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Assessment on the synergistic effect of pollution and carbon reductions in low-carbon city pilot policy: based on effectiveness and efficiency perspectives

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Abstract
This study focuses on the impacts of low-carbon city pilot policy (LCCP) on pollution and carbon emissions and synergistic emission reduction efficiency, and then explores whether it can realize the synergistic effect of pollution and carbon reduction. Based on the panel data of 282 cities in China from 2006 to 2019, this paper treats LCCP as a quasi-natural experiment and tests its effect using difference-in-differences model. The results show that LCCP reduces pollution and carbon emissions and improves synergistic emission reduction efficiency, realizing synergistic effect of pollution and carbon reduction. The policy effects are mainly realized through strengthening technological innovation, tertiary industry employment and human capital. Heterogeneity analysis shows that the synergistic effect of pollution and carbon reduction of LCCP only exists in large cities and non-resource cities. Furthermore, LCCP promotes economic growth, so that it realizes the synergetic effect of pollution and carbon reduction without sacrificing GDP growth.

Keywords Pollution emissions · Carbon emissions · Synergistic emission reduction efficiency · Synergistic effect of pollution · Carbon reduction

1 Introduction

Environmental pollution has become an inescapable problem in the development of many countries. Numerous studies have shown that environmental pollution not only causes economic losses but also harms citizens' health (Currie & Neidell, 2005; Pönkä, 1990; Zivin & Neidell, 2012). Over more than 30 years of rapid economic growth, China has also experienced significant environmental pollution, for which it has paid a high economic price. According to China's National Bureau of Statistics, economic losses caused

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by environmental pollution accounted for 3.05% of GDP in 2004, with water and air pollution accounting for 98.2%.[1] According to the World Bank (2007), direct economic losses caused by environmental pollution in China were 5.8% of the total GDP, excluding health losses. Wang et al. (2020) quantified the economic loss of health caused by environmental pollution using the AHC approach. The results found that the average annual health economic loss from 2007 to 2017 was approximately 283.8 billion dollars, or 4.05% of the total GDP. At the same time, one of the biggest worldwide concerns facing humanity is global warming, which is brought on by greenhouse gas emissions, primarily carbon dioxide, and poses a serious threat to the survival and sustainable development of humankind. Facing increasingly severe climate change, more than 100 countries around the world have committed themselves to achieving carbon neutrality by the middle of the twenty-first century. As the largest developing country, China has also proposed to achieve carbon neutrality by 2060. Under the pressures of achieving the carbon neutrality target and preventing environmental pollution, in June 2022, China's Ministry of Ecology and Environment and seven other departments jointly issued the "implementation plan for the synergistic effect of pollution and carbon reduction", which provides a guide for action on pollution and carbon reduction. It also determines that China should not only reduce pollution emissions but also reduce carbon emissions, and at the same time enhance efficiency. Therefore, how to promote the synergistic effect of pollution and carbon reduction has become the priority of China's ecological civilization construction.

To solve the environmental pollution problem and respond to the climate challenge, China has implemented a series of environmental policies, including the emissions trading pilot policy (Cui et al., 2014), two control zones policy (Cai et al., 2016), LCCP (Khanna et al., 2014), air pollution prevention and control plan (Yang et al., 2022), carbon emissions trading pilot policy (Lo & Chang, 2014), and environmental accountability system (Tan & Mao, 2021), which together provide an institutional guarantee for sustainable development. However, several scholars question the effectiveness of environmental policies. Li et al., (2016) argued that government environmental policies frequently encounter considerable resistance during implementation. Constrained by the economic cycle, policy design, etc., environmental policies have not been effective (Borghesi et al., 2015; Hoffmann, 2007; Wang et al., 2021). Although environmental policies mitigate environmental pollution or carbon emissions, they often come at the expense of economic development and social welfare, such as scale of production, productivity, GDP growth or employment (Barbera & McConnell, 1990; Chen et al., 2018; Gray, 1987; Khastar et al., 2020; Zhu et al., 2023). Governments are often at an impasse between environmental regulation and economic development, which cannot be reconciled. In this context, the question of whether environmental policies can realize synergistic effects of pollution reduction and carbon reduction is worth exploring.

With China's strategic goal of "achieving carbon peaking by 2030 and carbon neutrality by 2060", the effect of environmental policies focusing on carbon reduction has become a hot research topic in recent years. As an important initiative of low-carbon city construction, LCCP has provided valuable practical experience and representative classical cases for China to achieve the "double carbon" goal. As an environmental policy focusing on carbon reduction, can LCCP achieve synergistic effects of pollution and carbon reduction? If so, through what channels? Are there heterogeneous effects? And will the realization of

[1] China Green National Accounts Research Report 2004.

the synergistic effects of pollution and carbon reduction of LCCP result in GDP growth losses? This paper will focus on these issues.

The following three contributions are made by this study. First, based on the concept of the synergistic effect of pollution and carbon reduction, this paper quantifies the synergistic effect of pollution and carbon reduction by simultaneously introducing industrial "three wastes" and carbon emissions, and further introducing economic, social and environmental benefits to construct synergistic emission reduction efficiency indicator. Second, this paper incorporates pollution reduction, carbon reduction and synergistic emission reduction efficiency into the same framework to assess whether LCCP can realize the synergistic effect of pollution and carbon reduction from two dimensions of effectiveness and efficiency. Third, to objectively evaluate the costs and benefits of LCCP, this paper explores the impact of LCCP on GDP growth, which is a useful supplement to the evaluation of the economic effects of LCCP.

2 Literature review

The literature applicable to this study covers two primary aspects. First, the effects of LCCP are reviewed. Scholars have mainly studied the emission reduction effect or economic effect of low-carbon city pilot policies from a single dimension. Regarding the emission reduction effects, scholars focus more on the synergy between air pollution and carbon emission, and study the emission reduction effect of LCCP on $PM_{2.5}$, SO_2, CO_2, etc., as well as synergistic emission reduction effect (Gehrsitz, 2017; He et al., 2023; Li et al., 2022; Liu et al., 2022; Wang et al., 2022; Wolff, 2014). Concerning the economic effects. Scholars have evaluated the positive effects of LCCP from the perspectives of enterprise labor force employment (Wang & Ge, 2022), enterprise total factor productivity (Chen et al., 2021), enterprise R&D investment (Huang et al., 2021), urban carbon emission efficiency (Yu & Zhang, 2021), urban innovation or green low-carbon innovation (Chen et al., 2022; Pan et al., 2022; Tian et al., 2021), and industrial structure upgrading (Zheng et al., 2021). Regarding the study of green economic effects, scholars have mostly investigated the impact of LCCP on the balanced relationship between economic growth and environmental protection through green total factor productivity (Cheng et al., 2019; Qiu et al., 2021; Wang et al., 2023). Based on the indicator of green total factor productivity, Chen and Wang (2022) introduced municipal sewage, municipal solid waste and carbon dioxide emissions as non-desired outputs to measure urban green development efficiency, and assessed the spatial spillover effects of LCCP on it. Yao and Shen (2021) investigated whether LCCP could achieve a win–win situation for environmental protection and economic efficiency and found that LCCP improved air quality but reduced economic efficiency.

