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The Impact of Low-Carbon City Pilot Policies on Air Quality: Quasi-Natural Experimental Evidence from China

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Abstract: Low-carbon cities have become a new trend in regional development around the world. Whether they can improve the environment in China, especially the air quality, remains to be tested. In this paper we take low-carbon city construction as a quasi-natural experiment and empirically test the net effects, influencing factors, and dynamic effects of low-carbon city construction on air quality by constructing a multistage propensity score matching and Difference-in-Differences model. After a series of robustness tests, the following conclusions are drawn: first, low-carbon city construction reduces the regional Air Quality Index, inhalable particulate matter, fine particulate matter, and NO_2 concentrations. Among them, the construction effect in 2017 was the most significant. Therefore, it is necessary to continue to promote low-carbon city policies and accurately identify different types of air pollutants to improve the overall effectiveness of low-carbon city policies. Second, temperature, humidity, wind level, and other meteorological factors, as well as gross domestic product for the proportion of secondary industry, will affect air quality. Therefore, it is necessary to comprehensively consider meteorological, economic, social, and other influencing factors in an early stage of the construction of the next batch of low-carbon cities, so as to avoid falling into the trap of "building first and managing later". Third, the impact of secondary industry on air quality is significantly greater than that of tertiary industry. Therefore, the upgrading of industrial structure promoted by low-carbon city policy is effective in improving air quality. Fourth, the construction of low-carbon cities in western China has the most significant impact on air quality improvement. Therefore, the joint prevention and control mechanism of air pollution control in urban agglomeration should be established.

Keywords: low-carbon city; air quality; Multi-period PSM-DID model

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1. Introduction

As the world's second largest economy and the largest developing country in the world [1], China's economic growth level and urbanization are advancing by leaps and bounds [2], which is a double-edged sword and may be an important factor affecting urban environmental pollution, especially air pollution [3]. As we know, air pollution not only affects the objective health level of urban residents, causing them to suffer from respiratory system, heat, and skin disease [4,5]; it also may reduce the subjective well-being of residents, damage cognitive function, and produce negative emotions and behaviors [6]. In recent years, not only to show a pragmatic image in the international community, but also to achieve sustainable development at home, the Chinese government has attached great importance to coordination between economic development and environmental protection. China has formally put forward the new concept of ecological civilization development and the "double carbon" strategic goal of "carbon peak in 2030 and carbon neutralization in 2060". Low-carbon pilot cities are an important environmental reform program launched by China in 2010, although low-carbon technologies, as an important means to reduce air pollution [7], improve residents' well-being, and enhance the competitiveness of cities and even countries, have been used in European developed cities for many years [8,9]. China has constructed low-carbon cities in three rounds, which include adjusting the industrial structure, encouraging circular economy, using green energy, advocating building energy conservation, and developing a low-carbon transportation system, which are also closely related to ecological civilization, people's well-being, and coping with the deterioration of air quality. Therefore, what mechanism a low-carbon city uses to improve air quality and the impact of such a city on pollution control in China has become an issue that attracts global attention.

Academic circles have engaged in heated discussions on urban construction and air quality, but the conclusions are inconsistent. Some scholars believe that urban development will accelerate the deterioration of air quality [10–12]. With the improvement of cities' economic level, energy consumption continues to increase, and the emission of urban, industrial, and domestic pollution intensifies, resulting in the deterioration of air quality. Some scholars believe that urban development contributes to improving air quality [13,14]. Because the development of urbanization brings industrial and population agglomeration, it is conducive to the concentration of superior resources to deal with industrial and domestic pollution and it realizes the benefits of low-cost centralized pollution control. As an important link between urban economic development and environmental governance, building low-carbon cities may become a key factor in solving the contradiction between urban energy consumption and environment [15]. To more accurately estimate the effects of low-carbon city construction, some scholars use the differential difference method to evaluate low-carbon pilot policies. Studies have shown that in the short term, low-carbon city construction reduces carbon dioxide emissions by promoting industrial structure upgrading in pilot cities [16], increasing green technology innovation activities of enterprises [17–20], and improving the air pollution index [21]. The policy effect is relatively ideal. However, from a long-term perspective, some scholars have questioned the effect of "weak incentives and weak constraints" existing in low-carbon cities [22]. At present, no scholar has adopted the multistage Difference-in-Differences (DID) method to evaluate the net effects of low-carbon city construction on air quality and to identify the dynamic effects of policies within the time interval covering the establishment of all pilot cities.

In addition, the literature on air quality is mainly focused on the effects, causes, mechanisms, paths, and prevention of air pollution [23,24]. Most scholars take Air Quality Index (AQI) [25], fine particulate matter ($PM_{2.5}$), or inhalable particulate matter (PM_{10}) and other single indicators as research objects [26,27], ignoring that each specific pollutant represents different meanings in reality. It is worth pointing out that few researchers have considered the impact of NO_2 produced by manufacturing on air [28]. Further studies show that among the three batches of low-carbon pilot cities, the time and mode of joining the eastern, central, and western urban agglomerations have been different [29,30], but no scholar has identified the effect of the policy from the perspective of the heterogeneity of low-carbon urban agglomerations. It is worth emphasizing that although the low-carbon city pilot policy has been implemented in China for twelve years since 2010, no researcher has scientifically evaluated the effects of this program from the perspective of economics [21]. In addition, it is obvious that low-carbon city pilot construction's process in different cities is not completely consistent. Using a standard model to estimate the result of the double difference is likely to appear biased, while multiple-phase double difference is able to capture the dynamic change of policy to more accurately measure the effects of low-carbon city construction.

