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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RESEARCH ARTICLE

Abstract

The low-carbon city pilot (LCCP) policy is an important initiative for China to fulfill its international commitment to carbon emission reduction and achieve low-carbon transformation. In this context, this study investigated whether the LCCP policy of China has achieved carbon emission reduction from the production and consumption perspectives and how its underlying mechanism and spatial spillover effect. Using the panel dataset of 285 Chinese prefecture-level cities from 2003 to 2019, this study applied the staggered DID model to examine the effects and its underlying mechanism of the LCCP policy on carbon intensity (CI) and carbon emission per capita (CP). We also conducted heterogeneity and spatial spillover effect analyses using the textual quantification method and spatial DID. Our results show that 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. Reducing industrial emissions, 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. 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. The carbon emission abatement of the LCCP policy has also demonstrated a spatial spillover impact on neighboring cities. This study focused on analyzing the mechanism paths and spatial spillover effects of the LCCP policy impact and provided an important decision-making reference in promoting the LCCP policy for not only China but also other developing countries. Specifically, low-carbon pilot experiences and typical cases should be refined, ways for accelerating the greening and cleaning of energy usage must be explored, and regional joint control and collaborative governance should be established to achieve China’s low-carbon transformation.

Keywords

Low-carbon city pilot policy · CO₂ emission reduction · Staggered DID · Underlying mechanism · Policy tool · Spatial spillover effect

Nomenclature

LCCP
Low-carbon city pilot
CI
Carbon intensity

CP
Carbon emission per capita
CO₂
Carbon dioxide
DID
Difference-in-difference
PSM-DID
Propensity score matching-DID
2SLS
Two-stage least squares
SDID
Spatial difference-in-difference
SUTVA
Stable unit treatment value assumption
NDRC
National Development and Reform Commission
CNY
Chinese Yuan (currency unit)
treat
The cross-term of the LCCP policy variable and time dummy variable
lnpgdp
Economic growth
lnpd
Population density
secindp
Industrial structure
fdip
Foreign direct investment
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’s carbon peak and carbon neutrality targets are expected to be achieved by 2030 and 2060, respectively (Li et al. 2021). Thus, it is foreseeable that low-carbon mode has become an inevitable trend of future development.

Cities have been made the focal point to implement low-carbon development and mitigate global greenhouse gas emissions (Lee and Erickson 2017). It is estimated that 70% of all CO$_2$ emissions in China are from cities due to their high population density, vast public transportation networks, massive infrastructure demands, and rapid industrialization, resulting in environmental degradation concerning CO$_2$ emission that cannot be overlooked (Cai et al. 2019; Ahmad et al. 2021a, b; Ahmed et al. 2022). 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 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.

The LCCP policy has gained 12 years of experience in carbon emission mitigation in China. Some pilot regions have played a leading role in low-carbon development, with their carbon intensity decreasing at a rate significantly higher than the national average level, forming a reversed pressure mechanism for industrial structure upgrade, energy structure optimization, technological innovation progress, and lifestyle change (Chen et al. 2021a). It provides replicable experiences and practices for other non-pilot cities to explore green and low-carbon development paths. In addition, not only that, but it has played a positive role in driving other low-carbon transformation efforts, such as the 7 provincial and municipal carbon trading pilots carried out all came from low-carbon city pilots. Accordingly, the driving effect of the LCCP policy is of great significance to achieve China’s long-term low-carbon transformation goals. Therefore, low-carbon city pilot construction must be systematically assessed.

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

### Introduction

Climate change has been perceived as the gravest threat to human survival and development in the twenty-first century (Li et al. 2018a), and CO$_2$ emissions are a big problem that can accelerate global climate change and become a major concern in the world (Rehman et al. 2021). To hinder the environmental and social issues caused by climate change, many international agreements have set clear targets to reduce greenhouse gas emissions. However, despite these ambitious commitments, environmental sustainability targets of carbon emission mitigation remain far from realization, even with the most optimistic scenario (WEF 2022; Ahmad et al. 2020a). 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); those emissions induce the adverse economic influence of productivity slowdown (Ahmad et al. 2020b). 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
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 carbon peak times.

