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How Industrialization Stage Moderates the Impact of China's Low-Carbon Pilot Policy?

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Abstract: The goal of China's low-carbon pilot policy (LCP) is not only to solve the problem of climate change but, more importantly, to achieve the low-carbon transformation of cities. This paper analyzes the industrialization stage's moderating effect on LCP policy implementation using the difference-in-difference model (DID) with the Low Carbon Development Index (LCDI) as the explained variable. We find that for the low-carbon pilot cities (LCPCs) at the later stage of industrialization, the LCP policy has a positive impact on LCDI, gradually increasing with the study period's extension. The marginal impact reaches its maximum in the second year after its implementation. For the LCPCs at the middle stage of industrialization, the LCP policy has a weakly negative impact on LCDI. The marginal impact does not change to positive until the fourth year after its implementation. In terms of mechanism analysis, the LCP policy enhances LCDI by slowing down the industrialization process and boosting innovation; the industrialization stage does not constrain the effect. In contrast, the LCP policy's impact on LCDI by facilitating FDI (Foreign Direct Investment)inflows is strongly influenced by the industrialization stage. For the LCPCs at the later stage of industrialization, the LCP policy can enhance LCDI through FDI. For the LCPCs at the middle stage of industrialization, the LCP policy reduces the inflow of FDI, and the positive effect of FDI on LCDI does not pass the significance test. Thus, this paper argues that a one-size-fits-all strategy to policy implementation should be avoided. Instead, the industrialization stage should be considered a criterion for city classification, and a differentiated target responsibility assessment mechanism should be adopted according to local conditions.

Keywords: low-carbon development index; industrialization stage; low-carbon pilot policy; difference-in-difference

1. Introduction

The Paris Agreement (2015) sets a long-term goal of limiting the global temperature rise to no more than 2 °C and striving to limit it to 1.5 °C compared to before the industrial revolution [1,2]. Therefore, extensive cooperation has been undertaken in various fields to reduce member countries' greenhouse gas emissions. To lead international collaboration to address climate change, the Chinese government has set a series of goals and objectives, including achieving peak carbon emissions by 2030, reducing CO_2 emissions per unit of GDP by 60 percent compared to 2005, increasing the share of non-fossil energy in primary energy consumption to 20 percent, and increasing forest storage by 4.5 billion cubic meters compared to 2005 [3,4]. To achieve these targets, since 2010, the National Development and Reform Commission (NDRC) of China has conducted three batches of low-carbon pilot policy (LCP) policies in six provinces and 77 cities [5–8]. This paper defines the LCP policy as a public policy tool where the government implements procedures that promote low-carbon development in a particular city to overcome the negative externalities caused by high-carbon development. Public policy theory suggests that the implementation of a policy is likely to achieve the objectives it was initially set out to achieve but also that there may be a lag in its entry into force or policy failure (Pal (1992)) [9]. Thus, we should propose a city classification method to identify the three possible effects of LCP policy implementation. After several experiments, we find that using the industrialization stage as a city classification criterion can reflect the heterogeneity of LCP policy in different cities.

Moreover, the LCP policy's expected targets are not only to reduce the total carbon emissions but also to require a low-carbon transformation of major high-carbon source sectors, improve the carbon sequestration capacity, and change the way urban residents live and consume. According to those expected targets, we construct a set of low-carbon development evaluation index systems covering the city's primary carbon source industries and carbon sink fields, including the aspects of macro, energy, industry, environment, land, and life and 24 quantitative indicators. We also use the improved TOPSIS(Technique for Order Preference by Similarity to an Ideal Solution)model to measure the Low Carbon Development Index (LCDI). Taking the LCDI as the explanatory variable, this paper applies the DID model to analyze the industrialization stage's moderating effect on the implementation of LCP policy and to profoundly understand its influence mechanism. This is of great significance for exploring the low-carbon development path of Chinese cities. It helps the promotion of LCP policy and the mitigation of greenhouse gas emissions in China.

Why can the industrialization stage moderate the impact of China's LCP policy? The change of per capita income and economic structure is the sign of industrialization (Chen et al. (2006)) [10]. Thus, we try to analyze the link between the industrialization stage and the low-carbon development from these two aspects. First, as per capita income is at different levels, the carbon emission characteristics and carbon source structure of cities at different industrialization stages are different. During the rapid industrialization stage, the rapid growth of per capita consumption level is the main factor for carbon emissions growth. According to statistics, the increase in GDP per capita is the largest positive driver of China's carbon emissions, with an average contribution rate of 15.82% (Wang et al. (2010)) [11]. However, as the population ages, this trend gradually weakens. During the post-industrialization period, as urban residents' low-carbon consciousness increases, low-carbon consumption methods will be selected more, and carbon emissions will decouple from industrialization. Zhang et al. (2013) indicated that the input of high-energy-consuming products such as cement and steel in the early stage of industrialization indirectly caused more construction-oriented greenhouse gas emissions. With the increase in per capita income and living standards, the greenhouse gases caused by consumption emissions occupy the mainstream [12]. With the increase in the per capita income level, the carbon emissions of households increased rapidly. The urban residents' demand for indirect carbon emission products such as induction cookers and air conditioners and direct carbon emission products such as cars is growing faster. Second, there are significant differences in the urban economic structure at different industrialization stages, which will impact the city's carbon emission characteristics. Syrquin et al. (1989) concluded that in the process of industrialization, the changes in the industrial structure had the following regularities: the city experienced the early stage of industrialization characterized by labor-intensive industries, transformed into the mid-term stage of industrialization characterized by capital-intensive industries, and finally entered a post-industrial period characterized by intensive technology [13]. In the short term, the city's energy consumption structure and industrial structure are relatively stable. The growth of total economic volume will drive the same proportion of total carbon emissions. In the long term, with the optimization and upgrading of the industrial structure, a difference in carbon emission intensity can appear due to the city's different industrial structures. Cities with low-value-added energy products as production targets have relatively high carbon emission intensity. In contrast, cities with high-value-added technology products as production targets have relatively low carbon emission intensity. Shan et al. (2018) investigated cities with service industries as the pillar industry, such as Shenzhen, whose carbon emission intensity was as low as 0.04 tons of carbon dioxide per thousand yuan; cities with steel production as pillar industries, such as Panzhihua, whose carbon emission intensity was as high as 1.55 tons of carbon dioxide per thousand yuan; cities with energy production and resource extraction as pillar industries, such as Hegang, whose carbon emission intensity was as high as 1.72 tons of carbon dioxide per thousand yuan [14]. Liu et al. (2012) [15] indicated that Chongqing and Tianjin, with energy-intensive manufacturing as the core industry, had higher coal consumption in the thermal power generation industry. Their total carbon emissions were in a stage of substantial increase. In contrast, Beijing and Shanghai, which had the service industry as the core industry, implemented the policy to purchase electricity. Their carbon emissions growth rate tended to be slow. Third, heterogeneity in the structure of carbon sources in cities at different industrialization stages is due to significant differences in economic structure. The IPCC's(Intergovernmental Panel on Climate Change) fifth climate change assessment indicated that human-induced greenhouse gas emissions had increased by 10 billion tons of carbon dioxide equivalent between 2000 and 2010, of which 47% came directly from the energy supply sector, 30% from industry, 11% from transportation, and 3% from construction [16]. In this paper, the energy supply sector, the industrial sector, etc., are defined as the main sources of carbon emission for cities. Differences in driving factors and pillar industries in cities at different industrialization stages lead to heterogeneity in carbon sources' structure. This is shown in Figure 1 below. At the early and middle stages of industrialization, the input of labor and the primitive accumulation of capital drove the industrialization in China's cities. The industrial production process in China's cities has led to a surge in carbon emissions. Between 1998 and 2006, China's industry generated 40% of the value-added of GDP, while energy consumption and carbon emissions accounted for 68% and 83% of the national total, respectively (Chen (2011)) [17]. At the later stage of industrialization, technological progress drove the industrialization process in Chinese cities, and the processing and assembly manufacturing industry became the pillar industry of the cities. As production efficiency increased, the growth of carbon emissions slowed. At the post stage of industrialization, institutions and innovation drive the industrialization process of Chinese cities, and high-tech industries become the cities' pillar industries. The substitution effect of fossil energy is gradually increasing, as the cost of clean energy is gradually decreasing. The city thus achieves peak carbon emissions.

