities has become an essential global response to climate change threats (Glaeser and Kahn 2010; Tan et al. 2017; Fu et al. 2021).

Ever since its reform and opening in the late 1970s, China has made remarkable achievements in social and economic development. Its economy maintains an average annual growth of 9.5% during the past 40 years, and its urbanization rate soared from 17.92% in 1978 to 58.52% in 2017. With rapid industrialization and urbanization, CO_2 emissions are gradually increasing in China (Peters et al. 2020; Yang et al. 2020). Given that cities have become the significant battlefields for energy saving and CO_2 emission reduction, the Chinese government launched the first batch of pilot low-carbon cities in 2010, followed by the second and third installments of pilot low-carbon cities in 2012 and 2017, respectively (Tang et al. 2018b; Chen et al. 2021). In this context, it is of great importance to evaluate the effects of Low-Carbon City Policy (LCCP) implementation on pilot cities' carbon emission performance along with its impacting mechanism, which can help governments to formulate appropriate environmental, economic policies and facilitate the realization of carbon emission peak targets before 2030.

In the past decade, the low-carbon city has become a hot topic at home and abroad (Liu et al. 2014; Fremstad et al. 2018; Bagheri et al. 2019). In theoretical level, existing studies focus on the definition and connotation for the low-carbon city as well as its evaluation criteria; and in a practical level, previous studies mainly focus on the action plan for the low-carbon city along with revenant practices in some specific fields.

For the concept and connotation of the low-carbon city, (Liu and Qin 2016) point out that the core objective of the low-carbon city construction is to reduce urban carbon dioxide emission, to make them the implementation sites of the low-carbon economy or even low-carbon society. Liu et al. (Liu et al. 2017) consider that the low-carbon city development is a process of public participation, calling for carbon reduction efforts from governments, enterprises, and individuals. The concept of a low-carbon city is part of sustainable development (Khanna et al. 2014). Carbon emission can be effectively reduced by adopting low-carbon development measures without lowering urban economic growth.

Besides, as lots of cities in the world have set the low-carbon city as their development goal, it is of considerable significance to build Energy Conservation Target Responsibility System (ECTRS) for the low-carbon city (Lo 2014). In this context, many scholars endeavored to establish key indicators in evaluating low-carbon city development (Lin et al. 2014; Yang et al. 2018).

For the action plan of low-carbon city, it includes various contents such as the planning and design (Freeman and Yearworth 2017), the urban transition experiments (Williams 2016), the policy arrangements (Peng and Bai 2018), and the formulation of explanatory framework for low-carbon city practice (Van Doren et al. 2018). Moreover, since low-carbon city construction is a complex system building involving infrastructure, industry, technology, and energy (Wang et al. 2018), numerous studies discuss

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relevant practices for low-carbon city development in specific fields such as infrastructure strategies (Kennedy et al. 2014), energy consumption (Silver and Marvin 2017; Ohnishi et al. 2018), and financial support (Van der Heijden 2017).

In recent years, the low-carbon city practices in China have also attracted much attention. Wang et al. (Wang et al. 2015) have summarized the low-carbon development plans. Tang et al. (Tang et al. 2018b) use the Difference-in-Differences (DID) method to analyze the effects of LCCP from the perspective of land transfer in energy-intensive industries. Li et al. (Li et al. 2018) study the progress of pilot low-carbon city construction in China in terms of their development and governance systems. Wang et al. (Wang et al. 2018) pointed out that promoting technological innovation, upgrading the industrial structure, and transforming energy consumption structure are the directions for low-carbon development. In recent years, attention has also been given to case studies of low-carbon economic development in individual cities in China, such as Beijing (Shen et al. 2018), Ningbo (Yang et al. 2017), Xiamen (Lin et al. 2014), and Shenzhen (Zhan and de Jong 2018).

Literature review shows that current studies on the low-carbon city are mostly qualitative analysis focusing on the connotation, development model, policy tools, and path selection; while few studies provide a scientific quantitative assessment of the effects of China's low-carbon city policies. In order to fill this gap, the present study employs DID method to empirically examine the actual impact and mechanism of China's LCCP implementation on pilot cities' carbon emission performance. The remainder of the paper is organized as follows: Section 2 describes the policy background of pilot low-carbon city in China; Section 3 introduces the methodology employed in this study and the dataset; Section 4 presents the empirical results; Section 5 examines the mechanism of LCCP implementation on pilot cities' carbon emission performance; Section 6 concludes the paper.

Policy background

To effectively promote the decoupling of China's rapid urbanization and the considerable greenhouse gas emission in the city-level, the National Development and Reform Commission (NDRC) issued "*Notice on the Piloting Work of Low-carbon Provinces and Cities*" (Fagai • Qihou (2010) No. 1587, thereafter the "Notice") on July 19, 2010, which identified five provinces, namely Guangdong, Liaoning, Hubei, Shaanxi and Yunnan, and eight cities including Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, and Baoding, as pilot low-carbon provinces and low-carbon cities. The Notice requires the pilots to do explicit low-carbon development planning, formulate a series of supporting policies for promoting local low-carbon and green development, accelerate the establishment of the low-carbon industrial system, build a management system for greenhouse gas emission statistics, and encourage low-carbon lifestyles and green consumption patterns.

