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Can Energy-Consuming Rights Trading Policies Help to Curb Air Pollution? Evidence from China

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Abstract: Energy-consuming rights trading policies (ECRTPs) represent a significant institutional innovation for China aimed at achieving the dual control targets of total energy consumption and energy consumption intensity. However, the effectiveness of these policies in curbing air pollution remains uncertain. This study treats ECRTPs as a quasi-natural experiment to empirically analyze their impact on air pollution, utilizing panel data encompassing 277 prefecture-level cities in China covering the period from 2011 to 2021. Analytical methods applied include a Difference-in-Differences model, a mediation effects model, and a triple differences model to explore the effects of ECRTPs on air pollution. The findings reveal that ECRTP can significantly suppress air pollution, and this conclusion remains valid even after conducting robustness tests. Mechanism analysis indicates that ECRTPs suppress air pollution by boosting energy efficiency, advancing industrial structure upgrading, and facilitating technological innovation. Further heterogeneous studies show that ECRTPs have a more pronounced inhibitory effect on air pollution in cities that are economically and socially developed, exhibit greater energy-saving potential, are characterized as resource-based cities, and serve as key regions for the prevention and control of air pollution. The research conclusion provides empirical evidence and policy implications for evaluating the environmental effects of ECRTPs and further improving China's energy-consuming rights trading system, as well as offering references and guidance for other developing countries to put forward ECRTPs.

Keywords: energy-consuming rights trading policy; air pollution; industrial structure upgrading; energy efficiency; technological innovation; heterogeneity; mechanism

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1. Introduction

The detrimental effects of global environmental pollution and the threats stemming from extreme climate conditions have serious adverse impacts on both the economy and human health [1,2]. Following hypertension and smoking, air pollution is the third leading risk factor involved in global mortality [3]. The "2023 Global Air Quality Report" released by the IQAir global air quality data platform pointed out that, among the 134 countries and regions studied, 124 did not meet the WHO $PM_{2.5}$ guideline standards, reaching as high as 92.5%. Air pollution not only alters the frequency of extreme climate events [4] but also harms human health [5–7] and affects economic development [8], all of which are closely related to people's production and livelihood. Therefore, identifying the influencing factors of air pollution and implementing effective control measures have become central concerns for both the academic community and the government. Numerous scholars, both domestically and internationally, have discerned economic activities [9], population factors [10], environmental regulations [11], rail transportation [12,13], openness to international trade [14], industrial structure [15], financial development [16], and urbanization [17] as significant factors influencing air pollution. Of all these factors, environmental regulations are regarded with high expectations and have the potential to serve as an effective tool for controlling air pollution. As a result, various countries worldwide have implemented a range of environmental regulations, such as the White Certificate System in the European Union [18], renewable energy policies in Latin American nations [19], the carbon emissions trading system in China [20], and the Energy-Consuming Rights Trading Policy (ECRTP) in China [21]. Among them, the ECRTP is particularly noteworthy as a novel institutional innovation that fills the gap in the forefront governance of environmental regulation. Whether it can achieve environmental benefits while driving energy efficiency improvement is a question of concern for policymakers and researchers.

Currently, research on ECRTP can be classified into three main categories. The first category pertains to the design of institutional systems, with a focus on ECRTP's regulatory objectives [22], legal systems [23], trading rules [24], and implementation paths, as well as issues related to the connection with carbon emission trading systems [25,26]. The second category involves simulating the economic benefits of ECRTP as well as its potential for energy savings and emission reduction. For example, Liu et al. used non-parametric DEA to simulate energy policy combinations under three different scenarios and found that the combination of ECRTP and carbon emission trading policies can achieve optimal economic dividend effects [27]. Li Yuan et al. developed a mathematical model where ECRTP coexists with the carbon market, and the results showed that these two policies are complementary in reducing energy consumption [28]. Zhang et al. discovered, through constructing a non-parametric optimization model, that ECRTP can bring higher average economic potential and energy-saving potential at the industrial level in comparison to command control policies [29]. The third category relates to evaluating the policy effects of ECRTP. Research in this area primarily focuses on the impact of ECRTP on economic benefits [30], technological innovation or green innovation [31,32], total factor productivity [33], industrial structure [34], energy consumption intensity [35], energy utilization efficiency [36], energy consumption structure [37], as well as the effects on carbon emissions [30,38].

While the existing literature predominantly focuses on the institutional design of the ECRTP, as well as its economic benefits, potential for energy conservation, emission reduction, and policy implications, research on the impact of the ECRTP on air pollution is still in its nascent stage. Wang et al. conducted a study utilizing data from 282 prefecture-level cities in China, covering the period from 2013 to 2019, employing a Difference-in-Differences (DID) model to investigate the effects of the ECRTP on pollution and carbon reduction. Their findings demonstrated that the ECRTP achieved dual environmental benefits by simultaneously reducing pollution and carbon emissions [39]. In another study, Wang et al. analyzed panel data from 290 cities in China spanning the years 2010 to 2021, utilizing the Propensity Score Matching-Difference in Differences (PSM-DID) model to examine the impacts of the ECRTP. They found that pilot cities participating in the ECRTP experienced substantial improvements in pollution and carbon reduction levels compared to non-pilot cities [40]. Similarly, Han et al. carried out regression analyses on panel data from 266 prefecture-level cities in China from 2011 to 2020, employing a DID model. Their research revealed that CO_2 and SO_2 emissions in pilot cities decreased by 84.8% and 34.5%, respectively [41]. Additionally, Song et al. undertook an empirical analysis to assess the impact of the ECRTP on the environment, utilizing panel data from Chinese prefecture-level cities over the period of 2012–2019. They employed a multi-period PSM-DID approach in their study. The results demonstrated that the ECRTP effectively reduced both the total emissions and the emission intensity of soot pollutants, exhibiting a more pronounced inhibitory effect on the emission intensity [42]. In contrast, Wang et al. investigated the impacts of the ECRTP on various pollutants, including nitrogen oxides (NO_x), sulfur dioxide (SO_2), carbon dioxide (CO_2), and smoke, and they concluded that the estimated coefficients were not statistically significant [43].

Existing studies reveal several limitations. Firstly, although some of the literature has begun to explore the impact of ECRTP on air pollution, there remains a lack of consensus regarding the research findings. The effectiveness of ECRTP in suppressing air pollution lacks robust empirical support. Secondly, the existing literature predominantly focuses on ECRTP's effects on pollutants, such as CO_2, SO_2, NO_x, and smoke, while neglecting to assess the policy's impact on air pollution through the lens of $PM_{2.5}$, a crucial representative of air pollutants. Thirdly, current research is deficient in regard to providing a comprehensive analysis of the transmission mechanisms and the heterogeneity of effects related to ECRTP. Consequently, further research is warranted. This study applies the DID model, mediation effect model, and triple differences model to explore the influence of ECRTP on air pollution and its intrinsic mechanisms, leveraging panel data encompassing 277 prefecture-level cities in China during the period of 2011–2021.

Compared to the existing literature, this study offers innovations in the following four aspects. Firstly, this study delves into the theoretical aspects of ECRTP by analyzing its impact on air pollution from multiple perspectives and exploring the mechanisms of action involved. In contrast to previous studies, this paper provides a more comprehensive observational viewpoint in its theoretical analysis, thereby enriching the theoretical framework. Secondly, considering that the governance of $PM_{2.5}$ has emerged as a global challenge, this study notably departs from existing research by employing $PM_{2.5}$ as a proxy variable for air pollution in evaluating the policy effects of ECRTP. This approach effectively bridges a substantial gap in the current literature. Thirdly, the study identifies and examines the intrinsic mechanisms of ECRTP's impact on air pollution through three pathways: energy efficiency, industrial structure upgrading, and technological innovation, providing new insights for addressing urban air pollution issues.

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Fourthly, to comprehensively evaluate the policy effects of ECRTP on air pollution, this study investigates the heterogeneous impacts of ECRTP on air pollution from various perspectives, including geographic location, resource endowment, energy-saving potential, and environmental protection types. This analysis offers more targeted support and decision-making grounds for air pollution governance in cities with diverse characteristics.

The structure of the remaining sections of this paper is organized as follows: Section 2 entails theoretical analysis and research hypotheses. Section 3 covers research design, including model construction, variable design, and data description. Section 4 is dedicated to empirical analysis, encompassing variable descriptive statistics, parallel trend tests, baseline regression analysis, and robustness tests. Section 5 focuses on mechanism testing, while Section 6 explores heterogeneity analysis. Section 7 provides a discussion, and Section 8 presents the conclusions, policy implications, and limitations.

2. Theoretical Analysis and Research Hypotheses

2.1. ECRTP and Air Pollution

ECRTP pertains to the comprehensive energy consumption quota acquired through issuance or transactions within a specific period, enabling the consumption of a specific amount of integrated energy consumption units under the premise of controlling the total amount and intensity of energy consumption. Energy-consuming rights trading refers to the activities of relevant entities engaging in market-based transactions of energy-consuming rights indicators in compliance with the law [44]. According to the definition established by the International Organization for Standardization (ISO), air pollution refers to the introduction of certain substances into the atmosphere due to human activities or natural processes. When these substances accumulate to sufficiently high concentrations over extended periods, they pose a threat to human comfort, health, and welfare, as well as to the environment. Recognizing that $PM_{2.5}$ is a major pollutant with serious implications for human health, this paper employs $PM_{2.5}$ concentration as a metric for assessing air pollution. If ECRTP demonstrates the ability to reduce $PM_{2.5}$ levels in the atmosphere, it would indicate its potential in alleviating air pollution. Moreover, ECRTP represents a form of market-based environmental regulation, possessing policy attributes similar to general environmental regulations. It can incentivize micro-enterprises to engage in green production through cost-increasing effects and the Porter hypothesis effect, thereby influencing air pollution. Unlike pollution rights and carbon emission trading policies, which are market-based environmental regulations relying on end-of-pipe governance, ECRTP focuses on achieving energy saving and emission reduction through controlling energy use at the source, optimizing energy structures, and enhancing resource allocation efficiency on the supply side. According to the Coase theorem of property, as long as property rights are well defined and the transaction costs are zero or very low, the outcome of market equilibrium is efficient, achieving Pareto optimality in resource allocation. Applying the Coase theorem of property to the field of ECRTP can bring two main advantages. Firstly, ECRTP can leverage market forces to find the marginal cost of energy conservation and emission reduction, consequently minimizing the overall cost of energy conservation and emission reduction while achieving optimal energy resource allocation within the region. Secondly, as long as the cost of technological improvements is lower than the price of resource and environmental rights certificates, ECRTP will incentivize companies to adopt more advanced and environmentally friendly production technologies, thereby reducing emissions of $PM_{2.5}$ air pollutants [45]. Given this, the following hypothesis is proposed:

H1: *ECRTP can significantly suppress air pollution.*

2.2. The Conduction Mechanism of ECRTP on Air Pollution

2.2.1. Energy Efficiency Effect

ECRTP can enhance energy efficiency through three primary avenues. Firstly, it guides decision-making by price signaling. According to the environmental economics theory, ECRTP influences energy-consuming enterprises to purchase or sell energy-consuming rights indicators through price signals, which can greatly promote the rational flow and efficient allocation of energy resources, thereby remedying the limitation of government direct control measures in tackling energy efficiency concerns. Secondly, ECRTP imposes cost constraints. In ECRTP pilot areas, the total energy consumption index is regulated. If the actual energy consumption of controlled energy-consuming enterprises exceeds the energy-consuming rights allocated by the government, they have to purchase excess quotas at market prices. To lower costs, enterprises must optimize production processes by actively adjusting production modes, incorporating energy-saving technologies, and implementing other strategies to boost efficiency, ultimately decreasing overall energy consumption. Thirdly, ECRTP provides reward incentives. Enterprises holding surplus energy-consuming rights indicators can benefit from energy savings by trading these indicators in the energy-consuming rights market. Motivated by these additional incentives, enterprises are prompted to optimize production processes, upgrade production technologies, and promote energy efficiency. Furthermore, researchers like Song [43], Gong [46], and Xu [47] suggest that improving energy efficiency is vital in reducing air pollution and controlling pollutant emissions from unit energy consumption. Given this, the following hypothesis is proposed:

H2: *ECRTP suppresses air pollution by enhancing energy efficiency.*

2.2.2. The Industrial Structure Upgrading Effect

Industrial structure upgrading refers to the process or trend of the transformation of the industrial structure from a lower-level form to a higher-level form, mainly manifested by the continuous increase in the proportion from the primary industry to the secondary industry and then, further, to the tertiary industry [48]. On the one hand, the ECRTP pilot projects are primarily situated in vital energy-consuming industries. When high-energy consumption and high-emission enterprises encounter constraints on energy-consuming rights quotas, they are compelled to transform, upgrade, relocate, or exit. As a result, this restructuring induces a shift in production factors, including capital and talent, from energy-intensive to technology-intensive sectors, driven by market mechanisms. This transition ultimately fosters the optimization and advancement of the industrial structure. On the other hand, the government's allocation of energy quotas tends to favor advanced manufacturing, high-tech industries, strategic emerging industries, and modern service sectors, thereby aiding in the optimization and advancement of the industrial structure. Moreover, the technology spillover effect resulting from industrial structure upgrading can promote the efficient use of energy, facilitate the transition of industries towards cleaner sectors with higher outputs and lower emissions, expedite the elimination of obsolete production capacity, reduce resource wastage, and effectively decrease the emission of air pollutants. Building on the previous discussion, the following hypothesis is proposed:

H3: *ECRTP alleviates air pollution by promoting industrial structure upgrading.*

2.2.3. Technological Innovation Effect

According to the Porter hypothesis, the implementation of ECRTP may increase production costs for enterprises, resulting in negative cost effects. However, a well-designed ECRTP can also generate innovation compensation effects, partially or fully offsetting the costs and thereby stimulating technological innovation within enterprises [49,50]. On the one hand, to alleviate the cost burden of implementing ECRTP, enterprises may opt for technological innovation to decrease unit production energy consumption, thereby circumventing the expenses associated with acquiring energy-consuming right indicators. Simultaneously, technological innovation paves the way for enterprises to attain economies of scale by enhancing overall production levels and cutting production costs, which offsets research and development expenditures, establishing a virtuous cycle that constantly drives technological innovation within enterprises [33]. On the other hand, the establishment of the energy-consuming rights trading market presents opportunities for technical cooperation and transfer among enterprises. This kind of technical cooperation and transfer is beneficial for the exchange of knowledge and experience, thereby broadening and deepening the dissemination of innovative knowledge. This process simplifies the achievement of economies of scale, leading to significant innovation benefits and accelerating the spread and adoption of technologies. [51]. Furthermore, technological innovation, especially green innovation in the low-carbon and green energy-saving fields, can help drive enterprises towards clean production, accelerate the optimization of energy usage structure, and improve energy efficiency. This can reduce energy consumption both in the areas of production and consumption, thus reducing air pollutant emissions from business operations and residential consumption. Simultaneously, it can achieve the primary objectives of energy saving and emission reduction. In consideration of this, the subsequent hypotheses are formulated:

H4: *ECRTP inhibits air pollution by fostering technological innovation.*

2.3. The Heterogeneity Analysis of the Effects of ECRTP on Air Pollution

The impact of ECRTP on air pollution may exhibit regional heterogeneity, meaning that the air pollution mitigation effects of ECRTP can vary due to differences in factors such as urban geographic location, energy-saving potential, resource endowments, and the types of environmental protection measures implemented. Firstly, regions characterized by advanced economic and social development typically exhibit a high degree of industrial agglomeration, robust government regulatory oversight, and a substantial pool of human capital in relevant sectors. These factors contribute to the effective implementation of the policy benefits associated with ECRTP, leading to a more pronounced suppressive effect on air pollution. Secondly, in areas with considerable potential for energy savings, the efficiency of energy utilization tends to be relatively low, and the costs associated with energy conservation are comparatively minimal. This situation creates a pronounced marginal effect of ECRTP on energy savings, thereby enhancing its overall effectiveness in mitigating air pollution. Thirdly, resource-based cities, in contrast to non-resource-based cities, often possess a more simplistic industrial structure, being predominantly centered around the extraction and processing of natural resources, such as minerals and forests. This reliance on resource extraction frequently leads to considerable air pollution. The implementation of the ECRTP can assist these cities in restructuring their industries, allowing them to diminish their long-standing dependence on fossil fuels and, consequently, improving their capacity for air pollution reduction. Fourthly, key control cities, as opposed to those where air pollution is not prioritized for control, serve as principal targets for national and local government initiatives aimed at improving air quality management. These governments implement preferential fiscal and taxation policies, facilitating the concentration of talent, technology, and financial resources. Furthermore, key control cities adopt supplementary environmental regulations that enhance the effectiveness of the ECRTP in reducing air pollution, thereby intensifying their air pollution mitigation effects. Based on this analysis, the following research hypothesis is proposed.

H5: *ECRTP can more effectively mitigate air pollution in cities that are economically and socially developed, demonstrate significant energy-saving potential, are categorized as resource-based cities, and serve as critical areas for air pollution prevention and control.*

Following the theoretical analysis and research assumptions above, the theoretical framework and study hypotheses of this paper are illustrated in Figure 1.

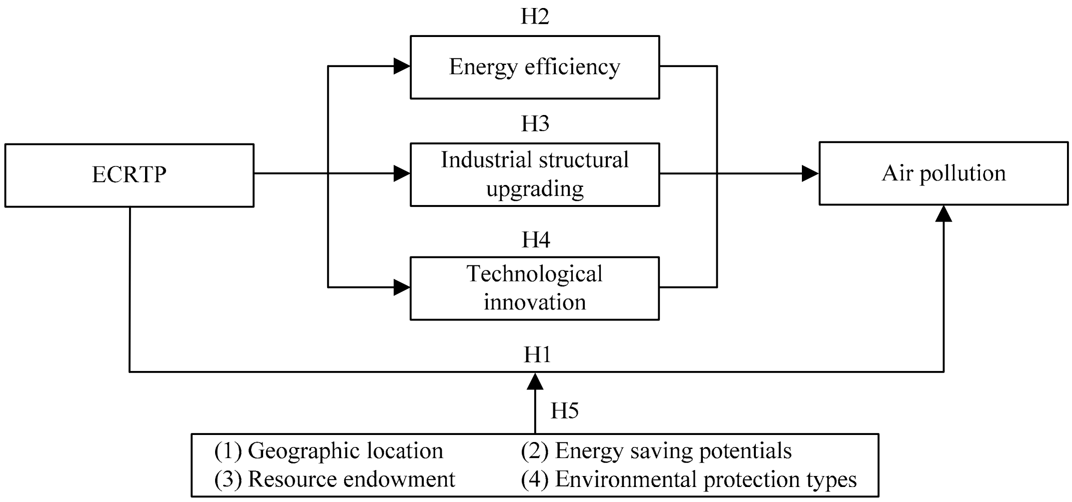

Figure 1. Theoretical framework and study hypotheses.

3. Research Design

3.1. Model Construction

To address the limitations of traditional regression models in assessing policy effects, this study utilizes a DID model for its analysis. In this model, individuals affected by the policy are classified as the treatment group while those not impacted by the policy serve as the control group. The differences observed in the control group before and following policy implementation are interpreted as a pure time effect. The net effect of the policy implementation is derived by subtracting the changes recorded in the control group before and after the policy was enacted from the changes observed in the treatment group during the same intervals. The "Trial Scheme for Paid Use and Trading System of Energy-Consuming Rights" initiated by China in 2017 constitutes an exogenous policy shock to air pollution. This study regards it as a quasi-natural experiment and utilizes a DID model to evaluate the impact of ECRTP on air pollution. The baseline regression model is set as follows:

$$\mathrm{lnpoll}_{it} = \alpha_0 + \alpha_1 \mathrm{ECRTP}_{it} + \alpha_2 X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

where i and t denote cities and time, respectively. The variable "lnpoll" is the explained variable representing air pollution while "ECRTP" stands for the dummy variable for the pilot policy of energy-consuming rights trading. The variable "X" serves as a set of control variables influencing "lnpoll". The variables μ_i and η_t represent city-fixed effects and year-fixed effects, respectively. The notation "ε_{it}" refers to the random disturbance term. Of particular interest is the core variable "ECRTP", with its estimated coefficient α_1 reflecting the net effect of ECRTP on air pollution. If α_1 is significantly negative, it means that ECRTP can effectively suppress air pollution. The theoretical analysis in the preceding discussion suggests that ECRTP suppresses air pollution through three pathways: enhancing energy efficiency, promoting industrial structure upgrading, and stimulating technological innovation. Building upon the baseline regression, the following mediation effect model is constructed to examine the action mechanism:

$$M_{it} = \beta_0 + \beta_1 \mathrm{ECRTP}_{it} + \beta_2 X_{it} + \eta_i + \eta_t + \varepsilon_{it} \quad (2)$$

$$\mathrm{lnpoll}_{it} = \varphi_0 + \varphi_1 \mathrm{ECRTP}_{it} + \varphi_2 M_{it} + \varphi_3 X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (3)$$

Here, the symbol "M" represents the mediating variable, denoting three variables in this study: energy efficiency (lnene), industrial structure upgrading (lnind), and technological innovation (lnpat), while other variables are explained as previously mentioned. The baseline regression model has already evaluated the overall impact of ECRTP on air pollution. Therefore, the focus is on the regression coefficients β_1, φ_1, and φ_2 in the impact mechanism under examination. If both β_1 and φ_2 are statistically significant, it indicates that the mediating mechanism is established. If at least one of β_1 and φ_2 is not significant, additional testing using the Sobel or Bootstrap method is necessary to examine whether $\beta_1 \times \varphi_2 = 0$ holds. If $\beta_1 \times \varphi_2$ is significantly deviated from 0, the mediating mechanism is established; otherwise, it is not. Under the assumption of the mediating mechanism being established, a significant φ_1 indicates the presence of a partial mediation effect, whereas a non-significant φ_1 suggests a full mediation effect.