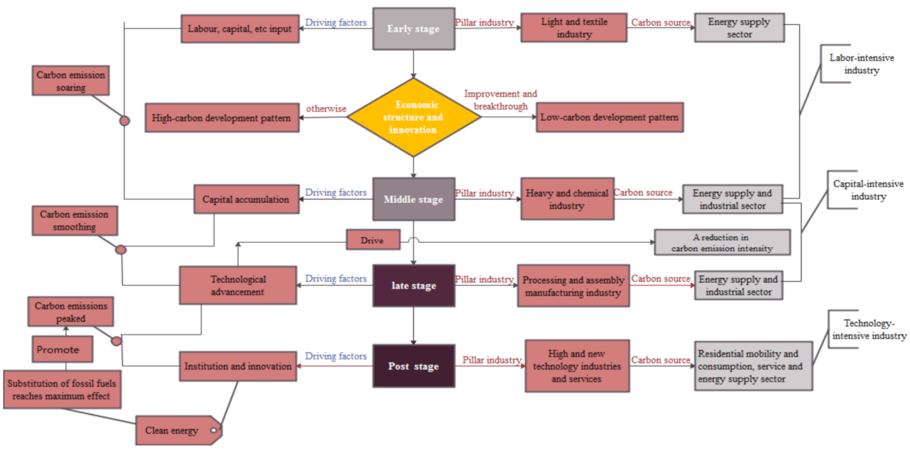

Figure 1. Industrialization stage, driver factors, and pillar industries in Chinese cities.

In summary, because the cities are at different industrialization stages, the economic structure and per capita income levels are significantly different, resulting in heterogeneity in the city's carbon source structure and carbon emission characteristics, which affect the implementation effect of LCP policy. Therefore, it is significant to analyze the moderating influence of the industrialization stage on LCP policy.

Scholars have not reached a consensus on the impact effects of environmental public policy. Traditional studies have argued that environmental public policy raises the production costs of firms and that firms are forced to invest more in response to government-imposed environmental governance mandates [18]. This view is supported by Greenstone et al. (2012). His research showed that air quality regulations reduced the TFP(Total Factor Production) in U.S. manufacturing plants [19]. Rogge et al. (2011) argued that the EU ETS(Emissions Trading Scheme) could not provide sufficient incentives for fundamental changes in firms' innovative activities to ensure that political long-term goals could be achieved [20]. Another point of view comes from Porter's hypothesis, which argues that environmental public policies can improve the innovation and competitiveness of firms [21]. There are other scholars who also support the Porter hypothesis, for example, Rassier et al. (2015) [22], Skoczkowski et al. (2018) [23], and Wang et al. (2019) [24].

Based on the two different views described above, scholars have discussed the impact of China's LCP policy [25–27]. Our study contributes to the previous literature in the following aspects. First, previous researchers have mainly studied the implementation effect of LCP policy from a qualitative perspective. Fewer studies have investigated the implementation effect of LCP policy through empirical analysis methods. Khanna et al. (2014) [28] and Wang et al. (2015) [29] collected documentation and data from the Chinese government on low-carbon pilot cities, providing some critical observations on the response to LCP policy. Li et al. (2018) [30] provided an overview of 32 low-carbon pilot cities' progress based on their official self-assessment reports. However, these studies only present the effects of LCP policy implementation from a qualitative perspective, which is incomplete and parochial. This paper examines the implementation effects of LCP policies from the perspective of empirical analysis. We also estimate the impact of LCP policy on the LCDI. This will help to promote the implementation of low-carbon transition in cities and will play a vital role in promoting the LCP policy.

Second, as the expected implementation goal of LCP policy not only is to reduce carbon emissions or carbon emission intensity but also involves the low-carbon development of energy, industry, land, environment, living and consumption, and other fields, we chose the LCDI as the indicator to reflect the implementation effect of LCP policy. The LCDI is an index measured by the improved TOPSIS model according to the low-carbon development evaluation index system constructed in this paper (Table 1). Compared with the traditional indicators to reflect the effectiveness of LCP policy implementation, such as carbon emissions (Yu et al. 2019) [26], green development index (Liu et al. 2019) [18], or land transfer intensity of high-energy-consuming industries (Tang et al. 2018) [25], the LCDI more comprehensively reflects the effectiveness of a city's low-carbon development and is more in line with the content of Chinese government's expected implementation goals for LCP policy.

Third, the propensity score matching–difference in difference model (PSM-DID) is extremely difficult to use to study the impact of LCP policies on urban LCDI in China, as the lack of a unified and authoritative database of Chinese cities limits the application of this method, which requires a large number of data to ensure the match between the treat and control groups effectively. The classification of low-carbon pilot cities by industrialization stage proposed in this paper overcomes the imbalance in the data between the treat and control groups due to the large differences in development stages among the cities. Such an approach also does not require a large number of control groups as a prerequisite. Our results show that such a classification has both theoretical and practical implications. This paper's findings also provide an essential reference for the Chinese government to adopt a differentiated assessment method to evaluate the effect of LCP policy implementation.

The remainder of the paper is organized as follows. Section 2 presents the background of the LCP policy and construction of a low-carbon development evaluation index system. Section 3 presents the methodology and data description. Section 4 presents the results and discussion of the empirical analysis and robustness tests. Section 5 presents the conclusion and discussion.

Table 1. Evaluation Index System of China's urban low carbon development.

Criterion	Indicator	Effect	Unit	Data Source
Macro system	Total Energy Consumption of Industrial Enterprises (A1)	−	$MtCO_2$	Statistical Yearbook of 120 cities
	Total carbon emissions of industrial enterprises (A2)	−	million tons of standard coal	CEADs database
	Carbon emissions per unit of industrial value-added (constant price in 2010) (A3)	−	tCO_2/RMB	CEADs database
Energy system	Coal consumption as a percentage of total fossil energy consumption (B1)	−	%	Statistical Yearbook of 120 cities
	Natural gas consumption as a proportion of fossil energy consumption (B2)	+	%	Statistical Yearbook of 120 cities
	Energy consumption reduction rate per unit of GDP (B3)	+	%	Statistical Yearbook of 120 cities
	power consumption reduction rate per unit of GDP (B4)	+	%	Statistical Yearbook of 120 cities
	water consumption reduction rate per unit of GDP (B5)	+	%	China Urban and Rural Construction Statistical Yearbook
Industrial system	The proportion of tertiary industry to GDP (C1)	+	%	China City Statistical Yearbook
	The proportion of industrial added value to GDP (C2)	−	%	China City Statistical Yearbook
	Energy consumption reduction rate per unit of industrial added-value (C3)	+	%	Statistical Yearbook of 120 cities
Environmental system	PM10 annual average concentration (D1)	−	μg/m^3	Bulletin of Environmental Quality in 120 Cities
	Industrial sulfur dioxide emissions per unit of industrial value-added (D2)	−	ton/RMB	China City Statistical Yearbook
	Industrial wastewater discharged per unit of industrial added-value (D3)	−	ton/RMB	China City Statistical Yearbook
	Sewage treatment rate (D4)	+	%	China City Statistical Yearbook
Land system	Green area per capita (E1)	+	m^2/person	China City Statistical Yearbook
	The green coverage rate of urban built-up area (E2)	+	%	China City Statistical Yearbook
	Forest coverage (E3)	+	%	Statistical Yearbook of 120 cities
	Rate of decline in construction area per unit of GDP (E4)	+	%	China Urban and Rural Construction Statistical Yearbook
Living system	Annual per capita production of urban household waste (F1)	−	kg/person/year	China Urban and Rural Construction Statistical Yearbook
	Urban water consumption per capita (F2)	−	L/person	China Urban and Rural Construction Statistical Yearbook
	Annual electricity consumption per capita for urban residents (F3)	−	Kwh/person	China City Statistical Yearbook
	Urban per capita living construction area (F4)	+	m^2/person	China Regional Statistical Yearbook
	Number of buses owned by ten thousand people (F5)	+	Vehicles/10^{4}person	China City Statistical Yearbook

2. Policy Background and Construction of a Low-Carbon Development Evaluation Index System

2.1. The Background of LCP

In 2010, the Chinese government began to carry out initial experiments in five provinces (Guangdong, Liaoning, Hubei, Shaanxi, Yunnan) and eight cities (Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, Baoding). In 2012 and 2017, the second and third batches of low-carbon pilot cities were identified, collectively including 6 provinces and 81 cities (districts).

Compared to the first batch of low-carbon pilot cities, the Chinese government implemented the Target Responsibility System (TRS) for implementing emission reduction control in the second and third batches of low-carbon pilot cities, intending to incentivize the local governments to promote low-carbon development in their cities through institutional innovation and technological progress (Cheng et al. (2019)) [31].

