

Article

Air Quality Benefits of Renewable Energy: Evidence from China's Renewable Energy Heating Policy

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Abstract: This paper examines the impact of renewable energy heating on air quality in China, using the Qinling Mountains–Huaihe River line as a quasi-natural experiment to distinguish between regions with central heating and those without. Employing a difference-in-differences approach and analyzing panel data from 298 cities between 2014 and 2022, our findings indicate that the renewable energy heating policy has significantly improved air quality. Specifically, the policy led to substantial improvements in air quality, reducing concentrations of key pollutants: SO₂ by 28.31%, CO by 7.57%, NO₂ by 5.72%, and PM_{2.5} by 7.15%. The policy's effects are most pronounced in regions with lower temperatures and in the eastern parts of the country. Further analysis emphasizes the critical role of energy transition, environmental regulations, and government investment in technology as key drivers of these air quality improvements.

Keywords: air quality; central winter heating; renewable energy



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1. Introduction

The escalating air pollution problem severely threatens public health and environmental quality worldwide, particularly in rapidly industrializing countries like China. The relationship between energy consumption and air quality is a central concern, as the use of traditional fossil fuels, especially coal, significantly exacerbates urban pollution [1–4]. According to the China Building Energy and Emission Yearbook 2023, in northern China, where winter heating is predominantly coal-based (accounting for 85.8% of the total), air pollution levels are notably high [5]. The 2023 China Ecological and Environmental Quality Bulletin reports that, of all 339 prefecture-level and above cities across the country, 136 still exceed air quality standards, accounting for 40.1% of the total. Renewable energy is increasingly viewed as a viable substitute for fossil fuels, with the potential to mitigate environmental damage and promote environmental sustainability [6,7]. Given this context, transitioning to renewable energy sources and reducing pollution from winter heating are critical to China's sustainable development. This paper seeks to address a critical question: Can promoting renewable energy heating improve air quality?

This study examines the impact of promoting renewable energy heating policies (REHP) on air quality in China, engaging with three strands of the literature. First, the existing literature on coal combustion, winter heating, and resulting pollution has received considerable attention. Prior research has demonstrated a correlation between coal combustion and deteriorated air quality [8–11]. Some studies examine the impact of air pollution from coal combustion during the winter season on human health. Chen et al. [12] use a regression discontinuity design based on China's Huai River policy, revealing a significant increase in particulate matter and a 5.52-year reduction in life expectancy in northern regions due to elevated cardiorespiratory mortality. Fan et al. [13] further refined this analysis by incorporating precise start dates for winter heating, with similar findings. In order to

reduce air pollution, the “Air Pollution Prevention and Control Action Plan” was introduced in 2013. Following the implementation of the “coal-to-gas” and “coal-to-electricity” initiatives, the literature initially evaluated these clean energy policies [14,15]. This was followed by the “Winter Clean Heating Plan for Northern China (2017–2021)”. A large body of the literature has emerged to evaluate the effects of clean energy policies and calculate the cost of clean energy heating [15–18]. However, these studies often focus on a limited number of pilot cities and do not address the broader applicability of the policies or provide a detailed analysis of their mechanisms. Our paper complements the existing research by using a broader sample of 298 Chinese cities with diverse winter heating situations (e.g., municipal central heating, partial heating, and no heating). Detailed information is presented in Table A1. We evaluate the universality of REHP, offering a more comprehensive analysis of its effectiveness, heterogeneity, and underlying mechanisms.

Second, this paper is supported by research on environmental regulation and clean energy consumption. The impact of environmental regulations on fossil energy consumption has been studied extensively. Most findings indicate that such regulations often reduce fossil fuel use by improving energy efficiency. This effect is achieved through the promotion of more efficient technologies and practices [19,20]. However, research specifically addressing the relationship between environmental regulation and clean energy consumption, particularly within the context of China, remains limited. Zhao et al. [20] utilized province-level panel data and demonstrated that environmental regulation positively influences natural gas consumption. Wang and Lee [21] revealed that environmental regulations enhance the positive impact of clean energy consumption on economic growth, thereby encouraging provinces to pursue a clean growth trajectory, using balanced panel data from 27 provinces from 2000 to 2015. Building on these studies, this research further explores the mechanism through which environmental regulation affects renewable energy policies. The results verify that the efficacy of renewable energy policies is significantly bolstered by government regulations and a strong commitment to environmental protection.

Third, numerous studies have underscored the positive relationship between technological innovation and sustainable energy development [22,23]. Technological progress is widely recognized as enhancing energy efficiency [24], facilitating energy transitions [25], and enabling the substitution of labor and capital in production processes [22]. These advancements collectively contribute to the promotion of sustainable energy practices. Lee and Wang [26] integrate natural resources, technological innovation, technological introduction, and energy sustainability into a unified research framework, affirming that technological innovation positively impacts sustainable energy development. It is worth noting that the effectiveness of technological introduction is contingent upon its alignment with local natural resource endowments. The impact of technological innovation on sustainable energy development depends on the foundational capabilities and capacity to absorb new technologies [26]. This paper further substantiates the positive impact of technological innovation on energy transitions by incorporating interaction terms to explore how innovation influences sustainable energy practices.

The Qinling Mountains–Huaihe River line, which differentiates regions with municipal central heating from those without, offers a unique setting for a quasi-natural experiment to evaluate REHP. Quasi-natural experiments are commonly applied in social sciences for policy evaluations, environmental studies, and economic reforms where randomized controlled trials (RCTs) are often impractical or unethical [27–29]. Our research utilizes a difference-in-differences (DID) methodology to evaluate the impact of REHP on air quality across 298 cities from 2014 to 2022. To reduce selection bias, we employed a propensity score-matching (PSM) method with a DID design to ensure that the treatment and control groups are comparable in terms of their observed characteristics, thereby creating a more balanced comparison. We further explore the policy’s effect on major pollutants like sulfur dioxide (SO₂), carbon monoxide (CO), nitrogen dioxide (NO₂), and particulate matter (PM_{2.5}). In addition to the primary analysis, we investigate the roles of the energy transition, stricter environmental regulations, and increased government expenditures on technology as key

drivers of these improvements. Our results underscore the effectiveness of renewable energy policies in enhancing air quality and highlight the broader implications for urban planning and policy-making in pollution-intensive regions.

The contributions of this paper are threefold. First, unlike previous studies, which focused on a limited number of pilot cities, this research analyzes a broader sample of 298 Chinese cities, allowing us to evaluate the universality of renewable energy heating policies and explore regional heterogeneity. Second, it provides a detailed analysis of the mechanisms through which environmental regulation and technological innovation influence sustainable energy practices. Third, the paper accurately classifies municipal central heating systems, categorizing cities into municipal centralized, partially centralized, or no centralized heating. It also accounts for cities along the Qinling Mountains–Huaihe River boundary, where heating systems have recently expanded in densely populated communities.

The subsequent sections of this paper are organized as follows: Section 2 provides background information on China’s heating policies and their evolution. Section 3 details the sources of the data and presents the empirical strategy. Section 4 presents the empirical results, including baseline regression and robustness checks. Section 5 further discusses heterogeneity and explores the potential mechanisms. Finally, Section 6 concludes with a summary of the findings and policy recommendations.

2. Policy Background

This section provides an overview of China’s winter heating system, including its scope, modes of heating, and the development and reform of municipal central heating projects in the country’s energy transition.

China’s winter heating system was initiated in the 1950s, modeled after the former Soviet Union. Centralized heating, which relies on large boiler plants or thermal power stations distributing heat through extensive networks of thermal pipes, became the dominant method in China. However, due to energy constraints and financial constraints, the government restricted centralized heating to northern regions. The boundary between northern and southern China roughly follows the Huaihe River and Qinling Mountains, where the average January temperature hovers around zero degrees Celsius, forming the basis of the well-known “Huai River Policy” [12,30].

In recent years, with rapid economic development and changing climate patterns, China’s winter heating system has expanded geographically and transitioned toward cleaner energy sources. On the one hand, some southern cities have experienced colder winters due to climate variability, driving the increased demand for heating solutions. In response, local governments in cities such as Lianyungang, Changzhou, Nanjing, Yangzhou, and Suzhou expanded central heating in densely populated urban communities. Additionally, pilot central heating projects have been implemented in cities such as Lhasa in 2012, Aba County in 2013, and Liupanshui in 2014, among others. In communities where municipal heating pipelines are inaccessible, decentralized systems, such as distributed energy central heating, have been adopted, alongside traditional electric heaters and air conditioners. Sampled cities are categorized into three groups: (1) cities with municipal central heating, (2) cities with partial central heating in some communities (less than 60% coverage), and (3) other southern cities without a central heating infrastructure.

