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The Carbon Emission Reduction Effect of City Cluster—Evidence from the Yangtze River Economic Belt in China

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Abstract: Climate anomalies are affecting the world. How to reduce carbon emissions has become an important issue for governments and academics. Although previous researchers have discussed the factors of carbon emission reduction from environmental regulation, economic development, and industrial structure, limited studies have explored the carbon emission reduction effect of a city's spatial structure. Based on 108 Chinese cities from the Yangtze River Economic Belt between 2003 and 2017, this paper examines the impact of the city cluster policy on city carbon emissions using the difference-in-differences (DID) method. We find that: (1) The city cluster policy has significantly reduced the cities' carbon emissions by 7.4%. Furthermore, after a series of robust and endogenous tests, such as parallel trend and PSM-DID, the core conclusion still remains. (2) We further identify possible economic channels through this effect, and find that city cluster policy would increase city productivity, city technological innovation, and industrial structure optimization. The conclusions of this paper have important practical significance for China to achieve carbon neutrality and facilitate future deep decarbonization.

Keywords: carbon emission reduction; city cluster policy; difference-in-difference method

Citation: Li, X.; Huang, C.; Zhan, S.; Wu, Y. The Carbon Emission Reduction Effect of City Cluster—Evidence from the Yangtze River Economic Belt in China. *Energies* **2022**, *15*, 6210. https://doi.org/10.3390/en15176210

Academic Editor: Donato Morea

Received: 22 July 2022
Accepted: 19 August 2022
Published: 26 August 2022

1. Introduction

Air pollution, from sources such as climate anomalies, melting glaciers, and haze, has become an important issue around the world. China, as the world's largest emitter of CO_2 and SO_2 [1,2], is facing serious domestic environmental pollution problems and tremendous international community pressure [3]. In 2021, China committed to peaking its carbon emissions by 2030 and becoming carbon neutral by 2060. Therefore, the question of how to balance economic development and ecological protection has become an important issue. The city cluster policy can provide a potential solution. the city cluster is not only the most promising and dynamic area in China's economic development, but also the area with the highest concentration of ecological and environmental problems. The city cluster will have a profound impact on regional resource utilization and environmental protection, but it is not clear through which specific path. These are issues of interest to many cities and economists.

How to reduce carbon emissions is a crucial issue for sustainable development. The Chinese government has established a series of environmental regulation policies, such as the Air Pollution Prevention and Control Action Plan in 2013, which is also noted as China's Clean Air Action [4–6], carbon emission trading system in 2014 [7–10], and so on. Although previous scholars have discussed the air governance effect of environmental regulation [11,12], they have seldom exploited the environmental effect of a city's spatial layout [13,14], especially the impact of the city cluster on carbon emission reduction. Therefore, to fill academic gaps, this paper will examine the impact of the city cluster policy on carbon emissions, based on the sample of China's Yangtze River Economic Belt.

Based on city-level panel data from 108 Chinese cities in the Yangtze River Economic Belt between 2003 and 2017, this paper examines the impact of city cluster policy on carbon emissions using the difference-in-differences (DID) method. We found that: (1) The city cluster policy has significantly reduced the cities' carbon emissions, with an average reduction of 7.4% in city carbon emissions; furthermore, after a series of robust and endogenous tests, such as parallel trend and PSM-DID, the core conclusion still remains. (2) We further identify possible economic channels through this effect, and find that city cluster policy would increase city productivity, city technological innovation, and industrial structure optimization. (3) The emission reduction effect of the city cluster policy only exists in the nation's city clusters.

There are three reasons why we choose China as the background to study the impact of city clusters on carbon emission reduction. First, China is the world's most populous country and the world's second-largest economy. It is of practical significance to evaluate the impact of carbon trading pilot policies. Secondly, China is the largest carbon emission emitter and an emerging country [15]. Conclusions from such research on China may provide a useful reference for other developing countries to implement carbon trading pilot programs. Finally, China is a centralized country that adopts a vertical management and organizational structure. The environmental policies are initially formulated by the central government of China, and then implemented by local governments, which ensures the exogenous nature of the policy. In addition, there are 30 provinces in China, allowing us to use this cross-sectional variation to determine the policy effect of the city cluster.

There are two main contributions to this paper. For one thing, this paper has a potential academic contribution. Previous scholars have discussed the air governance effect from the perspective of environmental regulation [4–6], but they have seldom discussed the city's spatial layout. In this paper, we use China's city cluster policy in 2011 to examine the effect of city integration on carbon emissions. For another thing, this paper has strong policy implications. Based on China's city cluster policy in 2011, this paper examines the effects of the city cluster on carbon emissions. We found that the city cluster will reduce carbon emissions. The conclusions provide useful policy implications for policy-makers to reduce city carbon emissions. Rich results from a heterogeneity analysis provide policy-makers with an understanding of economic facts, and point out the direction for improving the carbon trading system.

