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Original Research

Evaluation of Carbon Reduction Effect of the Low-Carbon Policy: Evidence from 47 Low-Carbon Pilot Cities of China

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Abstract

Based on panel data from 204 prefecture-level cities in China spanning from 2010 to 2019, this study examines the low-carbon city pilot program as a quasi-natural experiment. The propensity score matching-double difference model (PSM-DID) is utilized to analyze the effects of the low-carbon city pilot policy on carbon emission intensity. The research findings found: Firstly, the low-carbon city pilot policy has significantly reduced the intensity of urban carbon emissions. Secondly, the primary factors contributing to the reduction in urban carbon emissions intensity due to the low-carbon city pilot policy include adjustments in industrial structure, energy consumption control, and advancements in green technology innovation. Thirdly, heterogeneity analysis indicates that the impacts of the low-carbon city pilot policy differ across various regions. Resource cities, eastern cities, as well as cities in the southeast and northwest regions, experience significant effects.

Keyword: low-carbon city pilot policy, carbon emission intensity, propensity score matching-double difference model, quasi-natural experiment

Introduction

Global warming and frequent extreme weather disasters pose a great threat to global biodiversity and humans. After the industrial revolution, due to the large-scale consumption of fossil fuels, carbon dioxide emissions continued to accumulate. The greenhouse gas content in the atmosphere rose sharply, leading to global warming. At present, China has become the world's largest carbon emitter. In 2020, China's total carbon emissions accounted for more than 30% of global emissions [1]. China is facing enormous pressure to reduce emissions. However, in order to fulfill its responsibility as a major country and address climate change, the Chinese government has actively committed to reducing carbon emissions. At the Copenhagen Climate Conference in 2009, China made a commitment: by 2020, it aimed to reduce carbon dioxide emissions per unit of GDP (Gross Domestic Product) by 40%-45% compared to the levels in 2005 [2]. Additionally, the government initiated low-carbon city pilot projects in three batches in 2010, 2012, and 2017. The purpose of these projects is to promote the concept of a low-carbon economy, adjust the industrial structure, improve energy efficiency, and foster the development of low-carbon cities. During

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the seventy-fifth session of the United Nations General Assembly in 2020, China clearly put forward the goals of reaching the peak of carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060 [3]. China also incorporated these goals into the overall layout of economic and social development, as well as ecological civilization construction. In 2022, the 20th National Congress of the Communist Party of China (CPC) was held in Beijing. The report to Congress emphasized the need to strengthen environmental pollution control and continue efforts for clean air, clean water, and a pristine environment. The high carbon emissions and pollution caused by the energy and industrial structure remain the root causes of ecological and environmental problems in China. Therefore, addressing pollution and reducing carbon emissions are crucial issues that need attention when improving the ecological environment in China. Currently, China urgently needs to improve policies related to energy conservation and emission reduction and promote the transformation and upgrading of the economic structure to solve the contradiction between resources and environmental constraints, achieving the organic unity of carbon emissions and economic development.

In the pursuit of implementing a low-carbon strategy, cities play a crucial role in achieving green and sustainable development. In 2010, the Chinese Development and Reform Commission issued a notice on the Pilot of Low-Carbon Provinces and Cities, designating five provinces and eight cities as the initial batch of low-carbon cities. Subsequently, in 2012 and 2017, the second and third batches of low-carbon cities were introduced, totaling 74 cities [4]. The low-carbon city pilot program serves as a significant measure to promote the construction of low-carbon cities in China, representing an active exploration of implementing the low-carbon development strategy. However, there is a lack of comprehensive research discussing how the low-carbon pilot policy reduces carbon emission intensity in these pilot cities. Therefore, this paper aims to address this gap by focusing on the second and third batches of low-carbon pilot areas to analyze the carbon reduction effect of low-carbon city pilot policies. The findings are expected to provide valuable theoretical insights into China's efforts to promote green, low-carbon, and high-quality development.

Literature Review

This paper provides a summary of the literature on two main aspects: low-carbon city pilot policies and carbon emission intensity. By examining the relevant literature, it is observed that current academic research on the construction of low-carbon city pilots primarily focuses on evaluating carbon emission performance and measuring factors that influence urban carbon emissions. In terms of evaluating low-carbon city pilot performance, there is a consensus among academic circles that these initiatives significantly enhance carbon emission performance. For instance, Xiao et al. conducted a study using panel data from 285 cities in China between 2005 and 2016, and their research demonstrates that the establishment of innovative cities effectively increases carbon emission performance, thereby promoting green and low-carbon development [5]. Similarly, Lu et al. employed the PSM-DID model to examine the impact of low-carbon city pilot policies on urban carbon emission performance [6]. However, further research is needed to validate the effectiveness of reducing carbon emissions through urban carbon sinks. Li et al., based on environmental regulation theory, argued that low-carbon city pilot policies directly influence regional carbon emissions through the "green paradox" effect [7]. Regarding the factors influencing urban carbon emissions, most existing studies integrate intermediary variables to explore the channels through which policies affect carbon emissions. Yin et al. considered the low-carbon city pilot as an important pathway for sustainable development and suggested that carbon emission reductions have long-term effects due to the inertia of economic development and industrial structure optimization [8]. Tu et al. developed a carbon emission decomposition model based on the optimized Laspeyres complete exponential decomposition method [9]. Their findings reinforce the importance of reducing energy intensity as a crucial path toward energy conservation and emission reduction. Niu et al., through a comprehensive analysis of mechanisms, channels, and policy coordination, empirically tested that policies targeting energy efficiency improvements and production factor structure enhancements effectively decrease carbon emissions [10]. Notably, the key lies in coordinating and aligning policies to achieve a synergistic effect in reducing pollution and carbon emissions.

