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The Influence of China's Carbon Market on Green Total Factor Productivity: Spatial Spillovers and the Moderating Role of Green Technological Innovation

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Abstract— This study provides a comprehensive evaluation of China's Carbon Emissions Trading System (CETS) and its impacts on Green Total Factor Productivity (GTFP) using provincial panel data from 2005 to 2020. Employing a quasi-experimental approach combining Difference-in-Differences (DID) and Spatial DID (SDID) methodologies to analyze seven pilot regions (Beijing, Shanghai, Guangdong, Tianjin, Hubei, Chongqing, and Fujian). Key findings indicate: CETS significantly promotes regional GTFP growth; Green Technological Innovation (GTI) acts as a moderating variable that enhances CETS' positive effect; Spatial analysis reveals CETS generates local GTFP growth and positive spillovers to neighboring regions; Robustness checks confirm result reliability. This research provides empirical evidence for optimizing carbon trading policies and achieving green development, highlighting the synergy between technological innovation and market mechanisms.

Keywords: Carbon Emissions Trading System; Green Total Factor Productivity; Green Technological Innovation; Spatial Spillover Effects; Difference-in-Differences.

I. INTRODUCTION

With the rapid advancement of global industrialization, human activities and industrial production are significantly altering the Earth's climate system. Climate change is getting worse because carbon emissions reached a record 37.4 billion tons in 2024. China produces 32% of the world's emissions, so its actions are very important for fighting climate change. Reducing emissions is not only a domestic imperative but also a key factor influencing global carbon reduction trends. China faces the dual challenge of sustaining economic growth while transitioning toward a low-carbon development model. In response, the country has implemented various environmental policies, with the CETS emerging as a critical market-based tool for emission reduction.

CETS is a market-driven environmental regulatory tool that sets an upper limit on emissions while allowing trading of emission quotas. Compared to traditional administrative measures, CETS provides a cost-effective mechanism to internalize carbon costs, incentivizing firms to adopt green technologies and improve resource efficiency. This system aligns with Porter's hypothesis, which suggests that well-designed environmental regulations can drive technological innovation and enhance economic efficiency(Porter, 1997). The development of CETS has been observed globally, with the European Union launching its Emissions Trading System (EU ETS) in 2005. In China, the concept was first proposed in 2011, with pilot programs starting in 2013 across seven regions. After a decade of development, China officially launched its nationwide CETS in 2021, initially covering the power sector and planning to expand to other high-emission industries.

As carbon trading policies develop, researchers have increasingly studied their economic and environmental impacts. Scholars have examined CETS' cost-effectiveness in emission reduction, particularly regarding marginal abatement costs and allowance allocation methods (Peng et al., 2022). Other studies focus on its influence on firm behavior and market value, revealing varying effects across different industries and company types (Niu et al., 2024; Zhang et al., 2025). Additional research has demonstrated CETS' role in regional economic performance, green finance development, and industrial restructuring (Bian et al., 2024), , along with its positive effects on corporate green investment and innovation efficiency (Chen et al., 2023; Zhou et al., 2023). Studies also confirm CETS contributes to carbon efficiency improvements, especially in non-state-owned enterprises and market-oriented regions (Yu et al., 2024).

However, important research gaps persist regarding how CETS specifically affects green total GTFP through GTI and spatial spillover effects. While existing literature supports the Porter hypothesis by showing CETS promotes green innovation (Niu et al., 2024), the extent to which GTI moderates the relationship between CETS and GTFP remains underexplored. Furthermore, although some studies employ spatial econometric models to investigate the spatial effects of CETS (Bian et al., 2024), the specific channels of these spillover effects require deeper investigation.

This study systematically addresses these gaps by examining how CETS enhances GTFP through GTI's moderating role, building on the Porter hypothesis that environmental regulation can simultaneously drive innovation and productivity gains. Additionally, through spatial DID analysis, we investigate whether CETS generates spillover effects in neighboring regions through knowledge diffusion, industrial restructuring, and policy imitation. These findings provide valuable insights for optimizing regional carbon policies and promoting balanced low-carbon development.

II. Literature Review

The foundation of carbon trading traces back to John Dales' pioneering work in the 1960s, which introduced market-based mechanisms for pollution control. This concept later evolved into the Carbon Emissions Trading System (CETS), formalizing carbon emission rights as tradable commodities (Button, 2008; Pan et al., 2022). By capping total emissions and allocating allowances, CETS creates economic incentives for firms to reduce emissions while monetizing surplus quotas (Liu et al., 2021).

