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The Impact of Carbon Peak Pilot Policy on Air Quality: Evidence from China

Chuchan Wu [1,*] and Haoran Zhang [2]

[1] School of Economics, Guangdong University of Finance and Economics, Guangzhou 510320, China
[2] School of Statistics and Data Science, Guangdong University of Finance and Economics, Guangzhou 510320, China; zhr20@126.com
* Correspondence: chuchanwu@163.com

Abstract

Against the backdrop of China's carbon-peaking and carbon-neutrality goals and its initiative to build a Beautiful China, direct causal evidence remains limited on whether the carbon-peaking pilot policy improves urban air quality and through which channels it operates. This study uses monthly data for 282 Chinese cities from January 2020 to May 2026. Cities included in the first batch of carbon-peaking pilots constitute the treatment group. We evaluate the policy using a two-way fixed-effects difference-in-differences (DID) model. The baseline estimates show that, after the policy was implemented, the average AQI in pilot cities decreased by approximately 1.429 points, while PM2.5 concentrations fell by approximately 1.018 μg/m^3. These findings suggest that the policy improved urban air quality. The mechanism analysis identifies the entry of newly registered new-energy enterprises and green technological innovation as potential transmission channels. The heterogeneity analysis further shows that the policy effect was more pronounced in northern cities and in cities with a lower population density. Overall, the findings indicate that the carbon-peaking pilot policy can promote coordinated pollution and carbon reduction. Policy implementation should therefore be accompanied by stronger joint assessments of carbon reduction and air quality. Governance resources should be allocated in light of city-specific characteristics, while the development of the new-energy industry and the application of green technologies should be supported.

Keywords: carbon peaking pilot policy; air quality; difference-in-differences; new-energy enterprises; green technological innovation

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Academic Editor: Giouli Mihalakakou

Received: 25 September 2026
Revised: 18 October 2026
Accepted: 25 October 2026
Published: 30 October 2026

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1. Introduction

As climate change and environmental constraints intensify, achieving a comprehensive green transformation of the economy and society has become central to China's pursuit of high-quality development. Since China announced its carbon-peaking and carbon-neutrality goals, carbon governance has gradually moved from broad national strategies toward local implementation and institutionalization. In 2022, the Action Plan for Synergizing the Reduction of Pollution and Carbon Emissions further emphasized the coordinated control of greenhouse gases and air pollutants. It called for synergies between carbon reduction, pollution abatement, and ecological improvement.

Within this policy framework, improving urban air quality has become increasingly important. Although air quality in China has generally improved, pollution control remains challenging. Urban air pollution also varies across space and seasons and is affected by

regional transport. Some areas face combined PM2.5 and ozone pollution [1–3]. Fossil-fuel combustion, industrial production, and transport activities often emit both carbon dioxide and conventional air pollutants. Reducing the consumption of coal and oil, improving energy efficiency, and substituting clean energy for fossil fuels may therefore reduce both carbon and pollutant emissions. These changes could generate synergistic benefits from pollution abatement and carbon reduction [4–7]. It is thus important to assess and explain the causal effect of comprehensive institutional arrangements designed to achieve carbon peaking. Such an assessment has practical value and can provide empirical evidence on pathways to coordinated governance.

Existing studies offer substantial evidence on the synergies between pollution abatement and carbon reduction. Research on policy areas related to the comprehensive carbon-peaking pilots examined here has considered how low-carbon and carbon-pricing policies affect air quality. Quasi-natural-experiment studies have found that carbon markets and emissions trading can reduce PM2.5 concentrations, indicating the existence of co-benefits [8,9]. Related research has also found that carbon-emissions-trading pilots can improve air quality in China, although their effects vary across locations and over time [10]. Low-carbon city pilots have likewise been found to alleviate urban haze pollution [11]. Potential explanations include industrial restructuring and the diffusion of green technologies, as well as improvements in local governance capacity and policy enforcement. From a mechanism perspective, many studies attribute these synergies to improvements in green production, industrial upgrading, and technological innovation. Incentives and constraints associated with carbon pricing or low-carbon pilots can encourage firms to adopt cleaner production methods, thereby reducing pollutant emissions alongside carbon emissions [8–12]. Overall, the existing research establishes a link between climate policies and air quality. However, it has focused mainly on emissions trading and low-carbon city pilots. Direct causal evidence remains limited for the carbon-peaking pilot policy, which was launched at the end of 2023 and combines a broader set of policy instruments. In particular, evidence is scarce on its short-term effects, mechanisms, and conditions under which it is effective.

This study addresses three questions. First, can the carbon-peaking pilot policy reduce urban air pollution in the short term? Second, can the policy effect be explained by channels such as the entry of newly registered new-energy enterprises and green technological innovation? Third, does the policy effect vary across cities or depend on specific conditions? To answer these questions, we use the first batch of pilot cities as the treatment group and construct a city–month panel. We estimate a two-way fixed-effects DID model and use additional methods, including propensity score matching combined with DID (PSM-DID), to assess the reliability of the estimates.

This study makes three contributions. First, it directly evaluates the carbon-peaking pilot policy as an independent policy intervention. It addresses the gap in research on the relationship between carbon-peaking pilots and air quality and extends the evidence on the environmental effects of China's "dual-carbon" policies beyond emissions trading and low-carbon city pilots. Second, it uses monthly city-level air-quality data. This higher-frequency data allow us to examine the short-term responses to policy implementation and better identify the timing of policy effects. Third, the mechanism analysis focuses on two potential transmission channels that reflect the policy's intended direction: newly registered new-energy enterprises and green technological innovation. We also conduct robustness and heterogeneity analyses to identify the conditions and boundaries of the policy's effects.

2. Literature Review and Research Hypotheses

2.1. Literature Review

2.1.1. Research on Air Quality

The existing studies on air quality generally examine four areas: spatial and temporal patterns, formation mechanisms, determinants, and the evaluation of policy effects. Empirical evidence shows that urban air quality in China varies substantially across regions and is characterized by regional transport. Heavily polluted areas often face greater risks of cross-regional accumulation and transport [1–3]. Air pollution also varies by season. As pollution control advances, the composition of pollutants and the dominant forms of pollution may change, creating distinct stages in the need for coordinated control of multiple pollutants [1–3].

In terms of determinants, urban industrial structure, energy consumption, and transport activity affect air quality by changing the intensity and scale of emissions. Urban form and development patterns also shape the spatial and temporal distribution of pollutants [13–20]. Meteorological conditions, including temperature, precipitation, and wind patterns, play a key role in pollutant dispersion, dilution, and removal. Studies therefore commonly incorporate weather variables into their air-quality analyses to improve the credibility of their estimates [21–24]. As the demand for policy evaluation has increased, researchers have applied DID, regression discontinuity, spatial econometric, and machine-learning methods to assess the environmental effects of governance measures. Their findings suggest that industrial transformation, digital technologies, and changes in urban transport structures may affect air quality by altering production methods and governance efficiency [13–17].

2.1.2. Low-Carbon Policies and Air Quality

The potential effects of climate and emissions-reduction policies on air quality are commonly explained by the co-benefits of pollution abatement and carbon reduction. Fossil-fuel combustion and industrial activity emit both carbon dioxide and conventional pollutants, including SO_2 and NO_x. Energy substitution and improvements in energy efficiency may therefore reduce carbon emissions as well as particulate matter and precursor emissions, improving air quality [4–7].

Empirical studies have found that policies such as emissions trading can deliver pollution-abatement co-benefits alongside carbon reductions. For example, these policies may reduce PM2.5 concentrations, although their effects vary across space and time [8–12]. Research on carbon emission trading pilots has not only examined their emission reduction effects but also explored the issue of carbon leakage in depth, providing empirical evidence for evaluating the effectiveness of market-based policies. This further suggests that the environmental benefits of market-based policies may be shaped by institutional design [25,26]. Low-carbon city pilots have been found to improve haze pollution. Their effects may operate through industrial restructuring, the diffusion of green technologies, and stronger local environmental governance [11,13–17,27]. Related research has also examined the emissions-reduction effects of low-carbon city pilots and their relationship with carbon-market efficiency [15].