On November 26, 2012, the NDRC released the "Notice on the Second Batch of Piloting Work on Low-carbon Provinces and Cities" (Fagai • Qihou (2012) No. 3760), which issues the list of the second batch of national pilot low-carbon provinces and cities, including Beijing, Shanghai, Hainan, Shijiazhuang, Qinhuangdao, Jincheng, Hulunbeier, Jilin, Daxinganling, Suzhou, Huai'an, Zhenjiang, Ningbo, Wenzhou, Chizhou, Nanping, Jingdezhen, Cangzhou, Qingdao, Jiyuan, Wuhan, Guangzhou,

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Guilin, Guangyuan, Zunyi, Kunming, Yan'an, Jinchang, and Urumqi. On January 7, 2017, the "Notice on the Third Batch of National Piloting Work on Low-carbon Cities" (Fagai • Qihou (2017) No. 66) was issued by the NDRC, which adds 45 cities (districts or counties) such as Wuhai in Inner Mongolia Autonomous Region as the third batch of low-carbon cities. With the LCCP implementation, some elementary accomplishments have been achieved, and the specific tasks for the third batch of pilot low-carbon cities have been adjusted into: (1) setting explicit targets and principles, (2) making low-carbon development planning, (3) building a target assessment system for the control of greenhouse gas emission, (4) actively exploring the innovation experiences, and (5) enhancing the management ability for low-carbon development. To date, there are at least one pilot low-carbon city in each province across the country.

Since the launch of the low-carbon city pilot project, relevant cities have urgently formulated specific action plans according to the low-carbon city development goals and put them into implementation. For example, in December 2011, Tianjin formulated an action plan for low-carbon city development, setting an ambitious target of reducing its CO_2 emission intensity by 19% and energy intensity by 18% by 2015 over the year 2010. In September 2013, Hangzhou issued a "Low-carbon City Development Planning in the Twelfth Five-year Plan", proposing reductions in CO_2 emission intensity by 45% and energy intensity by 40% by 2020 over the year 2005. Nanchang has also formulated an action plan for building the low-carbon city, setting a target of reducing its CO_2 emission intensity by 38% by 2015 over the year 2005.

In specific practices, the secondary industry including manufacturing and construction industries, and the transportation industry have become the key areas for low-carbon development. Taking Guangzhou as an example, this city has set up a special fund with a total amount of 2 billion Yuan each year to cultivate emerging industries of strategic importance to promote the optimizing and upgrading of industrial structure. In construction industry, several pilot low-carbon cities such as Shenzhen, Kunming, and Guiyang all issued the "*Regulations on Building Energy Conservation*", which impose stricter design standards on energy efficiency of all new buildings, with a view to promote green buildings and make full use of renewable energy. In terms of low-carbon transportation, Hangzhou invests heavily in green public transportation and gradually establishes a green public transportation system comprising taxis, public bicycles, subways, water buses and low-carbon buses.

Besides, Wenzhou and Guangzhou took carbon sink as a critical measure to reduce CO_2 emission and created demonstration zones for carbon sequestration. Qingdao, Shenzhen, Ningbo, Wenzhou, Wuhan, and some other cities developed carbon certification systems in industries such as cement, building materials, and automotive manufacturing to encourage the application of the low-carbon technologies and products. Shijiazhuang and Nanchang formulated a series of laws and regulations to promote the development of low-carbon city. Overall, various measures have been well adopted by the pilot low-carbon cities for low-carbon economic growth, and most of them have achieved beneficial accomplishments to date.

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Research design

Empirical strategy

To examine the net effect of LCCP implementation on pilot low-carbon cities' CO_2 emission performance. This study employs DID method for empirical testing. The DID method is currently a prevalent econometric instrument (Yang et al. 2021) (Yang et al. 2021), especially in policy effect evaluations (Hering and Poncet 2014; Gehrsitz 2017; Blackman et al. 2018) (Hering and Poncet 2014; Gehrsitz 2017; Blackman et al. 2018).

It can be seen from the policy background that some cities are low-carbon pilot cities, and some are non-pilot cities. Which provides a good quasi-natural experiment for policy effect evaluation with the DID method. Following Beck et al. (2010) and Liu et al. (2021) (Beck et al. 2010; Liu et al. 2021). This paper builds a time-varying DID model as follows:

$$Efficiency_{it} = a_0 + \beta \times (du_i \times dt_{it}) + \delta Z_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{1}$$