The rest of the paper is organized as follows: the second part is the theoretical analysis, the third part presents the data and empirical design, the fourth part presents the empirical results, the fifth part is the further discussion, and the sixth part consists of the conclusions and policy implications.

2. Theoretical Analysis

A large number of theoretical and empirical studies show that the city cluster can have a positive effect on economic productivity, technological innovation capacity, and industrial structure optimization through the agglomeration of factors. Details are as follows.

First, the city cluster can reduce carbon emissions by improving city productivity. Generally speaking, the public infrastructure construction of member cities in the city cluster can be further improved, by, for example, improving the railway station [16]. Infrastructure improvements can help foster city networks that enable the flow of people and capital among cities [17]. The formation of a city cluster can improve the capacity of resource allocation in a larger region. It helps the flow of production elements from large to small and medium-sized cities, and improves the aggregation economic and ecological efficiency of small and medium-sized cities [18]. In addition, the scale effect generated by the city cluster has contributed to an increase in city productivity.

With the implementation of the city cluster, the production costs and price index of products would decrease, leading to the expansion of local demand and market size. The increased returns to scale resulting from this expansion will further promote agglomeration and thus increase regional productivity. The increasing returns to scale generated by expansion further promote agglomeration and improve regional production productivity.

Secondly, the city cluster can reduce carbon emissions through technology. On the one hand, economic growth in cities is accompanied by the build-up of human capital and the overflow of knowledge. The city cluster can increase opportunities for the inter-regional exchange of people and learning, and promote collaborative research and development [19], thus accelerating the diffusion and application of knowledge and new technologies within the region and promoting technological progress. Therefore, the clustering spillover effects of sharing, matching, and learning mechanisms within large cities are more obvious than those in small cities [20], which will accelerate the dissemination and application of knowledge and new technologies within the region and thus promote technological progress.

On the other hand, the city cluster significantly improves market openness and facilitates the aggregation of high-quality factors in the city cluster. Non-local enterprises bring the cross-regional flow of enterprise innovation factors, creating favorable conditions for inter-regional knowledge spillover and improving innovation efficiency [21]. In conclusion, the knowledge spillover brought by the city cluster can not only promote local technological progress, but also have a significant impact on the technological progress of neighboring regions as well through the cross-regional flow of innovation factors.

Finally, the city cluster can reduce carbon emissions through industrial structure upgrading. The optimization of industrial structure and energy efficiency are key factors in carbon reduction [22,23]. The city cluster reduces barriers for non-local enterprises and foreign investment to enter the local market by lowering trade barriers within cities, which accelerates competition among enterprises within the market. To survive, enterprises will eventually choose industrial structure upgrading through the market competition mechanism. At the same time, the hierarchy produced in the development of the city cluster is inevitably accompanied by various degrees of specialization. Diversified metropolises will take on the role of incubators for innovative industries, while small and medium-sized cities will use their comparative advantage in production factors to reduce production costs and become agglomerations for some industries [24]. Referring to Ó Huallacháin and Lee (2011) [25], specialized production facilitates eco-efficiency through channels such as the promotion of economic factor aggregation, technological progress, resource intensification, and Marshallian externalities. Therefore, the optimization of a city system stemming from the development of the city cluster will promote the industrial structure upgrading.

Therefore, based on the above analysis, this paper puts forward three assumptions, as shown in Figure 1.

Hypothesis 1. *City cluster pilot policy can reduce carbon emissions by increasing city productivity.*

Hypothesis 2. *City cluster pilot policy can reduce carbon emissions by improving the level of technological innovation.*

Hypothesis 3. *City cluster pilot policy can reduce carbon emissions through optimizing industrial structures.*

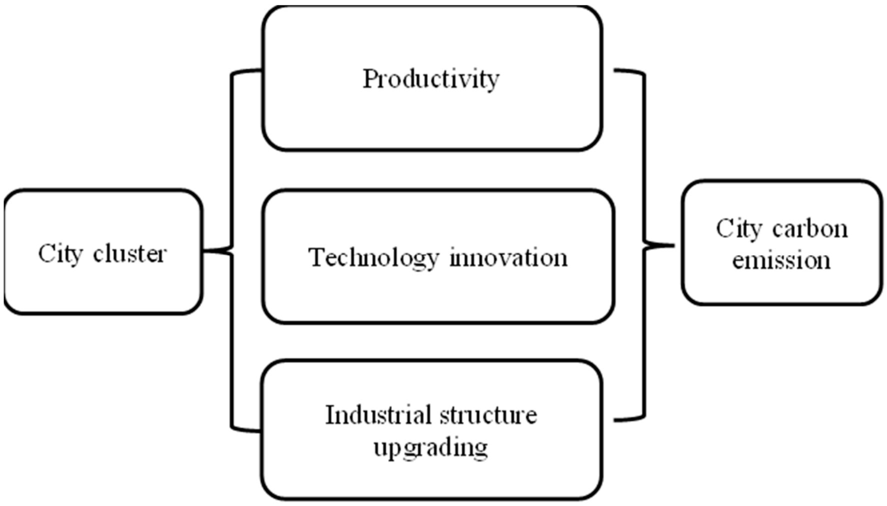

Figure 1. Theoretical hypothesis framework.