On the other hand, significant efforts have focused on transitioning from coal-based heating to cleaner alternatives. Historically, coal has dominated centralized heating in China, but its incomplete combustion has resulted in severe winter air pollution [11,30]. A total of 87% of sulfur dioxide (SO₂) and 76% of nitrogen oxide (NO_x) emissions are attributed to coal combustion [31]. Over the past decade, the government has implemented policies promoting the use of natural gas, renewable energy (e.g., geothermal and solar), and energy-efficient technologies. In 2013, the “Air Pollution Prevention and Control Action Plan” was introduced, mandating the replacement of coal-fired boilers with gas or electric systems in urban areas and providing subsidies for rural households to transition

from coal stoves to cleaner alternatives. In 2017, the central government launched the “Winter Clean Heating Plan for Northern China (2017–2021)”, which focused on the “2 + 26” cities in the Beijing–Tianjin–Hebei air pollution corridor. The plan aimed to replace bulk coal with natural gas and electric heating, increasing the share of clean heating in northern China to 50% by 2019 and 70% by 2021. In 2021, the National Energy Administration issued a circular on “Promoting Renewable Energy Heating According to Local Conditions”, encouraging the use of geothermal, biomass, solar, and wind energy for heating. However, alternatives to coal heating also have limitations [5,32]. For example, natural gas heating is not considered a viable long-term solution due to its high costs, and the insufficient security of its supply. Electrified heating options, including direct electric heating and electric heat pumps, also face challenges. While direct electric heating converts electricity into heat with minimal investment, it is less economical than centralized low-grade heat transmission. Electric heat pumps are efficient at extracting low-grade heat from natural sources such as soil, air, and water, but their low heat density makes it difficult for them to meet the heating demands of high-density urban buildings. Additionally, barriers such as equipment conversion costs, technical limitations, and safety concerns limit the development of energy transitions [33,34].

Our analysis focuses on the implementation of REHP in 2021. While the air quality benefits of the “Winter Clean Heating Plan” have been demonstrated [16–18], it is essential to evaluate the effectiveness of the policy and explore its mechanisms. The shift toward renewable energy heating is critical for China’s energy transition, contributing to energy conservation, emission reductions, and the better management of overall energy consumption. It also plays a key role in achieving non-fossil energy targets, building a low-carbon society, and advancing sustainable energy development. This study employs the REHP as a quasi-natural experiment and applies the DID model to evaluate the impacts on air quality during the period from 2014 to 2022, considering recent reforms to China’s winter heating system and exploring their underlying mechanisms.

3. Data and Methodology

3.1. Data

3.1.1. Air Quality Data

The city-level atmospheric pollutant data were obtained from the national urban air quality real-time release platform of the China Environmental Monitoring Center. This platform provides hourly concentrations of six key air pollutants, including PM_{2.5}, PM₁₀, sulfur dioxide (SO₂), nitrogen dioxide (NO₂), carbon monoxide (CO), and ozone (O₃), across 337 cities at prefecture-level and above since 2013. The air quality index (AQI) is also reported as a comprehensive measure of these pollutions, with higher AQI values indicating more severe pollution. The calculation process proceeds as follows. First, the monthly average concentrations for SO₂, NO₂, PM₁₀, and PM_{2.5} are calculated, along with the 95th percentile of daily average CO values and the 90th percentile of daily maximum 8 h O₃ levels. Next, the individual air quality index (IAQI) is calculated as the concentration of each pollutant relative to its respective secondary annual standard. Finally, the AQI is determined by finding the highest IAQI among the six pollutants. (The data are openly accessible at <https://air.cnemc.cn:18007/>, accessed on 20 October 2024.) In contrast, the European AQI, developed by the European Environment Agency (EEA), covers five main pollutants: PM_{2.5}, PM₁₀, SO₂, NO₂, and O₃. This categorizes air quality into qualitative levels ranging from 1 (good) to 6 (extremely poor).

3.1.2. Municipal Central Heating

Traditionally, the Qinling Mountains–Huaihe River boundary has been used to demarcate northern and southern China, with temperature serving as the primary determinant. However, this classification overlooks other crucial factors, such as humidity, which substantially affect perceived warmth. As economic development has progressed, the demand

for winter heating has risen in the relatively humid southern regions, prompting some cities near this boundary to introduce central heating systems.

As illustrated in Figure 1, in our sample of 298 cities, 134 cities provided citywide central heating, 19 provided partial district heating with less than 60% coverage, and 145 did not have central heating.

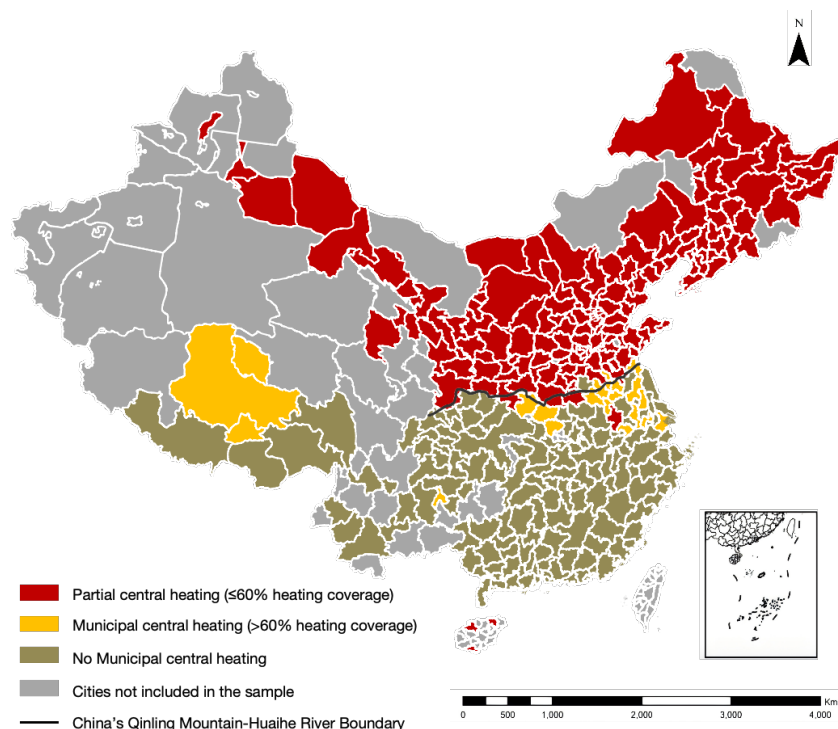


Figure 1. Municipal Central Heating in China.

China's central heating landscape can be categorized into three groups: (1) Municipal central heating: This group comprises cities across 17 provinces, autonomous regions, and municipalities, where all cities offer central heating. These regions include Beijing, Tianjin, Hebei, Inner Mongolia, Shanxi, Shandong, Heilongjiang, Jilin, Liaoning, Shaanxi, Ningxia, Gansu, Qinghai, and Xinjiang. (2) Partial or district-based heating: Certain cities near the Qinling Mountains–Huaihe River boundary, particularly in the Henan, Anhui, and Jiangsu Provinces, have implemented partial or district-based heating systems. Most cities in Henan Province have central heating, except for Xinyang and Zhoukou. In Anhui Province, Hefei provides citywide central heating, whereas cities such as Wuhu, Bengbu, and Huainan have limited district heating. Similarly, in Jiangsu Province, Xuzhou has citywide central heating, whereas cities such as Lianyungang, Chang-zhou, and Nanjing offer limited heating in specific residential areas. Additionally, high-altitude regions south of the dividing line, particularly near the Tibetan Plateau, gradually adopted central heating because of their prolonged cold winters. Notable examples include Lhasa (since 2012) and Nagqu (since 2016) in the Tibet Autonomous Region, and Liupanshui in Guizhou Province (since 2014). Some cities, such as Shiyan in Hubei Province, leverage waste heat from local industries to facilitate large-scale heating projects. Jingmen and Xiangyang have also initiated central heating projects, although their scope remains limited. (3) No municipal central heating: Provinces such as Shanghai, Chongqing, Zhejiang, Fujian, Jiangxi, Hunan, Guangdong, Guangxi, and Hainan do not have a central heating infrastructure. Detailed information on the heating situation across Chinese cities is presented in Table A1. The data were sourced from the 2022 China Urban Construction Statistical Yearbook, supplemented with publicly available materials.