3.2. Variable Design

3.2.1. Explained Variable

The explained variable in this research is air pollution (lnpoll). Air pollutants typically consist of fine particulate matter, sulfur dioxide, carbon monoxide, nitrogen oxides, etc. [52]. $PM_{2.5}$, a component of fine particulate matter with an aerodynamic diameter of 2.5 μm or less, contains a significant amount of toxic and harmful substances, remains in the atmosphere for prolonged periods, and can travel long distances, resulting in substantial impacts on both human health and atmospheric quality. To ensure data representativeness and accessibility, the research designates $PM_{2.5}$ concentration as the indicator for measuring air pollution, denoted by lnpoll.

3.2.2. Core Explanatory Variable

ECRTP is the core explanatory variable, which reflects whether a city implemented ECRTP in a given year. ECRTP is defined as $\mathrm{ECRTP}_{it} = \mathrm{Treat}_i \times \mathrm{Time}_t$, where Treat_i denotes the dummy variable for pilot cities and Time_t represents the dummy variable for the implementation period of the policy. In the prefecture-level cities of the Zhejiang, Fujian, Henan, and Sichuan provinces, Treat_i is designated as 1, while in the prefecture-level cities of other provinces, Treat_i is set to 0. Although the National Development and Reform Commission of China released the pilot program in September 2016, this paper designates 2017 as the year of policy implementation to account for delays in execution. In this context,

$Time_t$ is set to 0 before 2017, and from 2017 onwards, $Time_t$ is set to 1. The magnitude and sign of the estimated coefficients for ECRTP indicate both the size and direction of its impact on air pollution. A significantly negative estimated coefficient implies that ECRTP effectively mitigates air pollution, thereby supporting the research hypothesis H1.

3.2.3. Control Variables

To account for the influence of additional variables on air pollution, this study references the STIRPAT model as well as the research conducted by Shao Shuai [53] and Luo et al. [54]. Accordingly, six control variables have been selected: economic development (lngdp), which represented by the ratio of gross domestic product to the total population; population density (lnpop), which is determined by the ratio of urban total population to the administrative area; foreign openness (lnfdi), which is indicated by the precise amount of foreign capital utilized; financial development (lnfin), which is gauged by the year-end RMB loan balance of financial institutions; urbanization (lnurb), which is determined by the proportion of the urban population to the total population; and, lastly, government support (lngov), which is inferred from the proportion of government public financial expenditure to GDP.

3.2.4. Mechanism Variables

In consideration of the scientific foundation, the following mechanism variables are selected. Firstly, we shall look at energy efficiency (lnene). Following the study by Li, Yan et al. [55], energy efficiency is measured by the reciprocal of energy intensity, defined as the ratio of energy consumption to GDP. Due to the unavailability of data on primary energy consumption at the prefecture-level cities, the electricity consumption for the entire city is used as a substitute for energy consumption. Secondly, we shall look at industrial structure upgrading (lnind). Since the process of industrial structure upgrading is often accompanied by a gradual rise in the proportion of the tertiary industry, the ratio of the tertiary industry's output value to GDP is chosen as a metric to evaluate industrial structure upgrading. Thirdly, technological innovation (lnpat). Existing research commonly measures technological innovation using two indicators: innovation input and innovation output. Innovation output is preferred as it more accurately reflects the actual innovation level of a region compared to innovation input. Among the various metrics for innovation output, the number of patent applications and the number of patents granted are frequently utilized. However, the patent granting process entails a lengthy approval procedure, resulting in a time lag that complicates the measurement of innovation output for a specific year. In contrast, the number of patent applications, especially those for invention patents, provides a more immediate and accurate representation of a region's innovation achievements within a given year. Therefore, this paper utilizes the number of invention patent applications as a measure of technological innovation.

3.3. Data Description

Considering the accessibility and comprehensiveness of the data, the study selected panel data from 277 prefecture-level cities in China spanning from 2011 to 2021 as the sample, systematically investigating the influence of ECRTP on air pollution. The original data of $PM_{2.5}$ is obtained from the openly available $PM_{2.5}$ surface grid data provided by the Atmospheric Composition Analysis Group at Washington University in St. Louis, USA. To calculate the annual average $PM_{2.5}$ concentration values for each prefecture-level city in China from 2011 to 2021, ArcGIS was utilized to fit these data with the vector data of China's prefecture-level cities annually. The quantity of invention patent applications was obtained from the CNRDS database, while additional data were gathered from the "China Urban Statistical Yearbook", "China Urban Construction Statistical Yearbook", statistical yearbooks of provinces and prefecture-level cities, and government work reports. Interpolation methods were employed for individual missing values in the data. Furthermore, a logarithmic transformation was utilized on variables outside the core explanatory variables to decrease data dispersion and address heteroscedasticity. It should be noted that the data presented in this paper are sourced from reputable databases and research institutions and have been processed using rigorous scientific methods to guarantee the authenticity and reliability of the data. Table 1 presents the specific definitions of each variable and Table 2 offers the overall descriptive statistics for these variables.

Table 1. Definitions of each variable.

Variable Type	Variable Name	Variable Symbol	Variable Description
Explained variable	Air pollution	lnpoll	$PM_{2.5}$ concentration
Core explanatory variable	Energy-consuming rights trading policies	ECRTP	The interaction term between pilot city dummy variable and pilot implementation time dummy variable.
Control variable	Economic development	lngdp	The ratio of gross domestic product (GDP) to the total population.
	Population density	lnpop	The ratio of the total urban population to the area of the administrative division.
	Openness to foreign	lnfdi	The actual utilized foreign investment amount.
	Financial development	lnfin	The year-end balance of various RMB loans from financial institutions.
	Urbanization	lnurb	The ratio of the urban population to the total population.
	Government support	lngov	The ratio of government public fiscal expenditure to GDP.
Mechanism Variable	Energy efficiency	lnene	The reciprocal of energy intensity.
	Industry structure	lnind	The ratio of the output value of the tertiary industry to the regional gross domestic product (GDP).
	Technological innovation	lnpat	The number of invention patent applications.

Table 2. Descriptive statistics of all variables.

Variables	N	Mean	SD	Min	Max
lnpoll	3047	3.6049	0.3445	2.3812	4.5227
ECRTP	3047	0.0903	0.2866	0	1
lngdp	3047	10.7762	0.5772	8.7729	15.6752
lnpop	3047	5.7621	0.9799	1.7077	9.0886
lnfdi	3047	11.8305	2.0291	−5.0146	16.8344
lnfin	3047	16.5767	1.1650	13.7234	20.5984
lnurb	3047	3.9993	0.2659	3.0445	4.6052
lngov	3047	2.9734	0.5299	1.4789	6.4037
lnene	3047	2.7388	0.8526	−1.1305	5.4134
lnind	3047	3.7314	0.2472	2.6644	4.4293
lnpat	3047	6.4445	1.7031	1.9459	11.6865

4. Empirical Analysis

4.1. Descriptive Statistics of Variables

Descriptive statistics of the main variables grouped are shown in Table 3. Out of the 3047 observations, there are 605 observations in the treatment group and 2442 observations in the control group. As there are significant differences in urban characteristics between the treatment and control groups, it is necessary to incorporate control variables into the regression model to control for these differences.

Table 3. Descriptive statistics of variable groups.

Variables	Treatment Group			Control Group			Comparison of Mean Differences
	N	Mean	SD	N	Mean	SD	
lnpoll	605	3.6451	0.3948	2442	3.5950	0.3303	−0.0501 ***
lngdp	605	10.8195	0.5626	2442	10.7655	0.5803	−0.0540 **
lnpop	605	6.1490	0.7089	2442	5.6662	1.0137	−0.4828 ***
lnfdi	605	12.1581	1.6371	2442	11.7494	2.1075	−0.4087 ***
lnfin	605	16.7012	1.1093	2442	16.5458	1.1766	−0.1554 ***
lnurb	605	3.9551	0.2281	2442	4.0102	0.2734	0.0551 ***
lngov	605	2.8456	0.4744	2442	3.0050	0.5382	0.1594 ***

Note: *** and ** denote significance levels at 1% and 5%, respectively.

4.2. Parallel Trend Test

This study utilizes the DID model to examine whether ECRTP can suppress air pollution. An essential assumption of this method is that both the treatment group and the control group must meet the parallel trend hypothesis before the pilot implementation. This analysis depicts the trend of lnpoll in ECRTP pilot and non-pilot cities, as illustrated in Figure 2. It can be observed from the figure that, before 2017, the lnpoll in non-pilot and pilot cities maintained a parallel trend, with no significant difference between them. After 2017, the amplitude of decline in lnpoll in pilot cities was greater than that in non-pilot cities, and this trend continues until the end of the sample period. The findings above suggest that employing the DID model to assess the policy impacts of ECRTP on air pollution is feasible. To further ensure the identifiability of the regression results, an event study method was utilized to perform a parallel trend test. This study employs dummy variables for the five years preceding the implementation of ECRTP, the year of implementation, and the four subsequent years as explanatory variables in the regression analysis. The regression coefficients and their corresponding 90% confidence intervals are illustrated in Figure 3. The results presented in Figure 3 indicate that all regression outcomes before 2017 are statistically insignificant, suggesting that, before the implementation of ECRTP, the trends of change for the treatment and control groups were consistent, with no significant differences being observed. This finding indicates that the research sample passes the parallel trend test required by the DID model.