where the dependent variable $Efficiency_{it}$ indicates the city-level carbon emission performance, which is measured by the Slacks-Based Measure of Super-efficiency in Data Envelopment Analysis (Super-SBM DEA). The subscripts i and t represent city i and period t, respectively. According to the above policy background, the first batch of low-carbon pilot cities in 2010 and the second batch of low-carbon pilot cities in 2012. du_i is used to identify the cities defined as pilot low-carbon cities in 2010 and 2012, or not. The value 1 is assigned to a city defined as a pilot low-carbon city; the value 0 is assigned to a city not defined as a pilot low-carbon city. dt_{it} is used to identify the LCCP implementation, or not. Among them, the first batch of low-carbon pilot cities in 2010 and after were defined as 1, the second batch of low-carbon pilot cities in 2012 and after were defined as 1, and the rest of the time as 0. μ_i stands for the fixed effects of region; γ_t indicates the period fixed effect; a_0 indicates the constant term; ε_{it} is an error term. Z_{it} refers to a matrix of control variables, including the level of economic development, foreign direct investment, fiscal decentralization, a ratio of secondary industry in Gross Domestic Product (GDP), population density and regional infrastructure, etc. Much more attention should be paid to the estimation of the coefficient β of the interaction term, $du_i \times dt_{it}$, which measures the net effect of the LCCP implementation on pilot cities' CO_2 emission performance. If $\beta > 0$, it implies that the LCCP implementation can increase pilot cities' CO_2 emission performance. If $\beta < 0$, it implies that the LCCP implementation can increase pilot cities' CO_2 emission performance. If $\beta = 0$, there is no effect of the LCCP implementation.

Measurement of CO_2 emission performance

Super-SBM DEA model

To maximize the consistency with actual production situation, this study introduces undesired output into Super-SBM DEA model. Following Tone (2002); Zhou et al. (2018) (Tone 2002; Zhou et al. 2018), considering n Decision-Making Units (DMUs), with each DMU comprising m types of input, it is expressed as x_i. r_1 kinds of desired output, it is expressed as y^d, and r_2 kinds of undesired output, it is expressed as y^u. Inputs and outputs can be represented in:

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$x = [x_1, ..., x_n] \in R^{m \times n}$, $y^d = [y_1^d, ..., y_n^d] \in R^{r_1 \times n}$, $y^u = [y_1^u, ..., y_n^u] \in R^{r_2 \times n}$. Assuming that their values are all greater than zero, the SBM model can be expressed by Eqs. (2) and (3):

$$\min \rho = \frac{1 - (1/m) \sum_{i=1}^{m} \left(w_i^-/x_{ik}\right)}{1 + \frac{1}{(r_1 + r_2)} \left(\sum_{s=1}^{r_1} \left(w_s^d/y_{sk}^d\right) + \sum_{q=1}^{r_2} \left(w_q^u/y_{qk}^u\right) \right)} \tag{2}$$

$$s.t. \quad x_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + w_i^- \qquad i = 1, ..., m$$

$$y_{sk}^d = \sum_{j=1}^{n} y_{sj}^d \lambda_j - w_s^d \qquad s = 1, ..., r_1 \tag{3}$$

$$y_{qk}^u = \sum_{j=1}^{n} y_{qj}^u \lambda_j + w_q^u \qquad q = 1, ..., r_2$$

and, $\lambda_j \geq 0, w_i^- \geq 0, w_s^d \geq 0, w_q^u \geq 0$.

where ρ indicates the efficiency value, λ denotes the linear combination coefficient of DMU, w_i^- represents the slack variable of input, w_s^d and w_q^u represent the slack variable of output. If and only if $\rho = 1$, i.e., $w^- = 0$, $w^d = 0$, $w^u = 0$. Based on Eq. (2), the Super-SBM DEA model with undesired output can be further expressed as:

$$\min \theta = \frac{(1/m) \sum_{i=1}^{m} (\bar{x}_i/x_{ik})}{\frac{1}{(r_1 + r_2)} \left(\sum_{s=1}^{r_1} (\bar{y}_s^d/y_{sk}^d) + \sum_{q=1}^{r_2} (\bar{y}_q^u/y_{qk}^u) \right)} \tag{4}$$

$$s.t. \quad \bar{x}_i \geq \sum_{j=1, \neq k}^{n} x_{ij}\lambda_j \qquad i = 1, ..., m$$

$$\bar{y}_s^d \leq \sum_{j=1, \neq k}^{n} y_{sj}^d \lambda_j \quad s = 1, ..., r_1 \tag{5}$$

$$\bar{y}_q^u \geq \sum_{j=1, \neq k}^{n} y_{qj}^u \lambda_j \quad q = 1, ..., r_2$$

and, $\lambda_j \geq 0, \bar{x}_i \geq x_{ik}, \bar{y}_s^d \leq y_{sk}^d, \bar{y}_q^u \geq y_{qk}^u$. The variables definition is the same as Eq. (2).

Input and output indicator selection

In order to evaluate the CO_2 emission performance of the 282 prefecture-level cities with Super-SBM DEA model, the input and output data required during 2003–2016 is collected as follows:

- **Desired output.** Represented by city-level GDP. In order to eliminate the impact of the price factor, the nominal GDP of each city is deflated by the corresponding provincial GDP index where it is located taking 2003 as the base period.
- **Undesired output** (CO_2 emission). Carbon dioxide emissions mainly caused by fossil energy consumption. As China's statistics on energy consumption primarily derive from a top-down statistical system, the existing statistics comprise only the

provincial-level energy consumption balance sheet, lacking energy consumption data at city-level. Due to the absence of necessary data, this study estimates city-level CO_2 emissions by multiplying the proportion of a city's GDP to the whole province where it is located by the total CO_2 emissions of this province, following Su et al. (2014) (Su et al. 2014); Wang and Li (2017) (Wang and Li 2017); and Ren et al. (2018) (Ren et al. 2018).