The purpose of this study is to examine the net effects, influencing factors, and dynamic effects of low-carbon city construction on air quality and to find possible improvement measures. To this end, we took low-carbon city construction as a quasi-natural experiment and, based on atmospheric data and socioeconomic data for 109 cities from 2010–2020, adopted the propensity score matching model (PSM) and a multistage DID model to evaluate the effects of policies. This paper provides some important insights: First, we provide a quasi-natural experiment based on low-carbon city construction to estimate the impact of non-low-carbon cities on air quality, thereby creating a control group. PSM method is adopted to reduce sample bias. The use of multistage DID not only effectively alleviates the endogenous problems such as the correlation between error terms and explanatory variables caused by the absence of dependent variables but also accurately captures the dynamic effects of different batches of low-carbon city construction. Second, we analyze the heterogeneity of four pollutants and six socioeconomic factors affected by low-carbon city construction, finding effective ways to improve air quality in low-carbon city construction. Third, we evaluate the effectiveness of regional differences in low-carbon cities to provide a reference for future policy improvement. These are also likely to be general lessons which other countries may draw from the available evidence on China's atmospheric governance.

The main contributions of the paper include: (1) Under the condition of a quasi-natural experiment, a Multi-period PSM-DID model was adopted to identify the impact of low-carbon urban policies on air quality improvement, avoid potential endogenous problems, and provide useful reference for the scientific evaluation of air pollution prevention and control policies; (2) The dynamic effects of pilot policies for low-carbon cities are investigated by stages and the differentiation of air pollutants, which breaks through the previous evaluation of the effects of air pollution prevention and control policies from a simple static and average sense, and the conclusions are richer and more refined; (3) The heterogeneity effect of a low-carbon city pilot on air improvement from a regional perspective can provide more targeted policy suggestions for air pollution work in different regions.

The rest of the paper presents the methodology and data in Section 2, empirical results in Section 3, and robust test in Section 4. Finally, our conclusions are set out in Section 5.

2. Data and Methodology

2.1. Data and Variables

Considering the availability and completeness of air quality data, Air Quality Index (AQI), Fine Particulate Matter ($PM_{2.5}$), Inhalable Particles (PM_{10}), and Nitrogen Dioxide (NO_2) were selected as the dependent variables, and the data came from China's Online Air Quality Monitoring and Analysis platform (https://www.aqistudy.cn/, accessed on 1 May 2022). AQI is a dimensionless comprehensive index developed by the State Environmental Protection Administration to quantitatively describe air quality. It overcomes the defect that a single pollution index cannot measure air pollution changes within the "system scope" and it has been adopted by many scholars owing to its high authority and timely updating [31]. The higher the value, the more serious the air pollution and the greater the harm to human health. $PM_{2.5}$, PM_{10}, and NO_2 were selected from the pollutants in the evaluation system of Ambient Air Quality Standards. The higher the concentration in the air, the more serious the air pollution. Because the pilot construction of low-carbon cities spans a long time period, meteorological data for some years are missing, which are supplemented using the interpolation method.

As for the control variables, existing studies on air quality have shown that meteorological factors will have an impact on air quality [32,33]. Therefore, to accurately identify the net effect of low-carbon city construction on air quality, we chose average temperature (*Temp*), humidity (*Humi*), and wind (*Wind*) as the control variables of meteorological factors. In addition, it is worth noting that existing studies on urban air pollution have shown that social and economic factors will also have a certain impact on urban air quality [34]. Therefore, to make this study more credible, the control variables were also selected on the basis of the aforementioned economic development level, industrial structure adjustment, population, energy-consuming industry, environmental pollution industry, and other social and economic variables. Among them, economic development level is measured by the gross domestic product (*GDP*) of the region; industrial structure adjustment is measured by the proportion of the output value of secondary industry to GDP (*Ind2*), and the proportion of the output value of tertiary industry in GDP (*Ind3*); population (*Popu*) is measured by the total population of a region; manufacturing is measured by industrial waste emissions (*Waste*); and air pollution industry is measured by industrial smoke emission (*Gas*) [35]. The demographic, economic, and industrial data are from the Statistical Yearbook of Chinese Cities, and the meteorological data are from the Online Monitoring and Analysis Platform of China's Air Quality (https://www.aqiresearch.cn/, accessed on 1 May 2022). Finally, the annual data of socioeconomic indicators and daily data of meteorological factors were converted into monthly data suitable for this research model by the interpolation method.

2.2. Methodology

PSM is a statistical method that uses nonexperimental or observational data to analyze the effects of interventions. In studies, there are many data biases and confounding variables for various reasons, and the PSM model is used to find one or more individuals with the same or similar background characteristics as each individual in the experimental group as controls. This minimizes the interference of other confounding factors and reduces the bias so as to make a more reasonable comparison between the experimental group and the control group. The PSM method is particularly suitable for studies using non-random data. Computing the average processing effect of the treatment group samples through the common support hypothesis test and the balance hypothesis test can obtain basic unbiased estimates, thus obtaining a natural experiment under the condition of using non-random data. The influence of selective bias and confounding factors in the performance evaluation process can be excluded as far as possible by the propensity score matching method, ensuring that the final estimated performance results are an unbiased "net effect". In this manuscript, the PSM method is used to eliminate the problem that the treatment group and the control group do not completely meet the common trend hypothesis under the influence of other conditions, and to provide data conditions for estimating the effect of the low-carbon city policy on air quality by using the DID method.

The DID model is usually used to study policy effects. The natural experiment is a necessary step in the differential method. For a natural experiment, all the sample data were divided into two groups: one group was affected by intervention, that is the experimental group; the other group was not affected by the same intervention, that is the control group; the data before and after intervention were differentiated twice to obtain the difference between the two groups, representing the relative relationship between the experimental group and the control group before and after intervention. The second difference between the two groups was made to eliminate the original difference between the experimental group and the control group, and finally the net effect caused by the intervention was obtained. PSM can solve the problem of sample selection bias, but it cannot avoid the endogeneity problem caused by variable omission. Though DID can solve the endogeneity problem through dual difference, it cannot adequately solve the problem of sample selection bias [36,37]. Nonrandom distribution policy implementation test called natural experiment group and control group (natural trials), there are significant features of such test, the sample before the implementation of the policy may exist between the different groups differences, only through the analysis of the contrast before and after single or lateral comparison method will ignore these differences, which in turn lead to biased estimates of the effect of policy implementation. The DID model is based on the data obtained from natural experiments, which can effectively control the ex ante differences among research objects through modeling and effectively separate the real results of policy impact [38,39].

