Assessing The Low-Carbon City Pilot Policy On Carbon Emission From Consumption And Production In China: How Underlying Mechanism And Spatial Spillover Effect?

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Abstract

With the acceleration of industrialization and urbanization, China's greenhouse gas emissions have gradually become one of the major constraints to its sustainable development. As a comprehensive environmental regulation policy, Low-carbon city pilot (LCCP) policy is widely used to mitigate carbon dioxide emissions and guide low-carbon development in China. Based on the panel data of 285 cities from 2003 to 2019 in China, this study mainly applied the staggered DID method to examine the effects of LCCP policy on carbon intensity (CI) and carbon emission per capita (CP) from production and consumption perspectives. The textual quantification and spatial DID method were also employed to explore the mechanism, heterogeneity and spatial spillover effect in an integrated manner. Our results show that: (1) The LCCP policy effectively reduced CI and CP, but these effects did not appear until the third year of implementation. The above conclusions passed a series of robustness and endogeneity tests. (2) Reducing industrial emission, improving technological innovation and optimizing the efficiency of energy usage were three important mechanisms to reduce CI and CP, validating the effectiveness of the LCCP policy. (3) Command-mandatory and voluntary LCCP policy tools achieved better results and the LCCP policy exerted a significant emission reduction effect on second-tier pilot cities as compared to others. (4) This abatement effect of LCCP policy had also demonstrated a spatial spillover impact on neighboring cities. Findings from this study provide empirical evidence for the promotion of low-carbon city pilots and offer a replicable and effective path to implement environmental regulation.

Introduction

Climate change has been perceived as the gravest threat to human survival and development in the 21st century (Li et al., 2018; Feng et al., 2021a). To hinder the environmental and social issues caused by climate change, many international agreements have set clear targets to reduce greenhouse gas emissions (UNFCCC, 2015). However, despite these ambitious commitments, the 1.5°C goal established in the Paris Climate Agreement is believed to be unattainable even with the most optimistic scenario (WEF, 2022). Owing to its rapid economic development and accelerating urbanization, China is still the world's largest carbon emitters (Cai et al., 2020). In 2020, China's CO_2 emission reached 10.24 billion tons, accounting for 32.58% of the world's CO_2 emission for that year (BP, 2021). It is estimated that 70% of all these CO_2 emissions in China are from cities, due to their high population density, vast public transportation networks and massive infrastructure demands, which are key drivers of CO_2 emission (Cai et al., 2019). Hence, based on these issues, the Chinese government has incorporated carbon emission reduction in its national low-carbon development strategy (Khanna et al., 2014). At the 2015 Paris Summit, China pledged to reduce its carbon emission per unit of gross domestic product (GDP) by 60%-65% by 2030 compared with its 2005 level, and at the 75th session of the UN General Assembly, China detailed its goal to achieve its CO_2 emission peak by 2030 and carbon neutrality by 2060 (Liu et al., 2022). Thus, it is foreseeable that low-carbon mode has become an inevitable trend of future development.

To achieve such severe reduction in CO_2 emission, cities have been made the focal point to implement low-carbon development and mitigate global greenhouse gas emissions (Lee and Erickson, 2017). Linking low-carbon development to existing local low-carbon policy is considered an effective way to reduce greenhouse gas emissions on a city level (Bai, 2007). Countries or regions are adopting to building low-carbon cities as their primary policy to deal with global climate change (Ellison et al., 2013; Cyrys et al., 2014; Santos et al., 2019). During the initial years, China strategically implemented command-mandatory low-carbon policies to seek a win-win path for economic development and low-carbon transition. In recent years, innovative practices have been gradually explored, of which the low-carbon city pilot (LCCP) policy is seen as one of the effective environmental regulations.

China's National Development and Reform Commission (NDRC) started by implementing the LCCP policy in batches and regionally to obtain practical experiences and identify appropriate strategies that could be applied to the whole country. In 2010, the NDRC first rolled out five provinces and eight cities to prepare low-carbon development plans and execute the pilot programs. In 2012, the NDRC then selected 28 pilot cities as the second batch of LCCP policy to further establish a target responsibility system for controlling greenhouse gas emissions. In 2017, based on the first and second batches, the NDRC identified 45 pilot cities (district and county level) to carry out the third batch of LCCP policy to propose CO_2 emission peak times.

According to documents issued by the NDRC, the fundamental purpose of the LCCP policy is to promote the implementation of China's CO_2 emission control goals. However, its effects depend on the economic base of the pilot cities and the local

government's implementation efforts. Some pilot cities, such as Suzhou and Baoding, have effectively implemented a series of measures to reduce carbon emission intensity to meet LCCP policy standards (Wang et al., 2014). Others, like Guiyang, have shown no noticeable improvements to comply with low-carbon city development (Li and Liang, 2015). Given these above references, the effectiveness of the LCCP policy remains unknown. The two main objectives of this study are: First, this study rigorously discusses the empirical effects of the LCCP policy on CO_2 emission intensity (CI) and CO_2 emission per capita (CP) from the perspectives of consumption and production, offering additional insights into the government's carbon emission reduction. Second, this study deconstructs the mechanism of LCCP policy on CO_2 emission, explores the heterogeneity of CO_2 emission reduction between different policy tools and city development levels, and investigates the spatial spillover effect of LCCP policy, which provides a replicable effective path and policy reference for CO_2 emission reduction.

The main contributions of this study are as follows. (i) Since the Chinese government has not yet compiled city-level CO_2 emissions data, a top-down approach was used to measure city CO_2 emissions based on nighttime light data in this study. From the perspective of consumption and production, this study provided a rigorous empirical assessment of the effect of LCCP policy on CI and CP, enriching our understanding of the government's CO_2 emission reduction strategies. (ii) The LCCP policy was treated as a quasi-natural experiment to address endogeneity problems, such as non-random selection, other environmental policies' interference, placebo test, the hysteresis effect of LCCP policy, PSM-DID and IV method. These endogeneity problems were considered together to present reliable empirical findings under the condition that these were as robust as possible. (iii) We revealed that the LCCP policy's mechanism on CI and CP was based on the following three effects: industry emission reduction, technological innovations and improved energy usage. (iv) It is the first study to investigate the heterogeneity of LCCP policy tools, including command-mandatory, market-economic and voluntary LCCP policy tools based on the quantification of policy instrument texts, which offers a concrete reference for the government to develop future LCCP policy. (v) This study used an SDID model based on the spatial Durbin model to investigate the spatial spillover effect of the LCCP policy's effects on CI and CP in neighboring cities, which brought a fresh perspective to the understanding of the spatial effects of the LCCP policy on CO_2 emissions.

The rest of this paper is organized as follows. The next section offers a review of existing literature, in which four research hypotheses are proposed. The "Research design" presents the econometric model, selected variables and data description. The "Empirical results" illustrates the empirical results of benchmark regression, robustness tests, heterogeneity analysis and the expansion analysis of spatial spillover effect. The "Discussion" discusses the reasons for the results. The last section is the conclusion and policy implications.