The co-benefits of climate policies are not automatic. Policy design and enforcement may determine the scale of these benefits by shaping firms' directed technological change, innovation incentives, and adoption of cleaner production processes [28–33]. For example, environmental policies can encourage firms to use resources more efficiently, potentially yielding a "double dividend" of lower pollution and higher production efficiency. These improvements can, in turn, provide a firm-level basis for further gains in air quality [30–34].

In summary, the existing evidence has begun to answer whether some low-carbon policies can improve air quality. However, the research has focused mainly on emissions trading and low-carbon city pilots. Direct short-term causal evidence remains limited for the carbon-peaking pilot policy, which was launched at the end of 2023 and uses a more comprehensive policy mix. To address this gap, we use monthly city-level panel data from January 2020 to May 2026 and the first batch of carbon-peaking pilot cities to estimate a two-way fixed-effects DID model. We also conduct robustness and heterogeneity analyses to identify the conditions under which the policy affects air quality.

2.2. Policy Background and Theoretical Analysis

2.2.1. Policy Background

China's carbon-peaking pilot policy was introduced as the "dual-carbon" goals shifted from national strategy toward local implementation and as coordinated governance of pollution abatement and carbon reduction gained prominence. In September 2020, China announced its goals of reaching peak carbon emissions before 2030 and achieving carbon neutrality before 2060. In October 2021, the State Council issued the Action Plan for Carbon Dioxide Peaking Before 2030, translating the carbon-peaking goal into key actions across energy, industry, urban and rural development, and transport.

In June 2022, the Ministry of Ecology and Environment and other government departments issued the Action Plan for Synergizing the Reduction of Pollution and Carbon Emissions. Recognizing that pollutant and carbon emissions share common sources, the plan called for stronger source control, structural adjustment, and the coordinated control of multiple pollutants and greenhouse gases. It identified such coordination as an important means of promoting the green transformation of the economy and society.

Building on these policy initiatives, the National Development and Reform Commission issued the Implementation Plan for National Carbon-Peaking Pilots in 2023. The plan proposed selecting 100 representative cities and industrial parks nationwide to explore carbon-peaking pathways suited to different resource endowments and development conditions, and to develop practices that could be replicated and scaled up. The first batch, announced in December of that year, included 25 pilot cities and 10 pilot industrial parks.

Unlike earlier pilots that focused on a single policy instrument or a specific sector, the national carbon-peaking pilots constitute a comprehensive policy package. Their tasks cover the green and low-carbon transformation of the energy system, industrial upgrading, energy conservation and carbon reduction, and the transformation of industry, buildings, and transport. The policy also emphasizes institutional support, including scientific and technological innovation, fiscal and financial support, standards, carbon-emissions accounting, and project-level carbon-emissions assessment. Accordingly, the pilots may directly change energy use and production methods. They may also affect urban emissions structures indirectly by improving policy expectations, promoting technology adoption, and encouraging market participation.

Prior research has examined the air-quality effects of related policies, including emissions trading and low-carbon city pilots. Studies of the air-quality co-benefits of carbon reduction suggest that emissions-reduction measures can improve air quality and generate health benefits, although these outcomes depend on the emissions-reduction pathway and the energy structure [6,7,35]. Quasi-natural-experiment studies have found that China's carbon-emissions-trading pilots can reduce PM2.5 concentrations, indicating that carbon policies may produce air-quality co-benefits [8,10]. Evidence that low-carbon city pilots improve air quality and promote coordinated pollution abatement and carbon reduction also supports the link between low-carbon policies, energy or industrial adjustment, and improved air quality [11,26].

The existing research has focused mainly on emissions trading and low-carbon city pilots. Less attention has been paid to the air-quality effects of national carbon-peaking pilots and the mechanisms behind them. This study therefore treats the national carbon-peaking pilot policy as an independent policy intervention. We examine its effects on urban air quality and test whether the entry of newly registered new-energy enterprises and green technological innovation serve as potential transmission channels.

2.2.2. Theoretical Analysis

The carbon-peaking pilot policy may improve urban air quality because the green transition it promotes can affect both fossil-fuel combustion and energy-intensive, high-emission production. These activities are common sources of carbon dioxide and conventional air pollutants. Under the logic of coordinated governance, reducing coal and oil consumption, improving energy efficiency, and substituting clean energy for fossil fuels [36] may reduce carbon emissions as well as particulate matter and precursor emissions. This can generate air-quality co-benefits [4–7]. The pilots may also improve urban air quality at a more structural level. They can promote energy-saving and carbon-reduction upgrades in key industries, optimize industrial structure, and strengthen environmental governance capacity. These changes can alter emission intensity and composition, thereby reducing urban air pollution [13–17]. The pilots also emphasize coordinated governance across energy, industry, transport, buildings, and technology. This approach may shift environmental governance away from end-of-pipe treatment toward source reduction and structural adjustment. We therefore propose the following hypothesis:

Hypothesis H1. *Other things being equal, the carbon-peaking pilot policy significantly improves urban air quality and reduces urban air pollution.*

At the mechanism level, the policy may improve air quality by signaling support for the establishment and development of new-energy businesses. Specifically, the pilot plans emphasize fiscal, financial, investment, and pricing policies, as well as the dissemination and application of green and low-carbon technologies. These measures may create more stable policy expectations and a more supportive institutional environment, reducing uncertainty and institutional costs for new-energy businesses preparing to establish operations in a city. To measure this channel, we use the annual number of newly registered new-energy enterprises in each city as an indicator of new business registration and as a proxy for the expansion of new-energy market participants. In the early stages of policy implementation, new registrations may provide an early indication of how market participants respond to signals supporting the clean transition. Such activity may be temporally associated with the subsequent expansion of clean-energy supply, investment in green equipment, and adoption of related technologies. The diffusion of clean energy and low-carbon technologies can reduce fossil-fuel use and generate air-quality co-benefits through energy substitution and technological progress [35,36]. We therefore propose the following:

Hypothesis H2. *The carbon-peaking pilot policy improves urban air quality by promoting the entry of new-energy enterprises.*

The policy may also affect air quality through green technological innovation. The pilot plan emphasizes support for green and low-carbon science and technology, stronger capabilities in key technology research and development, and wider technology application. Its institutional design may also encourage firms to undertake green and low-carbon innovation. According to the Porter hypothesis, well-designed and effectively enforced environmental regulation can prompt firms to identify resource waste and technological

deficiencies in their production processes. Innovation may then reduce pollution while improving production efficiency. However, the effect of environmental regulation on innovation depends on the policy instruments used, enforcement intensity, firms' technological capabilities, and the type of innovation involved. Stringent constraints may encourage both clean-technology innovation and changes in production methods [29–33]. If the pilot policy increases firms' green innovation inputs and outputs, it may improve air quality through higher energy efficiency, lower pollution emissions per unit of output, and cleaner production [13,14,17]. We therefore propose the following:

Hypothesis H3. *The carbon-peaking pilot policy improves urban air quality by promoting green technological innovation.*

3. Model Specification and Data Processing

3.1. Sample Selection and Data Sources

This study examines prefecture-level and larger cities in China. Based on the availability of air-quality monitoring data, we initially obtained air-quality data for 292 cities, including municipalities directly administered by the central government. The carbon-peaking pilot policy includes both city-level and industrial-park pilots. Because the effects of industrial-park pilots are concentrated within specific parks, and park boundaries do not necessarily coincide with city administrative boundaries, citywide air-quality data cannot accurately identify the effects of those pilots. We therefore exclude the 10 cities hosting carbon-peaking pilot industrial parks. The final sample consists of 282 cities, including 25 treatment-group cities designated as carbon-peaking pilots [37]. (The cities containing carbon peaking pilot industrial parks include Changzhi (Changzhi High-Tech Industrial Development Zone), Chifeng (Chifeng High-Tech Industrial Development Zone), Harbin (Harbin Economic and Technological Development Zone), Suzhou (Suzhou Industrial Park), Nanjing (Nanjing Jiangning Economic and Technological Development Zone), Hefei (Hefei High-Tech Industrial Development Zone), Dezhou (Dezhou Economic and Technological Development Zone), Zhaoqing (Zhaoqing High-Tech Industrial Development Zone), and Xi'an and Xianyang (Xixian New Area). Kuqa, which contains the Kuqa Economic and Technological Development Zone, was excluded from the initial sample because air-quality monitoring data were unavailable; therefore, it was not excluded separately.) The pilot cities are listed in Table S1 in the Supplementary Materials. The Pilot City Distribution Map is shown in Supplementary Materials, Figure S1.