The Multi-period DID model is as follows: (1) The mean value of the treatment group after the occurrence of policies is subtracted from the mean value before the occurrence of policies to obtain the change situation (policy effect + time effect); (2) For the control group, the mean value after the policy occurred was subtracted from the mean value before the policy occurred to obtain the change (time effect); (3) The policy effect is obtained by subtracting the two changes (excluding the time effect)

Based on this, in this paper we take the low-carbon city pilot construction policy as a quasi-natural experiment and combine PSM and DID to estimate the net effect of a low-carbon city pilot on air quality. It can be seen from the following analysis of the policy implementation time that the pilot construction policies of low-carbon cities have obvious characteristics from pilot to promotion, so the model in this paper is a multiperiod DID model. First, to reduce sample bias, we used PSM to select 3880 samples from meteorological indicators and socioeconomic indicators from 109 cities for DID analysis. Then, the influences of low-carbon city construction on AQI and various types of pollution were identified by multiperiod DID. Then, we analyzed the specific causes of air pollution; finally, the difference in air quality for different regions and policy dynamics were studied using the DID model.

2.2.1. Model Construction

At present, there are three methods to evaluate the effect of low-carbon city construction and air pollution policy. One is the single difference method. The effect of the policy was investigated by simply comparing air quality changes before and after the implementation of the policy, but other factors affecting air quality were not controlled. The second is the breakpoint regression method. The effect of the policy can be evaluated by examining whether there is a sudden change in air quality at the implementation point of the policy, but its conclusion is easily disturbed by the estimation method [37]. The third is the PSM-DID method. The Propensity Score Model (PSM) was used to select other non-low-carbon cities with characteristics as similar as possible to low-carbon cities for the control group. Sample selection bias can be effectively eliminated. Control the common air quality trend of the experimental group and the control group. Then, the difference of air quality between the experimental group and the control group before and after the implementation of the policy was investigated using the DID method. In this paper, the multi-period PSM-DID method was used to evaluate the effect of low-carbon city pilot establishment and air quality improvement, and the model was constructed as follows:

$$Y_{ct} = \partial + \beta Group_c \times Policy_t + \beta_1 X_{ct} + \mu_c + \delta_t + \varepsilon_{ct} \tag{1}$$

where Y_{ct} represents the air quality index and single pollutant concentration of low-carbon city C on date T, which are dependent variables. $Group_c$ indicates whether city C is the experimental group or the control group. If it is the experimental group, the value is 1; otherwise, the value is 0. $Policy_t$ represents the dummy variable of whether the policy is implemented or not. The value is 0 before the policy is implemented and 1 after the policy is implemented. The cross term $Group_c \times Policy_t$ represents the change of air quality in the experimental group after the implementation of the low-carbon city policy, and its coefficient β can be used to measure the effect of implementing air pollution prevention and control policy. X_{ct} is a control variable, indicating other factors affecting air quality, including weather factors (temperature, humidity, and wind level) and social and economic factors (industrial smoke dust emission, Gross Domestic Product, the proportion of added value of secondary industry in GDP, the proportion of added value of tertiary industry in GDP, industrial wastewater discharged, population). μ_c represents the city-fixed effect, representing the unobserved variable that does not vary with time but with cities. δ_t represents time-fixed effects, unobserved variables that do not vary with cities but with time. ε_{ct} represents the random perturbation term.

The policy implementation time was determined. In order to reduce carbon emission intensity and alleviate the negative problems caused by excessive consumption of urban energy, the state has issued a series of policies to promote energy conservation and emission reduction through promoting the construction of low-carbon city pilot projects. In 2010, the National Development and Reform Commission (NDRC) issued the Circular on Pilot Low-carbon Provinces and Low-carbon Cities, launching the first batch of low-carbon pilot projects in Guangdong, Liaoning, Hubei, Shaanxi, and Yunnan provinces and in Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, and Baoding cities. In

2013, 29 pilot low-carbon areas were identified in 26 prefecture-level cities, including Beijing, Shanghai, Hainan province, and Shijiazhuang. In 2017, the list of the third batch of low-carbon pilots was released. According to the document "Notice On the Third Batch of National Low-carbon City Pilot Work", 45 cities (districts and counties) including Wuhai city of Inner Mongolia Autonomous Region were included in the list. Obviously, the multi-period DID model is necessary, but the data before 2010 is seriously missing. Therefore, this paper sets the second batch of 26 low-carbon cities as 1 after January 1, 2013. The third batch of 35 low-carbon cities will be set to 1 after January 1, 2017.

Experimental and control groups were determined. Overall, more than half of the cities selected for the low-carbon pilot list are in the eastern region. Through construction over about 10 years, the development of clean energy, industrial structure adjustment, and the transformation of high emission and high pollution enterprises' development path aimed to reduce greenhouse gas emissions and reduce the content of air pollutants. Since the list of low-carbon pilot cities involves duplicate regions and county-level cities, and considering the availability of data, we excluded county-level cities lacking social and economic data from the complete list of low-carbon pilot cities published in three batches at different times. The final experimental group included 69 prefecture-level cities such as Beijing. The initial data of the control group (Figure 1) are 40 non-low-carbon cities in our database that meet the data integrity requirements. On this basis, we selected PSM for matching screening. The results obtained after PSM are the final control data of our paper.