Overall, the expected target content of the LCP policy implementation covers the following five areas: (1) building an industrial system characterized by low-carbon and green features and developing strategic emerging industries and modern service industries; (2) implementing green and low-carbon lifestyle and consumption; (3) integrating industrial structure, optimizing energy structure, energy conservation, and efficiency, and increasing carbon sinks through the preparation of low-carbon development plans; (4) establishing a statistical and management system for greenhouse gas emissions and a target responsibility system for controlling greenhouse gas emissions; (5) providing priority policy support and incentive funds for low-carbon management system innovation and technological advancement. The above analysis shows that the expected target content of LCP policy implementation is diversified and wide-ranging. Thus, to accurately reflect the policy's implementation effect, the explanatory variables used to measure the impact of the system's performance should also meet such features. The LCDI measured in this paper is in line with the above characteristics, reflecting the city's low-carbon development. Cities at different stages of industrialization make up the second group of low-carbon pilot cities. According to the industrialization criteria in this paper, a total of 13 cities are at the middle stage of industrialization, including Qinhuangdao, Jincheng, Hulunbuir, Guilin, Chizhou, Nanping, Ganzhou, Guangyuan, Zunyi, and Jingdezhen, Yan'an, Jinchang, and Jiyuan; 11 cities (i.e., Jilin, Suzhou, Huai'an, Zhenjiang, Ningbo, Wenzhou, Qingdao, Wuhan, Kunming, Urumqi, Shijiazhuang) are at the later stage of industrialization; Beijing, Shanghai, and Guangzhou are cities at the post-stage of industrialization. In addition to these pilot cities, there are many other cities in China at different industrialization stages, which provides the conditions for this paper to apply the DID model to investigate the impact of the LCP policy implementation.

The implementation of the LCP will stimulate the interest of cities and industries in low-carbon development, help China accumulate experience in the low-carbon field, and ensure the implementation of the strategy of ecological civilization in Chinese cities, which has profoundly influenced the shape of urban development, promoted low-carbon transition, and reduced urban greenhouse gas emissions. The LCP policy has also made outstanding contributions to the low-carbon synergistic development of urban energy, environment, land, living, and other important areas.

2.2. Construction of Low-Carbon Development Evaluation Index System

China's official government has not defined the criteria for determining whether a city is low-carbon. Macro-level low-carbon development indicators, such as energy use per unit area or CO_2 emissions per unit GDP, may be too aggregated to be meaningful measurements of whether a city is truly "low carbon" (Lynn et al. (2013)) [32]. The expected implementation targets of the LCP policy described above also verify that the Chinese government's determination for low-carbon development is not limited to reducing carbon emissions or carbon emission intensity. In Section 1, this paper concludes that the structure of carbon sources and the characteristics of carbon emissions in cities at different industrialization stages are different. Thus, we try to construct a low-carbon development index system for Chinese cities based on the major carbon source sectors and carbon sink fields. Our indicator system is built on the principle of achieving the expected implementation targets of the LCP policy. Expected Target (4) is reflected by the macro system, Expected Target (1) is reflected by the industrial system, the living system reflects Expected Target (2), the energy and land system reflect Expected Target (3), and the environmental system is the external manifestations of low-carbon development, inspired by the greenhouse gas emissions from waste in the IPCC's Fifth Climate Change Assessment. The low-carbon development evaluation index system for China we have built covers the city's primary carbon source industries and carbon sink fields, including 24 quantitative indicators, which belong to a total of six dimensions of macro, energy, industry, environment, land, and life. The details are as follows in Table 1. The results of the comprehensive measurement of indicators (LCDI) can be used as a measure of the degree of low-carbon development of a city.

In the process of constructing the index system, we searched the keyword "low-carbon evaluation" through Google Scholar, extracted the content related to low-carbon development from the literature, and constructed a database of urban low-carbon development evaluation indexes. We also convened research experts in the field of low-carbon development and selected appropriate indicators by a questionnaire survey to form the low-carbon development evaluation index system in China based on the expected implementation target of China's LCP policy and the availability and comparability of data in Chinese cities. Some of the more important literature that we draw on is listed below, such as the low-carbon eco-city evaluation tool for China (ELITE) developed by Lawrence Berkeley National Laboratory (Zhou et al. (2015)) [33], China green development index (Li et al. (2015)) [34], the Global Green Economy Index (GGEI) 2014 (Tamanini (2013)) [35], the evaluation index system for the sustainable–smart–resilient–low carbon–eco–knowledge cities (De et al. (2015)) [36], a holistic low carbon city indicator framework Tan et al. (2017) [37], the global city indicators (Bhada and Hoornweg (2009)) [38], a low-carbon indicator system for China ((Lynn et al. (2013)) [32]. We thank the World Bank's "Promoting Clean and Green Cities in China through International Cooperative Projects" project for its support of this paper [39].

In addition, we held academic seminars and conducted field research with relevant government departments to discuss the applicability and scientific validity of the indicator system. If necessary, we have deleted or added some of the indicators to ensure that the calculation results (LCDI) can be used to measure the degree of low-carbon development of a city.

In order to ensure the reliability and authority of the data source, the calculation of carbon emissions in this paper comes from the CEADS (China Emission Accounts and Datasets), which has been proven to be effective in measuring the carbon emissions of Chinese cities and has been published in authoritative journals, as shown in Equation (15). All other data are from official data published by the Chinese government, as shown in Table 1.

3. Research Design

3.1. The Measurement Process of LCDI

Giving each indicator a suitable weight is an important step in LCDI accounting. The methods of assigning weights mainly include the entropy method [40], fuzzy comprehensive evaluation method [41], TOPSIS method [42], hierarchical analysis method [43], etc. Due to the shortcomings of each method, the combination of the above methods has become a more reliable way to assign weights to indicators.

In this paper, we combined the hierarchical analysis method with the CRITICS method, the TOPSIS method, and the gray correlation method in a model called the improved TOPSIS model. The introduction of the CRITICS method overcomes the defect that the entropy method cannot consider the influence of attributes among indicators. The subjective–objective optimal weight method overcomes the over-reliance on subjective weights of the single hierarchical analysis method, effectively alleviates the problem of inaccurate weights due to individual subjective factors, and provides weights for the application of the TOPSIS method. The improved TOPSIS model effectively overcomes the problem of inaccurate evaluation results of TOPSIS model due to the same distance between evaluation objectives and positive and negative ideal solutions. The introduction of the gray correlation model solves the drawback that it is difficult to explore the typical distribution of the LCDI due to large differences in data fluctuations.

The specific steps are as follows:

(1) Entropy value—CRITICS method to obtain the criterion layer matrix.

The target matrix C is standardized by the extreme value method to obtain the matrix C_S. The combined method of entropy and CRITICS is used to measure the weight matrix of C_S, named W_{index}, the matrix C_S is multiplied by the matrix W_{index}, and the result is called the matrix M = $(s_{ij})_{t \times k}$, where t represents the year and k represents the standard number of layers.

(2) Calculation of the weight matrix of the TOPSIS model.

The subjective weights of matrix M are measured by AHP(Analytic Hierarchy Process), named $\mathbf{w_1}$. The matrix $\mathbf{w_1}$ = (0.283 0.283 0.164 0.09 0.09 0.09), which is determined by using a questionnaire administered to experts in the field of low-carbon development.; the objective weights of matrix M are measured by the CRITICS method, named $\mathbf{w_2}$. Then, we constructed a matrix that combines w_1 and w_2, named W = $\beta(w_1,w_2)_{2 \times k}$. The purpose is to provide the weight for the TOPSIS model. The key to the problem is how to obtain the coefficient matrix β of the matrix W. To get the matrix β, the weight function W_{ck} was constructed, as shown in Equation (1).

$$W_k^c = \sum_{j=1}^{k} \beta_j W_j = \beta_1 W_1 + \beta_2 W_2 + \ldots + \beta_k W_k \tag{1}$$

Then, the following equation can represent the *LCDI*.

$$C = \sum_{t=1}^{n} S_{i_t j} \times W_{i_t j}^{c} \tag{2}$$

According to Equation (2), the distance objective function of the *LCDI* of adjacent years is constructed as follows:

$$\begin{aligned} f(d_{c_t c_{t+1}}) &= \sum_{i=1}^{m} d^2{}_{i_t i_{t+1}}(c_t c_{t+1}) \\ &= \sum_{i_t=1}^{m} \sum_{i_{t+1}=1}^{m} \left[\sum_{j=1}^{k} (S_{i_t j} - S_{i_{t+1} j}) w_{cj} \right]^2 \\ &= \sum_{i_t=1}^{m} \sum_{i_{t+1}=1}^{m} \left[\sum_{j_1=1}^{k} \sum_{j_2=1}^{k} (S_{i_t j_1} - S_{i_{t+1} j_1}) w_{cj_1} (S_{i_t j_2} - S_{i_{t+1} j_2}) w_{cj_2} \right] \\ &= \sum_{i_t=1}^{m} \sum_{i_{t+1}=1}^{m} \left[\sum_{j_1=1}^{k} \sum_{j_2=1}^{k} (S_{i_t j_1} - S_{i_{t+1} j_1})(S_{i_t j_2} - S_{i_{t+1} j_2}) \right] w_{cj_1} w_{cj_2} \end{aligned} \tag{3}$$

assuming the matrix $S' = \sum_{j_1=1}^{k} \sum_{j_2=1}^{k} (S_{i_t j_1} - S_{i_{t+1} j_1})(S_{i_t j_2} - S_{i_{t+1} j_2})$, for which it is easy to prove that the matrix S' is an n-order non-negative symmetric positive definite matrix.