Second, the impact of environmental policies on pollution and carbon emission reductions, and economic development. With regard to pollution and carbon emission reductions, scholars have studied the impact of environmental policies such as the emissions trading scheme, carbon emissions trading pilot policy, environmental protection tax, air pollution prevention and control action plan on air pollution, water pollution and carbon emissions, and verified that environmental policies have a positive impact on pollution emissions reduction, carbon emission reduction and the synergy of the two (Dong et al., 2022; Feng et al., 2019; Gao et al., 2022b; Yang et al., 2022; Zhu et al., 2023). With regard to economic development, the research has mainly revolved around the Porter hypothesis, but the conclusions have been inconclusive. Porter and Linde (1995) found that environmental policies can stimulate innovation, improve competitiveness, and generate positive economic growth. Subsequently, many scholars have explored the impact of environmental policies on firm innovation and productivity around Porter's hypothesis, providing literature evidence for the "weak Porter hypothesis" and "strong Porter hypothesis" of environmental policies (Cui et al., 2018; Hamamoto, 2006; Martínez-Zarzoso et al., 2019; Milani, 2017; Rubashkina et al., 2015; Testa et al., 2011). However, some scholars have argued that the implementation of environmental policies increases firms' production costs, which is detrimental to firms' productivity (Greenstone et al., 2012; Tang et al., 2020). Furthermore, to evaluate the expenses and advantages produced by environmental regulations, additional scholars have examined their effects on economic expansion while confirming their capacity to reduce pollution. However, discrepancies in conclusions arise among various environmental regulatory policies. Chen et al., (2018) found that China's two control zone policy significantly reduced pollution emissions but also sacrificed GDP growth. Cao et al., (2021) reached similar conclusions when assessing the impact of carbon emissions trading policies on the power sector. However, Wu et al., (2019) reached a different conclusion. They found that the emissions trading scheme promotes economic growth while reducing SO_2 emissions. Zhang et al., (2021) also found that the carbon emissions trading pilot policy can realize the double dividend of regional carbon equality and green development efficiency.

Through the above literature, we found that when scholars assessed the pollution and carbon reduction effects of environmental regulatory policies such as LCCP, they mainly studied the synergistic effects of single pollutants such as air pollution and carbon emissions, while ignoring water pollution and solid waste pollution. Less literature analyzes the synergistic effect of industrial wastewater emission, industrial SO_2 emission and industrial soot emission with carbon dioxide. Therefore, it is necessary to construct a comprehensive index of industrial "three wastes" and carbon dioxide emissions to analyze the synergistic effect of pollution and carbon reduction. In addition, scholars have already studied the implementation effect of LCCP from a single dimension such as the emission reduction effect or economic effect, but few literatures have assessed the implementation effect of LCCP from the perspective of synergistic pollution and carbon reductions.

3 Policy background and mechanism analysis

3.1 Policy background

In 2006, total carbon emissions in China reached almost 6.6 billion tons, surpassing those of the United States to become the largest carbon emitter worldwide. In 2009, China proposed reducing carbon emissions by between 40 and 45% per unit of GDP by 2020 compared to 2005. To cope with global climate change and achieve the carbon emission reduction target, on July 19, 2010, China officially launched the first batch of low-carbon pilot project, which identified five provinces and eight cities for the exploration stage of LCCP. The main purpose of the first batch of pilots is to mobilize enthusiasm and accumulate pilot experience. The selection of pilot provinces and cities adopted a "top-down" approach designated by central government, and the main task of this pilot is to monitor carbon emissions in each region, develop low-carbon development policies, build a low-carbon emission industrial system, and prepare low-carbon development plans. However, due to the large number of provinces involved in the first pilot project, the pilot project was affected by the large pilot area of the provinces, and the results were not satisfactory. On November 26, 2012, China launched the second batch of low-carbon pilot project including three provinces (municipalities directly under the Central Government) and 26 cities, with the selection of provinces and cities based on a "bottom-up" self-declaration and expert selection process. This second batch pilot is the promotion stage of LCCP. The main purpose is to explore the path of carbon emission reduction and achieve carbon emission reduction, and the main task is to implement the carbon emission target responsibility system. On January 7, 2017, 45 cities were established as the third batch of low-carbon pilots, and the scope of the pilots was further expanded. The pilot list is a city-based unit for the summary phase of implementing LCCP, with the major objective of further exploring and summarizing the experience of low-carbon development. The main task is to complete the peak target and innovation highlights based on the carbon emission target responsibility system. Combined with the tasks of low-carbon city pilot arrangement, LCCP mainly focuses on adjusting industrial structure, improving quality and efficiency, energy saving and consumption reduction, etc. to carry out a series of work, and then achieve carbon emission reduction targets. LCCP has produced positive policy effects and provided a lot of valuable experience for China's green low-carbon development and the achievement of the "double carbon" target. China's CO_2 emissions per unit of GDP decreased by 48.1% from 2005 to 2019. Figure 1 shows the distribution of the low-carbon pilot cities in China.

3.2 Mechanism analysis

The primary goal of LCCP is to control and reduce carbon emissions. Since pollution and carbon emissions are characterized by a high degree of homogeneity, this provides viability for realizing the synergistic effect of pollution and carbon reduction. Therefore, this study analyzes the synergistic effect of pollution and carbon reduction of LCCP by combining the associated implementation strategies and objectives.

First, LCCP can promote technological innovation. LCCP requires pilot cities to configure environmental pollutant monitoring equipment to collect data on environmental pollution of air and water, and solid waste. When monitored for environmental compliance, enterprises will use clean energy for production and accelerate the innovation and development of green production technologies. Simultaneously, low-carbon pilot cities undertake intensive R&D, particularly on low-carbon technologies, introduce energy-saving and environmental protection technologies, and establish a comprehensive public service platform for R&D, including incubation, promotion, and application of low-carbon technology innovation. It is evident that this process undoubtedly accelerates technological innovation. With technological innovation, polluting enterprises can renovate and upgrade high energy-consuming equipment, and more advanced technology can also be developed for the treatment of pollutants and waste products to achieve pollution and carbon reduction synergies at the beginning and end of production. The technological innovation and progress of enterprises result in cleaner and more efficient production, which can effectively reduce the intensity of energy consumption and improve energy use efficiency (Fisher-Vanden et al., 2006). This makes corporate production more clean and efficient, resulting in more ecologically friendly products, thereby promoting the synergistic effect of pollution and carbon reduction.