Literature review and research hypotheses

Literature review

With the promotion of the LCCP policy in China, previous studies mainly focused on the theoretical framework and developmental paths of the LCCP policy. Peng and Bai (2017) highlighted the emergence and evolution of low-carbon policy by examining new institutional setups and corresponding financial mechanisms. Chen and Zhu (2009) emphasized the decoupling of economic development from CO_2 emissions in low-carbon pilot cities. Others investigated the implications of low-carbon infrastructure, low-carbon transportation, consumption pattern, green lifestyle and carbon sequestration for achieving low-carbon transition (Liu et al., 2009; Li et al., 2012; Zhou et al., 2018). In addition, some have assessed the performance of the LCCP policy in China. For example, the Chinese Academy of Social Sciences issued 12 indicators encompassing economic development, energy infrastructure, and environmental quality to assess the LCCP policy. Li et al. (2018) reviewed the LCCP policy's progress and investigated its effects in the first two batches of the 32 pilot cities. Shen et al. (2021) performed a temporal-spatial evolution analysis on low-carbon city performance in China by constructing a low-carbon city evaluation indicator system.

Existing studies have also closely followed the effects of the LCCP policy in specific areas, such as technological progress (Dong et al.,2014), energy intensity (Hong et al., 2021), ecological efficiency (Song et al., 2020), green development (Cheng et al., 2019) and low-carbon lifestyle (Sun and Wang, 2021). Most relevant to this paper are studies which investigated the impact of LCCP policy on carbon emission. In this regard, scholars have obtained different conclusions on the carbon emission reduction effects of the LCCP policy, and these can be regarded the two conflicting views of "promotion" and "inhibition".

The “promotion” aspect based on the evidence showing that the LCCP policies have been successful in reducing carbon emissions. Using the low-carbon city data from European regions, Wolff (2014) concluded that low-carbon city policies had a significant air pollution reduction effect in transportation centers. Likewise, Zhang (2020) also found that low-carbon city construction significantly reduced carbon emissions. Zhou et al. (2019) further showed that the LCCP policy had a significant and sustained effect on local carbon intensity reduction, and similarly, Ren et al. (2020) pointed out that China’s low-carbon pilot policy had significantly reduced CO_2 emission and emission intensity, and that it is necessary to promote and popularize the low-carbon policy nationwide.

On the other hand, the “inhibition” aspect is based on findings showing exacerbation of carbon emission where the LCCP policy was applied. Lo (2014) found that implementation of the LCCP policy in Changchun failed to reduce CO_2 emission due to a weak target responsibility system and a poorly designed scoring system. This finding echoes with that of Feng et al. (2021b), who showed that the LCCP policy did not meet expectations and led to an increase of carbon intensity by approximately 15%-20%. Peng and Deng (2021) used Guiyang’s development process as a case study and found that Guiyang still has a long way before genuinely transforming into a low-carbon city. In addition, Feng (2017) believed that the LCCP policy was ineffective in reducing carbon intensity in the capital cities of East China, and had a hindering effect. Based on such evidence, we have to rethink the following questions: Can the LCCP policy really reduce CO_2 emissions? What factors are causing the same policy to yield opposing policy effects among cities? Is there a heterogeneity among different LCCP policy tools and city development levels for CO_2 emission reduction? Are there spatial spillover effects from the LCCP policy?

Although the above studies provided insightful understandings on the implementation of the LCCP policy, more in-depth analyses are required to fully interpret its real impact. First, some of the studies used fossil fuels and electricity consumption data to estimate a city’s CO_2 emission, and this might have led to an underestimation of the CO_2 emissions reported. Second, the existing studies faced common endogenous problems when evaluating of the LCCP policy due to a lack of systematical assessment of the LCCP policy to fully address the endogeneity of these problems. Third, previous studies paid little attention to the heterogeneity of the LCCP policy tool, often examining it through a dummy binary variable and therefore, could not accurately reflect the policy performance among different LCCP policies in a low-carbon pilot city. Finally, few studies have investigated the impact of the LCCP policy on the CO_2 emission reduction of neighboring cities from a spatial spillover perspective. Neglecting spatial effects is not conducive to accurately estimate the CO_2 emission reduction effects of the LCCP policy (Liu et al., 2022).

Research hypotheses

The core idea of the LCCP policy is to gradually reduce CO_2 emission in the production process of industries, change the dependence on fossil energy through technological innovations and follow a sustainable low-carbon development path (Baeumler et al., 2012). Under the LCCP policy constraints, each pilot city is required to introduce low-carbon development plans, establish CO_2 emission data management system and encourage low-carbon production patterns and green lifestyles. Hence, we believe that the LCCP policy can reduce CO_2 emissions. However, due to the high energy consumption of China’s industrial sectors, substantial breakthrough in renewable energy technology is yet to be made (Zheng et al., 2021). It is difficult for the LCCP policy to change the patterns of traditional fossil energy-based consumption in the short term. Thus, there is a lag in the CO_2 emission reduction effects of the LCCP policy. Given these considerations, the first hypothesis is presented here:

Hypothesis 1

The LCCP policy is conducive to CO_2 emission reduction, but there is a lag before the CO_2 emission reduction effects are observed.

The LCCP policy makes high-polluting industries bear high “environmental compliance costs”. It raises their production costs and survival threshold, forcing them to shift to low-carbon and clean productions to meet emission standards (Cheng et al., 2019). The LCCP policy can provide management guidelines to the polluting industries whereby the demonstration and push-back effects can greatly promote polluting industries to reduce CO_2 emissions (Shi et al., 2018). In addition, the LCCP policy can act as an “environmental barrier” that screens new entrants to the market and avoid new CO_2 emissions to a certain extent.

The Porter hypothesis suggests that a reasonable environmental regulation policy can stimulate the “innovation compensation” effect (Porter and Van, 1995). Directly, low-carbon pilot cities subsidize contributive researchers through fund matching, project management fee subsidies and investment subsidies to stimulate scientific research. Indirectly, the “bottom-up competition” of local governments, at the expense of the ecological environment, could be weakened. Researchers are guided and motivated to carry out low-carbon patent research to achieve CO_2 emission reduction.

Low-carbon city construction can reduce CO_2 emissions by improving energy usage in the following ways. First, when local governments levy CO_2 emission tax and energy tax on producers and users of high CO_2 emissions, this increases their environmental costs, and they are forced to invest in low-carbon technologies to reduce their use of highly polluting energy (Rexhaeuser and Rammer, 2014). Second, governments can promote circular economic development and encourage cleaner production via the use of alternative renewable energy such as solar, wind, water and other renewable clean energy. Based on the above considerations, we propose the second hypothesis:

Hypothesis 2

The LCCP policy can reduce CI and CP via three mechanisms: technological innovations, improving energy usage and reducing industrial emissions.

As an environmental regulation policy for cities, the LCCP policy has a combination of policy tools. Based their local development characteristics, each pilot city can adopt command-mandatory, market-economic and voluntary policy tools to promote local low-carbon developments (Wang, 2015). Command-mandatory tools restrict the CO_2 emission of industries by setting stricter emission reduction targets and forcing enterprises to make low-carbon upgrades by eliminating backward production capacity. In contrast, market-economic policy tools are more flexible. They mainly work through subsidies, taxes and other tools to internalize the cost of pollution control (Bergquist et al., 2013). Voluntary tools guide environmental awareness and promote green behaviors. Based on these policy tools, the third hypothesis is proposed:

Hypothesis 3

Under the joint action of the command-mandatory, market-economic and voluntary policy tools, the LCCP policy can have an inhibitory effect on CI and CP.