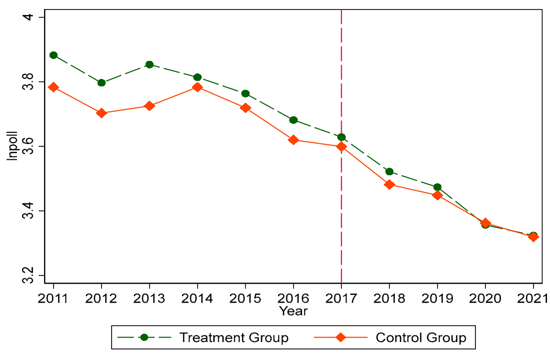

Figure 2. Trends in lnpoll concentrations in pilot and non-pilot cities.

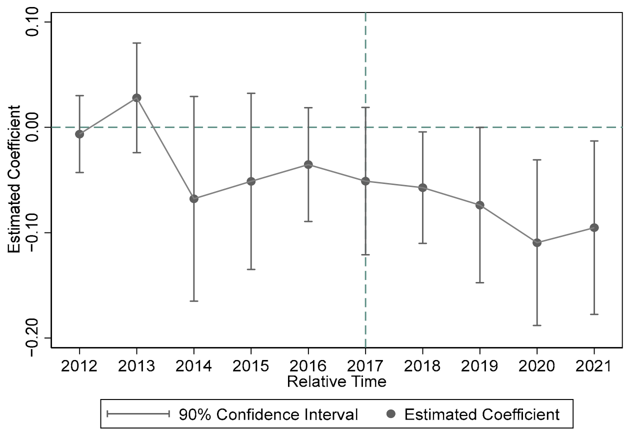

Figure 3. Parallel trend test chart. Note: The vertical dashed line indicates the starting year of policy implementation, while the horizontal dashed line represents the zero-value boundary.

4.3. Baseline Regression Analysis

Based on Model (1), the DID model is employed to evaluate the impact of ECRTP on air pollution. The baseline regression estimations are detailed in Table 4. The table illustrates that, when accounting for city-fixed effects, time-fixed effects and utilizing robust standard errors clustered at the city level, the estimated coefficients of ECRTP remain consistently negative in the regression results as control variables are added sequentially. Furthermore, all coefficients pass the significance test at the 1% level. Therefore, it is evident that ECRTP markedly inhibits air pollution. This inhibitory effect remains robust across the estimated results with or without control variables, thus confirming research hypothesis H1. ECRTP can address the issue of mismatched energy resource allocation at the source, aiding in the achievement of the "dual control" objectives of regulating total energy consumption and energy intensity, consequently curbing air pollution. Moreover, this pilot policy offers a fresh strategy for other developing nations in regard to tackling air pollution challenges.

Table 4. Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ECRTP	−0.0577 ***	−0.0483 ***	−0.0433 ***	−0.0415 ***	−0.0455 ***	−0.0460 ***	−0.0461 ***
	(0.0112)	(0.0112)	(0.0114)	(0.0110)	(0.0103)	(0.0104)	(0.0103)
lngdp		−0.0667 ***	−0.0638 ***	−0.0571 ***	−0.0435 ***	−0.0443 ***	−0.0480 ***
		(0.0144)	(0.0137)	(0.0130)	(0.0113)	(0.0114)	(0.0119)
lnpop			−0.1762 ***	−0.1543 ***	−0.1378 ***	−0.1335 ***	−0.1393 ***
			(0.0395)	(0.0370)	(0.0355)	(0.0347)	(0.0348)
lnfdi				−0.0080 ***	−0.0063 ***	−0.0062 ***	−0.0062 ***
				(0.0024)	(0.0023)	(0.0023)	(0.0023)
lnfin					−0.0828 ***	−0.0842 ***	−0.0849 ***
					(0.0225)	(0.0230)	(0.0230)
lnurb						0.0332	0.0327
						(0.0435)	(0.0437)
lngov							−0.0149
							(0.0095)
Constant	3.6101 ***	4.3275 ***	5.3119 ***	5.2069 ***	6.3189 ***	6.1918 ***	6.3234 ***
	(0.0010)	(0.1555)	(0.2496)	(0.2305)	(0.3759)	(0.3894)	(0.3942)
City effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3047	3047	3047	3047	3047	3047	3047
Adj. R^2	0.9389	0.9404	0.9404	0.9420	0.9433	0.9433	0.9434

Note: *** reveals statistical significance at the 0.01 level, Robust standard errors are reported in parentheses.

The estimated coefficients in column (7) of Table 4 reveal that economic development (lngdp) significantly inhibits air pollution, which is consistent with the findings of Deng

Rongrong and Zhang Aoxiang (2022) [56]. Higher levels of economic development lead to increased public awareness of environmental protection, stricter constraints on enterprise environmental violations, and enhanced government supervision of pollution control, all of which are conducive to inhibiting air pollution. Population density (lnpop) also shows a pronounced inhibitory effect on air pollution, in line with Liang Wei et al.'s (2017) [57] research, indicating that as population density rises, costs decrease and technological spillovers aid in reducing air pollution. Foreign direct investment (lnfdi) demonstrates a significant inhibitory effect on air pollution, supporting the "pollution halo hypothesis", which suggests that inflows of foreign capital bring advanced technology and management expertise that greatly assist in air pollution control. Financial development (lnfin) also displays a pronounced inhibitory effect on air pollution, as the advancement of digital finance and green finance guides resources towards low-energy consumption and low-pollution industries, phasing out high-energy consumption and high-pollution enterprises, thus benefiting the inhibition of air pollution. The estimated coefficient for urbanization (lnurb) is positive but insignificant, indicating that current urbanization is not conducive to air pollution governance, highlighting the necessity to enhance the quality of urbanization development. Although the estimated coefficient for government support (lngov) is negative but insignificant, it suggests that government support has a certain inhibitory effect on air pollution, implying there is still room for enhancement in the strength and direction of government support.

4.4. Robustness Test

4.4.1. Placebo Test

Despite incorporating control variables that may affect air pollution into the baseline regression model, there still exists a potential impact of unobserved omitted variables. Therefore, this study conducts a placebo test on the baseline regression. From the research sample, an equal number of cities to those involved in the ECRTP pilot are randomly selected to serve as a pseudo-treatment group. Pseudo-policy times are then randomly assigned to these selected cities, whereas the other cities act as the control group. Subsequently, a dummy policy variable $\mathrm{Treat}_i^{\mathrm{false}} \times \mathrm{Time}_t^{\mathrm{false}}$ is created, and parameter estimation of the baseline model is carried out using the new sample group. To avoid interference from other low-probability events on the estimation results, the regression analysis process described above is repeated 500 times. Figure 4 displays the kernel density and distribution of corresponding *p*-values for the estimated coefficients of the dummy policy variable over 500 random iterations. It is observed that the mean estimated coefficient of the dummy policy is close to 0 and the majority of *p*-values are above 0.1. Additionally, the vertical dashed line in Figure 4 denotes the real estimated results of ECRTP in column (7) of Table 4 of the baseline regression model. These results appear as outliers in the estimated coefficients of the placebo test. Thus, we can deduce that the estimation results of the baseline model are not severely biased due to omitted variables.

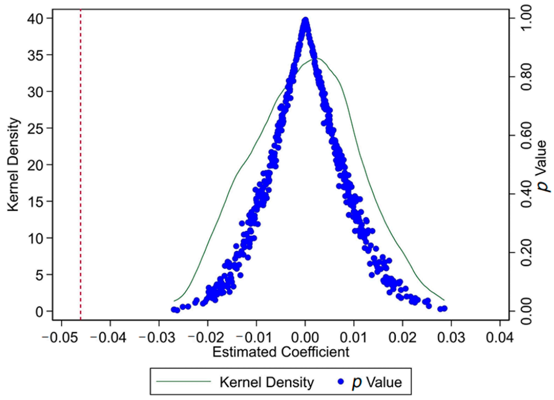

Figure 4. Placebo Test.

4.4.2. Instrumental Variable Test

The DID model to some extent excludes the effects of time-varying and other unobservable factors, yet the selection of ECRTP pilot cities may still be non-random, leading to endogeneity concerns. Drawing on the practices of Li Shaolin and Bi Zhixue (2022) [33] and Xiaoping He (2023) [58], we select the interaction term IV between city topography undulation and ECRTP as instrumental variables. Topography undulation affects a region's population density, economic development, and industrial agglomeration, all of which are closely linked to the selection of ECRTP pilot cities, thus establishing a correlation between topography undulation and ECRTP. The topography undulation is a natural geographical feature that is not directly related to air pollution. Apart from its impact on ECRTP, which in turn affects air pollution, there are no other mechanisms of action. Therefore, this instrumental variable possesses exogeneity. The outcomes of the instrumental variable test are presented in Table 5. Regardless of the inclusion of control variables, the estimated coefficient of the IV in the first stage is significantly positive at the 1% level, indicating that the instrumental variable satisfies the relevance conditions and passes the Kleibergen–Paap rk Wald F statistic test, confirming the effectiveness of the instrumental variable. In the second stage, the estimated coefficient of ECRTP is significantly negative, indicating that the air pollution suppression effect is slightly weaker than the benchmark regression results. These findings imply that, after excluding endogeneity issues arising from the non-random selection of pilot areas, ECRTP continues to exhibit a notable inhibitory effect on air pollution.

Table 5. The results of the instrumental variable test.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	The First Stage	**The Second Stage**	**The First Stage**	**The Second Stage**
IV	0.6325 ***		0.6272 ***	
	(0.1266)		(0.1228)	
ECRTP		−0.0349 ***		−0.0323 ***
		(0.0100)		(0.0096)
Constant	0.0495 ***	3.7030 ***	−2.7300 ***	6.1827 ***
	(0.0082)	(0.0272)	(0.7877)	(0.2428)
Controls	No	No	Yes	Yes
City effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	3047	3047	3047	3047
Adj. R^2	0.7091	0.9387	0.7158	0.9431
Kleibergen–Paap rk LM statistic		360.3470		372.4150
		[0.0000]		[0.0000]
Kleibergen–Paap rk Wald F statistic		242.1170		252.5380
		{16.38}		{16.38}

Note: The value in the square brackets of the Kleibergen–Paap rk LM statistic represents the *p*-value, while the value in the curly braces of the Kleibergen–Paap rk Wald F statistic represents the 10% critical value for the Stock–Yogo weak identification test. Robust standard errors are reported in parentheses, and *** reveals statistical significance at the 0.01 level.