Second, LCCP promotes employment restructuring. Industrial restructuring is one of the key tasks of low-carbon pilot cities. LCCP motivates local governments to pursue the

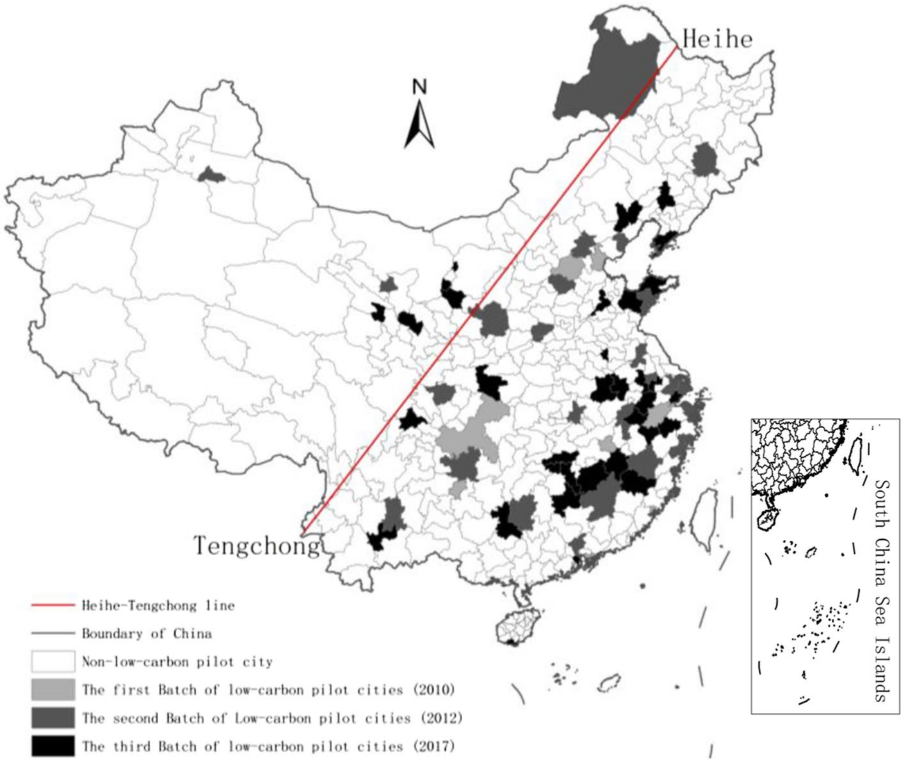

Fig. 1 Distribution of low-carbon pilot cities in China

development of low-carbon industries. Local governments eliminate backward production capacity by establishing an adjustment and exit directory for highly polluting enterprises. To continue operating, highly polluting enterprises must transform to clean, environmentally friendly, and low-carbon production. Simultaneously, quantitative development goals for the tertiary industry are set by local governments. New high-technology industries are introduced and policy support for environmentally friendly and clean production technology is increased resulting in the provision of funds, talent, and technology. This plays a positive role in the transfer of labor to high-technology industries, and labor gradually moves from secondary to tertiary industries. In general, LCCP suppresses the production scale of polluting enterprises and promotes the development of high-technology and service industries. The urban functions transform from industrialized to service trade functions, which is conducive to upgrading the industrial structure, thus adjusting employment structure. Industrial structure upgrading reduces dependence on resources and environmental damage from industry production activities, which is conducive to achieving pollution and carbon reduction synergies, and enhancing eco-efficiency (Zhu et al., 2019). Industrial structure upgrading also results in production factors such as the labor force gradually moving to high-production efficiency sectors, which is conducive to improving the total production efficiency of society and promoting high-quality economic growth. Then, the synergistic effect of pollution and carbon reduction can be realized.

Third, LCCP increases human capital. LCCP greatly improves urban environmental quality, making cities more livable and better able to meet the health requirements of people. This is conducive to the transfer of population, particularly those with high education levels, to low-carbon cities (Li et al., 2017; Lu et al., 2018), promoting human capital accumulation in these cities. In addition, LCCP increases the demand for highly skilled personnel. The local governments pay more attention to human capital investment. For example, by increasing investment in education and performing low-carbon technology training, highly skilled talent can be cultivated and human capital can be increased. Higher human capital growth can direct production resources to high-technology fields and eliminate resource constraints (Kurtz & Brooks, 2011). At the same time, with high-quality human capital, there is a strong environmental awareness, which is conducive to the development of environmentally friendly enterprises, where environmental performance is improved and Synergistic governance for pollution and carbon reduction is realized (Lan & Munro, 2013). LCCP requires human capital for technological innovation and the upgrading of industry structure. Human capital can develop and apply low-carbon technologies and promote the low-carbon development of industries. The introduction and cultivation of human capital promote innovation at the source, which is conducive to improving labor productivity and providing an endogenous impetus for the synergistic effect of pollution and carbon reduction.

4 Methods and data

4.1 The DID model

The DID model is a method used to assess policy effects. Its logic is as follows: choose a group of areas or individuals not affected by the policy as the control group, and those affected by the policy as the treatment group. The difference between the control group before and after the implementation of the policy can be regarded as a pure time effect, and the "net effect" of the policy can be obtained by subtracting the before and after the change of the control group from the before and after the change of the treatment group. The quasi-natural experiment with DID method can effectively avoid the problems of endogeneity and omitted variables.

As a quasi-experiment, LCCP divides the sample cities into low-carbon pilot cities (treatment group) and non-low-carbon pilot cities (control group), which provides an opportunity to set up a DID model. The benchmark model is set as follows.

$$Y_{it} = \beta_0 + \beta_1 \mathrm{LCCP}_{it} + \lambda \mathrm{Control}_{it} + u_i + v_t + \varepsilon_{it} \quad (1)$$

In Eq. (1), i and t denote the city and time, respectively. The explained variable is Y, including pollution and carbon emissions, and synergistic emission reduction efficiency. Core explanatory variable is LCCP, coefficient of interest is β_1. Series of control variables is represented by Control, urban fixed effect model is u_i, time fixed effect is v_t, and β_0 is a constant term.

Table 1 Indicator system of synergistic emission reduction efficiency

Variable type	Indicator	Variable description and units
Factor input	Capital input	the capital stock (billions of yuan) (Huang et al., 2018)
	Labor input	Number of urban employees at the end of the year (10,000)
	Land input	Urban built-up land area (square kilometers)
Desired output	Economic benefit	GDP (billions of yuan)
	Social benefit	Public budget revenues (billions of yuan)
	Environmental benefit	Greening coverage of built-up areas(%)
Undesired output	Carbon emissions	Carbon dioxide emissions (10 kilo-tons)
	Industrial pollution emissions	Industrial wastewater, SO_2, and dust emissions (10 kilo-tons)

4.2 Variables and data

4.2.1 Explained variables

Pollution and carbon emissions (*pce*). The "implementation program of the synergistic effect of pollution and carbon reduction" pointed out that it is necessary to integrate the requirements of emission reduction in multiple fields, such as air, water, soil, solid waste and greenhouse gases, so as to organically connect the targets of pollution and carbon reduction. Therefore, this paper first adopts the entropy weight method to measure the comprehensive index of industrial wastewater, industrial sulfur dioxide, industrial smoke and dust emissions to measure pollution emissions. Then, the cross-multiplier of carbon emissions and pollution emissions is used to characterize the level of pollution and carbon emissions. The cross-multiplier term is consistent with the concept of synergistic management of pollution and carbon reduction (Lu et al., 2022).