The study period runs from January 2020 to May 2026, covering 77 months. Air-quality data are obtained from the National Urban Air Quality Real-Time Publishing Platform of the China National Environmental Monitoring Centre. Data for Beijing are obtained from the website of the Beijing Municipal Environmental Monitoring Center. The original data are daily observations from monitoring stations. We first match monitoring stations to cities, calculate daily averages across each city's monitoring stations, and then aggregate the daily data to monthly city-level averages. This procedure produces a city-month panel.

Meteorological data are from the ERA5 reanalysis dataset released by the European Centre for Medium-Range Weather Forecasts. We use 2 m temperature, mean sea-level pressure, 10 m zonal wind, 10 m meridional wind, and total precipitation. Each city is matched to the nearest grid point to its urban center. Precipitation is measured as the monthly total, while temperature, pressure, and wind speed are measured as monthly averages.

Data on city economic and social characteristics are primarily obtained from the China City Statistical Yearbook and provincial statistical yearbooks. These data include the resident population, GDP per capita, enrollment in regular higher-education institutions, and the shares of secondary- and tertiary-industry value added in GDP. New-energy enterprise

data are obtained from the CNRDS database, and green-patent data are obtained from the PPData database.

3.2. Variable Definitions

3.2.1. Dependent Variables

We use the Air Quality Index (AQI) and PM2.5 concentration as joint measures of urban air quality. The AQI summarizes the pollution levels of major pollutants, including PM2.5, PM_{10}, SO_2, and NO_2, and captures overall urban air pollution. PM2.5 is primarily associated with coal combustion, industrial production, and transport emissions, and has important implications for human health. We therefore use a composite index and a pollutant-specific measure to construct the main dependent variables.

For robustness checks, we replace AQI and PM2.5 with PM_{10} and NO_2. PM_{10} measures particulate pollution and is associated primarily with coal combustion, industrial production, dust, and motor-vehicle emissions. NO_2 is closely related to fossil-fuel combustion, industrial production, and transport emissions. Using alternative dependent variables allows us to assess whether the findings depend on particular air-pollution measures and thus strengthens the reliability of the results.

3.2.2. Core Explanatory Variable

The core explanatory variable is the carbon peaking pilot policy indicator (DID_{it}),defined as follows:

$$DID_{it} = Treat_i \times Post_t \quad (1)$$

where $Treat_i$ equals 1 if city (i) belongs to the first batch of carbon peaking pilot cities and 0 otherwise; $Post_t$ equals 1 for December 2023 onward, when the policy was implemented, and 0 before implementation.

3.2.3. Mechanism Variables

(1) Newly registered new-energy enterprises. We use the annual number of newly registered new-energy enterprises in each city to measure new registrations in the sector. This measure serves as a proxy for the expansion of new-energy market participants. A significant policy-induced increase in new registrations may indicate that the pilot policy has encouraged the entry of new market participants, potentially laying the groundwork for subsequent changes in energy efficiency, pollution control, and air quality.

(2) Green technological innovation. The number of green patents held by listed companies in prefecture-level cities is used to measure the level of green technological innovation. Green patents reflect firms' research and development output in areas such as clean production, pollution control, resource recycling, and new-energy utilization.

Because the two mechanism variables are primarily available at the annual frequency and the data are currently updated through 2025, the monthly data are converted into annual data for the mechanism analysis, and the study period is adjusted to 2020–2025.

3.2.4. Control Variables

The control variables include meteorological conditions and city characteristics. Meteorological variables comprise temperature, mean sea-level pressure, precipitation, and the 10 m zonal and meridional wind components. Temperature affects the structure of the atmospheric boundary layer and chemical reactions among pollutants. High-pressure conditions are generally unfavorable for pollutant dispersion. Precipitation can remove particulate matter through wet deposition, while stronger winds can disperse and dilute pollutants [21,23,24].

City-characteristic variables include GDP per capita, population density, the shares of secondary- and tertiary-industry value added, and human capital. GDP per capita measures the level of economic development. Population density captures population concentration and the intensity of production and daily activities. The secondary-industry share reflects the degree of industrialization, while the tertiary-industry share indicates the extent to which the economy is oriented toward services. Human capital captures the city's foundation for innovation and governance.

3.3. Model Specification

This study constructs the following two-way fixed-effects difference-in-differences model:

$$Y_{it} = \alpha + \beta DID_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (2)$$

where Y_{it} denotes the air-quality indicator of city (i) in month (t), primarily including AQI and PM2.5; DID_{it} denotes the carbon peaking pilot policy variable; X_{it} denotes the control variables, including meteorological conditions and city characteristics. For city characteristics, we use the baseline values interacted with month fixed effects; that is, baseline city characteristics are interacted with month indicators and included in the regression; μ_i denotes city fixed effects; λ_t denotes month fixed effects; and ϵ_{it} denotes the random error term. Standard errors are clustered at the city level.

Carbon-peaking pilot cities were not selected randomly. The National Development and Reform Commission selected them based on factors such as carbon-emissions levels and growth trends, socioeconomic conditions, resource endowments, and development foundations, as set out in the Implementation Plan for National Carbon-Peaking Pilots. This selection process may generate endogeneity due to selection bias. To address this concern, we supplement the baseline DID analysis with propensity score matching combined with DID. We estimate each city's propensity score using a Logit model and match pilot cities to non-pilot cities with similar observable characteristics. This procedure improves comparability between the treatment and control groups and helps assess the policy's effect on air quality.

3.4. Descriptive Statistics

Table 1 reports the descriptive statistics for the variables used in the analysis. The monthly sample contains 21,672 observations. The mean values of AQI and PM2.5 are 58.22 and 31.57, respectively. Their ranges are wide: AQI varies from 13 to 242.9, while PM2.5 ranges from 1.6 to 167.6. This variation indicates substantial differences in air-pollution levels across city-month observations. Meteorological variables, including temperature, mean sea-level pressure, precipitation, and wind conditions, also vary across the sample, reflecting differences in regional climate and pollutant-dispersion conditions. City characteristics—GDP per capita, population density, human capital, and industrial structure (the shares of secondary- and tertiary-industry value added in GDP)—are annual data. We match these data to the monthly observations by year and assign the same annual value to each month in that year. These city-characteristic data cover only 2020–2024; data for 2025 and 2026 have not yet been updated. Observations without these annual variables are excluded from their summary statistics and from the relevant regressions. The variation in city characteristics indicates that sample cities differ in their development foundations and governance conditions. Controlling for these characteristics and their interactions with time helps mitigate the influence of such differences on the estimates. The mechanism variables—new-energy enterprise registrations and green patents held by listed companies—are also annual and are used in the mechanism analysis.

Table 1. Descriptive statistics of the study variables.

	Observations	Mean	Standard Deviation	Minimum	Maximum
AQI	21,672	58.22	26.092	13	242.9
PM2.5	21,672	31.569	17.971	1.6	167.6
DID	21,672	0.035	0.183	0	1
Temperature (°C)	21,672	14.594	10.813	−29.098	33.747
Mean sea-level pressure (hPa)	21,672	1015.799	7.852	999.489	1041.898
Precipitation (mm)	21,672	3.19	3.394	0	34.149
Wind U-component (10 m)	21,672	−0.14	1.000	−8.034	6.055
Wind V-component (10 m)	21,672	−0.094	1.071	−8.005	7.336
Per capita GDP (yuan)	16,908	74,914.648	38,760.701	15,524.87	284,001.81
Population density (persons/km^2)	16,908	489.586	731.417	2.035	9008.263
Share of secondary-industry value added (%)	16,908	0.388	0.103	0.096	0.731
Share of tertiary-industry value added (%)	16,908	0.492	0.084	0.224	0.853
Human capital (%)	16,908	0.024	0.024	0	0.166
Newly registered new-energy enterprises	1691	49.989	216.959	0	4088
Green patents held by listed companies in prefecture-level cities	1691	2960.463	4829.845	6	57,698

4. Regression Results

4.1. Baseline Results

To assess the causal effect of the carbon-peaking pilot policy on urban air quality, we estimate a two-way fixed-effects model. The dependent variables are AQI and the 24 h average concentration of PM2.5. The key explanatory variable is the policy indicator, did. A negative and statistically significant coefficient on DID indicates that air quality improved more in pilot cities than in non-pilot cities after policy implementation. The error terms may be correlated within cities. In addition, conventional cluster-robust inference may be biased in finite samples. We therefore report *p*-values from the wild cluster bootstrap (WCB). Standard errors are clustered at the city level, and the bootstrap procedure is based on 9999 replications.