According to documents issued by the NDRC, the fundamental purpose of the LCCP policy is to promote the implementation of China’s CO₂ 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 et al. 2015). Given these above references, the effectiveness of the LCCP policy remains unknown. The two main objectives of this study are as follows: first, this study rigorously discusses the empirical effects of the LCCP policy on CO₂ emission intensity (CI) and CO₂ 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 CO₂ emission, explores the heterogeneity of CO₂ 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 CO₂ emission reduction.

The potential contributions of this study lie in the following aspects. First, considering the “low-carbon city pilot policy” as an identification strategy, this study employs the staggered DID method with multi-periods to examine the average treatment effects of the LCCP policy on CO₂ emissions from production and consumption. This method can avoid the contemporaneous trends of confounding treatment effects compared with the classical DID method (it only includes two time periods, namely, “pre” and “post”). Second, we construct a moderating effect model to identify the underlying mechanisms of the LCCP policy on CI and CP using industrial emission reduction, technological innovation, and energy usage as the mechanism channels, thereby providing alternative paths for dealing with the long-term dilemma of low-carbon transformation. Third, this study is the first to take advantage of the textual quantification method to capture the heterogeneous effect of different LCCP policy tools on CO₂ emissions. In addition, we explore the heterogeneous impacts of carbon abatement in cities at different development levels. Our findings may provide action guidance for the government to formulate a concretized LCCP policy using the above-mentioned heterogeneity tests. Finally, this study applies the SDID model to investigate the impacts of the LCCP policy on CI and CP in the pilot cities and their neighboring cities. We overcome the shortcomings of other studies that focus only on the CO₂ reduction effects of the LCCP policy while ignoring its spatial spillover effects, giving a new perspective to understanding the spatial effects of the LCCP policy on CO₂ 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 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

Synopsis of studies on the assessment of the LCCP policy

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 (2018) 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 CO₂ 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. (2018b) 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).
Synopsis of studies on the effect of LCCP policy on carbon emissions

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 as 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 CO2 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 CO2 emission due to a weak target responsibility system and a poorly designed scoring system. This finding echoes with that of Feng et al. (2021), 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 CO2 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 CO2 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 CO2 emission, and this might have led to an underestimation of the CO2 emissions reported. Second, the existing studies faced common endogenous problems when evaluating 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 CO2 emission reduction of neighboring cities from a spatial spillover perspective. Neglecting spatial effects is not conducive to accurately estimate the CO2 emission reduction effects of the LCCP policy.

Research hypotheses

The core idea of the LCCP policy is to gradually reduce CO2 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 CO2 emission data management system, and encourage low-carbon production patterns and green lifestyles. Hence, we believe that the LCCP policy can reduce CO2 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 CO2 emission reduction effects of the LCCP policy. Given these considerations, the first hypothesis is presented here:

Hypothesis 1. The LCCP policy is conducive to CO2 emission reduction, but there is a lag before the CO2 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 CO2 emissions. In addition, the LCCP policy can act as an “environmental barrier” that screens new entrants to the market and avoid new CO2 emissions to a certain extent. The Porter hypothesis suggests that a reasonable environmental regulation policy can stimulate the “innovation compensation” effect (Porter and Linde 1995).

Immediately, low-carbon city pilots 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 CO₂ emission reduction.

Low-carbon city construction can reduce CO₂ emissions by improving energy usage in the following ways. First, when local governments levy CO₂ emission tax and energy tax on producers and users of high CO₂ 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 on their local development characteristics, each pilot city can adopt command-mandatory, market-economic, and voluntary policy tools to promote local low-carbon developments (Wang et al. 2015). Command-mandatory tools restrict the CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emission reduction. Thus, neighboring cities could reduce CO₂ 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