4.4.3. Estimation of the SC-DID Model

Although this article has a possibility of weak pre-parallel trends, it should be noted that, even if pre-parallel trends are satisfied, it does not guarantee that post-parallel trends will be met. The Synthetic Control Method (SCM) can assign weights to data from various control groups, allowing the pre-trends of the synthetic control group to closely resemble those of the treatment group, thereby effectively resolving the issue encountered by traditional DID models related to meeting pre-parallel trends [59]. However, the SCM method is unable to assign time weights and requires that there be only one treatment group. Therefore, this study draws on the SC-DID model proposed by Arkhangelsky et al. (2021) [60], which incorporates individual weights and time weights to match pre-trends in the control and treatment groups, considering both pre- and post-periods, thereby reducing the dependence of parameter estimates on the assumption of parallel trends. The fundamental operational steps of SC-DID involve not only identifying control group individuals that closely resemble the treatment group through unit-specific weights but also locating pre-treatment periods that are analogous to the post-treatment period using time-specific weights. In this process, greater individual weights and time weights are assigned to these identified individuals and periods, respectively. This paper utilizes the SDID command for estimating the SC-DID model. The estimated results of the SC-DID model are shown in Table 6, as depicted in column (1). The average treatment effect of ECRTP is −0.0362, which remains significant at the 1% level, signifying the effectiveness of ECRTP in suppressing air pollution. Additionally, Figure 5 illustrates the dynamic effects of air pollution estimated by the SC-DID model during each period, both when ECRTP was implemented and after its operation. The results exhibit negative estimated coefficients of the policy intervention for each period, with confidence intervals excluding zero, indicating the sustained and dynamic impact of ECRTP in curbing air pollution. These findings suggest that the SC-DID model's estimates further validate the robustness of the baseline regression outcomes. The data presented in Figure 5 reveal that the estimated coefficients of the pilot policies in each period are negative, with confidence intervals excluding 0. This signifies the dynamic persistence of the air pollution suppression effect resulting from ECRTP. Moreover, the estimated results of the SC-DID model corroborate the robustness of the baseline regression results.

Table 6. Robustness test results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	SC-DID	**PSM-DID**	**Entropy Balancing**	**Environmental Protection Tax**	**Carbon Emission Rights**	**Joint Policy**
ECRTP	−0.0362 ***	−0.0402 ***	−0.0366 ***	−0.0467 ***	−0.0536 ***	−0.0536 ***
	(0.0088)	(0.0119)	(0.0103)	(0.0095)	(0.0102)	(0.0096)
EPT				−0.0407 ***		−0.0339 ***
				(0.0097)		(0.0096)
CER					−0.1052 ***	−0.0987 ***
					(0.0147)	(0.0148)
Constant		5.8094 ***	5.8799 ***	6.1559 ***	6.2729 ***	6.1363 ***
		(0.6265)	(0.5174)	(0.3878)	(0.3828)	(0.3802)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3047	1346	3047	3047	3047	3047
Adj. R^2		0.9578	0.9633	0.9442	0.9453	0.9458

Note: *** reveals statistical significance at the 0.01 level, Robust standard errors are reported in parentheses.

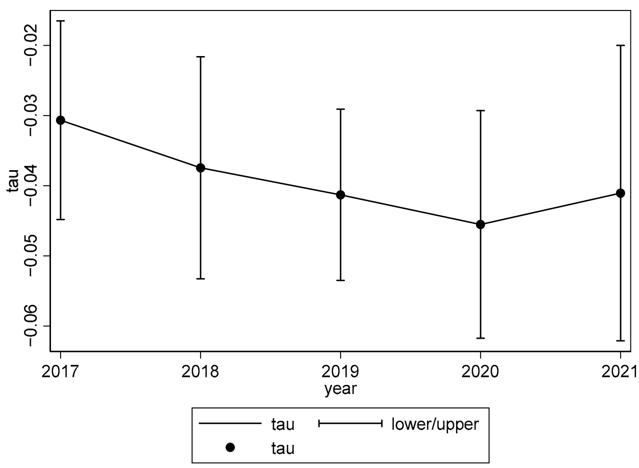

Figure 5. SC-DID dynamic effect diagram.

4.4.4. PSM-DID Model Estimation

The selection of ECRTP pilot cities in China may be selective. Therefore, there may be differences in individual characteristics between pilot cities and non-pilot cities, which can lead to sample selection bias. Propensity Score Matching (PSM) is a robust sample-matching technique that addresses the effects of sample selection bias. However, PSM is unable to avoid endogeneity issues resulting from omitted variables, while the DID model can effectively tackle endogeneity concerns but falls short in adequately addressing sample selection bias. To address this issue, a PSM-DID model is applied for robustness testing, with the specific steps being outlined as follows: Firstly, using the control variables from the baseline regression model as covariates, a logit model is employed with a 1:2 nearest neighbor matching strategy with replacement to conduct propensity score matching (PSM), aiming to match the treatment group with a control group that is as similar as possible. Secondly, the balance of the matched sample is tested and specific results are shown in Figure 6. The standardized biases of each variable significantly decrease following matching, with all biases falling below 10%, which indicates a strong matching effect. Ultimately, the matched sample is employed for re-estimation using the DID model. The estimated results, as displayed in column (2) of Table 6, exhibit that the estimated coefficient of ECRTP remains significantly negative, validating the robustness of the baseline regression conclusions.

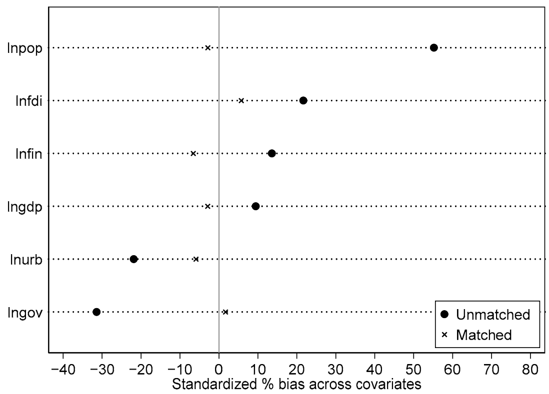

Figure 6. Standardized deviations of various variables.

While PSM can match the treatment group with a control group that has similar characteristics, it depends heavily on the first-stage matching model and may lead to sample loss during egression [61]. The entropy balancing (EB) method assigns weights to the control group data to make the covariates as similar as possible to the treatment group in terms of mean, variance, and skewness without sacrificing samples based on matching. Therefore, additional reconstruction of the control group using the EB method and regression with the matched sample yields the results shown in column (3) of Table 6. These results demonstrate that the estimated coefficient of ECRTP is significantly negative at the 1% level, still supporting the conclusions of the baseline regression.

4.4.5. Consideration of the Impacts of Other Policies during the Same Period

If other policy shocks highly correlated with air pollution occurred during the study period, it could affect the accuracy of the baseline regression results. In addition to ECRTP, the implementation of environmental protection taxes and carbon emission trading policies is intricately linked to the research in this article. In the baseline regression, the dummy variables EPT and CER, respectively representing the environmental protection tax and carbon emission trading policy, are sequentially added to consider the impacts of other policies. The results are presented in columns (4) and (5) of Table 6. Taking into account the synergistic effects of policies, the dummy variables representing the two policies are simultaneously included in the baseline regression, as displayed in column (6) of Table 6. After removing the contemporaneous effects of other policies, the estimated coefficient of

ECRTP remains significantly negative, indicating that the estimated results obtained in the preceding section are not affected by the interference of other policies.

4.4.6. Other Robustness Tests

The study also conducted the following additional robustness tests. Firstly, the explained variable was replaced to alleviate potential measurement errors associated with $PM_{2.5}$ concentration. High-resolution $PM_{2.5}$ concentration data released by the China Qinghai-Tibet Plateau Data Center was employed as an alternative variable for air pollution. The regression findings based on this substitution are displayed in column (1) of Table 7. Additionally, considering the spatiotemporal correlation between $PM_{2.5}$ and harmful gases, such as SO_2, this study employs SO_2 as a proxy variable for $PM_{2.5}$. The regression results are presented in column (2) of Table 7. Secondly, the standard errors were adjusted to account for potential spatial-temporal correlation within the error term. This adjustment was accomplished through two-way clustering by city and year. The regression results after standard error adjustment are demonstrated in column (3) of Table 7. Thirdly, we controlled to province time-varying trends. Although city-fixed effects and year-fixed effects were controlled in the baseline regression, the potential issue of omitted variables may originate from time-varying macroeconomic conditions. To address this issue, the product terms of province and year were added to the baseline regression, and the regression results are shown in column (4) of Table 7. Fourthly, outliers must be removed. To remove the influence of outliers on the regression results, a two-tailed winsorizing at the top and bottom 1% was applied to all continuous variables. The regression outcomes after excluding outliers are demonstrated in column (5) of Table 7. The estimated coefficients of the regression results above remain significantly negative, further confirming the robustness of the baseline regression results.

Table 7. Other robustness test results.

Variables	(1)	(2)	(3)	(4)	(5)
	Replaced Explained Variable	**lnSO_2**	**Adjusted Standard Error**	**Controlled Province Time Trends**	**Winsorization**
ECRTP	−0.0347 ***	−0.2235 *	−0.0461 ***	−0.0299 *	−0.0480 ***
	(0.0090)	(0.1140)	(0.0104)	(0.0177)	(0.0105)
Constant	5.3759 ***	11.2545 ***	6.3234 ***	4.2214 ***	6.1509 ***
	(0.2841)	(3.2798)	(0.3961)	(0.3045)	(0.3948)
Controls	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
N	3047	3047	3047	3047	3047
Adj. R^2	0.9713	0.8733	0.9428	0.9809	0.9413

Note: *** reveals statistical significance at the 0.01 level, and * indicates statistical significance at the 0.1 level. Robust standard errors are reported in parentheses.