Energy conservation and emission reduction are inevitable requirements for high-quality economic and social development. Academia has produced a lot of research results around carbon emissions. Currently, there are many studies on the combination of green development and carbon emission intensity in academic circles. Firstly, some scholars have investigated the relationship between green financial innovation and carbon emission intensity. Based on panel data from 275 cities in China from 2011 to 2019, Wang et al. confirmed that after the implementation of the green finance pilot policy, the carbon emission intensity of the pilot cities decreased significantly compared to non-pilot cities [11]. Scott et al., using the PVAR model of inter-provincial panel data, found that the development of green finance and the intensity of carbon emissions were mutually inhibited [12]. The development of green finance played a key role in the process of carbon emission reduction. Secondly, some scholars have discussed the impact of green technology development on carbon emission intensity. Based on panel data from BRICS countries from 1994 to 2014, Haseeb et al. found that the net effect of green technology innovation on carbon emission intensity was both promotion and reduction [13]. Finally, some scholars have found that the digital economy has a partial impact on the intensity of carbon emissions. However, the relationship between the development of the digital economy and the intensity of carbon emissions is not linear and needs to be analyzed according to the specific circumstances. James et al. believed that the development of information and communication technology would not have a significant impact on the carbon emission intensity in the short term, but it would affect the intensity of carbon emissions in the long run [14]. Based on panel data from 10 ASEAN countries, Nabila et al. confirmed that there was an inverted U-shaped relationship between the digital economy and carbon emission intensity [15].

In summary, the existing literature mostly focuses on the analysis of the current situation of low-carbon city pilot policies and the influencing factors of carbon emission intensity. The performance of low-carbon city construction, the development status of the low-carbon economy, and the relationship between green development and carbon emission intensity have been discussed in depth. However, there are also some shortcomings. The existing research mainly focuses on the impact of low-carbon city pilot policies on carbon emissions, while the influence of the low-carbon city pilot on urban carbon emission intensity is rarely considered, and the research on the influence mechanism between them is limited. Therefore, based on the PSM-DID model, this paper analyzes the impact of the low-carbon city pilot on carbon emission intensity. At the same time, this paper discusses the influence mechanism of the low-carbon city pilot policy on carbon emission intensity in order to provide enlightenment for the promotion of the low-carbon city pilot policy.

Materials and Methods

Research Methods

Model Construction

The purpose of this paper is to analyze the impact of pilot low-carbon city policies on carbon emission intensity. According to the Notice of the National Development and Reform Commission on Launching the Third Batch of National Low-carbon Cities, as of January 7, 2017, the China National Development Commission has launched three batches of low-carbon cities. The evaluation of the policy effect is complicated by the fact that the first batch of cities is mainly divided into provinces. Therefore, it is challenging to carefully assess the policy effect. The selection of the second and third batches of pilot cities considers different characteristics such as development stages, industrial characteristics, and resource endowments. This approach aims to be more representative and scientific by using the method of "declaration+selection" to choose pilot cities. Thus, this study excludes the first batch of pilot cities and focuses on the second and third batch as the treatment group, while considering other non-pilot cities as the control group. In addition, since the first pilot was launched in 2010 and the pilot period is relatively long, the effect of policy implementation is difficult to estimate. Therefore, the first batch of pilot cities was excluded from this study. Based on this, the quantitative analysis examines the effect of carbon emission reduction before and after the implementation of the policy from 2010 to 2019. The low-carbon city pilot can be seen as a "quasi-natural experiment". To address potential endogeneity issues, this study follows Peter's ideas and adopts a double difference model [16].

The model is defined as follows:

$$Ci_{it} = \alpha + \beta LCPC_{it} + \delta Y_{it} + \varepsilon_i + \theta_t + \varphi_{it} \quad (1)$$

In Equation (1), i represents the city and t represents the year; Ci_{it} represents the explained variable, which indicates the carbon emission intensity of the city; α represents the intercept term; $LCPC_{it}$ represents the core explanatory variable, indicating the interaction between pilot cities and time. If i city is a low-carbon pilot city in t year, $LCPC_{it}$ is 1, otherwise, it is 0. Y_{it} is the control variables, including economic development level (*pgdp*), population density (*dep*), financial development level (*fde*), and foreign direct investment (*fdi*); ε_i and θ_t are individual fixed effects and time fixed effects, respectively; φ_{it} is a random interference term. β is the key parameter, if β<0, it means that the low-carbon city pilot policy has significantly reduced the intensity of urban carbon emissions and vice versa.

In fact, due to the great differences in economic development level, industrial structure, and energy structure between cities, the selection of low-carbon pilot cities will be affected. In addition, the self-selection of samples will be biased, which will lead to the regression results deviating from expectations. However, the propensity score matching-double difference model can narrow the gap between the treatment group and the control group in all aspects and ensure the randomness of the experiment. Therefore, this paper drew lessons from Lukman et al. and Li et al. and adopted the PSM-DID model to consider the impact of the low-carbon city pilot policy on urban carbon emission intensity [17, 18]. The basic idea of the PSM-DID method is derived from matched estimators. This method can better alleviate a series of problems caused by the fact that the treatment group and the control group do not have a common trend assumption before being affected by the low-carbon city pilot policy, thus effectively estimating the net effect of the policy. The specific settings of the PSM-DID model are as follows:

$$Ci_{it}^{PSM} = \alpha + \beta LCPC_{it} + \delta Y_{it} + \varepsilon_i + \theta_t + \varphi_{it} \quad (2)$$

In Equation (2), Ci_{it}^{PSM} represents the matched urban carbon emission intensity.

Explained Variable

The explained variable in this paper is urban carbon emission intensity. For the calculation of carbon emission intensity, this paper used the calculation method provided by the United Nations Climate Change Committee (IPCC) to estimate the carbon emissions generated by fossil energy consumption in 204 cities in China from 2010 to 2019 [19]. Eight types of fossil energy, such as natural gas, kerosene, fuel oil, diesel oil, gasoline, crude oil, coal, and coke, were selected. Multiply the total amount of energy consumption by the carbon emission factor of unit energy consumption of different varieties to obtain the total amount of carbon emission of various fossil energy sources [20], as shown in Equation (3) and Table 1. The carbon emission intensity is the amount of carbon dioxide per unit GDP, as shown in Equation (4).

$$CE = \sum_{i=1}^{8}(co_2)_i = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \quad (3)$$

$$CI=CE/GDP \quad (4)$$

In the above Equations, CE represents the total carbon emission of eight types of fossil energy; NCV_i represents the average low calorific value ($KJ/kg \cdot m^3$) corresponding to i fossil energy; CEF_i represents the carbon emission coefficient ($kgco_2/TJ$); CI represents the carbon emission intensity; and GDP represents the gross domestic product.