3.1.3. City-Level Socioeconomic Data

City-level socioeconomic data were mainly collected from the China City Statistical Yearbook, covering the years from 2014 to 2022. This yearbook contains major statistical data on the socioeconomic development of cities, encompassing various dimensions, such as the economy, population, environment, education, culture, and transportation. The key variables in our paper include GDP per capita as a measure of economic development, population density as a proxy for urban congestion, the number of industrial enterprises as an indicator of industrial development, the proportion of the tertiary industry's added value as a measure of industrial structure, and the proportion of general public budget expenditure as a gauge of government intervention. Additionally, the proportion of government expenditure on science and technology serves as an indicator of the level of scientific and technological development. We also employ the frequency of environment-related words in government work reports as a measure of environmental governance, following the methodology of Chen et al. [35]. The higher the frequency of these terms, the greater the governmental focus on environmental issues. The work reports were sourced from local government websites, and the frequency of specific environment-related terms was systematically counted. These terms included “environmental protection”, “pollution”, “energy”, “emission”, “sewage”, “ecology”, “green”, “low carbon”, “air”, “sulfur dioxide”, “carbon dioxide”, “PM10”, “PM2.5”, etc.

Given the absence of city-level energy consumption statistics in China, urban energy consumption was estimated using efficient inverse models based on global night-time light imagery and provincial energy consumption data, following Su et al. [36] and Shi et al. [37]. The linear correlation between nightlight data and energy consumption has been well-documented in prior research [38–40]. We employed a linear model without an intercept to disaggregate provincial energy consumption data into prefecture-level estimates according to nightlight data. In the linear model, the dependent variable is energy consumption per province for the year, while the independent variable is nightlight intensity, calculated by summing the Digital Number (DN) values from all grids in each province. The DN values from the Nighttime Stable Lights (NSL) data reflect the nighttime light emissions from human activities captured in satellite imagery. Using the estimated coefficient and the nightlight intensity for each city, we can calculate prefecture-level energy consumption estimates. These data were unified into 100 tons of standard coal for simplification. The nightlight data were obtained from the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA), and the provincial energy consumption data were obtained from the China Energy Statistical Yearbook published by the National Bureau of Statistics (NBS).

3.2. Summary Statistics

Detailed definitions of the main variables are presented in Table 1, and Table 2 reports summary statistics. Panel A compares the air quality of regions with and without municipal central heating, with significantly higher mean AQI values being obtained in areas with central heating than in unheated areas, with statistical significance at the 1% level. This suggests that central heating contributes to poorer air quality. Similarly, the concentrations of pollutants such as SO₂, CO, NO₂, and PM_{2.5} are significantly elevated in cities with central heating. Numerous studies have demonstrated that winter heating deteriorates air quality, primarily due to the energy sources used for heating and emissions from combustion processes (e.g., Chen et al. [12], Fan et al. [13], Almond et al. [30]). According to the China Building Energy and Emission Yearbook 2023, fossil fuels still account for 85.8% of heating methods. The combustion of these fuels releases pollutants, contributing to the formation of smog and respiratory issues. Furthermore, coal consumption is notably higher in regions with centralized heating compared to those without centralized heating, with the difference also being statistically significant at the 1% level, confirming the above findings. Panel B presents descriptive statistics for all variables from 2014 to 2022. The average AQI during the sample period is 76.44. The mean concentrations of SO₂, CO, NO₂, and PM_{2.5}

are 16.68 $\mu\text{g}/\text{m}^3$, 0.89 $\mu\text{g}/\text{m}^3$, 28.58 $\mu\text{g}/\text{m}^3$, and 41.36 $\mu\text{g}/\text{m}^3$, respectively. Statistics for other control variables at the city level are also provided.

Table 1. Definition of main variables.

Variable	Definition
LnAQI	Natural logarithm of Air Quality Index (dimensionless)
LnSO ₂	Natural logarithm of the average annual SO ₂ concentration ($\mu\text{g}/\text{m}^3$)
LnCO	Natural logarithm of the average annual CO concentration ($\mu\text{g}/\text{m}^3$)
LnNO ₂	Natural logarithm of the average annual NO ₂ concentration ($\mu\text{g}/\text{m}^3$)
LnPM2.5	Natural logarithm of the average annual PM2.5 concentration ($\mu\text{g}/\text{m}^3$)
LnGDP	Natural logarithm of GDP per capita (CNY)
LnPop	Natural logarithm of population density (people/ km^2)
LnInd	Natural logarithm of number of industrial enterprises above designated size
Exp	Ratio of government general public budget expenditure of GDP
IndStr	Proportion of added value of tertiary industry
LnCoal	Total consumption of standard coal (million tons)
EnvReg	Natural logarithm of (1+word frequency of environment in government reports)
TechExp	Ratio of government expenditure on science and technology to GDP

Table 2. Summary Statistics.

Panel A: Comparison of air quality and energy consumption								
Variable	Central heating Regions			Non-Central Heating Regions			Diff. in Mean	T-stat
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.		
LnAQI	1180	4.401	0.238	1349	4.214	0.259	0.188 ***	18.908
LnSO ₂	1180	2.808	0.645	1349	2.417	0.552	0.391 ***	16.415
LnCO	1180	−0.136	0.361	1349	−0.197	0.288	0.061 ***	4.698
LnNO ₂	1180	3.381	0.338	1349	3.208	0.377	0.174 ***	12.107
LnPM2.5	1180	3.732	0.370	1349	3.566	0.421	0.166 ***	10.441
LnCoal	1242	11.58	0.866	1431	11.46	0.830	0.119 ***	3.628
Panel B: Descriptive statistics of variables in whole sample								
Variable	Obs.	Mean	Min	Max	Median	Std. Dev		
LnAQI	2529	4.301	3.521	5.129	4.313	0.266		
LnSO ₂	2529	2.600	0.734	4.770	2.519	0.628		
LnCO	2529	−0.169	−1.147	1.017	−0.193	0.325		
LnNO ₂	2529	3.289	1.540	4.190	3.320	0.370		
LnPM2.5	2529	3.643	1.720	4.817	3.648	0.407		
LnCoal	2673	11.52	7.406	13.60	11.53	0.849		
LnGDP	2642	10.88	9.227	12.46	10.85	0.527		
LnPop	2654	5.663	0.244	8.100	5.848	1.092		
LnInd	2647	6.556	1.099	9.536	6.600	1.203		
Exp	2642	0.221	0.0440	2.060	0.184	0.141		
IndStr	2642	0.454	0.198	0.839	0.450	0.0920		
EnvReg	2549	3.831	1.386	4.942	3.871	0.409		
TechExp	2649	10.57	6.252	15.53	10.47	1.511		

Notes: Panel A compares air quality and energy consumption between regions with central heating and those without. The differences in means are reported, with statistical significance indicated by *** at 1% level. Panel B provides descriptive statistics for all variables in the whole sample.

3.3. Model Specification

In this study, we employed a DID approach to evaluate the impacts of the REHP on air quality across 298 Chinese cities from 2014 to 2022. The benchmark model is specified as follows:

$$AQI_{it} = \alpha + \beta(Treat_i \times Post_t) + Controls'_{it} \delta_i + \theta_t + \epsilon_{it}, \quad (1)$$

where AQI_{it} represents the air quality index of city i in year t ; higher AQI_{it} values indicate more severe air pollution. The variable $Treat_i$ is a dummy variable equal to 1 if the city has municipal central heating (including both citywide and partial heating), and 0 otherwise. The variable $Post_t$ is a time dummy set to 1 for years after the implementation of the renewable energy policy in 2021, and 0 for prior years. The coefficient β captures the policy's effect on air quality. According to the hypothesis, this coefficient is expected to be significantly negative. This would demonstrate that the implementation of the REHP leads to improved air quality. The vector $Controls_{it}$ includes key city characteristics that may influence air quality, such as GDP per capita ($LnGDP_{it}$), population density ($LnPop_{it}$), industrial development ($LnInd_{it}$), degree of government intervention (Exp_{it}), and industrial structure ($IndStr_{it}$). The city fixed effects δ_i account for time-invariant characteristics at the city level, such as natural endowments and geographic location, and the year fixed effects θ_t control for shocks common to all cities in a given year. ϵ_{it} is the error term clustered at the city level to address potential correlations in random perturbations within the same city over time. To mitigate the influence of outliers, all continuous variables are winsorized at the 5% level.