5. Mechanism Testing

To further explore the underlying reasons for the suppression effect of air pollution achieved by ECRTP, this study utilized the mediation effect model to empirically investigate the mechanisms through three paths: energy efficiency, industrial structure upgrading, and technological innovation.

5.1. Path 1: Energy Efficiency

Energy efficiency is crucial to ensuring sustainable economic development, reducing environmental pollution, and guaranteeing national energy security. It reflects the effectiveness and economy of energy utilization. Table 8 examines the existence of the pathway in which ECRTP suppresses air pollution through energy efficiency in columns (1) and (2). The estimated coefficient of ECRTP in column (1) is significantly positive, indicating a significant improvement in energy efficiency due to ECRTP. Under the constraint of ECRTP, enterprises that exceed their energy usage limits are required to purchase energy-consuming quota indicators from the market, leading to increased production costs. This compels enterprises to reconfigure production factors, enhance production processes, decrease energy consumption, and consequently improve energy efficiency. Moreover, the estimated coefficients of ECRTP and lnene in column (2) are both significantly negative, suggesting a partial mediating effect of energy efficiency between ECRTP and air pollution. As a result, research hypothesis H2 is confirmed.

Table 8. Results of mechanism test.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	lnene	**lnpoll**	**lnind**	**lnpoll**	**lnpat**	**lnpoll**
ECRTP	0.1314 *	−0.0451 ***	0.0865 ***	−0.0429 ***	0.0881 *	−0.0451 ***
	(0.0788)	(0.0106)	(0.0211)	(0.0106)	(0.0500)	(0.0103)
lnene		−0.0203 ***				
		(0.0059)				
lnind				−0.0560 **		
				(0.0275)		
lnpat						−0.0104 **
						(0.0041)
Constant	12.0083 ***	6.7394 ***	3.7624 ***	6.7066 ***	0.2815	6.3264 ***
	(2.3564)	(0.4242)	(0.5725)	(0.3905)	(2.2274)	(0.3970)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
N	3047	3047	3047	3047	3047	3047
Adj. R^2	0.7962	0.9437	0.8601	0.9434	0.9340	0.9435

Note: *** reveals statistical significance at the 0.01 level, ** reveals statistical significance at the 0.05 level, and * indicates statistical significance at the 0.1 level. Robust standard errors are reported in parentheses.

5.2. Path 2: Industrial Structure Upgrading

The upgrading of industrial structure is the process in which various production factors exit from low value-added, low efficiency, and high consumption production sectors, and subsequently shift towards high value-added, high efficiency, and low consumption production sectors. This is mainly manifested in the service-oriented transformation of the economic structure. Table 8 examines the existence of the pathway through which ECRTP inhibits air pollution by promoting the upgrading of industrial structures. The estimated coefficient of ECRTP in column (3) is significantly positive, indicating that ECRTP can promote the upgrading of the regional industrial structure, leading to a transformation from a lower stage to a higher stage. The estimated coefficients of both ECRTP and lnind in column (4) are significantly negative, suggesting that the upgrading of industrial structure has a partial mediating role in the relationship between the pilot of energy rights trading and air pollution. It is evident that ECRTP can promote the optimization and upgrading of industrial structures, leading to decreased resource consumption and reduced air pollution emissions in cities. As a result, research hypothesis H3 is corroborated.

5.3. Path 3: Technology Innovation

Utilizing technological innovation as an endogenous driving force to address environmental and resource constraints is an important driver for high-quality economic development. Table 8 examines the existence of the path through which ECRTP inhibits air pollution through technological innovation. The estimated coefficient of ECRTP in column (5) is significantly positive, indicating that ECRTP can significantly promote technological innovation. The estimated coefficients of ECRTP and lnpat in column (6) are both significantly negative, indicating that technological innovation plays a partial mediating role in the relationship between ECRTP and air pollution. According to the innovation compensation theory, ECRTP, as a market-oriented environmental regulatory tool, can compel enterprises to engage in technological innovation activities such as production process optimization and process restructuring, thereby improving production efficiency, lowering energy consumption, and ultimately curbing air pollution. Based on this, research hypothesis H4 is validated.

To further validate the robustness of the mechanism test conclusions in this research, the Sobel test and bootstrap test were conducted to determine whether the indirect effects of energy efficiency, industrial structure upgrading, and technological innovation were significant. The specific results are shown in Table 9. The Sobel test results indicate that the indirect effects of energy efficiency, industrial structure enhancement, and technological innovation all passed the significance test. Moreover, the bootstrap test results demonstrate that the confidence intervals of the indirect effects for Bias-Corrected and Percentile do not include 0 at the 95% level. As a result, research hypotheses H2, H3, and H4 are reaffirmed.

Table 9. Further mechanism test results.

Paths	Sobel Test			Bootstrap Test: 95% Conf. Interval			
	Indirect Effect	Z	$p > \lvert z \rvert$	Bias-Corrected		Percentile	
ECRTP→lnene→lnpoll	−0.0027	−2.9649	0.0030	−0.0049	−0.0011	−0.0050	−0.0010
ECRTP→lnind→lnpoll	−0.0048	−3.1489	0.0016	−0.0085	−0.0016	−0.0085	−0.0016
ECRTP→lnpat→lnpoll	−0.0009	−1.7068	0.0879	−0.0021	−0.0002	−0.0020	−0.0001

Note: The bootstrap sample size is 2000 times.

6. Heterogeneity Analysis

Although the previous text has confirmed that ECRTP has a significant inhibitory effect on air pollution, is there heterogeneity in the impact of pilot policies on different cities? Based on this, this article further examines the heterogeneous policy effects of ECRTP on air pollution in different cities using a triple differences model. The specified triple differences model is as follows:

$$\text{lnpoll}_{it} = \gamma_0 + \gamma_1 \text{Treat}_i \times \text{Time}_t \times \text{City}_i + \gamma_2 X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (4)$$

Here, City represents the characteristic variables at the city level, including geographic location (Geo), energy-saving potential (Sav), resource endowment (Res), and environmental type (Env). If γ_1 passes the statistical significance test, it means that ECRTP will have a heterogeneous impact on air pollution in various types of cities; conversely, there is no heterogeneous impact.

6.1. Heterogeneity of Geographic Location

The impact of ECRTP on air pollution may exhibit heterogeneity due to differences in the geographic location of cities. The Hu Huanyong Line, proposed by the geographer Hu Huanyong in 1935, is a demarcation line for population density in China and also serves as a dividing line for the level of economic and social development in China. The regions located to the northwest of this line exhibit relatively lower population densities and lower levels of economic and social development, while the southeast side displays higher population densities and relatively higher levels of economic and social development [62]. Thus, in this study, a dummy variable, Geo, is constructed based on the Hu Huanyong Line as a boundary. If a city is located to the southeast of the Hu Huanyong Line, Geo = 1; if it is located to the northwest, Geo = 0. Subsequently, a triple difference Treat × Time × Geo model is incorporated into the regression analysis, with the results being shown in column (1) of Table 10. The estimated coefficient of Treat × Time × Geo is −0.0461, significant at the 1% level, indicating that ECRTP has a stronger inhibitory effect on air pollution in cities southeast of the Hu Huanyong Line. This variation could be attributed to the higher levels of economic and social development in the southeast region of the Hu Huanyong Line, leading to greater availability of funds, technology, and talent, thereby enhancing the emission reduction effect of ECRTP.

Table 10. Results of the heterogeneity regression.

	(1)	(2)	(3)	(4)
Variables	Geographical Location	Energy-Saving Potential	Resource Endowment	Environmental Protection Types
Treat × Time × Geo	−0.0461 ***			
	(0.0103)			
Treat × Time × Sav		−0.0273 **		
		(0.0133)		
Treat × Time × Res			−0.0546 ***	
			(0.0143)	
Treat × Time × Env				−0.0382 ***
				(0.0125)
Constant	6.3234 ***	6.3949 ***	6.4078 ***	6.3859 ***
	(0.3942)	(0.3879)	(0.3947)	(0.3899)
Controls	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
N	3047	3047	3047	3047
Adj. R^2	0.9434	0.9428	0.9431	0.9428

Note: *** reveals statistical significance at the 0.01 level, ** reveals statistical significance at the 0.05 level. Robust standard errors are reported in parentheses.

6.2. Heterogeneity of Energy Saving Potentials

In general, the larger the energy consumption of a city, the greater its energy-saving potential. ECRTP may have heterogeneous effects on air pollution in cities with different energy-saving potentials. As it is difficult to obtain energy consumption data at the prefecture-level city level in China, this study will use the total electricity consumption of the whole society as a proxy indicator of urban energy consumption and construct a dummy variable, Sav, representing energy-saving potential. If a city's overall electricity consumption exceeds the city's average, Sav = 1; otherwise, Sav = 0. Subsequently, the triple difference term Treat × Time × Sav is included in the regression model, and the specific results are shown in column (2) of Table 10. The estimated coefficient of Treat × Time × Sav is −0.0273, significantly negative at the 5% level, indicating that ECRTP exhibits a stronger effect on air pollution control in cities with higher energy-saving potential. One possible explanation is that the government prioritizes cities with higher energy-saving potential in the implementation of ECRTP to effectively reach energy-saving and emission reduction objectives. Therefore, more stringent energy consumption targets and intensity control goals are set for these cities, which in turn compel companies to develop energy-saving and emission reduction technologies, leading to a stronger air pollution control effect in these cities.

6.3. Heterogeneity of Resource Endowment

Due to differences in resource endowment, resource-based cities and non-resource-based cities exhibit variations in economic development, industrial structure, and energy consumption [63]. Therefore, resource endowment may lead to heterogenous impacts in regard to ECRTP and air pollution. According to the "National Sustainable Development Plan for Resource-based Cities (2013–2020)" released by China, a corresponding dummy variable, Res, is constructed. If it is a resource-based city, Res = 1, and if it is a non-resource-based city, Res = 0. Subsequently, a triple difference interaction term, Treat × Time × Res, is constructed to examine the impact of ECRTP on air pollution in cities with different resource endowments, as shown in the regression results in column (3) of Table 10. It can be observed that the estimated coefficient of Treat × Time × Res is −0.0546, significantly negative at the 1% level, indicating that ECRTP has a stronger inhibitory effect on air pollution in resource-based cities. This could be attributed to the fact that resource-based cities possess abundant mineral, coal, and fossil fuel resources, which often leads to higher energy consumption and environmental pollution. Given that ECRTP is primarily designed for such cities and faces more significant policy impacts, its air pollution mitigation effect is more pronounced in resource-based cities.