Considering the existence of spatial spillover effect, assessments of LCCP policy should also consider its effects on the CO_2 emission of neighboring cities. On the one hand, implementing the LCCP policy could inevitably eliminate or transfer high energy consumption, high emission, and high pollution industries to the neighboring areas (Shen et al., 2017), thereby generating a negative spatial spillover effect on CO_2 emission. On the other hand, the LCCP policy can have a demonstration effect and warning effect on neighboring cities by promoting industry technology innovations and CO_2 emission reduction. Thus, neighboring cities could reduce CO_2 emissions by learning from pilot cities and applying similar environmental regulation tools. Based on such effect, the fourth hypothesis in this paper is stated:

Hypothesis 4

Implementation of the LCCP policy can have a spatial spillover effect on the CI and CP of neighboring cities.

Research Design

Econometric model

The main question explored in this study is whether the LCCP policy effectively reduces CI and CP. To address the common endogeneity problem in regressions, we used DID method using the LCCP policy as a quasi-natural experiment: the first layer is generated from city-level and the second layer from year-level. Based on Athey and Imbens (2022) and the implementation of the LCCP policy in three batches, the staggered DID method was applied to compare the differences in CI and CP between pilot and non-pilot cities before and after implementation of the LCCP policy. The benchmark regression model is formulated as follows:

$$y_{it} = \alpha_0 + \alpha_1 treat_{it} + \beta X_{it} + \eta_i + \gamma_t + \varepsilon_{it}$$

1

Where *i* denotes city, *t* denotes year. y_{it} is CI or CP for the city *i* at year *t*. $treat_{it}$ is a dummy variable equal to one if city *i* implemented the LCCP policy at year *t*, and zero if otherwise. α_0, α_1 and β are the parameters to be estimated. The coefficient α_1 is the effect of the LCCP policy on CI and CP. X_{it} represents a set of city control variables, including economic growth, population density, industrial structure, openness, science and education, and human capital. η_i represents city fixed effects. γ_t represents time fixed effects. ε_{it} is a random disturbance term. The coefficient of interest is α_1. If the obtained estimate $\hat{\alpha}_1 < 0$, it means that the LCCP policy reduces CI and CP in a pilot city compared to a non-pilot city, or otherwise if $\hat{\alpha}_1 \geq 0$.

Variable selection

Independent variable and dependent variables

The $treat_{it}$ term is regarded as the independent variable, with its coefficient showing the effect of the LCCP policy on CI and CP. Based on the relevant documents of NDRC, the LCCP policy was implemented in three batches based on the scales of cities and provinces. There was crossover in the lists of different batches. Following Song et al. (2019), the policy implementation time of low-carbon pilot cities in low-carbon pilot provinces was adjusted to the earliest batch of both. This means that the policy implementation years of Wuhan, Guangzhou, Kunming, and Yan'an were adjusted to 2010, while the policy implementation year of Sanya was changed to 2012. Due to the lack of data in some pilot cities or regions, 69 low-carbon pilot cities were identified as the treatment group while the remaining 216 cities were the control group in the three batches. Figure 1 shows the distribution of the three batches of low-carbon pilot cities in different colors.

This paper refines the metrics of CO_2 emission from both production and consumption perspectives. *CI* and *CP* were set as the dependent variables, where CP is taken as the natural logarithm. However, the government has not yet compiled CO_2 emission data at the city scale. This study assumes a linear relationship between nighttime lights and that CO_2 emission was constant within a specific province (Meng et al., 2014). Following the findings of Chen et al. (2021), this study used continuous nighttime light data corrected across NPP and VIIRS sensors as a proxy variable for measuring CO_2 emission at the city scale. Applying the nighttime lighting data, the CO_2 emission data of provinces and nighttime lighting data of cities, this study estimates CI and CP via a top-down method.

Mechanism variables

Existing studies usually accounted the utilization rate of industrial solid wastes and industrial wastewater discharge (Greenstone and Hanna, 2017), but since these indicators do not reflect the emission reduction effect brought by the LCCP policy, we measure industrial emission reduction using the natural logarithm of industrial sulfur dioxide ($lnindSO_2$) and industrial fumes emission (*lnindfume*s). Considering that it takes one to three years for low-carbon patents to be declared and larger cities tend to produce more patents, the low-carbon patent applications per 10,000 people (*wrlcpat*) were used to measure technology innovation. Cities with high human capital levels can have a higher amount of CO_2 emission reduction as they can adopt more advanced technologies (Lan et al., 2012). Scientific researcher as a percentage of the year-end population (*scireseap*) was therefore employed to measure the level of technological innovation. Considering energy intensity can reflect the dependence of economic development on energy, high energy dependence for economic growth was not conducive to reducing CO_2 emissions. Hence, the ratio of total energy consumption to GDP (*energyint*) was taken as a proxy variable for energy usage. Moreover, since clean renewable energy could mitigate climate change (Pata and Caglar, 2020), the proportion of primary electricity and natural gas in energy consumption (*renewstr*) was applied to characterize the share of renewable energy in energy usage.

Control variables and other variables

Seven control variables were selected in the regression model to control the impact of each city's characteristics. Economic growth (*lnpgdp*) was accounted for the natural logarithm of GDP per capita. Population density (*lnpd*) was measured by the natural

logarithm of the population per unit area. Proportion of the industrial added value in the GDP (*secindp*) was incorporated into the model to control the effect of industrial structure. Openness was measured by the proportion of FDI in the GDP (*fdip*) and total imports and exports as a percentage of GDP (*eximp*). The proportion of governmental expenditures on science and education out of the total fiscal expenditure (*scieddp*) was taken as a proxy variable for science and education. Human capital was measured as the natural logarithm of the number of students enrolled in college per 10,000 perple (*lnwrcolstu*).

The new energy vehicle subsidy pilot policy (*nenervehicle*), the atmospheric emission limit pilot policy (*atomemi*) and the carbon emission trading rights pilot policy (*cemitra*) were the variables used in the robustness test. The air circulation coefficient (*VC*) and relief degree of land surface (*RDLS*) were selected as the instrumental variables in the endogeneity test. The variables of city development level heterogeneity for *first-tier*, *second-tier*, *third-tier*, *fourth-tier* and *fifth-tier* corresponded to first, second, third, fourth and fifth-tier cities, respectively. Command-mandatory (*control*), market-economic (*market*) and voluntary (*voluntary*) policy tools were selected as policy tool heterogeneous variables.