The function in Equation (3) can be expressed as follows:

$$f(d_{c_t c_{t+1}}) = W S' W^T \tag{4}$$

Since the function in Equation (4) is a non-negative symmetric matrix, according to the definition of Rayleigh entropy, the function in Equation (4) has a unitized eigenvector K corresponding to the largest eigenvalue, making the function in Equation (4) take the maximum value λmax. The vector K is the coefficient matrix β, which is also the solution of Equation (1).

The vector K is substituted into Equation (1), and after normalization, the weights W_k^c are obtained, as shown in Equation (5).

$$W_k^c = (W_{i_t j} \times K) / \sum_{i=1}^{k} W_{i_t j}{}^{c},\ j = 1, 2 \ldots\ldots n \tag{5}$$

(3) Improved TOPSIS model to measure urban low-carbon development index.

The matrix M obtained in step (1) is multiplied by the weight matrix W_k^c. The result obtained is named A, and the matrix A is normalized to obtain a weighted normalized matrix D. The TOPSIS method is used to calculate the positive ideal solution matrix and the negative ideal solution matrix of the matrix D, and the obtained results are named as the matrices R^+ and R^-.

The gray correlation between matrix D and matrix R^+ is calculated. The result is named matrix $C_i{}^+$, as shown in Equation (6). The gray correlation between matrix D and matrix R^- is calculated, and the result is named matrix $C_i{}^-$, as shown in Equation (6). According to the experience, the resolution coefficient κ is equal to 0.5.

$$\begin{array}{ll} c^+ = \left(c_{ij}^+\right)_{m\times n} = \left(\dfrac{\min\left|R_j^+ - R_{ij}\right| + \kappa\max\left|R_j^+ - R_{ij}\right|}{\left|R_j^+ - R_{ij}\right| + \kappa\max\left|R_j^+ - R_{ij}\right|}\right)_{m\times n} & C_i^+ = \frac{1}{n}\sum\limits_{j=1}^{n} c_{ij}^+ \\ c^- = \left(c_{ij}^-\right)_{m\times n} = \left(\dfrac{\min\left|R_j^- - R_{ij}\right| + \kappa\max\left|R_j^- - R_{ij}\right|}{\left|R_j^- - R_{ij}\right| + \kappa\max\left|R_j^- - R_{ij}\right|}\right)_{m\times n} & C_i^- = \frac{1}{n}\sum\limits_{j=1}^{n} c_{ij}^- \end{array} \tag{6}$$

The Euclidean distance between the matrix D and the matrix R^+ is calculated and named matrix D^+, as shown in Equation (7). The Euclidean distance between matrix D and matrix R^- is calculated and named matrix D^-, as shown in Equation (7).

$$\begin{array}{l} D^+ = \sqrt{\sum\limits_{j=1}^{n}\left(R_{ij} - R_j^+\right)^2} \\ D^- = \sqrt{\sum\limits_{j=1}^{n}\left(R_{ij} - R_j^-\right)^2} \end{array} \tag{7}$$

According to the matrices $C_i{}^+$, $C_i{}^-$ obtained from Equation (6), and the matrices D^+, D^- obtained from Equation (7), the proximity of Euclidean distance is calculated, and the results are named $T_i{}^+$, $T_i{}^-$, as shown in Equation (8).

$$\begin{array}{l} T_i^+ = a\frac{c^+}{c_{\max}^+} + b\frac{D^-}{D_{\max}^-} \\ T_i^- = a\frac{c^-}{c_{\max}^-} + b\frac{D^+}{D_{\max}^+} \end{array} \tag{8}$$

In Equation (8), $0 \le a, b \le 1, a + b = 1$, the decision-maker can determine the amount of a and b. The a and b in this paper are equal to 0.5.

The comprehensive closeness (*LCDI*) is calculated, as shown in Equation (9).

$$LCDI = \frac{T_i^+}{T_i^+ + T_i^-} \tag{9}$$

$T_i{}^+$ and $T_i{}^-$ respectively reflect the positional relationship and shape closeness of the data curve between each evaluation object and the positive ideal solution and negative ideal solution.

3.2. Industrialization Index Calculation Process and Judgment Criteria for Industrialization Stage

Based on the research results of Syrquin et al. (1989) [13], Chen et al. (2006) [10], Huang (2018) [44], this paper uses a weighting method that combines threshold and hierarchical analysis to measure the city's industrialization index as shown in Equation (10)

$$I\_INDEX_{it} = \omega_1 ZPERGDP_{it} + \omega_2 ZIR_{it} + \omega_3 ZMR_{it} + \omega_3 ZURBAN_{it} + \omega_3 ZER_{it} \tag{10}$$

I_INDEX_{it} is the industrialization index. $I\_INDEX_{it} = 0$ represents that the city is at the pre-industrialization stage. Zero < I_INDEX_{it} < 33 means that the city is at the early industrialization stage. $33 \le I\_INDEX_{it} < 66$ represents that the city is at the middle stage of industrialization. $33 < I\_INDEX_{it} \le 66$ means that the city is at the later stage of industrialization. $I\_INDEX_{it} = 100$

represents that the city is at the post stage of industrialization. ω is the 5×1 column weight matrix obtained by the analytic hierarchy process. According to the research results of Huang (2018) [44], the matrix ω = [0.36,0.22,0.22,0.12,0.08]. $ZPERGDP_{it}$ represents the standardized value of GDP per capita (USD). ZIR_{it} represents the standardized value of the added-value of the primary industry to GDP. ZMR_{it} represents the standardized value of the ratio of manufacturing value added to value added of goods-producing sectors. $ZURBAN_{it}$ represents the standardized value of the urbanization rate. ZER_{it} represents the standardized value of the proportion of employees in the primary industry to the total number of employees.

In this paper, the threshold method is used to standardize the variables, as shown in Equation (11).

$$\begin{cases} Z_{ij} = (I_{ij} - 2) \times 33 + (N_{ij} - \min_{ij}) / (\max_{ij} - \min_{ij}) \times 33, I_{ij} = 2, 3, 4 \\ Z_{ij} = 0, I_{ij} = 1 \\ Z_{ij} = 100, I_{ij} = 5 \end{cases} \tag{11}$$

The standardized reference values of the various indicators at different industrialization stages are shown in Table 2.

Table 2. The standardized reference values of the indicator at different stages of industrialization.

Indicators	**Industrialization Stage**		
	(*I_INDEX* = 2)	**(*I_INDEX* = 3)**	**(*I_INDEX* = 4)**
PRGDP (2010USD)	$\min_{12}$ = 1654 $\max_{12}$ = 3308	$\min_{13}$ = 3308 $\max_{13}$ = 6615	$\min_{14}$ = 6615 $\max_{14}$ = 12398
IR (%)	$\min_{22}$ = 33 $\max_{22}$ = 20	$\min_{23}$ = 20 $\max_{23}$ = 10	$\lambda_{ij} = 66 + S / (S + I) \times 33$
MR (%)	$\min_{32}$ = 20 $\max_{32}$ = 40	$\min_{33}$ = 40 $\max_{33}$ = 50	$\min_{34}$ = 50 $\max_{34}$ = 60
URBAN (%)	$\min_{42}$ = 30 $\max_{42}$ = 50	$\min_{43}$ = 50 $\max_{43}$ = 60	$\min_{44}$ = 60 $\max_{44}$ = 75
ER (%)	$\min_{52}$ = 60 $\max_{52}$ = 45	$\min_{53}$ = 45 $\max_{53}$ = 30	$\min_{54}$ = 30 $\max_{54}$ = 10

Note: I represents the proportion of the secondary industry in GDP, and S represents the proportion of the tertiary industry in GDP.

