systems

MDPI

Article

Blue Sky Defense for Carbon Emission Trading Policies: A Perspective on the Spatial Spillover Effects of Total Factor Carbon Efficiency

Da Gao [1], Linfang Tan [1], Xinlin Mo [2] and Ruochan Xiong [2,*]

[1] School of Law and Business, Wuhan Institute of Technology, Wuhan 430205, China; gaoda@wit.edu.cn (D.G.)
[2] School of Economics, Huazhong University of Science and Technology, Wuhan 430074, China
* Correspondence: m202074251@hust.edu.cn

Abstract: In the pursuit of China's environmental targets to achieve a carbon peak by 2030 and carbon neutrality by 2060, the carbon emission trading scheme (CETs) has emerged as a critical policy instrument. Since the 14th Five-Year Plan, China has been on a two-wheel drive to prevent pollution and combat climate change and proposes to fight the Blue Sky Defense. Therefore, this study focuses on prefecture-level cities in China and employs a spatial difference-difference (SDID) model to investigate the spatial spillover effects of CETs on urban total factor carbon emission efficiency (TFCEE). Furthermore, a mediating effect model is constructed to explore the channels through which CETs influence carbon emission efficiency. The results show that (1) implementing urban CETs can significantly improve urban itself and the surrounding carbon emission efficiency. (2) The CETs can indirectly promote the improvement of carbon efficiency by optimizing the allocation of labor resources and strengthening the level of green technology innovation. (3) Compared with the cities in central and western China, implementing the CETs has a stronger promotion effect on the carbon emission efficiency of the cities in eastern China.

Keywords: CETs; TFCEE; spatial difference-difference model; mediating effect

Citation: Gao, D.; Tan, L.; Mo, X.; Xiong, R. Blue Sky Defense for Carbon Emission Trading Policies: A Perspective on the Spatial Spillover Effects of Total Factor Carbon Efficiency. *Systems* **2023**, *11*, 382. https://doi.org/10.3390/systems11080382

Academic Editor: Alberto Paucar-Caceres

Received: 14 June 2023
Revised: 9 July 2023
Accepted: 25 July 2023
Published: 27 July 2023

1. Introduction

The environmental problems caused by global warming have seriously affected the ecological environment and the sustainable development of society. From 2000 to 2019, global carbon dioxide emissions increased by 40%. Therefore, reducing carbon emissions and other harmful gases has become a common goal for all countries to combat climate change [1]. As the world's largest CO_2 emitter, China's emission reduction initiatives have attracted widespread global attention [2]. China has implemented a series of action plans for the prevention and control of air pollution, resolutely fought the battle against pollution, won the battle to protect the blue sky, and concentrated on overcoming prominent ecological and environmental problems. Among a range of environmental policies, the carbon emissions trading Scheme (CETs) is the most influential. The plan is a major institutional innovation that uses market mechanisms to regulate greenhouse gas emissions and reduce air pollution while facilitating the transition to a green and low-carbon economic development model, contributing to the realization of sustainable environmental goals, and fighting for blue skies [3,4].

In 2013, the Chinese government initiated carbon emission trading pilot programs in key regions, including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen. These programs successfully established carbon emission trading markets in the pilot areas and began online trading activities. Subsequently, in December 2016, Fujian Province launched its carbon trading market, marking the country's eighth carbon trading pilot initiative. From 2017 onwards, the carbon emission trading market has gradually expanded its coverage from pilot areas to encompass the entire nation, with a particular focus on the power generation industry as an entry point for market expansion. By August 2020, the carbon emission market in pilot provinces and cities has expanded to encompass nearly 3000 enterprises across more than 20 industries, including steel, electricity, and cement [5]. Notably, the national carbon emission trading market was officially launched in July 2021 [6]. By July 2022, this market had facilitated the trading of 194 million tons of carbon emission allowances, equivalent to a total value of nearly 8.5 billion yuan. Consequently, the CETs have emerged as an indispensable tool in the government's efforts to regulate and mitigate overall greenhouse gas emissions in China.

As a typical market-based environmental governance policy, the CETs can effectively reduce carbon emissions through market incentives and technological innovation based on the theory of property rights [7,8]. Previous literature focused on the construction of DID models to study the effects of CETs on improving energy efficiency [9], reducing carbon emissions [10], promoting technological innovation [11,12], and controlling air pollution [13,14]. However, few studies have explored the spatial effects of CETs on carbon efficiency. Carbon efficiency, which represents the level of productivity achieved at a given level of carbon emissions, serves as a crucial indicator for assessing carbon emission performance. The implementation of the CETs not only influences the carbon emission efficiency within the pilot areas but also has spillover effects on the carbon emissions of neighboring cities, thereby generating spatial dependencies [15]. This spatial spillover effect manifests itself in the transmission of the promotion or inhibition effect of the CETs on carbon efficiency from one local region to its neighboring regions. However, the traditional Difference-in-Differences (DID) model fails to account for this spatial aspect, potentially resulting in estimation bias. To address this limitation, this study employs a multi-period Spatial Difference-in-Differences (SDID) approach to comprehensively analyze the spatial effects of the CETs and provide a more nuanced understanding of their impact.

The existing literature mainly explores the emission reduction effect of CETs at the provincial level, while there is little literature focusing on the influencing factors of carbon emission efficiency at the city level. More importantly, the second batch of pilot implementation in Fujian in 2016 was taken into account in the model, and there might be deviations in policy evaluation if a single-period DID was adopted. For example, Shao and Zhang (2022) [16] analyzed the emission reduction effect of CETs based on China's provincial panel data rather than the city level. Zhang et al. (2020) [10] tested the effect of CETs on energy and environmental efficiency by using the single-period DID instead of taking the pilot in Fujian in 2016 as the second batch and using the multi-period DID analysis model. We considered the prefecture-level city as the research object and Fujian, the second batch of cities, and used the multi-period SDID model to make the empirical results more accurate and reliable.

In addition, the existing literature has not yet reached a consensus on the influence mechanism of the CETs on carbon efficiency, ignoring the intermediary role of labor resource allocation and green technology innovation in the influence channel. This paper argues that the CETs can effectively promote carbon emission efficiency in the pilot and surrounding areas through two potential channels. Firstly, the implementation of the CETs can reduce the degree of labor mismatch, make the allocation of labor resources more reasonable, and thus promote the improvement of carbon emission efficiency [17]. Secondly, green technology innovation brought about by the pilot CETs is considered an important driving force for the low-carbon transition [18,19].

Therefore, this study uses data from prefecture-level cities in China to construct an SDID model and examine the spatial spillover effect of CETs on carbon emission efficiency. The Moreland index of carbon emission efficiency from 2004 to 2019 is calculated to confirm the presence of spatial correlation in carbon emission efficiency, providing a foundation for the subsequent analysis using a multi-period SDID model to test the spatial spillover effects of multi-batch CETs on carbon efficiency. Additionally, this study employs an intermediary effect model to investigate the potential mediating roles of labor resource allocation and green innovation in the influencing mechanisms.

This paper mainly contributes to the following three aspects: First, this paper considers the first and second batches of pilot cities and explores the spatial spillover effect of CETs on urban total factor carbon emission efficiency (TFCEE) by constructing a multi-period SDID model. Most of the existing literature uses DID to explore its environmental effects while ignoring the spatial spillover effect of CETs. Second, a mediation effect model is constructed with labor resource allocation and green technology innovation as the mediating variables, and the mechanism of CETs on the carbon emission efficiency of the pilot and surrounding cities is further analyzed. Most of the previous studies only discussed the impact of CETs on carbon emissions efficiency but did not deeply explore the channels of their impact on carbon emissions efficiency. Third, this paper uses total factor carbon emission efficiency to measure carbon efficiency. The measurement of carbon emission efficiency mainly uses single-factor carbon emission efficiency. However, the definition of carbon emission efficiency in this paper is to obtain maximum economic benefits and minimum CO_2 emissions on the premise that labor, capital, and energy input remain unchanged.

The structure of the paper is as follows: Section 2 shows the literature review; Section 3 is the theoretical analysis and research hypothesis; Section 4, Methods and Data, introduces the research design of the paper; Section 5 shows the empirical results; Section 6 is further analysis; Section 7 summarizes the research conclusions and policy recommendations.