Data description

After taking into consideration district readjustment and data availability, this study adopted a panel data set of 285 Chinese cities from 2003 to 2019. The list of low-carbon pilot cities is manually compiled based on relevant documents issued by the NDRC. Nighttime lighting observation data were obtained from Harvard Dataverse (https://doi.org/10.7910/DVN/YGIVCD). Cities' characteristic data and other raw data used for this study were obtained from the annual China City Statistical Yearbooks, Statistical Yearbooks of various provinces and CEIC Economic Database. Energy consumption data at the provincial-level were obtained from the China Energy Statistical Yearbook. Low-carbon patent application data were derived from the Incopat Patent Database and retrieved with the instruction of "CCP-Y02 classification number + city where the application is located". Air circulation coefficient (VC) was soured from the ERA dataset of the European Center for Medium-Range Weather Forecasts (ECMWF). Relief degree of land surface (RDLS) was obtained from the Relief Degree of Land Surface Dataset of China (1km) (http://www.geodoi.ac.cn/). Missing values were extrapolated by the interpolation method. To ensure comparability of the data, this study deflated all economic data to 2003 constant prices. All the data were collected manually. The descriptive statistics of the above variables are shown in Table 1.

Table 1
Descriptive statistics of variables

Variables	Definition	Obs.	Mean	Std. Dev.	Min	Max
CI (ton/10^4 yuan)	CO_2 intensity	4845	3.098	3.659	0.201	38.586
CP (person/ton)	CO_2 emission per capita	4845	1.545	1.098	-1.704	5.074
treat (-)	LCCP policy	4845	0.084	0.277	0	1
lnpgdp (yuan)	Economic growth	4845	10.028	0.848	7.545	12.488
secondp (%)	Industrial structure	4845	0.470	0.112	0.114	0.91
lnpd (person/km^2)	Population density	4845	5.717	0.914	1.547	7.882
fdip (%)	Openness	4845	0.019	0.022	0.000	0.376
lnwrcolstu (person)	Human capital	4845	4.258	1.677	-6.226	7.29
exmip (%)	Openness	4845	0.203	0.386	0.000	8.117
techeddp (%)	Science and education	4845	0.044	0.130	0.000	2.602
lnindSO_2 (ton)	Industrial emission	4845	10.289	1.229	0.000	13.434
lnindfumes (ton)	Industrial emission	4845	10.309	1.200	0.693	13.434
scireseap (%)	Technology innovation	4845	0.023	0.037	0.000	0.432
wrlcpat (piece)	Technology innovation	4845	0.621	1.998	0.001	77.937
renewstr (%)	Energy usage	4845	0.322	0.196	0.019	2.019
energyint (standard coal ton /10^4 yuan)	Energy usage	4845	0.811	0.686	0.064	10.081

Empirical Results

Parallel trend test

An essential prerequisite for the validity of the DID model is that the control and treatment groups should satisfy the parallel trend to ensure unbiased estimation. Since the LCCP policy was implemented in three batches, rather than one single implementation, the grouping of a city (control or treatment) could change. Therefore, this study applied the event study method, instead of the plotting trend method, to detect parallel trends more precisely (Moser and Voena,2012). The time window was set to 17 years, covering the 7 years that preceded the implementation of the LCCP and the 9 years that followed it. Based on the study of Yu and Zhang (2021), the following equation was used for the event study method:

$$y_{it} = \alpha_0 + \sum_{-7}^{9} \alpha_k \times D_{i,\, t_0+k} + \beta X_{it} + \eta_i + \gamma_t + \varepsilon_{it}$$

2

Where $D_{i,\, t0+k}$ represents a series of dummy variables associated with the years of implementation of the LCCP policy, t_0 represents the first year of the LCCP policy implementation, and k denotes the k_{th} year of the start of the LCCP policy. The other variables have the same meaning as in Eq. (1). Parameter α_k reflects dynamic effects of the LCCP policy on CO_2 emission reduction. α_{-7}-α_{-1} test the parallel trend assumption, i.e., if the hypothesis $\alpha_k = 0$ cannot be rejected, implying that there is no difference in CI and CP between the treatment and control groups before the implementation of the LCCP policy.

Figure 2 illustrates the test coefficients of the 95% confidence interval of $D_{i,\, t0+k}$. The horizontal axis represents the year before and after implementation of the LCCP policy, the vertical axis indicates the difference in change of the two dependent variables.

According to the coefficients in the pre-treatment period, we can deduce that the CI and CP of treatment and control groups would follow a similar trend without the LCCP policy. Hence, the parallel trend assumption could not be rejected. Figure 2 also shows that after the implementation of the LCCP policy, the carbon emission reduction effect started to be significant in the third year, supporting Hypothesis 1.

Baseline results

Table 2 demonstrates the estimation of the benchmark regression results. Columns (1) and (2) show the average impact of the LCCP policy on CI. Columns (3) and (4) show the average impact of the LCCP policy on CP. The fixed effects of city and year were controlled in columns (1)-(4). According to the results of columns (1) and (3), the LCCP policy not only significantly decreased CI but also significantly reduced CP, with regression coefficients of -0.719 and − 0.199, respectively. That is, the implementation of the LCCP policy simultaneously achieved carbon emission reduction effect from both production and consumption sides. For robustness, columns (2) and (4) contained the control variables. The regression results still showed a significance level of 1%, which further validates Hypothesis 1.

Table 2
Benchmark regression results

	CI	CI	CP	CP
treat	-0.719***	-0.579***	-0.199***	-0.181***
	(-6.212)	(-5.119)	(-9.529)	(-8.693)
constant	3.465***	46.375***	0.825***	-1.036
	(36.431)	(11.607)	(48.119)	(-1.412)
lnpgdp		-6.220***		0.011
		(-17.614)		(0.163)
lnpd		1.773***		0.204***
		(4.223)		(2.639)
secind		5.848***		1.119***
		(10.783)		(11.229)
fdip		-2.171		-0.694**
		(-1.302)		(-2.264)
eximp		0.096		0.079***
		(0.799)		(3.560)
scieddp		0.254		0.152
		(0.369)		(1.208)
lnwrcolstu		0.270***		0.031***
		(8.111)		(5.145)
Control variables	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Observations	4845	4845	4845	4845
R-squared	0.065	0.140	0.595	0.613

Note: *** and ** represent significance levels of 1% and 5%, respectively. The values in parentheses are obtained by robust t-statistic.

Robustness tests

A series of auxiliary tests were performed to ensure the robustness of the results, including mitigating the bias of non-random selection, excluding the interference from other environmental policies, placebo test, PSM-DID, and the hysteresis effect analysis of the LCCP policy.

The ideal sample case for the DID model is that pilot and non-pilot cities are randomly selected. However, the list of low-carbon pilot cities is not random, and is closely related to their corresponding geographical location, economic development and industrial structure. To control for estimation bias from these factors, the cross term of benchmark factors and temporal linear trends were added to Eq. (1), including whether it was a “two-control zone,” a provincial capital city, and a northern city requiring heating. Columns (1) and (2) of Table 3 show the regression results after introducing these variables. Although the magnitude of the

coefficients differs slightly from Table 2, the direction and significance of the coefficients remained consistent with the benchmark model.

Assessment of the CO_2 emission reduction effect of the LCCP policy is inevitably affected by other environmental policies, especially those implemented during the same period, leading to possible overestimation or underestimation. To address this problem, we collected and summarized environmental policies since 2010, which included the new energy vehicle subsidy pilot policy (*nenervehicle*), the atmospheric emission limit pilot policy (*atomemi*), and the carbon emission trading rights pilot policy (*cemitra*). The above environmental policies were included in the regression model with the cross term of time linear trend. The regression results after adding the other environmental policies' dummy variables are displayed in columns (3) and (4) of Table 3. The coefficients of *treat* were similar to those of the benchmark regression. It should be noted that other environmental policies were not statistically significant, indicating that the above environmental policies did not bias the estimated results.