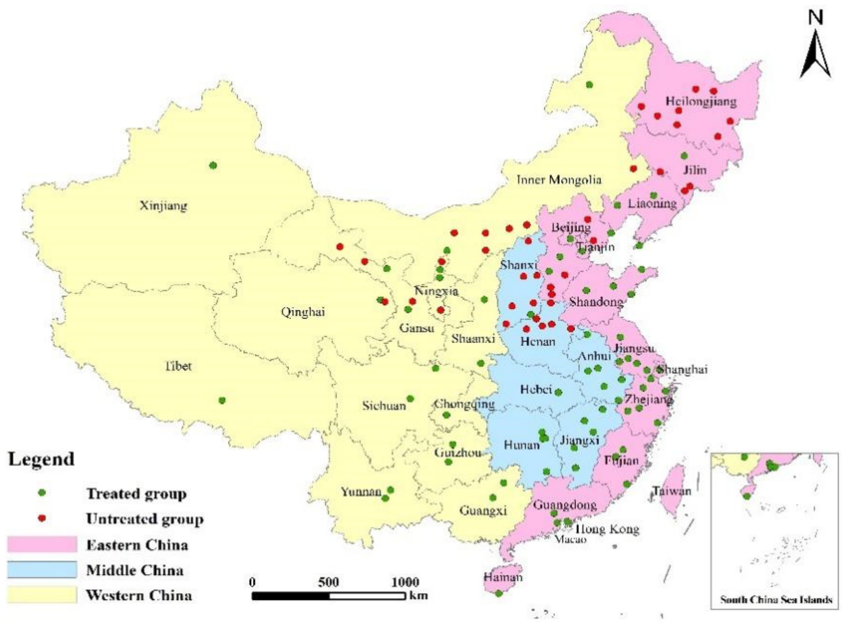

Figure 1. Geographical location map.

2.2.2. Descriptive Statistics

After data processing by the interpolation method in the early stage, the sample size was 3880, and there was no missing value, indicating that interpolation filling processing was effective. Data after interpolation filling processing may be overfilled. For example, if the trend is always downward, negative values may appear, but this situation does not conform to the reality. Therefore, we substituted 0 for samples less than 0, which is why the minimum value of multiple indicators is 0 (Table 1).

From the four air indicators of the experimental group before and after the implementation of the low-carbon city pilot policy (Table 2), basically there was a significant decline. For example, the AQI dropped from 97.868 to 75.616, a drop of about 22%. $PM_{2.5}$ dropped from 59.025 to 38.411, and so on.

Table 1. Description of variables and data.

Variables	Meaning	Units Value	N	Mean	Median	SD	Max	Min
AQI	Air Quality Index	-	3880	93.60	79.20	70.50	481.00	0
$PM_{2.5}$	Fine particulate matter	ug/m^3	3880	50.00	40.10	42.70	274.00	0
PM_{10}	Inhalable particles	ug/m^3	3880	99.60	79.50	84.50	549.00	0
NO_2	Carbon monoxide	ug/m^3	3880	38.00	32.20	31.40	251.00	0
Temp	Daily mean temperature	°C	3880	13.20	13.30	4.53	25.50	0.62
Wind	Wind scale	-	3880	1.68	1.66	0.57	3.81	0
Humi	Daily mean humidity	%	3880	59.90	59.40	11.60	106.00	23.40
Gas	Industrial smoke dust emission	ton	3880	47,487.00	24,341.00	7840.00	603,059.0	0
GDP	Gross Domestic Product	a hundred million	3880	2183.00	1271.00	2585.00	19,500.00	104.00
Ind2	The proportion of added value of secondary industry in GDP	%	3880	47.50	46.90	11.10	80.90	17.40
Ind3	The proportion of added value of tertiary industry in GDP	%	3880	40.80	39.90	10.20	72.70	15.30
Waste	Industrial wastewater discharged	10,000-ton	3880	5424.00	3632.00	5796.00	45,180.00	0
Popu	Population	ten thousand	3880	470.00	336.00	494.00	3392.00	44.00

Table 2. Changes in policy implementation.

Variables	Before Implementation	After Implementation
AQI	97.868	75.616
$PM_{2.5}$	59.024	38.411
PM_{10}	116.564	76.915
NO_2	49.937	30.240

3. Results

3.1. PSM Model Results

The main purpose of PSM treatment is to reduce the deviation between the experimental group and the control group, which is reflected in the differences of control variables and related factors in different cities in our study. When analyzing the impact of policies, the characteristics of individuals—that is, cities themselves—also need to be considered. If there are large differences among individuals, the different results after the implementation of policies are more likely to be caused by differences between individuals rather than the impact of policies. To match suitable samples more frequently, we adopted one-to-three matching, put back sampling, and used Logit as the calculation model of PSM. The dependent variable was *AQI*, and the control variables were *Temp*, *Humi*, *GDP*, *Ind3*, *Water*, and *Popu*. Not all control variables were used because the deviation of some control variables (such as *Waste*) was small, but as a covariable of PSM, the deviation would increase. More strict matching methods, such as one-to-one matching and no-put sampling, were not adopted because they would lead to too few available samples and too large sample loss, which would be detrimental to subsequent analysis. The results of PSM were as follows (Table 3).

First, we observed the results of the Logit model used to calculate PSM. The p values representing the significance of the control variables we selected were all far less than 0.01, almost all close to 0, indicating that they were extremely significant and that the influence of control variables on AQI was highly obvious. In terms of the effect of specific indicators, the deviations have been reduced to a certain extent, among which the deviations of the *Humi* and *Temp* variables have been reduced by 91.1% and 89.2%, respectively, while the deviations of other variables were about 70%. This shows that PSM treatment achieved our expected effect.

Table 3. PSM model results.