2. Literature Review

Since the European Union established the world's largest carbon emissions trading market in 2005, scholars have been concerned about its effectiveness in reducing carbon emissions [20]. Some scholars have proposed that the CETs, as a typical market-oriented environmental governance policy, are more effective than traditional government regulation in carbon reduction. However, due to differences in basic national conditions and technical levels, scholars have yet to reach a unified conclusion on the emission reduction effect of CETs. On the one hand, certain scholars hold the view that the carbon reduction effect resulting from the implementation of CETs is not substantial. For example, Streimikiene and Roos (2009) [21] studied the carbon emission data of European countries and found that the EU emission trading system has not been able to reduce carbon dioxide emissions at a low cost, and the CETs are not strong in reducing carbon emissions. On the other hand, some scholars believe that the CET policies can effectively achieve carbon emission reduction and improve carbon emission efficiency. For example, Camila et al. (2018) [22] believe that the CETs have a stronger effect on carbon reduction than the carbon tax and other mechanisms. Zhang and Zhang (2019) [23] and Shen et al. (2017) [24] respectively point out at the national and enterprise levels that the implementation of China's carbon trading pilot policies can effectively promote the emission reduction of the whole country and enterprises. Zhang et al. (2020) [10] pointed out that the implementation of CETs significantly reduced industrial CO_2 emissions in pilot areas, and the average carbon emission efficiency of China's seven CETs increased year by year.

Meanwhile, scholars have gradually explored the carbon emission reduction mechanisms of CETs. Lin and Huang (2022) [20] found that the inhibition effect of carbon emissions is realized through government implementation rather than market mechanisms. Meanwhile, Cai and Ye (2022) [2] pointed out that CETs can promote low-carbon development by improving the efficiency of low-carbon technologies. Dong et al. (2022) [13] believed that CETs indirectly affect carbon emissions by improving the innovation level of cities and guiding the location choice of local industries. However, this literature ignores the indirect effects of labor resource allocation and green technology innovation on the influence channels of carbon trading pilot policies on carbon emissions.

In addition, most scholars use the traditional differential method to explore the economic impact of CETs. For example, Zhang et al. (2020) [10] used the DID method to assess the impact on carbon emissions after the implementation of the CETs in pilot cities and found that in all seven pilot regions of the carbon trading policy, the emission reduction effect of the CETs was significant. Shao and Zhang (2022) [16] employed the DID method to examine the 31 provinces in China from 2000 to 2015. Their findings indicated that the implementation of CETs in pilot areas effectively led to a reduction in local carbon emissions. However, previous literature focused on the provincial level did not take the two groups of pilot cities into account in the model and ignored the spatial effects of CETs. Since the CETs are implemented gradually in two groups of cities, the traditional DID method is limited in evaluating the policy's effect. Moreover, the implementation of CETs in a specific region may have spillover effects on the carbon emission intensity of neighboring areas, which the conventional DID model might not adequately capture, leading to potential biases in assessing these effects. To address this limitation, scholars have extensively utilized the Spatial Difference-in-Differences (SDID) model, which combines spatial econometrics with the DID framework, to examine the impacts of various policies. The SDID model allows for the consideration of spatial interactions and dependencies among regions, providing a more comprehensive understanding of the spatial spillover effects of the CETs on carbon emission intensity.

The measurement of carbon emission efficiency in previous literature has predominantly relied on single-factor methods, which may introduce measurement deviations [25,26]. To overcome these shortcomings, this study employs the Slack-Based Measure (SBM) model with non-expected outputs to comprehensively evaluate the total factor carbon emission efficiency of 253 prefecture-level cities in China. By incorporating relaxation variables into the objective function, the non-expected SBM model offers a more comprehensive and accurate measurement of carbon emission efficiency. In line with the approach taken by Gao et al. (2022) [27], this paper extends the SBM model to include carbon dioxide emissions as an undesirable output, thereby capturing a more comprehensive assessment of total factor carbon emission efficiency.

In summary, previous literature has laid a certain foundation for studying the economic effect of CETs, but there are some limitations: First, most of the studies used the seven provinces of the first batch of pilots in 2013, without considering the second batch of pilots in Fujian Province in 2016. So, the traditional single-period DID may lead to inaccurate estimates. Secondly, the spatial spillover effect of CETs on carbon emission efficiency has been largely neglected in the existing literature. Although the implementation of CETs in pilot cities may have repercussions on the carbon emissions of neighboring cities, the spatial dimension of CETs has been largely overlooked. Consequently, the understanding of the spatial spillover effect of CETs on carbon emission efficiency remains limited and requires further scholarly attention. Thirdly, the previous studies did not provide a comprehensive analysis of the impact mechanism of CET policies on carbon emission efficiency, ignoring the mediating role of labor resource allocation and green technology innovation. Fourthly, most of the literature uses single-factor methods to measure carbon emissions efficiency, and few have taken environmental factors into account to measure the total factor carbon emission efficiency.

3. Theoretical Analysis and Research Hypothesis

Based on the inter-regional competition for strategic energy efficiency, the emission reduction effect of CETs implemented in the pilot regions will not only have a demonstration effect on neighboring regions [28] but will also exert intangible pressure on enterprises in non-pilot regions. Companies in non-pilot regions will monitor their carbon emissions and increase their carbon efficiency to reduce them and avoid high emission costs when they are included in the carbon market in the future [29,30]. On the other hand, as an important market-based environmental regulatory instrument, CETs can induce firms to engage in technological innovation, helping firms with carbon quota restrictions reduce their carbon emissions and even gain additional benefits by upgrading their technology. The technological innovations undertaken by firms in these pilot areas may be transferred to surrounding areas, effectively reducing the carbon intensity of non-pilot areas through technology spillovers and contributing to carbon efficiency. However, carbon trading pilot policies may also have negative spatial spillover effects. The implementation of the

CETs may increase the cost of excessively carbon-emitting firms in the pilot areas, and surrounding cities may then become potential areas to take over high-carbon industries. The relocation of enterprises with high CO_2 emissions from the pilot area to surrounding regions can potentially lead to an upsurge in carbon emissions within the surrounding cities. This phenomenon poses a challenge to the enhancement of carbon efficiency. Based on the above analysis, we propose the following hypothesis.

Hypothesis 1a: *The CETs have a positive spatial spillover effect on the TFCEE of neighboring cities.*

Hypothesis 1b: *The CETs have a negative spatial spillover effect on the TFCEE of neighboring cities.*

The implementation of CETs has the potential to optimize labor resources and effectively improve carbon emission efficiency. By promoting free competition and the unrestricted exchange of resources within trading markets, CET policies facilitate the efficient allocation of resources. One key aspect is the market mechanism of carbon trading, which enables a rational allocation of labor by distinguishing between inefficient and efficient participants. Inefficient players are required to purchase carbon credits from efficient businesses to operate within emission limits. This process of buying and selling quotas allows for the movement of labor capital, leading to a more efficient allocation of resources. Additionally, market-oriented trade promotes labor mobility, allowing labor to flow from sectors with low efficiency to sectors with high efficiency. This reduces labor mismatch and optimizes the allocation of labor resources within the pilot zone, extending to the integration of labor resources in neighboring cities and the optimal allocation of labor resources in neighboring regions [27]. Therefore, the implementation of CETs can promote the flow of labor resources across regions and reduce labor mismatches. Moreover, the rational allocation of labor resources can also contribute to the reduction of carbon dioxide emissions in the production process of labor-intensive products. It is worth noting that the carbon emissions of intermediate products are closely related to the export volume of labor-intensive products, suggesting that the rational allocation of labor resources may significantly enhance the carbon emission efficiency of local and surrounding cities. Based on the above analysis, we propose the following hypothesis.

