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Impact of Low-Carbon City Pilot Policies on Regional Green Total Factor Productivity: A Study

Wenbin Liu[1,a,*]

[1]*School of Management, Hangzhou Dianzi University, Hangzhou, China*
a. 211030023@hdu.edu.cn
**corresponding author*

Abstract: Based on data from 246 prefecture-level cities in China spanning the years 2006 to 2019, this paper employs a multi-temporal double-difference model to empirically examine the effects of low-carbon pilot policies implemented since 2010 on green total factor productivity. Furthermore, the paper conducts a mechanism analysis and heterogeneity analysis to explore the policy's impact mechanisms and effects on different regions. The study reveals that low-carbon pilot policies have enhanced China's green total factor productivity. Results from the mechanism analysis indicate that these policies increase green total factor productivity by promoting the agglomeration of productive service industries and the innovation of green technologies, with the mechanism test for manufacturing industry agglomeration showing non-significant effects. Heterogeneity analysis results suggest that the impact of low-carbon pilot policies on the improvement of green total factor productivity is significant in China's eastern and western regions as well as in non-resource-based cities.

Keywords: Low-Carbon Pilot Policies, Multi-Temporal Double-Difference, Green Total Factor Productivity, Industry Agglomeration, Green Technology Innovation

1. Introduction

The global emission of greenhouse gases and the resulting climate change accompanying economic growth pose a common challenge that must be addressed globally. Various measures have been introduced by entities such as the European Union, the United Kingdom, Japan, and South Korea to limit carbon emissions. In October 2003, the European Union officially promulgated the "Emission Trading Directive" [1], which mandates that manufacturers in the 27 EU countries must comply with the carbon dioxide emission reduction standards set by the IEU-ETS. Exceeding emission reduction targets allows them to sell carbon dioxide emission rights known as "EU Emission Allowances" (EUA), while falling short requires them to purchase corresponding emission rights from the market. The United Kingdom [2], through the "Climate Change Act" enacted in 2008, became the first country globally to establish a legally binding long-term framework aimed at reducing greenhouse gas emissions and adapting to climate change. Japan [3], through the "Guidelines for Measures to Prevent Global Warming", outlined its climate change policy, providing a systematic action plan for all sectors and international cooperation [4]. On April 14, 2010, the South Korean government announced the implementation of the "Basic Law for Low Carbon Green Growth," officially initiating the enforcement of this legislation. The implementation of this basic law establishes the

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fundamental framework for South Korea's green growth, and future efforts will comprehensively implement low-carbon green growth plans in accordance with the law.

As the world's largest developing country and a major emitter of greenhouse gases, China has consistently taken an active role in addressing global climate change. In 2010, 2012, and 2017, the National Development and Reform Commission successively conducted three batches of national low-carbon province and city pilot programs in six provinces and 81 cities, aiming to explore low-carbon development models and effective pathways to achieve carbon emission peaks in different regions.

The 19th Party Congress report pointed out that "building an ecological civilization is a millennium-long task for the Chinese nation. It is necessary to review and implement the concept that green mountains and clear waters are as valuable as mountains of gold and silver, and adhere to the basic state policy of conserving resources and protecting the environment." The establishment of effective environmental governance measures and their practical implementation is becoming increasingly important. The implementation of low-carbon pilot policies is aimed at reducing carbon emissions and achieving green economic development. Achieving green development and enhancing green total factor productivity are fundamental strategies. Green total factor productivity, as a source of economic growth, truly reflects the engine and quality of economic development [5]. Therefore, this paper starts from the perspective of low-carbon city pilot policies, focusing on exploring the impact and pathways of these policies on China's green total factor productivity. This is of great significance for the implementation of low-carbon city pilot programs and the dual carbon goals in China.

2. Literature Review

Since the implementation of the low-carbon pilot policies in 2010, scholars have adopted various perspectives to assess the effectiveness of these policies. Initially, many researchers focused on studying the impact of low-carbon policies on carbon emissions reduction. For instance, Yang Bowen [6] applied a synthetic control method to analyze the carbon reduction effects in the pilot provinces of Hubei and Guangdong. The results indicated a noticeable impact on carbon reduction in Guangdong, while the effect in Hubei was not significant. Chen Jingdong [7] and others used a double-difference model to examine the actual impact of carbon trading policies on carbon reduction in the power industry. Guo Shihong [8] and colleagues, through qualitative comparative analysis and case studies based on empirical experiences of low-carbon pilot projects, identified funding mechanisms and monitoring and accounting systems as necessary conditions for achieving carbon reduction targets. Ren Yayun [9] and others, using a double-difference model, found that the pilot policies in China significantly reduced carbon dioxide emissions and intensity. Wang Huiying [10] discovered that the policy primarily achieved carbon reduction by influencing total energy consumption and changing the energy consumption structure.