3. Data and Empirical Design

3.1. Data

We investigate the impact of city cluster policy on carbon emissions according to the panel data of 108 Chinese cities in the Yangtze River economic belt from 2003–2017. Our carbon emissions data were obtained from the Carbon Emission Accounts and Database https://www.ceads.net/ (accessed on 5 May 2022); other city data are from the China City Statistics Yearbook. The carbon emissions data are only updated to 2017. Our final sample consists of 1620 city-year observations covering the 2003–2017 period.

3.2. Empirical Design

The purpose of this study is to examine the effect of city cluster policy on CO_2 emissions. As a classical method for policy evaluation, the difference-in-differences (DID) model has been widely adopted by most scholars, and we also use this method. This method can examine the difference in CO_2 emissions before and after the city cluster policy implementation, and assess the average effect of city cluster policy on carbon emissions. The benchmark model is as Formula (1).

$$\mathrm{LnCO}_{2c,t} = \alpha + \beta \times \mathrm{Treat}_c \times \mathrm{Post}_t + \varnothing \times \mathrm{Control}_{c,t} + \delta_c + \mu_t + \varepsilon_{c,t} \quad (1)$$

where c is the city and t is the year. Independent variable $\mathrm{LnCO}_{2c,t}$ indicates the carbon emissions of city c in year t. Our dependent variable is the city cluster policy (Treat*Post). The coefficient on Treat*Post, β, is the one with the main interest. Thus, β reflects the impact of the city cluster policy on carbon emissions. A negative β implies that a city cluster policy will reduce carbon emissions in cities. Control is our control variable. δ_c and μ_t are city-fixed effect and year-fixed effect, respectively, and $\varepsilon_{c,t}$ is a random error term.

3.3. Variables

3.3.1. Independent Variables

Our independent variable consists of city-level CO_2 emissions (LnCO_2). Unfortunately, only provincial-level CO_2 data and county-level CO_2 data are available in the Carbon Emission Accounts & Database. Meanwhile, we have also noticed that county-level CO_2 is measured by light intensity, not real CO_2 emissions. Given such two dimensions of CO_2 data structure, this paper uses two methods to construct city-level CO_2 emissions. One method uses county-level CO_2 emission data directly added to the city level [26]. Another method uses county-level CO_2 data to calculate the proportion of each city in its province. Based on this proportion, provincial-level CO_2 is allocated to each city by this proportion weight, and the weighted city CO_2 is constructed. We would use weighted city

CO_2 emissions from the second method in the benchmark regression. We also use the CO_2 emissions from the first method in the robustness test.

3.3.2. Dependent Variables

Our dependent variable is the city cluster policy (Treat*Post). It is an interaction item between Treat and Post. The Treat variable equals one in the city cluster list. The city cluster list in the Yangtze River economic belt contains the Chengyu city cluster (Nation), the Dianzhong city cluster (Region), the Yangtze River city cluster (World), the Yangtze middle river city cluster (Nation), the Qianzhong city cluster(Region), and zero otherwise. Post equals one in a year that is equal to or larger than 2011, and zero otherwise.

3.3.3. Control Variables

Following prior research, we add several control variables to the model, which include: city economic development (LnGDP), city openness (Open), city financial development (Finance), city government scale (Gov), the ratio of city secondary industry (Sec_Ind), and the ratio of city tertiary industry (Ter_Ind). Table 1 provides detailed definitions of all variables. The definitions of the main variables are shown in Table 1.

Table 1. Variables Definition.

Variable	Definition
$LnCO_2$	The logarithm of city CO_2
Treat*Post	An indicator variable that equals one if the city is eventually included in the low-carbon city pilot list by the end of our sample period, and zeroes otherwise
LnGDP	the logarithm of city GDP
Open	The ratio of the city actual utilization of foreign direct investment to city GDP
Finance	The ratio of the city balance of bank deposits and loans to city GDP
Gov	The ratio of the city government public finance expenditure to city GDP
Sec_Ind	The ratio of the city added value of the secondary industry to city GDP
Ter_Ind	The ratio of the city added value of the tertiary industry to city GDP

3.4. Descriptive Statistics

The dependent variable consists of city-level CO_2 emissions ($LnCO_2$). The average $LnCO_2$ is 2.704, the standard deviation is approximately 0.830, the average Treat*Post value is 0.321, and the standard deviation is 0.467. This indicates that there are significant differences in various cities. In terms of the standard deviation of the control variables, there is a degree of variation among the cities; city-level CO_2 emissions may be affected by these differences. The descriptive statistics of the main variables are shown in Table 2.