Table 2 reports the baseline regression results. In column (1), the estimated coefficient on DID for AQI is negative and statistically significant at the 10% level under the conventional test. In column (2), the estimated coefficient for PM2.5 is also negative, but it is not statistically significant at the 10% level under a conventional two-sided test. The coefficient-to-standard-error ratio is approximately −1.60, corresponding to a two-sided *p*-value of about 0.11, which is close to the 10% threshold. The WCB results for both columns support a negative policy effect.

Columns (3) and (4) add meteorological controls, including temperature, mean sea-level pressure, precipitation, and wind speed. Columns (5) and (6) further add interactions between city characteristics and month fixed effects. The policy coefficients remain negative across specifications, suggesting that the results are not sensitive to these changes in model specification.

In the full specification, the policy reduced AQI in pilot cities by approximately 1.429 points and PM2.5 concentrations by approximately 1.018 μg/m^3, relative to non-pilot cities, holding other factors constant. The WCB *p*-values are below 0.10 in all six specifications. Overall, the results support the conclusion that the carbon-peaking pilot policy improved urban air quality. Hypothesis 1 is supported.

Table 2. Baseline regression results.

	(1) AQI	(2) PM2.5	(3) AQI	(4) PM2.5	(5) AQI	(6) PM2.5
DID	−1.239 *	−0.917	−1.271 **	−0.994 *	−1.429 **	−1.018 *
	(0.636)	(0.574)	(0.620)	(0.570)	(0.670)	(0.602)
Temperature			0.035	−0.002	−0.382 **	−0.376 ***
			(0.144)	(0.113)	(0.152)	(0.123)
Mean sea-level pressure			1.357 ***	1.179 ***	0.949 ***	0.785 ***
			(0.205)	(0.166)	(0.221)	(0.180)
Precipitation			−0.745 ***	−0.365 ***	−0.766 ***	−0.394 ***
			(0.073)	(0.046)	(0.068)	(0.040)
Wind U-component			1.324 ***	0.044	1.072 **	−0.082
			(0.426)	(0.329)	(0.444)	(0.370)
Wind V-component			−0.278	0.446	0.461	1.086 ***
			(0.452)	(0.329)	(0.434)	(0.351)
City characteristics × month	No	No	No	No	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
WCB *p*-values	0.0326	0.0649	0.0200	0.0493	0.0250	0.0558
Observations	21,672	21,672	21,672	21,672	21,672	21,672
R^2	0.757	0.743	0.771	0.761	0.793	0.791

Notes: The dependent variable is AQI in columns (1), (3), and (5), and PM2.5 in columns (2), (4), and (6). All regressions include city and month fixed effects. Columns (3)–(6) additionally control for temperature, mean sea-level pressure, precipitation, and the U- and V-components of 10 m wind. Columns (5) and (6) further include interactions between month fixed effects and the 2022 baseline values of city characteristics: GDP per capita, population density, the shares of secondary- and tertiary-industry value added, and human capital. Parentheses contain standard errors clustered at the city level. WCB *p*-values are one-sided wild cluster bootstrap *p*-values for the coefficient on DID, with the alternative hypothesis that the policy effect is negative. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Robustness Checks

4.2.1. Parallel-Trends Test

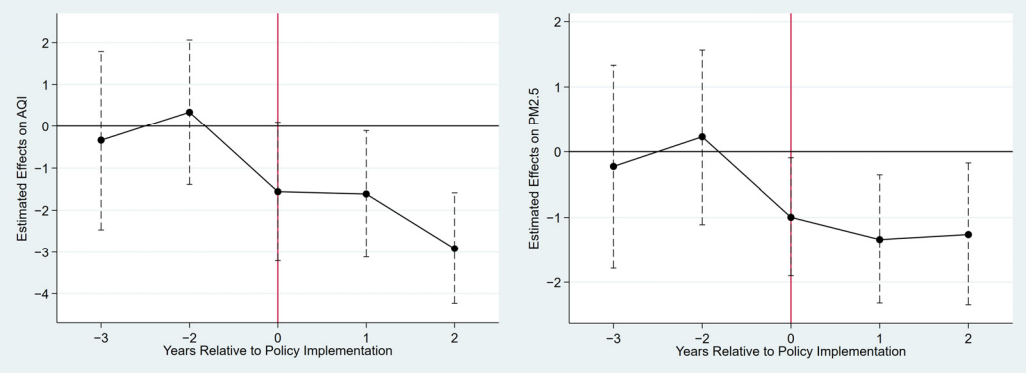
An important prerequisite for the validity of the difference-in-differences (DID) model is that, prior to the implementation of the carbon peaking pilot policy, the dependent variable should exhibit the same or similar trend in the treatment and control groups. To test this prerequisite and further examine the dynamic effects of the policy, this study employs an event-study approach and specifies the following model:

$$Y_{it} = \alpha + \sum_{k=-3}^{k=2} \beta_k \times D_{it}^k + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where D_{it}^k denotes a series of dummy variables indicating that city *ii* is in the *kk*-th year before or after the implementation of the carbon peaking pilot policy in year tt. Specifically, $k = -3$ and $k = -2$ represent the third and second years prior to policy implementation, respectively; $k = 0$ denotes the year in which the policy was implemented; and $k = 1$ and $k = 2$ represent the first and second years following policy implementation, respectively. The year immediately preceding policy implementation is taken as the reference period and is therefore omitted from the model. Accordingly, the sample period covers the three years prior to policy implementation and the two years following implementation. The parallel-trends test is conducted using annual data, with the sample period ending in 2025. Since the monthly data for 2026 do not cover a complete year, they are excluded from the annual analysis to avoid bias arising from incomplete data; λ_t denotes the year fixed effect.

As shown in Figure 1, the estimated pre-policy coefficients for both AQI and PM2.5 are close to zero, and their 90% confidence intervals include zero. This indicates that the treatment and control groups DID not exhibit significantly different trends before policy implementation. Joint tests of the pre-policy coefficients also fail to reject the null hypothesis

that all pre-policy effects are jointly zero: for AQI, F = 1.809 and $p = 0.166$; and, for PM2.5, F = 0.551 and $p = 0.577$. After implementation, the estimated coefficients for AQI and PM2.5 generally decline. The effects become more apparent in the later post-policy periods and remain negative in subsequent years. The estimates and 90% confidence intervals for each period are reported in Table S2 in the Supplementary Materials.



(**a**) (**b**)

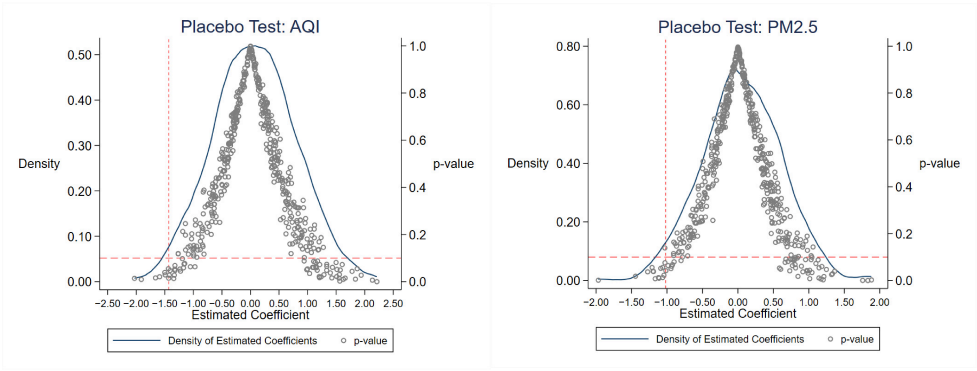
Figure 1. Parallel-trends tests for the effects on air quality. (**a**) AQI and (**b**) PM2.5. The *x*-axis denotes "Years Relative to Policy Implementation" and the red vertical line at year 0 indicates the time of policy implementation. The black points and line represent the estimated coefficients from regression model (3) for each relative year, while the vertical dashed lines and error bars show the corresponding confidence intervals. The horizontal solid line at 0 indicates no effect.