Subsequently, some scholars conducted research from the perspectives of technological innovation, industry agglomeration, and green total factor productivity. First, in terms of technological innovation, most literature mainly revolved around studies related to "cost compliance" and "Porter hypothesis." Scholars supporting the "cost compliance" perspective believed that the implementation of low-carbon pilot policies would increase enterprise expenditures to reduce technological innovation. Scholars adhering to the "Porter hypothesis" argued that appropriate environmental regulations would force enterprises to innovate technologically. For example, Wang Xing [11] analyzed and tested the theoretical mechanisms and actual effects of the impact of low-carbon city pilot policies on green technological innovation from both theoretical and empirical perspectives. The study found that low-carbon city pilot policies enhanced the level of urban green technological innovation. Zhang Zhixin [12] found that although the implementation of low-carbon city pilot policies significantly promoted

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the increase in the quantity of green technological innovation, it led to a decline in the quality of enterprise green technological innovation. Xu Jia [13], based on green patent application data from A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2005 to 2015, found that low-carbon city pilot policies could induce green technological innovation at the overall company level to some extent. Second, Wang Yafei and others [14] empirically verified that the agglomeration of productive service industries, manufacturing industry agglomeration, and the synergistic agglomeration of manufacturing and productive service industries all contribute to the improvement of green total factor productivity. Third, research on the impact of low-carbon pilot policies on green total factor productivity, such as Li Hui and others [15], studied the influence of low-carbon city pilot policies on the green total factor productivity of thermal power listed companies at the enterprise level. Zhang Zhe and others [16] found through their study that low-carbon city pilot policies significantly increased the industrial green total factor productivity of pilot cities.

In recent years, with rapid economic development, environmental issues arising as a byproduct have become a rigid constraint on the quality of economic development. Total factor productivity, insufficient for adequately measuring today's high-quality economic development, has led to the emergence of green total factor productivity. This approach introduces factors such as energy and resource consumption on the basis of total factor productivity, becoming a most effective comprehensive indicator for measuring high-quality economic development in the new era. The Data Envelopment Analysis (DEA) method proposed by Charnes [17] is the most commonly used method for calculating green total factor productivity. Early domestic scholars typically used the SBM directional distance function combined with the ML index to calculate total factor productivity. However, this calculation method cannot measure efficiency values that include unexpected outputs. To address this issue, Chung [18] proposed the DDF function, successfully resolving the aforementioned problem. Building on previous work, Oh [19] introduced the GML index. Commonly used models in the academic community for calculating green total factor productivity include the SBM-GML model, DDF-GML, SYS-GMM [20-21], and others. For example, Wu Guosong [22] used the SBM model and ML method to measure the green total factor productivity of agriculture in China. Chen Haisheng et al. [23], based on the SBM-GML model, calculated the environmental total factor productivity of provincial-level agriculture in China. Cao Tingqiu [24] and others used the DDF-GML index to calculate the green total factor productivity of the Beijing-Tianjin-Hebei region, estimating the green development status of 29 provinces and cities in China. Bai Ke et al. [25] used the EBM-ML model, which includes unexpected outputs, to calculate industrial green total factor productivity.

The review and summary of the above literature have important implications for this study. Therefore, this paper first collects a list of low-carbon pilot cities, constructs a green total factor productivity index, and, using panel data from 246 prefecture-level cities from 2009 to 2019, empirically tests the impact of low-carbon pilot cities on green total factor productivity. The paper also explores their impact mechanisms, analyzes regional heterogeneity and urban abundance heterogeneity. The innovations of this paper are as follows: firstly, the use of the DDF function combined with the GML index to calculate the green total factor productivity of prefecture-level cities improves the theoretical analysis framework of low-carbon pilot cities and green total factor productivity. Secondly, employing a multi-temporal double-difference model accurately identifies the green development effects of low-carbon pilot policies. From the perspectives of industry agglomeration and green technological innovation, the paper will explore the internal mechanisms through which pilot policies affect total factor productivity. Finally, the paper conducts heterogeneity analysis of the impact of pilot policies on green total factor productivity in different regions and cities with varying levels of resource abundance.

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3. Hypotheses

3.1. The Driving Effect of Low-Carbon City Pilot Policies on Green Total Factor Productivity

Low-carbon pilot policies serve as comprehensive tools or means of environmental regulation at the urban level. The essence of urban low-carbon initiatives lies in reducing carbon dioxide emissions and enhancing the city's carbon sequestration and offsetting capacity. To achieve this goal, in pilot cities, local governments typically establish corresponding energy consumption and emission standards. They directly control the energy use and pollution emissions in the production processes of enterprises, restraining and penalizing environmental pollution through legislation and administrative measures. Alternatively, they may employ methods such as pollution emission rights trading and pollution taxes, fully utilizing market mechanisms to release signals in the market, encouraging enterprises to actively reduce pollution emissions. This, in turn, aims to achieve the dual objectives of increasing local economic levels while reducing carbon emissions and enhancing environmental quality. Based on the analysis above, this paper proposes the following research hypothesis:

H1: Low-carbon pilot policies promote the improvement of green total factor productivity.

3.2. The Driving Paths of Low-Carbon City Pilot Policies on Green Total Factor Productivity

Building upon this, the paper explores the low-carbon advancement paths of city policies from two perspectives: industrial specialization and green technological innovation. Furthermore, industrial agglomeration is subdivided into manufacturing industry agglomeration and productive service industry agglomeration, as illustrated by the theoretical mechanism in Figure 1.