Hypothesis 2: *The CETs promote TFCEE in the pilot and surrounding cities by optimizing the allocation of labor resources.*

Green technology innovation brought about by the CETs is considered to be the key to achieving emission reduction breakthroughs. Both traditional theories and empirical studies emphasize that technological innovation is one of the important factors affecting CO_2 emission efficiency, especially green R&D activities [31]. The implementation of green technology innovation in enterprises can bring economic and environmental benefits by reducing raw material input and energy consumption. According to the new economic growth theory, different levels of technological progress will lead to regional differences in economic productivity [32], which will further affect the level of CO_2 emissions. However, the academic circle has not reached a unified conclusion on the emission reduction effect of green technology innovation. On the one hand, green technology innovation can optimize production technology and curb carbon emissions by promoting the progress of cleaner production technology and the efficiency of CO_2 treatment and conversion [33,34]. In the meantime, innovations in green technology can effectively increase carbon efficiency by improving the energy efficiency of enterprises in their operations and then curbing carbon emissions by strengthening end-pipe controls [35,36]. In addition, the green technology innovation carried out by enterprises in the pilot areas may be transferred to surrounding cities, effectively reducing the carbon emission intensity of non-pilot cities through technology spillover and thus improving carbon emission efficiency. Based on this, we propose Hypothesis 3:

Hypothesis 3: *The CETs promote TFCEE in the pilot and surrounding cities by promoting green technology innovation.*

The influence mechanism depicted in Figure 1 illustrates the potential mechanisms examined in this study. The CETs can exert direct effects on the carbon emission efficiency of both the pilot and surrounding cities, which can vary in either positive or negative spatial spillover effects. Furthermore, the CETs may indirectly enhance the carbon emission efficiency of these cities by optimizing the allocation of labor resources and promoting the adoption of green technology innovation. Hence, there exists the possibility of a mediating effect facilitated by labor resource allocation and green technology innovation within the influence channel.

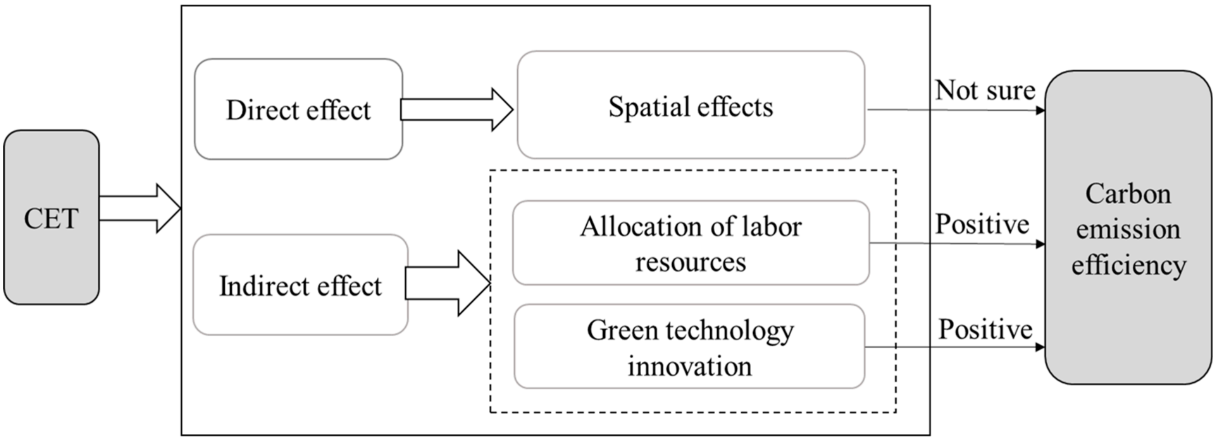

Figure 1. The impact of CETs on carbon efficiency.

4. Methods and Data

4.1. Model Design

4.1.1. Moran's I Index

The spatial DID model is founded on the premise that there is a spatial correlation between variables, so we use the global Moran's I index to analyze the spatial correlation of total factor carbon emission efficiency. Based on Shahnazi and Shabani (2021) [37], the Moran's I index is calculated by the formula:

$$I = N \cdot \frac{\sum_{ij} W_{ij}(x_i - x)(x_j - x)}{\sum_{ij} W_{ij} \sum_i (x_i - x)^2} \tag{1}$$

where N is the 253 prefecture-level cities in China and W_{ij} denotes the spatial weight matrix. To more comprehensively reflect the economic and geographical interactions among different cities, the economic-geographic weight matrix is chosen in this paper. x_i and x denote the sample observation and the sample observation mean of a city. x_i is the TFCEE of city i and x_j denotes the total factor carbon emission efficiency of city j. The Moran's I index takes a range of $[-1, 1]$, and the larger the absolute value of the Moran index, the stronger the spatial autocorrelation between the variables.

4.1.2. Spatial DID Model

The conventional DID model often overlooks the potential spatial spillover effects of carbon emissions among neighboring cities and disregards the spatial dynamics associated with the evaluation of carbon trading pilot policies. Consequently, this approach may introduce biases in the assessment of policy effectiveness. To address this limitation, this study incorporates the spatial interdependence of carbon emission efficiency across cities and accounts for the spatial spillover effects induced by carbon trading pilot policies. To quantitatively examine the spatial impact of these policies on carbon emission efficiency, a multi-period spatial difference-in-difference model is employed. The model is specified as follows:

$$TFCEE_{it} = \beta_0 + \beta_1 CET_{it} + \beta_2 WCET_{it} + \rho WCEE_{it} + \delta_i \sum X_{it} + \lambda_i W \sum X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

where $TFCEE_{it}$ is the explained variable of this paper and represents the total factor carbon emission efficiency in t years of city i. Since the carbon trading pilot policy was promoted in batches in 2013 and 2016 respectively, we used two batches of pilot policies, taking the first and the second batch into account at the same time, and constructed a multi-period spatial DID model for analysis. CET_{it} is the policy effect term, which represents the dummy variable of carbon trading policy implementation, equal to 1 if city i implements carbon trading pilot policy in year t and 0 otherwise; X_{it} indicates other control variables; W indicates the economic-geographic weight matrix; $WCET_{it}$ indicates the spatial effect of CETs on carbon emission efficiency of surrounding cities; $WCEE_{it}$ denotes the effect of carbon emission efficiency of one city on carbon emission efficiency of neighboring cities; ρ represents spatial correlation coefficient; μ_i represents city fixed effect; γ_t represents time-fixed effect; and ε_{it} represents random error term.

4.1.3. Mediating Effect Model

The carbon trading pilot policy can not only directly affect carbon emission efficiency but also indirectly affect carbon emission efficiency in the pilot and surrounding areas through optimizing the allocation of labor resources and promoting green technology innovation. Through the free exchange of resources in the trading market to achieve optimal allocation, the carbon trading policy can guide the flow of labor and other resources, reduce the degree of labor mismatch, make the allocation of labor resources more reasonable, and effectively promote the improvement of carbon emission efficiency. At the same time, the green technology innovation brought by the carbon trading pilot policy can promote clean production technology, promote carbon dioxide treatment and conversion efficiency to curb carbon emissions, and effectively improve carbon emission efficiency. To further explore the mediating role of labor resource allocation and green technology innovation in the channel of carbon trading pilot policy's impact on carbon emission efficiency and to test hypotheses H2 and H3, we take labor resource allocation and green technology innovation as mediating variables, refer to the three-step method of mediating effect [38], and combine the spatial econometric model to construct the mediating effect model as follows:

$$TFCEE_{it} = \alpha_1 + \beta_1 CET_{it} + \beta_2 WCET_{it} + \rho WTFCEE_{it} + \delta_i \sum X_{it} + \lambda_i \sum WX_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (3)$$

$$MV_{it} = \alpha'_1 + \beta'_1 CET_{it} + \beta'_2 WCET_{it} + \rho' WMV_{it} + \delta'_i \sum X_{it} + \lambda'_i \sum WX_{it} + \mu'_i + \gamma'_t + \varepsilon'_{it} \quad (4)$$

$$\begin{gathered} TFCEE_{it} = \alpha''_1 + \beta''_1 CET_{it} + \beta''_2 WCET_{it} + \rho'' WTFCEE_{it} + \varphi MV_{it} + \delta''_i \sum X_{it} \\ + \varphi_1 WMV_{it} + \lambda''_i \sum WX_{it} + \mu''_i + \gamma''_t + \varepsilon''_{it} \end{gathered} \quad (5)$$

where MV_{it} represents the mediating variable labor mismatch index *Taol* and the logarithm of green invention patents *LnGia* at the prefecture level. If the coefficients β', β'', and φ are significant, it indicates the existence of a partial mediation effect; if β' and φ are significant but β'' is not, it indicates the existence of a mediation effect.