Globally, CETS implementations have demonstrated measurable success. The EU ETS, operational since 2005, reduced emissions in energy-intensive sectors by 14–16% during its initial phases (Alberola et al., 2009; Colmer et al., 2024). Similarly, South Korea's K ETS achieved significant emission cuts in its first compliance period of 2015 to 2017 (Oh et al., 2023). In China, the CETS began as pilot programs in 2013 in regions such as Beijing, Shanghai, Shenzhen, and Guangdong. Tianjin, Chongqing, and Hubei joined in 2014, followed by Fujian in 2016. In China, regional CETS pilots launched in 2013–2016 targeted high-emission industries, culminating in a national carbon market in 2021 focused initially on the power sector. Empirical studies confirm these pilots reduced emissions, particularly in state-owned enterprises and economically advanced regions (Ma et al., 2023), with potential for further reductions under expanded coverage (Jia et al., 2025). These findings provide strong support for the first hypothesis:

H1: The CETS enhances regional GTFP in China.

Beyond emission reductions, CETS reshapes economic behavior. Firms under emission constraints increase R&D investments to enhance productivity (Boungou & Dufau, 2024), aligning with Porter's hypothesis that environmental regulations can spur innovation (Cui et al., 2022). In China, CETS has accelerated industrial green transitions, especially in resource-dependent cities (Lin & Xie, 2023). A critical outcome of CETS is its impact on GTFP, which evaluates economic output efficiency while accounting for environmental costs. Studies employing Slack-Based Measure Global Malmquist-Luenberger (SBM-GML) and Data Envelopment Analysis (DEA) methods show CETS elevates GTFP in pilot regions, though effects may diminish over time (C. Li et al., 2022). Notably, agricultural GTFP improvements strengthen as carbon quotas tighten (Yu et al., 2022), suggesting policy design influences long-term efficacy.

The relationship between CETS and GTFP is further mediated by GTI. Regions with robust innovation systems exhibit amplified GTFP gains under CETS (Zhang et al., 2022), as GTI enables firms to reconcile compliance costs with operational efficiency. This synergy underscores Porter's "innovation offset" effect (Ma et al., 2022). leading to the second hypothesis:

H2: GTI plays a moderating role in the relationship between CETS and GTFP.

Furthermore, CETS generates spatial spillover effects to neighboring non-pilot regions. These spillovers occur through technology diffusion, trade, and industrial interactions (S. Li et al., 2022; Zhang et al., 2022). Firms in non-pilot regions may adopt innovative technologies developed in pilot regions, benefiting from CETS-driven advancements without directly participating in the system. Research utilizing the Spatial Difference-in-Differences (SDID) model has demonstrated that improvements in GTFP within pilot regions can positively impact adjacent non-pilot regions, emphasizing broader regional development and environmental benefits (Zhang et al., 2022). However, the specific channels of these spillovers—whether through knowledge transfer, labor mobility, or policy imitation—require deeper examination (Bian et al., 2024). This spatial dimension forms the basis of the third hypothesis:

H3: CETS generates spatial spillover effects to neighboring non-pilot regions.

III. Model Setup and Data Description

2.1 Model Setup

This study treats the implementation of the CETS policy as a quasi-natural experiment. Provinces that implemented the CETS policy are designated as the treatment group, while provinces without the policy serve as the control group. To examine the causal relationship between the CETS policy and urban GTFP, we construct the following baseline Difference-in-Differences (DID) model:

$$\mathrm{GTFP}_{it} = \beta_0 + \beta_1 \mathrm{DID}_{it} + \rho X_{it} + \delta_i + \mu_t + \varepsilon_{it} \tag{1}$$

GTFP_{it} is the dependent variable, representing the GTFP of a city. DID is the key explanatory variable, which is a dummy variable used to measure the implementation of the CETS policy for region i in year t. X_{it} represents a set of control variables used to account for other important factors that may influence provincial GTFP. δ_i denotes individual fixed effects, controlling for time-invariant characteristics specific to each region. μ_t denotes year fixed effects, controlling for time-specific shocks common to all regions. ε_{it} is the random error term, capturing unobserved factors that may affect the dependent variable.