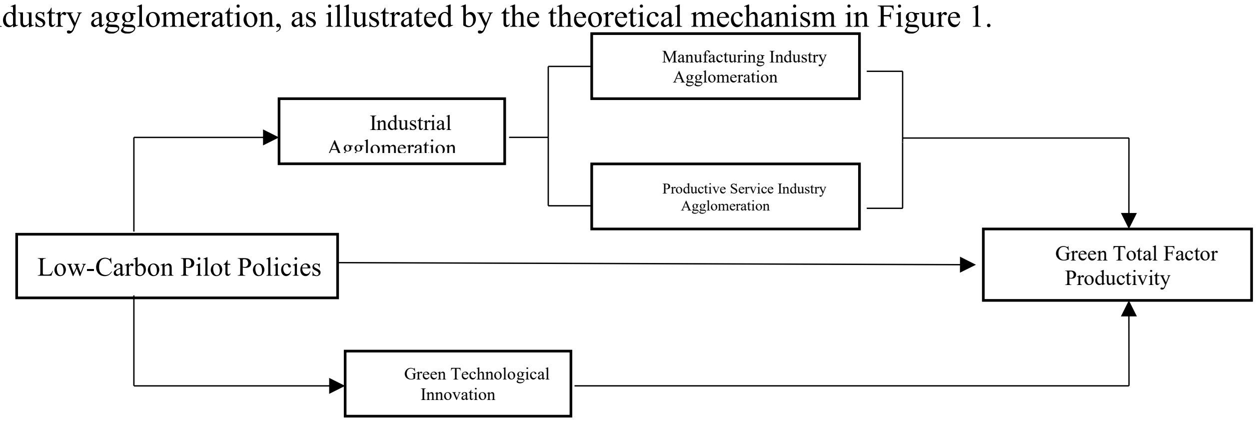

Figure 1: The Pathways of Low-Carbon City Pilot Policies Influencing Green Total Factor Productivity

3.2.1. Industrial Agglomeration

In accordance with Ren Yangjun et al. [26], industrial agglomeration is subdivided into manufacturing industry agglomeration and productive service industry agglomeration. Firstly, one of the goals of low-carbon pilot policies is to reduce corporate carbon emissions. To achieve this, companies may outsource pollution control services, thereby creating economies of scale and ultimately enhancing green total factor productivity. Secondly, industrial agglomeration fosters knowledge sharing among different enterprises, increasing economic vitality and achieving a win-win situation among companies. However, the current excessive agglomeration of manufacturing industries has led to issues such as scarce land, rising labor costs, and traffic congestion [27], hindering the economic development of regions in China. Productive service industries belong to typical knowledge-intensive industries. The agglomeration of productive service industries not only accelerates the spillover of knowledge, promotes face-to-face communication opportunities for high-tech talents but also alleviates the phenomenon of resource misallocation [28], improving the efficiency of resource allocation. Therefore, it remains to be verified whether low-carbon pilot cities can improve the agglomeration status of manufacturing and productive service industries and promote the enhancement of green total factor productivity. In summary, this paper proposes the research hypothesis:

H2: The mediating effect of productive service industry agglomeration on the significant positive relationship between low-carbon pilot policies and green total factor productivity is evident, while the mediating effect of manufacturing industry agglomeration is not significant.

3.2.2. Green Technological Innovation

The impact of green technological innovation has been a subject of continuous debate in the academic community. Some scholars argue that technological innovation leads to a “crowding-out effect” on corporate funds, where companies are compelled to allocate a portion of funds to reduce environmental pollution. This, in turn, reduces the funds available for research and development, diminishing the impetus for independent innovation. Simultaneously, the high-risk nature of technological innovation [29] may decrease the demand for independent innovation by companies, ultimately hindering the growth of green total factor productivity.

This paper posits that companies, after engaging in technological innovation, acquire new technologies that enhance the efficiency of resource allocation, thereby boosting green total factor productivity. According to the Porter hypothesis [30], stringent yet reasonable environmental regulations prompt companies to engage in technological innovation. This results in improved production efficiency, allowing companies to offset the additional costs brought about by environmental regulations and, in some cases, even yielding returns greater than the costs incurred. As a form of environmental regulation, low-carbon city pilot policies internalize the externalities companies impose on the environment. They effectively and flexibly adjust various impacts of environmental policies on companies, promoting production technology reforms and innovation. Indirectly, these policies encourage companies to adopt high-tech, low-carbon emission technologies, subsequently enhancing production performance and ultimately elevating green total factor productivity. In summary, this paper proposes the research hypothesis:

H3: Low-carbon pilot policies promote the improvement of green total factor productivity by fostering green technological innovation.

4. Model Construction and Variable Introduction

4.1. Model Specification

In this study, the construction of low-carbon cities is considered a quasi-natural experiment. Given the varying pilot years across the three batches of low-carbon cities, a multi-period double-difference model [31] is employed to assess the differences in green total factor productivity between pilot cities (experimental group) and non-pilot cities (control group). This approach enables the derivation of the net effects of the policy.

$$GTFP_{it} = \alpha_0 + \alpha_1 did_{it} + \alpha_3 Control_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

Where, $GTFP_{it}$ represents the green total factor productivity of city i in period t, did_{it} indicates whether city i implemented the low-carbon pilot policy at time t, with did_{it}=1 denoting policy

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implementation and did_{it}=0 otherwise. $Control$ represents a series of control variables affecting the impact of the low-carbon pilot policy on green total factor productivity. μ_i and τ_t denote city fixed effects and time fixed effects, respectively; ε_{it} represents the random disturbance term. Due to the use of panel data, a two-way fixed effects model is employed.

4.2. Data Source and Variable Introduction

All data in this study are sourced from the 2007-2020 "China Urban Statistical Yearbook," "China Statistical Yearbook," and "China Energy Statistical Yearbook" from the official websites of local statistical bureaus. Regions with severe data missingness are excluded, and missing values are supplemented using linear interpolation or mean imputation. The final research sample comprises 246 prefecture-level cities. The low-carbon pilot cities are identified based on documents such as the "Notice on Conducting Pilot Work for Low-Carbon Provinces and Low-Carbon Cities" released by the National Development and Reform Commission. Data from areas where the pilot covers specific districts within a municipal region are excluded. Only samples from cities where the entire municipal region is part of the pilot are retained. The final dataset includes 71 cities in 2010, 23 cities in 2012, and 20 cities in 2017, totaling 114 pilot cities.