Core Explanatory Variable

The core explanatory variable in this paper is low-carbon pilot cities. Based on the availability of panel data of prefecture-level cities, after excluding the first batch of pilot cities, the cities in 2012 and 2017 were included in the research sample. A total of 47 low-carbon pilot cities and 157 non-pilot cities were selected. Since the second batch of pilot cities began at the end of 2012, considering the possible lag in policy implementation, 2013 was set as the second batch of policy implementation time.

Other Variables

First of all, in order to control the endogenous problems caused by omitting the relevant variables that affect the carbon emission intensity of cities, this paper referred to Meng et al.; the control variables such as economic development level (*pgdp*), population density (*dep*), financial development level (*fde*), and foreign direct investment (*fdi*) were included in the model [21]. Secondly, the following intermediary variables were selected to investigate the theoretical mechanism of the impact of the low-carbon pilot policy on carbon emission intensity: Referring to the practice of An et al., the industrial structure level of the city was expressed by the proportion of the output value of the secondary industry to GDP [22]. Referring to the practice of Liu et al., the innovation level of urban green technology was measured by the amount of urban green invention patents obtained [23]. Referring to the practice of Tang et al., the energy structure of the city was represented by the per capita energy consumption value [24]. Finally, using the idea of Wen et al. for reference, the per capita carbon emissions and carbon emissions were respectively replaced by dependent variables for the robustness test [25]. Drawing on the practice of Ren, the following mediation effect model was adopted [26].

$$W_{it} = \alpha_1 + \beta_1 LCPC_{it} + \gamma_1 Control_{it} + \delta_i + \varepsilon_t + \theta_1 Trend_{it} + \varphi_{it} \quad (5)$$

$$Ci_{it} = \alpha_2 + \mu W_{it} + \beta_2 LCPC_{it} + \gamma_2 Control_{it} + \delta_i + \varepsilon_t + \theta_2 Trend_{it} + \varphi_{it} \quad (6)$$

In the above Equations, i represents the city and t represents the year; W_{it} represents the intermediary variables, including industrial structure (*is*), urban green technology innovation (*inno*), and per capita energy consumption value (*pec*). $Control_{it}$ represent the control variables, including economic development level (*pgdp*), population density (*dep*), financial development level (*fde*), and foreign direct investment (*fdi*); $Trend_{it}$ represents a time trend item; δ_i and ε_t represent individual fixed effect and time fixed effect, respectively; and φ_{it} represent a random error term.

Data sources

This study utilized panels from 204 prefecture-level cities in China from 2010 to 2019 to analyze the impact of the low-carbon city policy on urban carbon emission intensity. The data was sourced from the *China City Statistical Yearbook* and *China Energy Statistical Yearbook*. To ensure data accuracy, Hong Kong, Macao, Taiwan, Tibet, and Chaohu City were excluded due

Table 1. Average low calorific value and carbon emission coefficient of various energy sources.

	Natural Gas	Kerosene	Fuel Oil	Diesel Oil	Gasoline	Crude oil	Coal	Coke
NCV	38931	43070	41816	42652	43070	41816	20908	28435
CEF	56100	71500	77400	74100	70000	73300	95333	107000

Table 2. Descriptive statistics of variables.

Variable	Calculation method	Sample size	Average value	Standard deviation	Minimum value	Maximum value
Carbon emission intensity(*ci*)	Total carbon emissions/real GDP(t/yuan)	2040	0.5122	0.6131	0.0237	9.6120
Low-carbon city pilot project(*LCPC*)	The pilot is 1, otherwise it is 0.	2040	0.1210	0.3260	0.0000	1.0000
Level of economic development(*pgdp*)	Real GDP/total urban population(Yuan/person)，take the logarithm	2040	10.6100	0.6860	8.5550	13.1600
Population density(*dep*)	Total population at the end of the year/urban area(person/km^2), take the logarithm	2040	5.6970	0.9700	1.6190	7.7480
Financial development level(*fde*)	Year-end loan balance of financial institutions/real GDP/%	2040	2.0940	1.1210	0.2330	21.3000
Foreign direct investment (*fdi*)	Actual foreign investment in the current year/real GDP/%	2040	0.0167	0.0168	0.0000	0.2100
Industrial structure(*is*)	Proportion of output value of secondary industry to GDP	2040	47.0900	11.0300	8.5670	89.7500
Urban green technology innovation(*inno*)	Obtained amount of urban green invention patents/piece, take the logarithm	2040	3.8960	1.8920	0.0000	9.2700
Per capita energy Consumption value(*pec*)	Ten thousand tons of standard coal/year-end total population/(t/person)	2040	0.5650	1.0780	0.0044	18.7700
Per capita carbon emission(*pe*)	Carbon emissions/real GDP/(t/Yuan)	2040	2.9370	5.7810	0.0293	97.3900
Carbon dioxide(*carbon*)	Total urban carbon emissions/ten thousand tons, take the logarithm	2040	6.2770	1.1050	2.1260	9.5330

to limited data availability. Descriptive statistics of relevant variables can be found in Table 2.

Results and Discussion

Tendency Score Matching and Test

In order to effectively prevent the deviation caused by non-random sample selection and to minimize the differences in urban characteristics between pilot cities and non-pilot cities, thus improving the accuracy and scientificity of the evaluation of the low-carbon city pilot policy, it is necessary to initially test the balance of propensity score matching for the. The results of this test can be seen in Table 3.

Firstly, it is evident that the difference between matched the treatment group and the control group is significantly reduced, as indicated by the standardized mean of covariates. Additionally, the standard deviation

Table 3. The propensity score matches the balance test result.