Variables	Unmatched	Mean		Reduce (%)		t-Test	
	Matched	Treated	Control	Bias (%)	ǀBiasǀ	T	$p > t$
Temp	U	16.445	11.165	117.600		67.570	0.000
	M	15.533	14.963	12.700	89.200	7.800	0.000
Humi	U	68.181	58.075	85.600		0.01	
	M	66.180	65.281	7.600	91.100	3.730	0.000
GDP	U	4891.00	1838.100	68.000		34.970	0.000
	M	2799.100	3622.500	−18.300	73.000	−14.100	0.000
Ind3	U	46.245	41.541	43.500		24.480	0.000
	M	43.258	42.128	10.500	76.000	6.290	0.000
Water	U	9346.500	3949.900	67.300		34.840	0.000
	M	5964.100	7353.60	−17.300	74.300	−13.480	0.000
Popu	U	539.100	393.360	37.900		20.260	0.000
	M	498.760	528.620	−7.800	79.500	−4.300	0.000

3.2. DID Model Baseline Analysis

In the baseline analysis, we made two sets of DID models, and each set contained four regression models with different variables. The first set of models was a model with only control variables. Models 1–4 were regression models constructed by using AQI, $PM_{2.5}$, PM_{10}, and NO_2 as dependent variables respectively. On the basis of the first set, the second set of models is based on the addition of the independent variable DID. From the regression results, *Temp* has a significant positive effect in all four models, indicating that the higher the temperature, the greater the air index; that is, the worse the air quality. *Humi* has a significant negative impact on the air index; that is, the lower the humidity, the higher the air index, and the worse the air quality. *Wind* has a significant positive impact on the first three air indicators (Table 4); that is, the larger the value, the worse the air quality. However, it has no significant effect on NO_2. *Gas* represents the discharge of industrial waste gas, and *Waste* represents the discharge of industrial wastewater. The two have similar meanings and functions, so they are analyzed together. Generally speaking, both emissions will cause the decline of air quality, so both have a significant positive impact. Just because the unit problem coefficient is small, it does not mean that its effect is small. *GDP* and *Popu* are both economic and social indicators, and they have a direct impact on the economy, so they are analyzed together. The effect of *GDP* is obvious. It has a significant negative impact; that is, the higher the GDP level, the lower the air index, and the better the air quality. However, the impact of population on air quality is not significant, and only in Model 4 does it have a significant negative impact on NO_2. *Ind2* and *Ind3* represent the proportions of secondary and tertiary industries. Although they have similar definitions and functions, their impacts on air quality are quite different. The development of secondary industry has a significant positive effect on the four models; that is, the higher the proportion of secondary industry, the greater the air index and the worse the air quality. However, the role of tertiary industry is not significant, and there is no significant influence on the four models, indicating that the influence of secondary industry is significantly greater than that of tertiary industry. From the model fitting effect, the R^2 of each model is basically about 0.2, which is within the normal range. Except for model 4, the R^2 of the other models is above 0.2. The R^2 of the second set of models is slightly higher than that of the first set, indicating that the DID variable improves the model fitting effect, but by comparison, the improvement is not significant.

Table 4. Variable regression results table.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	AQI	$PM_{2.5}$	PM_{10}	NO_2
Temp	8.362 ***	4.325 ***	8.392 ***	3.091 ***
	(30.31)	(25.87)	(25.25)	(23.22)
Humi	−1.079 ***	−0.302 ***	−0.766 ***	−0.432 ***
	(−10.56)	(−4.87)	(−6.22)	(−8.75)
Wind	14.293 ***	3.288 ***	7.019 ***	−0.317
	(7.35)	(2.79)	(3.00)	(−0.34)
Gas	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(9.24)	(11.72)	(11.63)	(8.23)
GDP	−0.006 ***	−0.004 ***	−0.008 ***	−0.001 **
	(−7.71)	(−8.30)	(−8.34)	(−1.97)
Ind2	0.942 ***	0.651 ***	1.235 ***	0.325 ***
	(6.07)	(6.92)	(6.60)	(4.33)
Ind3	0.016	0.055	0.016	−0.017
	(0.09)	(0.53)	(0.08)	(−0.21)
Water	0.003 ***	0.001 ***	0.002 ***	0.001 ***
	(8.28)	(4.75)	(5.32)	(3.00)
Popu	−0.002	0.002	0.002	−0.004 *
	(−0.41)	(0.61)	(0.36)	(−1.68)
Constant	63.437 ***	31.920 ***	76.093 ***	39.393 ***
	(3.66)	(3.04)	(3.64)	(4.71)
Observations	3880	3880	3880	3880
R^2	0.276	0.226	0.221	0.181
Adj-R^2	0.274	0.224	0.219	0.179
F	163.7	125.4	121.8	94.99

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

In Table 5, we can see that the DID variable has a significant negative impact on the four dependent variables, and the negative indicates a downward trend; that is, air quality is improved. Model 3 has the largest coefficient of −7.170, which means it has the greatest influence on the PM_{10} index. But for other indexes, the difference of coefficients is not obvious. On the whole, through the role of the DID variable and the comparison with the first set of models with only control variables, it can be seen that the influence of the policy is highly effective. However, the degree of impact of the policy is still slightly less than that of the environmental and socioeconomic conditions of the city. Therefore, policies must be based on the city's own conditions, and it is impossible to solve all problems only through policies.

3.3. Dynamic Effect of Multistage Low-Carbon City Construction

The pilot construction of low-carbon cities was divided into three stages, which are 2010, 2013, and 2017. However, owing to the small number of cities involved in the first batch, the policy implementation variable Policy1 is set in this paper for the first stage, and the policy implementation interval is from 2013–2017 [40]. The policy implementation variable Policy2 is set for the second stage (Policy1 represents the second batch of samples, the 2013 sample, while Policy2 is the third batch of samples, the 2017 sample), and the policy implementation interval is from 2017–2020. As can be seen from Table 6, Policy1 has an insignificant positive effect in all four models, so it can be concluded that the implementation effect of the second batch of policies is worse than that of the third batch. The dummy variable Policy2 of the third batch of policies has a significant negative effect on all dependent variables, with not only a large coefficient but also to an extremely significant degree. The results show that Policy2 is much more effective and powerful. This indicates that the third batch of low-carbon city construction policies had the most significant effect; that is, the expansion of policy scope was conducive to better and faster collective action.

Table 5. DID model results.