(1) Dependent Variable:

This study selects green total factor productivity as the dependent variable. In the literature, the measurement of green total factor productivity often employs Data Envelopment Analysis (DEA). DEA possesses the advantage of extensive applicability. It is a relatively comparative analytical method that can be employed to address non-parametric technical efficiency issues among decision-making units. However, traditional DEA models have not addressed the problem of unexpected outputs. Chung et al. proposed Directional Distance Function (DDF) in 1997, which, when combined with the GML index, offers several advantages. For instance, the model references the same frontier in each period, providing a single Malmquist index instead of the traditional geometric mean of ML indices. Moreover, its efficiency change calculation allows for comparability of efficiency values across periods.

Traditional radial CCR and BBC models of DEA assume constant output and proportional input reduction. In reality, when inputs are reduced proportionally, output factors also change correspondingly. Hence, the traditional CCR and BBC models are not widely applied in practical computations. Scholars have proposed the Directional Distance Function (DDF) considering simultaneous changes in inputs and outputs. The specific formula for the DDF function is as follows:

$$\vec{D}\left(x, y, b, \vec{g}\right) = max\left\{\beta : \left(x - \beta\vec{g}_x, y + \beta\vec{g}_y, b - \beta\vec{g}_b\right) \in P(x)\right\}$$

In the above formula, (x, y, b) represents the input vector, expected output vector, and non-expected output vector for each city, while $\vec{g} = (\vec{g}_x, \vec{g}_y, \vec{g}_b)$ represents the directional vectors for inputs, expected outputs, and non-expected outputs, indicating whether each factor increases or decreases. The production possibility set is denoted as $P(x)$.

The ML index is expressed in a geometric mean form, lacking loop multiplicativity during the analysis. Therefore, it is difficult to observe long-term trends in the productivity index. Additionally, when calculating the directional distance function across periods using the ML index, there is the issue of linear programming having no feasible solution. To address the shortcomings of the ML index, Wu Dongxuan proposed the GML index method. This index is widely used for calculating green total factor productivity due to its advantages, such as transitivity, loop multiplicativity, and the ability to compare across periods [32].

According to Oh's research, the GML productivity index indicator between periods t and t+1 is expressed as:

$$\mathrm{GML}^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^G(x^t, y^t, b^t; g^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}$$

In the above formula, $D^G(x^t, y^t, b^t)$ represents the global directional distance function, and $\mathrm{GML}^{t,t+1}$ indicates the green total factor productivity from period t to t+1. When $\mathrm{GML}^{t,t+1} > 1$, it signifies an increase in green total factor productivity; when $\mathrm{GML}^{t,t+1} < 1$, it indicates a decrease, while $\mathrm{GML}^{t,t+1} = 1$ means that green total factor productivity remains unchanged.

The input indicators for calculating green total factor productivity include capital input, labor input, and energy input. Firstly, capital input is calculated using Zhang Jun's [33] sustainable inventory method, with a depreciation rate of 9.6%. The formula is as follows: $K_{i,t} = I_{i,t} + K_{i,t-1}(1-\delta)$, where K is the physical capital stock, I is the total capital formation for the year, and δ is the depreciation rate. Secondly, labor input is represented by the end-of-year employment in cities. Coal consumption in prefecture-level cities is used to measure energy input.

Industrial indicators consist of expected and non-expected outputs. Expected output refers to the actual Gross Domestic Product (GDP) of prefecture-level cities, converted to constant prices based on the 2006 base year. Non-expected output includes industrial wastewater discharge, industrial sulfur dioxide emissions, and industrial particulate matter emissions for each prefecture-level city.

(2) Core explanatory variable:

The variable "did" represents the key explanatory variable in this study. It is the focal point of attention, indicating whether city i was approved for a low-carbon pilot project in period t. The coefficient of "did" reflects the impact of low-carbon pilot policies on GTFP. It signifies the effect of the pilot policy on the region after its implementation in low-carbon cities, referred to as the disposal effect brought about by low-carbon city-related behaviors or policies. This study designates 114 low-carbon pilot cities as the treatment group and the remaining 132 cities as the control group. When "did" is 1, it indicates that the city in the treatment group was designated as a low-carbon pilot city in year t; otherwise, when "did" is 0, it signifies that "did" is not designated.

(3) Control variables:

Factors influencing green total factor productivity include not only whether a city is a pilot city, but also government fiscal expenditure, foreign direct investment, population density, and more. Therefore, this study selects the following control variables: regional Gross Domestic Product (gdp), represented by the logarithm of GDP at constant prices based on the 2006 base year; the ratio of government fiscal expenditure to GDP (gov), measured as the proportion of government fiscal expenditure to total production value; foreign direct investment (fdi), representing the ratio of actual foreign investment used to GDP in each region; capital-labor ratio (asslabor), which is commonly used to judge the factor endowment structure of an economic entity, potentially having a positive effect; population density (pop), which is an effective indicator reflecting the degree of spatial population concentration. Its reasonable growth can effectively promote resource utilization, thereby generating economies of scale and driving the growth of green total factor productivity. The specific formula for calculating population density in this paper is the ratio of the total population at the end of the year to the land area of the urban area. Urbanization rate (urban): The logarithm of the number of urban employed population is used to represent the urbanization rate. Refer to Table 1 for the main variables.