Synergistic emission reduction efficiency (sere). The synergistic effect of pollution and carbon reduction is not only to realize the synergistic control and management of carbon and pollution emissions but also to bring about social and economic benefits while generating environmental benefits. In other words, the synergistic control and management of carbon and pollutant emissions should be carried out to provide a variety of synergistic benefits, including environmental, economic, and social benefits. Based on the above understanding, and referring to Yang et al., (2022), this paper constructs a synergistic emission reduction efficiency indicator system (Table 1). At the same time, this paper adopts the super-efficient SBM model considering non-desired output to measure efficiency. The formula is the non-radial, non-angle SBM model proposed by Tone (2002). Each city is considered a production decision unit (DMU). Suppose there are n DMUs and each DMU has 3 vectors, i.e., input, desired output and non-desired output, which are X, Y^d, Y^u, respectively. The matrix X, Y^d, Y^u can be defined as follows (Lee & Lee, 2022).

$$
\begin{aligned}
X &= \left[x_1, \cdots, x_n\right] \in R^{m\times n} > 0 \\
Y^d &= \left[y_1^d, \cdots, y_n^d\right] \in R^{s1\times n} > 0 \\
Y^u &= \left[y_1^u, \cdots, y_n^u\right] \in R^{s2\times n} > 0
\end{aligned} \tag{2}
$$

The production possibility set is then defined as:

$$
P=\left\{ \left(x, y^d, y^u\right) \middle| x \geq X\lambda, y^d \leq Y^d\lambda, y^u \geq Y^u\lambda, \lambda \geq 0 \right\} \tag{3}
$$

The mathematical expression of the super-efficient SBM model is

$$
\rho = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{l=1}^{s_1}\frac{\bar{y}_l^d}{y_{l0}^d}+\sum_{k=1}^{s_2}\frac{\bar{y}_k^u}{y_{k0}^u}\right)} \text{s.t.}\begin{cases} \bar{x} \geq \sum_{j=1,j\neq j_0}^{n} x_{ij}\lambda_j; \bar{y}^d \leq \sum_{j=1,j\neq j_0}^{n} y_{lj}^d\lambda_j; \bar{y}^u \geq \sum_{j=1,j\neq j_0}^{n} y_{kj}^u\lambda_j \\ \bar{y}^d \leq y_{lj}^d; \bar{y}^u \geq y_{kj}^u \\ \lambda_j \geq 0,\ i = 1,2,\cdots,m; j = 1,2,\cdots,n; l = 1,2,\cdots,s_1,\ k = 1,2,\cdots,s_2 \end{cases} \tag{4}
$$

In Eq. (4), ρ is synergistic emission reduction efficiency value. n is the number of production decisions. m, s_1 and s_2 represent the number of input variables, expected output variables and undesired output variables, respectively.x_{i0}, y_{l0}^d and y_{k0}^u are input indicators, desired output indicators and undesired output indicators, respectively. The input matrix, the desired output matrix, and the undesired output matrix, is represented by $x_{ij}\lambda_j$, $y_{lj}^d\lambda_j$ and $y_{kj}^u\lambda_j$, respectively. λ is the weight variable of each decision unit.

4.2.2 Explanatory variables

Low-carbon city pilot policy (LCCP). If city i is approved as a low-carbon city pilot in year t, it takes the value of 1; otherwise, it takes the value of 0. Since China's LCCP is divided into three batches, and the time of policy implementation is not uniform, if the policy is implemented after July of the current year, the latter year is chosen as the year of policy implementation.

4.2.3 Mechanism variables

The total number of urban patents was selected to measure technological innovation (ti). For employment restructuring, this study mainly observed the number of employed persons reallocated from the secondary to tertiary industry. The number of employed persons in extractive and manufacturing industries was selected to measure employment in secondary industries (manu-labor), while the number of employed persons in science and technology was adopted to reflect employment in high-technology industries (tech-labor). The number of school students per 10,000 population in general higher education institutions was selected to represent human capital (hc).

4.2.4 Control variables

To control the influence of other factors on the regression results, referring to previous literature (Cheng et al., 2019; Yu & Zhang, 2021), the following control variables are selected. Foreign direct investment (fdi) was measured by the ratio of actual foreign capital utilization

Table 2 Data descriptive statistics

Variable	Obs	Mean	Std. dev	Min	Max
pe	3948	0.064	0.061	0.000	0.701
ce	3948	6.150	1.211	2.019	9.603
pce	3948	0.422	0.479	0.000	5.690
sere	3948	0.280	0.186	0.060	1.397
LCCP	3948	0.090	0.286	0.000	1.000
fdi	3948	0.018	0.019	0.000	0.198
is	3948	−0.767	0.254	−2.146	−0.095
market	3948	0.820	0.099	−0.027	0.977
fix	3948	0.728	0.296	0.087	2.413
ti	3948	0.393	1.051	0.000	16.610
manu-labor	3948	16.799	25.600	0.218	256.280
tech-labor	3948	1.191	3.943	0.010	71.715
hc	3948	12.762	19.246	0.000	140.905

to GDP. Industrial structure (is) is measured by the ratio of value added of secondary industry to GDP after logarithm. The degree of marketization (market) was calculated using 1-(fiscal expenditure/GDP). Fixed asset investment (fix) was expressed by the ratio of total fixed asset investment to GDP.

The sample includes a total of 282 cities, and the sample interval is from 2006 to 2019. The list of low-carbon city pilots was obtained from the website of China's National Development and Reform Commission. Other collected data are mainly from three databases: the China Urban Statistical Yearbook, the China Urban Construction Statistical Yearbook, and the State Intellectual Property Office. A few missing data were supplemented by interpolation. Table 2 shows the descriptive statistics of the variables.

5 Empirical analysis

5.1 Baseline regression results

Table 3 presents the results of the baseline regressions. It can be seen that the regression coefficients of LCCP on pollution emissions, carbon emissions and the cross-multiplier term of the two are significantly negative, indicating that LCCP reduces pollution emissions and carbon emissions simultaneously, realizing the synergistic management of pollution and carbon reduction. The regression coefficient of LCCP on synergistic emission reduction efficiency is significantly positive, indicating that LCCP enhances synergistic emission reduction efficiency. The above regression results show that LCCP has a statistically significant synergistic effect of pollution and carbon reduction. Furthermore, the regression coefficients of pollution and carbon emissions and synergistic emission reduction efficiency are -0.0976 and 0.0687, respectively. This indicates that the synergistic emission reduction effect of LCCP is greater than the synergistic efficiency effect. The reason may be that China's ecological civilization construction in the 14th Five-Year Plan period takes carbon reduction as the key strategic direction, and promotes the synergistic effect of pollution and carbon reduction. LCCP is also aimed at carbon reduction.