4.2.2. Placebo Test

To rule out the interference of other observable or random factors with the baseline regression results, this section conducts a placebo test using a fictitious treatment group as an additional robustness check. Following the method of Tang et al. [34], we keep the policy implementation date unchanged. In each repetition, we randomly select 25 cities to form a placebo treatment group and interact this assignment with the post-policy period to construct a placebo DID indicator. We repeat this procedure 500 times and obtain placebo policy-effect estimates for AQI and PM2.5. The distributions of the placebo estimates are presented in Figure 2. The placebo estimates are concentrated around zero, and most are not statistically significant. More importantly, only a small proportion of the placebo estimates have absolute values greater than the baseline estimates: 0.0500 for AQI and 0.0700 for PM2.5. The baseline estimates are therefore located in the more extreme tails of the placebo distributions. This suggests that the baseline results are unlikely to be driven by random group assignment or chance.

4.2.3. Excluding the Interference of Other Contemporaneous Policies

To assess whether other policies implemented around the same time affect the baseline estimates, we control for three additional policies: the climate-adaptive city pilot, the new-energy vehicle battery-swapping pilot, and the collaborative innovation pilot for pollution and carbon reduction. For each policy, we construct an indicator based on the officially announced pilot cities and implementation date [38–41]. The indicator equals 1 for a city included in the relevant pilot during the post-policy period and 0 otherwise. The relevant pilot lists and implementation dates are provided in Table S3 in the Supplementary Materials. We also include key-region-by-month fixed effects to control for time-varying common shocks in the key regions covered by the Action Plan for Continuous Improvement of Air Quality. This specification does not separately estimate the effect of that plan; rather, it controls for potential region-month-level shocks associated with it.



(**a**) (**b**)

Figure 2. Placebo tests for the effects on air quality. Panels (**a**) and (**b**) show placebo estimates for AQI and PM2.5, respectively. The *x*-axis reports the estimated policy coefficients from the placebo regressions. The blue curve shows the kernel density of these estimates under the null of no policy effect, and the open circles represent estimates from individual placebo iterations. The right-hand *y*-axis reports the *p*-values associated with the placebo regressions. The red dashed horizontal line marks the 0.10 significance threshold. The red dashed vertical line marks the corresponding baseline estimate: −1.4293 for AQI in panel (**a**) and −1.0180 for PM2.5 in panel (**b**).

The results are reported in columns (1) and (2) of Table 3. After these controls are added, the estimated coefficients on DID are −1.367 for AQI and −0.910 for PM2.5. They are statistically significant at the 5% and 10% levels, respectively. Thus, the estimated effect of the carbon-peaking pilot policy remains negative. Among the three contemporaneous policies, the coefficients for the climate-adaptive city pilot and the collaborative innovation pilot for pollution and carbon reduction are not statistically significant at conventional levels. The estimated effect of the battery-swapping pilot is −2.571 for AQI, but is not statistically significant. Its estimated effect on PM2.5 is −2.101 and is significant at the 10% level. One possible explanation is that battery swapping reduces refueling time and eases range and operational constraints. This may make electric vehicles more viable in high-intensity uses, such as taxis, ride-hailing services, and urban logistics. If the pilot encourages the replacement of fuel-powered vehicles with electric vehicles, it could directly reduce primary particulate matter and nitrogen oxide emissions and indirectly lower PM2.5 concentrations. Battery-swapping infrastructure may also reduce operational barriers to fleet electrification, extending the policy's reach beyond private vehicles to intensively used commercial fleets. Overall, the main results remain when we control for the three contemporaneous policies and key-region-by-month shocks.

Table 3. Robustness-check results I.

	(1) AQI	(2) PM2.5	(3) AQI	(4) PM2.5	(5) AQI	(6) PM2.5
DID	−1.367 **	−0.910 *	−2.014 ***	−1.231 *	−1.498 **	−1.089 *
	(0.579)	(0.517)	(0.736)	(0.661)	(0.698)	(0.605)
Climate-adaptive city pilot policy	0.547	0.604				
	(0.770)	(0.533)				
Collaborative innovation pilot policy for pollution and carbon reduction	−0.396	−0.336				
	(0.771)	(0.727)				
New-energy vehicle battery-swapping pilot policy	−2.571	−2.101 *				
	(1.737)	(1.262)				
Temperature	−0.203	−0.256 *	−0.297 **	−0.310 ***	−0.465 ***	−0.454 ***
	(0.159)	(0.132)	(0.144)	(0.108)	(0.169)	(0.142)
Mean sea-level pressure	0.952 ***	0.729 ***	1.192 ***	0.975 ***	0.793 ***	0.644 ***
	(0.237)	(0.194)	(0.197)	(0.143)	(0.257)	(0.212)

Table 3. *Cont.*

	(1) AQI	(2) PM2.5	(3) AQI	(4) PM2.5	(5) AQI	(6) PM2.5
Precipitation	−0.694 ***	−0.391 ***	−0.748 ***	−0.388 ***	−0.701 ***	−0.384 ***
	(0.069)	(0.041)	(0.070)	(0.042)	(0.076)	(0.043)
Wind U-component	0.655	−0.309	0.999 **	−0.126	1.441 ***	0.435
	(0.482)	(0.399)	(0.458)	(0.372)	(0.479)	(0.396)
Wind V-component	0.235	0.876 **	0.441	1.020 ***	0.428	0.933 **
	(0.476)	(0.386)	(0.394)	(0.291)	(0.511)	(0.418)
Key region × month	Yes	Yes	No	No	No	No
City characteristics × month	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,672	21,672	19,593	19,593	14,819	14,819
R^2	0.819	0.818	0.801	0.801	0.788	0.786

Notes: The dependent variable is AQI in columns (1), (3), and (5), and PM2.5 in columns (2), (4), and (6). Columns (1) and (2) control for the climate-adaptive city pilot policy, the collaborative innovation pilot policy for pollution and carbon reduction, and the new-energy vehicle battery-swapping pilot policy; they also include key-region-by-month fixed effects. Columns (3) and (4) exclude municipalities and provincial capitals from the sample. Columns (5) and (6) exclude cities bordering the pilot cities. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2.4. Excluding Municipalities and Provincial Capitals

Because municipalities directly under the central government and provincial capitals differ systematically from ordinary prefecture-level cities in terms of administrative status, policy resources, and governance capacity, this study excludes Beijing, Tianjin, Shanghai, Chongqing, and all provincial capitals and re-estimates the baseline model using only ordinary prefecture-level cities to test the robustness of the air-quality improvement effect of the carbon peaking pilot policy. The results are reported in columns (3) and (4) of Table 3. After these cities are excluded, the estimated coefficients on DID are −2.014 for AQI and −1.231 for PM2.5. They are significant at the 1% and 10% levels, respectively. The absolute values of the coefficients are larger than those in the baseline model. This indicates that the estimated air-quality improvement is not driven by the inclusion of municipalities or provincial capitals; the effect remains among ordinary prefecture-level cities.

4.2.5. Excluding Cities Adjacent to Pilot Cities

Air pollution can be transported across administrative boundaries. The carbon-peaking pilot policy may also affect nearby cities through industrial adjustment or coordinated pollution control. If non-pilot cities adjacent to pilot cities are included in the control group, they may be exposed to spatial spillovers. This could alter the difference between the treatment and control groups and affect the baseline estimates. To examine this possibility, we identify cities sharing a land border using administrative boundaries and exclude non-pilot cities that border pilot cities. The results are reported in columns (5) and (6) of Table 3. After adjacent cities are excluded, the estimated policy effects are −1.498 for AQI and −1.089 for PM2.5. They are significant at the 5% and 10% levels, respectively. The baseline findings are therefore not primarily driven by potential spillovers to neighboring control cities.