Table 1: Descriptive Statistics of Variables

Variable Name	(1) Sample Size	(2) Mean	(3) Standard Deviation	(4) Minimum	(5) Maximum
gtfp	3,444	1.007	0.047	0.576	1.701

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Table 1: (continued).

did	3,444	0.277	0.448	0	1.000
fdi	3,444	0.0242	0.0260	0	0.399
gov	3,444	0.158	0.084	0.010	2.702
urban	3,444	6.661	0.871	4.205	10.990
gdp	3,444	15.350	1.170	12.01	19.500
pop	3,444	2.950	0.974	0.652	6.708
asslabor	3,444	4.697	0.714	2.227	6.901

5. Empirical Analysis

5.1. Baseline Regression

We first conduct a double-difference model test, and the regression results are shown in Table 2. Equations (1)-(6) represent models without control variables and models with progressively added control variables, respectively. In Equation (1), without introducing control variables, the coefficient of the virtual variable representing the low-carbon pilot policy is 0.006, passing the significance test at a 10% level, indicating that this policy significantly enhances urban green total factor productivity. In Equations (2)-(6), as control variables are gradually introduced, it can be observed that the virtual variable representing the low-carbon city pilot policy remains consistently significant.

Table 2: Benchmark Regression Results

VARIABLES	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP	(5) GTFP	(6) GTFP
did	0.006*	0.006*	0.010***	0.009***	0.008**	0.008**
	(1.80)	(1.83)	(3.16)	(2.74)	(2.46)	(2.35)
gdp		0.043***	0.052***	0.072***	0.071***	0.070***
		(8.59)	(10.26)	(13.22)	(13.00)	(12.59)
asslaobor			0.024***	-0.016***	-0.014**	-0.014***
			(7.14)	(-2.95)	(-2.53)	(-2.64)
pop				-0.068***	-0.067***	-0.067***
				(-9.42)	(-9.24)	(-9.33)
fdi					-0.111**	-0.098**
					(-2.45)	(-2.14)
gov						-0.028**
						(-2.07)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Constant	1.006***	0.352***	0.088	0.171**	0.176**	0.210**
	(838.99)	(4.62)	(1.04)	(2.05)	(2.11)	(2.47)
Observations	3,444	3,444	3,444	3,444	3,444	3,444
R-squared	0.090	0.111	0.125	0.148	0.150	0.151

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5.2. Robustness Checks

5.2.1. Common Trends Test

The premise of using the double-difference model is to satisfy the common trends assumption, which means that before the implementation of low-carbon urban construction, the changing trends in green total factor productivity (GTFP) for the treatment group and the control group are not significantly different. This study employs the dynamic double-difference method to conduct the common trends test, and the specific model settings are as follows:

$$GTFP_{it} = \beta_0 + \sum_{j=-5}^{j=6} \alpha_j policy_{it}^{j} + \beta_1 Control_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

Where, the variable $policy_{it}^{j}$ represents the policy variable for each relative year generated based on the year of low-carbon urban construction as the base year, and other variables are the same as those in the benchmark regression model. If city i implements the low-carbon pilot policy in year t, the value of $policy_{it}^{j}$ is 1; otherwise, it is 0. j and -j respectively represent the jth year after and before the policy implementation, and so on; the ordinate represents the estimated coefficient of the treatment effect. This study takes the sample of the year before the low-carbon city pilot as the reference group during the estimation, i.e., the removal of the dummy variable j= -1 during the estimation process [34]. Figure 2 reports the results of the common trends test. The regression coefficients for the first 5 years before the implementation of the low-carbon urban construction policy fluctuate around 0, indicating no significant difference in green total factor productivity (GTFP) between pilot and non-pilot cities. In the year of policy implementation, the GTFP of pilot cities does not show a significant increase. Three years after policy implementation, the improvement effect of the low-carbon pilot policy on GTFP gradually becomes significant, possibly due to the lag effect of policy implementation.

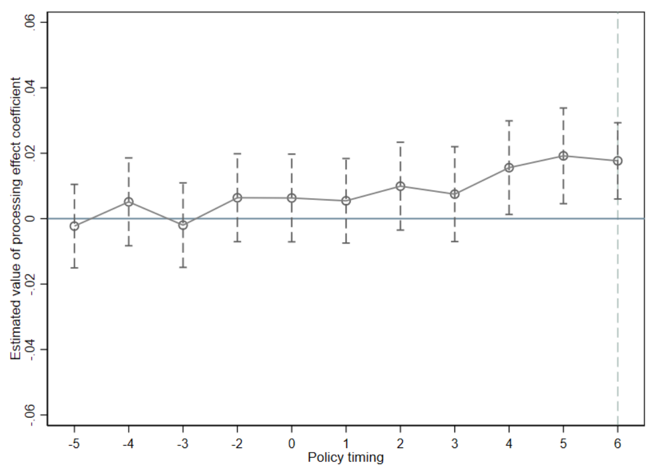

Figure 2: Common Trends Test

5.2.2. Placebo Test

In this study, a placebo test was conducted by randomly changing the treatment group. The placebo test involved randomly generating treatment and control groups for double-difference estimation across all samples, creating new interaction terms to test the robustness of the original research conclusions. In the specific operational method, new treatment groups were randomly generated, and

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the regression estimation was repeated 500 times. Subsequently, the results of the 500 regressions were aggregated and plotted in Figure 4. The blue dashed line in the figure represents a p-value equal to 0.1, and the blue scattered points represent the coefficients and p-values of the newly generated interaction terms. The red dashed line represents the true coefficient of the baseline regression, and the red solid line represents the mean of the coefficients of the newly generated interaction terms. Observing Figure 3 reveals that the newly generated coefficients are distant from the true coefficients, and most of the estimated coefficients have p-values greater than 0.10, indicating that they are not significant at the 10% level. This further validates the significant positive impact of the low-carbon city pilot policy on green total factor productivity.