DID models are widely used for policy assessments that estimate the net effects of ex ante and ex post policy implementation by eliminating the influence of individual heterogeneity bias and time-varying factors (Dimick and Ryan 2014; Liu et al. 2022). Staggered DID models are an extension of classical DID models. We used staggered DID with the following two considerations. In comparison with the classical DID models in which the policy is implemented at a uniform point in time, staggered DID is applicable to the progressive implementation of the same policy in the affected objects, which can well circumvent the contemporaneous trends of confounding treatment effects (Athey and Imbens 2022). The LCCP policy was gradually implemented across different cities in 2010, 2013, and 2017. This policy provides us with an ideal setting to use a staggered DID method to examine how the LCCP policy affects cities’ CI and CP. We treated the LCCP policy as a quasi-natural experiment: the first layer is generated from the city level and the second layer from the year level. The benchmark regression model is formulated as follows:

\[ y_{it} = \alpha_0 + \alpha_1 \text{treat}_{it} + \beta X_{it} + \eta_i + \gamma_t + \epsilon_{it} \]  

(1)

where \( i \) denotes city and \( t \) denotes year. \( y_{it} \) is CI or CP for the city \( i \) at year \( t. \) \( \text{treat}_{it} \) is a dummy variable equal to one if city \( i \) implemented the LCCP policy at year \( t \) and zero if otherwise. \( \alpha_0, \alpha_1, \) and \( \beta \) are the parameters to be estimated. The coefficient \( \alpha_1 \) 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. \( \eta_i \) represents city fixed effects; \( \gamma_t \) represents time fixed effects. \( \epsilon_{it} \) is a random disturbance term. The coefficient of interest is \( \alpha_1. \) 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 \( \hat{\alpha}_1 \geq 0. \)

In the spatial econometric model, we have to consider the spatial correlation between cities. The significant spatial effects of the LCCP policy and CO₂ emissions facilitate the influence of cities implementing the LCCP policy (treatment group) on neighboring cities (control group). However, this mechanism is inconsistent with the basic DID model estimation results because of the violation of SUTVA (Kolak and Anselin 2019). Recently, spatial effects have been introduced
into basic DID models. SDID models can address the problem that basic DID models lack the treatment effect of spatial data with regional interactions (Chagas et al. 2016; Delgado and Florax 2015). Therefore, we embedded the spatial effects in the basic DID model using the following SDM-based SDID model to accurately assess the spillover effects of LCCP policies on CO₂ emission reduction. The equation is as follows:

\[ y_{jt} = \alpha_0 + \varphi \sum_{j} W_{ij} y_{jt} + \alpha_1 \text{treat}_{jt} + \theta \sum_{j} W_{ij} \text{treat}_{jt} + \beta X_{jt} + \gamma_i + \eta_t + \epsilon_{jt} \]  

(2)

where \( j \) denotes city and \( W_{ij} \) represent spatial weight matrices. The other variables have the same meaning as in Eq. (1).

**Variable selection**

**Independent variable and dependent variables**

The \( \text{treat}_{jt} \) 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 CO₂ emission from the 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 CO₂ emission data at the city scale. This study assumes a linear relationship between nighttime lights, and that CO₂ emission was constant within a specific province (Meng et al. 2014). Following the findings of Chen et al. (2021b), this study used continuous nighttime light data corrected across NPP and VIIRS sensors as a proxy variable for measuring CO₂ emission at the city scale. Applying the nighttime lighting data, the CO₂ 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 2014), 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 \((\ln\text{indSO}_2)\) and industrial fumes emission \((\ln\text{indfumes})\). Considering that it takes 1 to 3 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 \((\text{wrlecpat})\) were used to measure low-carbon technology innovation. The importance of high-level human capital in the mitigation processes of polluting gas emissions has been widely documented because they can adopt more advanced technologies \((\text{Alvarado et al. 2020})\). Scientific researcher as a percentage of the year-end population \((\text{sciereaseap})\) was therefore employed to measure the level of scientific 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 \(\text{CO}_2\) emissions. Hence, the ratio of total energy consumption to GDP \((\text{energyint})\) was taken as a proxy variable for energy usage. Renewable and clean energy sources are relatively significant factors affecting the emission levels \((\text{Fareed et al. 2022})\), thereby the proportion of primary electricity and natural gas in energy consumption \((\text{renewstr})\) 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 \((\ln\text{pgdp})\) was accounted for the natural logarithm of GDP per capita. Population density \((\ln\text{pd})\) was measured by the natural logarithm of the population per unit area. Proportion of the industrial added value in the GDP \((\text{secindp})\) was incorporated into the model to control the effect of industrial structure. Openness was measured by the proportion of FDI in the GDP \((\text{fdip})\) and total imports and exports as a percentage of GDP \((\text{eximp})\). The proportion of governmental expenditures on science and education out of the total fiscal expenditure \((\text{scieddp})\) 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 people \((\ln\text{wrcolstu})\).