4.2.6. Replacing the Dependent Variables

To examine the robustness of the estimated effect of the carbon peaking pilot policy, this study replaces the dependent variables in the baseline regression, using PM10 and NO_2 instead of AQI and PM2.5. PM_{10} captures inhalable particulate pollution, while NO_2 reflects pollution associated with fossil-fuel combustion, transport, and industrial production. Examining these alternative outcomes allows us to assess whether the baseline findings depend on a particular

air-pollution measure. The results are reported in columns (1) and (2) of Table 4. The estimated coefficients on DID are −2.224 for PM_{10} and −1.226 for NO_2. Both are statistically significant at the 5% level, and their signs are consistent with the baseline results. The negative policy effect therefore persists when alternative dependent variables are used.

Table 4. Robustness checks II.

	Replacing Dependent Variable		**PSM-DID**	
	(1) **PM10**	**(2)** **NO2**	**(3)** **AQI**	**(4)** **PM2.5**
DID	−2.224 **	−1.226 **	−1.965 **	−1.494 *
	(1.097)	(0.485)	(0.820)	(0.766)
Temperature	−0.249	−0.134 ***	0.060	0.053
	(0.165)	(0.046)	(0.279)	(0.191)
Mean sea-level pressure	0.694 ***	0.446 ***	1.287 ***	1.103 ***
	(0.221)	(0.077)	(0.411)	(0.278)
Precipitation	−0.881 ***	−0.077 ***	−0.447 ***	−0.203 ***
	(0.089)	(0.017)	(0.132)	(0.070)
Wind U-component	3.026 ***	0.379 *	0.269	−0.247
	(0.565)	(0.198)	(0.752)	(0.514)
Wind V-component	0.117	0.663 ***	0.663	1.017 *
	(0.469)	(0.185)	(0.775)	(0.527)
City characteristics × month	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Observations	21,672	21,672	5440	5440
R^2	0.764	0.863	0.815	0.812

Notes: Columns (1) and (2) replace the dependent variables with PM_{10} and NO_2, respectively. Columns (3) and (4) report PSM-DID estimates for AQI and PM2.5. *** $p < 0.01$, ** $p < 0.05$,* $p < 0.1$.

4.2.7. Propensity-Score-Matching Difference-in-Differences Test

Considering that the designation of carbon peak pilot cities is not a random process, there may exist systematic differences between the pilot group and the non-pilot group even before the policy is implemented, which, in turn, leads to sample selection bias. We therefore use propensity score matching combined with DID (PSM-DID) as an additional robustness check. Using city characteristics from the three years before policy implementation, we estimate each city's propensity score with a Logit model. We then conduct 1:3 nearest-neighbor matching within the common-support region to improve the comparability of the treatment and control groups in terms of observable characteristics (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008) [42,43]. The matched sample contains 20 treatment-group cities and 51 control-group cities. To document the comparability of the matched sample and provide diagnostics relevant to the identifying assumptions, the Supplementary Materials include three figures: pre-policy AQI trends for the matched sample (Figure S2a), pre-policy PM2.5 trends (Figure S2b), and the propensity-score distributions of the treatment and control groups within the common-support region (Figure S2c). The pre-policy trend plots compare the outcome trends of the two groups before policy implementation. The propensity-score plot shows the score distributions within the common-support region. We then estimate the DID model using the matched sample. The method identifies the policy effect from the difference in pre- and post-policy changes between the pilot and comparison cities while controlling for time-invariant differences between the groups. Its identification still depends on assumptions such as conditional parallel trends after matching (Heckman et al., 1997; Abadie, 2005) [44,45].

The matching-balance results are reported in Table 5. After matching, the differences between the treatment and control groups in population density, human capital, GDP per

capita, and the shares of secondary- and tertiary-industry value added are not statistically significant. The t-test *p*-values for all variables exceed 0.1. Standardized biases also decline, with reductions of approximately 38.3–98.6%. These results indicate that matching improves balance in observable characteristics. Columns (3) and (4) of Table 4 report the DID estimates for the matched sample. The estimated coefficient on DID is −1.965 for AQI, significant at the 5% level, and −1.494 for PM2.5, significant at the 10% level. Both estimates are negative and consistent with the baseline results. The findings therefore continue to indicate improved air quality after matching on observable characteristics.

Table 5. PSM balance test.

Variable	Unmatched / Matched	Mean		%bias	%Reduct |bias|	*t*-Test		V(T)/V(C)
		Treated	Control			t	$p > \|t\|$	
Population density	U	5.819	5.615	16.10	52.90	0.840	0.400	1.520
	M	5.783	5.688	7.600		0.220	0.827	0.520
Human capital	U	0.0320	0.0228	39.20	38.30	1.900	0.0580	1.080
	M	0.0317	0.0374	−24.20		−0.600	0.551	0.470
Per capita GDP	U	110,000	68,823	96.40	98.60	5.740	0.000	2.52
	M	92,752	92,158	1.400		0.0500	0.960	0.990
Share of secondary-industry value added	U	41.85	38.96	24.60	69.10	1.310	0.191	1.630
	M	40.27	41.17	−7.600		−0.240	0.812	0.960
Share of tertiary-industry value added	U	49.49	48.29	12	48	0.660	0.511	1.840
	M	49.43	50.05	−6.200		−0.190	0.850	0.770

4.3. Mechanism Analysis

4.3.1. Mechanism Model

The theoretical analysis suggests that the carbon-peaking pilot policy may promote sustained pollution and carbon reduction by supporting the development of the new-energy industry and encouraging green technological innovation. We examine these two potential channels: new registrations of new-energy enterprises and green technological innovation. Because the mechanism variables are annual, we aggregate the air-quality, policy, and control variables to the annual level. The mechanism analysis covers 2020–2025. Following Jiang [46], we estimate the mechanism models shown in Equations (4) and (5).

$$Y_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (4)$$

$$M_{it} = \gamma_0 + \gamma_1 DID_{it} + \gamma_2 X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (5)$$

where M_{it} denotes either the entry of new-energy enterprises or green technological innovation. If the carbon peaking pilot policy significantly affects the mechanism variable and the mechanism variable is significantly associated with air quality, this indicates that the mechanism may constitute an important channel through which the policy affects air quality; λ_t denotes the year fixed effect.

4.3.2. New Registrations of New-Energy Enterprises

We use the annual number of newly registered new-energy enterprises in each city to measure new registrations and as a proxy for expansion in the number of market participants in the new-energy sector. Enterprise registrations indicate newly registered market entities, but do not necessarily imply that the firms have begun operating or made investments. We therefore interpret this measure as a proxy for changes in the number of new-energy market participants, not as a direct measure of actual investment.

The relevant regression results are reported in column (3) of Table 6. The estimated coefficient of the carbon-peaking pilot policy on new registrations is 0.197 and is statistically

significant at the 10% level. This suggests that new registrations of new-energy enterprises increased in pilot cities after policy implementation, in line with the expectation that the policy would encourage the development of the new-energy sector. Although the policy has been in place for a relatively short time, changes in the number of new-energy market participants could affect air quality relatively quickly. Policy signals and complementary support may encourage firms to register, establish operations, or accelerate project development. In addition, some mature technologies and projects in the new-energy and energy-conservation sectors—such as distributed renewable energy, energy storage, end-use electrification, and energy-efficiency upgrades—may have relatively short construction and deployment periods. They could therefore contribute to energy substitution, higher energy efficiency, or lower pollutant emissions during the early stages of policy implementation. Together with the negative policy estimates for AQI and PM2.5 in columns (1) and (2) of Table 6, the results are consistent with the expansion in new-energy market participants being one potential channel through which the policy affects air quality. Hypothesis 2 is supported.

Table 6. Mediation-mechanism test.