4.2. Variable Description

Dependent variable: total factor carbon emission efficiency $(TFCEE_{it})$. Referring to Gao et al. (2022) [27], we use the undesirable-SBM model to measure the total factor carbon emission efficiency of 253 prefecture-level cities in China. We assume that in the production system's N numbers of decision-making units (DMU), each decision-making unit has three vectors: input vector: $x \in R^m$, undesirable output vector: $y^g \in R^{S_1}$, and expected output vector: $y^b \in R^{S_2}$. They are respectively represented as three matrices: input matrix $X = [x_1, x_2, \ldots\ldots, x_n] \in R^{m \times n}$, expected output matrix $Y^g = \left[y_1^g, y_2^g, \ldots\ldots, y_n^g\right] \in R^{S_1 \times n}$, and undesirable output matrix $Y^b = \left[y_1^b, y_2^b, \ldots\ldots, y_n^b\right] \in R^{S_2 \times n}$. The production possibility set can be expressed as:

$$P = \left\{ \left(x, y^g, y^b\right) | x \geq \sum_{j=1}^{n} \lambda_j x_j, y^g \leq \sum_{j=1}^{n} \lambda_j y_j^g, y^b \geq \sum_{j=1}^{n} \lambda_j y_j^b, y^g \geq 0, \lambda \geq 0 \right\} \quad (6)$$

The SBM-DEA model that considers undesirable outputs is as:

$$\tau^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{S_r^g}{y_{r0}^g} + \sum_{l=1}^{S_2} \frac{S_l^b}{y_{l0}^b}\right)} \quad (7)$$

$$s.t. \begin{cases} y_0^b = \sum\limits_{j=1, j \neq j_0}^{n} \lambda_j y_j^g - S^b \\ y_0^g = \sum\limits_{j=1, j \neq j_0}^{n} \lambda_j y_j^g - S^g \\ \\ x_0 = \sum\limits_{j=1, j \neq j_0}^{n} \lambda_j x + S^-, \lambda \geq 0\# \end{cases} \quad (8)$$

where S^-, S^b and S^g represent the redundancy of input, undesirable output and the insufficiency of the desired output. λ represents the weight vector $(\lambda \geq 0, S^- \geq 0, S^g \geq 0, S^b \geq 0)$; τ^* is the target super-efficiency value. Referring to Fan et al. (2022) [34], Zhang and Liu (2022) [39], we use GDP (Y), which reflects economic growth, as the desired output for measuring total factor carbon efficiency, carbon emissions (C) as the undesired output, and capital (K), labor (L), and energy (E) as inputs. Referring to Wang and Liu (2017) [40], we use the satellite image inversion technique to estimate the total CO_2 emissions of each city for the measurement of undesirable output CO_2 emissions; for the input indicator, we use the "perpetual inventory method" to measure the capital stock of a city and the total number of employees in a city at the end of the year to measure the city's labor force, while the product of the gross regional product and the energy intensity of each city were used to estimate energy consumption.

Independent variable: carbon emissions trading policy (CET_{it}). The carbon trading pilot policy was promoted in batches in 2013 and 2016: in 2013, China launched carbon trading pilot projects in seven provinces and cities, including Beijing, Shanghai, and Tianjin; in 2016, the second batch of pilot projects was launched in Fujian. For different pilot cities, the policy is set to 1 for the year of implementation and subsequent years and to 0 for the rest of the years. CET_{it} is set to 1 if region i is a pilot region and the year is in the year of policy implementation and later years in this city, and 0 otherwise. CET_{it} coefficient indicates the impact of the carbon trading pilot policy on carbon emission efficiency.

Mechanism variables: Drawing on the research of Chen et al. (2020) [41], this study incorporates labor resource allocation and green technology innovation as mediating variables. Labor resource allocation is captured by the labor mismatch index, which measures the degree of mismatch between labor supply and demand. Green technology innovation is quantified by the logarithm of the number of green invention patents filed in prefecture-level cities. By including these mediating variables, we aim to examine the respective roles of labor resource allocation and green innovation in shaping the relationship between carbon trading policies and carbon emission efficiency.

Other variables: In addition to the above variables, we add the following control variables, drawing on Gao et al. (2022) [27] and Zheng et al. (2023) [18], including fiscal decentralization $(Caiz)$: log of public revenue/public expenditure; population density (Pd): log of population in the land area of the city's administrative area at the prefecture-level; economic development level (Dev): logarithm of GDP per capita; Infrastructure $(Road)$:

logarithm of road mileage per capita; and Greening coverage (*Gre*): greening coverage of urban built-up areas.

4.3. Data

This study utilizes a dataset comprising information from 253 prefecture-level cities in China spanning the period from 2004 to 2019. First, the input variables used to calculate TFCEE in this paper are derived from the China City Statistical Yearbook (http://www.stats.gov.cn/, accessed on 12 July 2023) and the China Energy Statistical Yearbook (https://www.yearbookchina.com/, accessed on 12 July 2023). Second, on CET's dummy variable of whether to implement carbon emissions trading policy, we are referring to Li et al. (2023) [3]. Meanwhile, the control variables are obtained from the China Statistical Yearbook (http://www.stats.gov.cn/sj/ndsj/, accessed on 12 July 2023) and the CEIC database (https://www.ceicdata.com/en, accessed on 12 July 2023). Descriptive statistics for all variables are presented in Table 1.

Table 1. Descriptive statistics results.

		(1)	(2)	(3)	(4)	(5)
Variables	**Description**	**N**	**Mean**	**Sd**	**Min**	**Max**
TFCEE	Total factor carbon emission efficiency	4048	0.286	0.0957	0.106	1.000
CET	Dummy variable of whether to implement carbon emissions trading policy	4048	0.0501	0.218	0.000	1.000
Road	Logarithm of road mileage per capita	4048	3.144	0.541	0.468	5.207
Dev	Logarithm of GDP per capita	4048	10.19	0.807	4.595	13.06
Gre	Greening coverage of urban built-up area	4048	37.74	13.72	0.000	386.6
Caiz	Logarithm of public revenue/public expenditure	4048	−0.811	0.485	−3.664	0.433
Pd	Logarithm of population in the land area	4048	5.844	0.776	2.872	7.887
Gia	Logarithm of the number of green invention patents	4048	2.646	1.807	0.000	8.536
Taol	The labor mismatch index	4048	−0.003	0.415	−0.918	2.442

5. Empirical Results

5.1. Spatial Correlation Test

The spatial model is established on the premise of spatial correlation among variables, and Moran's I index is an important indicator to evaluate whether the variables are spatially correlated. The calculated results of Moran's I index for TFCEE of 253 prefecture-level cities in China based on the economic-geographic weight matrix are shown in Table 2. It can be seen that the Moran's index of total factor carbon emission efficiency of each city from 2004 to 2019 is significantly positive at the 1% significance level, indicating that there is a spatial agglomeration phenomenon of carbon emission efficiency values among 253 cities in China with a strong positive spatial correlation. The improvement of the TFCEE of one city can promote its surrounding cities through spatial effects. Meanwhile, Moran's I index shows an overall increasing trend over time, indicating that the spatial correlation of carbon emission efficiency among different cities increases year by year. Therefore, when examining the influence of CETs on carbon emission efficiency, the spatial factor cannot be ignored, and it is more reasonable to employ the spatial DID model to make empirical tests.

Table 2. Moran's I index results.

Variables	I	E (I)	Sd (I)	z	*p*-Value
2004	0.154	−0.004	0.024	6.527	0.000
2005	0.178	−0.004	0.024	7.499	0.000
2006	0.167	−0.004	0.024	7.057	0.000
2007	0.176	−0.004	0.024	7.427	0.000
2008	0.208	−0.004	0.025	8.653	0.000
2009	0.230	−0.004	0.025	9.490	0.000
2010	0.255	−0.004	0.025	10.496	0.000
2011	0.268	−0.004	0.025	11.034	0.000
2012	0.295	−0.004	0.024	12.262	0.000
2013	0.276	−0.004	0.024	11.801	0.000
2014	0.297	−0.004	0.024	12.668	0.000
2015	0.385	−0.004	0.024	15.927	0.000
2016	0.388	−0.004	0.024	16.472	0.000
2017	0.431	−0.004	0.024	18.162	0.000
2018	0.441	−0.004	0.024	18.519	0.000
2019	0.426	−0.004	0.024	17.842	0.000

5.2. Parallel Trend Test

The application of the spatial difference-in-differences (DID) model relies on meeting the assumption of parallel trends. Specifically, it is necessary to determine whether the TFCEE of the experimental and control groups follow the same trajectory before policy implementation and exhibit diverging trends after policy implementation. Referring to Jacobson et al. (1993) [42], we have incorporated spatial effects and developed a novel model to further examine the parallel trend assumption as follows:

$$TFCEE_{it} = \beta_0 + \sum_{k \geq -4}^{4} \beta_k CET_{i,t_0+k} + \beta_5 WCET_{it} + \rho WCEE_{it} + \delta_i \sum X_{it} + \lambda_i W \sum X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{9}$$

t_0 is the implementation time of the CET for different batches. $k < 0$ and $k > 0$ are the k years before and after the implementation of the carbon trading policy. The value of CET_{i,t_0+k} is 1 if a city is in the first k (k = −1, −2, −3, −4) years of carbon trading policy implementation and 0 otherwise. The value of CET_{i,t_0+k} is 1 if a city is in the last k (k = 1, 2, 3, 4) years after the carbon trading policy's implementation and 0 otherwise. β_k indicates whether there is a significant difference between the total factor carbon efficiency of the experimental and control groups in year k. μ_i, τ_t, and ε_{it} is the same as before. Figure 2 shows the results of the parallel trend test.