2.2 Data Description

2.2.1 Dependent Variable

The dependent variable in this study is GTFP, which is measured using the SBM-GML index. The SBM-GML method is an extension of DEA that incorporates slack variables for inputs and outputs, providing a more comprehensive evaluation of efficiency. Following the methodologies of C. Li et al. (2022) and Jiakui et al. (2023), we calculate GTFP using the input and output variables listed in Table 1.

Table 1. *Variables Used for Calculating GTFP with SBM-GML.*

Variable	Measurement	Unit	Source
Labor Input	Total employment in each province	10^4 persons	Statistical yearbook of China
Capital Input	Capital stock estimated using the Perpetual Inventory Method	10^9 CNY	Statistical Yearbook of China
Energy Input	Total energy consumption, measured in standard coal equivalents	10^4 tons	China Energy Statistical Yearbook
Desirable Output	Deflated Gross Domestic Product (GDP) of each province	10^9 CNY	Statistical Yearbook of China
Undesirable Output	Environmental pollution in the form of CO2 emission.	10^4 tons	China Environmental Statistical Yearbook

Since the SBM-GML method yields a change index, GML2004 is used as the base period to calculate the GTFP from 2005 to 2020. Thus, the input variables, desirable output, and undesirable output values are selected for the years 2004–2020.

For the calculation of capital input (K), capital stock was derived using the Perpetual Inventory Method (Zhang, 2008).Specifically, the capital stock of the i-th region in the t-th year is calculated as: $K_{i,t} = K_{i,t-1} - (1 - \delta_{i,t}) + I_{i,t}$. Where $I_{i,t}$ represents the actual gross fixed capital formation in the t-th year, calculated at constant prices for the i-th region, and $\delta_{i,t}$ represents the depreciation rate, which is set at 9.6% in this research. Furthermore, capital stock is calculated at constant 2003 prices, and the initial capital stock in 2003 is determined as the gross fixed capital formation divided by 10%.

For the calculation of Desirable Output (D), this paper refers to the research of Lai and Zhu (2022).The regional GDP indices (previous year = 100) and nominal regional GDP (in 100 million yuan) were downloaded from the Statistical Yearbook of China. Constant-price GDP (using 2003 as the base year) was calculated as follows: Actual GDP in 2004 = Nominal GDP in 2003 × Regional GDP Index in 2004 / 100, and so forth.

2.2.2 Explanatory Variables

The explanatory variable in this study is DID_{it}, which is constructed as $CETS_{it} \times TIME_{it}$. The interaction term DID_{it} captures the net effect of the CETS policy on the treated provinces. Here, $CETS_{it}$ is a grouping dummy variable that takes the value of 1 if the province is CETS pilot and 0 otherwise. In this study, CETS pilot provinces are Shanghai, Beijing, Guangdong (includes Shenzhen), Tianjin, Hubei, Chongqing, and Fujian. $TIME_{it}$ is a time dummy variable that takes the value of 1 for the years 2013 and onward (the period after the implementation of the CETS pilots) and 0 otherwise.

2.2.3 Control Variables and Moderating Variable

To account for other factors that may influence productivity, this study includes a set of control variables (Xit) based on the methodologies of Liu et al. (2024) and Zhang et al. (2024). These control variables include the degree of openness (OPE), urbanization level (URB), human capital (EDU), degree of government intervention (INT), and the number of green technological innovation applications (GTI). To mitigate issues of heteroscedasticity and right-skewed distributions, as well as to facilitate the interpretation of elastic relationships between variables, continuous control variables and the moderating variable are transformed using natural logarithms.Detailed descriptions of these variables are provided in Table 2.

Table 2. *Variables Descriptions*

Variable	Abbreviation	Measurement	Source
Degree of Openness	OPE	The ratio of actual foreign investment to GDP (%)	Statistical Yearbook of China
Urbanization Level	URB	The ratio of the urban population to the total population at the end of the year (%)	Statistical Yearbook of China

Human Capital Level	EDU	The ratio of the Number of higher education students to the total population (%)	Statistical Yearbook of China
Degree of Government Intervention	INT	The ratio of Government Fiscal Expenditure to Regional GDP (%)	Statistical Yearbook of China
Numbers of Green Technological Innovation Applications	GTI	The logarithm of the number of green patent applications (including invention and utility model patents) (piece)	China Intellectual Property Right