Table 3 Baseline regression results

Variable	pe	ce	pce	sere
LCCP	−0.0105***	−0.1147***	−0.0976***	0.0687***
	(0.0021)	(0.0289)	(0.0149)	(0.0090)
fdi	−0.0664*	0.9040*	−0.3928	−0.1105
	(0.0388)	(0.5394)	(0.2779)	(0.1684)
is	0.0090*	0.5536***	0.0920***	−0.0648***
	(0.0046)	(0.0634)	(0.0327)	(0.0198)
market	−0.0358***	−0.1180	−0.2578***	0.1850***
	(0.0127)	(0.1763)	(0.0908)	(0.0551)
fix	0.0047*	−0.0634*	0.0416**	−0.1397***
	(0.0025)	(0.0354)	(0.0182)	(0.0110)
_cons	0.0987***	6.7115***	0.6892***	0.1759***
	(0.0122)	(0.1695)	(0.0873)	(0.0529)
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	3948	3948	3948	3948
R^2	0.8245	0.9154	0.8564	0.6489

Robust standard errors clustered at the city level in parentheses; *$p<0.10$, p ** <0.05, p *** <0.01

Therefore, LCCP is more conducive to the synergistic management of pollution and carbon reduction.

5.2 Parallel trend test

The ability of the treatment and control groups to meet parallel trends before policy implementation is a prerequisite assumption that must be considered in DID estimation. In other words, β_1 should reflect the treatment effect after the implementation of the policy, rather than the existing trend of LCCP on pollution and carbon emissions and synergistic emission reduction efficiency. This study used event analysis to test for parallel trends. The specific model is configured as follows.

$$Y_{it} = \beta_0 + \sum_{k=-4}^{6} \beta_k D_{it}^k + \lambda \text{control}_{it} + u_i + v_t + \varepsilon_{it} \tag{5}$$

In Eq. (5), D_{it}^k represents the year after the pilot was approved (if k is negative, the sample is in the year k before the pilot was approved). To avoid the multicollinearity problem, this paper takes the first period before the policy (pre1) as the base year and excludes this time dummy variable. Meanwhile, in terms of the dynamic effects of the policy, considering that although the first batch of pilot cities has been implementing the policy for nearly 9 years as of 2019, the first batch of pilots is mainly provincial pilots and is not representative, while the number of pilot cities in the second and third batch of pilots is significantly higher (the pilot time is set to 2013 and 2017), for this reason, this paper mainly analyzes the dynamic effects within the 6-period and merges the time after the 6-period for other cities to the 6-period. Figure 2 shows the estimated results of the coefficients at 95%

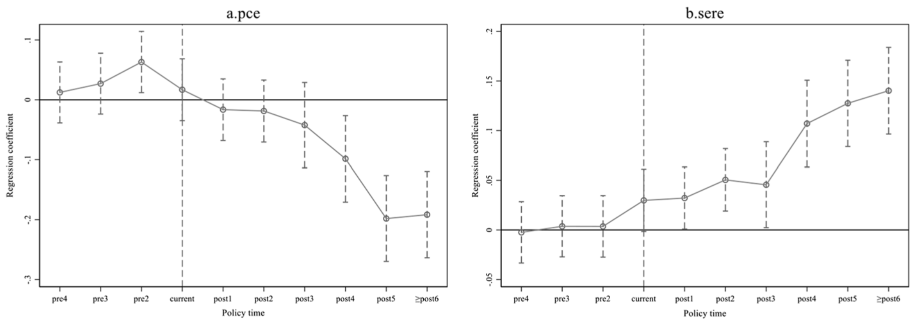

Fig. 2 Parallel trend test

confidence intervals (this paper focuses on the test results of pollution and carbon emission levels and synergistic emission reduction efficiencies, the same as below). Figure 2a shows the test results of pollution and carbon emission levels, and Fig. 2b shows the test results of synergistic emission reduction efficiency. Before the implementation of LCCP, the regression coefficients of LCCP on them are not significant and fluctuate around 0, which satisfies the parallel trend assumption.

5.3 Placebo test

The effect of unobservable factors on the regression results is a concern when conducting a DID estimation. While this study controls for fixed effects such as time and location, unobservable effects of city characteristics may still exist. To exclude this issue, this study performs an indirect placebo test by randomly generating treatment groups (Chetty et al., 2009). The specific logic is defined below. First, according to Eq. (6), the expression for the coefficient can be derived as $\hat{\beta}$.

$$\hat{\beta} = \beta + \gamma \times \frac{\mathrm{cov}(LCCP, \varepsilon_{it}|H)}{\mathrm{var}(LCCP|H)} \tag{6}$$

In Eq. (6), observable control variables and control effects are represented by H and γ indicates the effect of unobservable factors. If $\gamma = 0$, the estimation results are not affected by unobservable factors, however, whether $\gamma = 0$ cannot be directly verified. For this reason, this paper uses an indirect placebo method to generate a "pseudo-treatment group" based on the number of treatment groups. Because the list of low-carbon pilot cities is randomly generated, then $\beta = 0$. It can be further inferred that if $\hat{\beta} \neq 0$, then the results are affected by unobservable factors. In this paper, the generated pseudo-policy dummy variables are selected for regression and the randomization process is repeated 1000 times. The kernel density distribution of the estimation results is shown in Fig. 3. It is evident that the kernel density of $\hat{\beta}$ is concentrated around 0 and normally distributed, which is consistent with the expected placebo test results.

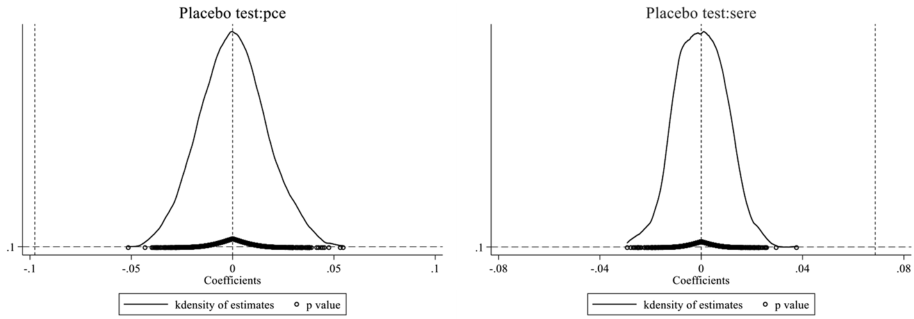

Fig. 3 Placebo test

Table 4 Robustness tests I

Variable	PSM-DID		IV estimation		Considering spatial spillover effects	
	pce	sere	pce	sere	pce	sere
LCCP	−0.0961***	0.0664***	−2.5796***	0.4873***	−0.0960***	0.0691***
	(0.0149)	(0.0089)	(0.8448)	(0.1484)	(0.0142)	(0.0086)
W*LCCP					0.0051	−0.0238
					(0.0283)	(0.0172)
_cons/ρ	0.7693***	0.1036*	4.2761***	0.7448***	0.1686***	0.1181***
	(0.0977)	(0.0581)	(0.3505)	(0.0616)	(0.0214)	(0.0225)
Control	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3932	3932	3948	3948	3948	3948
R^2/F test	0.8563	0.6561	34.89***	34.89***	0.0117	0.0010