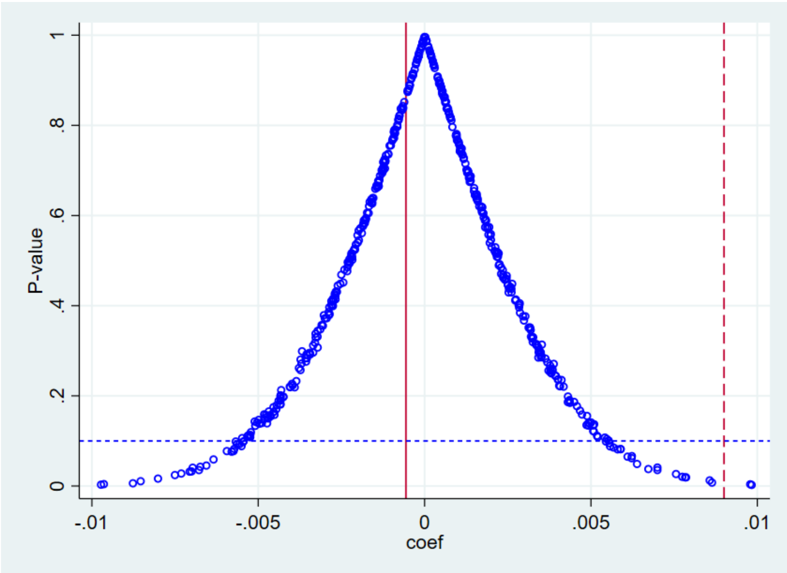

Figure 3: Placebo Test

5.2.3. PSM-DID Test

Following the approach of Shi Daqian [35] and others, in order to control for systematic biases resulting from different policy choices between the treatment and control groups, this study employs the PSM-DID model to re-estimate the samples using a one-to-one nearest-neighbor matching method. In the matching process, whether a city is a low-carbon pilot city is used as the dependent variable, and variables such as regional gross domestic product (GDP), foreign direct investment (FDI), urbanization rate (urban), government fiscal expenditure (gov), and capital-labor ratio (asslabor) are selected as matching variables. The nearest-neighbor matching method is employed, with a matching ratio of 1:5 between the treatment group and the control group. The test checks the sample size within the common value range for both groups, as shown in Figure 4. This indicates that the vast majority of samples from the treatment and control groups fall within the common value range, while samples outside this range have extreme propensity score values, suggesting that the majority of samples are eligible for matching.

Figure 5 displays the standardized differences in variables before and after matching, with all variable differences being less than 10% and significantly smaller than before matching. This result indicates that there is no systematic bias in the matching variables between the treatment and control groups.

Figures 6 and 7 respectively show the kernel density plots before and after matching, examining whether there are differences in propensity score values between the two groups before and after matching. If the kernel density curves between the two groups deviate significantly before matching

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but become closer after matching, it indicates effective matching. It can be observed that both kernel density curves deviate significantly before matching, but they become closer after matching, indicating the effectiveness of our matching.