- **Capital input**. Capital input is represented by city-level capital stock, which is calculated using perpetual inventory method following Hall and Jones (1999) (Hall and Jones 1999), Wang and Feng (2015) (Wang and Feng 2015).
- **Labor input**. Referring to Cheng et al. (2018) (Cheng et al. 2018), this study uses the employees at the end of the year in each city as the labor input indicator.
- **Energy input.** This study incorporates energy consumption as an essential input factor when measuring carbon emission performance. The overall electricity consumption of the city is used as the proxy indicator of energy input in the present study. There are three reasons why we used the electricity consumption to measure energy input. First, coal is the main source of power generation in China, and natural gas also accounts for a part of power generation. Therefore, from this perspective, there is a close positive correlation between power consumption and energy consumption. Second, according to China's resource situation and the proportion of coal in the energy production and consumption structure, the energy structure dominated by coal will not change for a long time. Since the founding of the People's Republic of China, coal consumption has long accounted for more than 60% of total energy consumption. Third, we had to consider the availability of data because the China City Statistical Yearbook does not provide statistics on energy input.

Variable and data description

- **Dependent variable.** The dependent variable of this paper is city-level carbon emission performance, which is measured by the Super-SBM DEA model introduced above.
- **Independent variable.** According to annual "China City Statistical Yearbook" as well as the unified value assignment base on the time of establishment as pilot low-carbon cities by the National Development and Reform Commission, the interaction term du × dt can be obtained.
- **Control variables.** Following existing literature (Xie et al. 2017; Grunewald et al. 2017; Leslie 2018) (Xie et al. 2017; Grunewald et al. 2017; Leslie 2018), the control variables affecting carbon emission performance mainly include the level of economic development measured by the logarithm of actual per capita GDP, industrial structure regulated by the ratio of gross product of the secondary industry to overall regional GDP, fiscal decentralization measured by the ratio of government public financial expenditure to regional GDP, openness measured by the rate of the actual use of foreign investment to regional GDP, population density measured by the ratio of the year-end population to the total land area of the

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region, and infrastructure development measured by bus number per 10,000 people. The specific variable selections and calculation methods, as shown in Table 1.

Based on the panel data of 282 prefecture-level cities in China from 2003 to 2016, the study evaluates the effects of LCCP on pilot cities' carbon emission performance. The data collected from China Stock Market & Accounting Research database, the annual China Statistical Yearbooks, the annual China City Statistical Yearbooks. The descriptive statistics of each variable, as shown in Table 2.

Empirical results analysis

Baseline results

In order to examine the net effect of LCCP on the carbon emission performance of pilot cities, the results of the baseline model, as shown in Table 3. It can be observed that the estimated parameter of the interaction term is positive and statistically significant at the 5% critical level, indicating that the LCCP implementation has played a substantial role in promoting the pilot cities' carbon emission performance. Moreover, in order to test the robustness of the regression result shown in Model (1), the control variables are added one by one into the econometric model, and the estimation results are reported in Models (2) ~ (7) in Table 3. All the estimated parameters of the interaction term are positive and statistically significant, which does not vary by a wide range with the gradual additions of the control variables, indicating that the empirical results are of excellent robustness.

Robustness test

Parallel trend test

The basic premise for the DID method to be effective is that the treated group and the untreated group have parallel trends before the policy is implemented. For the study of this article, that is, before the LCCP implementation, the carbon emission efficiency trends of the treated group and the untreated group need to have parallel trends. Figure 1 shows the change trend of carbon emission efficiency of the treated group and

Table 1 Key variables and calculation methods

Variable		Variable description	Calculation method
Dependent variable	Efficiency	carbon emission performance	calculated by Super-SBM DEA
Independent variable	du × dt	pilot low-carbon city	dummy variable (0, 1)
Control variables	pctgdp	economic development	the logarithm of actual per capita GDP
	fisdec	fiscal decentralization	the ratio of government public financial expenditure to regional GDP
	forinv	openness	the rate of the actual use of foreign investment to regional GDP
	indsru	industrial structure	the rate of the gross product of the secondary industry to regional GDP
	popden	population density	the logarithm of year-end population per unit area
	infras	infrastructure	the logarithm of number of buses per 10,000 people

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Table 2 Descriptive statistics of the variables

Variable	Obs	Mean	Std. Dev.	P25	P75
Efficiency	3948	0.7005	0.1426	0.6124	0.7668
du × dt	3948	0.1581	0.3648	0.0000	0.0000
pctgdp	3948	0.0912	0.7015	−0.4006	0.5010
fisdec	3948	0.1567	0.1330	0.0997	0.1864
forinv	3948	0.0210	0.0270	0.0053	0.0281
indsru	3948	0.4875	0.1103	0.4184	0.5555
popden	3948	−3.4917	0.8998	−3.9967	−2.7880
infras	3948	1.7199	0.7659	1.2879	2.2523

the untreated group before and after the LCCP implementation. It can be seen from the left side of the dotted line that before the LCCP implementation, the carbon emission efficiency curves of the treated group and the untreated group basically have a parallel trend. At the same time, it can be seen from the right side of the dotted line that after the LCCP implementation, there is a difference between the carbon emission efficiency of the treated group and the untreated group, and the carbon emission efficiency of the treated group is greater than the untreated group. Therefore, the above results indicate that the treated group and the untreated group can basically meet the parallel trend condition.