	Model 1	**Model 2**	**Model 3**	**Model 4**
VARIABLES	AQI	$PM_{2.5}$	PM_{10}	NO_2
DID	−4.750 *	−3.734 **	−7.170 **	−2.465 **
	(−1.87)	(−2.36)	(−2.28)	(−2.06)
Temp	8.032 ***	4.281 ***	8.308 ***	2.893 ***
	(29.83)	(25.47)	(24.86)	(22.70)
Humi	−1.037 ***	−0.301 ***	−0.763 ***	−0.400 ***
	(−10.46)	(−4.85)	(−6.20)	(−8.51)
Wind	14.487 ***	3.656 ***	7.725 ***	−0.028
	(7.62)	(3.08)	(3.27)	(−0.03)
Gas	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(8.92)	(11.44)	(11.36)	(7.84)
GDP	−0.006 ***	−0.004 ***	−0.008 ***	−0.001 **
	(−7.76)	(−8.35)	(−8.39)	(−2.02)
Ind2	0.876 ***	0.637 ***	1.207 ***	0.283 ***
	(5.80)	(6.76)	(6.44)	(3.96)
Ind3	0.090	0.089	0.081	0.032
	(0.53)	(0.84)	(0.38)	(0.40)
Water	0.002 ***	0.001 ***	0.002 ***	0.001 ***
	(8.27)	(4.77)	(5.34)	(2.94)
Popu	−0.002	0.002	0.002	−0.004 *
	(−0.45)	(0.57)	(0.33)	(−1.74)
Constant	58.029 ***	30.694 ***	73.740 ***	34.901 ***
	(3.44)	(2.92)	(3.53)	(4.38)
Observations	3880	3880	3880	3880
R^2	0.274	0.227	0.222	0.178
Adj-R^2	0.272	0.225	0.220	0.176
F	146.0	113.6	110.2	83.71

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

Table 6. Dynamic effect results.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	AQI	$PM_{2.5}$	PM_{10}	NO_2
Policy1	0.614	0.867	0.567	0.289
	(0.20)	(0.45)	(0.15)	(0.20)
Policy2	−12.989 ***	−10.800 ***	−19.052 ***	−6.696 ***
	(3.54)	(−4.71)	(−4.18)	(−3.85)
Temp	8.131 ***	4.366 ***	8.450 ***	2.944 ***
	(30.02)	(25.84)	(25.15)	(22.97)
Humi	−1.071 ***	−0.330 ***	−0.812 ***	−0.417 ***
	(−10.74)	(−5.30)	(−6.57)	(−8.84)
Wind	14.359 ***	3.546 ***	7.540 ***	−0.094
	(7.55)	(2.99)	(3.20)	(−0.10)
Gas	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(8.93)	(11.47)	(11.38)	(7.85)
GDP	−0.006 ***	−0.004 ***	−0.008 ***	−0.001 **
	(−7.75)	(−8.34)	(−8.38)	(−2.00)
Ind2	0.877 ***	0.638 ***	1.208 ***	0.284 ***
	(5.82)	(6.78)	(6.46)	(3.98)
Ind3	0.120	0.114	0.124	0.047
	(0.71)	(1.08)	(0.59)	(0.59)
Water	0.002 ***	0.001 ***	0.002 ***	0.001 ***
	(8.12)	(4.58)	(5.17)	(2.79)
Popu	−0.002	0.002	0.002	−0.004 *
	(−0.42)	(0.63)	(0.37)	(−1.70)
Constant	57.929 ***	30.608 ***	73.595 ***	34.850 ***
	(3.44)	(2.92)	(3.53)	(4.38)
Observations	3880	3880	3880	3880
R^2	0.276	0.231	0.224	0.180
Adj-R^2	0.274	0.228	0.222	0.178
F	133.8	105.4	101.7	77.33

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

4. Robust Test

4.1. Parallel Trend Test

The important premise for the effectiveness of the DID model is to satisfy the parallel trend hypothesis; that is, if there is no low-carbon city construction policy, the air quality change trend of pilot cities and other cities should be parallel. To test this point, in this paper we use the regression method to test the parallel trend [41]. Four time dummy variables are set: *before2*, which is 1 in the two months before the implementation of the policy, or 0 otherwise, and *before1*, for which the value is 1 one month before the policy is implemented. *Month_before3* and *Month_before2* are dummy variables in the parallel trend test, representing 2 and 3 months before the event, respectively. Otherwise, the value is 0. It can be seen (Table 7) that dummy variables before2 and before3 are not significant in all dependent variables, which indicates that there is no obvious and sufficiently significant trend change in the four air indicators we choose before the event occurs, indicating that the parallel trend test has been passed.

Table 7. Parallel trend test results.

	Model 1	**Model 2**	**Model 3**	**Model 4**
VARIABLES	AQI	$PM_{2.5}$	PM_{10}	NO_2
Month_before3	11.123	13.427	23.141	5.880
	(0.63)	(1.23)	(1.06)	(0.71)
Month_before2	10.502	10.400	18.799	5.118
	(0.65)	(1.03)	(0.93)	(0.67)
DID	−5.104 **	−4.121 **	−7.853 **	−2.645 **
	(−1.99)	(−2.57)	(−2.47)	(−2.18)
Temp	8.034 ***	4.283 ***	8.311 ***	2.894 ***
	(29.83)	(25.48)	(24.87)	(22.70)
Humi	−1.040 ***	−0.305 ***	−0.770 ***	−0.401 ***
	(−10.48)	(−4.91)	(−6.25)	(−8.55)
Wind	14.450 ***	3.616 ***	7.654 ***	−0.047
	(7.59)	(3.04)	(3.24)	(−0.05)
Gas	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(8.92)	(11.45)	(11.36)	(7.84)
GDP	−0.006 ***	−0.004 ***	−0.008 ***	−0.001 **
	(−7.76)	(−8.35)	(−8.39)	(−2.02)
Ind2	0.879 ***	0.640 ***	1.213 ***	0.285 ***
	(5.82)	(6.80)	(6.48)	(3.99)
Ind3	0.091	0.089	0.081	0.032
	(0.54)	(0.85)	(0.39)	(0.40)
Water	0.002 ***	0.001 ***	0.002 ***	0.001 ***
	(8.26)	(4.76)	(5.33)	(2.94)
Popu	−0.002	0.002	0.002	−0.004 *
	(−0.45)	(0.58)	(0.33)	(−1.73)
Constant	58.417 ***	31.123 ***	74.494 ***	35.099 ***
	(3.47)	(2.96)	(3.56)	(4.40)
Observations	3880	3880	3880	3880
R^2	0.274	0.227	0.222	0.178
Adj-R^2	0.272	0.225	0.220	0.176
F	121.7	94.88	92.01	69.82