Robust standard errors clustered at the city level in parentheses; *$p<0.10$, p **<0.05, p ***<0.01

5.4 Robustness test

5.4.1 Propensity score matching (PSM)

Possible sample selection bias between low-carbon pilot cities and non-low-carbon cities could lead to unreliable regression results. To solve the problem, neighbor matching in PSM method is used to identify control groups similar to the treatment group and eliminate the differences between the pilot and non-pilot cities before conducting the DID estimation. The results are shown in Table 4. The regression results are robust.

5.4.2 Instrumental variable estimation

The problems of possible self-selection of low-carbon pilot cities, the possible omitted variable of the regression model, and possible measurement error of the regression data can highlight the endogeneity problem that cannot be solved by the DID model. To address these issues, this study uses the ventilation coefficient as an instrumental variable for revalidation (Hering & Poncet, 2014). The estimated results are presented in Table 4, and the regression results remain robust.

5.4.3 Considering spatial spillover effects

Considering the possible spatial correlation of pollution emissions and carbon emissions, this paper introduces spatial factors for robustness testing based on the baseline model. The spatial model is chosen as the spatial Durbin model. The spatial weight matrix adopts the spatial neighbor matrix. The regression results are shown in Table 4, which are robust considering the influence of spatial factors.

5.4.4 Additional robustness tests

The regression results are also influenced by many benchmark factors, This paper specifically assessed the effects of urban specificity, the Heihe-Tengchong line, and other environmental policies. To control for these benchmark factors, these factors with a linear trend over time are included in the regression (Edmonds et al., 2010). The following equation is used in the estimation.

$$Y_{it} = \beta_0 + \beta_1 \mathrm{LCCP}_{it} + \beta_2 \mathrm{d}t + \lambda \mathrm{Control}_{it} + u_i + v_t + \varepsilon_{it} \tag{7}$$

In Eq. (7), dt is the cross term between the baseline factor and linear trend over time, and the remaining variables are consistent with the baseline model.

The first is the specificity of the city. The presence of differences in political and economic characteristics among different cities in China, whether the pilot city is a provincial capital, a planned city, or a special economic zone city can result in the selected pilot cities being significantly different from non-pilot cities, and cause bias in the estimation. we included these prior factors with a linear trend of time for regression. The second is the Heihe-Tengchong line.[2] The unbalanced population distribution on the east and west sides of the Heihe-Tengchong line is accompanied by an unbalanced energy supply and demand, with a higher population density and energy consumption on the eastern side than on the western side. The majority of low-carbon pilot cities are located on the east side of the Heihe-Tengchong line, and this distribution characteristic may affect the estimation results. Therefore, this study adds the dummy variables of the east and west sides of the Heihe-Tengchong line for regression. Third, the impact of other environmental policies is also a concern. As a result, various environmental policies implemented concurrently with the LCCP have been collated. The air emission limit policy[3] and the carbon emission trading

[2] The Heihe-Tengchong Line is a comparison of population density in China proposed by Chinese geographer Hu Huanyong in 1935. In this paper, the cities in Tibet, Xinjiang, Qinghai, Gansu, Inner Mongolia, and Ningxia are classified as the area west of the Heihe-Tengchong Line, whereas the cities in the remaining provinces (excluding Hong Kong, Macao, and Taiwan) are classified as the area east of the Heihe-Tengchong Line.

[3] See the announcement on the implementation of special emission limits for air pollutants issued by the Chinese Ministry of Ecology and Environment https://www.mee.gov.cn/gkml/hbb/bgg/201303/t20130305_248787.htm.

Table 5 Robustness tests II

Variable	City specificity		Heihe-Tengchong line	
	pce	sere	pce	sere
LCCP	−0.0654***	0.0373***	−0.1996***	0.1161***
	(0.0177)	(0.0107)	(0.0195)	(0.0119)
dt	−0.0965***	0.0944***	0.1285***	−0.0597***
	(0.0286)	(0.0173)	(0.0161)	(0.0098)
_cons	0.6728***	0.1920***	0.6954***	0.1731***
	(0.0873)	(0.0528)	(0.0866)	(0.0527)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	3948	3948	3948	3948
R^2	0.8568	0.6518	0.8589	0.6525

Robust standard errors clustered at the city level in parentheses; $*p<0.10$, p $**<0.05$, p $***<0.01$

Table 6 Robustness tests III

Variable	Air emission limitation policy		Carbon emissions trading policy	
	pce	sere	pce	sere
LCCP	−0.0963***	0.0684***	−0.0973***	0.0684***
	(0.0148)	(0.0090)	(0.0149)	(0.0090)
Air policy	−0.1019***	0.0259**		
	(0.0192)	(0.0117)		
Carbon policy			−0.0440**	0.0501***
			(0.0171)	(0.0103)
_cons	0.6704***	0.1807***	0.7017***	0.1617***
	(0.0871)	(0.0529)	(0.0874)	(0.0528)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	3948	3948	3948	3948
R^2	0.8575	0.6494	0.8567	0.6512

Robust standard errors clustered at the city level in parentheses; $*p<0.10$, p $**<0.05$, p $***<0.01$

policy[4] are selected and the dummy variables of the two policies are introduced for the regression. The above regression results are shown in Tables 5 and 6. The main regression

[4] The National Development and Reform Commission of China issued the Notice on the Pilot Project of Carbon Emission Trading in October 2011, and Shenzhen City took the lead in carbon trading in China in June 2013. Subsequently, Shanghai City, Beijing City, Tianjin City, Chongqing City, Hubei Province, and Guangzhou Province established carbon trading markets in 2014. Fujian Province was selected as a pilot region in 2017.

Table 7 Regression results of city size heterogeneity

Variable	Large cities pce	Small cities pce	Large cities sere	Small cities sere
LCCP	−0.1416***	0.0100	0.0974***	0.0172
	(−4.57)	(0.66)	(0.0102)	(0.0135)
_cons	1.3008***	0.2539***	0.1763*	0.2793***
	(0.2797)	(0.0717)	(0.0922)	(0.0643)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	1274	2674	1274	2674
R^2	0.8795	0.7654	0.7774	0.6074

Robust standard errors clustered at the city level in parentheses; $*p<0.10$, $p**<0.05$, $p***<0.01$

coefficients do not change, indicating that the above factors do not affect the baseline regression results.