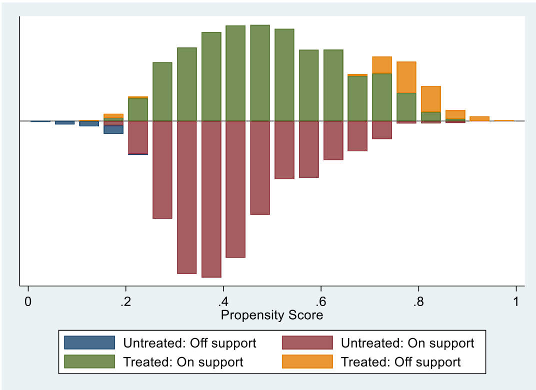

Figure 4: Common Value Range

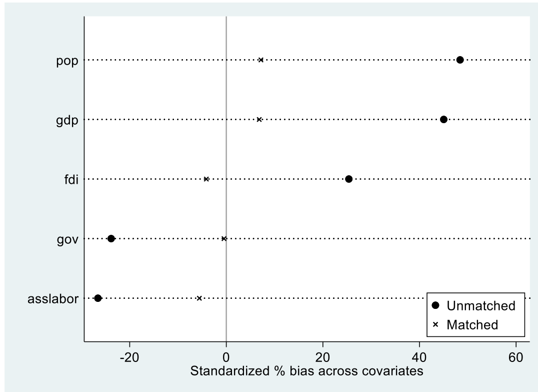

Figure 5: Standardized Differences Before and After Matching

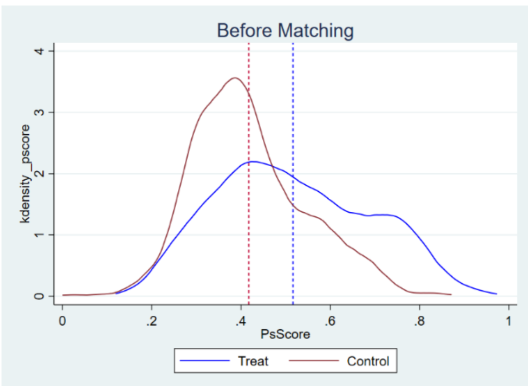

Figure 6: Kernel Density Plot Before Matching

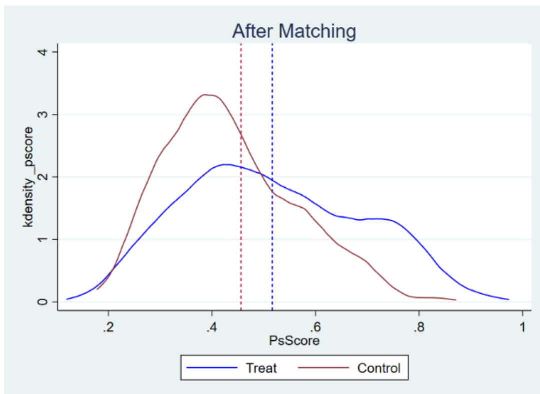

Figure 7: Kernel Density Plot After Matching

Finally, based on the above, the study, after excluding cities that were not matched, conducted a double difference estimation again. The regression results are shown in Table 3, column 1. The estimated coefficients of the core explanatory variables passed significance tests at the 1% level, providing further robustness testing for the baseline regression.

5.2.4. Counterfactual Test

To further eliminate interference from other random factors, a counterfactual test was conducted by artificially changing the policy implementation years. The counterfactual test assumes that the implementation years of low-carbon urban construction are 2006, 2007, and 2016, and different sample intervals are selected. If the estimated coefficients of the double-difference variables are not significant, the model passes the counterfactual test, indicating that the improvement in the green total factor productivity (GTFP) in the pilot cities is indeed caused by low-carbon urban construction. Column 2 of Table 3 reports the results of the counterfactual test. When the policy implementation time changes, the coefficients of the double-difference estimation are not significant, confirming that the improvement in GTFP is indeed caused by low-carbon urban construction and not by random factors.

Table 3: PSM-DID Test, Counterfactual Test, and Exclusion of Other Policies

VARIABLES	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP
did	0.008***	0.003	0.006*	0.008**
	(2.61)	(0.56)	(1.89)	(2.37)
Carbon Emission Trading			0.005	
			(0.98)	
Innovative City Pilot				-0.002
				(-0.54)
Time Fixed Effects	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES
Observations	3,058	3,444	3,444	3,444
R-squared	0.175	0.150	0.151	0.151

5.2.5. Excluding Interference from Other Policies

The policy of innovative city pilots was initiated in China in 2008, with the first national innovative city established, and the pilot work for innovative cities has been gradually implemented in 78 cities by 2018. The carbon emission trading policy began to be implemented in seven provinces and cities across the country in 2012. To eliminate the impact of these policies on the regression results, interaction terms representing the above-mentioned representative policies and their implementation times were constructed. These terms were then included as control variables in the model for regression analysis. In Table 3, the core explanatory variables for models (3) and (4) are 0.006 and 0.008, passing robustness tests at the 10% and 5% levels, further confirming the robustness of the baseline regression results.

5.3. Mechanism Test

Based on the conclusions drawn earlier, we found that low-carbon urban construction can enhance a city's green total factor productivity (GTFP). However, through which mechanisms does it achieve this enhancement? This paper will conduct a mechanism analysis on these two influencing channels. In terms of model construction, we refer to the approach taken by Fan Ziying, et al. [36], embedding mechanism variables into the baseline regression to test the significance of the impact on the mechanism. If the coefficient of the interaction term $did * MED$ is significant, it demonstrates that low-carbon urban construction enhances GTFP through the mechanism variable MED. The specific model setting is as follows:

$$GTFP_{it} = \alpha_0 + \alpha_1 did_{it} * MED + \alpha_2 did_{it} + \alpha_3 MED_{it} + \alpha_4 Control_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

MED represents the mechanism variable, including industrial agglomeration and green technological innovation. Other variables are the same as those in the baseline regression model.

(1) Industrial Agglomeration:

Following the approach of Ren Yangjun, industrial specialization is divided into manufacturing agglomeration and productive service industry agglomeration. The locational entropy index is used to measure the level of industrial agglomeration in different regions, as shown below:

$$S_{i,m,t} = (E_{i,m,t}/E_{i,t})/(\max(E_{m,t}/E_t))$$

Here, $E_{i,m,t}$ represents the employment in industry m of city i at time t, $E_{i,t}$ is the total employment in city i at time t, $E_{m,t}$ is the national employment in industry m at time t, and E_t is the total national employment at time t. $\max(E_{m,t}/E_t)$ represents the maximum value of the proportion of employment in manufacturing or productive service industry for all years. $S_{i,m,t}$ is the agglomeration index, mainly referring to the agglomeration of manufacturing (ma) and productive service industries (ps), with productive service industries including the aggregate of the four sectors: "Transportation, Warehousing, and Postal Services," "Information Transmission, Computer Services, and Software Services," "Scientific Research, Technical Services, and Geological Exploration," and "Finance" [37].

(2) Green Technological Innovation (gti):

Referring to the research of Wang Xiaowen [38] and others, this study measures the intensity of green technological innovation by taking the logarithm of the number of green invention applications plus 1.