As depicted in Figure 2, the coefficients corresponding to the initial four years of CETs implementation intersect the zero scale line and exhibit insignificance. This indicates that there was no disparity in carbon emission efficiency between the experimental and control groups of cities before the policy shock. Conversely, the coefficients after the implementation of CETs surpass the zero scale line and demonstrate significant positive effects. This signifies that the CETs have had a noteworthy positive impact on the carbon efficiency of cities from the early stages of implementation. These findings imply that the observed increase in carbon efficiency can be attributed to the policy shock rather than pre-existing trends. Therefore, the results successfully fulfill the requirements of the parallel trend test, validating the applicability of the multi-period spatial DID model in examining the effect of CETs on the urban TFCEE.

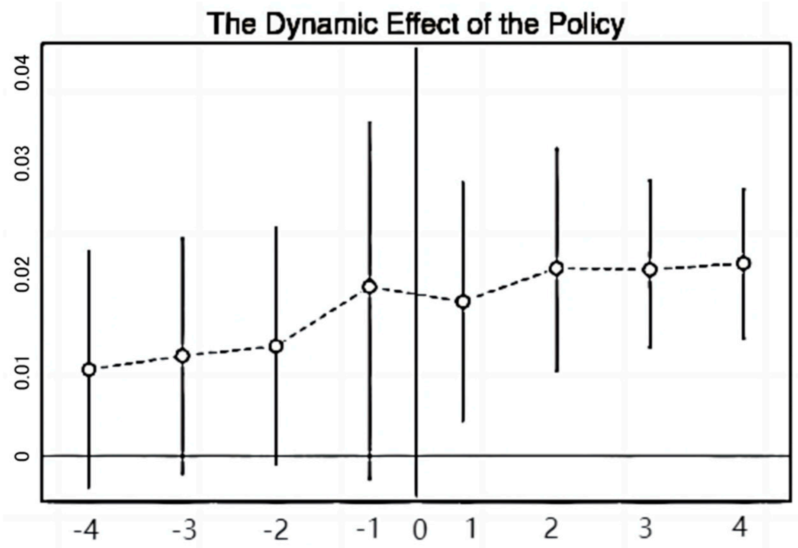

Figure 2. Parallel trend graph.

5.3. Benchmark Regression Result

To analyze the spatial effects, three spatial measures are employed: the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). The weight matrix W in the benchmark regression results is based on the economic and geographic weight matrix. As compared with other spatial econometric models, SDM can effectively deal with the spatial correlation between dependent variables and also solve problems such as the lack of spatial heterogeneity analysis. Therefore, the subsequent empirical results mainly report the results of the SDM model.

The findings presented in Table 3 demonstrate that the regression coefficients associated with the CETs are highly significant at the 1% level, irrespective of the spatial econometric model employed. Notably, in the spatial Durbin model (SDM), the coefficient of CETs exhibits significant positive effects at the 5% level. This implies that the implementation of CETs plays a crucial role in enhancing urban TFCEE, and the implementation of the policy in one city not only leads to a substantial improvement in carbon emission efficiency within that city but also positively influences neighboring cities.

Table 3. Benchmark regression result.

	(1)	**(2)**	**(3)**
Variables	**SAR**	**SEM**	**SDM**
CET	0.018 ***	0.035 ***	0.031 ***
	(4.51)	(5.14)	(3.51)
Ciaz	0.014 ***	0.009 **	0.007
	(3.72)	(1.99)	(1.45)
Pd	0.025 ***	0.019 ***	0.016 **
	(4.19)	(3.02)	(2.56)
Dev	0.002	−0.005	−0.013 ***
	(0.90)	(−1.16)	(−2.60)
Road	−0.010 ***	−0.030 ***	−0.034 ***
	(−3.49)	(−7.42)	(−8.16)
Gre	−0.000	−0.000 *	−0.000 **
	(−1.59)	(−1.85)	(−2.18)
W×CET			0.055 **
			(2.087)
W×Caiz			−0.018
			(−1.33)
W×Pd			0.042 ***
			(4.39)

Table 3. *Cont.*

	(1)	(2)	(3)
Variables	**SAR**	**SEM**	**SDM**
W×Dev			0.032 *
			(1.80)
W×Road			0.009
			(1.50)
W×Gre			0.046 ***
			(7.48)
ρ	0.773 ***		0.749 ***
	(36.16)		(33.72)
λ		0.799 ***	
		(40.03)	
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
N	4048	4048	4048
R-squared	0.400	0.389	0.521

Note: *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Values in parentheses are T statistics.

Several plausible explanations can account for these results. Firstly, the emission reduction effect of CETs in the pilot regions can serve as an effective motivation for neighboring regions. Enterprises in non-pilot regions are likely to monitor their carbon emissions more closely and enhance their carbon emission efficiency to reduce emissions. This proactive approach helps them avoid incurring high emission costs when they become part of the carbon market in the future. Secondly, CETs can effectively assist enterprises with carbon quota restrictions in achieving their carbon reduction targets by promoting technological advancements in pilot areas. These technological innovations may subsequently transfer to neighboring regions, leading to a decrease in carbon intensity in non-pilot regions through technological spillover [43,44]. As a result, carbon emission efficiency is enhanced, contributing to overall improvement. Therefore, CETs have a significant positive spatial influence on carbon emission efficiency, and Hypothesis 1a is verified.

6. Further Analysis

6.1. Mediating Effect Analysis

Since carbon trading policies can potentially impact carbon efficiency through indirect channels, such as optimizing labor resource allocation and promoting green technology innovation, we have constructed a mediating effect model to investigate the mediating role of labor resource allocation and green technology innovation in the influence channel.

The empirical results are presented in Table 4. Columns (1) and (2) examine the mediating effect of labor resource allocation. From column (1), it is observed that the coefficient of CETs is significantly negative at the 1% level, indicating that the implementation of CETs reduces the degree of labor mismatch. In column (2), the coefficient of the labor mismatch index is also significantly negative at the 1% level, suggesting that a higher degree of labor mismatch hinders the improvement of carbon emission efficiency. Hence, labor resource allocation partially mediates the channel through which CETs influence carbon emission efficiency, and the optimization of labor resource allocation facilitated by carbon trading policies contributes to the improvement of carbon emission efficiency. Thus, Hypothesis 2 is confirmed.

Columns (3) and (4) analyze the mediating effect of green technology innovation. In column (3), the coefficient of CETs is significantly positive at the 1% level, indicating that the policy implementation promotes the level of green technology innovation. Furthermore, in column (4), the coefficient of green technology innovation is also significantly positive at the 1% level, suggesting that an increase in the level of green technology innovation promotes the improvement of carbon emission efficiency. Therefore, green technology innovation also acts as a partial mediator in the influence channel, and CETs significantly enhance carbon emission efficiency by fostering the development of green technology innovation. Thus, Hypothesis 3a is supported.

Table 4. Mediating effect result.