3.3. Construction of the DID Model

The DID model was first introduced in 1985, and it was widely used in the quantitative evaluation of public policy or project implementation effects in econometrics [45]. This paper uses the DID method to analyze the industrialization stage's moderation of LCP policy implementation. Since each variable selected in this paper is from 10 years (2008–2017), the DID model is realized by the two-way fixed effect model, which controls the time's fixed effect and the city's individual fixed effect. The model is set as follows:

$$LDCI_{i,t} = \lambda_0 + \lambda_1 I\_STAGE_{i,t} \times DIFF_{i,t} + \lambda_2 X_{i,t} + \mu_i + \nu_i + \varepsilon_{i,t} \tag{12}$$

where i represents the city and t represents the year. $LDCI_{i,t}$ is an index measured by Equations (1)–(9), which represents the level of low-carbon development. $DIFF_{i,t}$ is the dummy variable. $DIFF_{i,t}$ = 1 indicates that city i is the low-carbon pilot city (LCPC) in year t, and $DIFF_{i,t}$ = 0 indicates that city i is not an LCPC in year t. $I\_STAGE_{i,t}$ represents the industrialization stage measured by Equations (10) and (11). X_{it} is the control variable, and it includes the industrialization index, innovation, and FDI(Foreign Direct Investment). The details of these variables are shown in Table 3. μ_i represents time fixed effect, ν_i represents urban individual fixed effects, and ε_{it} represents random disturbance terms. λ_1 in Equation (12) captures the average impact of LCP policy.

Table 3. Description of variables and data.

Variable	Definition	Mean	S.D.	Min	Max
C	Carbon emissions of urban industrial enterprises in million tons of CO_2	48.51	55.87	0.12	396.74
LDCI	Low-carbon development index measured by Equations (1)–(9)	0.49	0.06	0.36	0.66
I_INDEX	Industrialization index measured by Equations (10) and (11)	67.54	20.17	13.53	100
I_STAGE	Stage of industrialization judged by Industrialization index (I)	2.53	0.50	2	3
FDI	Openness level indicated by total FDI in ten billion U.S. dollars	10.99	15.83	0	112.16
RD	Enterprise technology innovation indicated by innovation index	67.93	24.98	1.37	99.66
PERGDP	Level of economic development measured by per capita GDP in ten thousand U.S. dollars	7324.38	4632.87	1314.29	43755
IR	The added value of the primary industry as a proportion of GDP	9.25	6.14	0.79	32.5
MR	Urban manufacturing development level measured by ratio of manufacturing value-added to value-added of goods-producing sectors	57.92	16.34	0.6	91.53
URBAN	The urban spatial structure measured by the proportion of urban permanent residents in the total population	56.47	13.66	21	94.7
ER	The urban employment structure measured by the ratio of the number of employees in the primary industry to the total number of employees	26.74	16.61	0.04	88.9
I	The added value of the secondary industry as a proportion of GDP	50.16	8.11	27.87	82.08
S	The added value of the tertiary industry as a proportion of GDP	40.69	8.29	16.75	70.22

This paper draws on the model constructed by Kudamatsu (2012) [46], employing the following model to identify the marginal impacts of the LCP policy on the *LCDI*:

$$LDCI_{i,t} = \beta_0 + \sum_{j=2013}^{2017} \beta_j I\_STAGE_{i,t} \times T_j + \beta_2 X_{i,t} + \mu_i + \nu_i + \varepsilon_{i,t} \quad (13)$$

where T_j is the dummy variable and β_j corresponds to the LCP policy marginal impact on the *LCDI* in year *j* (*j* = 2013, 2014, 2015, 2016, 2017).

To identify the mechanism by which LCP policy affect the *LCDI*, we set up the following regression model to analyze the effects of LCP policies on industrialization index, innovation index, and *FDI*:

$$I\_INDEX_{i,t}, FDI_{i,t}, RD_{i,t} = \theta_0 + \theta_1 I\_STAGE_{i,t} \times DIFF_{i,t} + \mu_i + \nu_i + \varepsilon_{i,t} \quad (14)$$

where *I_INDEX* represents the urban industrialization index measured by Equations (10) and (11). *FDI* represents foreign direct investment. *RD* represents innovation. θ_1 represents the effects of the LCP policy on industrialization index, innovation, and FDI.

3.4. Sample Selection, Data, and Variables

3.4.1. Sample Selection

This article selects the second batch of LCPCs as the treatment group. Based on the principles of data availability and comparability, the LCPCs, including Yan'an, Jinchang, and Jiyuan, where data could be obtained, were excluded, and the LCPCs at the post stage of industrialization, including Shanghai, Beijing, and Guangzhou, which cannot be matched to the control group, are eliminated. The final experimental group includes, first, the LCPCs at the middle stage of industrialization, including Qinhuangdao, Jincheng, Hulunbuir, Guilin, Chizhou, Nanping, Ganzhou, Guangyuan, Zunyi, and Jingdezhen; second, the LCPCs at the later stage of the industrialization, including Jilin, Suzhou, Huai'an, Zhenjiang, Ningbo, Wenzhou, Qingdao, Wuhan, Kunming, Urumqi, and Shijiazhuang. As the control group, 283 non-pilot cities were selected. Cities with missing data wre eliminated. Considering that Guangdong, Liaoning, Hubei, Shanxi, Yunnan, and Hainan were the low-carbon pilot provinces, the cities belonging to them as the control group may interfere with the policy evaluation results. Therefore, cities belonging to the above six provinces were excluded. Tfirst batch of low-carbon pilot cities was also eliminated. The control group was finally determined to include 32 non-pilot cities at the middle stage of industrialization and 36 non-pilot cities at the later stage of industrialization.

3.4.2. Data Description

The data come from the China City Statistical Yearbook (2009–2018), China Environmental Statistics Yearbook (2009–2018), China Urban and Rural Construction Statistical Yearbook (2009–2018), China Regional Statistical Yearbook (2008–2018), China Energy Statistical Yearbook (2009–2018), urban statistical yearbooks (2009–2018), Environmental Statistics Bulletin of each city (2008–2017), etc. All monetary value data are calculated at constant prices in 2007.

(1) Indicators in the LCDI accounting process. The accounting method of the total carbon emissions of industrial enterprises (Indicators A2) in Table 1 comes from the CEADs database (http://www.ceads.net) [47]. The equation is as follows:

$$C_j = AD'_j \times NCV_j \times EF_j \times O_j \tag{15}$$

where j represents the energy types, coming from the accounting of each city. C_j represents the energy consumption of industrial enterprises of different energy types. AD'_j is the energy consumption of different energy types (unit: 10^4 t). NCV_j is the net heating value of different energy types (unit: PJ/10^4 t). EF_j represents the carbon emission factor (unit: $MtCO_2$/PJ). O_j represents the oxygenation efficiency of different types of energy (unit: %). The values of NCV_j, EF_j, and O_j come from Shan, Y et al. (2018) [14].

The indicators in Table 1, such as carbon emissions per unit of industrial value-added (Indicator A3), industrial sulfur dioxide emissions per unit of industrial value added (Indicator D2), and industrial wastewater emissions per unit of industrial value added (Indicator D3), are all indicators divided by the value added per unit of the industry to obtain the treatment indicators. The value added per unit of the industry was calculated in constant 2007 prices. The indicators in Table 1, including annual per capita production of urban household waste (Indicator F1), urban water consumption per capita (Indicator F2), annual electricity consumption per capita for urban residents (Indicator F3), were divided by the resident population for each indicator, respectively, to obtain the treatment indicator. The rest of the indicators in Table 1 are direct data obtained from the government's statistical yearbook, with the sources indicated in Table 1.