According to the results of the parallel trend test, the expected CO_2 emission reduction effect in the current implementation year of the LCCP policy was not achieved. This led us to consider the possible temporal path-dependent characteristics of CO_2 emissions. Following Chen et al. (2021), all explanatory variables were made to lag by one period to eliminate the possibility of reverse causality of the dependent variable on the independent variable. As shown in columns (5) and (6) of Table 3, the results remained robust after considering the hysteresis effect of the LCCP policy.

Table 3
The results of the robustness test

	CI	CP	CI	CP	CI	CP
treat	-0.563***	-0.146***	-0.571***	-0.132***	-0.607***	-0.192***
	(-4.796)	(-6.780)	(-4.872)	(-6.184)	(-5.024)	(-8.755)
nenervehicle×trend			0.040	-0.008		
			(0.877)	(-0.999)		
atomemi×trend			0.055	0.005		
			(0.991)	(0.539)		
cemitra×trend			-0.007	-0.026		
			(-0.045)	(-0.950)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4845	4845	4845	4845	4845	4845
R-squared	0.143	0.618	0.142	0.621	0.142	0.559

Note: *** represents significance levels of 1%. The values in parentheses are obtained by robust t-statistic.

A series of crucial observable city characteristics were added to the benchmark model, including economic growth, population density, industrial structure, openness, human capital, and science and education. However, the effect of unobservable characteristics was not controlled by the model. To solve this problem, a placebo test was used to assess whether any omitted variables would affect the obtained results. The estimated coefficients were expressed as:

$$\hat{\alpha}_1 = \alpha_1 + \gamma \times \frac{\mathrm{cov}(treat_{it}, \varepsilon_{it} | x)}{\mathrm{var}(treat_{it} | x)}$$

Where *x* comprises of all control variables and fixed effects, and γ represents the effect of unobservable factors on the explanatory variables. When γ = 0, the unobserved factors do not affect the estimation results. Based on this, we randomly generated the list of low-carbon pilot cities (by computer).

Figure 3 plots the distribution of $\hat{\alpha}_1^{random}$ (500 replications). The $\hat{\alpha}_1^{random}$ distribution was in the vicinity of zero and obeyed a normal distribution, as expected from the placebo test, and again, demonstrated the robustness of the results of this study. Meanwhile, to alleviate the impact of sample selection bias and systematic differences, the PSM-DID method was employed to estimate the robustness of the results. The results of PSM-DID further supported the previous benchmark regression (Appendix 1. and Appendix 2.). Based on the above test, it could be deduced that the observed CO_2 emission reduction of the 285 cities were derived from the implementation of the LCCP policy.

Endogeneity test using the IV method

The instrumental variable approach is applied to overcome endogeneity as much as possible. Specifically, the instrumental variable is chosen to satisfy the two conditions of being correlated with the endogenous variables and uncorrelated with the random disturbance terms (Shi and Li, 2020). The air circulation coefficient (VC) and relief degree of land surface (RDLS) were selected as the instrumental variables. First, the VC and RDLS are determined by meteorological and geographical conditions, satisfying the exogeneity hypothesis. Second, cities with smaller VC typically are considered to typically adopt stricter environmental regulations, while cities with lower RDLS tend to be more densely populated and economically active. Such cities have a higher probability of being selected as low-carbon pilot cities, which is consistent with the hypothesis of correlation of instrumental variables. The VC coefficient is the product of the wind speed and atmospheric boundary layer height, and is the natural logarithm of the annual average coefficients. Table 4 reports the two-stage least squares (2SLS) regression results. Panel A reflects the first-stage regression results of VC and RDLS on the LCCP policy, and indicates that VC and RDLS were significantly correlated with the LCCP policy. In addition, we observed that the F-statistics were greater than 10, thereby rejecting the hypothesis of “weak instrument variable”. Panel B also demonstrates that implementation of the LCCP policy significantly decreased CI and CP.

Table 4 2SLS results of instrumental variables

	treat	CI	CP	treat	CP	CP
Panel A: First-stage						
lnVC	0.132***					
	(758.111)					
RDLS				0.616***		
				(59.107)		
Panel B: Second-stage						
treat		-0.549***	-0.183***		-0.847***	-0.141***
		(-4.835)	(-8.785)		(-4.934)	(-4.465)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.994	0.140	0.613	0.546	0.139	0.613
F-statistics	10.72			10.41		

Note: *** represents significance levels of 1%. The values in parentheses are obtained by robust t-statistic.

Mechanism identification

The previous staggered DID estimation results and a series of robustness tests confirmed that the LCCP policy significantly reduced CI and CP, but how could this effect be achieved? Identification of its underlying mechanism is required. Based on the implementation paths of the LCCP policy, we investigated the mechanism of CO_2 emission reduction from the LCCP policy using industrial emission reduction, technological innovation, and energy usage data. Following the practice of existing literature (Li et al.,2018), we assumed that the underlying mechanisms were from variables regressed by policy variables, and constructed the following regression model:

$$X_{it} = \alpha_0 + \alpha_1 treat_{it} + \lambda_i + \tau_t + \sigma_{it}$$

4

where X_{it} represents the matrix vector of the mechanism variables (*lnindSO$_2$*, *lnindfumes*, *wrlcpat*, *scireseap*, *energyint*, *renewstr*). λ is the year fixed effect. τ is the city fixed effect. σ is the stochastic disturbance term. The other variables have the same meaning as in Eq. (1).

Table 5
The results of the mechanism test

	lnindSO$_2$	lnindfumes	wrlcpat	scireseap	energyint	renewstr
treat	-0.114***	-0.125***	1.054***	0.005***	-0.146***	0.032***
	(-2.751)	(-3.180)	(11.293)	(3.909)	(-5.989)	(4.960)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4845	4845	4845	4845	4845	4845
R-squared	0.493	0.480	0.269	0.790	0.269	0.709
Note: *** represents significance levels of 1%. The values in parentheses are obtained by robust t-statistic.						

The estimated results are shown in Table 5. Columns (1) and (2) show the results of the LCCP policy affecting CO_2 emission reduction through industrial emission reduction. It can be observed that the LCCP policy significantly decreased industrial SO_2 and fumes emissions. Columns (3) and (4) list the technological innovation results, and show that the LCCP policy significantly increased the number of low-carbon patent applications and researchers. It is worth noting that the enhancement of low carbon patent was most effective in reducing CO_2 emissions. These results provide new empirical evidence for the weak Porter hypothesis. Columns (5) and (6) show the impact of the LCCP policy on energy usage, and demonstrate that the LCCP policy could indeed achieve CO_2 reduction effects by improving energy intensity and using renewable energy. These findings concord with those of Hong et al. (2021), and support Hypothesis 2.