Table 2. Descriptive statistics of the variables.

Variables	Observations	Mean	Sd	Min	Max
		Dependent Variables			
$LnCO_2$	1620	2.704	0.830	0.250	5.128
		Independent Variables			
Treat*Post	1620	0.321	0.467	0	1
		Control Variables			
LnGDP	1620	16.02	1.081	12.93	19.46
Open	1620	0.023	0.022	0	0.201
Finance	1620	2.084	0.873	0.764	6.255
Gov	1620	0.165	0.090	0.049	1.485
Sec_Ind	1620	0.482	0.093	0.187	0.759
Thi_Ind	1620	0.371	0.075	0.207	0.698

4. Empirical Results

4.1. The Effect of City Cluster Policy on CO_2 Emissions

The estimated results of Equation (1) are shown in Table 3. It can be seen that the coefficient estimates of Treat*Post are significantly negative, suggesting that city carbon emissions have decreased after the city cluster policy. This negative impact has economic implications. For example, during our sample period, carbon emissions from cities declined by an average of 7.4% after cities were classified as a city cluster. This result supports our previous hypothesis. The path of the effect may come from the positive impact of the city cluster on production efficiency, technological innovation ability and the rationalization of industrial structure, which will be further examined in this paper. To sum up, the city cluster policy helps cities reduce carbon emissions.

Table 3. The effect of city cluster policy on CO2 emissions.

	(1)	(2)
	$LnCO_2$	$LnCO_2$
Treat*Post	−0.099 ***	−0.074 ***
	(−6.235)	(−5.032)
LnGDP		0.405 ***
		(5.486)
Open		0.580 *
		(1.746)
Finance		0.056 *
		(1.879)
Gov		0.196
		(1.249)
Sec_Ind		0.070
		(0.409)
Thi_Ind		0.043
		(0.202)
Constant	2.736 ***	−3.975 ***
	(418.071)	(−3.311)
City FE	YES	YES
Year FE	YES	YES
Observations	1620	1620
Adj_R2	0.957	0.959

Note: *t* statistics are shown in parentheses; *** and * represent significance at the 1%, and 10% levels, respectively. All variable definitions are in Table 1. The sample period covers 2003 through 2017. Regressions in all columns control for year-fixed effects and city-fixed effects.

4.2. Parallel Trend Analysis

A parallel trend is a prerequisite for the DID model. It means that there is no systematic difference in carbon emission trends between the two groups before the policy, or, even if there are differences, the differences are fixed. Therefore, we followed Li et al. (2016) [27] and Zhu and Xu (2022) [5], and constructed our model as:

$$\mathrm{LnCO}_{2c,t} = \alpha + \beta_t \times \mathrm{Treat} \times \mathrm{D}^{\mathrm{Year}(t)} + \varnothing \times \mathrm{Control}_{c,t} + \delta_c + \mu_t + \varepsilon_{c,t} \quad (2)$$

$\mathrm{D}^{\mathrm{Year}(t)}$ is year dummy variables, and it is equal to 1 when year is t. For example, D^{2006} is equal to 1 when year is 2006, and 0 otherwise. Therefore, the parameters of β_t identify t year policy effects. To avoid Treat $\times$ $\mathrm{D}^{\mathrm{Year}(t)}$ collinearity, we use the policy year (i.e., 2011) as the base year. The estimation results are presented in Figure 2. We can see that there is no pre-policy effect (before 2011), indicating that our identification satisfies the parallel trend assumption. Furthermore, the policy has a strong continuity effect.

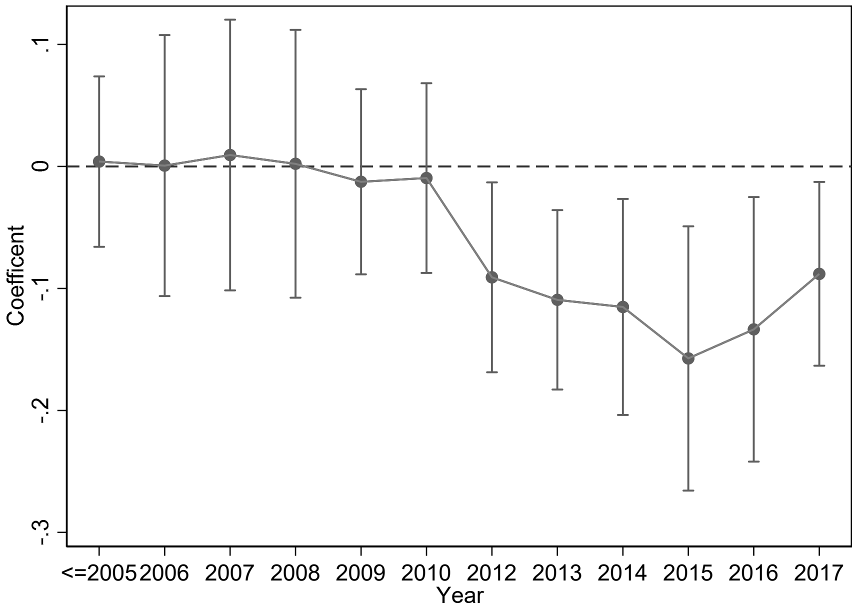

Figure 2. Dynamic effects of the City Cluster.