The results of the mechanism regression are presented in Table 4. Columns (1), (2), and (3) of Table 4 test the impact of pilot policies on green total factor productivity after introducing the three intermediary variables: manufacturing agglomeration, productive service industry agglomeration, and green technological innovation. The estimated coefficients are 0.002, 0.002, and 0.014, respectively. Among them, the coefficient of manufacturing specialization is not significant, while productive service industry specialization and green technological innovation are both significant at the 10% level. This indicates that low-carbon pilot policies can enhance green total factor productivity through the specialization of productive service industries and green technological innovation. As for manufacturing specialization, although agglomeration can bring about knowledge spillover effects and economies of scale, excessive agglomeration can lead to problems such as rising labor costs, decreased efficiency in enterprise resource allocation, environmental pollution, and traffic congestion. These issues are not conducive to the improvement of green total factor productivity.

Table 4: Mechanism Test Results

VARIABLES	(1) GTFP	(2) GTFP	(3) GTFP
did*ma	0.002		
	(0.43)		
did*ps		0.002*	
		(1.65)	
did*gti			0.014*
			(1.79)
Time Fixed Effects	YES	YES	YES
City Fixed Effects	YES	YES	YES
Constant	0.090	0.047	0.071
	(1.01)	(0.52)	(0.80)
Observations	3,444	3,444	3,444
R-squared	0.132	0.130	0.130

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5.4. Heterogeneity Analysis

5.4.1. Regional Heterogeneity Analysis

Due to significant differences in economic development levels and resource endowments among regions in China, this study divides the overall sample into Eastern, Central, and Western cities to analyze the variations in the impact of low-carbon city pilot policies on green total factor productivity (GTFP). The regression results are presented in Table 5. The coefficients for the Eastern and Western regions are 0.012 and 0.014, respectively, both significant at the 5% level. However, the coefficient for the Central region is negative and statistically insignificant. These findings demonstrate that, for the Eastern and Western regions, the policy significantly enhances GTFP, while its effect on the Western region is not as pronounced. Under the impetus of low-carbon city pilot policies, there is a greater advantage for Eastern and Western cities in accumulating technology and innovation elements related to green and ecological economic development, thereby promoting green development in these regions.

Table 5: Regional Heterogeneity Analysis

VARIABLES	(1) Entire Sample	(2) Eastern Region	(3) Central Region	(4) Western Region
did	0.008**	0.012**	-0.004	0.014**
	(2.35)	(2.00)	(-0.97)	(2.46)
Constant	0.210**	0.059	0.395***	0.278*
	(2.47)	(0.37)	(3.23)	(1.75)
Observations	3,444	1,372	1,246	826
R-squared	0.151	0.155	0.201	0.164
City Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.4.2. Resource Abundance Heterogeneity Analysis

Taking into account the differences in natural resources, economic structure, and employment structure among different cities, this study refers to the “National Sustainable Development Plan for Resource-based Cities (2013-2020)” released by the State Council. The sample is divided into 108 resource-based cities and 162 non-resource-based cities. Resource-based cities refer to those that take natural resources as their dominant industries. The regression results are shown in Table 6. It is not difficult to find that the coefficient for resource-rich cities, although positive, is not significant, while the coefficient for non-resource-rich cities is significantly positive. Compared to resource-rich cities, the low-carbon pilot policy is more conducive to promoting economic green development in non-resource-rich cities.

Table 6: Resource Abundance Heterogeneity Analysis

VARIABLES	(1) Resource-rich Cities	(2) Non-resource-rich Cities
did	0.003	0.009**
	(0.64)	(2.17)
Constant	-0.038	0.357***
	(-0.31)	(2.96)
Observations	1,330	2,114
R-squared	0.216	0.127
Urban Fixed Effects	YES	YES
Year Fixed Effects	YES	YES

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion and Implications

This study employs a multi-period difference-in-differences model to investigate the impact of the low-carbon pilot policy on China's green total factor productivity (GTFP). The research results indicate that the low-carbon pilot policy significantly enhances China's GTFP. After a series of robustness tests, the above conclusions remain valid. Mechanism tests reveal that the low-carbon pilot policy can increase China's GTFP by improving the agglomeration of productive service industries and the level of green technological innovation. However, the mechanism test for manufacturing industry agglomeration is not significant. Regional heterogeneity results show that the low-carbon pilot policy has a significant positive effect on the improvement of GTFP in China's eastern and western regions, while the effect on the central region is not evident. Heterogeneity analysis based on resource abundance shows that the policy has a significant positive effect on the GTFP of non-resource-based cities, while the effect on resource-based cities is not significant.

The policy implications of the above research conclusions:

Firstly, the low-carbon pilot policy can promote the improvement of China's GTFP, indicating its crucial role in achieving sustainable economic growth. Given the vast land area of China, there are still many regions where this policy has not been implemented. The experience of pilot cities should be extended to non-pilot cities to achieve the country's early transition to a low-carbon economy.

Secondly, in the process of implementing the low-carbon pilot policy, it is essential to guide the agglomeration of productive service industries reasonably and fully leverage the mediating role of such agglomeration. Encouraging enterprises to engage in green research and development can facilitate China's energy transition and achieve the "dual-carbon goals."

Finally, based on heterogeneity analysis, attention should be paid to the impact of the low-carbon pilot policy on GTFP in China's eastern and western regions, as well as in resource-based cities. Efforts should be intensified to promote pilot policies in cities in the east, west, and resource-based areas. For central regions and non-resource-based cities, there is a need to increase public awareness of the necessity of low-carbon transformation and provide relevant policy and financial support.

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