	(1)	**(2)**	**(3)**	**(4)**
Variables	**Taol**	**CEE**	**LnGia**	**CEE**
CET	−0.036 ***	0.004 *	0.4075 ***	0.039 ***
	(−4.02)	(1.67)	(3.09)	(4.70)
Caiz	−0.043 **	0.005	−0.2559	0.002
	(−2.36)	(1.07)	(0.32)	(0.44)
Pd	0.012	0.016 **	0.6420 **	0.006
	(0.51)	(2.57)	(2.31)	(0.99)
Dev	0.420 ***	0.001	0.7340 ***	−0.003
	(22.06)	(0.20)	(4.07)	(−0.60)
Road	0.021	−0.033 ***	0.0377	−0.019 ***
	(1.30)	(−7.91)	(0.08)	(−4.82)
Gre	0.003 ***	−0.000	0.2514 ***	−0.000
	(11.15)	(−1.30)	(4.05)	(−1.21)
W×CET	0.134 **	0.042 ***	0.312 **	0.038 ***
	(2.50)	(3.09)	(2.03)	(2.94)
W×Caiz	0.059	0.059 ***	0.854	0.056 ***
	(1.58)	(6.15)	(1.36)	(6.12)
W×Pd	−0.194 ***	0.016	−0.686 *	0.043 **
	(−2.79)	(0.90)	(−1.94)	(2.56)
W×Dev	−0.343 ***	0.008	0.291 ***	−0.013 **
	(−15.12)	(1.38)	(7.07)	(−2.30)
W×Road	−0.067 ***	0.036 ***	0.595 ***	0.036 ***
	(−2.80)	(5.92)	(6.90)	(6.23)
W×Gre	−0.005 ***	−0.000	−0.968 ***	0.000
	(−5.35)	(−1.16)	(−4.11)	(1.04)
ρ	0.663 ***	0.633 ***	0.581 ***	0.689 ***
	(27.78)	(24.10)	(3.42)	(8.61)
Taol		−0.074 ***		
		(−7.85)		
Gia				0.001 ***
				(4.29)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	4048	4048	4048	4048
R-squared	0.101	0.221	0.218	0.303

Note: *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Values in parentheses are T statistics.

This phenomenon can be attributed to the mechanisms underlying CETs, which facilitate optimal resource allocation through free resource exchange in the trading market. The capital flow guided by CETs leads to more rational capital allocation. Additionally, this market-based transaction also facilitates labor mobility, enabling the flow of labor from regions with low efficiency to those with high efficiency. Consequently, the degree of labor mismatch is reduced, and the allocation of labor resources becomes more rational, effectively controlling carbon emissions and promoting improvements in carbon emission efficiency [45–47]. Moreover, the introduction of CETs stimulates green technology innovation, which optimizes production technologies. By promoting the adoption of cleaner production technologies, the innovation brought about by CETs helps mitigate carbon emissions and enhances the efficiency of carbon dioxide treatment and conversion, ultimately leading to improved carbon emission efficiency.

6.2. Robustness Test

To make the results reliable, we use the following two methods for robustness testing. The PSM-DID test is performed first. We selected other control variables as matched characteristic variables and matched them using the kernel matching method. The results are shown in Table 5, where we find that the standard deviation of the matched characteristic variables decreases and the t is not significant, indicating that the matching results pass the equilibrium measurement.

Table 5. PSM matching result.

	Unmatched	Mean		%Reduct		*t*-Test	
Variable	**Matched**	**Treated**	**Control**	**%Bias**	**∣Bias∣**	***t***	***p* > ∣*t*∣**
Pd	U	6.223	5.823	53.8	84.0	7.19	0.000
	M	6.223	6.159	8.6		0.93	0.352
Dev	U	10.897	10.152	105.3	87.9	13.08	0.000
	M	10.897	10.806	12.8		1.42	0.156
Road	U	3.215	3.14	12.6	84.9	1.93	0.053
	M	3.215	3.227	−1.9		−0.21	0.837
Caiz	U	−3.541	−4.513	73.3	86.8	9.31	0.000
	M	−3.541	−3.669	9.7		0.98	0.325

We reanalyzed the matched data using a benchmark regression, and the results are presented in Table 6. In the SDM model, the regression coefficients of the carbon trading policy (CET) are significantly positive at the 1% level, indicating that the implementation of carbon trading policy significantly contributes to the improvement of the carbon emission efficiency and exhibits a significant positive spatial spillover effect. Additionally, the coefficient is significantly positive at the 10% level, further supporting the positive impact of the carbon trading policy on carbon emission efficiency. These results are consistent with the findings from the benchmark regression, confirming the robustness of our results.

Table 6. The results of PSM-DID.

	(1)	**(2)**	**(3)**
Variables	**SAR**	**SEM**	**SDM**
CET	0.051 ***	0.071 ***	0.075 ***
	(24.68)	(28.10)	(18.36)
Caiz	−0.020 ***	−0.021 ***	−0.022 ***
	(−11.07)	(−10.69)	(−10.09)
Pd	−0.002	−0.001	0.000
	(−0.64)	(−0.50)	(0.06)
Dev	0.003 ***	0.000	0.002
	(3.32)	(0.08)	(0.87)
Road	−0.008 ***	−0.007 ***	−0.004 **
	(−5.84)	(−4.03)	(−2.18)
Gre	−0.000	0.000	0.000
	(−0.15)	(0.19)	(0.32)
W × CET			0.036 *
			(1.98)
W × Caiz			0.043 ***
			(6.78)
W × Pd			0.010 **
			(2.34)
W × Dev			−0.015 *
			(−1.80)
W × Road			−0.000
			(−0.04)
W × Gre			−0.003
			(−0.92)
ρ	0.463 ***		0.510 ***
	(17.25)		(18.54)

Table 6. *Cont.*

	(1)	(2)	(3)
Variables	**SAR**	**SEM**	**SDM**
λ		0.520 ***	
		(19.08)	
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
N	4048	4048	4048
R-squared	0.443	0.419	0.560

Note: *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Values in parentheses are T statistics.

We also conducted a robustness test by replacing the spatial weight matrix. Specifically, we utilized the 0–1 weight matrix, the distance weight matrix, and the economic weight matrix to perform separate regression analyses. The results of these regressions are presented in Table 7. The coefficients of the CETs remain significantly positive across all weight matrices. This indicates that regardless of the specific spatial weight matrix employed, the implementation of the policy consistently exhibits a significant promoting effect and a positive spatial spillover effect on the improvement of carbon emission efficiency. These findings align with the results from the benchmark regression, providing further evidence for the robustness of our regression results.

Table 7. Replace the spatial weight matrix regression results.

	(1)	(2)	(3)
Variables	**0–1 Weight**	**Distance Weight**	**Economic Weight**
CET	0.023 ***	0.034 ***	0.005 *
	(2.93)	(3.77)	(1.79)
Caiz	0.021 ***	0.006	0.032 ***
	(4.30)	(1.36)	(4.06)
Pd	0.018 ***	0.016 **	−0.002
	(2.73)	(2.53)	(−0.26)
Dev	−0.034 ***	−0.014 ***	0.051 ***
	(−6.84)	(−2.77)	(4.49)
Road	−0.023 ***	−0.034 ***	−0.016 *
	(−5.56)	(−8.09)	(−1.91)
Gre	−0.000 *	−0.000 **	0.000
	(−1.89)	(−2.13)	(0.23)
W × CET	0.031 ***	0.020 *	0.044 **
	(3.51)	(1.67)	(2.01)
W × Caiz	0.011	−0.020	−0.029 ***
	(0.99)	(−1.59)	(−3.38)
W × Pd	0.015 *	0.040 ***	0.011
	(1.72)	(4.49)	(1.35)
W × Dev	0.035 **	0.031 *	−0.051 ***
	(2.23)	(1.86)	(−4.45)
W × Road	0.030 ***	0.009	0.017 *
	(5.32)	(1.52)	(1.89)
W × Gre	0.028 ***	0.046 ***	−0.000
	(5.11)	(7.77)	(−0.27)
ρ	0.497 ***	0.695 ***	0.843 ***
	(24.31)	(32.93)	(108.06)
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
N	4048	4048	4048
R-squared	0.240	0.293	0.371

Note: *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Values in parentheses are T statistics.

6.3. Heterogeneity Analysis

The empirical analysis conducted in this study explores the regional heterogeneity in the impact of carbon trading policies on carbon emission efficiency in China. To account for the regional imbalances in economic development, the sample of Chinese prefecture-level cities is divided into three distinct regions: eastern, central, and western [48]. The results, as presented in Table 8, reveal a significantly stronger effect of the carbon trading pilot policy on carbon emission efficiency in the eastern cities compared with their central and western counterparts.

Table 8. Heterogeneity analysis.