4.3. Robustness Test

4.3.1. Propensity Score Matching DID (PSM-DID)

Of course, the city cluster policy is not a perfect quasi-natural experiment. There is a certain degree of randomness in the selection of the city cluster. Strictly speaking, whether a city can be selected as one of the city clusters is not a completely random selection process. It will be disturbed by economic factors, political factors, and human factors.

These differences will affect the validity of the DID model. In order to reduce the interference caused by these differences in model estimation, we will use the propensity score matching (PSM) method proposed by Heckman et al. (1998) [28] to select comparable treatment and control groups, and then use a DID model to estimate the policy effects [26]. We adopt the 1:1 nearest neighbor matching method. The estimation result is shown in column (1) of Table 4. It can be seen that the Treat*Post is still significantly negative with the city's carbon emissions (lnCO_2), indicating that our core findings remain valid after alleviating the problem of sample selection bias.

Table 4. Robustness check of the effect of city cluster policy on CO_2 emissions(PSM-DID).

	(1)	(2)	(3)	(4)	(5)	(6)
	LnCO_2		**LnCO_2_2**		**LnCO_2**	
Treat*Post	−0.026 *	−0.064 ***	−0.025 **	−0.069 ***	−0.060 ***	−0.056 ***
	(−1.698)	(−2.653)	(−2.159)	(−4.787)	(−4.460)	(−4.216)
PSM	YES					
Two-Stage		YES				
Replace Y			YES			
CAA Policy				YES		YES
CET Policy					YES	YES
Control Vars	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	727	216	1620	1620	1620	1620
R-squared	0.987	0.996	0.969	0.962	0.963	0.963
Adj_R2	0.985	0.992	0.967	0.959	0.960	0.960

Note: *t* statistics are shown in parentheses; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

4.3.2. Two-Period DID

The regression coefficients in the baseline regression may be overestimated due to sequential correlation issues. To solve this problem, we will adopt a two-period estimation strategy according to Bertrand et al. (2004) [29]. The data will be divided into two periods based on the point in time of the policy. That is, the variables in the two periods are averaged to construct a two-period DID sample.

The estimation result is shown in column (2) of Table 4. We find that the coefficient on Treat*Post is significantly negative at the 1% level, suggesting that the city cluster policy can reduce city carbon emissions even after considering potential serial correlation issues.

4.3.3. Alternating the Explained Variable

The estimated results may be sensitive to different definitions of critical variables. To ensure whether the measurement of carbon emissions is robust, we use unweighted CO_2 emissions ($LnCO_2$_2) as alternative measurements. The estimation result is shown in column (3) of Table 4. It can be seen that the coefficient on Treat*Post is significantly negative with $LnCO_2$_2, suggesting that the basic conclusion remains unchanged even with the replacement of the core explanatory variables.

4.3.4. The Impact of Related Environmental Policies

During our sample period, some environmental regulatory policies occurred in China, which may affect carbon emissions. To eliminate the impact of these environmental policies on city carbon emissions, in this section we will further control the effect of these policies.

Two major environmental regulatory policies were instituted during the sample period. The first is the Clean Air Action policy (CAA) in 2013. Following Zhu and Xu (2022), we manually collect cities' air pollution targets and generate the variable CAA [5]. Following Zhu and Xu (2022), we measure CAA: CAA = Ln(air pollution targets) * Post(year $\geq$ 2013) [5]. Adding CAA variables to the baseline model (1), the result is shown in column (4) of Table 5. The Treat*Post is still significantly negative with the city carbon emissions ($LnCO_2$), suggesting that the basic conclusion is robust even if we control the effect of the Clean Air Action policy on city carbon emissions.

Table 5. Other robustness check of the effect of city cluster policy on CO_2 emissions.

	(1)	**(2)**	**(3)**
		$LnCO_2$	
Treat*Post	−0.057 *** (−3.615)	−0.074 *** (−4.661)	−0.054 *** (−3.936)
Control Pro_Trend	YES		
Control 2008 Finance Crisis		YES	
Control outlier			YES
Control Vars	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	1620	1512	1620
Adj_R2	0.960	0.958	0.964

Note: *t* statistics are shown in parentheses; *** represent significance at the 1% levels, respectively.