Covariate	Before matching U After matching M	Average		Standardized deviation	Decrease of standardized deviation/%	*t* test	
		Processing group	Control group			*t* value	*p* value
pgdp	U	10.964	10.504	69.2		13.31	0.00
	M	10.832	10.865	-5.0	92.8	-0.70	0.49
dep	U	5.7977	5.6665	13.8		2.58	0.01
	M	5.6676	5.6230	4.7	66.0	0.64	0.53
fde	U	2.6749	1.9206	64.9		13.34	0.00
	M	2.3227	2.3058	1.5	97.8	0.24	0.81
fdi	U	0.0221	0.0151	41.9		8.10	0.00
	M	0.0208	0.0203	3.3	92.1	0.39	0.70

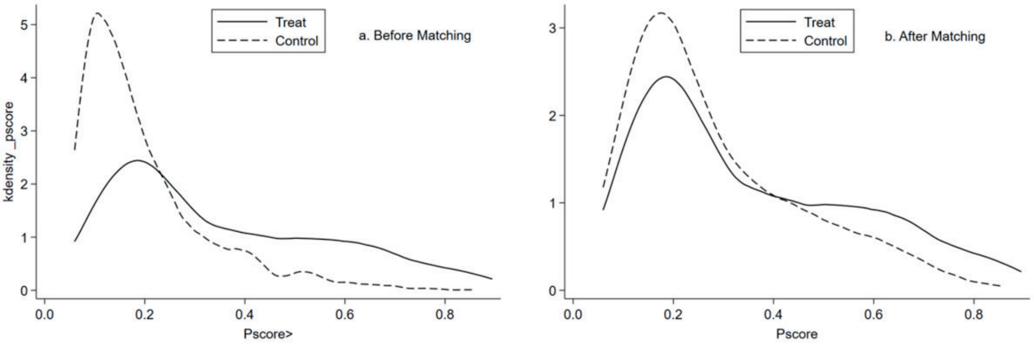

Fig. 1. Kernel density diagram before and after matching.

of *pgdp*, *dep*, *fde*, and *fdi* after matching is less than 10%, portraying the robustness and lack of significant difference in the matched sample data. Furthermore, none of the matched covariates passed the 10% significance level test, implying no systematic bias in covariates between the two groups. Thus, the initial hypothesis is rejected, confirming the successful matching of the sample propensity score and passing the balance test.

To visually represent the fitting effect of propensity scores before and after sample matching, kernel density maps of the treatment group and the control group were plotted (Fig. 1). It is evident that before matching, there was a considerable disparity between the treatment group and the control group, with significant differences in the distribution of kernel density. However, after matching, the kernel density lines of the treatment and control groups exhibit close proximity, indicating a reduction in the distance between the pilot and non-pilot groups after matching the propensity score. This improved fitting effect of the propensity score effectively mitigates result deviation caused by sample selection.

Benchmark Regression

After matching the samples with PSM, the DID model was used to explore the impact of the low-carbon city pilot policy on urban carbon emission intensity. Table 4 reports the specific regression results. Columns (1) and (2) report the estimated results based on the double difference method. Columns (3) and (4) are the regression results after the PSM method is added. Among them, columns (1) and (3) perform benchmark regression without adding control variables. Columns (2) and (4) show the regression results by adding control variables.

On the whole, all of the core explanatory variables (LCPC) have passed the significance level test. For the full sample regression of columns (1) and (2), the regression coefficients of LCPC are -0.0519 and -0.0813, respectively. Both of them are significantly negative at the 5% level, indicating that the lowbon city pilot has played a role in promoting the carbon emission intensity and has had certain effects. After adding the PSM method, the regression coefficients of the core explanatory variables in columns (3) and (4)

Table 4. Benchmark regression results of the low-carbon city pilot policy on carbon emission intensity.

Variable	Full sample (1)	Full sample (2)	PSM-DID (3)	PSM-DID (4)
LCPC	-0.0519**	-0.0813**	-0.0636*	-0.0888**
	(-2.45)	(-2.01)	(-1.76)	(-2.11)
Control variable	NO	YES	NO	YES
Constant term	0.5105***	-0.7307***	0.5222***	-0.7348***
	(31.59)	(-3.15)	(30.86)	(-2.94)
Urban fixed effect	YES	YES	YES	YES
Fixed year effect	YES	YES	YES	YES
Observed value/piece	2040	2040	1962	1962
R^2	0.976	0.987	0.988	0.987

Note: * * *, * *, and * mean significant at the levels of 1%, 5%, and 10%, respectively, and the *t* value is in brackets, the same below.

are still negative and significant. This suggests that the benchmark regression results are still consistent with expectations after controlling for sample selectivity deviation. In addition, compared with the model without control variables, the regression coefficient of the core explanatory variable in the model with control variables is lower. Taking columns (3) and (4) as examples, column (3) represents PSM-DID regression with control variables. During the implementation of the low-carbon city pilot policy, the carbon emission intensity of pilot cities decreased by about 6%. After adding the control variables, the regression coefficient of the core explanatory variable in column (4) is -0.0888. This means that the low-carbon city pilot policy is projected to reduce the carbon emission intensity of cities by approximately 9%. These results reflect that the choice of control variables in this paper is reasonable.

Robustness Test

Parallel Trend Test

The premise of the double difference model is to test the parallel trend, which means that there is no systematic difference in carbon emission intensity between low-carbon pilot cities and non-pilot cities before and after the implementation of the policy. The parallel trend test result is shown in Fig. 2.

In Fig. 2, the horizontal axis represents three years before the implementation of the low-carbon city pilot policy to five years after the implementation. The vertical axis is the regression coefficient. It can be clearly seen from Fig. 2 that in the first three years before the implementation of the policy, the estimated values of the DID coefficient of the low-carbon city pilot policy are not significant. Within the 95% confidence interval, the estimated values of the parameters do not reject the original hypothesis of zero. It shows that there is no obvious difference in carbon emission intensity between low-carbon pilot cities and non-pilot cities before the implementation of the policy, which meets the parallel trend test conditions. Due to the lag of the low-carbon city pilot policy, the estimated values of the DID coefficient of the policy are significantly negative in the second to third years after the implementation of the policy. It shows that the carbon emission reduction effect of the low-carbon city pilot policy begins to appear. The intensity of urban carbon emissions decreases significantly. In the fourth year after the implementation of the policy, the coefficient rebounded and gradually shows a downward trend. It showed that although the low-carbon city pilot policy is effective at present, it has not produced long-term effects. The sustainability of the policy needs to be further strengthened.