	(1)	(2)	(3)
Variables	**Eastern Region**	**Central Region**	**Western Region**
CET	0.093 ***	0.024 **	0.011
	(6.05)	(2.05)	(1.33)
Caiz	0.001	0.004	0.043 *
	(0.05)	(0.66)	(1.73)
Pd	0.014	0.011	0.005
	(1.54)	(1.16)	(0.72)
Dev	−0.059 ***	0.037 ***	−0.005
	(−6.48)	(4.56)	(−0.63)
Road	−0.046 ***	−0.031 ***	−0.001 ***
	(−6.14)	(−5.97)	(−3.81)
Gre	−0.000	−0.001 ***	0.011
	(−0.80)	(−3.79)	(1.33)
W × CET	0.093 ***	0.047 **	−0.003
	(4.81)	(2.55)	(−0.16)
W × Caiz	0.054 ***	0.030 ***	0.116 ***
	(3.25)	(2.90)	(2.86)
W × Pd	0.004	0.113 ***	−0.039 ***
	(0.21)	(4.47)	(−4.10)
W × Dev	0.069 ***	−0.041 ***	0.033 ***
	(6.49)	(−4.56)	(2.74)
W × Road	0.053 ***	0.033 ***	0.002 ***
	(5.08)	(4.67)	(2.81)
W × Gre	−0.000	−0.000	−0.003
	(−1.43)	(−0.17)	(−0.16)
ρ	0.674 ***	0.628 ***	−0.053
	(23.93)	(19.53)	(−0.77)
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
N	1680	1648	720
R-squared	0.535	0.482	0.341

Note: *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Values in parentheses are T statistics.

The possible explanations for the results are as follows: since the eastern cities are located in coastal areas, they have more convenient economic cooperation with other countries and have more international trade opportunities, so they have richer resources, better economic development prospects, and better infrastructure. Therefore, cities in the eastern region can take advantage of their geography and resources to better develop and improve their carbon emission technology; at the same time, the superior economic conditions of eastern cities can attract more human capital and high-tech enterprises, so that enterprises have more resources and factors to promote technological progress. These development advantages make the CETs more efficient in reducing emissions, thus significantly reducing excessive carbon emissions and effectively improving carbon emission efficiency [49]. Therefore, the implementation of CETs has a stronger effect on carbon emission efficiency in eastern cities than in central and western regions.

7. Conclusions and Policy Recommendations

This study examines the impact of carbon emission trading policies (CETs) on carbon emission efficiency in a sample of 253 prefecture-level cities in China. Firstly, the findings indicate a significant positive spatial effect and spatial spillover effect of carbon trading policies on the enhancement of carbon emission efficiency. Various robustness tests, such as employing the PSM-DID model and alternative spatial weight matrices, are conducted to validate the robustness of the results. Secondly, a mediating effect model is developed to examine the mediating role. The results demonstrate that CETs can significantly enhance carbon emission efficiency in pilot cities and neighboring cities by optimizing labor resource allocation and promoting the adoption of green technology innovation. Thirdly, regional heterogeneity is explored by categorizing cities into eastern, central, and western regions. The results reveal that the implementation of carbon trading policies exhibits a stronger effect on carbon emission efficiency in the eastern cities compared with the central and western cities.

Based on the above analysis, this study proposes several policy recommendations. Firstly, it is recommended to strengthen and expand the implementation of the carbon trading pilot policy. The results indicate that the policy not only enhances carbon emission efficiency within the cities themselves but also stimulates neighboring cities to improve their carbon emission efficiency. Therefore, the government should establish a unified carbon emission trading system across all pilot cities, enhance the carbon trading mechanism and rules, and lay the groundwork for the broader implementation of CETs. Drawing on the experiences of pilot cities, the scope of policy implementation can be expanded [50], leading to the establishment of a comprehensive carbon emission trading market nationwide.

Secondly, optimizing the allocation of urban labor resources and promoting green technology innovation are crucial to maximizing the effectiveness of CETs in emissions reduction. Since the carbon trading policy demonstrates the potential to improve emission reduction through labor resource optimization and the advancement of green technology innovation, the government can regulate the flow of labor resources in the carbon trading market by issuing regulations and provisions that ensure rational allocation of labor resources, consequently effectively controlling urban carbon emissions. Additionally, increased funding for green technology innovation in cities and the implementation of incentive policies to encourage enterprises to engage in green technology innovation can be instrumental. By fostering advancements in clean production technology, the efficiency of carbon dioxide conversion can be improved, leading to reduced carbon emissions [51].

Thirdly, targeted regional emission reduction strategies should be implemented by the government. Given the evident regional imbalance in China's development, it is essential to acknowledge that the carbon trading pilot policy exhibits the strongest promotion effect on carbon emission efficiency in eastern cities. Consequently, the government should assume a leading role in developing emission reduction strategies specific to the eastern region [52]. This initiative would stimulate development and progress in the central and western regions, thereby raising the overall carbon emission efficiency level across China.

Author Contributions: Conceptualization, D.G. and L.T.; methodology, D.G.; software, X.M.; validation, L.T., X.M. and R.X.; formal analysis, R.X.; investigation, X.M.; resources, L.T.; data curation, D.G.; writing—original draft preparation, D.G.; writing—review and editing, D.G. and L.T.; visualization, D.G.; supervision, R.X.; project administration, R.X.; funding acquisition, X.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Soft Science Project of Science and Technology Department of [Research on Carbon Trading Market in Henan Province under the constraints of Dual carbon Targets], grant number [232400411036].

Data Availability Statement: Not applicable.

Acknowledgments: Thanks to Lulu Liu from Xinyang Agriculture and Forestry University for her help with this manuscript.

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

References

1. Li, S.; Liu, J.; Wu, J.; Hu, X. Spatial spillover effect of carbon emission trading policy on carbon emission reduction: Empirical data from transport industry in China. *J. Clean. Prod.* **2022**, *371*, 133529. [CrossRef]
2. Cai, W.; Ye, P. Does carbon emission trading improve low-carbon technical efficiency? Evidence from China. *Sustain. Prod. Consum.* **2022**, *29*, 46–56. [CrossRef]
3. Li, G.; Gao, D.; Li, Y. Impacts of Market-based Environmental Regulation on Green Total Factor Energy Efficiency in China. *China World Econ.* **2023**, *31*, 92–114. [CrossRef]
4. Wen, H.; Liang, W.; Lee, C.C. China's progress toward sustainable development in pursuit of carbon neutrality: Regional differences and dynamic evolution. *Environ. Impact Assess. Rev.* **2023**, *98*, 106959. [CrossRef]
5. Hong, Q.; Cui, L.; Hong, P. The impact of carbon emissions trading on energy efficiency: Evidence from quasi-experiment in China's carbon emissions trading pilot. *Energy Econ.* **2022**, *110*, 106025. [CrossRef]
6. Tan, X.; Liu, Y.; Dong, H.; Zhang, Z. The effect of carbon emission trading scheme on energy efficiency: Evidence from China. *Econ. Anal. Policy* **2022**, *75*, 506–517. [CrossRef]
7. Gao, D.; Yan, Z.; Zhou, X.; Mo, X. Smarter and Prosperous: Digital Transformation and Enterprise Performance. *Systems* **2023**, *11*, 329. [CrossRef]
8. Chen, L.; Dong, T.; Nan, G.; Xiao, Q.; Xu, M.; Ming, J. Impact of the introduction of marketplace channel on e-tailer's logistics service strategy. *Manag. Decis. Econ.* **2023**, *44*, 2835–2855. [CrossRef]
9. Zhou, C.; Qi, S. Has the pilot carbon trading policy improved China's green total factor energy efficiency? *Energy Econ.* **2022**, *114*, 106268. [CrossRef]
10. Zhang, W.; Li, J.; Li, G.; Guo, S. Emission reduction effect and carbon market efficiency of carbon emissions trading policy in China. *Energy* **2020**, *196*, 117117. [CrossRef]
11. Liu, Y.; Liu, S.; Shao, X.; He, Y. Policy spillover effect and action mechanism for environmental rights trading on green innovation: Evidence from China's carbon emissions trading policy. *Renew. Sustain. Energy Rev.* **2021**, *153*, 111779. [CrossRef]
12. Li, G.; Wen, H. The low-carbon effect of pursuing the honor of civilization? A quasi-experiment in Chinese cities. *Econ. Anal. Policy* **2023**, *78*, 343–357. [CrossRef]
13. Dong, Z.; Xia, C.; Fang, K.; Zhang, W. Effect of the carbon emissions trading policy on the co-benefits of carbon emissions reduction and air pollution control. *Energy Policy* **2022**, *165*, 112998. [CrossRef]
14. Gao, D.; Li, Y.; Tan, L. Can environmental regulation break the political resource curse: Evidence from heavy polluting private listed companies in China. *J. Environ. Plan. Manag.* **2023**, 1–27. [CrossRef]
15. Dai, S.; Qian, Y.; He, W.; Wang, C.; Shi, T. The spatial spillover effect of China's carbon emissions trading policy on industrial carbon intensity: Evidence from a spatial difference-in-difference method. *Struct. Chang. Econ. Dyn.* **2022**, *63*, 139–149. [CrossRef]
16. Shao, Q.; Zhang, Z. Carbon mitigation and energy conservation effects of emissions trading policy in China considering regional disparities. *Energy Clim. Chang.* **2022**, *3*, 100079. [CrossRef]
17. Wang, S.-H.; Li, Z.-Z.; Song, M. How embodied carbon in trade affects labor income in developing countries. *Sci. Total. Environ.* **2019**, *672*, 71–80. [CrossRef]
18. Zheng, L.; Zhao, Y.; Zhu, J.; Qian, Z.; Zhao, Z.; Fan, S. Could carbon emissions trading scheme improve total factor carbon emissions performance? Evidence from cities of China. *Energy Environ.* **2023**, 0958305X231183686. [CrossRef]
19. Zhou, F.; Wang, X. The carbon emissions trading scheme and green technology innovation in China: A new structural economics perspective. *Econ. Anal. Policy* **2022**, *74*, 365–381. [CrossRef]
20. Lin, B.; Huang, C. Analysis of emission reduction effects of carbon trading: Market mechanism or government intervention? *Sustain. Prod. Consum.* **2022**, *33*, 28–37. [CrossRef]
21. Streimikiene, D.; Roos, I. GHG emission trading implications on energy sector in Baltic States. *Renew. Sustain. Energy Rev.* **2009**, *13*, 854–862. [CrossRef]
22. Govoni, C.; Chiarelli, D.D.; Luciano, A.; Pinotti, L.; Rulli, M.C. Global assessment of land and water resource demand for pork supply. *Environ. Res. Lett.* **2022**, *17*, 074003. [CrossRef]
23. Zhang, Y.; Zhang, J. Estimating the impacts of emissions trading scheme on low-carbon development. *J. Clean. Prod.* **2019**, *238*, 117913. [CrossRef]
24. Shen, H.T.; Huang, N.; Liu, L. A study of the micro-effect and mechanism of the carbon emission trading scheme. *J. Xiamen Univ.* **2017**, *1*, 13–22.
25. Zhou, Q.; Li, T.; Gong, L. The effect of tax incentives on energy intensity: Evidence from China's VAT reform. *Energy Econ.* **2022**, *108*, 105887. [CrossRef]
26. Yu, H. The influential factors of China's regional energy intensity and its spatial linkages: 1988–2007. *Energy Policy* **2012**, *45*, 583–593. [CrossRef]
27. Gao, D.; Li, G.; Yu, J. Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* **2022**, *247*, 123395. [CrossRef]
28. Barragán-Beaud, C.; Pizarro-Alonso, A.; Xylia, M.; Syri, S.; Silveira, S. Carbon tax or emissions trading? An analysis of economic and political feasibility of policy mechanisms for greenhouse gas emissions reduction in the Mexican power sector. *Energy Policy* **2018**, *122*, 287–299. [CrossRef]