2.2.4 Data sources and explanations

This study spans the period from 2005 to 2020, aiming to conduct an empirical analysis based on panel data from 30 provinces and municipality cities (because provinces and municipality city belong to the same level, we use the collective name province in the following text) in China. However, due to incomplete and limited availability of data for Tibet, Hong Kong, and Macau, these regions are not included in the study. Since Shenzhen is under the jurisdiction of Guangdong Province, and the provincial-level panel data for Guangdong already includes Shenzhen, the study integrates Shenzhen's data into Guangdong. Data primarily obtained from the China Statistical Yearbook, China Environmental Statistical Yearbook, statistical yearbooks of relevant provinces and China Intellectual Property Right. For the few missing values, the interpolation method was applied to fill the data gaps.

2.2.5 Descriptive statistics and Unit Root Test Results

This section presents the descriptive statistics and unit root test results for the variables used in the analysis. Table 3 summarizes the key characterization indicators, including the count, mean, standard deviation (sd), minimum (min), and maximum (max) values for each variable. Additionally, the results of the Levin-Lin-Chu (LLC) unit root test are reported to examine the stationarity of the panel data.

Table 3. *Descriptive Statistics and Unit Root Test Results*

	count	mean	sd	min	max	Unit Root Test Results	
						Statistic LLC	P-Value
GTFP	480	1.20	0.38	0.43	2.36	-2.1550	0.0156*
ln_OPE	480	-1.73	0.98	-4.88	0.54	-3.8138	0.0001***
ln_URB	480	-0.64	0.28	-1.57	-0.11	-2.5048	0.0061**
ln_EDU	480	-4.06	0.35	-5.20	-3.19	-7.1959	0.0000***
ln_INT	480	-1.57	0.40	-2.53	-0.44	-3.4000	0.0003***
ln_GTI	480	1.83	0.31	0.33	2.35	-6.4405	0.0000***

*Notes: LLC test examines the null hypothesis of a unit root. ***, *, and * denote significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table 3, the LLC test results reject the null hypothesis of a unit root for all variables at the 1% or 5% significance level, suggesting that the data are stationary.

III. Empirical Result and Analysis

3.1 Parallel Test

The parallel trend test is conducted to verify whether the treatment and control groups exhibit similar trends before the implementation of the policy, ensuring that any observed effects can be attributed to the policy rather than pre-existing differences between the groups. This assumption is critical for the validity of the Difference-in-Differences (DID) approach, as it ensures that the treatment and control groups would have followed parallel paths in the absence of the policy intervention. To test this assumption, we construct the following model:

$$GTFP_{it} = \beta_0 + \sum_{k=1}^{7} \beta_k \, TPTP_{it}^{-k} + \rho_1 ln\_OPE_{it} + \rho_2 ln\_URB_{it} + \rho_3 ln\_EDU_{it} + \rho_4 ln\_INT_{it} + +\delta_i + \mu_t + \varepsilon_{it} \tag{2}$$

$TPTP_{it}^{-k}$ represents the annual dummy variables for the k-th year before the policy implementation in pilot regions, where k = 1,2,3,4,5,6,7. Since the CETS policy was implemented in 2013, for the treatment group, $TPTP_{it}^{-k}$ = 1 when k = 1 in 2012, and equals 0 for all other years. For the control group, $TPTP_{it}^{-k}$ = 0 for all years. The regression coefficient (β_k) reflects the magnitude of the policy's impact, specifically its effect on GTFP. Observing whether β_k is statistically significant is crucial; if none of the coefficients are significant, the parallel trend assumption is considered to hold.

This study first conducted parallel trend testing for analysis (shown in Fig. 1). Based on Fig. 1, the following preliminary observations are made：