(2) Variables in the industrialization index accounting process. The variable *PERGDP* represents GDP per capita in constant 2010 prices in thousands of US dollars. It is based on the World Bank's data on China's historical GDP, using the purchasing power evaluation method, with the same proportional weighting to obtain each city's GDP per capita. The variable MR represents the level of urban industrial structure, and the goods-producing sector value added is replaced by the sum of primary and secondary industry value added. The *URBAN* is a variable that uses the resident population as a uniform caliber, representing the state of urban spatial structure. Suppose the proportion of the primary industry in the GDP is less than 10%. In that case, the variable *IR* is transformed into the weighted value of *I* and *R*, as shown in Table 2, where *I* represents the value-added of the secondary sector as a proportion of GDP and S represents the proportion of the tertiary sector as a proportion of GDP. The variable *ER*

represents the employment structure of the city. In this process, all the variables are obtained directly from statistical yearbooks or bulletins from all government levels in China, as shown in Table 3.

(3) Variables in the DID model construction process. We used the China Innovation and Entrepreneurship Index (Zhang 2019) [48] to measure the innovation capacity. The data come from the Peking University Open Research Data Platform. FDI is measured in terms of the amount of real foreign investment in the year. We used 2007 constant prices to generate deflation. Industrialization index was measured by Equations (10) and (11). By choosing the industrialization index as a control variable, we aimed to determine whether the LCP policy affects its industrialization progress. The data descriptions of the above variables are presented in Table 3.

4. Empirical Results

4.1. Parallel Trends Test

The critical hypothesis of the DID model is to find a suitable control group as a counterfactual substitute for the treatment group. This means that the assumption of parallel trends needs to exist between the treatment group and the control group. Therefore, it is necessary to conduct the parallel trend test of variables before empirical analysis. This paper regards 2012 as the baseline year. P's significance is used to determine whether there is a significant LCDI difference between the treatment and control groups.

The results in Table 4 show that before implementing the LCP policy, for the cities at the middle stage of industrialization and the later stage of industrialization, as wis no significant difference in the LCDI between the treatment group and the control group. However, a significant difference appears in the LCDI between the treatment group and the control group in the second year after implementing the LCP policy if the sample of the regression model is the cities at the later stage of industrialization. In contrast, for the cities at the middle stage of industrialization, it was not until the fourth year of policy implementation that a significant difference appeared. Therefore, the assumption of parallel trends cannot be rejected. In addition, taking the industrialization stage as the city classification standard can reflect the different marginal impact of LCP policy on different types of cities, indicating that the industrialization stage can moderate the effect of LCP implementation.

Table 4. Test of the parallel trend.

Variables	I_STAGE = 2	I_STAGE = 3	All Sample
4 years before the policy implement × $Treated_{it}$	−0.0018 (0.043)	0.048 (0.046)	−0.027 (0.032)
3 years before the policy implement × $Treated_{it}$	−0.035 (0.044)	0.008 (0.045)	−0.013 (0.032)
2 years before the policy implement × $Treated_{it}$	0.022 (0.043)	−0.01 (0.045)	0.005 (0.032)
1 year before the policy implement × $Treated_{it}$	−0.045 (0.043)	−0.018 (0.045)	−0.03 (0.032)
year of the policy implement × $Treated_{it}$	−0.05 (0.043)	−0.013 (0.045)	−0.03 (0.032)
1 year after the policy implement × $Treated_{it}$	−0.045 (0.043)	0.008 ** (0.045)	−0.018 (0.031)
2 years after the policy implement × $Treated_{it}$	−0.003 (0.043)	0.014 (0.045)	0.025 (0.032)
3 years after the policy implement × $Treated_{it}$	−0.054 (0.043)	0.028 (0.045)	−0.011 (0.031)
4 years after the policy implement × $Treated_{it}$	0.009 ** (0.043)	0.040 (0.045)	0.016 (0.032)
5 years after the policy implement × $Treated_{it}$	0.002 (0.043)	0.049 (0.045)	0.027 (0.032)
LNI_INDEX	−0.064 ** (0.06)	−0.02 *** (0.1)	−0.028 ** (0.041)
LNRD	0.002 * (0.016)	0.018 ** (0.06)	0.006 * (0.016)
LNFDI	0.015 (0.01)	0.009 *** (0.01)	0.015 *** (0.07)
R-squared	0.50	0.30	0.38
No. of Obs.	420	470	89
Time fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Average and the Marginal Impact of LCP Policy on the LCDI of Cities at Different Stages of Industrialization

Since the LCDI is a result measured by multiple indicators, we excluded the impact of industrial structure, energy structure, and energy efficiency on LCDI due to endogenous considerations. To unify the dimensions and eliminate the influence of heteroscedasticity, we performed logarithmic processing on the variables. Table 5 presents the average and marginal impacts of the LCP policy on LCDI of the LCPC at different industrialization stages. The samples used in columns (1) to (4) are all cities at the middle stage of industrialization, and the samples in columns (5) to (8) are all cities at the later stage of industrialization.

Table 5. Average and the marginal LCP policy impact on LCDI.

Variables	**I_STAGE = 2**				**I_STAGE = 3**			
	Average		**Marginal**		**Average**		**Marginal**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
DIFF($Treat_{i\,t} \times T$)	−0.007 *	−0.007 *			0.041 **	0.041 **		
	(0.019)	(0.019)			(0.02)	(0.02)		
$Treat_{it} \times T \times year_{2013}$			−0.032	−0.024			0.014 **	0.014 **
			(0.033)	(0.033)			(0.035)	(0.035)
$Treat_{it} \times T \times year_{2014}$			−0.016	−0.025			0.06 ***	0.054 ***
			(0.033)	(0.033)			(0.035)	(0.035)
$Treat_{it} \times T \times year_{2015}$			−0.039 *	−0.032 *			0.038	0.035
			(0.033)	(0.033)			(0.035)	(0.035)
$Treat_{it} \times T \times year_{2016}$			0.0024 *	0.013 *			0.048	0.047
			(0.033)	(0.033)			(0.035)	(0.035)
$Treat_{it} \times T \times year_{2017}$			0.014 **	0.023 **			0.046	0.056
			(0.033)	(0.033)			(0.035)	(0.035)
LNI_INDEX		−0.016 **		−0.013 **		−0.028 **		−0.022 **
		(0.057)		(0.058)		(0.1)		(0.1)
LNRD		0.003 **		0.0018 **		0.021 **		0.019 **
		(0.016)		(0.016)		(0.06)		(0.06)
LNFDI		0.016		0.016		0.008 **		0.008 **
		(0.01)		(0.01)		(0.01)		(0.01)
CONS	−0.721 **	−0.520 ***	−0.721 ***	−0.505 **	−0.731 ***	−0.715 **	0.731 ***	−0.735 **
	(0.12)	(0.20)	(0.013)	(0.21)	(0.013)	(0.45)	(0.013)	(0.45)
R-squared	0.48	0.49	0.48	0.50	0.30	0.29	0.30	0.30
No.of Obs.	420	420	420	420	470	470	470	470
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

From column (1) in Table 5, the result shows that the coefficient of DIFF is −0.0007 at the 10% significance. This indicates that the LCP policy did not significantly enhance the LCDI of LCPC at the middle stage of industrialization during the study period (2008–2017). From column (5), the result shows that DIFF's coefficient was 0.041 at 5% significance. This indicates that LCP policy can significantly enhance the LCDI of LCPCs at the later stage of industrialization during the study period (2008–2017). After controlling the industrialization index, innovation, and FDI in columns (2) and (6), we found that the results are still significant.

The results of the marginal analysis in columns (3) and (4) shows that for the LCPCs at the middle stage of industrialization, the LCP policy effect was negative in the first three years, did not become positive until the fourth year of policy implementation, and was most significant in the fifth year after it is issued. The LCP policy reduces LCDI by approximately 0.7% throughout the study period. The marginal analysis results in columns (7) and (8) indicates that for the LCPC at the later stage of industrialization, the effect increases in the first two years and is most significant in the second year after it is issued. The LCP policy enhances the LCDI by approximately 4.1% throughout the study period.

The results show that, gradually adding control variables, for the cities in the middle and later stages of industrialization, the industrialization indexes were significantly negative at the 5% level. This indicates that the more profound the industrialization process in China, the lower the LCDI. This result is explained by Wang and Su (2019) [49], who argued that industrialization's economic benefits are far greater than the environmental pollution it generates. In terms of the size of the coefficient, a 1% increase in LCDI decreases the industrialization index of mid-industrialization cities by about 2.5%. In comparison, the industrialization index of later-industrialization cities only decreases by about 1.45%. From the perspective of carbon emission trends, the study by Zhou et al. (2018) [50] concluded that the post-industrialization-stage cities (i.e., Hong Kong, Shenzhen) had achieved the peak of total carbon emissions. The cities at the later stage of industrialization, such as Dongguan and Jiangmen, showed a slowdown in the growth rate of total carbon emissions. In contrast, in those cities (i.e., Zhuhai, Zhongshan, Zhaoqing, Maoming, Yangjiang, Shanwei, Shaoguan, and Zhanjiang) at the middle stage of industrialization, carbon emissions experienced soaring increases. The control of greenhouse gas emissions had a negative impact on the industrialization process, and it was difficult for local governments to find a harmonious development path between the two. This is why the Chinese government uses relative indicators such as carbon emissions intensity as a quantitative indicator for Target Responsibility System (TRS) rather than absolute indicators such as the total amount of carbon emissions.