The second is the provincial carbon emissions trading policy implemented in 2013 http://www.tanpaifang.com/tanjiaoyi/2012/0219/41.html (accessed on 5 May 2022). We set a policy dummy variable CET that equals one if the province is eventually included in the carbon emission system list by the end of our sample period, and zero otherwise. Adding CET variables to the baseline model (1), the result is shown in column (5) of Table 5. The Treat*Post is still significantly negative with the city's carbon emissions

($LnCO_2$), suggesting that the basic conclusion is robust even if we control the effect of carbon emissions trading policy on city carbon emissions.

Finally, we control the impact of both the Clean Air Action (CAA) and the carbon emissions trading policy (CET). The result in column (6) of Table 5 shows that the core explanatory variable Treat*Post is still significantly negative with the city carbon emissions. Although considering the interference of these two environmental regulatory policies, the city cluster policy can still significantly reduce the city carbon emissions.

4.3.5. Other Robustness Check

In addition to the above four robustness tests, other robustness tests are discussed to ensure the robustness of the results in this paper.

Control provincial trend. To exclude the impact of the variation of some characteristics of provinces over time trend on the city carbon emission, we add to control the provincial trend. The result is shown in column (1) of Table 5. The Treat*Post is still significantly negative with the $LnCO_2$.

Eliminate the impact of the financial crisis. A financial crisis affects economic development, which affects the city's carbon emissions. Therefore, we should exclude the 2008 sample, which would eliminate the impact of the 2008 financial crisis on city carbon emissions. The result is shown in column (2) of Table 5. The Treat*Post is still significantly negative with $LnCO_2$.

Winsorize the data. In baseline regression, some variables may lead to extreme values in the data. Therefore, to alleviate the impact of extreme values on the estimated results in this paper, we process the data with 1% winsorizing. The result is shown in column (3) of Table 5. The Treat*Post is still significantly negative with $LnCO_2$.

Placebo test of the experimental group. Following Li et al. (2016) [27], we randomly select a city cluster for placebo testing. Figure 3 shows the distribution of the regression coefficients of the "artificial" processing variable Treat*Post in the simulation. It can be observed that the randomly assigned estimated values are concentrated around zero, while the truly estimated coefficients are on the left side of Figure 3. It verifies that the city cluster policy has significantly reduced the city's carbon emissions.

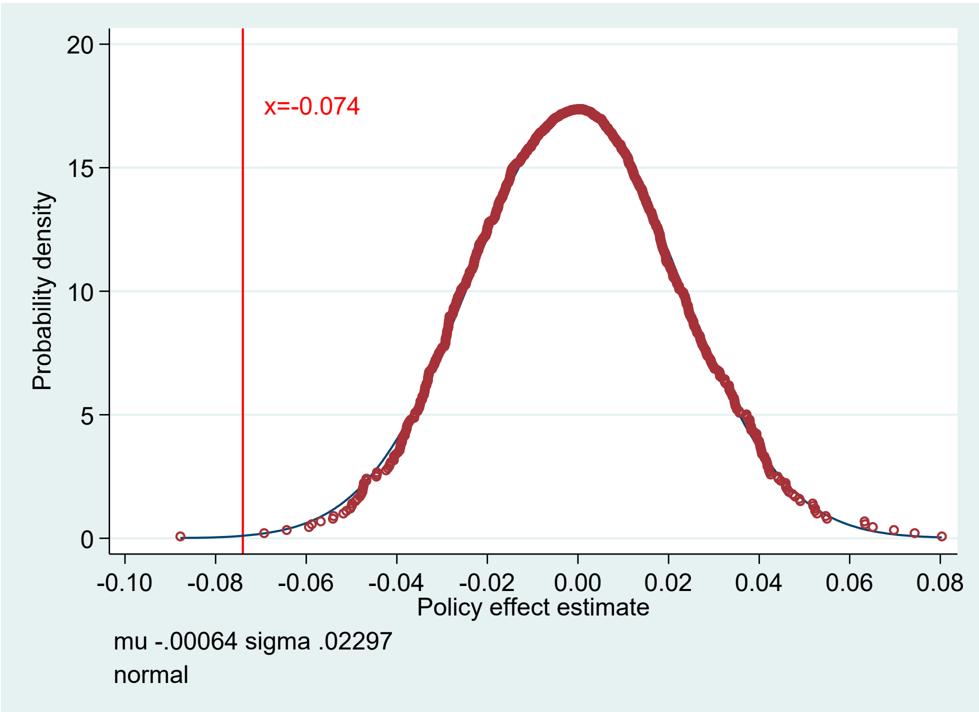

Figure 3. Placebo test of the experimental group.

In a word, the robustness above indicates that the core conclusion still remains when a series of possible and potential interference factors are excluded.