Table 3 Results of the benchmark model

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
du × dt	0.0104**	0.0086**	0.0090**	0.0109**	0.0092**	0.0103**	0.0103**
	(0.0045)	(0.0044)	(0.0044)	(0.0044)	(0.0043)	(0.0043)	(0.0043)
pctgdp		0.1287***	0.1571***	0.1572***	0.1934***	0.2275***	0.2265***
		(0.0084)	(0.0098)	(0.0098)	(0.0106)	(0.0108)	(0.0108)
fisdec			0.0656***	0.0300**	0.0435***	0.0645***	0.0629***
			(0.0119)	(0.0150)	(0.0149)	(0.0148)	(0.0148)
forinv				0.2872***	0.3609***	0.4018***	0.4111***
				(0.0737)	(0.0735)	(0.0723)	(0.0724)
indsru					−0.2195***	−0.2461***	− 0.2484***
					(0.0263)	(0.0260)	(0.0260)
popden						0.2568***	0.2602***
						(0.0220)	(0.0221)
infras							0.0074**
							(0.0034)
Constant	0.6905***	0.7041***	0.7002***	0.6954***	0.7956***	1.7176***	1.7201***
	(0.0041)	(0.0040)	(0.0041)	(0.0042)	(0.0127)	(0.0800)	(0.0800)
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Obs	3948	3948	3948	3948	3948	3948	3948
R^2	0.256	0.301	0.307	0.310	0.323	0.347	0.348
F	89.7385	104.9396	101.0747	96.3935	96.6056	102.0759	97.3081

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

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Fig. 1 Time trend of Efficiency between treated group and untreated group
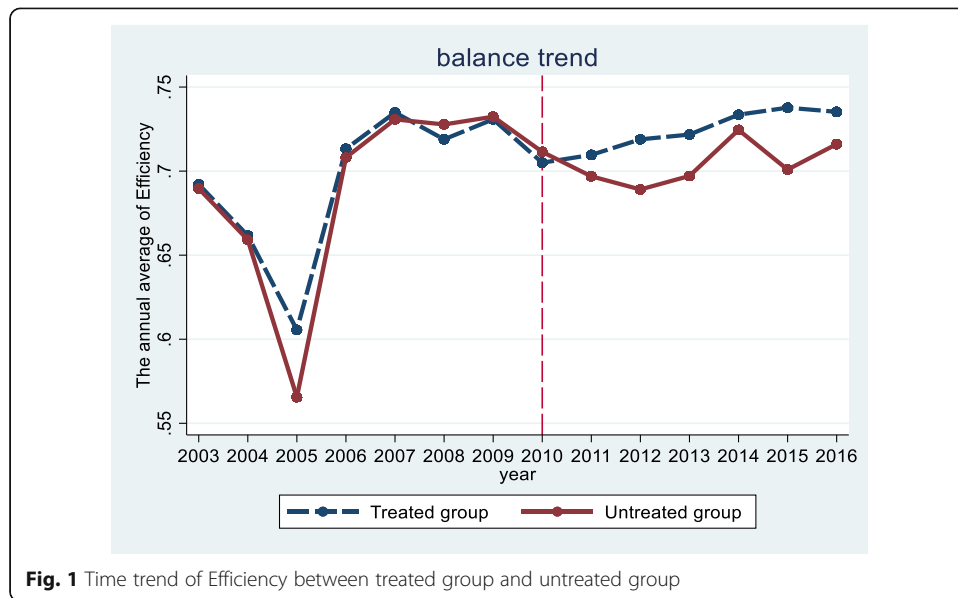
Changing the width of the time window

To examine whether the effects of LCCP on pilot cities' carbon emission performance change with the length of the test period, another three empirical study programs with different widths of time window are investigated. First, taking the starting year of 2012 as the reference year, and the time windows before and after the policy implementation are both shortened; Second, taking the starting year of 2012 as the reference year, only the time window before the policy implementation is shortened; Third, taking the starting year of 2012 as the reference year, only the time window after the policy implementation is shortened. The regression results of all the alternative study programs are reported in Table 4. It can be observed from Models (1) ~ (6) in Table 4 that the regression coefficients of the interaction term are all positive. And all the regression results are statistically significant at the 5% or even 1% critical level, indicating that the conclusions drawn above are of excellent robustness.