The DID method is a widely used statistical technique in econometrics and social sciences for estimating causal effects. It effectively analyzes situations where a policy is implemented at a specific point in time, allowing for researchers to compare outcomes before and after the intervention between treatment and control groups (e.g., Moser and Voena [41]; Chari et al. [42]). As a result, it serves as a valuable tool for policymakers assessing the effectiveness of specific programs or initiatives. Moreover, a key prerequisite for applying DID is the exogeneity of the policy. This means that the decision to implement the policy does not depend on the trends in the outcome variable being studied. In our study, the Qinling Mountains–Huaihe River line, serving as a geographical boundary, perfectly guarantees the exogeneity of the policy.

To reduce selection bias, we adopted a PSM-DID design. Propensity score matching was used to ensure that the treatment and control groups are comparable in terms of observed characteristics, thereby creating a more balanced comparison group [43,44]. We employed logit regression to estimate propensity scores and match treated and untreated subjects with similar propensity scores to create an individually matched sample. In the benchmark analysis, nearest neighbor matching was applied to identify the control group samples most similar to the treatment group. To ensure robustness, we also employed alternative matching methods, including radius and kernel matching.

4. Empirical Results

4.1. Baseline Results

Table 3 presents the baseline results of the analysis. Columns (1) and (2) display the estimates from the benchmark DID model, revealing that the coefficients for the interaction terms are negative and statistically significant. This indicates that after the implementation of the REHP, air pollution (measured by AQI) decreases by 1.95% to 2.15% more in central heating cities than those in the control cities. Columns (3) and (4) present the results after applying 1:1 nearest neighbor matching, in which each treated city is matched to a control city with the closest propensity score. Table 4 and Figure 2 provide the results of the balance test for matching variables. After matching, the estimated bias for most variables decreased significantly, with nearly all falling within the 10% threshold. The only exception was the industrial structure variable ($IndStr$), which, although slightly above 10%, remained within the acceptable range of below 20%. Figure 3 shows the distribution of propensity scores for the treatment and control groups before and after matching. The notable convergence of the two density curves after matching suggests that the matched samples are well-suited to subsequent DID analysis. After accounting for sample heterogeneity through propensity score matching, the findings indicate a greater improvement in air quality, with a 3.59% to 4.04% reduction in the AQI during the post-REHP period. These results align with the anecdotal evidence and the findings of previous studies, including

Zhang et al. [16], Song et al. [17], Tan et al. [18]. The implications of the other explanatory variables are described as follows: *LnGDP* is positive, indicating that air quality deteriorates with economic development. A higher GDP per capita often correlates with increased industrial production, and in developing countries like China, pollution typically rises during early economic growth before declining as economies transition to cleaner technologies. Similarly, a higher population density and more industrial growth usually lead to worse air quality due to concentrated human activities and production (e.g., transportation, energy use), which increase pollutant emissions [45]. Industrial structure (*IndStr*) is measured by the ratio of less-polluting sectors, like services. The higher the service sector ratio, the greater the improvements in air quality [46]. The relationship between air quality and government general public budget expenditure (*Exp*) is generally positive [47,48]. Increased public budget expenditure, particularly for environmental protection, infrastructure, and clean energy initiatives, tends to improve air quality by funding pollution control programs, enforcing regulations, and promoting cleaner technologies. The coefficient of *Exp* is negative, although it is not statistically significant.

Table 3. Effect of REHP on the Air Quality Index.

Model	(1)	(2)	(3)	(4)
	Benchmark DID		PSM-DID	
Dep.Variable	AQI	AQI	AQI	AQI
Treat × Post	−0.0215 *** (0.0074)	−0.0195 *** (0.0068)	−0.0404 *** (0.0096)	−0.0359 *** (0.0088)
LnGdp		0.0695 *** (0.0213)		0.1213 *** (0.0273)
LnPop		0.1960 ** (0.0831)		0.0414 (0.1596)
LnInd		0.0052 (0.0118)		−0.0220 (0.0192)
Exp		−0.0864 (0.1035)		−0.1710 (0.1559)
IndStr		−0.2040 *** (0.0623)		−0.1583 (0.1040)
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observation	2529	2504	1146	1146
adj. R ²	0.923	0.929	0.935	0.938

Notes: This table presents the baseline results on the effect of REHP on the Air Quality Index (AQI). Columns (1) and (2) provide estimates from the benchmark DID model, while Columns (3) and (4) show the results after applying 1:1 nearest neighbor matching. Robust standard errors are reported in parentheses. Significance levels are indicated by ** and *** for the 5% and 1% levels, respectively.

Table 4. Balance test results of nearest neighbor matching.

Variable	Unmatched Matched	Mean		%bias	%Reduct bias	t-Test	
		Treated	Control			t	p > t
LnGDP	U	10.849	10.893	−9.4	98.8	−2.34	0.019
	M	10.852	10.851	0.1		0.03	0.978
LnPop	U	5.466	5.995	−65.3	94.7	−16.49	0.000
	M	5.484	5.513	−3.5		−0.77	0.444
LnInd	U	6.325	6.866	−52.8	85.1	−13.26	0.000
	M	6.341	6.421	−7.8		−1.74	0.081
Exp	U	0.218	0.192	32.1	100.0	8.08	0.000
	M	0.218	0.218	0.0		0.00	0.999
IndStr	U	0.458	0.447	14.7	13.9	3.68	0.000
	M	0.457	0.466	−12.6		−3.04	0.002

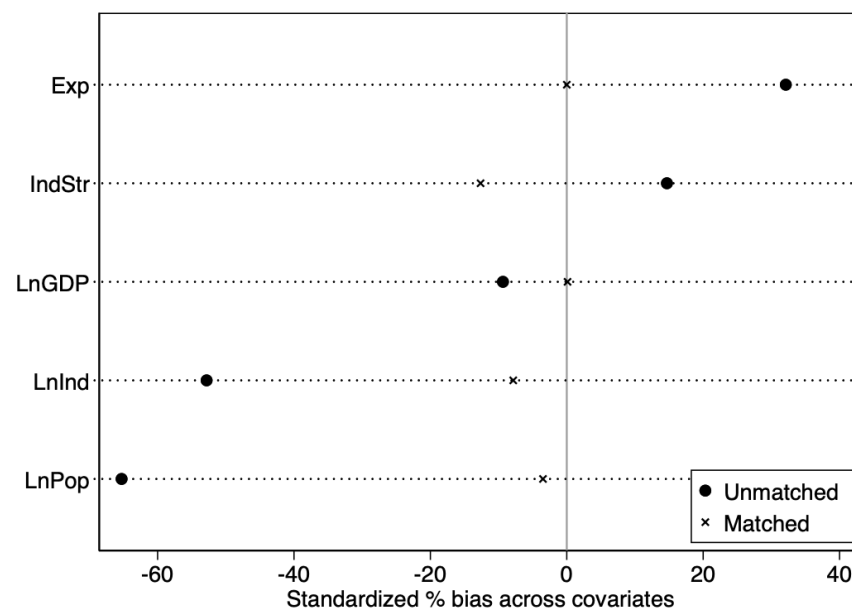


Figure 2. PSM Balance test results.

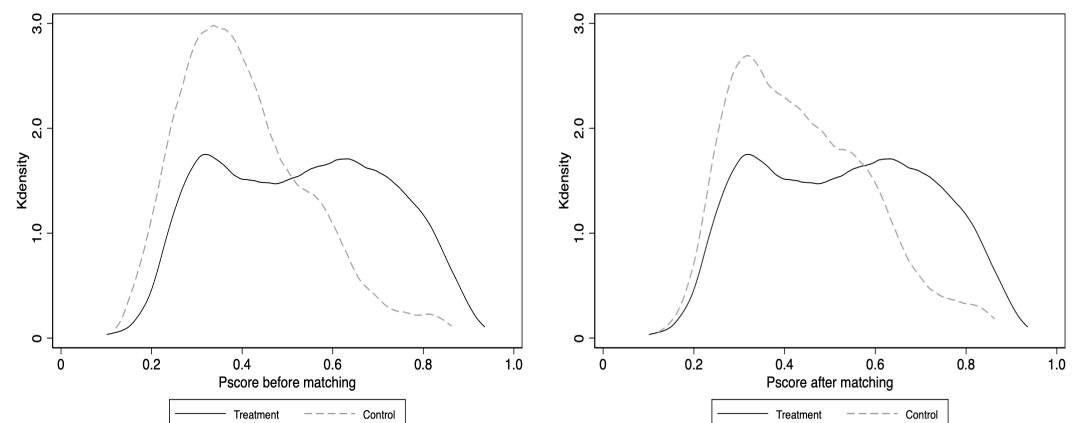


Figure 3. Kernel density curve of propensity score before and after matching.