5. Further Discussion

5.1. Economic Channels

In this section, we will explore the three plausible underlying economic channels by which city cluster policy affects city carbon emissions. The economic channels build on existing theories, and factors such as productivity, technological innovation, and industrial structure optimization are important in reducing city carbon emissions.

5.1.1. Productivity Effect

In this section, we will examine whether the city cluster improves city productivity through the city scale effect, which reduces carbon emissions. Based on the article of Chen et al. (2022) [30], we measure an index of the city's total factor productivity (TFP) and examine whether the city cluster has an impact on city productivity based on model (3).

$$\mathrm{TFP}_{c,t} = \alpha + \beta \times \mathrm{Treat}_c \times \mathrm{Post}_t + \varnothing \times \mathrm{Control}_{c,t} + \delta_c + \mu_t + \varepsilon_{c,t} \quad (3)$$

The empirical results are shown in Column (1) of Table 6. The core explanatory variable Treat*Post is significantly positively correlated with the explained variable TFP at the confidence level of 5%. The TFP level of the city increased by 22% after cities were classified as the city cluster. Compared to other cities, China's Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei region have more advanced infrastructure development, providing a more favorable environment for the flow of production factors. This urban network further creates a scale effect and promotes urban productivity.

Table 6. Mechanism analysis of the effect of city cluster policy on CO_2 emissions.

	(1)	**(2)**	**(3)**
	TFP	LnRD	ISO
Treat*Post	0.22 **	0.611 ***	−0.006 *
	(2.515)	(11.235)	(−1.796)
Control Vars	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	1547	1584	1618
R-squared	0.845	0.951	0.971
Adj_R2	0.842	0.946	0.969

Note: *t* statistics are shown in parentheses; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

5.1.2. Technological Innovation Effect

In this section, we will examine whether the city cluster enhances city innovation, which reduces carbon emissions, through city knowledge spillovers. Therefore, based on the article of Du et al. (2021) and Lyu et al. (2019) [31,32], we take city R&D input as a proxy variable of city innovation and will examine whether the city cluster has an impact on city innovation based on model (4).

$$\mathrm{LnRD}_{c,t} = \alpha + \beta_t \times \mathrm{Treat}_c \times \mathrm{Post}_t + \varnothing \times \mathrm{Control}_{c,t} + \delta_c + \mu_t + \varepsilon_{c,t} \quad (4)$$

The empirical results are shown in Column (2) of Table 6. It can be seen that the core explanatory variable Treat*Post is significantly positively correlated with the explained variable LnRD at the confidence level of 5%. The city R&D input increased by 61.1% after cities were classified as the city cluster. It can be seen that the flow of production factors brought by the city cluster does significantly enhance the knowledge spillover effect, and cross-regional knowledge spillover creates favorable conditions for improving innovation efficiency.

5.1.3. Industrial Structure Optimization

In this section, we will examine whether the city cluster improves city industrial structure upgrading by reducing the proportion of secondary industries, which reduces carbon emissions. Therefore, based on the article of Liu et al. (2021) [33], we measured an index of the rationalization of industrial structure, which can reflect the coupling degree of the element inputs and outputs.

Formula (5) will be used to measure the rationalization degree of industrial structure.

$$\mathrm{ISO}_{i,t} = \sum_{j=1}^{3} \frac{y_{ijt}}{Y_{it}} \ln\left(\frac{y_{ijt}}{Y_{it}} / \frac{l_{ijt}}{L_{it}}\right) \quad (5)$$

where i is the city, t is the year, and j is the industry. Variable y_{ijt} indicates the carbon emissions of the industry j in city i and year t. Variable Y_{it} indicates the gross of the industry of city c in year t. Variable l_{ijt} indicates the number of employees of the industry j in city i and year t. Variable L_{it} indicates the total number of employees of city c in year t. Obviously, the closer ISO is to 0, the higher the coupling degree between the allocation and output ratio of employees in the three industries is and the more reasonable the industrial structure is. On the contrary, the industrial structure is unreasonable.

We will examine whether the city cluster has an impact on city industrial structure upgrading based on model (6).

$$\mathrm{ISO}_{c,t} = \alpha + \beta_t \times \mathrm{Treat}_c \times \mathrm{Post}_t + \varnothing \times \mathrm{Control}_{c,t} + \delta_c + \mu_t + \varepsilon_{c,t} \quad (6)$$

The empirical results are shown in Column (3) of Table 6. It can be seen that the core explanatory variable Treat*Post is significantly negatively correlated with the explained variable ISO at the confidence level of 10%. The ISO index decreased by 0.6% after cities were classified as the city cluster. Therefore, the optimization of a city system stemming from the development of the city cluster will promote the industrial structure upgrading.