Table 4 Results of robustness test (with changed time widths)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
du × dt	0.0088**	0.0138***	0.0144***	0.0116**	0.0142***	0.0088**
	(0.0043)	(0.0044)	(0.0049)	(0.0058)	(0.0044)	(0.0044)
Constant	1.5154***	1.5054***	1.5704***	1.3044***	1.4580***	1.7719***
	(0.1190)	(0.1190)	(0.1514)	(0.1494)	(0.0989)	(0.0888)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Time window	2006–2014	2007–2015	2008–2013	2009–2015	2007–2016	2003–2015
Obs	2538	2538	1692	1974	2820	3666
R^2	0.117	0.113	0.134	0.102	0.113	0.365
F	19.7714	19.1189	18.0500	14.6024	20.1344	101.9827

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

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Counterfactual test on regression estimation results

In practices, there might be other policies or random factors that affect city-level carbon emission performance in the process of LCCP implementation, thus resulting in differences in carbon emission performances between cities. If this is the case, the above estimation results may be unpersuasive and can be queried. To exclude the influences of other random factors affecting city-level carbon emission performance and further verify the robustness of the previous estimates, this study conducts counterfactual tests by changing the enforcement time of LCCP. First, it is assumed that the LCCP is implemented in a random year between 2003 and 2009 rather than 2010 and 2012. For example, we choose 2006 as the year of LCCP implementation. Then the regression estimation is conducted using the DID method, and the results are shown in Table 5. It can be seen in Models (1) ~ (3) in Table 5 that all the regression coefficients of the interaction term are negative and statistically insignificant, indicating that the assumed policy implementation year does not affect pilot cities' carbon emission performance. When we further conduct the counterfactual test taking 2007 as the year of LCCP implementation, the results are very similar to those of the year 2006. As a result, the robustness and reliability of the above estimation results have further been verified.

Tests for heterogeneity

Heterogeneous effects by city locations

China is a country with a vast territory, and the development disparity between different regions is severe. Will this sizeable regional disparity also lead to a significant difference in the effects of LCCP implementation on pilot cities' carbon emission performance? In this part, we intend to further discuss the different impacts of pilot LCCP in terms of geographical location.

According to the classification criteria for eastern, central and western regions by the National Bureau of Statistics, the 282 prefecture-level cities studied are categorized into 101 eastern cities, 108 central cities, and 73 western cities. The regression estimation

Table 5 Counterfactual test of regression results

	Model (1)	Model (2)	Model (3)	Model (4)
du × dt	−0.0104	− 0.0049	− 0.0094	− 0.0104
	(0.0081)	(0.0073)	(0.0064)	(0.0067)
Constant	0.6905[***]	2.0862[***]	2.0157[***]	2.0149[***]
	(0.0042)	(0.1765)	(0.1608)	(0.1608)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Control variables	NO	YES	YES	YES
Assumed time	2006	2006	2006	2007
Time window	2003–2007	2003–2007	2003–2008	2003–2008
Obs	1410	1410	1692	1692
R^2	0.416	0.554	0.540	0.540
F	159.8455	125.9055	136.6154	136.6536

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

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results are shown in Table 6. It can be seen from Table 6 that the implementation of pilot LCCP in the eastern region has a significantly positive effect in promoting local carbon emission performance; in the central area, the result is fragile and statistically insignificant; while in the western area, the impact is even negative and statistically significant at the 5% critical level. The central and western regions have relatively backward economic development, weaker emission reduction technologies and infrastructure development as compared to those of the eastern region. Especially in the western region, even after the pilot low-carbon cities have been identified, the specific policies often fail to be implemented due to the constraints in economic development and technology capability. Thus, the effects of pilot low-carbon city on carbon emission performance have not been effectively reflected in the central and western regions.

Heterogeneous effects by city sizes

Compared with small-scale cities, large-scale cities usually hold distinct advantages in resource allocation, technological progress, and economic agglomeration. Based on this consideration, this study further evaluates the different effects of pilot LCCP on carbon emission performance in terms of city sizes. The classification of city sizes in the present study is based on two standards: first, the latest rule stipulated in "*Notice on Adjusting the Standard of City Scale Classification*" issued by the State Council in 2014; second, further considering the distribution of the urban population.

The regression results are shown in Table 7. It can be seen from Table 7 that for the small and medium-sized cities with the population less than 5 million, the pilot LCCP does not significantly improve their carbon emission performance; while for the large-scale cities with the population more than 5 million, the impact of pilot LCCP on their carbon emission performance are positive and statistically significant. In this regard, the larger the city is, the stronger the effect of pilot LCCP on emission reduction performance is. In particular, the promoting effects of the pilot LCCP are also quite different for different types of large cities: compared with the cities with 5–8 million

Table 6 Regression test results in the eastern, central and western regions

	Model (1) eastern	Model (2) central	Model (3) western
du × dt	0.0356[***]	−0.0038	− 0.0206[**]
	(0.0063)	(0.0079)	(0.0097)
Constant	1.9191[***]	1.5412[***]	0.7682[***]
	(0.1166)	(0.1099)	(0.2512)
City FE	YES	YES	YES
Year FE	YES	YES	YES
Control variables	YES	YES	YES
Obs	1414	1512	1022
R^2	0.341	0.438	0.394
F	33.4999	53.9372	30.1605

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

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Table 7 Regression results at different city sizes

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	<1million	1-3million	3-5million	> 5 million	5-8million	> 8 million
du × dt	−0.0310	0.0027	0.0130	0.0239***	0.0139*	0.0385***
	(0.0392)	(0.0074)	(0.0083)	(0.0067)	(0.0083)	(0.0125)
Constant	0.7226	1.3943***	1.7818***	1.3733***	1.1932***	1.9980***
	(0.7828)	(0.1614)	(0.2865)	(0.2028)	(0.2979)	(0.3912)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Obs	169	1315	1128	1336	988	348
R^2	0.371	0.357	0.426	0.338	0.329	0.408
F	4.0131	33.0978	37.4436	30.9587	21.6097	10.2157

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

population, the regression coefficient of large-scale cities with a population over 8 million is much larger, which further supports our inference.