Placebo Test

To account for time changes and prevent the influence of the difference in carbon emission intensity between the treatment and control groups, this study followed the methodology of Nils et al. and randomly chose one year to implement the policy [27]. A virtual interaction item was constructed, and a placebo test using difference-in-differences (DID) analysis was conducted. With 47 pilot cities in the overall sample, random sampling was employed to select an equivalent number of cities as the virtual treatment group, while the remaining cities formed the virtual control group. Standard regression analysis was then performed. Fig. 3 illustrates the distributions of coefficient kernel density and p-values for 500 and 1000 random samples, respectively. The solid line represents the kernel density estimation of the regression coefficient, while the scattered points

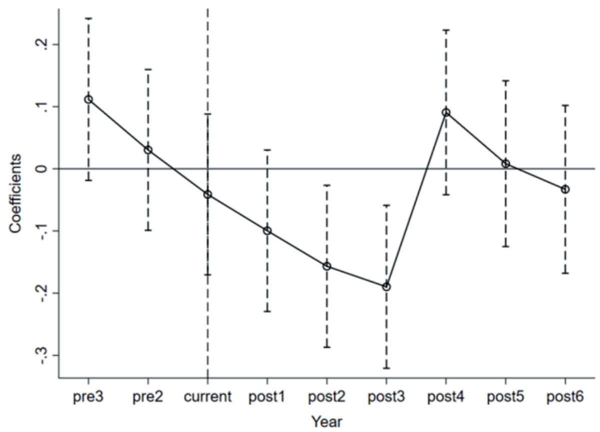

Fig. 2. Parallel trend test.

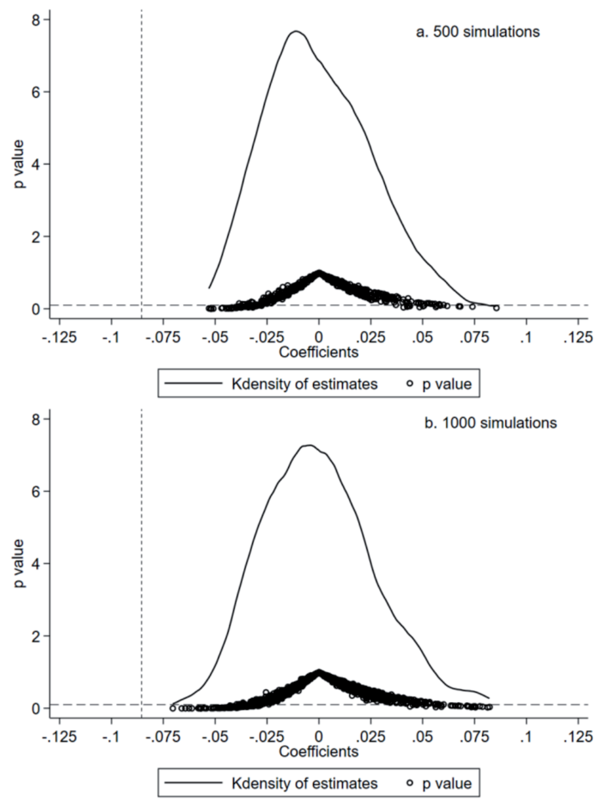

Fig. 3. Placebo test.

denote the *P* values. The vertical dotted line represents the actual regression coefficient value, and the horizontal dotted line represents the 10% significance level.

As can be seen from Fig. 3, most regression coefficients and P values are distributed around 0 and conform to normal distribution. Most p values are higher than the significance level of 10%. Most scattered points are distributed above the horizontal dotted line, which meets the hypothesis of the placebo test. It further verifies that the impact of low-carbon city pilots on carbon emission intensity has not been disturbed by other factors. The research results are still robust.

Remaining Robustness Test

Considering that economic, demographic factors, and regional differences will affect the effectiveness of the implementation of the low-carbon city pilot policy and bring a series of endogenous problems, this study also conducted the following robustness tests. First, the per capita carbon emissions (*pe*) and carbon dioxide (*carbon*) were respectively replaced by dependent variables for regression. The regression results are shown in columns (1) and (2) in Table 5. Secondly, on the basis of excluding northern cities, this paper focused on the carbon emission reduction effect of southern cities and made benchmark regression again. The results are shown in column (3), Table 5. Finally, in order to avoid the interference of the outliers of dependent variables on the regression results, this paper drew lessons from Matthias et al. and truncated the samples with the maximum and minimum carbon emission intensity of 1% [28]. The results are shown in column (4) of Table 5.

The results in Table 5 show that, first, on the basis of considering the level of urban economic development and population factors, the low-carbon city pilot policy has a significant negative impact on per capita carbon emissions and total carbon emissions. It can be verified that the implementation effect of the low-carbon city pilot policy is obvious. Because the northern city of China is relatively located in the north, central heating produces a lot of energy consumption, which will lead to an increase in carbon emissions. However, southern cities have less central heating. The difference in energy consumption between northern and southern cities will affect the intensity of carbon emissions. Secondly, after excluding the northern cities, the low-carbon city pilot policy still plays a significant role in reducing the intensity of carbon emissions. Finally, after truncating the dependent variable, the regression coefficient of the core explanatory variable is still significantly negative. The result is still stable, further verifying the policy effect of the low-carbon city pilot.