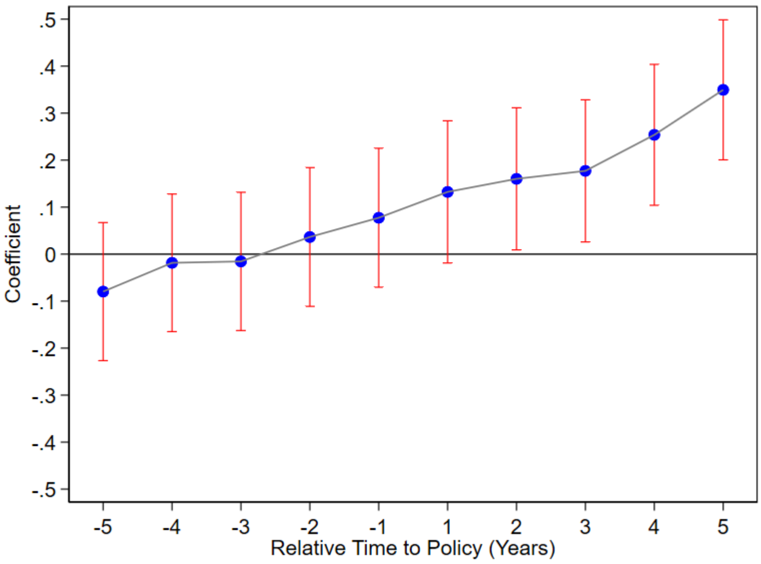

Figure 1. *Parallel Trend Test*

This Fig.1. presents the results of the parallel trend test before and after the policy implementation. The horizontal axis represents the relative time to the policy implementation (Relative Time to Policy, Years), while the vertical axis represents the regression coefficients (Coefficient). The blue dots indicate the estimated coefficient values, and the red error bars represent the confidence intervals.

Before the policy implementation ($t < 0$), the estimated coefficients are close to zero, and the error bars include zero, indicating that the treatment and control groups exhibited similar trends prior to the policy implementation. This satisfies the parallel trends assumption, which is a critical precondition for the validity of the DID approach.

After the policy implementation ($t \geq 0$), the estimated coefficients gradually increase, suggesting that the policy has a positive impact on the dependent variable, and this effect strengthens over time. This demonstrates that the implementation of the policy effectively enhances GTFP, aligning with the expected outcomes. As shown in Fig. 1, the DID coefficients are not statistically significant in the pre-policy periods (Pre-5 to Pre-1), confirming that the treatment and control groups followed parallel trends in GTFP before the policy implementation. This result validates the parallel trends assumption and supports the reliability of the baseline regression results.

Furthermore, the dynamic effects after the policy implementation (Post-1 and beyond) reveal that the policy's impact on GTFP increases year by year, indicating that the carbon trading policy has a sustained and growing positive effect on GTFP. This underscores the effectiveness of the policy in promoting green development and provides robust empirical evidence for its continued implementation and optimization.

3.2 Baseline Regression

$$GTFP_{it} = \beta_0 + \beta_1 DID_{it} + \rho_1 ln\_OPE_{it} + \rho_2 ln\_URB_{it} + \rho_3 ln\_EDU_{it} + \rho_4 ln\_INT_{it} + \delta_i + \mu_t + \varepsilon_{it} \tag{3}$$

This study employs a DID model to evaluate the net effect of China's CETS pilot policy on city-level GTFP. To control for potential confounding factors, we progressively introduced various control variables and accounted for both time and individual fixed effects. The baseline regression results are reported in Table 4.

Table 4. *The baseline regression results*

	(1)	(2)
	GTFP	GTFP
DID	0.240***	0.0974**
	(0.0352)	(0.0339)
ln_OPE		0.0721***
		(0.027)
ln_URB		-0.0357
		(0.124)
ln_EDU		-0.698***
		(0.066)
ln_INT		-0.270***
		(0.081)
_cons	1.005***	-2.525***
	(0.030)	(0.340)
Year FE	Yes	Yes
id FE	Yes	Yes
N	480	480
F	24.04***	30.62***
r2	0.470	0.587

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In column (1), we first estimate the basic model without including control variables. The results show that the implementation of the ETS policy has a significantly positive impact on GTFP, with a coefficient of 0.240, which is statistically significant at the 1% level. This indicates that, without considering other factors, the ETS pilot policy significantly enhances the GTFP of cities.

In column (2), we further introduce multiple control variables, including the level of economic development (ln_OPE), urbanization rate (ln_URB), education level (ln_EDU), and technological innovation level (ln_INT), while controlling for year and city fixed effects. The results show that although the coefficient of the ETS policy decreases to 0.0974, it remains statistically significant at the 5% level. This suggests that even after controlling for other factors that may influence GTFP, the ETS policy still has a significantly positive impact on GTFP. It is proved hypothesis 1 .