The results also show that regions with higher FDI present higher LCDI. However, compared with the cities at the later stage of industrialization, the FDI's promotion effect on the LCDI of cities at the middle stage of industrialization was not significant at the 5% level. Zhang et al. (2020) found that the impact of FDI on carbon emissions in different regions of China was heterogeneous and that foreign investment behavior in eastern China can curb carbon emissions. In contrast, the opposite effect was seen in the western and central regions [51]. Therefore, we try to explain this result from the perspective of regional heterogeneity. In this article's sample structure, the cities at the middle stage of industrialization located in central and western China accounted for 78% of the sample size. In comparison, the cities at the later stage of industrialization located in central and western China accounted for only 42%. China's eastern region has stricter environmental policies, which has prompted those low-quality foreign direct investments to gradually shift to the west and central areas in China, where economic development and environmental policies are more relaxed, to reduce costs. In the long run, it will bring more advanced technology and management experience to enterprises in central and western China, but in the short term, it may cause a decline in LCDI.

According to the regression results of columns (2), (4), (6), and (8) in Table 5, the innovation effect on LCDI of cities at the middle or later stages of industrialization is significantly positive at the 5% level. This is because innovation can dramatically reduce carbon emissions in the energy supply and industrial sectors in the short term. According to the IPCC's fifth climate change assessment, between 2000 and 2010, the greenhouse gas emissions generated by the energy supply sector and the industrial sector accounted for 47% and 30% of the total anthropogenic greenhouse gas emissions. This means that technological innovation in carbon emission reduction can directly affect about 77% of greenhouse gas emissions [52]. Thompson (2006) [53] indicated that the carbon emissions caused by fossil energy use were related to a series of issues such as environmental monitoring costs, carbon taxes, and energy demand expectations. Its substitution relationship with other production factors directly determines the economic effect of carbon emission reduction technologies. In most cities in China, fossil energy's substitution effect, especially of coal, is small. Once more capital and labor are invested in production, carbon emission reduction technologies will inevitably affect enterprises' survival and growth.

4.3. Mechanism Analysis

In this section, we draw on the analysis method adopted by Liu et al. (2019) [18] and use the DID model constructed by Equation (15) to analyze the impact of LCP policy on the industrialization index, innovation, and FDI of cities at different industrialization stages.

From columns (1) and (4) in Table 6, the results show that the LCP policy has a significant and negative impact on the industrialization index, reflecting that it has effectively reduced the city's industrialization index at different industrialization stages. This is because the central government has imposed a target responsibility system on the second batch of low-carbon pilot cities' industrial structure, requiring them to build a low-carbon industrial system characterized by low-carbon, green environmental protection and recycling. Therefore, in the short term, the industrial structure's transformation may reduce the manufacturing industry's added value, leading to a decline in the industrialization index. This point is consistent with the research of Li et al. (2019) [54], who believes that the central government's attitude towards environmental policies and whether it imposes a target accountability system on local governments will affect the effect of policy implementation. Wang et al. (2015) indicated that officials were afraid of losing their jobs if the energy-saving target was not met. Local officials competed to impress their superiors with enthusiastic energy cuts—sometimes with surprising outcomes. Chinese steel, cement, and other energy-intensive factories were kept on hold. Thousands of homes in some areas were left without electricity as local governments ordered power cuts to meet the energy-saving targets [55], which will undoubtedly harm the local manufacturing industry's development. Obviously, due to the lack of the material basis for industrial transformation, the LCP policy has a more pronounced impact on the manufacturing industries of the LCPC at the middle stage of industrialization, so the decline in their industrialization index is even more pronounced.

Table 6. The impact of LCP policy on urban industrialization index, innovation index, and FDI.

	I_STAGE = 2			I_STAGE = 3		
	(1)	(2)	(3)	(4)	(5)	(6)
	I_INDEX	RD	FDI	I_INDEX	RD	FDI
DIFF($Treat_{it} \times T$)	−1.53 *	0.571 *	−1.61 **	−0.63 *	1.15 *	3.66 ***
	(0.8)	(2.32)	(0.55)	(0.76)	(0.93)	(1.38)
CONS	38.03 ***	52.9 ***	2.41 ***	73.92 **	79.84 ***	11.16 ***
	(0.54)	(1.56)	(0.37)	(0.51)	(0.62)	(0.92)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.34	0.12	0.32	0.24	0.30	0.21
No.of Obs.	420	420	420	470	470	470

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

It can be seen from columns (2) and (5) that the LCP policy positively impacts innovation, indicating that it has effectively improved the pilot regions' innovation level. This is similar to the findings of Liu et al. (2019) [18]. Their research indicated that LCP policy could encourage companies in pilot regions to conduct more technological progress.

According to the regression results in columns (3) and (6), the LCP policy hurts the FDI of the LCPCs at the middle stage of industrialization at a significance level of 5%. In comparison, the LCP policy positively affects the FDI of the LCPC at the later stage of industrialization at a significance level of 1%. For the LCPC at the middle stage of industrialization, the research results on LCP policy and FDI's relationship are consistent with those of Cai et al. (2016) [56]. Their results show that strict environmental regulations can prevent the inflow of low-quality foreign investment and help the local government avoid becoming a "pollution shelter" for multinational companies. Obviously, due to the underdeveloped service industry and the low proportion of the added value of high-tech industries in the manufacturing industry's added value, this type of city does not have the basis for building a low-carbon industrial system. Therefore, local governments are suffering from the slowdown in economic growth and rising unemployment caused by foreign investment loss. For this reason, stimulating domestic demand and vigorously developing tourism have become the main strategies for stimulating the economy of this type of city. For the LCPCs at the later stages of industrialization, the per capita income of urban residents is higher, and the demand for urban environmental health is more urgent, which forces city leaders to pay attention to the treatment of urban environmental pollution. Moreover, to complete the low-carbon pilot program's objectives and tasks, win the favor of superiors and maintain official positions, city officials are more willing to receive high-quality foreign investment. For this reason, the implementation of a wide range of investment subsidy policies for low-carbon foreign-funded enterprises has attracted more foreign capital. This investment subsidy policy's continuity determines whether this type of city can successfully achieve a low-carbon transition.

4.4. Robustness Test

This paper conducts a robustness test by changing the study period of LCP policy, including 2008–2013, 2008–2014, 2008–2015, 2008–2016, 2009–2017, 2010–2017, 2011–2017, and 2012–2017, respectively. The results are shown in Tables 6 and 7.

Table 7. Robustness test for changing the LCP policy study period (I_STAGE = 2).

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
	2008–2013	2008–2014	2008–2015	2008–2016	2009–2017	2010–2017	2011–2017	2012–2017
DIFF($Treat_{it} \times T$)	−0.02	−0.022 *	−0.031 *	−0.012 *	−0.022 *	−0.012 *	−0.008 *	−0.003 *
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
LNI_INDEX	−0.1 **	−0.07 ***	−0.05 **	−0.04 **	−0.06 **	−0.09 **	−0.01 **	−0.009 **
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.09)	(0.02)	(0.11)
LNRD	0.03 ***	0.01 **	0.01 **	0.001 *	0.001 **	0.003 **	0.01 **	0.002 **
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
LNFDI	0.003	0.002 *	0.02	0.02 *	0.02 *	0.02 *	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CONS	−0.27	−0.44 *	−0.52 *	−0.59 **	−0.52 **	−0.41	−0.79 **	−0.83 **
	(0.26)	(0.25)	(0.24)	(0.22)	(0.25)	(0.32)	(0.37)	(0.43)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.29	0.24	0.30	0.39	0.53	0.58	0.64	0.61
No.of Obs.	255	295	335	375	380	340	300	260

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results of the regression models for different study periods in Table 6 show that for the LCPCs at the middle stage of industrialization, the DIFF coefficients were negative at the 10% significance level for all study periods except for 2008–2013. This is consistent with the results obtained in the previous section. Further, it verifies that the LCP policy could significantly enhance the LCDI of LCPCs at the middle stage of industrialization during the different study periods. According to the results in Table 7, for the LCPCs at the middle stage of industrialization, the industrialization index hurt the LCDI, while innovation positively impacted the LCDI. This is consistent with the previous results. FDI has a positive effect on LCDI but remains insignificant in some regressions.