Mechanism Analysis

This paper further analyzes the transmission mechanism of carbon emission intensity influenced by the low-carbon city pilot policy proposed above. Industrial structure, urban green technology innovation, and per capita energy consumption were selected as intermediate variables to test. Firstly, the intermediate variable was taken as the core explanatory variable, the carbon emission intensity was taken as the explained variable for regression, and the influence of the intermediate variable on the carbon emission intensity was considered. Secondly, the low-carbon city pilot policy was taken as the core explanatory variable, the intermediary variable was taken as the explained variable to regress again, and the influence of the low-carbon city pilot policy on the intermediary variable was considered. The mediating effect model mainly focused on whether the coefficients were significant and whether the symbols were consistent. If the symbols are the same, it shows that the low-carbon city pilot policy promotes the reduction of carbon emission intensity through mediating variables. If the symbols are different, it shows that mediating variables inhibit the positive role of the low-carbon city pilot policy

Table 5. Robustness test result.

Variable	Substitution dependent variable (1) *pe*	Substitution dependent variable (2) *carbon*	Eliminate northern cities (3) *ci*	Tailing of dependent variable (4) *ci*
LCPC	-0.4433**	-0.2398***	-0.0572**	-0.0472*
	(-2.12)	(-2.83)	(-1.98)	(-1.34)
Control variable	YES	YES	YES	YES
Constant term	-34.2648***	-6.4746***	-0.9985***	-0.4990**
	(-13.35)	(-20.83)	(-3.27)	(-2.96)
Urban fixed effect	YES	YES	YES	YES
Fixed year effect	YES	YES	YES	YES
Observed value/piece	2040	2040	1249	2040
R^2	0.736	0.842	0.894	0.932

in reducing carbon emission intensity to some extent. See Table 6 for specific inspection results.

First of all, the industrial structure was used as an intermediary variable to test the impact of the low-carbon city pilot policy on carbon emission intensity. The results are shown in columns (1) and (2) in Table 6. Column (1) shows that the low-carbon city pilot policy has a negative impact on the industrial structure and passes the significance level test of 5%, which shows that the low-carbon city pilot policy reduces the proportion of the secondary industry in cities and improves the rationalization level of industrial structure. According to column (2), the core explanatory variable is significantly negative, indicating that the low-carbon city pilot policy can reduce the intensity of urban carbon emissions through the intermediary variable of industrial structure. Pilot cities can realize regional green sustainable development by adjusting industrial structure, accelerating the transformation of green industries, and developing emerging industries with low energy consumption and low emissions to replace high energy consumption industries.

Secondly, the per capita energy consumption value was used as an intermediary variable to investigate whether it was a channel for the low-carbon city pilot policy to reduce carbon emission intensity. The results are shown in columns (3) and (4) in Table 6. Column (3) shows that the core explanatory variable is significantly negative at the level of 10%, indicating that the implementation of the low-carbon city pilot policy has effectively reduced energy consumption and inhibited energy waste and unreasonable demand to some extent. According to column (4), the coefficient of the core explanatory variable is negative and it is significant at the level of 1%, which indicates that the reduction of per capita energy consumption can significantly reduce the intensity of urban carbon emissions. In the process of implementing the low-carbon city pilot policy, the purpose of carbon emission reduction can be achieved through effective control of energy consumption.

Finally, the carbon emission reduction effect of urban green technology innovation as an intermediary variable was tested. The results are shown in columns (5) and (6) in Table 6. Column (5) shows that the low-carbon city pilot policy has significantly improved the level of urban green technology innovation at the level of 10%. From the coefficient of the core explanatory variable, during the implementation of the low-carbon city pilot policy, the level of urban green technology innovation in the approved pilot cities has increased by about 2.3% compared with that in the non-pilot cities. According to column (6), the coefficient of the core explanatory variable is negative. It has passed the significance level test of 1%, which shows that the low-carbon city pilot policy can reduce the intensity of urban carbon emissions by improving the level of urban green technology innovation.

The analysis of mechanisms shows that the low-carbon city pilot policy can reduce the intensity of urban carbon emissions by deepening the adjustment of industrial structure, reducing per capita energy consumption, and improving the level of urban green technology innovation.

Table 6. Test results of the action mechanism of the low-carbon city pilot policy.

Variable	(1) *is*	(2) *ci*	(3) *pec*	(4) *ci*	(5) *inno*	(6) *ci*
is		0.003***				
		(3.17)				
pec				0.3109***		
				(42.06)		
inno						-0.0493***
						(-8.30)
LCPC	-0.0781**	-0.0273**	-0.0184*	-0.0709***	0.0233*	-0.1039***
	(-2.16)	(-2.07)	(-1.88)	(-3.75)	(1.72)	(-3.90)
Control variable	YES	YES	YES	YES	YES	YES
Constant term	-0.4856***	0.3444***	1.7028***	0.3373***	-1.7879***	0.6636***
	(-2.92)	(7.22)	(6.29)	(34.69)	(-6.33)	(27.36)
Urban fixed effect	YES	YES	YES	YES	YES	YES
Fixed year effect	YES	YES	YES	YES	YES	YES
Observed value/ piece	2040	2040	2040	2040	2040	2040
R^2	0.954	0.836	0.638	0.978	0.783	0.912

Heterogeneity Analysis

Due to the vast territory of China, different exhibit differences in geographical locations, resource endowments, and development levels. These variations result in the influence of various natural factors on the implementation of the low-carbon city pilot policy, thereby affecting the effectiveness of the policy in reducing carbon emissions. To address this, the current study took inspiration from the work of Li et al. and categorized cities into resource cities and non-resource cities based on their level of resource endowment and utilization [29]. This categorization aimed to explore potential disparities in the driving effects of these two types of cities on urban carbon emission intensity. Additionally, the study divided cities into three geographical regions: eastern, central, and western cities. This division sought to examine the potential impact of geographical location on the implementation of the low-carbon city pilot policy. Furthermore, the study drew insights from the research conducted by Du et al. and considered the distinct natural environments and levels of economic and social development found on the east and west sides of the "Hu Huanyong Line" [30]. Consequently, the sample cities were divided into two categories: northwest cities of the Hu Huanyong Line and southeast cities of the Hu Huanyong Line. This classification aimed to investigate whether the intensity of the low-carbon city pilot policy's effect on carbon emission intensity was related to the level of urbanization within the sample cities. The specific regression results can be found in Table 7.