	(1) AQI	(2) PM2.5	(3) Newly Registered New-Energy Enterprises	(4) Green Technological Innovation
DID	−1.518 **	−1.196 **	0.197 *	0.282 ***
	(0.616)	(0.560)	(0.109)	(0.098)
Temperature	1.036 **	−0.003	−0.007	0.076
	(0.433)	(0.272)	(0.037)	(0.069)
Mean sea-level pressure	−0.136	−0.273	−0.017	−0.054
	(0.419)	(0.240)	(0.038)	(0.062)
Precipitation	−0.070 ***	−0.053 ***	0.001	0.004 *
	(0.014)	(0.009)	(0.002)	(0.002)
Wind U-component	0.584	−1.007 *	−0.013	0.067
	(0.977)	(0.602)	(0.074)	(0.139)
Wind V-component	−1.873 *	−0.625	0.040	0.068
	(1.003)	(0.669)	(0.069)	(0.155)
Climate-adaptive city pilot policy	0.393	0.527	0.090	0.106
	(0.761)	(0.502)	(0.112)	(0.115)
Collaborative innovation pilot policy for pollution and carbon reduction	−0.634	−0.345	0.186	−0.061
	(0.842)	(0.762)	(0.127)	(0.125)
New-energy vehicle battery-swapping pilot policy	−1.918	−1.691 *	−0.007	0.089
	(1.380)	(0.991)	(0.189)	(0.221)
Key region × Year	Yes	Yes	Yes	Yes
City characteristics × Year	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1691	1691	1691	1691
R^2	0.966	0.959	0.931	0.942

Notes: Columns (1) and (2) use AQI and PM2.5, respectively, as the dependent variable. Columns (3) and (4) examine the effects of the carbon-peaking pilot policy on newly registered new-energy enterprises and green technological innovation, respectively. DID is the interaction between the treatment-group indicator and the post-policy indicator. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.3. Mechanism of Green Technological Innovation

To examine whether green technological innovation is another potential channel, we measure urban green innovation using the number of green patents held by listed companies in each prefecture-level city. This is a flow measure of green-patent activity in a given year. We first compile patent information at the listed-company level and then aggregate the company-level patent data to the prefecture-level city using company information on location.

The results are reported in column (4) of Table 6. The estimated coefficient of the carbon-peaking pilot policy on green technological innovation is 0.282 and is statistically

significant at the 1% level. This indicates that annual green-patent activity among listed companies increased in pilot cities after policy implementation. Green technological innovation may affect air quality in the short term because some patents represent incremental improvements to existing production processes, energy-management systems, or pollution-control technologies, rather than technological breakthroughs that require long development periods. If the technologies are sufficiently mature, firms may apply them to energy-saving upgrades, cleaner production, more efficient energy use, or improved pollution-control equipment. Such applications may reduce energy consumption and pollutant emissions relatively quickly. The policy may also encourage firms to adopt existing green technologies sooner or adjust their research and production plans. In this way, increases in green innovation may affect air quality during the early stages of policy implementation through process improvements and the application of existing technologies. Previous research likewise suggests that moderate environmental regulation can encourage innovation and generate environmental benefits [21]. Hypothesis 3 is supported.

4.4. Heterogeneity Analysis

4.4.1. Heterogeneity by Geographic Location

Northern and southern China differ in their physical geography, climate, energy structure, industrial composition, and sources of air pollution. The effect of the carbon-peaking pilot policy may therefore vary by location. Following the Qinling–Huaihe line, we divide the sample into 147 southern cities and 135 northern cities.

Table 7 reports the results. For northern cities, the estimated policy effects on AQI and PM2.5 are −2.465 and −1.762, respectively, and both are statistically significant at the 1% level. The estimates for southern cities are not statistically significant. The estimated differences between the northern and southern effects are −2.629 for AQI, significant at the 5% level, and −1.841 for PM2.5, significant at the 10% level. These results indicate that the air-quality improvement was stronger in northern cities. One possible explanation is that some northern cities rely more heavily on coal and energy-intensive industries. If the pilot policy promotes energy substitution and industrial restructuring, these cities may have greater scope for pollution reduction. By contrast, differences in energy structure, industrial foundations, and pollutant-dispersion conditions may lead to smaller marginal improvements in southern cities.

Table 7. Heterogeneity regression results by geographic location.

	(1) **AQI**	**(2)** **PM2.5**
North	−2.465 *** (0.760)	−1.762 *** (0.604)
South	0.164 (0.877)	0.079 (0.953)
Difference (North–South)	−2.629 ** (1.100)	−1.841 * (1.098)
Temperature	−0.356 ** (0.149)	−0.353 *** (0.121)
Mean sea-level pressure	0.943 *** (0.223)	0.782 *** (0.183)
Precipitation	−0.764 *** (0.068)	−0.393 *** (0.040)
Wind U-component	1.064 ** (0.424)	−0.087 (0.345)
Wind V-component	0.538 (0.434)	1.145 *** (0.349)
City characteristics × month	Yes	Yes
City fixed effects	Yes	Yes

Table 7. *Cont.*

	(1) AQI	(2) PM2.5
Month fixed effects	Yes	Yes
Observations	21,672	21,672
R^2	0.793	0.790

Notes: The estimated effects are reported separately for northern and southern cities. The northern sample comprises 135 cities (10,365 observations), and the southern sample comprises 147 cities (11,307 observations). "Difference (North–South)" is the difference between the estimated coefficients for the two regions. All regressions control for temperature, mean sea-level pressure, precipitation, and the U- and V-components of 10-m wind. They also include interactions between month fixed effects and city characteristics, as well as city and month fixed effects. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.2. Heterogeneity by Population Density

Cities with different population densities vary in development scale and factor agglomeration. We divide the sample into lower- and higher-population-density groups, comprising 142 and 140 cities, respectively.

As shown in Table 8, the estimated policy effects on AQI and PM2.5 are −2.873 and −2.503 in lower-population-density cities. Both are significant at the 1% level. The estimates for higher-population-density cities are not statistically significant. The estimated differences between the higher- and lower-density groups are 2.404 for AQI and 2.390 for PM2.5; they are significant at the 10% and 5% levels, respectively. These results indicate that the air-quality improvement was stronger in lower-population-density cities. This difference may reflect the variation in industrial structure, energy use, and the foundations of pollution control. If lower-density cities have more energy-intensive activities or greater scope to improve governance, policy implementation may yield larger marginal reductions in emissions. In higher-density cities, industrial activity and pollution sources may be more complex. Traffic emissions and regional pollutant transport may also affect the extent of improvement.

Table 8. Heterogeneity regression results by population density.

	(1) AQI	(2) PM2.5
Lower population density	−2.873 ***	−2.503 ***
	(0.928)	(0.824)
Higher population density	−0.469	−0.114
	(0.814)	(0.706)
Difference (High–Low)	2.404 *	2.390 **
	1.234	1.085
Temperature	−0.355 **	−0.353 ***
	(0.149)	(0.121)
Mean sea-level pressure	0.944 ***	0.783 ***
	(0.223)	(0.183)
Precipitation	−0.764 ***	−0.393 ***
	(0.068)	(0.040)
Wind U-component	1.062 **	−0.090
	(0.425)	(0.346)
Wind V-component	0.541	1.148 ***
	(0.434)	(0.349)
City characteristics × month	Yes	Yes
City fixed effects	Yes	Yes

Table 8. *Cont.*

	(1) AQI	(2) PM2.5
Month fixed effects	Yes	Yes
Observations	21,672	21,672
R^2	0.793	0.790

Notes: The cities are divided into lower- and higher-population-density groups. The lower-density group comprises 142 cities (10,892 observations), and the higher-density group comprises 140 cities (10,780 observations). "Difference (High–Low)" is the difference between the estimated coefficients for the two groups. All regressions control for temperature, mean sea-level pressure, precipitation, and the U- and V-components of 10 m wind. They also include interactions between month fixed effects and city characteristics, as well as city and month fixed effects. Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion

The empirical results indicate that the carbon-peaking pilot policy improved urban air quality. The effect emerged gradually after implementation. This finding supports the hypothesis that China's dual-carbon policies can generate co-benefits for pollution abatement and carbon reduction. It is also broadly consistent with previous studies showing that carbon-trading pilots, low-carbon city pilots, and environmental regulation can improve air quality [8–16,26]. Unlike studies that focus primarily on individual emissions-reduction instruments, this study shows that a comprehensive policy package such as the carbon-peaking pilots may also address air pollution through source reduction and structural adjustment. The findings provide additional empirical evidence on the air-quality effects of China's dual-carbon policies.