Heterogeneous effects by economic development levels

The different effects of pilot LCCP on city-level emission reduction performance in terms of different economic development levels are also examined. The index of actual per capita GDP is chosen to represent the economic development level of respective cities. First, the mean value of the real per capita GDP of every city in 2003–2016 is calculated and ranged from small to large. Then, the sample cities are equally classified into four groups. Among them, the first group comprises cities with a low level of economic development; the second group includes cities with a relatively low level of economic development; the third group comprises cities with a medium-developed level of economic growth; the fourth group includes cities with a developed economy. The regression results are reported in Table 8. For the cities with low economic development level, the LCCP implementation does not adequately improve their carbon emission

Table 8 Regression results at different levels of economic development

	Model (1)	Model (2)	Model (3)	Model (4)
	low level	relatively low	medium-developed	developed level
du × dt	−0.0101	0.0140*	0.0185***	0.0104
	(0.0102)	(0.0079)	(0.0066)	(0.0093)
Constant	1.4072***	2.0183***	0.8619***	1.4673***
	(0.3192)	(0.2500)	(0.2172)	(0.1158)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Obs	994	980	980	994
R^2	0.304	0.333	0.557	0.360
F	19.7290	22.2602	55.9978	25.4283

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

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performance; in fact, it may even bring some negative effect, although the impact is not statistically significant. On the contrary, for the cities with relatively low or medium levels of economic development, the effects of the implementation of LCCP on pilot cities' carbon emission performance is significantly positive. This result is highly in line with the different effects in terms of urban size, because large-scale cities are generally in higher economic development level.

Mechanism analysis

Mediating effect model

The impact mechanism of how the LCCP implementation affects pilot cities' carbon emission performance is another critical subject worth probing. In this study, we try to investigate this subject from three aspects: scale effect, structural effect, and technological progress effect. First, the scale effect, as a country characterized by a resource composition of "rich coal, insufficient oil, and scarce gas", China has relatively low coal price, which leads to the high dependence of China's electricity production on coal consumption, increasing CO_2 emissions. Second, the structural effect; LCCP promotes the industrial upgrading of the pilot city, which can help drive down city-level carbon dioxide emission. Third, technological progress effect; technological innovation and progress are essential driving forces and favorable ways for carbon emission reduction. The development of pilot low-carbon cities inevitably propels the popularization of low-carbon technologies by promoting technological innovation, and strengthens the full adoptions of technologies on energy saving and emission reduction.

The present study constructs a mediating effect model by introducing electricity consumption, industrial structure, and technical innovation as mediating variables representing scale effect, structural effect, and technological progress effect, respectively, to verify the mechanism of the impact of LCCP on pilot cities' carbon emission performance. The mediating effect method developed by Baron and Kenny (1986) (Baron and Kenny 1986) can be divided into three steps:

First, examining the effects of LCCP implementation on carbon emission performance according to the benchmark model as Eq. (1). If the coefficient β of the interaction term is significantly positive, it indicates that the LCCP implementation improves pilot cities' carbon emission performance.

Second, examining the impact of LCCP implementation on the mediating variables with Eq. (6):

$$size_{it}(stru_{it}, teco_{it}) = \alpha_0 + \beta \times (du_i \times dt_{it}) + \lambda Z_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{6}$$

In Eq. (6), the dependent variable $size_{it}$ represents the scale effect, measured by the total amount of electricity consumption. $stru_{it}$ represents the structural effect, measured by the ratio of the secondary industry to the total amount of GDP. $teco_{it}$ represents technological progress level, which is measured by the city's science and technology innovation index; the larger the value is, the higher the level of technological progress is. Other variable definitions are the same as Eq. (1). If the regression coefficient β of the interaction term is statistically significant, then the LCCP implementation affects the mediating variables.

Third, placing the dummy variable of LCCP implementation and the three mediating variables simultaneously into Eq. (7):

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$$Efficiency_{it} = a_0 + \beta \times (du_i \times dt_{it}) + \phi \times size_{it}(stru_{it}, teco_{it}) + \delta Z_{it} + \gamma_t + \mu_i + \varepsilon_{it} \tag{7}$$

If the regression result of the interaction term is not statistically significant, or it is statistically significant, but the coefficient is reduced compared with that in Eq. (7), it indicates that the LCCP implementation affects pilot cities' carbon emission performance through the three mediating effects. In Eq. (7), the variables definition is the same as Eqs. (1) and (6).