From columns (1) and (2) in Table 7, it is evident that the low-carbon city policy has successfully reduced the carbon emission intensity of resource-based cities. However, the impact on non-resource-based cities did not yield significant results, which is consistent with the findings of Li et al. [31]. This suggests that resource-based cities possess strong resource reserve capacity and favorable conditions for transformation and development. These advantages can be leveraged to enhance the effectiveness of carbon emission reduction efforts in urban transformation and development. Additionally, the carbon emission intensity of urban areas can be effectively reduced by improving resource processing and utilization, advancing new urbanization construction, enhancing upstream and downstream industrial systems, and promoting the development of strategic emerging industries. Conversely, non-resource-based cities lack these advantages, resulting in limited carbon emission reduction effects.

Analyzing columns (3) to (5), it becomes apparent that the low-carbon city pilot policy has significantly reduced the carbon emission intensity of cities in the east and middle of the sample. However, the impact on cities in the Midwest was insignificant. The eastern region, being economically developed, can capitalize on its technological advancements to achieve carbon reduction. The energy saved through scientific and technological progress exceeds the energy consumption spurred by economic growth, creating favorable conditions for the implementation of the low-carbon city pilot policy. Meanwhile, limited urban policies' effectiveness in the central and western regions can be attributed to their lower level of economic development and the extensive industrial development mode. These regions exhibit lower energy utilization efficiency and fewer low-carbon environmental protection industries, leading to extensive energy consumption and carbon emissions. As a result, the low-carbon city pilot policy does not have a noticeable effect in reducing the carbon emission intensity of central and western cities.

Examining columns (6) and (7), it is evident that the low-carbon city pilot policy has significantly

Table 7. Heterogeneity analysis results.

Variable	Resource-based cities (1) *ci*	Non-resource cities (2) *ci*	Eastern cities (3) *ci*	Central cities (4) *ci*	Western cities (5) *ci*	Northwest of Hu Huanyong Line (6) *ci*	Southeast of Hu Huanyong Line (7) *ci*
LCPC	-0.1252*	-0.0594	-0.0697***	-0.0456	-0.1711	-0.4088**	-0.1438***
	(-1.88)	(-1.17)	(-2.78)	(-0.79)	(-0.95)	(-1.99)	(-8.59)
Control variable	YES	YES	YES	YES	YES	YES	YES
Constant term	-1.2778***	-0.5666*	-0.1151	-1.2169***	-4.0647***	-6.5167***	-0.1526
	(-6.46)	(-1.67)	(-0.61)	(-3.46)	(-3.63)	(-4.86)	(-1.40)
Urban fixed effect	YES	YES	YES	YES	YES	YES	YES
Fixed year effect	YES	YES	YES	YES	YES	YES	YES
Observed value/ piece	730	1310	700	940	400	290	1750
R^2	0.846	0.958	0.824	0.842	0.985	0.829	0.913

reduced the carbon emission intensity of cities in the northwest and southeast of the Hu Huanyong Line. In recent years, urbanization development in the southeast of the Hu Huanyong Line has shifted towards a greener and low-carbon direction, resulting in decreasing carbon emissions. Conversely, the northwest cities have experienced rapid economic and urbanization growth but still maintain a relatively sparse population. Recently, the Chinese government has placed great emphasis on addressing high-carbon emissions in northwest China, promoting the intensive expansion of urban construction land, optimizing industrial structure, and advocating a green and low-carbon lifestyle. Consequently, per capita carbon emissions in this region have declined.

Conclusions

Based on panel data spanning from 2010 to 2019, collected from 204 prefecture-level cities in China, this paper aims to analyze the impact of the low-carbon city pilot policy on carbon emission intensity. Furthermore, this study delves into the underlying mechanisms and heterogeneous effects influencing carbon emission intensity. The research findings can be summarized as follows:

Firstly, the low-carbon city pilot policy has been proven to play a significant role in reducing carbon emission intensity. The benchmark regression results reveal that, in comparison to non-pilot cities, pilot cities experienced an average reduction in carbon emission intensity of approximately 8%. Secondly, the mechanism analysis indicates that the low-carbon city pilot policy achieves its carbon emission reduction effects by influencing industrial structure, energy consumption, and fostering the adoption of green technologies. This implies that governments should allocate more investments towards green technology innovation, encourage the development and deployment of environmental technologies, and prioritize the growth of new energy and energy-saving industries in order to effectively reduce urban carbon emissions. Thirdly, the heterogeneity analysis demonstrates that the effects of the low-carbon city pilot policy vary across regions. Specifically, resource cities, eastern cities, as well as certain cities in the southeast and northwest, experience significant reductions in carbon emission intensity due to the policy. Nonetheless, the policy has limited impact on non-resource cities and cities in central and western China.

To achieve a more widespread impact, the Chinese government should consider expanding the coverage of the low-carbon city pilot policy. Furthermore, efforts should be made to enhance the modern development system of the low-carbon economy and promote high-quality economic development in the future.

Contributions

Xiaochun Zhao: Writing–review & editing, Writing–original draft, Visualization, Software, Methodology, Data curation, Conceptualization. Zijun Wu: Writing–review & editing, Supervision, Visualization, Data curation.

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Data Availability

Data will be made available on request.

Conflict of Interest

The authors declare no competing interests.

References

1. WU Y., LIU P., HUANG L., GE Y., CHEN L. Heat transfer performance of supercritical CO2 in a vertical U-tube. Applied Thermal Engineering. **250** (1), 123505, **2024**.
2. KAO X., LIU Y., WANG W., WEN Q., ZHANG P. The pressure of coal consumption on China's carbon dioxide emissions: A spatial and temporal perspective. Atmospheric Pollution Research. **15** (8), 102188, **2024**.
3. WANG L., ZHA S., ZHANG S., JIN J. Sulfonated Chitosan Gel Membrane with Confined Amine Carriers for Stable and Efficient Carbon Dioxide Capture. ChemSusChem.**2024**.
4. YUAN S., GE Y., SU P., CHENG H., WANG Z., YU F. Green technology for carbon dioxide utilization: Vermiculite based hydrotalcite for methane dry reforming. Journal of Environmental Chemical Engineering. **12** (2), 112308, **2024**.
5. XIAO D., FAN J., WANG W., WANG J., HOU L. Innovation city and low-carbon future: a quasinatural experiment from China. Environmental Science and Pollution Research International. **30** (43), 98004, **2023**.
6. LU Y., GUO J., AHMAD M., ZHANG H. Can Sci-Tech Finance Pilot Policies Reduce Carbon Emissions? Evidence from 252 Cities in China. Frontiers in Environmental Science. **10**, 933162, **2022**.
7. LI J., FANG L., CHEN S., MAO H. Can low-carbon pilot policy improve atmospheric environmental performance in China? A quasi-natural experiment approach. Environmental Impact Assessment Review. **96**, 106807, **2022**.