Based on the matched samples, this study evaluates the impact of the REHP on air pollutant concentrations using a PSM-DID approach. The regression results, as detailed in Table 5, reveal significant reductions in the emissions of key pollutants: sulfur dioxide (SO₂) decreases by 28.31%, carbon monoxide (CO) by 7.57%, nitrogen dioxide (NO₂) by 5.72%, and particulate matter (PM_{2.5}) by 7.15%. The pronounced reduction in SO₂ concentrations highlights the effectiveness of the policy in targeting one of the most harmful pollutants associated with coal combustion [17,49]. These results contribute to the growing body of evidence supporting the effectiveness of renewable energy policies in reducing air pollution.

Table 5. Effect of REHP on the air pollutant concentrations.

	(1)	(2)	(3)	(4)
Dep.Variable	SO ₂	CO	NO ₂	PM _{2.5}
Treat × Post	−0.2831 *** (0.0372)	−0.0757 * (0.0411)	−0.0572 *** (0.0204)	−0.0715 *** (0.0202)
LnGDP	−0.0906 (0.1326)	−0.0898 (0.0710)	0.1940 *** (0.0476)	0.0478 (0.0615)

Table 5. Cont.

	(1)	(2)	(3)	(4)
Dep.Variable	SO ₂	CO	NO ₂	PM2.5
LnPop	−0.1016 (0.5075)	0.0019 (0.2764)	−0.0816 (0.2632)	−0.3206 (0.2138)
LnInd	0.0819 (0.0674)	0.0490 (0.0540)	−0.1028 *** (0.0367)	0.0886 ** (0.0370)
Exp	−0.2803 (0.5118)	−0.8172 ** (0.4121)	−0.2974 (0.2926)	−0.2161 (0.2932)
IndStr	0.1656 (0.3666)	0.4083 (0.3381)	−0.0219 (0.2262)	−0.3149 (0.1922)
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observation	1146	1146	1146	1146
adj. R ²	0.887	0.862	0.939	0.933

Notes: This table presents the effects of the REHP on air pollutant concentrations, including sulfur dioxide (SO₂), carbon monoxide (CO), nitrogen dioxide (NO₂), and particulate matter (PM2.5), as estimated using a PSM-DID model. Robust standard errors are reported in parentheses. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

4.2. Robustness Checks

In this section, we verify the parallel pre-trend assumption necessary for the validity of the DID approach, and test the robustness of our results using a series of rigorous methods, including placebo tests, alternative treatment variables, different propensity score matching methods, reassessments of the impact on air quality during the heating season, and controlling for other concurrent policies.

4.2.1. Parallel Pre-Trends and Dynamic Effects of the REHP

We applied the event study method to analyze the dynamics of air quality improvements in response to the REHP by estimating the following equation:

$$AQI_{ik} = \alpha + \sum_{k=-6, k \neq -1}^{k=2} \beta_k (Treat_i \times Post_k) + Controls'_{ik} + \delta_i + \theta_k + \epsilon_{ik}, \quad (2)$$

where $Post_k$ is a time dummy variable, with β_k capturing the different trends in air quality between the treatment and control cities in the k_{th} year after the policy implementation ($-k$ refers to the k th year before the policy). We took period-1 as the base period. Figure 4 shows that the estimated coefficients of β_k for the periods before the policy implementation are not significant, confirming that there were no significant differences in air quality trends between the treated and control cities before the REHP. However, after the policy implementation, air quality begins to improve in the treated cities, and these effects are persistent.

4.2.2. Placebo Tests

To address the potential influence of unobservable omitted variables on the baseline regression results, we conducted two falsification tests. First, we performed a placebo test using a fictitious treatment group. Specifically, 295 cities from the sample were randomly assigned to a pseudo-treatment group, while the remaining cities served as the pseudo-control group. This process was repeated 500 times. As illustrated in Figure 5, the p -values and kernel density distributions of the coefficient estimates demonstrate that the regression coefficients cluster around zero and adhere to a normal distribution. This suggests that the majority of the regression results are not statistically significant. Furthermore, the coefficient estimates from the baseline regression fall within the lower end of the distribution of spurious regression coefficients, indicating that the baseline results are not influenced by unobservable factors. Second, we performed another placebo test by assigning a fictitious

treatment date. Specifically, we simulated the implementation of the REHP occurring one, two, and three years earlier than its actual introduction. Table 6 reports the regression results for these placebo treatment dates. The estimated coefficients of the interaction terms are not statistically significant, reinforcing the conclusion that the observed improvements in air quality are attributable to the actual implementation of the REHP, rather than being due to spurious factors.

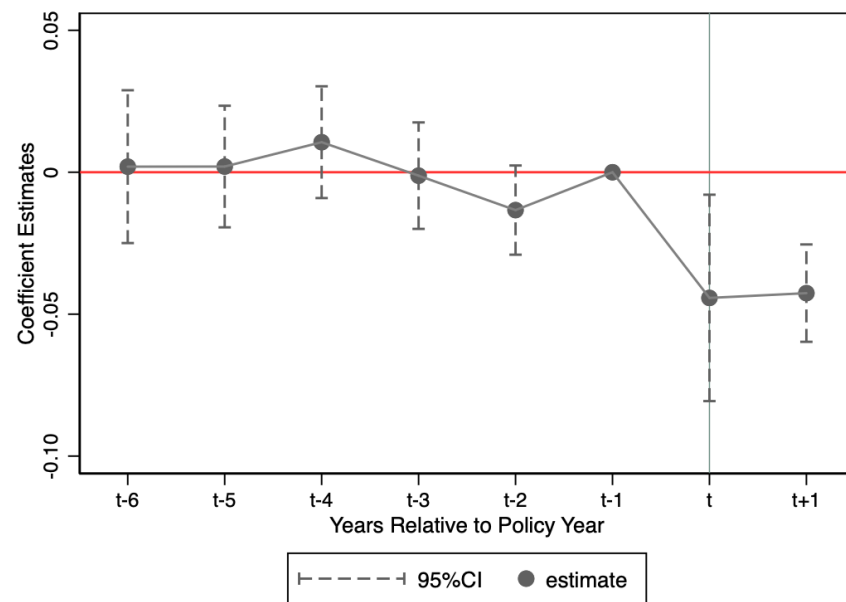


Figure 4. Parallel trend test and its dynamic implications.

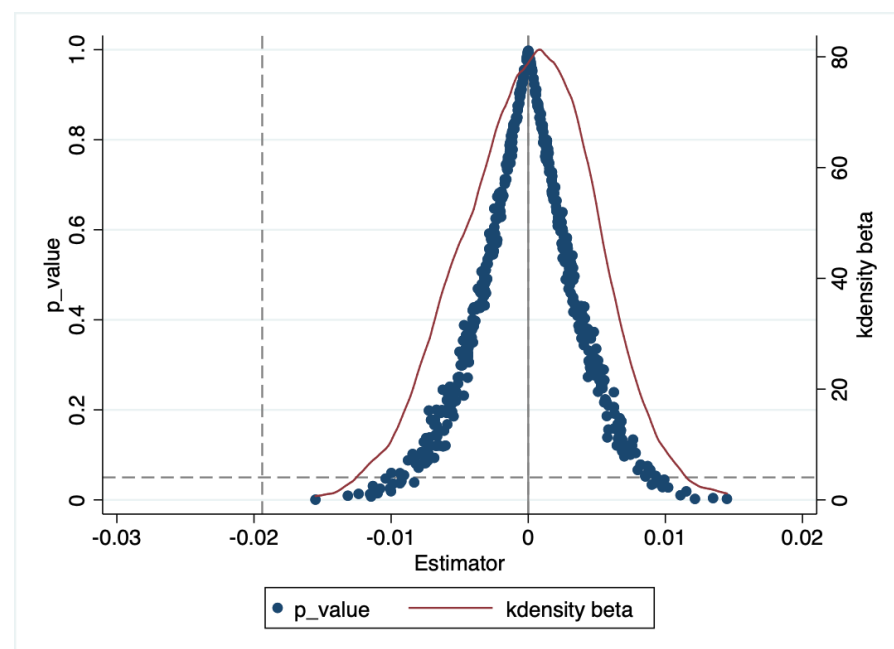


Figure 5. Placebo tests—fictitious treatment group.