5.2. The Effect of City Cluster Policy on CO_2 Emissions across City Cluster Positioning Level

The level of the city cluster positioning determines the resource allocation capacity of the city cluster. The city cluster with a high positioning level can provide favorable organizational leadership and abundant human, financial, and other resources, which support the implementation of the city cluster to reduce city carbon emissions. However, the regional-level city cluster governments have a limited ability to allocate resources. In this case, they cannot provide appropriate policies and funds to attract talents and promote the transformation and upgrading of enterprises. The world-level city cluster also does not affect the reduction of carbon emissions. The reason is that the goal of the world-class city cluster is to create a more open Chinese market, and attracting foreign investment is the top priority. As a result, the policy benefits of regional and world-level city cluster cannot be realized. The national-level city cluster has sufficient allocation capacity to reduce carbon emissions.

The result is shown in column (1) of Table 7. Only variable Nation*Treat*Post is significantly negative with $LnCO_2$, the regional and world city cluster positioning show weak policy effects, neither variables World*Treat*Post nor Region*Treat*Post are significantly affected.

Table 7. The effect of city cluster policy on CO_2 emissions across city cluster positioning level.

	(1)
	$LnCO_2$
World*Treat*Post	−0.020
	(−0.528)
Nation*Treat*Post	−0.103 ***
	(−6.854)
Region*Treat*Post	0.030
	(1.031)
Control Vars	YES
City FE	YES
Year FE	YES
Observations	1,620
R-squared	0.963
Adj_R2	0.959

Note: *t* statistics are shown in parentheses; *** represent significance at the 1% levels, respectively.

6. Conclusions and Policy Implications

6.1. Conclusions

Based on 108 Chinese cities from Yangtze River Economic Belt between 2003 and 2017, this study examines the impact of the city cluster policy on cities' carbon emissions using the difference-in-differences method. The main conclusions are as follows.

(1) The city cluster policy has significantly reduced the level of cities' carbon emissions. During our sample period, carbon emissions from cities declined by an average of 7.4% after cities were classified as the city cluster. After a series of robustness tests, the conclusion remains robust.

(2) Productivity, technological innovation, and industrial structure optimization are three essential mechanisms for the city cluster policy to reduce carbon emissions. We find that the TFP level of the city increased by 22%, the city R&D input increased by 61.1%, and the ISO index decreased by 0.6% after cities were classified as the city cluster. It means that cities are more productive, innovative, and have a more reasonable industrial structure.

(3) There is a difference in the effect of the positioning level of the city cluster on the reduction of carbon emissions. The effect of city cluster policies on carbon emission reduction is significant only in the national-level city cluster. The carbon emissions from the national-level city cluster declined by an average of 10.3%.

6.2. Policy Implications

This paper has the following three policy implications:

First, this paper finds that the city cluster will significantly reduce city carbon emissions. Therefore, the government should adopt a more diversified approach to air control. It can not only reduce air pollution through environmental regulation but also reduce carbon emissions by setting up the city cluster through city spatial layout. Policymakers should actively adhere to the city cluster model. They should not only continue to vigorously promote the development of mature city clusters in the Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei region, but also strengthen the concentration of city clusters in the Yangtze River, Chengdu–Chongqing, and Central Plains.

Second, based on the mechanism analysis, the city cluster can reduce city carbon emissions by improving productivity, improving innovation, and optimizing industrial structure. Therefore, the government can take "industrial transfer and innovation drive" as an opportunity to actively promote the transfer of traditional industries from core cities (or big cities) to non-core cities (or small and medium-sized cities). It can improve the efficiency of the utilization of production factors in the city cluster through specialization and industrial upgrading. At the same time, guide the core cities to build innovation systems. The government can achieve the goal of carbon emission reduction by optimizing the industrial structure of the city.

Third, based on the heterogeneity analysis, only the national-level city cluster can achieve the purpose of city emission reduction. Therefore, the government should set up more nation-level city clusters, rather than regional-level or world-level city clusters. It needs to further improve the resource support capacity of the national-level city cluster and promote the transformation and upgrading of enterprises through the introduction of talents and financial subsidies.

6.3. Limitations and Future Research Possibilities

However, this paper also has some limitations: on the one hand, the research sample of this paper is the data from the city level in China. In the future, when carbon emissions data at the corporate level becomes available, we can investigate the carbon effect of the city cluster policy from a micro-enterprise perspective. On the other hand, although this paper explores the carbon reduction effect of the city cluster policy, it does not examine its impact on human health. In the future, we will merge relevant micro-survey data to study the impact of city cluster policy on individual health.

Author Contributions: Conceptualization, X.L.; Data curation, C.H., S.Z. and Y.W.; Formal analysis, C.H.; Investigation, S.Z.; Methodology, X.L.; Project administration, X.L.; Supervision, Y.W.; Validation, S.Z.; Visualization, Y.W.; Writing—review & editing, C.H. and S.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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