The mechanism tests are consistent with two potential channels: new registrations of new-energy enterprises and green technological innovation. The policy may strengthen expectations of a green transition and improve the institutional environment for the new-energy sector, encouraging new enterprise registrations. It may also promote green innovation. Such innovation could reduce emissions through energy-efficiency improvements, cleaner production, and upgrades to pollution-control technologies. These results suggest that the environmental effects of the pilots may arise not only from direct constraints on energy-intensive and high-emission activities, but also from indirect reductions associated with industrial upgrading and technological progress. This interpretation is consistent with the theoretical proposition that environmental regulation can encourage innovation and generate environmental improvements. It also relates to previous discussions of the roles of green technology and industrial upgrading in coordinated governance [13,14,16].

The heterogeneity results show larger estimated effects in northern cities and in cities with a lower population density. Northern cities may rely more heavily on coal and energy-intensive industries, leaving a greater scope for pollution reduction when the policy promotes energy substitution and industrial restructuring. Lower-density cities may differ in their pollution sources, governance capacity, and degree of factor agglomeration, which could make marginal improvements more visible. The results therefore suggest that policy effectiveness depends partly on cities' resource endowments, industrial structures, and governance conditions. Tailoring policy implementation to local conditions may help realize the potential for coordinated pollution abatement and carbon reduction. Air-quality improvements may not occur uniformly across cities; they appear to depend on context.

More broadly, the findings suggest that carbon-peaking pilots may function not only as a carbon-reduction policy but also as an institutional arrangement for coordinating air-pollution control. Under the dual-carbon goals, carbon governance and air-quality management need not be treated as separate agendas. They may generate joint benefits

through energy-structure adjustment, green-technology diffusion, and industrial upgrading. Future research could extend this study in three ways. First, a longer sample period would help identify the policy's long-term environmental effects. Second, more granular pollution data combined with spatial-econometric methods could be used to examine cross-regional spillovers. Third, future work could examine more specific channels, including changes in the energy structure, fiscal incentives, the stringency of environmental regulation, and firm-level responses.

6. Conclusions and Policy Recommendations

6.1. Conclusions

Based on monthly panel data for 282 cities from January 2020 to May 2026, this study treats the first batch of carbon peaking pilot cities as the treatment group and employs a two-way fixed-effects difference-in-differences model to examine the impact of the carbon peaking pilot policy on urban air quality. The main conclusions are as follows:

First, the carbon-peaking pilot policy improved air quality in pilot cities overall. In the full baseline specification, the policy reduced AQI by approximately 1.429 points and PM2.5 concentrations by approximately 1.018 $\mu g/m^3$ The one-sided WCB *p*-values reported in this section are 0.0274 and 0.0558, respectively. The robustness checks show that, after controlling for contemporaneous policies, the estimated coefficients for AQI and PM2.5 are −1.367 and −0.910. When the dependent variables are replaced with PM_{10} and NO_2, the estimated coefficients are −2.224 and −1.226, both significant at the 5% level. In the PSM-DID estimates, the coefficient for AQI is −1.965, significant at the 5% level, and the coefficient for PM2.5 is −1.494, significant at the 10% level. Together with the parallel-trend, placebo, and other robustness tests, these results generally support an air-quality improvement effect of the carbon-peaking pilots.

Second, new registrations of new-energy enterprises and green technological innovation are potential channels through which the policy may affect air quality. The annual mechanism estimates show that the policy coefficient is 0.197 for new registrations of new-energy enterprises, significant at the 10% level, and 0.282 for green technological innovation, significant at the 1% level. These results indicate that policy implementation is associated with an expansion in new-energy market participants and an increase in green innovation activity. They are consistent with the proposed industry-development and technological-innovation channels. However, the number of newly registered enterprises does not necessarily indicate actual business operations or investment.

Third, policy effects vary across cities. Regional regressions show that the estimated effects for AQI and PM2.5 in northern cities are −2.465 and −1.762, respectively, both significant at the 1% level. The estimates for southern cities are not statistically significant. The estimated differences between northern and southern cities are −2.629 for AQI and −1.841 for PM2.5. When cities are grouped by population density, the estimated effects in lower-density cities are −2.873 for AQI and −2.503 for PM2.5, both significant at the 1% level. The estimates for higher-density cities are not statistically significant. These findings indicate that the policy effect is not uniform across cities. Location and population density are associated with differences in the magnitude of air-quality improvement.

6.2. Policy Implications and Recommendations

Based on the above conclusions, this study proposes the following policy recommendations.

First, establish a joint evaluation framework for carbon reduction and air quality. Annual evaluations of carbon-peaking pilots should assess carbon targets alongside air-quality indicators such as AQI, $PM_{2.5}$, PM_{10}, and NO_2. These indicators should be monitored

monthly and evaluated annually. If a city's air quality does not improve as expected, relevant authorities should examine changes in key industries, energy consumption, and pollutant emissions. They should distinguish between shortcomings in policy implementation and external influences, such as meteorological conditions and regional pollutant transport. Pilot performance should not be assessed solely by carbon emissions or the number of projects. This study directly evaluates changes in air quality; the associated carbon-reduction effects should therefore be verified separately using emissions data.

Second, allocate governance resources in light of the differences identified in the empirical analysis. Because the estimated effects are larger in northern cities and lower-population-density cities, these areas could be prioritized for energy audits in key industries, coal substitution, energy-efficiency upgrades, and cleaner-production projects. Funding should be directed to projects whose effects on energy use and pollutant emissions can be verified. Southern cities and higher-density cities should not simply adopt the same governance approach. Their priorities should be determined after identifying local pollution sources, including transport, buildings, industry, and regional pollutant transport.

Third, link support for the new-energy sector and green innovation to environmental performance. Green credit, earmarked funding for technological upgrades, and demonstration projects can support new-energy, energy-conservation, and environmental-protection firms. However, eligibility reviews and subsequent disbursements should consider whether projects have entered operation, whether technologies have been adopted, and whether energy use and pollutant emissions have declined. Enterprise registrations and patent counts alone should not be used as the basis for support. Collaboration among firms, universities, and research institutions—including joint research, demonstration applications, and technology-transfer projects—can help translate green research outputs into verifiable emission reductions.

Fourth, improve coordination across government departments and regions. During the implementation of the carbon-peaking pilots, relevant authorities in development and reform, ecology and environment, industry and information technology, and energy should coordinate project planning and monitoring data. They should regularly review policy overlap, duplicate investment, and potential industrial relocation. Given the regional transport of air pollution, pilot cities should also share monitoring information with neighboring areas and coordinate responses to heavy-pollution episodes and measures for key industries. Such cooperation can reduce the risk that local air-quality improvements are offset by emissions from elsewhere.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su182111034/s1. Figures: Figure S1. Pilot City Distribution Map; Figure S2a. Pre-treatment AQI trends in the matched samples; Figure S2b. Pre-treatment PM2.5 trends in the matched samples; Figure S2c. Distribution of propensity scores for the treated and control groups within the common support region. Tables: Table S1. List of the First Batch of Carbon-Peaking Pilot Cities and Parks in China; Table S2a. Lead/lag estimates for the parallel trends (mean-centered) with 90% confidence intervals: AQI; Table S2b. Lead/lag estimates for the parallel trends (mean-centered) with 90% confidence intervals: PM2.5; Table S3a. List of Pilot Cities under the Policy for Climate-Adaptation City Construction; Table S3b. List of Cities under the Pilot Policy for Synergistic Innovation in Pollution and Carbon Reduction; Table S3c. Cities under the Pilot Policy for the Application of Battery-Swapping Mode for New Energy Vehicles; Table S3d. List of Key-Region Cities in the Action Plan for Continuous Improvement of Air Quality.

Author Contributions: Conceptualization, C.W.; methodology, H.Z.; data curation, C.W.; empirical analysis, C.W.; writing—original draft preparation, C.W.; writing—review and editing, C.W. All authors have read and agreed to the published version of the manuscript.

Funding: Guangdong Provincial Philosophy and Social Sciences Planning Project (GD26CYJ16).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The air-quality, meteorological, and city-level statistical data used in this study were obtained from publicly available databases, statistical yearbooks, and relevant data platforms. Data on new-energy enterprises were obtained from the CNRDS database, and data on green patents were obtained from the PPData database. The specific data-processing procedures and variable-construction methods are described in the Sections 3.3 and 3.4.

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

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