The new energy vehicle subsidy pilot policy \((\text{nenervehicle})\), the atmospheric emission limit pilot policy \((\text{atomemi})\), and the carbon emission trading right pilot policy \((\text{cemitra})\) were the variables used in the robustness test. The air circulation coefficient \((\text{VC})\) and relief degree of land surface \((\text{RDLS})\) 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 \((\text{control})\), market-economic \((\text{market})\), and voluntary \((\text{voluntary})\) 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 dataset of 285 Chinese prefecture-level cities from 2003 to 2019. The list of low-carbon city pilots is manually compiled based on relevant documents issued by the NDRC. Nighttime lighting observation data were obtained from Harvard Dataverse \((\text{https://doi.org/10.7910/DVN/YGIVCD})\). 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 “CPC-Y02 classification number + city where the application is located.” Air circulation coefficient \((\text{VC})\) was sourced from the ERA dataset of the European Center for Medium-Range Weather Forecasts \((\text{ECMWF})\). Relief degree of land surface \((\text{RDLS})\) was obtained from the relief degree of land surface dataset of China \((\text{1 km})\) \((\text{http://www.geodoi.ac.cn/})\). 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.

**Empirical results**

**Parallel trend test**

An essential prerequisite for the validity of the DID model is that the treatment and control 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. 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 \(\text{Yu and Zhang (2021)}\), the following equation was used for the event study method:

\[
y_{it} = \alpha_0 + \sum_{k=7}^{9} \alpha_k \times D_{t0+k} + \beta X_{it} + \gamma_t + \eta_i + \varepsilon_{it}
\]

where \(D_{t0+k}\) 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 $\alpha_k$ reflects dynamic effects of the LCCP policy on $CO_2$ emission reduction. $\alpha_k - \alpha_{k-1}$ 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 $D_{i,t+k}$. The horizontal axis represents the year before and after implementation of the LCCP policy, and 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 treatment effect of the LCCP policy on CI. Columns (3) and (4) show the average treatment effect 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 the production and consumption. For robustness, columns (2) and (4) introduced the control variables. The regression results still showed a significance level of 1%, which further validates Hypothesis 1.

### Table 1 Descriptive statistics of variables

|       | Unit                        | Obs | Mean   | Std. dev | Min    | Max    |
|-------|-----------------------------|-----|--------|----------|--------|--------|
| CI    | Ton/10^4 CNY                | 4845| 3.098  | 3.659    | 0.201  | 38.586 |
| CP    | Person/ton                  | 4845| 1.545  | 1.098    | -1.704 | 5.074  |
| treat |                             | 4845| 0.084  | 0.277    | 0      | 1      |
| lnpgdp| CNY                         | 4845| 10.028 | 0.848    | 7.545  | 12.488 |
| secondp| %                          | 4845| 0.470  | 0.112    | 0.114  | 0.91   |
| lnpd  | Person/km^2                 | 4845| 5.717  | 0.914    | 1.547  | 7.882  |
| fdip  | %                           | 4845| 0.019  | 0.022    | 0.000  | 0.376  |
| lnwrcolstu| Person                   | 4845| 4.258  | 1.677    | -6.226 | 7.29   |
| exmip | %                           | 4845| 0.203  | 0.386    | 0.000  | 8.117  |
| techddp| %                          | 4845| 0.044  | 0.130    | 0.000  | 2.602  |
| lnindSO2 | Ton                     | 4845| 10.289 | 1.229    | 0.000  | 13.434 |
| lnindfumes| Ton                    | 4845| 10.309 | 1.200    | 0.693  | 13.434 |
| scireshape| %                         | 4845| 0.023  | 0.037    | 0.000  | 0.432  |
| wrlpat | Piece                      | 4845| 0.621  | 1.998    | 0.001  | 77.937 |
| renewstr| %                         | 4845| 0.322  | 0.196    | 0.019  | 2.019  |
| energyint| Standard coal ton/10^4 CNY | 4845| 0.811  | 0.686    | 0.064  | 10.081 |
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 geography, politics, and socio-economic. 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 CO₂ 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 right 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 were 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 CO₂ 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 CO₂ emissions. Following Chen et al. (2021a), 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.