6 Further analysis

6.1 Heterogeneity test

City size is a key factor affecting economic development and pollution and carbon reduction. On the one hand, there is an interactive mechanism between city size and economic growth. The expansion of city size can enhance urban production efficiency and promote economic development through the scale and agglomeration effects. Meanwhile, with the expansion of city size, the level of industrial agglomeration increases, and the industrial structure tends to be significantly service-oriented, which is conducive to reducing pollution and carbon emissions. Therefore, the city size may affect the synergistic effects of pollution and carbon reduction of LCCP. In this study, the sample was divided into large and small cities.[5] The regression results are shown in Table 7. LCCP significantly reduces pollution and carbon emissions and improves synergistic emission reduction efficiency in large cities. However, the impact of the LCCP on small cities is not significant. This indicates that LCCP only has a significant synergistic effect on pollution and carbon reduction in large cities. This may be because large cities have a higher population and can take advantage of population clustering to promote the spread of knowledge and technology. The excellent infrastructure of large cities attracts more highly skilled personnel, which provides the human capital for technological innovation and industrial structure upgrading, achieving the synergistic effect of pollution and carbon reduction in large cities. In contrast, owing to development constraints, existing technology and workforce in small cities may be incapable of supporting the effective implementation of emission reduction

[5] The 2019 population of municipal districts is used as the basis for classifying city size. Large cities have a population of more than 5 million, and small cities have a population of less than 5 million.

Table 8 Regression results of urban resource endowment heterogeneity

Variable	Resource-based cities	Non-resource-based cities	Resource-based cities	Non-resource-based cities
	pce	pce	sere	sere
LCCP	0.0158	-0.1253^{***}	0.0111	0.0775^{***}
	(0.0244)	(0.0195)	(0.0164)	(0.0112)
_cons	0.3996^{***}	0.9153^{***}	0.4964^{***}	-0.2541^{***}
	(0.0954)	(0.1507)	(0.0641)	(0.0869)
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	1596	2352	1596	2352
R^2	0.8484	0.8617	0.6410	0.6630

Robust standard errors clustered at the city level in parentheses; $^{*}p<0.10$, $p^{**}<0.05$, $p^{***}<0.01$

measures related to low-carbon city pilots promptly, resulting in an insignificant synergistic effect of pollution and carbon reduction in small cities.

Urban resource endowment is another important factor affecting economic development and pollution and carbon reduction. On the one hand, secondary industries dominate the industrial structure of resource-based cities, and resource-based industries account for a larger proportion of the economy. As a result, resource-based cities face more severe environmental pollution issues. On the other hand, cities with high resource endowments tend to form resource dependence, which leads to the “resource curse”, in which natural resources are believed to inhibit innovation and impede economic growth (Sachs & Warner, 1999). Therefore, urban resource endowment may affect the effects of LCCP. According to the resource-based cities delineated in the Sustainable Development Plan for China’s Resource Cities (2013–2020),[6] the sample is divided into resource-based cities and non-resource-based cities for regression, and the regression results are shown in Table 8. LCCP significantly reduces pollution and carbon emissions and improves the synergistic emission reduction efficiency in non-resource-based cities, while the effect on resource-based cities is not significant. In other words, LCCP only has a significant synergistic effect on pollution and carbon reduction in non-resource-based cities. This may be because the industrial structure of resource-based cities is mostly resource-consuming and environmentally polluting, and industrial transformation and upgrading and economic development model transformation confront more difficulties, which makes it difficult to realize the synergistic effect of pollution and carbon reduction of LCCP in the short term. The industrial structure in non-resource-based cities is less dependent on resources, LCCP enables enterprises in non-resource-based cities to invest more energy in low-carbon technology innovation and application, which is conducive to realizing the synergistic effect of pollution and carbon reduction.

[6] The planning scope includes 262 resource cities, of which 126 are prefecture-level administrative regions (including prefecture-level cities, regions, autonomous prefectures, leagues, etc.), and the list of specific resource cities is available at https://www.gov.cn/zwgk/2013-12/03/content_2540070.htm.

Table 9 Regression results of mechanism test: technological innovation and human capital

Variable	Technological innovation			Human capital		
	ti	pce	sere	hc	pce	sere
LCCP	0.7172***	−0.0385**	0.0355***	3.2791***	−0.0714***	0.0624***
	(0.0429)	(0.0150)	(0.0091)	(0.3542)	(0.0148)	(0.0091)
ti		−0.0823***	0.0463***			
		(0.0056)	(0.0034)			
hc					−0.0080***	0.0019***
					(0.0007)	(0.0004)
_cons	0.5756***	0.2398***	0.2341***	−5.2229**	0.6475***	0.1859***
	(0.0852)	(0.0519)	(0.0519)	(2.0767)	(0.0858)	(0.0528)
Control	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3948	3948	3948	3948	3948	3948
R^2	0.7526	0.8645	0.6659	0.9498	0.8616	0.6509

Robust standard errors clustered at the city level in parentheses; $*p<0.10$, $p ** <0.05$, $p *** <0.01$

Table 10 Regression results of mechanism test: employment structure

Variable	Secondary employment			Tertiary employment		
	manu-labor	pce	sere	tech-labor	pce	sere
LCCP	3.9867***	−0.0932***	0.0727***	1.2572***	−0.0607***	0.0437***
	(0.8051)	(0.0149)	(0.0090)	(0.0810)	(0.0152)	(0.0092)
Manu-labor		−0.0011***	−0.0010***			
		(0.0003)	(0.0002)			
tech-labor					−0.0293***	0.0199***
					(0.0030)	(0.0018)
_cons	8.4999*	0.6985***	0.1844***	−1.1720**	0.6548***	0.1993***
	(4.7195)	(0.0872)	(0.0528)	(0.4749)	(0.0863)	(0.0521)
Control	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3948	3948	3948	3948	3948	3948
R^2	0.8534	0.8569	0.6517	0.9374	0.8601	0.6601

Robust standard errors clustered at the city level in parentheses; $*p<0.10$, $p ** <0.05$, $p *** <0.01$