6.4. Heterogeneity of Environmental Protection Types

In 2023, the Chinese government released the "Action Plan for Continuous Improvement of Air Quality," which not only outlined the overall ideology, goals, and key tasks for the continuous improvement of air quality but also demarcated the scope of key prevention and control areas for atmospheric pollution. Therefore, this article argues that the impact of ECRTP on air pollution may exhibit heterogeneity due to different types of urban environmental protection. As outlined in the "Action Plan", which identifies key cities for pollution prevention and control in the greater region, a corresponding dummy variable, Env, is constructed where key prevention and control cities are represented as Env = 1 and non-key prevention and control cities as Env = 0. Subsequently, a triple difference term Treat $\times$ Time $\times$ Env is constructed to explore the heterogeneous impact of ECRTP on air pollution in cities with different environmental protection types. The regression results are shown in column (4) of Table 10. It can be observed that the estimated coefficient of Treat $\times$ Time $\times$ Env is -0.0382, which is also significantly negative at the 1% level, indicating that ECRTP exerts a stronger inhibitory effect on air pollution in key prevention and control cities. The reason for this may be that key prevention and control cities face more environmental regulatory constraints, allowing ECRTP to have a greater policy synergy with other environmental regulations, thereby demonstrating a stronger inhibitory effect on air pollution. Based on the above analysis, it can be concluded that the research hypothesis H5 has been verified.

7. Discussion

The establishment of a compensated use and trading system for energy rights represents a significant initiative for China in advancing the reform of its ecological civilization system. This system is crucial for achieving the targets outlined in the "13th Five-Year Plan", which aims to implement dual control over total energy consumption and energy intensity while also promoting green development. In this context, the National Development and Reform Commission of China issued a document entitled "Notice on the Pilot Implementation of Compensated Use and Trading of Energy Rights" in 2016. This document designated the Zhejiang, Henan, Fujian, and Sichuan provinces as pilot areas for ECRTP. The primary objective of this policy is to harness the market's essential role in resource allocation, thereby motivating enterprises to pursue green innovations and energy conservation through market-driven mechanisms. This approach aims to achieve dual gains in environmental performance and economic performance.

Upon reviewing the research presented in this paper, it can be concluded that ECRTP significantly reduces $PM_{2.5}$ concentrations in the pilot areas. This finding demonstrates ECRTP's effectiveness in mitigating air pollution and confirms its ability to adjust the energy structure through market mechanisms. Additionally, ECRTP improves energy efficiency, promotes energy conservation and emissions reduction, and facilitates the green transformation of China's economy. Nonetheless, the research reveals that ECRTP has resulted in an average reduction of only 4.61% in air pollution levels in pilot cities compared to non-pilot cities, which is substantially lower than the conclusions drawn by Han et al., who reported that CO_2 and SO_2 could be reduced by 84.8% and 34.5%, respectively. This discrepancy may arise from the fact that ECRTP has not effectively suppressed $PM_{2.5}$ concentrations across all pilot cities, indicating that the policy impacts of ECRTP may possess a degree of uncertainty. However, the research indicates that ECRTP has led to an average reduction of only 4.61% in air pollution levels in pilot cities compared to non-pilot cities, which is significantly lower than the findings of Han et al., who concluded that CO_2 and SO_2 could be reduced by 84.8% and 34.5%, respectively. This discrepancy may be because the implementation of ECRTP has not comprehensively suppressed $PM_{2.5}$ concentrations in every pilot city, suggesting that the policy effects of ECRTP may carry a certain degree of uncertainty. The conclusions of this study align with actual observations, indicating that air quality in some regions has not significantly improved and may have even degraded following the implementation of ECRTP. Several factors may contribute to this situation [64]: Firstly, ECRTP in China remains in the pilot phase, and the top-level design, regulatory framework, technological infrastructure, supportive policies, and trading systems require further enhancement. The current level of marketization is noticeably insufficient, which directly undermines the effectiveness of ECRTP implementation. Secondly, significant variations exist in quota allocation schemes among different pilot regions. For instance, Zhejiang Province focuses on controlling the newly added energy consumption while optimizing existing energy usage. This strategy has a relatively small impact on existing energy-consuming enterprises; however, it exhibits limited incentivizing capabilities, and its effectiveness in fostering market-oriented resource allocation is not evident. In contrast, the Henan and Fujian provinces adopt a quota trading method to control the total energy consumption by managing the annual total quota. At the same time, they implement classified management for various industries, existing production capacities, and newly established production capacities. In this context, enterprises in the pilot regions are frequently subject to dual regulation from both ECRTP and carbon emissions rights, leading to insufficient activity in the trading market. Thirdly, considerable disparities exist among cities regarding the intensity of policy implementation, the extent of support from local governments, and their levels of economic development. These variations may result in varied implementation outcomes of ECRTP.

8. Conclusions, Policy Implications, and Limitations

To evaluate the impact of ECRTP on air pollution, this paper takes the ECRTP pilot as a quasi-natural experiment and constructs a DID model. Empirical tests were conducted using panel data from 277 prefecture-level cities in China from 2011 to 2021. The conclusions are as follows:

Firstly, the baseline regression shows that ECRTP has a significant inhibitory effect on air pollution. This conclusion holds after a series of robustness tests. Secondly, the mechanism analysis indicates that ECRTP suppresses air pollution through pathways such as improving energy efficiency, promoting the upgrading of industrial structure, and stimulating technological innovation. Lastly, heterogeneity analysis shows that ECRTP has a stronger inhibitory effect on air pollution in areas that are economically and socially developed, possess greater energy-saving potential, are characterized as resource-dependent regions, and function as major areas for the prevention and control of air pollution.

The policy implications are as follows: Firstly, in leveraging ECRTP as an opportunity, it is essential to continuously summarize general rules and best practices to form replicable and generalizable experiences, practices, and systems. This includes expanding the pilot scope and promptly establishing a nationwide unified energy-consuming rights trading market system. Secondly, there is a need to broaden the scope of the pilot and establish more stringent targets for total energy consumption and intensity in the cities that are economically and socially developed, demonstrate greater energy-saving potential, are categorized as resource-based cities, and serve as key cities for the prevention and control of air pollution. Lastly, the government should not only focus on the direct inhibitory effect of ECRTP on air pollution but also consider comprehensively the formulation and implementation of relevant supporting policies to enhance energy efficiency, promote the upgrading of industrial structure, and stimulate technological innovation to maximize the energy-saving and emission reduction policy dividends of ECRTP.

There are limitations in this study that require further expansion and improvement in future research. Firstly, the research sample has certain limitations. This study only focuses on China's ECRTP, while the feasibility and effectiveness of ECRTP implementation in other countries still need to be explored. Secondly, due to our being limited by the length of the paper, more detailed categorization studies were not conducted on the research samples in terms of heterogeneity analysis. Lastly, while this study discusses potential underlying mechanisms, there is still room for further analysis. Subsequent research could consider mechanisms such as energy structure and green total factor productivity.

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References

1. Akcigit, U.; Baslandze, S.; Stantcheva, S. Taxation and the international mobility of inventors. *Am. Econ. Rev.* **2016**, *106*, 2930–2981. [CrossRef]
2. Kunda, J.J.; Gosling, S.N.; Foody, G.M. The effects of extreme heat on human health in tropical Africa. *Int. J. Biometeorol.* **2024**, *68*, 1015–1033. [CrossRef]
3. Murray, C.J.L.; Aravkin, A.Y.; Zheng, P.; GBD 2019 Risk Factors Collaborators. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: A systematic analysis for the Global Burden of Disease Study 2019. *Lancet Br. Ed.* **2020**, *396*, 1223–1249. [CrossRef] [PubMed]
4. Hou, P.; Wu, S. Long-term Changes in Extreme Air Pollution Meteorology and the Implications for Air Quality. *Sci. Rep.* **2016**, *6*, 23792. [CrossRef] [PubMed]
5. Mannucci, P.M.; Harari, S.; Martinelli, I.; Franchini, M. Effects on health of air pollution: A narrative review. *Intern. Emerg. Med.* **2015**, *10*, 657–662. [CrossRef]
6. Jiang, X.; Mei, X.; Feng, D. Air pollution and chronic airway diseases: What should people know and do? *J. Thorac. Dis.* **2016**, *8*, E31–E40.
7. Mannucci, P.M.; Franchini, M. Health Effects of Ambient Air Pollution in Developing Countries. *Int. J. Environ. Res. Public Health* **2017**, *14*, 1048. [CrossRef]
8. Hao, Y.; Peng, H.; Temulun, T.; Liu, L.; Mao, J.; Lu, Z.; Chen, H. How harmful is air pollution to economic development new evidence from PM2.5 concentrations of Chinese cities. *J. Clean. Prod.* **2018**, *172*, 743–757. [CrossRef]
9. Zhu, L.; Hao, Y.; Lu, Z.; Wu, H.; Ran, Q. Do economic activities cause air pollution? Evidence from China's major cities. *Sustain. Cities Soc.* **2019**, *49*, 101593. [CrossRef]
10. Cole, M.A.; Neumayer, E. Examining the Impact of Demographic Factors on Air Pollution. *Popul. Environ.* **2004**, *26*, 5–21. [CrossRef]
11. Wu, X.; Gao, M. Effects of different environmental regulations and their heterogeneity on air pollution control in China. *J. Regul. Econ.* **2021**, *60*, 140–166. [CrossRef]
12. Georgii, H.W. The effects of air pollution on urban climates. *Bull. World Health Organ.* **1969**, *40*, 624–635. [PubMed]
13. Zhang, K.; Batterman, S. Air pollution and health risks due to vehicle traffic. Sci Total Environ. *Sci. Total Environ.* **2013**, *450–451*, 307–316. [CrossRef] [PubMed]
14. Li, Z.; Wang, J. The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. *J. Clean. Prod.* **2022**, *351*, 131570. [CrossRef]
15. Lu, Y.; Chen, X. Digital economy, new-type urbanization, and carbon emissions: Evidence from China. *Environ. Prog. Sustain. Energy AIChE* **2023**, *42*, e14045. [CrossRef]
16. Chen, X.; Teng, L.; Chen, W. How does FinTech affect the development of the digital economy Evidence from China. *N. Am. J. Econ. Financ.* **2022**, *61*, 101697. [CrossRef]
17. Sun, J.; Wu, X. Research on the mechanism and countermeasures of digital economy development promoting carbon emission reduction in jiangxi province. *Environ. Res. Commun.* **2023**, *5*, 35002. [CrossRef]
18. Stede, J. Bridging the industrial energy efficiency gap—Assessing the evidence from the Italian white certificate scheme. *Energy Policy* **2017**, *104*, 112–123. [CrossRef]
19. Fuinhas, J.A.; Marques, A.C.; Koengkan, M. Are renewable energy policies upsetting carbon dioxide emissions? The case of Latin America countries. *Environ. Sci. Pollut. Res. Int.* **2017**, *24*, 15044–15054. [CrossRef]
20. Zhang, X.; Cao, X.; Song, L. The effect of pollution control and carbon reduction of the carbon emission trading system: An empirical analysis based on the Synthetic Control Method. *J. Nat. Resour.* **2024**, *39*, 712–730. [CrossRef]