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:

$$
\hat{\alpha}_i = \alpha_i + \gamma \times \frac{\text{cov}(treat_{it}, \epsilon_{it}|x)}{\text{var}(treat_{it}|x)}
$$

(4)

where x comprises of all control variables and fixed effects and \( \gamma \) represents the effect of unobservable factors on the explanatory variables. When \( \gamma = 0 \), 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 $\hat{\gamma}_{\text{random}}$ (500 replications). The $\hat{\gamma}_{\text{random}}$ 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.

The DID model has been found to have two estimation biases (homogeneity and random selection). The first one applies if the LCCPs were chosen based on geographical location, economic development, and industrial structure concerns. The second one arises if the CO₂ trends in the treatment and control groups differed before the LCCP policy implementation. In response to this phenomenon, the propensity score matching (PSM) method is applied to reduce potential bias. The results of PSM-DID further support the previous benchmark regression, which was provided in the Appendix Tables 10 and 11. Based on the above test, it could be deduced that the observed CO₂ emission reduction of the 285 cities was derived from the implementation of the LCCP policy.

### Endogeneity test using the IV method

The instrumental variable method was 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 are typically considered to 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 city pilots, 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 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.

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**Fig. 3** Distribution of estimations in the placebo test. Note: The vertical black dashed line indicates the “correct” estimated coefficient. Source: The figure was plotted by authors based on the results of running stata17.
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 underlying mechanisms of CO2 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. 2018a), we assumed that the underlying mechanisms were from variables regressed by policy variables and constructed the following regression model:

$$X_{it} = \alpha_0 + \alpha_t \text{treat}_{it} + \lambda_i + \tau_r + \sigma_{it}$$

where $X_{it}$ represents the matrix vector of the mechanism variables ($\ln\text{indSO}_2$, $\ln\text{indfumes}$, $\text{wrlcpat}$, $\text{scireseap}$, $\text{energyint}$, $\text{renewstr}$). $\lambda$ is the year fixed effect. $\tau$ is the city fixed effect. $\sigma$ is the stochastic disturbance term. The other variables have the same meaning as in Eq. (1).

The estimated results are shown in Table 5. Columns (1) and (2) show the results of the LCCP policy affecting CO2 emission reduction through industrial emissions. It can be observed that the LCCP policy significantly decreased industrial $\text{SO}_2$ emissions and industrial fumes emissions. Columns (3) and (4) list the results of technological innovation and show that the LCCP policy significantly increased the number of low-carbon patent applications and researchers engaging in technology innovation. It is worth noting that the enhancement of low-carbon patent was the most effective in reducing CO2 emissions. Columns (5) and (6) show the impact of the LCCP policy on energy usage and demonstrate that the LCCP policy could indeed achieve CO2 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

The text quantification method was applied to build appropriate policy tool variables to further discuss the heterogeneous effect of different LCCP policy tools on CO2 emission reduction. This study adopted the textual quantification method to measure the LCCP policy tools for two reasons.