Table 6. Placebo test: fictitious treatment time.

Dep.Variable	(1)	(2)	(3)
	AQI	AQI	AQI
Treat × Post-1	0.0026 (0.0068)		
Treat × Post-2		−0.0038 (0.0077)	
Treat × Post-3			−0.0032 (0.0088)
LnGDP	0.0695 *** (0.0214)	0.0685 *** (0.0213)	0.0686 *** (0.0213)
LnPop	0.2120 ** (0.0850)	0.2062 ** (0.0841)	0.2064 ** (0.0839)
LnInd	0.0079 (0.0119)	0.0068 (0.0119)	0.0069 (0.0119)
Exp	−0.1104 (0.1038)	−0.0989 (0.1041)	−0.1013 (0.1037)
IndStr	−0.1691 *** (0.0624)	−0.1817 *** (0.0627)	−0.1800 *** (0.0627)
City FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observation	2504	2504	2504
adj. R ²	0.929	0.929	0.929

Notes: This table presents the results of the placebo test conducted by creating a fictitious treatment date. The implementation of the REHP is set one, two, and three years before it actually occurred. Robust standard errors are reported in parentheses. Significance levels are denoted by ** and *** for the 5% and 1% levels, respectively.

4.2.3. Alternative Treatment Variable

To accurately reflect the heating situation, we explored various alternative specifications of the treatment variable. In Columns (1) and (2) of Table 7, the treatment variable is refined to encompass only those cities with citywide municipal central heating, excluding cases where heating is limited to certain residential areas. Unlike the time-invariant treatment variable employed in the baseline regression, Columns (3) and (4) take into account the possibility of time-varying heating cases. To illustrate this, the pilot urban heating project in Lhasa was implemented in 2012, that in Liupanshui in 2014, and that in Nagqu in 2016. The results confirm that REHP significantly reduces air pollution within the treatment group, consistent with previous findings.

Table 7. Alternative treatment variable.

Dep.Variable	(1)	(2)	(3)	(4)
	Excluding Heating Cases in Certain Residential Areas		Considering Time-Varying Heating Cases	
	AQI	AQI	AQI	AQI
Treat × Post	−0.0198 ** (0.0078)	−0.0179 ** (0.0072)	−0.0215 *** (0.0074)	−0.0195 *** (0.0068)
LnGDP		0.0692 *** (0.0213)		0.0695 *** (0.0213)
LnPop		0.1966 ** (0.0830)		0.1960 ** (0.0831)
LnInd		0.0061 (0.0118)		0.0052 (0.0118)
Exp		−0.0854 (0.1033)		−0.0864 (0.1035)

Table 7. Cont.

	(1)	(2)	(3)	(4)
	Excluding Heating Cases in Certain Residential Areas		Considering Time-Varying Heating Cases	
Dep.Variable	AQI	AQI	AQI	AQI
IndStr		−0.2029 *** (0.0627)		−0.2040 *** (0.0623)
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observation	2529	2504	2529	2504
adj. R^2	0.923	0.929	0.923	0.929

Notes: This table presents the results of replacing the alternative treatment variable. Columns (1) and (2) provide estimates excluding heating cases in certain residential areas, while Columns (3) and (4) show the results after considering time-varying heating cases. Robust standard errors are reported in parentheses. Significance levels are denoted by ** and *** for the 5% and 1% levels, respectively.

4.2.4. Alternative Propensity Matching Methods

To ensure the robustness of our analysis, we employed multiple matching techniques: 1:2 nearest neighbor matching, radius matching, and kernel matching. The 1:2 nearest neighbor matching method pairs each treated unit with two control units that have the closest propensity scores, thereby minimizing the differences between matched pairs. Radius matching extends this approach by pairing treated units with all control units within a specified radius of the propensity score, providing greater flexibility and reducing the risk of poor matches. Kernel matching, in contrast, employs a weighted average of all control units to form a comparison group, giving higher weights to control units with propensity scores closer to those of the treated units [50–52]. The results, as presented in Table 8, are both qualitatively and quantitatively consistent with the baseline findings reported in Table 3.

Table 8. Alternative propensity matching methods.

	(1)	(2)	(3)
	Nearest Neighbor Matching (1:2)	Radius Matching	Kernel Matching
Dep.Variable	AQI	AQI	AQI
Treat × Post	−0.0310 ** (0.0124)	−0.0246 *** (0.0090)	−0.0359 *** (0.0086)
LnGDP	0.1467 *** (0.0244)	0.1152 *** (0.0236)	0.1280 *** (0.0251)
LnPop	0.2206 (0.1397)	0.2134 ** (0.1013)	0.1156 (0.1262)
LnInd	−0.0428 ** (0.0198)	−0.0123 (0.0148)	−0.0259 (0.0161)
Exp	−0.1602 (0.1730)	−0.1192 (0.1176)	−0.0393 (0.1445)
IndStr	−0.1098 (0.1486)	−0.1361 (0.0920)	−0.1235 (0.1008)
City FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Observation	1699	2503	2482
adj. R^2	0.951	0.940	0.948

Notes: This table presents the results of using alternative propensity matching methods. 1:2 Nearest neighbor matching, radius matching, and kernel matching are presented in Columns (1), (2), and (3), respectively. Robust standard errors are reported in parentheses. Significance levels are denoted by ** and *** for the 5% and 1% levels, respectively.

4.2.5. The Effect on Air Quality During the Heating Season

We replaced the independent variable with the average air quality during the heating season (November to March) instead of the annual average, then tested the effect of REHP on air quality and pollutant concentrations during the heating season using the PSM-DID approach. The results, shown in Table 9, indicate larger coefficients than those in column (4) of Tables 3 and 5, reflecting a more significant improvement in air quality during the heating season and confirming the robustness of our results.

Table 9. The effect on air quality during the heating season.

	(1)	(2)	(3)	(4)	(5)
Dep.Variable	AQI	SO ₂	CO	NO ₂	PM2.5
Treat × Post	−0.0413 ** (0.0187)	−0.2922 *** (0.0670)	−0.1000 ** (0.0392)	−0.0477 ** (0.0211)	−0.0806 *** (0.0239)
LnGdp	0.1644 *** (0.0475)	0.1518 (0.1651)	−0.0209 (0.0985)	0.1012 (0.0747)	0.1996 *** (0.0608)
LnPop	0.1167 (0.2030)	0.5328 (0.6821)	0.1507 (0.2639)	−0.3369 (0.2223)	−0.1946 (0.2307)
LnInd	−0.0533 (0.0367)	0.0276 (0.0943)	0.0216 (0.0580)	0.0817 ** (0.0323)	−0.0668 (0.0431)
Exp	−0.6062 ** (0.2850)	−0.7707 (0.7832)	−0.9263 ** (0.4556)	−0.2043 (0.3345)	−0.7599 ** (0.3732)
IndStr	−0.2516 (0.2335)	0.6641 (0.6382)	0.3142 (0.3947)	−0.1228 (0.2148)	0.0155 (0.2590)
City FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observation	1163	1163	1163	1163	1163
adj. R ²	0.935	0.909	0.874	0.944	0.952

Notes: This table presents the results of the effect on air pollutant concentrations during the heating season, including the Air Quality Index (AQI), sulfur dioxide (SO₂), carbon monoxide (CO), nitrogen dioxide (NO₂), and particulate matter (PM2.5), as estimated using a PSM-DID model. Robust standard errors are reported in parentheses. Significance levels are denoted by ** and *** for the 5% and 1% levels, respectively.

4.2.6. Eliminating the Interference of Other Policies

During the sample period from 2014 to 2022, some policies related to energy and environment were promulgated. In 2014, the National Energy Administration released a notice announcing an initial list of 81 new energy demonstration cities. Subsequently, in 2017, the central government introduced the “Winter Clean Heating Plan for Northern China (2017–2021),” targeting the “2 + 26” cities within the Beijing–Tianjin–Hebei air pollution corridor. To account for potential interference from other policies, we conducted a robustness check by excluding two groups of cities from our sample. Columns (1) and (2) present estimates excluding the initial batch of new energy demonstration cities, while Columns (3) and (4) provide results after removing the “2 + 26” cities included in the Winter Clean Heating Plan. Our regression analysis, detailed in Table 10, demonstrates that these adjustments did not alter the main conclusions of our study. This consistency underscores the robustness of our findings, suggesting that the observed effects are attributable to the policies under investigation rather than the influence of other concurrent policies.