Among the control variables, the level of economic development (ln_OPE) has a significantly positive impact on GTFP (coefficient of 0.0721, significant at the 1% level), indicating that regions with higher economic development tend to have higher GTFP. However, the education level (ln_EDU) and technological innovation level (ln_INT) have negative impacts on GTFP, both significant at the 1% level. This may reflect that education and technological innovation have not yet effectively translated into improvements in green productivity in the short term, or that other unobserved factors may be influencing this relationship.

3.3 Robustness Test

Endogeneity issues in the model may lead to estimation errors. The primary sources of endogeneity include omitted variable bias, sample selection bias, measurement errors, and reciprocal causality (simultaneity bias). To address potential flaws in the model design and the influence of unobserved factors on the regression results, this study conducts further analysis and validation through both temporal and regional placebo tests, as well as Propensity Score Matching Difference-in-Differences (PSM-DID).

3.3.1 In-time Placebo Test

In the in-time placebo test, we shift the implementation time of the carbon trading policy forward by 1 to 7 periods and re-run the DID regression to examine whether the policy effect exhibits any pre-existing impact (i.e., whether it violates the parallel trends assumption). The regression results, as shown in Fig.2, indicate that the DID estimated coefficients (pink dashed line) are not statistically significant at any of the artificially set pre-treatment time points, and their 95% confidence intervals (blue error bars) all cross the zero line (black dashed line). This suggests that no significant policy effect is observed before the actual implementation of the policy, further validating the reliability of the baseline regression. Specifically, it confirms that the impact of the carbon trading policy indeed occurs after its implementation, rather than being a spurious relationship caused by other factors. This supports the validity of the parallel trends assumption.。

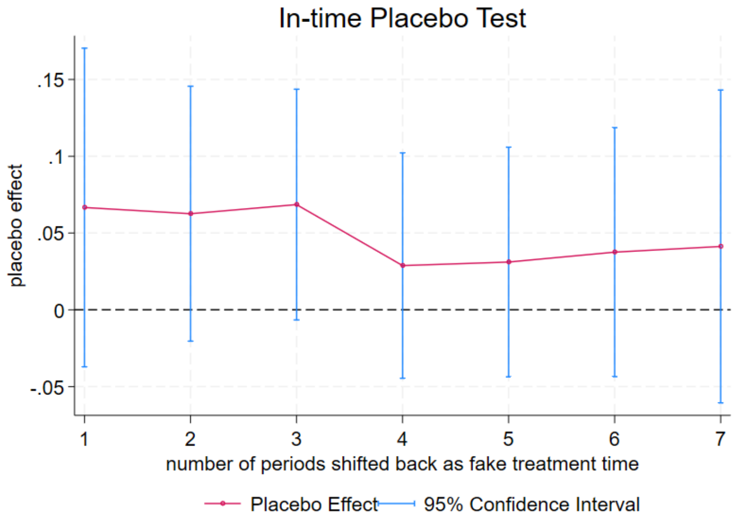

Figure 2. *In-time Placebo Test*

3.3.2Regional Placebo Test

In the regional placebo test, we randomly reassign the pilot cities to examine whether the policy effect is coincidental rather than driven by the carbon trading policy itself. The regression results show that the actual DID estimate is 0.0974, which is significantly positive in the baseline regression. In contrast, in the 500 randomly permuted placebo tests, the generated DID coefficients are uniformly distributed around zero, and the p-value of the Monte Carlo test is close to 1, indicating that the policy effect is not significant under random assignment of pilot cities. This suggests that the policy effect observed in the baseline regression is not driven by other random factors but is indeed caused by the carbon trading policy itself, thereby enhancing the robustness of the causal effect of the policy on GTFP. Furthermore, the density distribution plot of the regression coefficients shows that the actual DID estimate (indicated by the red dashed line) significantly deviates from the center of the distribution generated by the placebo tests, providing additional evidence for the effectiveness of the policy impact. This confirms that the improvement in GTFP due to the carbon trading policy is not a coincidental phenomenon but is both economically and statistically robust.