Heterogeneity analysis

Heterogenous analysis of policy tool

A text quantification method was applied to build appropriate policy tool variables to further discuss the heterogenous effect of different LCCP policy tools on CO_2 emission reduction. The LCCP policy tools are usually divided into the following three types: command-mandatory, market-economic, and voluntary policy tool (Wang et al., 2015). Following Chen et al. (2018), the frequency of words related to policy tools in provincial government work reports was selected as a proxy variable for LCCP policy tools on the city scale. The specific construction steps implemented were as follows: First, 30 provincial (excluding Tibet, Hong Kong, Macau and Taiwan) government work reports from 2003 to 2019 were manually collected from official government websites. Second, the texts of these government work reports were processed for word separation. Specifically, terms related to command-mandatory

LCCP policy tools included elimination, control, restriction, prohibition, compulsory, standard, emission reduction, governance, permit. Key words related to market-economy LCCP policy tools were set as tax, fee, subsidy, compensation, penalty, financing, investment, credit, market, emission trade, renewable, clean, low carbon. Terms related to voluntary LCCP policy tools included pilot, park, industrial park, nature reserve, town, green, ecology, environmental protection, public transportation, energy usage. It is worth noting that selection of provincial variables to measure policy tools at city levels alleviated endogeneity, but reduced the city's variability of the LCCP policy. Based on Chen and Chen (2018), we multiplied the proportion of cities' secondary industry by the natural logarithm of the frequency of policy tools in provincial government work reports, and finally obtained three policy tool variables on the city scale.

Table 6
Heterogeneity results of the policy tools

	CI	CP	CI	CP	CI	CP
control	-0.980*	-0.387***				
	(-1.816)	(-3.891)				
market			-0.304	0.085		
			(-0.412)	(0.626)		
voluntary					-0.911***	-0.387***
					(-2.642)	(-6.094)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4845	4845	4845	4845	4845	4845
R-squared	0.136	0.608	0.137	0.607	0.137	0.610

Note: *** and * represent significance levels of 1% and 10%, respectively. The values in parentheses are obtained by robust t-statistic.

Table 6 presents the estimated results of different LCCP policy tools on CO_2 emission reduction. The results of command-mandatory LCCP policy tools in columns (1) and (2) show significantly reduced CI and CP. The estimated coefficients absolute value of market-economic LCCP policy tools in columns (3) and (4) were smaller than command-mandatory LCCP policy tools, but the results were insignificant. This might be related to the effectiveness of market-economy LCCP policy tools, which are influenced by factors such as institutional design and degree of marketization (Xu and Cui, 2020). Columns (5) and (6) illustrate voluntary LCCP policy tools' negative CO_2 emission reduction effect at the 1% significance level. Compared to market-economic LCCP policy tools, command-mandatory and voluntary LCCP policy tools were more likely to reduce CO_2 emission under the LCCP policy. This partly validates Hypothesis 3.

Heterogenous analysis of city development level

Considering that the response to LCCP policy could be heterogeneous among different city development levels, we referred to the latest "Ranking of Commercial Attractiveness of Chinese Cities" released by the China New First-tier Cities Research Institute, and graded the cities based on the following five dimensions: commercial resource concentration, city hub, city activity, lifestyle diversity and future plasticity, reflecting the comprehensive city development level and CO_2 emission reduction potential. The 285 cities were classified and consolidated (merging first-tier and quasi-first-tier cities), rendering a list of new first-tier to fifth-tier cities. The number of cities in each tier was 19, 30, 70, 81 and 85, respectively. This study introduced the level of city development to the benchmark model, as shown in Eq. (5):

$$y_{it} = \alpha_0 + \alpha_1 treat_{it} \times citydevelop_j + \beta X_{it} + \eta_i + \gamma_t + \varepsilon_{it}$$

5

Where $citydevelop_j$ represents the level of city development, the other variables have the same meaning as the benchmark model.

Table 7
Heterogeneity results of city development level

	CI	CP	CI	CP	CI	CP	CI	CP	CI	CP
first-tier×treat	-0.319	-0.355***								
	(-1.452)	(-8.808)								
second-tier×treat			-0.853***	-0.261***						
			(-3.789)	(-6.285)						
third-tier×treat					-0.384*	0.003				
					(-1.723)	(0.082)				
fourth-tier×treat							0.024	-0.079		
							(0.093)	(-1.639)		
fifth-tier×treat									-0.921***	-0.030
									(-3.622)	(-0.640)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4845	4845	4845	4845	4845	4845	4845	4845	4845	4845
R-squared	0.135	0.297	0.138	0.300	0.135	0.298	0.135	0.297	0.137	0.302

Note: *** and * represent significance levels of 1% and 10%, respectively. The values in parentheses are obtained by robust t-statistic.

Table 7 lists the heterogeneous results of cities with different development levels on CO_2 emission reduction. Columns (1) and (2) indicate that first-tier cities' LCCP policy significantly reduced CP, with an insignificant effect on CI, possibly related to the crowding effect in cities whereby higher levels of city development outweighed the agglomeration effect and exacerbated CO_2 emissions. As seen in columns (3) and (4), second-tier cities' LCCP policy had a significantly negative effect on CI and CP. The results in columns (5) and (6), and columns (9) and (10) indicate that the LCCP policy of third-tier and fifth-tier cities was only effective on CI. Columns (7) and (8) indicate that fourth-tier cities' LCCP did not significantly affect CO_2 emission reduction. Thus, it could be seen that study demonstrates that the LCCP policy had the most significant CO_2 emission reduction effect on second-tier cities.

SDID analysis

Spatial correlation analysis

The basic assumption in classical DID is the stable unit treatment value assumption (SUTVA) (Rubin, 2014), i.e., individuals from treatment group do not affect those of the control group. Such could ignore the impact of CO_2 emission reduction on neighboring regions, leading to estimation errors (Anselin and Arribas-Bel, 2013). This assumption can be broken down if the spatial correlation is taken into account, or SUTVA no longer holds when there is a correlation between different spatial units, namely, the spatial spillover effect (Kolak and Anselin, 2019). Considering that spatial regional units do not exist in isolation, this means that the LCCP policy is inevitably affected by neighboring regions. Therefore, it is necessary to incorporate spatial dependence into DID in this study.

The premise of using the SDID model was to test for spatial autocorrelation of CI and CP via the global Moran's index. The inverse of the squared geographic distance weight matrix (W_1), economic distance weight matrix (W_2) and economic geography nested weight matrix (W_3) were constructed to estimate the spatial effect of the LCCP policy. Table 8 shows that the estimated results of the global Moran's index were all significantly positive at the 1% level, indicating that the spatial autocorrelation on CI and CP were significant and spatial analysis could not be ignored.