21. Zhang, N.; Zhang, W. Can sustainable operations achieve economic benefit and energy saving for manufacturing industries in China? *Ann. Oper. Res.* **2020**, *290*, 145–168. [CrossRef]
22. Wang, W. The realization of energy using right trading system from the perspective of law and policy. *J. Henan Univ. Technol. Soc. Sci. Ed.* **2021**, *37*, 44–51, 93.
23. Wang, W.; Fu, L. The improvement of the legal system of energy use right transaction supervision in China from the perspective of reflexive Law. *Acad. Explor.* **2021**, 124–133.
24. Chen, Z. Research on the perfection of China's energy-consuming right exchange rules under the background of carbon neutrality. *North. Leg. Sci.* **2022**, *16*, 37–48.
25. Yang, M.; Hou, Y.; Fang, C.; Duan, H. Constructing energy-consuming right trading system for China's manufacturing industry in 2025. *Energy Policy* **2020**, *144*, 111602. [CrossRef]
26. Wang, Y.; Hang, Y.; Wang, Q. Joint or separate? An economic-environmental comparison of energy-consuming and carbon emissions permits trading in China. *Energy Econ.* **2022**, *109*, 105949. [CrossRef]
27. Liu, H.; Wang, Y. The economic bonus effect generated by the tradable policy mixes of energy-consuming right and CO_2-emission right. *China Popul. Resour. Environ.* **2019**, *29*, 1–10.
28. Li, Y.; Zhu, L. Study on the Synergistic Effects Between Energy—Saving Trading and Carbon Market and the Strategic Choose of Energy—Intensive Industries. *J. Ind. Technol. Econ.* **2019**, *38*, 136–142.
29. Zhang, N.; Zhang, W. Can Energy Quota Trading Achieve WinWin Development for Economic Growth and Energy Savings in China? *Econ. Res. J.* **2019**, *54*, 165–181.
30. Zhang, Q.; Li, J.; Wang, J. Does energy-consuming right trading have double dividend effect on firm's economic performance and carbon emission? *Environ. Sci. Pollut. Res. Int.* **2023**, *30*, 105595–105613. [CrossRef]
31. Shao, W.; Liu, J. Does the energy-consuming right trading system promote green technology innovation of enterprises? *Heliyon* **2024**, *10*, e26458. [CrossRef] [PubMed]
32. Song, G.; Wang, Y.; Jiang, Y. Carbon emission control policy design based on the targets of carbon peak and carbon neutrality. *China Popul. Resour. Environ.* **2021**, *31*, 55–63.
33. Li, S.; Bi, Z. How does the energy-consuming rights trading policy impact the total factor productivity of enterprises? *Res. Financ. Econ. Issues* **2022**, 35–43.
34. Zhang, Y.; Zhou, L. Impact of energy-consuming right trading policy on the optimization and upgrading of regional industrial structure. *China Popul. Resour. Environ.* **2024**, *34*, 71–83.
35. Feng, C. Research on the impact of energy trading system on regional energy consumption intensity. *West Forum Econ. Manag.* **2023**, *34*, 71–79.
36. Xue, F.; Zhou, M. Can the energy-consuming right transaction system improve energy utilization efficiency? *China Popul. Resour. Environ.* **2022**, *23*, 54–65.
37. Lu, H.; Wu, Z. Relationship between Energy-consuming Right Trading System and low-carbon transformation of energy consumption structure. *Resour. Sci.* **2023**, *45*, 1181–1195. [CrossRef]
38. Zhang, X.; Lu, F.; Xue, D. Does China's carbon emission trading policy improve regional energy efficiency?—An analysis based on quasi-experimental and policy spillover effects. *Environ. Sci. Pollut. Res.* **2022**, *29*, 21166–21183. [CrossRef]
39. Wang, Z.; Sun, H.; Zhang, X.; Ding, C.; Gong, Y. Can the energy quota trading system achieve the double environmental benefits of reducing pollution and carbon emissions? *Ind. Econ. Res.* **2023**, *125*, 15–26.
40. Wang, M.; Wang, Y.; Yang, Z.; Guo, B. Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China. *Front. Environ. Sci.* **2024**, *12*, 1430031. [CrossRef]
41. Han, D.; Bi, C.; Wu, H.; Hao, P. Energy and environment: How could energy-consuming transition promote the synergy of pollution reduction and carbon emission reduction in China? *Urban Clim.* **2024**, *55*, 101931. [CrossRef]
42. Song, D.; Chen, M.; Zhu, W. Has the energy-consuming right trading system achieved win-win development for China's environment and economy? *China Popul. Resour. Environ.* **2022**, *32*, 134–145.
43. Wang, H.; Liu, C.; Shi, P.; Wang, Y. The social effects of energy regulation: Energy-consuming rights trading system and corporate labor demand. *J. Environ. Manag.* **2024**, *366*, 121842. [CrossRef] [PubMed]
44. Zhang, A.; Chen, Q. Research on the effect and transmission mechanism of energy-consuming right trading system on green technological innovation. *Sci. Technol. Prog. Policy* **2023**, *40*, 93–103.
45. Pei, Q. Comparative Study on China Energy Consumption Allowance trading system with other resources and environment related rights allowance trading system. *Ind. Econ. Rev.* **2017**, *4*, 39–44.
46. Gong, P.; Xin, S. Progress in the Use of the Energy-Consuming Right and Transaction Pilot. *Energy China* **2019**, *41*, 4–8.
47. Xu, Y.; Liu, X. Can the energy-consuming right transaction system alleviate air pollution. *J. Cent. South Univ. For. Technol. Soc. Sci.* **2023**, *17*, 47–58.
48. Meng, Z. Whether the Pilot Policy of "Trading with Energy Rights" Can Promote Regional Industrial Transformation and Upgrading: Evidence from 282 prefecture-level cities in China. *Sci. Technol. Ind.* **2023**, *23*, 40–46.
49. Porter, M.E.; Linde, C.V.D. Toward a New Conception of the Environment-Competitiveness Relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [CrossRef]
50. Li, W.; Bai, Y. Can Environmental Regulation Lead to "Innovative Offsets" Effect? Game Analysis Based on "Potter Hypothesis". *J. Audit. Econ.* **2018**, *33*, 103–111.

51. Wu, X.; Qiu, W. Analysis of the Synergistic Effects of Energy Consumption Permit Trading Scheme on Pollution Reduction and Carbon Abatement. *Environ. Sci.* **2023**, 1–11. [CrossRef]
52. Liu, W. The digital economy and environmental pollution: New evidence based on the support of logistics development. *J. Clean. Prod.* **2023**, *427*, 139210. [CrossRef]
53. Shao, S.; Li, X.; Cao, J.; Yang, L. Economic policy choice of haze pollution control in China: Based on the perspective of spatial spillover effect. *Econ. Res. J.* **2016**, *51*, 73–88.
54. Luo, Z.; Wan, G.; Wang, C.; Zhang, X. Urban pollution and road infrastructure: A case study of China. *China Econ. Rev.* **2018**, *49*, 171–183. [CrossRef]
55. Li, Y.; Yang, X.; Ran, Q.; Wu, H.; Irfan, M.; Ahmad, M. Energy structure, digital economy, and carbon emissions: Evidence from China. *Environ. Sci. Pollut. R.* **2021**, *28*, 64606–64629. [CrossRef] [PubMed]
56. Deng, R.; Zhang, A. Research on the Impact of Urban Digital Economy Development on Environmental Pollution and Its Mechanism. *South China J. Econ.* **2022**, 18–37. [CrossRef]
57. Liang, W.; Yang, M.; Li, X. The interactive effects of agglomeration and urban haze pollution. *Urban Probl.* **2017**, 83–93. [CrossRef]
58. He, X.; Yu, Y.; Jiang, S. City centrality, population density and energy efficiency. *Energy Econ.* **2023**, *117*, 106436. [CrossRef]
59. Xie, Z.; Jing, Z.; Yang, M. Water Constraint Mitigation and Regional Economic Growth: Evidence from the South-to-north Water Diversion Project. *J. Quant. Technol. Econ.* **2023**, *40*, 93–115.
60. Arkhangelsky, D.; Susan, A.; Hirshberg, D.A.; Imbens, G.W.; Wager, S.; Wager, S. Synthetic Difference-in-Differences. *Am. Econ. Rev.* **2021**, *111*, 4088–4118. [CrossRef]
61. Hu, J.; Fang, Q.; Wu, H. Environmental tax and highly polluting firms' green transformation: Evidence from green mergers and acquisitions. *Energy Econ.* **2023**, *127*, 107046. [CrossRef]
62. Ma, G.; Qin, J.; Zhang, Y. Does the carbon emissions trading system reduce carbon emissions by promoting two-way FDI in developing countries? Evidence From Chinese Listed Companies and Cities. *Energy Econ.* **2023**, *120*, 106581. [CrossRef]
63. Du, M.; Wu, F.; Ye, D.; Zhao, Y.; Liao, L. Exploring the effects of energy quota trading policy on carbon emission efficiency: Quasi-experimental evidence from China. *Energy Econ.* **2023**, *124*, 106791. [CrossRef]
64. Shen, H.; Xiong, P.; Zhou, L. The impact of the energy-consuming right trading system on corporate environmental performance: Based on empirical evidence from panel data of industrial enterprises listed in pilot regions. *Heliyon* **2024**, *10*, e29628. [CrossRef]