For the LCPC at the middle stage of industrialization, by transforming the different LCP policy study periods, we get that the average impact effect of the LCP policy started to improve during the study period 2008–2016 (the fourth year after the implementation of the LCP policy). This is consistent with the previous findings on the marginal impact of the LCP policy. Further, this verifies the robustness of our results.

The regression models' results for different study periods in Table 8 show that for the LCPCs at the later stage of industrialization, the DIFF coefficients are positive at the 10% significance level for all study periods. This is consistent with the previous section's results and further verifies that the LCP policy can significantly enhance the LCDI of LCPCs at the later stage of industrialization. According to the results in Table 8, for the cities at the later stage of industrialization, the industrialization index hurt the LCDI, while innovation and FDI had a positive impact on the LCDI. This is consistent with the previous results.

Table 8. Robustness test for changing the LCP policy study period (I_STAGE = 3).

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
	2008–2013	2008–2014	2008–2015	2008–2016	2009–2017	2010–2017	2011–2017	2012–2017
DIFF($Treat_{it} \times T$)	0.014 **	0.035 *	0.039 *	0.039 *	0.040 **	0.047 **	0.049 *	0.049 *
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
LNI_INDEX	−0.19 *	−0.14 **	−0.07 **	−0.007 *	−0.018 *	−0.097 *	−0.088 *	−0.047 *
	(0.19)	(0.17)	(0.13)	(0.11)	(0.11)	(0.12)	(0.14)	(0.15)
LNRD	0.03 **	0.06 ***	0.02 **	0.03 **	0.05 *	0.04 **	0.07 **	0.09 *
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)
LNFDI	0.003 **	0.003 *	0.008 *	0.005 *	0.009 **	0.01 **	0.007 **	0.001 *
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CONS	−1.69 **	−1.59 *	−1.11 *	−0.92 *	−0.89 *	−0.52	−0.77	−0.91
	(0.80)	(0.73)	(0.58)	(0.51)	(0.52)	(0.59)	(0.66)	(0.74)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.17	0.17	0.24	0.27	0.32	0.36	0.39	0.28
No.of Obs.	275	325	370	415	410	365	320	275

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

For the LCPCs at the later stage of industrialization, by switching different LCP policy study periods, we obtain that the average impact effect of LCP policy continues to strengthen as the study period lengthens, which is consistent with the previous findings on the marginal impact of LCP policy. This further validates the robustness of our results.

5. Conclusions and Discussion

Many cities in China are facing a dilemma between industrialization and low-carbon transition. To promote the green and low-carbon development of cities, the Chinese government has implemented the LCP policy. Cities at different stages of industrialization have apparent differences in their economic and industrial structures, which impact the implementation of the LCP policy. Therefore, it is of great significance to study industrialization stage's moderating effect on LCP policy implementation. This paper selects the second batch of low-carbon pilot cities as the object of study and does the following. First, based on the expected targets of the LCP policy implementation, this paper constructs a low-carbon development evaluation index system for Chinese cities and uses the improved TOPSIS model to measure the LCDI. Second, the industrialization index is measured using the threshold-hierarchy analysis, and the industrialization stage is judged using the relevant criteria. Finally, The DID model is applied to analyze the moderating effect of the industrialization stage on LCP policy implementation. We also tested the LCP policy's impact through industrialization index, innovation, and FDI. Our conclusions are as follows.

First, there is heterogeneity in LCP policy implementation on the LCDI of LCPCs at different industrialization stages. For the LCPCs at the later stage of industrialization, the effect is positive, and the marginal impact reaches its maximum in the second year after its implementation. The robustness test shows that the impact gradually increases with the extension of the study period. For the LCPCs at the middle stage of industrialization, the impact is weakly negative, and the marginal impact does not change to positive until the fourth year after its implementation. Second, we analyzed how the LCP policy affects LCDI through industrialization index, innovation, and FDI. The results show that the LCP policy hurts the industrialization index, regardless of whether the LCPC is at the middle stage of industrialization or the later stage of industrialization, and the higher the industrialization index, the lower the LCDI. China's industrialization reduces the LCDI of cities. The LCP policy can significantly stimulate the innovation activity of the LCPC at the middle stage of industrialization or at the later stage of industrialization. Innovation can enhance LCDI by improving energy efficiency and reducing the carbon emission intensity. The LCP policy can promote FDI inflow into the LCPC at the later stage of industrialization. In contrast, the impact is negative if the study sample is the LCPC at the middle stage of industrialization. FDI can improve the LCDI, but the impact of technology spillover from FDI is more significant on the LCDI of cities at the later stage of industrialization than that at the middle stage of industrialization.

Based on the conclusions above, we identify some implications for the Chinese government to facilitate the LCP policy implementation and propose some policy recommendations to promote low-carbon development. For Chinese government departments, a one-size-fits-all LCP policy Target Responsibility System (TRS) assessment is hugely unfair to the LCPCs at the middle stage of industrialization. It would force city leaders to take extreme measures, such as power restrictions and production shutdowns, to complete the assessment tasks to win favor with their superiors. This paper's findings indicate that the LCP policy's implementation needs to be tailored to local conditions. Using the industrialization stage as a criterion to classify cities and adopt differentiated assessment criteria will have a greater incentive to promote the implementation of LCP. For the LCPCs at the later stage of industrialization, the central government should set a series of absolute indicators, such as total carbon emissions, to comprehensively assess the policy implementation's effectiveness in the transport sector, construction sector, industrial sector, energy supply sector, and forest carbon sequestration sectors. For the LCPCs at the middle stage of industrialization, the central government should appropriately lengthen the period for examining the policy implementation effectiveness. In addition, relative indicators, such as carbon emission intensity, should be set to focus on assessing the policy implementation's effectiveness in the industrial and energy supply sector.

Furthermore, based on the reason that the LCP policy will lead to the reduction of FDI of the LCPCs at the middle stage of industrialization, it is evident that encouraging innovation becomes the leading choice for the city manager to complete the LCP assessment tasks. However, we need to pay more attention to the conditions of the LCPCs themselves at this stage. The lack of talent and inadequate institutional design result in apparent shortcomings in the city's innovation drive, so that cooperation and exchange with neighboring large cities, especially provincial capital cities, in the field of low-carbon development is incredibly important. The main cooperation methods include introducing more advanced thermal power-generation technology and energy-saving technology renovation for high-energy-consuming industrial enterprises and adopting more advanced demand-side energy efficiency management. The purpose of this is to slow down the growth of total carbon emissions in the industrial production process and energy supply sector and to shorten the time for the city's total carbon emissions to peak. For the LCPCs at the later stage of industrialization, the LCP policy, innovation, and FDI are mutually reinforcing. City managers should take advantage of the powerful conditions created by the innovation and FDI's technological spillover effect to spare no effort to promote the development of low-carbon industries and the deployment of clean energy technologies to achieve a low-carbon transition. Furthermore, institutional innovation should be more broadly focused on addressing potential inconsistencies between low-carbon development and government management systems.

Evaluating the effectiveness of policy implementation has been a hot topic of academic research. In this paper, we used the DID model to study the moderating effect of industrialization stage on China's LCP policy. We used the LCDI index as an explanatory variable to accurately reflect the Chinese government's intended goal of implementing LCP policy. However, our study has some limitations. First, this study is highly focused on how to promote the effective implementation of LCP policies in Chinese cities, and the research is extremely specific. Second, we adopted a combination of field research and theory to construct a low-carbon development evaluation index system in China, and the scope of application of the index system may be limited to the assessment of the Chinese government's effect on low-carbon pilot policies. Third, the subjective weights obtained by applying hierarchical analysis in the measurement process of LCDI were obtained by means of questionnaire analysis, which may be disturbed by human factors.

However, our research paradigm is recommendable. The established index system is practiced in a double difference model with the measured LCDI index through a large workload of field research and literature search. This in itself is somewhat innovative. In addition, the improvement of the measured model of LCDI is one of the main contributions of this paper. We always take the attitude that there must be variability in the evaluation system of urban low carbon development in each country, and the reason for this variability is that each country has different development stages and characteristics. Our next step is to explore the low-carbon development assessment systems adapted to cities in different continents through a larger survey and research in order to better disseminate the results we have obtained.

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