Table 8
Global Moran's index of CI and CP under three weighting matrices

	CI			CP		
	W_1	W_2	W_3	W_1	W_2	W_3
2003	0.355***	0.520***	0.273***	0.347***	0.634***	0.286***
2004	0.398***	0.599***	0.350***	0.374***	0.662***	0.318***
2005	0.370***	0.470***	0.319***	0.362***	0.633***	0.304***
2006	0.321***	0.465***	0.283***	0.344***	0.628***	0.286***
2007	0.293***	0.346***	0.220***	0.339***	0.609***	0.279***
2008	0.343***	0.535***	0.281***	0.351***	0.630***	0.291***
2009	0.365***	0.610***	0.295***	0.356***	0.608***	0.293***
2010	0.382***	0.614***	0.320***	0.366***	0.660***	0.312***
2011	0.395***	0.663***	0.337***	0.383***	0.673***	0.326***
2012	0.395***	0.752***	0.330***	0.373***	0.661***	0.318***
2013	0.373***	0.838***	0.280***	0.386***	0.678***	0.330***
2014	0.395***	0.855***	0.291***	0.385***	0.685***	0.329***
2015	0.399***	0.849***	0.288***	0.391***	0.684***	0.330***
2016	0.388***	0.854***	0.283***	0.392***	0.676***	0.333***
2017	0.402***	0.812***	0.290***	0.412***	0.695***	0.352***
2018	0.397***	0.795***	0.291***	0.415***	0.700***	0.362***
2019	0.412***	0.818***	0.302***	0.399***	0.707***	0.350***

Note: *** represents significance levels of 1%.

Spatial spillover effect analysis

After testing for the existence of spatial autocorrelation, following Chagas et al. (2016), the SDID model was constructed to capture the spillover effects of the LCCP policy on CI and CP, which was essentially adding *treat* to the spatial econometrics model. Before estimating model coefficients, we compared two competing models, i.e., the Spatial Lag Model and the Spatial Error Model. The LM test was significant at the 10% or 1% level, and the null hypothesis of no spatial lag term and spatial autoregressive term was rejected, indicating that the influence of spatial relationship could not be ignored in the model. In addition, the LR test and Hausman test results show that the Spatial Durbin Model was suitable for the time and space dual fixed effects of this study.

Table 9 shows the results of the SDID model. The significance and direction of *treat* were as expected. However, the regression coefficients of the LCCP policy did not directly reflect the degree of impact on CI and CP, and the partial differential method was applied to decompose the spatial effects into direct and spatial spillover effects (Le Sage and Pace, 2009). Columns (1)-(3) show that the spatial spillover effects of the LCCP policy on CI under W_1 was significantly negative and was 3.398 times greater than the direct effect. Further, the spatial spillover effect was not significant under W_2 and W_3, illustrating that the spatial spillover effect of the LCCP policy on CI was generated based on geographic distance. Columns (4)-(6) indicate that the spillover effects of the LCCP policy on CI was significant under the three weight matrices. Thus, Hypothesis 4 is verified.

Table 9
Spatial effect decomposition of SDID

	CI			CP		
	W_1	W_2	W_3	W_1	W_2	W_3
treat	-0.567***	-0.479***	-0.533***	-0.150***	-0.155***	-0.149***
	(-5.620)	(-4.890)	(-5.240)	(-7.950)	(-8.120)	(-7.910)
LR_Direct	-0.615***	-0.492***	-0.572***	-0.166***	-0.164***	-0.159***
	(-5.590)	(-4.540)	(-5.060)	(-8.050)	(-7.960)	(-7.670)
LR_Indirect	-1.683***	-0.120	-3.049	-0.564***	-0.083***	-0.679**
	(0.875)	(-0.790)	(-1.580)	(-3.1400)	(-3.020)	(-2.200)
LR_Total	-2.298***	-0.612***	-3.621*	-0.730***	-0.247***	-0.838***
	(0.920)	(-2.750)	(-1.830)	(-3.880)	(-6.110)	(-2.640)
LM error	2139.226***	1337.178***	1904.700***	3291.655***	1279.378***	3283.448***
Robust LM error	3.254*	2.303	33.363***	1570.985***	392.111***	1717.106***
LM lag	2536.263***	1410.723***	2109.699***	1724.61***	888.853***	1574.816***
Robust LM lag	400.290***	75.848***	238.361***	3.940**	1.585	8.474***
LR error	209.170***	226.11***	346.350***	109.560***	96.080***	224.840***
LR lag	291.230***	251.97***	143.670***	97.800***	111.450***	173.680***
Hausman	53.650***	53.650***	53.650***	100.940***	100.940***	100.940***
ρ	0.666***	0.350***	0.838***	0.697***	0.313***	0.818***
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.105	0.115	0.048	0.598	0.596	0.567

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The values in parentheses are obtained by robust t-statistic.

Discussion

The construction of low-carbon cities in developed countries is a useful strategy to reduce CO_2 emissions. Compared to developed countries, regional-based environmental policy in developing countries often faces greater obstacles and difficulties (Chen et al., 2021; Yu and Zhang, 2021). However, as the world's largest emitter of greenhouse gases and largest developing country, China's LCCP policy is considered an essential strategy to address climate change. By selecting cities of different types, developmental stages and resource endowments (see Fig. 1), China aims to explore win-win paths for economic growth and low-carbon transformation. To objectively assess the effectiveness of this policy in China, benchmark analysis was performed based on a quasi-natural experiment using year and city fixed effects. In contrast to other literature, this study examined the CO_2 emission reduction effect of the LCCP policy from both production and consumption perspectives. Table 2 shows that the LCCP policy had beneficial CO_2 emission reduction effects in China, and the CO_2 emission reduction in production was more than three times the

reduction in consumption. After introducing the control variables, the absolute value of the coefficient of LCCP policy decreased, revealing that the CO_2 emission reduction effect was overestimated without considering the cities' characteristics. One of the main reasons for this was that the pursuit of economic-related indicators cut the CO_2 emission reduction effects of the LCCP policy (Tang et al., 2018). Further, although the empirical results revealed that the CO_2 emission reduced significantly after the promotion of the LCCP policy, Fig. 2 demonstrates an interesting finding, whereby there was a lag in the response of policymakers to the expected effects of LCCP policy, which concords with the findings of Di Maria et al. (2012). Table 3–4 and Fig. 3 support the above results' robustness and avoid the endogeneity problems as much as possible. In short, the above benchmark analyses confirm the LCCP policy's CO_2 emission reduction effects in China.

In addition, this study also aims to comprehensively assess the effect of the LCCP policy on CO_2 emissions. Only examining the effect direction and size are not useful for future low-carbon development. To this end, we further investigated the mechanisms of CO_2 emission reduction of the LCCP policy. The text quantification method and staggered DID model were used to explore the heterogeneity of policy tools and city development levels, and extended the spatial analysis of LCCP policies using SDID. Table 5 identifies three mechanism paths that are conducive to the LCCP policy for CO_2 emission reduction. The main effect came from reducing industrial emissions and boosting low-carbon technology innovations, and the effects of technological innovations brought by scientific researchers and renewable energy usage were smaller. Such observations could be related to the need for re-assessment using longer time period since the implementation of clean technologies and relative researcher attraction policies may take several years before the corresponding beneficial impacts are noticeable. Table 6 presents the heterogeneity results of command-mandatory, market-economy, and voluntary LCCP policy tools for CO_2 emission reduction. Not giving consideration to the activeness of market players led to no significant reduction in CO_2 emission by the market-economy tools of the LCCP policy. Table 7 also provides heterogeneity findings of CO_2 emission reduction when the cities were divided into five different development levels, weakening the idea that better city development levels derived more substantial effects from the LCCP policy for CO_2 emission reduction (Qiu et al.,2021). Meanwhile, it is alerting to observe that the LCCP policy may widen cities' CO_2 emission reduction effect at different development levels, especially between second-tier low-carbon pilot cities and fourth-tier low-carbon pilot cities. When spatial relevance is taken into account, the LCCP policy's spatial effect on CO_2 emission could be more accurately estimated. Table 8 shows that spatial analysis cannot be ignored under W_1, W_2 and W_3. Meanwhile, Table 9 further shows that there is a spatial spillover effect of the LCCP policy to reduce CP under three spatial weight matrices, while the spatial spillover effect of reducing CI exists only under the geographic weight matrix (W_1). This indicates that the LCCP policy of one city did not affect the CI of neighboring cities with similar economic levels. These results provide insights and useful references for the government's low-carbon development planning and layout in the future.