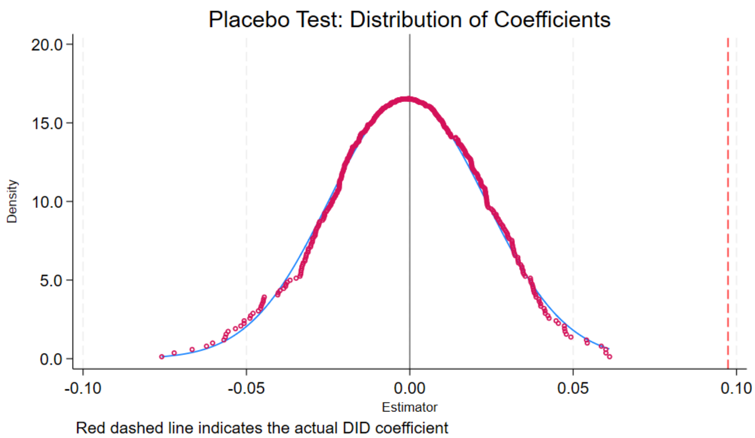

Figure 3. *Placebo Test: Distribution of Coefficients*

3.3.3 Propensity Score Matching Difference-in-Differences

Sample selection bias is a significant source of endogeneity issues. Although the DID model requires that the treatment and control groups be comparable before the policy implementation, the selection of pilot cities for the CETS was not entirely random. For example, the seven pilot provinces (such as Beijing, Shanghai, and Tianjin) are all located in economically developed regions of China, where firms may have had higher GTFP even before the policy implementation. As a result, sample selection bias may exist, leading to biased estimation results. To address this issue, this study adopts PSM-DID approach, following the methodology of Feng et al. (2021), for robustness testing. The specific steps are as follows:

First, propensity score matching (PSM) is conducted: Using the nearest neighbor matching method, the treatment and control groups are matched based on all control variables (such as the level of economic development, urbanization rate, education level, and technological innovation level) to ensure that the two groups have similar characteristics before the policy implementation. Subsequently, the DID model is re-estimated using the matched sample to eliminate the influence of sample selection bias on the results. The results are presented in Table 5.

Table 5. *PSM-DID Results*

	(1) GTFP	(2) GTFP
DID	0.0974***	0.150***
	(0.034)	(0.044)
ln_OPE	0.0721***	-0.223***
	(0.027)	(0.043)
ln_URB	-0.0357	-0.308***
	(0.124)	(0.091)
ln_EDU	-0.698***	0.502***
	(0.066)	(0.116)
ln_INT	-0.270***	0.276***
	(0.081)	(0.101)
N	-2.525***	277
F	(0.340)	61.24***
r2	480	0.987

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5. reports the estimation results of the PSM-DID analysis. Column (1) presents the baseline regression results, while Column (2) shows the results after applying the nearest neighbor matching method. The post-matching results reveal that the coefficient of the CETS on GTFP increases from 0.0974 to 0.150, and it is statistically significant at the 1% level. This indicates that after controlling for sample selection bias, the positive effect of CETS on GTFP is further enhanced.

3.3.4 Moderating Effect

The baseline regression results indicate that the CETS policy has a significant positive effect on GTFP. However, an important question remains unresolved: Does GTI play a moderating role in the impact of the CETS policy on GTFP? To address this question, this study further analyzes the moderating effect of green innovation.

To examine the moderating role of green innovation, this study introduces an interaction term between the CETS policy and green innovation (DID_GTI) as well as a standalone term for green innovation (ln_GTI) into the baseline regression model. The other terms remain consistent with Equation (3). The model is specified as follows:

$$\mathrm{GTFP_{it}} = \beta_0 + \beta_1 \mathrm{DID_{it}} + \beta_2 \mathrm{ln\_GTI_{it}} + \beta_3 \mathrm{DID\_ln\_GTI_{it}} + \rho_1 \mathrm{ln\ \_OPE_{it}} + \rho_2 \mathrm{ln\_URB_{it}} + \rho_3 \mathrm{ln\_EDU_{it}} + \rho_4 \mathrm{ln\_INT_{it}} + \delta_i + \mu_t + \varepsilon_{it} \quad (5)$$

Table 6. *Regression Results with Moderating Effects*

	(1)	(2)
	GTFP	GTFP
DID	0.0974**	-0.742**
	(0.0339)	(0.303)
ln_OPE	0.0721***	0.0453
	(0.027)	(0.029)
ln_URB	-0.0357	-0.184***
	(0.124)	(0.060)
ln_EDU	-0.698***	-0.393***
	(0.066)	(0.071)
ln_INT	-0.270***	0.137*
	(0.081)	(0.076)
DID_ln_GTI		0.114***
		(0.037)
ln_GTI		0.129***
		(0.017)
N	480	480
F	30.62***	53.46***
r2_a	0.587	0.983