29. Shen, J.; Tang, P.; Zeng, H. Does China's carbon emission trading reduce carbon emissions? Evidence from listed firms. *Energy Sustain. Dev.* **2020**, *59*, 120–129. [CrossRef]
30. Wen, H.; Jiang, M.; Zheng, S. Impact of information and communication technologies on corporate energy intensity: Evidence from cross-country micro data. *J. Environ. Plan. Manag.* **2022**, 1–22. [CrossRef]
31. Porter, M.E.; Van der Linde, C. Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [CrossRef]
32. Khalil, H.B.; Abas, N. Smart grids: An approach to integrate the renewable energies and efficiently manage the energy system of Pakistan. In Proceedings of the Fifth International Conference on Computing, Communications and Networking Technologies (ICCCNT), Hefei, China, 11–13 July 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 1–7.
33. Grossman, G.M.; Krueger, A.B. Economic growth and the environment. *Q. J. Econ.* **1995**, *110*, 353–377. [CrossRef]
34. Fan, M.; Li, M.; Liu, J.; Shao, S. Is high natural resource dependence doomed to low carbon emission efficiency? Evidence from 283 cities in China. *Energy Econ.* **2022**, *115*, 106328. [CrossRef]
35. Du, G.; Zhou, C.; Ma, Y. Impact mechanism of environmental protection tax policy on enterprises' green technology innovation with quantity and quality from the micro-enterprise perspective. *Environ. Sci. Pollut. Res.* **2023**, *30*, 1–19. [CrossRef] [PubMed]
36. Braun, E.; Wield, D. Regulation as a means for the social control of technology. *Technol. Anal. Strateg. Manag.* **1994**, *6*, 259–272. [CrossRef]
37. Shahnazi, R.; Shabani, Z.D. The effects of renewable energy, spatial spillover of CO2 emissions and economic freedom on CO_2 emissions in the EU. *Renew. Energy* **2021**, *169*, 293–307. [CrossRef]
38. Baron, R.M.; Kenny, D.A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173. [CrossRef]
39. Zhang, M.; Liu, Y. Influence of digital finance and green technology innovation on China's carbon emission efficiency: Empirical analysis based on spatial metrology. *Sci. Total. Environ.* **2022**, *838*, 156463. [CrossRef]
40. Wang, S.; Liu, X. China's city-level energy-related CO_2 emissions: Spatiotemporal patterns and driving forces. *Appl. Energy* **2017**, *200*, 204–214. [CrossRef]
41. Chen, S.; Shi, A.; Wang, X. Carbon emission curbing effects and influencing mechanisms of China's Emission Trading Scheme: The mediating roles of technique effect, composition effect and allocation effect. *J. Clean. Prod.* **2020**, *264*, 121700. [CrossRef]
42. Jacobson, L.S.; LaLonde, R.J.; Sullivan, D.G. Earnings Losses of Displaced Workers. *Am. Econ. Rev.* **1993**, *83*, 685–709. [CrossRef]
43. Yue, X.; Zhao, S.; Ding, X.; Xin, L. How the Pilot Low-Carbon City Policy Promotes Urban Green Innovation: Based on Temporal-Spatial Dual Perspectives. *Int. J. Environ. Res. Public Health* **2022**, *20*, 561. [CrossRef] [PubMed]
44. Yang, X.; Jia, Z.; Yang, Z. How new-type urbanization pilots reduce carbon emissions: A technology progress paths perspective. *J. Clean. Prod.* **2023**, *401*, 136663. [CrossRef]
45. You, J.; Ding, G.; Zhang, L. Heterogeneous Dynamic Correlation Research among Industrial Structure Distortion, Two-Way FDI and Carbon Emission Intensity in China. *Sustainability* **2022**, *14*, 8988. [CrossRef]
46. Chen, L.; Dong, T.; Peng, J.; Ralescu, D. Uncertainty Analysis and Optimization Modeling with Application to Supply Chain Management: A Systematic Review. *Mathematics* **2023**, *11*, 2530. [CrossRef]
47. Tang, A.; Xu, N. The Impact of Environmental Regulation on Urban Green Efficiency—Evidence from Carbon Pilot. *Sustainability* **2023**, *15*, 1136. [CrossRef]
48. Zhang, P.; Yang, D.; Qin, M.; Jing, W. Spatial heterogeneity analysis and driving forces exploring of built-up land development intensity in Chinese prefecture-level cities and implications for future Urban Land intensive use. *Land Use Policy* **2020**, *99*, 104958. [CrossRef]
49. Shin, S. China's failure of policy innovation: The case of sulphur dioxide emission trading. *Environ. Politics* **2013**, *22*, 918–934. [CrossRef]
50. Wang, S.-H.; Song, M.-L. Review of hidden carbon emissions, trade, and labor income share in China, 2001–2011. *Energy Policy* **2014**, *74*, 395–405. [CrossRef]
51. Zhou, X.; Zhang, J.; Li, J. Industrial structural transformation and carbon dioxide emissions in China. *Energy Policy* **2013**, *57*, 43–51. [CrossRef]
52. Xu, C.; Xu, Y.; Chen, J.; Huang, S.; Zhou, B.; Song, M. Spatio-temporal efficiency of fiscal environmental expenditure in reducing CO_2 emissions in China's cities. *J. Environ. Manag.* **2023**, *334*, 117479. [CrossRef] [PubMed]