Results of mechanism analysis

The regression results of the mediation effect model are reported in Table 9. Models (1) and (2) show the results of the scale effect. It can be seen in Model (1) that the coefficient of the interaction term is negative and statistically significant at the 1% critical level, indicating that the LCCP implementation can effectively reduce electricity consumption in pilot low-carbon cities. Model (2) shows the regression coefficient of the mediating variable standing for scale effect represented by total electricity consumption, is negative and statistically significant at the 1% critical level, which indicates that reducing electricity consumption is conducive to the improvement of cities' carbon emission performance. Combining Models (1) and (2), the mediating effect that LCCP implementation improves pilot cities' carbon emission performance through decreasing their total electricity consumption, can be empirically verified.

Models (3) and (4) show the results of the structural effect. The regression coefficient of the interaction term in Model (3) is significantly negative, indicating that the LCCP implementation can effectively restrain the expansion of the secondary industry. Model

Table 9 The result of the mechanism test

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	scale effect		structural effect		technological progress	
	size	Efficiency	stru	Efficiency	teco	Efficiency
du × dt	− 0.0506***	0.0057	− 0.0095***	0.0103**	0.1680***	0.0077*
	(0.0196)	(0.0039)	(0.0027)	(0.0043)	(0.0175)	(0.0043)
size		−0.0898***				
		(0.0033)				
stru				−0.2484***		
				(0.0260)		
teco						0.0155***
						(0.0040)
Constant	15.2430***	3.0892***	0.7114***	1.7201***	4.3229***	1.6531***
	(0.3673)	(0.0884)	(0.0500)	(0.0800)	(0.3284)	(0.0817)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Obs	3948	3948	3948	3948	3948	3948
R^2	0.657	0.459	0.350	0.348	0.150	0.351
F	348.7476	147.2296	109.0619	97.3081	32.0647	93.7305

Notes: (1) ***, **, * indicate that the levels of significance are at 1%, 5% and 10%, respectively
(2) Figures in the parentheses are standard errors

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(4) shows that the coefficient of the mediating variable in respect to the industrial structure is negative and statistically significant, indicating that the expansion of the secondary industry is not conducive to the improvement of cities' carbon emission performance. The underlying reason lies in the fact that the secondary industry is mainly energy-intensive sectors compared with the primary and tertiary industries, which in turn leads to a large amount of CO_2 emission. Combining Models (3) and (4), the mediating effect of industrial structure upgrade can also be empirically verified.

Models (5) and (6) in Table 9 show the empirical results of the technological progress effect. The significantly positive regression coefficient of the interaction term in Model (5) indicates that the LCCP implementation can effectively promote the technological progress of the city. Moreover, the significantly positive regression coefficient of the mediating variable with respect to technological innovation in Model (6) indicates that technological progress is conducive to improving the city's carbon emission performance. The underlying reason may be that technological progress can lead to the broader use of clean production technologies and more advanced equipment for energy saving and emission reduction, which in turn help to improve productivity over carbon emission while maintaining economic growth. Combining Models (5) and (6), the mediating effect of technological progress has also been well verified.

Conclusion and policy recommendation

Based on the panel data of 282 prefecture-level cities in China from 2003 to 2016, this study uses the DID method to evaluate the effects of LCCP implementation on pilot cities' carbon emission performance. The empirical results show that: First, the LCCP implementation can significantly improve the carbon emission performance of the pilot cities, indicating that this policy practice is an effective way to promote China's transformation of its economic development pattern towards a low-carbon society. Second, the effects of LCCP implementation on pilot cities' carbon emission performance demonstrate significant heterogeneity: in that, the CO_2 emission reduction effect from LCCP implementation is more significant in the cities with higher economic developed level, in the ones with more massive scale, and the ones located in the eastern area than their respective counterparts. Finally, the mechanism examination using the mediating effect model indicates that LCCP improves pilot cities' carbon emission performance in three ways, including reducing energy consumption, updating the industrial structure, and promoting technological progress.

According to the above conclusions, we put forward the following policy recommendations to forge China's green development mode and the ecological civilization: First, promoting industrial upgrade towards a low-carbon industrial system. Second, developing low-carbon technologies and expanding the market application of techniques on energy saving and emission reduction. On the one hand, the government should increase fiscal expenditure on science and technology innovation, and specifically increase financial support on the R&D and application of technologies on carbon recovery, carbon storage, etc.; on the other hand, governments need to actively guide research and development activities of science research institution and enterprises to take the market as the entry point, to avoid duplicated R&D, ineffective R&D, and low-level R&D. Finally, change the energy consumption structure and reduce power consumption. Efforts should be made to adjust the energy mix, transforming the coal-based energy consumption structure, and actively developing clean and renewable energy.

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Abbreviations
LCCP: Low-Carbon City Policy; ECTRS: Energy Conservation Target Responsibility System; DID: Difference-in-Differences; NDRC: National Development and Reform Commission; DMU: Decision-Making Unit; Super-SBM DEA: Slacks-Based Measure of Super-efficiency in Data Envelopment Analysis; GDP: Gross Domestic Product

Authors' contributions
M. Y.: Research design, Writing-original draft. Q. L.: Software, Data curation, Paper revision. F. X.: Writing review & editing. F. Y.: Methodology, Visualization. X. X.: Conceptualization. All authors read and approved the final manuscript.

Availability of data and materials
The datasets used during the current study are available from the annual China City Statistical Yearbooks, the annual China Statistical Yearbooks, and the China Stock Market & Accounting Research database, respectively.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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