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

4.2. Placebo Test

We reperformed the regression analysis after advancing the event date by one year to test the effect of DID2 (*DID2* is the interaction term in the placebo test, which can also be considered as the DID variable for the placebo test.). In the four models (Table 8), DID2 variables had no significant effect and only an insignificant negative effect. This indicates that the influence of the events selected by us is effective. After the occurrence of the change event, the variable of DID is no longer significant, indicating that its effect is directly related to the occurrence of the event, namely, the policy.

Table 8. Placebo test results.

	Model 1	**Model 2**	**Model 3**	**Model 4**
VARIABLES	AQI	$PM_{2.5}$	PM_{10}	NO_2
DID2	−3.682	−1.275	−4.573	−1.207
	(−1.55)	(−0.86)	(−1.55)	(−1.07)
Temp	8.048 ***	4.311 ***	8.342 ***	2.909 ***
	(29.92)	(25.66)	(24.98)	(22.85)
Humi	−1.027 ***	−0.298 ***	−0.752 ***	−0.397 ***
	(−10.33)	(−4.80)	(−6.09)	(−8.43)
Wind	14.381 ***	3.413 ***	7.468 ***	−0.152
	(7.57)	(2.88)	(3.17)	(−0.17)
Gas	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(8.93)	(11.57)	(11.41)	(7.92)
GDP	−0.006 ***	−0.004 ***	−0.008 ***	−0.001 **
	(−7.75)	(−8.32)	(−8.37)	(−2.00)
Ind2	0.868 ***	0.642 ***	1.203 ***	0.284 ***
	(5.73)	(6.79)	(6.39)	(3.96)
Ind3	0.088	0.069	0.067	0.023
	(0.52)	(0.66)	(0.32)	(0.29)
Water	0.002 ***	0.001 ***	0.002 ***	0.001 ***
	(8.22)	(4.73)	(5.28)	(2.91)
Popu	−0.002	0.002	0.002	−0.004 *
	(−0.45)	(0.59)	(0.33)	(−1.72)
Constant	57.136 ***	31.071 ***	73.048 ***	34.906 ***
	(3.38)	(2.94)	(3.48)	(4.36)
Observations	3880	3880	3880	3880
R^2	0.274	0.226	0.221	0.177
Adj-R^2	0.272	0.224	0.219	0.175
F	145.8	113.0	109.9	83.34

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

4.3. Robustness Test

In the robustness test, two variables that did not pass the parallel trend or placebo test, O_3 and NO_2, were used as dependent variables to replace the original dependent variables, and then regression was performed. It is worth noting (Table 9) that O_3 is positive; that is, the larger the value, the better. So was our result. NO_2 is still a significant negative influence, indicating that the influence of policy is significant, so it was consistent with the main analysis.

4.4. Urban Heterogeneity Test

In this part, the cities were grouped according to their location in the west, middle, and east, and then regression was conducted respectively. Owing to the large number of dependent variables, it was impossible to perform grouping regression for all dependent variables, so only the first two dependent variables were analyzed for heterogeneity. As can be seen from Table 10, urban agglomerations in different regions have different impacts on urban AQI and $PM_{2.5}$ concentrations within each sample range. Compared with the eastern and central regions, low-carbon city construction significantly reduced the AQI and $PM_{2.5}$ of urban agglomeration in western China.

Table 9. Robustness test results.

	Model 1	Model 2
VARIABLES	O_3	SO_2
DID	22.415 ***	−29.082 ***
	(14.11)	(−10.71)
Temp2	−0.004	3.356 ***
	(−0.02)	(11.63)
Humi2	−0.083	−0.883 ***
	(−1.33)	(−8.31)
Wind2	−2.659 **	−6.737 ***
	(−2.23)	(−3.30)
Gas2	−0.001 ***	0.001 ***
	(−2.76)	(16.53)
GDP2	0.004 ***	−0.008 ***
	(8.09)	(−10.32)
Ind2	0.110	0.724 ***
	(1.17)	(4.48)
Ind3	0.710 ***	0.986 ***
	(6.71)	(5.45)
Water2	−0.002 ***	0.001 ***
	(−11.62)	(4.53)
Popu2	0.007 **	0.006
	(2.38)	(1.33)
Constant	44.245 ***	3.484
	(4.19)	(0.19)
Observations	3880	3880
R^2	0.205	0.228
Adj-R^2	0.203	0.226
F	99.73	114.6

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Table 10. Urban heterogeneity test results.