6.2 Mechanism test

This paper has previously suggested that LCCP can promote technological innovation, facilitate employment restructuring, and increase human capital to achieve the synergistic effect of pollution and carbon reduction. Tables 9 and 10 present the regression results of the mechanism test. LCCP significantly promotes technological innovation. In terms of technological innovation, LCCP remarkably stimulates technological innovation. Further, technological innovation effectively suppresses pollution and carbon emissions, and also positively promotes synergistic emission reduction efficiency. It shows that LCCP realizes the synergistic effect of pollution and carbon reduction by promoting technological innovation. From the perspective of human capital, LCCP enhances human capital. At the same time, human capital suppresses pollution and carbon emissions and enhances synergistic emission reduction efficiency. It shows that LCCP realizes the synergistic effect of pollution and carbon reduction through the enhancement of human capital. It is consistent with the mechanism analysis section. In terms of employment structure adjustment, the effects of LCCP on employment in the secondary and tertiary industries are significantly positive. Further, employment in the secondary industry significantly inhibits pollution and carbon emissions, as well as the synergistic emission reduction efficiency. It indicates that LCCP only achieves the synergistic control of pollution and carbon reduction by promoting secondary industry employment. Employment in the tertiary industry significantly suppresses pollution and carbon emissions and is conducive to enhancing the synergistic emission reduction efficiency. It indicates that LCCP realizes the synergistic effect of pollution and carbon reduction by promoting employment in the tertiary industry. The reason for this may be that LCCP stimulates traditional industrial enterprises to implement technological transformation toward decarbonization, which significantly promotes the upgrading and innovation of industrial structure (Chen et al., 2022; Pan et al., 2022), and provides a favorable market environment for boosting employment in the secondary industry. Meanwhile, the increase in employment in the secondary industry is accompanied by green transformation and upgrading, which is conducive to the realization of pollution and carbon reductions. However, in the short term, the employment increase in the process of green transformation and upgrading of traditional industrial enterprises is more used for pollution control than for production, which makes the employment in the secondary industry have a masking effect on the synergistic emission reduction efficiency of LCCP. In addition, the low-carbon pilot cities vigorously develop low-carbon industries and set quantitative development goals for the tertiary industry, which promotes the development of the industrial structure toward the tertiary industry and increases the total labor demand in the tertiary industry, thus better exerting the green and low-carbon advantages of the tertiary industry and achieving synergistic emission reduction efficiency.

6.3 Expanded analysis

To evaluate whether the emission reduction effect of LCCP is attained at the expense of GDP growth, the explained variables are replaced with real GDP per capita. The results are shown in Table 11. With the introduction of control variables and fixed effects, the regression coefficient of LCCP on real per capita GDP is 0.0381. Relative to non-low-carbon cities, LCCP makes the low-carbon city's economic growth quantity increase by 3.81%. The above results indicate that LCCP does not achieve the synergistic effect of pollution and carbon reduction by sacrificing economic performance.

7 Discussion

This paper uses DID model to identify the causal relationship between LCCP and pollution and carbon emissions and synergistic emission reduction efficiency. This paper finds that LCCP significantly reduces pollution and carbon emissions, and enhances synergistic

Table 11 Regression results of expanded analysis

Variable	GDP	GDP	GDP	GDP
LCCP	0.0342**	0.1823***	0.5525***	0.0381***
	(0.0156)	(0.0156)	(0.0403)	(0.0142)
_cons	15.6907***	16.2683***	11.3193***	15.2205***
	(0.0035)	(0.0887)	(0.1591)	(0.0832)
Control	No	Yes	Yes	Yes
City FE	Yes	Yes	No	Yes
Time FE	Yes	No	Yes	Yes
N	3948	3948	3948	3948
R^2	0.9578	0.9526	0.4752	0.9656

Robust standard errors clustered at the city level in parentheses; $*p<0.10$, $p **<0.05$, $p ***<0.01$

emission reduction efficiency. Similar findings have been reported by Cheng et al., (2019) and Wang et al., (2022),. This could be because LCCP aims to reduce carbon dioxide emissions, and environmental pollution has the same source as carbon dioxide. As a result, LCCP efficiently reduces environmental pollution while simultaneously reducing carbon emissions. Previous studies have more often analyzed the mechanisms of LCCP from the perspectives of energy consumption, technological innovation, and industrial structure upgrading (Gao et al., 2022a; Li et al., 2022; Song et al., 2020; Zeng et al., 2023). This paper further explores the mechanisms of LCCP on the synergistic effect of pollution and carbon reduction based on employment structure and human capital. The results find that LCCP promotes the upgrading of employment structure and enhances human capital. This is similar to the findings of Zheng et al., (2021). They found that LCCP reduces the proportion of high-carbon industries and makes the industrial structure upgrade to tertiary industries. In addition, differing from the conclusion of previous studies that the emission reduction effect of environmental policies is achieved at the expense of GDP growth (Chen et al., 2018). This paper finds that LCCP improves GDP growth. This may be because the two-control zone policy adopted by Chen et al., (2018) was implemented earlier when China's economy was at a high growth stage and the competing concerns of economic expansion and environmental protection were extremely prominent. The implementation of the two control zone policy made it necessary to reduce the economic growth rate to achieve environmental protection. During the implementation of LCCP, China was undergoing economic transformation and upgrading, and under the guidance of the green development concept, the synergy between economic and social development and ecological environmental protection became the goal. Therefore, LCCP did not lose GDP growth while reducing pollution and carbon emissions. This is supported by Yang et al., (2019).

8 Conclusions and policy recommendations

The effectiveness of environmental policies has always been a popular topic in academic research. Whether environmental policies can achieve the synergistic effect of pollution and carbon reduction is a question that remains to be answered. Based on a quasi-natural experiment of LCCP in China, this paper empirically examined the synergistic effect of pollution and carbon reduction of LCCP from effectiveness and efficiency perspectives using DID model. The results find that LCCP significantly reduces pollution and carbon emissions by 9.76% and increases synergistic emission reduction efficiency by 6.87%, realizing the synergistic effect of pollution and carbon reduction. This result holds after conducting a series of robustness tests. The results of the mechanism analysis show that LCCP mainly promotes technological innovation, optimizes employment structure, and enhances human capital to achieve the synergistic effect of pollution and carbon reduction. The results of the heterogeneity analysis show that the synergistic effect of pollution and carbon reduction of LCCP only exists in large and non-resource cities, with no significant effect on small cities and resource cities. The expanded analysis finds that LCCP does not inhibit economic growth, but rather has a catalytic effect.

Based on the above findings, this paper draws some recommendations. First, the effectiveness of low-carbon cities as an important tool to enhance the competitiveness of countries has been effectively demonstrated in developed countries. This study shows that LCCP is also effective in developing countries. The experience of LCCP should be highlighted and LCCP initiatives should be promoted, to provide a replicable Chinese experience for LCCP in developing countries. Second, LCCP should be developed based on the differences in city size and resource endowment. Government support should be increased for small cities to compensate for the population disadvantage by providing financial subsidies for low-carbon R&D and innovation to promote the technological progress of cities. Large cities should actively communicate the success of low-carbon construction to the surrounding small cities. Simultaneously, the transformation of resource-based cities to low-carbon cities should be accelerated to reduce their dependence on resources. Third, as local governments increase investment in technological innovation and guide the upgrading of industrial structures, they should also develop corresponding policies for the introduction of talent. The construction of a low-carbon city needs to be supported by a combination of human, financial and material resources to maximize its effectiveness.

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Data availability Data for this work are available through the corresponding author.

Declarations

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Consent to participate Not applicable.

Consent for publication The authors declare that they agree with the submission and eventual publication of the environment, development and sustainability.

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