Conclusions And Policy Implications

Given the pressure of domestic environmental problems and the constraints of international treaties, it is particularly urgent and necessary to effectively reduce CO_2 emissions in China. The LCCP policy provides a new entry point for green development and low-carbon transformation. This study comprehensively assessed the CO_2 emission reduction effects of the LCCP policy from the micro perspective. The main conclusions are summarized as follows. (i) The implementation of the LCCP policy has indeed exerted a significantly positive effect on CI and CP. After a series of analyses, the results were still robust. In addition, these beneficial effects started appearing from the third year of LCCP policy implementation. (ii) Reducing industrial carbon emission, improving technology innovations and optimizing the efficiency of energy usage are three critical mechanisms for the LCCP policy to reduce CI and CP. The main effect was from the first two mechanisms, while those from renewable energy usage and technology innovations from scientific researchers were smaller. (iii) The effects of command-mandatory and voluntary LCCP policy tools were better for CO_2 emission reduction, while market-economy LCCP policy tools were either insignificant or positive for CP. The LCCP policy has indeed exerted more significant CO_2 emission reduction effects on second-tier pilot cities than others. (iv) The implementation of the LCCP policy had a negative spatial spillover effect on CO_2 emission. A city's LCCP policy could reduce the CP of neighboring cities that were geographically closer and similar economies, while it could only reduce the CI of neighboring cities that were geographically closer. Notably, the spatial spillover effects of the LCCP policy's CO_2 emission reduction were much larger than the direct effects.

To further push towards low-carbon city construction and achieve China's CO_2 emission reduction targets as early as possible, the following policy implications are proposed.

First, the government of low-carbon city pilots should provide replicable guidance to other cities by refining their low-carbon pilot experiences and typical cases. It is necessary to further promote low-carbon city pilots nationwide, which could help China to reach its CO_2 emission peak by 2030 and carbon neutrality by 2060, from a city level, and provide experience and reference for carbon- neutral pilot projects. Of note, CO_2 emission reduction is a long-term and arduous task, and the government must continue to effectively monitor and guide the LCCPs.

Second, low-carbon city construction should continue to explore ways to accelerate the "greening" of energy structure and "cleanliness" of energy usage. Although the LCCP policy covers the development of clean technology and other aspects, the policy outcome has not yet been reflected. In the long run, the government should first actively build a renewable energy research and development platform, provide energy-saving technology innovation with financial investment and personnel subsidies, strengthen the skills and ability of low-carbon technical researchers, and create a low-carbon and clean energy technology innovation environment to ensure the effectiveness of the LCCP policy implementation.

Third, the government should stay firm on its position when formulating the LCCP policy and avoid overstepping its position. In areas that need supports, the government should give corresponding supports without violating market rules. In the process of implementing the LCCP policy, the government should make efforts to play the role of a "night watchman," strengthen the unified environmental tax and emissions trading market, and devote to creating an orderly market environment for low-carbon pilot cities. In addition, to maximize the degree of CO_2 emission reduction of the LCCP policy combinations should be designed in accordance with the local region's situation. Both financial support and policy bias should be tilted towards fourth-tier pilot cities to achieve the CO_2 emission reduction effects of the LCCP policy nationwide.

Finally, the LCCP policy's spatial spillover effect should also be given full consideration in the future. As CO_2 emission reduction at a "single point" can radiate to "multiple points" across neighboring regions, the government should establish a regional joint control collaborative governance model, build cross-regional CO_2 emission trading markets, and encourage regular exchanges between low-carbon city pilots and non-low-carbon city pilots, to form a regional synergy for CO_2 emission reduction. As such, a low-carbon promotion with nationwide pilot implementation and collaborative CO_2 emission reduction could be an effective way for government to handle a city's CO_2 emission reduction problems.

Declarations

Author contribution (1) Huimin Ren: conceptualization, methodology, writing-original draft, and editing. (2) Guofeng Gu: visualization, writing-review, and investigation. (3) Honghao Zhou: resources, writing- review and editing, and supervision. Correspondence to Guofeng Gu.

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Figures

Figure 1

Spatial distribution of three batches of low-carbon city pilots in China

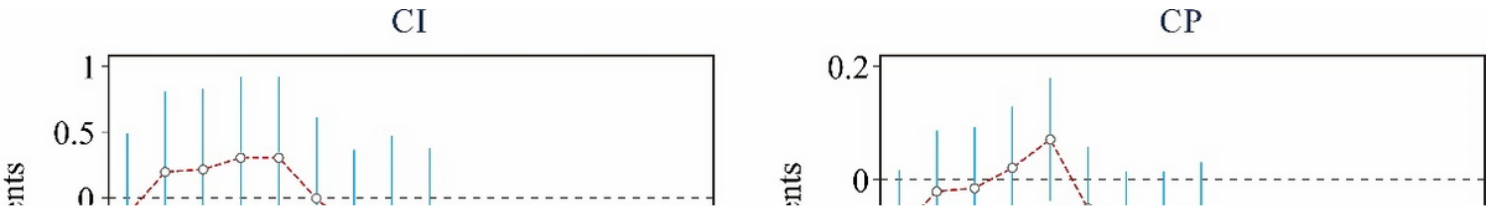

Figure 2

Parallel trend test results

Note: The hollow points are the estimated coefficients for each year, and the short vertical lines are the standard errors of the confidence intervals at the 95% level.

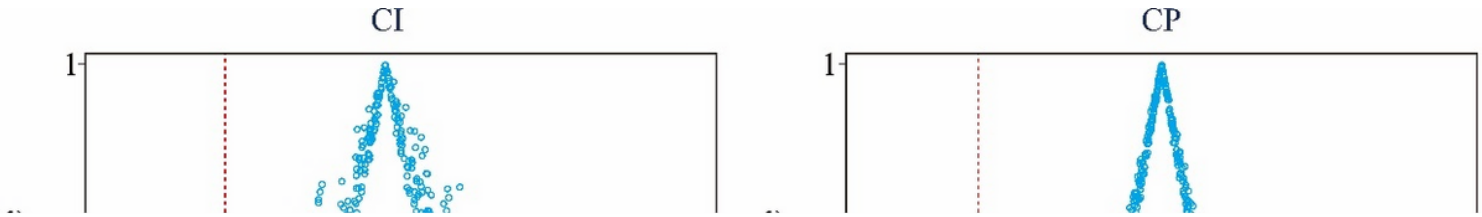

Figure 3

Distribution of estimations in the Placebo test

Note: The vertical red dashed line indicates the “correct” estimated coefficient.

Supplementary Files

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- Appendix.docx