8. YIN K., LIU L., GU H. Green paradox or forced emission reduction—the dual effects of environmental regulation on carbon emissions. International Journal of Environmental Research and Public Health. **19**, 11058, **2022**.
9. TU Z., CAO Y., KONG J. The impacts of low-carbon city pilot projects on carbon emissions in China. Atmosphere. **13**, 1269, **2022**.
10. NIU S., LUO X., YANG T., LIN G., LI C. Does the Low-Carbon City Pilot Policy Improve the Urban Land Green Use Efficiency? – Investigation Based on Multi-Period Difference-in-Differences Model. International Journal of Environmental Research and Public Health. **20**, 2704, **2023**.
11. WANG X., ZHANG X., SONG J. The analysis of solar energy investment, digital economy, and carbon emissions in China. Frontiers in Energy Research. **11**, 1183857, **2023**.
12. MCALISTER S., MORTON R.L., BARRATT A. Incorporating carbon into health care: adding carbon emissions to health technology assessments. The Lancet Planetary Health. **6** (12), e993, **2022**.
13. HASEEB A., XIA E.J., SAUD S., AHMAD A., KHURSHID H. Does information and communication technologies improve environmental quality in the era of globalization? An empirical analysis. Environmental Science and Pollution Research International. **26** (9), 8594, **2019**.
14. CARROLL J., BRAZIL W., HOWARD M., DENNY E. Imperfect emissions information during flight choices and the role of CO_2 labelling. Renewable and Sustainable Energy Reviews. **165**, 112508, **2022**.
15. AMIN N., SONG H., ALI M. Role of information and communication technology, economic growth, financial development and renewable energy consumption towards the sustainable environment: Insights from ASEAN countries. Environmental Science and Pollution Research International. **30** (38), 89381, **2023**.
16. BOEDEKER P. Propensity Score Methods and Difference-in-Differences with an Exogenous Time-Varying Confounder: Evaluation of Methods. Journal of Research on Educational Effectiveness. **16** (3), 377, **2023**.
17. ADAM L., JIN J., KHAN A. Does the Indonesian farmer empowerment policy enhance the professional farmer? Empirical evidence based on the difference-in-difference approach. Technology in Society. **68**, 101924, **2022**.
18. LI J., PENG R., LI Y., CHI Y. Environmental Benefits of the Central China Rise Strategy; Empirical Analysis Based on the PSM-DID Model. Recent Patents on Engineering. **17** (2), **2022**.
19. MIRZIYOYEVA Z., SALAHODJAEV R. Renewable energy and CO_2 emissions intensity in the top carbon intense countries. Renewable Energy. **192**, 507, **2022**.
20. ASHOORI S., GATES I.D. Carbon intensity of in-situ oil sands operations with direct contact steam generation lower than that of once-through steam generation. Journal of Cleaner Production. **367**, 133046, **2022**.
21. MENG Z., LI W., CHEN C., GUAN C. Carbon Emission Reduction Effects of the Digital Economy: Mechanisms and Evidence from 282 Cities in China. Land. **12** (4), 12040773, **2023**.
22. AN K., WANG X. Optimizing the Development Area to take the lead in Peaks-based on Location Quotient Analysis. IOP Conference Series: Earth and Environmental Science. **295** (2), 012062, **2019**.
23. LIU L., ZHANG Y., LIU B., XIU P., SUN L. How to Achieve Carbon Neutrality: From the Perspective of Innovative City Pilot Policy in China. International Journal of Environmental Research and Public Health. **19** (24), 16539, **2022**.
24. TANG Y., JIANG H. Analysis of the decoupling effect and driving factors of carbon emissions from the transportation sector in Guangdong Province. Scientific Reports. **13** (1), 18744, **2023**.
25. WEN L., SUN S. Can China's new rural pension scheme alleviate the relative poverty of rural households? An empirical analysis based on the PSM-DID method. Australian Economic Papers. **62** (3), 396, **2023**.
26. REN H., OU X., ZHU H. Spatial characteristics and coupling coordination between carbon emission efficiency and industrial structure in three metropolitan areas of Jiangsu Province, China. Science Progress. **106** (2), **2023**.
27. VERHEUVEL N., WITTEMAN J., VLAANDEREN M. Synthetic Control Method for Dutch Policy Evaluation. De Economist. **171** (1), 31, **2023**.
28. BETHGE M., FAUSER D., ZOLLMANN P., STREIBELT M. Utilisation of rehabilitation due to mental disorders during the SARS-CoV-2 pandemic: a difference-in-differences analysis. BMC Psychiatry. **23** (1), 137, **2023**.
29. LI L., BAI Y., YANG X., GAO Z., QIAO F., LIANG J., ZHANG C. A Low-Carbon Land Use Management Framework Based on Urban Carbon Metabolism: A Case of a Typical Coal Resource-Based City in China. Sustainability. **14** (21), 13854, **2022**.
30. DU X., YU Y., AHENKORA B.F., PANG Y. Decoupling economic growth from building embodied carbon emissions in China: A nighttime light data-based innovation approach. Sustainable Production and Consumption. **43**, 34, **2023**.
31. LI Z., CAI Y., LIN G. Pathways for sustainable municipal energy systems transition: A case study of Tangshan, a resource-based city in China. Journal of Cleaner Production. **330**, 129835, **2022**.