	West Area	Middle Region	Eastern Region	West Area	Middle Region	Eastern Region
VARIABLES	AQI	AQI	AQI	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$
DID	−24.966 ***	−4.847	34.867 ***	−23.032 ***	2.685	22.268 ***
	(−8.05)	(−0.92)	(4.82)	(−10.55)	(1.03)	(4.90)
Temp	6.983 ***	8.664 ***	13.735 ***	5.086 ***	3.630 ***	8.802 ***
	(16.26)	(20.33)	(15.92)	(16.83)	(17.21)	(16.25)
Humi	0.246	−1.004 ***	−1.763 ***	0.796 ***	−0.108	−1.093 ***
	(1.61)	(−6.85)	(−5.80)	(7.39)	(−1.49)	(−5.73)
Wind	30.386 ***	38.193 ***	13.802 ***	19.942 ***	16.227 ***	0.110
	(7.98)	(13.07)	(3.23)	(7.44)	(11.22)	(0.04)
Gas	−0.001 *	−0.001	0.001 ***	0.001	0.001 ***	0.001 ***
	(−1.77)	(−0.78)	(8.67)	(0.53)	(4.01)	(6.81)
GDP	−0.013 ***	0.006 ***	−0.018 ***	−0.007 ***	0.004 ***	−0.010 ***
	(−9.42)	(5.29)	(−6.89)	(−6.85)	(6.40)	(−5.83)
Ind2	0.206	−1.297 ***	2.744 **	−0.196	−0.630 ***	1.117 *
	(0.80)	(−6.11)	(2.55)	(−1.09)	(−6.00)	(1.65)
Ind3	1.447 ***	−0.927 ***	2.039 **	0.722 ***	−0.410 ***	0.481
	(5.46)	(−3.87)	(2.08)	(3.87)	(−3.46)	(0.78)
Water	0.002 ***	0.001 ***	0.001	0.001 **	−0.001 ***	0.001
	(3.72)	(2.76)	(1.58)	(2.57)	(−3.11)	(1.47)
Popu	0.024 **	−0.097 ***	0.097 ***	−0.002	−0.043 ***	0.051 ***
	(2.50)	(−10.63)	(11.26)	(−0.34)	(−9.56)	(9.55)
Constant	−109.279 ***	85.497 ***	−245.260 ***	−90.484 ***	27.447 **	−86.838 *
	(−3.57)	(3.94)	(−3.03)	(−4.20)	(2.56)	(−1.71)
Observations	1403	1758	719	1403	1758	719
R^2	0.285	0.252	0.645	0.324	0.184	0.669
Adj-R^2	0.280	0.248	0.640	0.319	0.180	0.665
F	55.50	58.99	128.7	66.68	39.47	143.3

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

5. Conclusions

In this study we took the low-carbon pilot city construction policy as a quasi-natural experiment, aiming to explore the net effect, influencing factors, and policy dynamics of three batches of low-carbon pilot city construction on air quality since 2010 and to find possible improvement measures. The results show that, first, overall, low-carbon city construction can improve the air quality of the city. From the perspective of the dynamic effect of policies, low-carbon city construction in 2017 (the third batch) had the most significant effect. Second, from the perspective of meteorological factors, the city's average temperature and wind level will increase the concentration of pollutant particles, leading to the deterioration of air quality; humidity can significantly reduce AQI and improve air quality. Among these, it is worth noting that the wind direction in the city is not significant to NO_2. This shows that, in reality, for the control of air pollution in thermal power and iron and steel industries, which mainly discharge NO_2 gas, we should rely not only on natural physical conditions but also on advanced acquired technological means to forcibly control pollution. Third, from the perspective of social and economic factors, GDP negatively affects the air index, indicating that low-carbon cities will improve air quality during economic development. This is because, with the promotion of a low-carbon urban policy, the original rapid growth of the extensive economic development mode at the cost of destroying the ecological environment has begun to change. Through a series of measures, such as encouraging the use of low-carbon and environment-friendly development technologies, and supporting the development of low-carbon and environment-friendly industries, the economic growth mode linking GDP with high pollution has gradually disappeared, and the development path of harmonious coexistence between economy and environment has been replaced. Fourth, the proportion of the output value of secondary industry in GDP worsens the air quality. More notably, we find that the impact of secondary industry on air quality is significantly greater than that of tertiary industry. It indicates that low-carbon city policy is effective in improving air quality in the test area through industrial structure upgrading. Fifth, the construction of low-carbon urban agglomerations has different impacts on air quality in different regions, with the greatest impacts in the western region. This is because most coal and steel manufacturing enterprises with high energy consumption and emissions are distributed in the western region, which requires more accurate identification of urban characteristics and basic conditions of different regions in the policy.

Therefore, according to the research conclusions of this paper, we put forward the following suggestions for the construction of low-carbon cities in China to help solve air pollution. First, tests have proved that the construction of low-carbon cities is beneficial for reducing the level of air pollution, and China should continue to adhere to the construction of low-carbon cities; however, the reduction of air pollutants is still hindered by natural factors such as wind speed and temperature. Therefore, it is necessary to strengthen the development concept of ecological and economic integration at the initial stage of urban agglomeration construction, according to the urban characteristics and actual conditions of different regions, formulating plans conducive to long-term development to avoid falling into the old trap of "pollution first, then treatment," so as to realize ecological industrialization and industrial ecology, balancing the dual needs of economic development and environmental protection. Second, the upgrading of capital and industrial structure are key elements for the transformation and development of low-carbon cities. The Chinese government needs to continue increasing financial subsidies, participating in and guiding enterprises to innovate green technologies and use green energy. In particular, according to specific pollutants, it is necessary to accurately develop low-carbon construction technologies and quickly change to the development track of improving energy efficiency and the proportion of clean energy and reducing pollutant emissions. Moreover, China should speed up the elimination of industries that significantly waste resources and pollute the environment in secondary industry and promote the transformation and upgrading of the industrial structure, promoting the transformation of urban agglomeration development to an intensive economic growth model. Third, from the third round of the pilot effect, it can be confirmed that the establishment of joint prevention and control mechanisms for air pollution in urban agglomerations is an effective channel to control air pollution. Thus, a coordination mechanism across urban agglomerations and administrative regions should be established to promote the emergency linkage among urban agglomerations and departments within urban agglomerations, and a strict supervision and accountability mechanism should be established to reduce the free-riding behavior of members in joint prevention and control. In view of this, because this issue is extremely important in reality, being related to the sustainable development of society and its people, we will continue to track the corresponding development and changes in our research.

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