Table 5: The results of the mechanism test

| Mechanisms          | Industrial emissions | Technological innovation | Energy usage |
|---------------------|----------------------|--------------------------|--------------|
|                     | $\ln\text{indSO}_2$ | $\ln\text{indfumes}$    | $\text{wrlcpat}$ | $\text{scireseap}$ | $\text{energyint}$ | $\text{renewstr}$ |
| treat               | $-0.114^{***}$ ($-2.751$) | $-0.125^{***}$ ($-3.180$) | $1.054^{***}$ (11.293) | $0.005^{***}$ (3.909) | $-0.146^{***}$ ($-5.989$) | $0.032^{***}$ (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                 |

*** represents significance levels of 1%. The values in parentheses are obtained by robust $t$-statistic
First, the government work report generally is carried out the beginning of the year, while carbon emission occurs throughout the year, thus effectively avoiding the endogeneity problem caused by reverse causality. Furthermore, the LCCP policy textual variables in our study are provincial-level variables, and the other related variables are prefecture-level municipal variables. The lower-level government actions cannot directly influence the decisions of the higher-level initiatives, which also helps in alleviating the endogeneity problem.

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, and permit. Keywords related to market-economy LCCP policy tools were set as tax, fee, subsidy, compensation, penalty, financing, investment, credit, market, emission trade, renewable, clean, and low carbon. Terms related to voluntary LCCP policy tools included pilot, park, industrial park, nature reserve, town, green, ecology, environmental protection, public transportation, and energy usage. 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 presents the estimated results of different LCCP policy tools on CO2 emission. 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, and 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. Columns (5) and (6) illustrate voluntary LCCP policy tools’ negative CO2 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 CO2 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 CO2 emission reduction potential. The 285 Chinese prefecture-level 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. (6):

$$y_{it} = \alpha_0 + \alpha_1 \text{treat}_{it} \times \text{citydevelop}_{j} + \beta X_{it} + \eta_i + \gamma_i + \epsilon_{it}$$  \hspace{1cm} (6)

where \(\text{citydevelop}_{j}\) represents the level of city development, and other variables have the same meaning as the benchmark model.

| Table 6 Heterogeneity results of the LCCP policy tools |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| CI          | CP          | CI          | CP          | CI          | CP          |
| Control      | −0.980**     | −0.387***   | −0.304       | 0.085 (0.626) | −0.911***     | −0.387***     |
|              | (−1.816)     | (−3.891)    | (−0.412)     | (0.626)     | (−2.642)     | (−6.094)     |
| Market       |              |              |              |              |              |              |
| Voluntary    | −0.136       | 0.608        | 0.137        | 0.607        | 0.137        | 0.610        |
| 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        |

*** 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 CO₂ 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 CO₂ 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 CO₂ emission reduction. Thus, it could be seen that study demonstrates that the LCCP policy had the most significant CO₂ emission reduction effect on second-tier cities.

**SDID analysis**

**Spatial correlation analysis**

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.

**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.

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...
Table 9 shows the results of the SDID model. The significance and direction of treat were as expected. 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.

Discussion

In terms of the carbon abatement effect of the LCCP policy, this study is consistent with existing results (Zhou et al. 2019; Hong et al. 2021; Liu et al. 2022). The difference is that this study examines the \( CO_2 \) reduction effect of the LCCP policy from the production and consumption perspectives rather than total carbon emissions. The main findings show that \( CO_2 \) emission reduction in production was more than three times higher than the reduction in consumption. However, from the perspective of the degree of influence, the impact of the LCCP policy on CI and CP was decreasing, and the magnitude of \( CO_2 \) emission decline has more potential for improvement. This finding shows that Chinese cities have not completely abandoned their traditional economic-based path dependence to a certain extent (Tang et al. 2018). A major reason for this is that, without a unified goal and sufficient guidance from the national government, cities were underpowered to deal with climate change (Cooper 2018). Moreover, the performance of the LCCP policy was not significant until the third year of implementation in the parallel trend test. It means that the LCCP policy needs a comparatively longer period to accumulate and should be assessed in the long run (Di Maria et al. 2012; Yu and Zhang 2021).

The mechanism analysis indicates that low-carbon technological innovation is an essential channel for the LCCP policy to reduce \( CO_2 \) emissions from production and consumption, providing new empirical evidence for the weak Porter hypothesis. Specifically, innovation compensation generated by the LCCP policy is greater than the bottom-up competition cost (Porter and Linde 1995; Qiu et al. 2021). Our results show that reducing industrial emissions and adjusting energy structure could reduce carbon emissions. 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 a longer period because the implementation of clean technologies and relative researcher attraction policies may take several years before the package of low-carbon policies yields fruits (Fu et al. 2021). Therefore, the usage of renewable and clean energy should be taken as an important measure to accelerate the low-carbon transformation (Zhao and Luo 2017; Ahmad et al. 2021c).