Table 10. Eliminating the interference of other policies.

	(1)	(2)	(3)	(4)
	New Energy Demonstration Cities Policy		Clean Heating Plan for Winter in the Northern Region	
Dep.Variable	AQI	AQI	AQI	AQI
Treat $\times$ Post	−0.0241 *** (0.0085)	−0.0206 *** (0.0076)	−0.0190 ** (0.0078)	−0.0156 ** (0.0071)
LnGDP		0.0677 *** (0.0216)		0.0689 *** (0.0212)
LnPop		0.1982 ** (0.0885)		0.2048 ** (0.0841)
LnInd		−0.0034 (0.0130)		0.0111 (0.0123)
Exp		−0.1816 (0.1111)		−0.1146 (0.1047)
IndStr		−0.2361 *** (0.0657)		−0.2207 *** (0.0627)
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observation	1993	1972	2394	2364
adj. R^2	0.923	0.930	0.916	0.924

Notes: This table presents the results after controlling for the interference of other policies. Columns (1) and (2) display estimates excluding the initial batch of new energy demonstration cities. Columns (3) and (4) show results after removing the “2 + 26” cities from the Winter Clean Heating Plan in the northern region. Robust standard errors are reported in parentheses. Significance levels are indicated by ** and *** for the 5% and 1% levels, respectively.

5. Further Discussions

5.1. Heterogeneity Effects

In this section, we explore the heterogeneity in the effects of the REHP on air quality in cities with different temperatures and geographical locations.

Air pollutant concentrations in ambient air are influenced by meteorological factors such as temperature, wind speed, and humidity [53–56]. To capture the effect of temperature on our baseline results, we divided the sample into groups based on whether city temperatures were above or below the average. Columns (1) and (2) of Table 11 report the estimated heterogeneity effects related to temperature. The results show that the REHP leads to more substantial improvements in air quality in low-temperature regions than in high-temperature regions. This pattern can be explained by several factors. On the one hand, higher temperatures tend to exacerbate pollution levels. Aw and Kleeman [53] report that non-volatile secondary particulate matter and ozone concentrations generally increase at relatively high temperatures due to the accelerated gas-phase reaction rates. Additionally, Jayamurugan et al. [55] confirm that the influence of temperature on gaseous pollutants (SO_2 and NO_x) is much greater in the summer than in other seasons, due to the higher temperature range. On the other hand, there is a strong demand for heating in low-temperature areas, and the use of renewable energy can bring more significant improvements in air quality, as opposed to traditional coal-based methods. The mechanisms related to coal consumption are discussed in Section 5.2.

The heterogeneity results based on geographical locations are presented in Columns (3), (4), and (5). The analysis reveals a significant negative effect of the REHP on air quality in the eastern region. However, the estimated coefficients for the interaction terms in the middle and western regions are not statistically significant. This regional variation in policy effectiveness can likely be attributed to several factors. The eastern region, characterized by a higher level of economic development, places greater emphasis on environmental protection [57,58]. Additionally, the region’s advanced green infrastructure [59] and the

high penetration rate of green technology [60] amplify the policy's impact, making its effects more pronounced than those in the less developed middle and western regions.

Table 11. Temperature and regional heterogeneity in the effects of the REHP on air quality.

Dep.Variable	(1)	(2)	(3)	(4)	(5)
	Temperature Heterogeneity		Region Heterogeneity		
	Low	High	East	Middle	West
	AQI	AQI	AQI	AQI	AQI
Treat × Post	−0.0542 *** (0.0122)	−0.0281 *** (0.0088)	−0.0648 *** (0.0081)	−0.0014 (0.0113)	0.0188 (0.0152)
LnGDP	0.1051 *** (0.0311)	0.0179 (0.0309)	0.0616 * (0.0315)	0.0856 ** (0.0355)	0.0679 (0.0511)
LnPop	0.0985 (0.0822)	0.3146 * (0.1628)	0.3028 *** (0.1151)	0.1291 (0.1578)	0.0672 (0.1236)
LnInd	0.0393 ** (0.0170)	−0.0409 ** (0.0160)	−0.0148 (0.0168)	0.0253 (0.0204)	−0.0400 (0.0315)
Exp	0.0818 (0.1325)	−0.3085 * (0.1568)	−0.2515 (0.1582)	−0.0913 (0.1825)	−0.1262 (0.2248)
IndStr	−0.1786 * (0.0916)	−0.1529 (0.0998)	−0.0164 (0.1113)	−0.2588 ** (0.1149)	−0.1116 (0.1073)
City FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observation	1000	1469	1009	918	489
adj. R ²	0.919	0.935	0.956	0.896	0.939

Notes: This table presents the results regarding the heterogeneous effect of REHP on the Air Quality Index (AQI). Columns (1) and (2) report the heterogeneity effects related to temperature, and Columns (3) and (4) report effects based on geographical location. Robust standard errors are reported in parentheses. Significance levels are indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

5.2. Mechanism Analysis

The REHP mitigates air pollution through three key mechanisms. First, it promotes the transition from coal-based heating to cleaner alternatives, thereby reducing the harmful emissions associated with traditional heating methods. Second, the efficacy of the policy is enhanced by the government's robust commitment to environmental stewardship. The government is actively promoting the replacement of coal-fired boilers with gas or electric systems in urban areas and providing subsidies for rural households to transition from coal stoves to cleaner alternatives. Additionally, government regulations have been shown to heighten public awareness of environmental protection, particularly regarding the potential link between air quality and health [61,62]. Third, the success of the energy transition policy is closely tied to advancements in green technology. The Porter Hypothesis [63] posits that stricter environmental regulations can stimulate innovation in cleaner technologies, leading to significant environmental improvements [60].

Table 12 reports the results of the mechanism analysis. First, as illustrated in Panel A, the reduction in coal consumption provides direct evidence of the REHP's effectiveness in promoting the transition from coal-based heating to cleaner alternatives. Second, the role of government environmental governance (*EnvReg*) is evaluated using a word frequency analysis of Chinese local government work reports. By incorporating an interaction term between *EnvReg* and the *Treat × Post*, the analysis in Columns (1) and (2) of Panel B reveals a negative and statistically significant coefficient at the 1% level, confirming that the government's strong commitment to environmental stewardship enhances the policy's effectiveness. Additionally, the estimates in Columns (3) and (4) of Panel B underscore the critical role of technology expenditure in improving the air quality of the REHP.

Table 12. Mechanism analysis.

Panel A: Consumption of Coal				
Dep.Variable	(1) LnCoal	(2) LnCoal		
Treat × Post	−0.1378 *** (0.0372)	−0.0700 ** (0.0308)		
Controls	No	Yes		
City FEs	Yes	Yes		
Year FEs	Yes	Yes		
Observation	6831	6584		
adj. R ²	0.942	0.951		
Panel B: Government Environmental Regulations and Technology Expenditure				
Dep.Variable	(1) AQI	(2) AQI	(3) AQI	(4) AQI
Treat × Post × EnvReg	−0.0050 *** (0.0019)	−0.0044 ** (0.0017)		
EnvReg	0.0005 (0.0058)	0.0005 (0.0055)		
Treat × Post × TechExp			−0.0434 * (0.0230)	−0.0396 * (0.0214)
TechExp			0.0049 (0.0201)	0.0040 (0.0195)
Controls	No	Yes	No	Yes
City FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observation	2438	2432	2508	2504
adj. R ²	0.923	0.927	0.925	0.929

Notes: This table presents the results of the mechanism analysis. In Panel A, the dependent variable is coal consumption. Control variables are excluded in Column (1) and included in Column (2), although they are not reported for brevity. In Panel B, the interaction terms between the policy and both government environmental regulation (EnvReg) and technology expenditure (TechExp) are added. Columns (1) and (3) exclude control variables, while Columns (2) and (4) include them. The control variables consist of LnGDP, LnPop, LnInd, Exp, and IndStr. Robust standard errors are reported in parentheses. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

6. Conclusions

This paper investigates the impact of promoting renewable energy heating on air quality in northern China. Using a difference-in-differences approach and panel data from 298 cities from 2014 to 2022, the study reveals that the renewable energy heating policy significantly enhances air quality. The policy not only reduces the overall air quality index (AQI) but also leads to notable decreases in key pollutants, with concentrations of SO₂, CO, NO₂, and PM_{2.5} dropping by 28.31%, 7.57%, 5.72%, and 7.15%, respectively. The effects of REHP on air quality are heterogeneous, with stronger impacts being observed in low-temperature and eastern regions. Further analysis indicates that the policy's success is driven by the shift from coal-based heating to cleaner alternatives, supported by the government's strong commitment to environmental governance and augmented technological investment. The conclusions remain robust when subjected to various tests, including checks for parallel pre-trends, placebo tests, alternative treatment variables, propensity score matching methods, reassessments the impact on air quality during the heating seasons, and controlling for the interference of other concurrent policies.