In comparison with the existing studies, it can be found that heterogeneity analysis mainly focused on the different geographical locations and cities sizes, and only a few
Table 9  Spatial effect decomposition of SDID

|       | CI       | W₁        | W₂        | W₃        | CP       | W₁        | W₂        | W₃        |
|-------|----------|-----------|-----------|-----------|----------|-----------|-----------|-----------|
| treat |          | -0.567*** (−5.620) | -0.479*** (−4.890) | -0.533*** (−5.240) |          | -0.150*** (−7.950) | -0.155*** (−8.120) | -0.149*** (−7.910) |
|       | LR_Direct| -0.615*** (−5.590) | -0.492*** (−4.540) | -0.572*** (−5.060) |          | -0.166*** (−8.050) | -0.164*** (−7.960) | -0.159*** (−7.670) |
|       | LR_Indirect| -1.683*** (0.875) | -0.120 (−0.790) | -3.049 (−1.580) |          | -0.564*** (−3.1400) | -0.083*** (−3.020) | -0.679** (−2.200) |
|       | LR_Total | -2.298*** (0.920) | -0.612*** (−2.750) | -3.621 (−1.830) |          | -0.730*** (−3.880) | -0.247*** (−6.110) | -0.838*** (−2.640) |
|       |          | (90.20)   |           |           |          |           |           |           |
|       | LM error | 2139.226*** | 1337.178*** | 1904.700*** |          | 3291.655*** | 1279.378*** | 3283.448*** |
|       | Robust LM error | 3.254* | 2.303 | 33.363*** | 3.940* | 1.585 | 8.474*** |
|       | 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 | Yes |
|       | Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
|       | City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
|       | R-squared | 0.105 | 0.115 | 0.048 | 0.598 | 0.596 | 0.567 |

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The values in parentheses are obtained by robust t-statistic.
studies have discussed whether different LCCP policy tools can achieve emission reduction performance. This condition is not conducive to a comprehensive understanding of the LCCP policy’s operational stages for low-carbon activities. Therefore, we focused on analyzing the heterogeneity of city development levels and policy tools. Specifically, the LCCP policy may widen cities’ CO₂ emission reduction effect at different development levels, especially between second-tier and fourth-tier low-carbon pilot cities. The impact of the first-tier LCCP policy on carbon emissions in the production aspect is not significant, weakening the idea that better city development levels derived more substantial effects from the LCCP policy for CO₂ emission reduction (Hong et al. 2021). In terms of the heterogeneity of policy tools, the market-economic LCCP policy tools were insignificant or even negative for carbon emissions. The reason may be that China’s LCCP policy is mainly promoted by the national and local governments, while the participation of market forces is not high (Liu et al. 2022).

Previous studies overlook the spatial spillover effects of the LCCP policy. This study provides insights beyond existing studies that discuss the spatial spillover effects of the LCCP policy on CO₂ emissions under three spatial weight matrices. Our SDID analysis results show that the LCCP policy has a spatial spillover effect to reduce CP under three spatial weight matrices, while the spatial spillover effect of reducing CI exists only under the geographic weight matrix. On the one hand, low-carbon city pilots would squeeze low-end production factors and polluting industries into neighboring cities to achieve the low-carbon goals. This “crowding out effect” may be the main reason why the expected significant spatial spillover effects of carbon emissions from the production aspect have not yet occurred in the low-carbon city pilots. On the other hand, a variety of policy tools adopted by local governments would inevitably have indirect effects on other cities through geographical or economic linkages given the existence of demonstration effects and regional economic linkage effects among cities to achieve low-carbon transformation, which means that a regional community must be built for low-carbon development.

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 CO₂ emissions in China. The LCCP policy provides a new entry point for green development and low-carbon transformation. This study comprehensively assessed the CO₂ emission reduction effects of the LCCP policy from the macro-perspective. The main conclusions are summarized as follows. First, 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. Second, 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. Third, the effects of command-mandatory and voluntary LCCP policy tools were better for CO₂ emission reduction, while market-economy LCCP policy tools were either insignificant or positive for CP. The LCCP policy has indeed exerted more significant CO₂ emission reduction effects on second-tier pilot cities than others. Finally, the implementation of the LCCP policy had a negative spatial spillover effect on CO₂ 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 CO₂ emission reduction were much larger than the direct effects.

To further push towards low-carbon city construction and achieve China’s CO₂ 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 carbon peak by 2030 and carbon neutrality by 2060, from a city level, and provide experience and reference for carbon–neutral pilot projects. Of note, CO₂ emission reduction is a long-term and arduous task, and the government must continue to effectively monitor and guide the low-carbon city pilots.

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 CO₂ 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 CO₂ 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 CO₂ emission reduction at a “single point” can radiate to “multiple points” across neighboring regions, the government should establish a regional joint control and collaborative governance model, build cross-regional CO₂ emission trading markets, and encourage regular exchanges between low-carbon city pilots and non-low-carbon city pilots, to form a regional synergy for CO₂ emission reduction. As such, a low-carbon promotion with nationwide pilot implementation and collaborative CO₂ emission reduction could be an effective way for government to handle a city’s CO₂ emission reduction problems.

This study still has some limitations that warrant further attention in future research. A total of 285 Chinese prefecture-level cities were used as research samples from a macro-level perspective to assess the LCCP policy on the CO₂ emission reduction effect. Although this initiative might have yielded empirical evidence on CO₂ emissions, the association between the LCCP policy and micro-firm-level on CO₂ emission deserves further in-depth discussion. The inclusion of available long-term time-series data of firms in future studies could also be useful. This study mainly analyzed the static impact of the LCCP policy on CO₂ emissions and ignored the dynamic influence of this policy on the entry of low-carbon pilot cities. Therefore, the long-term dynamic effects of the LCCP policy should be tracked to further identify other possible influencing mechanisms, such as carbon sequestration, low-carbon lifestyle, and green building.

Appendix

Table 10 Estimation results of the PSM-DID model (CI)

|        | 2003   | 2004   | 2005   | 2006   | 2007   | 2008   | 2009   | Average |
|--------|--------|--------|--------|--------|--------|--------|--------|---------|
| treat  | -0.618 | -0.616 | -0.602 | -0.639 | -0.618 | -0.626 | -0.641 | -0.604 |
|        | (-5.092) | (-5.246) | (-4.955) | (-5.170) | (-5.183) | (-5.107) | (-5.288) | (-4.993) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4675 | 4675 | 4505 | 4641 | 4658 | 4573 | 4607 | 4607 |
| R-squared | 0.131 | 0.141 | 0.145 | 0.139 | 0.144 | 0.143 | 0.143 | 0.142 |

⁎⁎⁎ represents significance levels of 1%. The values in parentheses are obtained by robust t-statistic. Average refers to the average of 2003 to 2009

Table 11 Estimation results of the PSM-DID model (CP)

|        | 2003   | 2004   | 2005   | 2006   | 2007   | 2008   | 2009   | Average |
|--------|--------|--------|--------|--------|--------|--------|--------|---------|
| treat  | -0.158 | -0.160 | -0.155 | -0.160 | -0.158 | -0.145 | -0.150 | -0.156 |
|        | (-7.163) | (-7.243) | (-6.799) | (-7.138) | (-7.087) | (-6.311) | (-6.628) | (-6.899) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4675 | 4675 | 4505 | 4641 | 4658 | 4573 | 4845 | 4607 |
| R-squared | 0.619 | 0.618 | 0.618 | 0.619 | 0.620 | 0.622 | 0.623 | 0.621 |

⁎⁎⁎ represents significance levels of 1%. The values in parentheses are obtained by robust t-statistic. Average refers to the average of 2003 to 2009
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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Declarations

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