Based on our findings, we recommend a strategic focus on advancing energy transition, strengthening government regulations, and fostering technological innovation to promote energy conservation and emission reductions. First, the optimization of the thermal energy

structure is crucial. Under the carbon peak and neutrality goals, coal-fired boilers with a low energy efficiency and high carbon intensity should be prioritized for gradual decommissioning. In northern cities, fossil fuels still account for 85.8% of the heating methods [5]. Therefore, expanding the use of clean energy sources such as solar, wind, and geothermal energy is imperative for diversifying the energy supply and enhancing efficiency. The Yangtze River Basin is projected to experience a substantial increase in heating demand, reaching 35 billion m² by 2050, but over 99% of the region's heating remains decentralized. Thus, residents who rely on inefficient and polluting coal should be integrated into centralized heating networks or distributed renewable systems to improve energy efficiency and reduce air pollution. Additionally, promoting distributed renewable energy systems, such as rooftop solar panels and small-scale wind turbines, will support decentralized clean heating solutions. Second, government environmental regulations should be strengthened. Policymakers should implement financial incentives like subsidies, tax credits, and low-interest loans for households, businesses, and industries investing in renewable energy heating technologies, such as electric heat pumps or solar thermal systems. Furthermore, emission reduction standards for heating systems should be updated regularly to align with carbon neutrality goals. Finally, sustained investment in R&D is vital for maintaining technological innovations in renewable energy heating. Government funding should focus not only on advancing heating technologies but also on improving energy efficiency across the entire heating value chain. This includes developing energy-efficient building designs, retrofitting existing structures with superior insulation, and implementing smart heating controls to optimize energy use. A promising area for future research is the development of regional heating balance models to evaluate the sufficiency of waste heat resources and determine the necessary seasonal heat storage capacity for each region. Collaboration between academic institutions, technology companies, and the heating industry is critical for accelerating the commercialization of innovative technologies. By addressing these areas, we can foster a more sustainable energy landscape, significantly reduce emissions, and improve the effectiveness of renewable energy solutions.

Author Contributions: Conceptualization, A.T. and Y.Z.; methodology, A.T.; software, A.T.; validation, A.T.; formal analysis, W.G.; resources, Y.Z.; data curation, Y.Z.; writing—original draft preparation, W.G.; writing—review and editing, C.W.; visualization, C.W. All authors have read and agreed to the published version of the manuscript.

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

Appendix A

Table A1. Classification of Central Heating in Chinese Cities.

Province	Num.	Cities
(1) Municipal Central Heating (Treatment Group)		
Beijing	1	Beijing
Tianjin	1	Tianjin
Hebei	11	Baoding, Tangshan, Langfang, Zhangjiakou, Chengde, Cangzhou, Shijiazhuang, Qinhuangdao, Hengshui, Xingtai, Handan

Table A1. Cont.

Province	Num.	Cities
Inner Mongolia	9	Ulanqab, Wuhai, Baotou, Hulunbuir, Hohhot, Bayannur, Chifeng, Tongliao, Ordos
Shanxi	11	Linfen, Luliang, Datong, Taiyuan, Xinzhou, Jinzhong, Jincheng, Shuozhou, Yuncheng, Changzhi, Yangquan
Shandong	16	Dongying, Linyi, Weihai, Dezhou, Rizhao, Zaozhuang, Tai 'an, Jinan, Jining, Zibo, Binzhou, Weifang, Yantai, Liaocheng, Heze, Qingdao
Heilongjiang	12	Qitaihe, Yichun, Jiamusi, Shuangyashan, Harbin, Daqing, Mudanjiang, Suihua, Jixi, Hegang, Heihe, Tsitsihar
Jilin	8	Jilin, Siping, Songyuan, Baicheng, Baishan, Liaoyuan, Tonghua, Changchun
Liaoning	14	Dandong, Dalian, Fushun, Chaoyang, Benxi, Shenyang, Panjin, Yingkou, Huludao, Liaoyang, Tieling, Jinzhou, Fuxin, Anshan
Shaanxi	10	Xianyang, Shangluo, Ankang, Baoji, Yan'an, Yulin, Hanzhong, Weinan, Xi'an, Tongchuan
Ningxia	5	Zhongwei, Wuzhong, Guyuan, Shizuishan, Yinchuan
Gansu	12	Lanzhou, Jiayuguan, Tianshui, Dingxi, Pingliang, Qingyang, Zhangye, Wuwei, Baiyin, Jiuquan, Jinchang, Longnan
Qinghai	3	Haidong, Hainan Tibetan Autonomous Prefecture, Xining
Xinjiang	4	Urumqi, Karamay, Turpan, Hami
Henan	15	Sanmenxia, Nanyang, Shangqiu, Anyang, Pingdingshan, Kaifeng, Xinxiang, Luoyang, Luohe, Puyang, Jiaozuo, Xuchang, Zhengzhou, Zhumadian, Hebi
Anhui	1	Hefei
Jiangsu	1	Xuzhou
Total	134	
(2) Partial or District-based Heating (Treatment Group)		
Anhui	7	Wuhu, Bengbu, Huainan, Suzhou, Huaibei, Fuyang, Bozhou
Jiangsu	6	Lianyungang, Changzhou, Nanjing, Yangzhou, Suzhou, Huai 'an
Hubei	3	Shiyan, Xiangyang, Jingmen
Guizhou	1	Liupanshui
Tibet	2	Lhasa, Naqu
Total	19	
(3) No municipal Central Heating (Control Group)		
Henan	2	Xinyang, Zhoukou
Anhui	8	Lu'an, Anqing, Xuancheng, Chizhou, Chuzhou, Tongling, Maanshan, Huangshan
Jiangsu	6	Nantong, Suqian, Wuxi, Taizhou, Yancheng, Zhenjiang
Hubei	9	Xianning, Xiaogan, Yichang, Wuhan, Jingzhou, Ezhou, Suizhou, Huanggang, Huangshi
Guizhou	5	Anshun, Bijie, Guiyang, Zunyi, Tongren
Sichuan	18	Leshan, Neijiang, Nanchong, Yibin, Bazhong, Guangyuan, Guang'an, Deyang, Chengdu, Panzhihua, Luzhou, Meishan, Mianyang, Zigong, Ziyang, Dazhou, Suining, Ya'an
Yunnan	8	Lincang, Lijiang, Baoshan, Kunming, Zhaotong, Pu'er, Qujing, Yuxi
Tibet	4	Shannan, Xigaze, Qamdo, Nyingchi
Shanghai	1	Shanghai
Chongqing	1	Chongqing
Zhejiang	11	Lishui, Taizhou, Jiaxing, Ningbo, Hangzhou, Wenzhou, Huzhou, Shaoxing, Zhoushan, Quzhou, Jinhua
Fujian	9	Sanming, Nanping, Xiamen, Ningde, Quanzhou, Zhangzhou, Fuzhou, Putian, Longyan
Jiangxi	11	Shangrao, Jiujiang, Nanchang, Ji'an, Yichun, Fuzhou, Xinyu, Jingdezhen, Pingxiang, Ganzhou, Yingtan
Hunan	13	Loudi, Yueyang, Changde, Zhangjiajie, Huaihua, Zhuzhou, Yongzhou, Xiangtan, Yiyang, Hengyang, Shaoyang, Chenzhou, Changsha
Guangdong	21	Dongguan, Zhongshan, Yunfu, Foshan, Guangzhou, Huizhou, Jieyang, Meizhou, Shantou, Shanwei, Jiangmen, Heyuan, Shenzhen, Qingyuan, Zhanjiang, Chaozhou, Zhuhai, Zhaoqing, Maoming, Yangjiang, Shaoguan
Guangxi	14	Beihai, Nanning, Chongzuo, Laibin, Liuzhou, Guilin, Wuzhou, Hechi, Yulin, Baise, Guigang, Hezhou, Qinzhou, Fangchenggang
Hainan	4	Sanya, Sansha, Danzhou, Haikou
Total	145	

Data Source: 2022 China Urban Construction Statistical Yearbook, supplemented with publicly available materials.

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