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The interaction term DID_ln_GTI coefficient of 0.114, significant at the 1% level, demonstrates that green innovation significantly amplifies the positive impact of the CETS policy on GTFP. Specifically, regions with higher levels of green innovation experience a more substantial boost in GTFP due to the CETS policy. Additionally, the standalone term for green innovation (ln_GTI) shows a coefficient of 0.129, also significant at the 1% level, indicating that green innovation independently contributes to GTFP improvement. These results robustly support Hypothesis 2, highlighting the dual role of green innovation in both directly enhancing GTFP and strengthening the effectiveness of the CETS policy.

3.3.5 Spatial effect analysis

The impact of the CETS is not limited to pilot cities but may also extend to non-pilot provinces. Given the interregional economic and environmental linkages, the effects of CETS pilot policies may diffuse to untreated neighboring cities, leading to spatial spillover effects.

Before constructing the spatial regression model, it is essential to examine the spatial correlation of the dependent variable, GTFP. This study applies Global Moran's I test using a geographical distance weight matrix to assess the spatial autocorrelation of GTFP. The results, presented in Table 7, indicate a significant spatial correlation over time.

Table 7. *Global Moran's I test*

year	I	E(I)	Sd(I)	Z	P-value
2005	0.0006	-0.0345	0.0300	1.1697	0.2421
2010	0.0287	-0.0345	0.0358	1.7636	0.0778
2015	0.0616	-0.0345	0.0365	2.6344	0.0084

2020	0.0990	-0.0345	0.0365	3.6594	0.0003

From 2010 onwards, the Z-statistics increase, and the corresponding p-values drop below 0.05, suggesting that the spatial clustering of GTFP becomes more pronounced over time. To further determine the suitability of the spatial model, this study conducts the Lagrange Multiplier (LM) Test. The test results (see Table 8) show that the Lagrange Multiplier statistics for both the Spatial Error Model (SEM) and the Spatial Lag Model (SLM) are significant (p-values less than 0.01) indicating the presence of spatial dependence in the data. Additionally, the Robust Lagrange Multiplier Test confirms the significance of spatial effects.

Considering the potential spatial spillover effects of the independent variables and the need to capture more complex spatial dependencies, this study adopts the Spatial Durbin Model (SDM) as the primary analytical model. The SDM not only accounts for the spatial lag effect of the dependent variable but also incorporates the spatial lag effects of the independent variables, providing a more comprehensive framework for analyzing the impact of CETS on GTFP. This approach aligns with the research objectives and theoretical expectations, allowing for a robust examination of both direct and indirect spatial effects.

Table 8. *LM Test*

Test	Statistic	df	p-value
Spatial error:			
Moran's I	5.487	1	0.000
Lagrange multiplier	23.800	1	0.000
Robust Lagrange multiplier	1.976	1	0.160
Spatial lag:			
Lagrange multiplier	50.780	1	0.000
Robust Lagrange multiplier	28.956	1	0.000

Accordingly, this study establishes the following Spatial Difference-in-Differences (SDID) model to analyze the spatial spillover effects of CETS:

$$\begin{aligned}\mathrm{GTFP}_{it} = {} & \alpha + \rho \mathrm{WGTFP}_{it} + \beta_1 \mathrm{SDID}_{it} + \gamma_1 \mathrm{WSDID}_{it} + \beta_2 \mathrm{ln\_OPE}_{it} + \beta_3 \mathrm{ln\_URB}_{it} + \beta_4 \mathrm{ln\_EDU}_{it} + \beta_5 \mathrm{ln\_INT}_{it} \\ & + \gamma_2 \mathrm{Wln\_OPE}_{it} + \gamma_3 \mathrm{Wln\_URB}_{it} + \gamma_4 \mathrm{Wln\_EDU}_{it} + \gamma_5 \mathrm{Wln\_INT}_{it} + \delta_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{GTFP}_{it} = {} & \alpha + \rho \mathrm{WGTFP}_{it} + \beta_1 \mathrm{SDID}_{it} + \gamma_1 \mathrm{WSDID}_{it} + \beta_2 \mathrm{ln\_OPE}_{it} + \beta_3 \mathrm{ln\_URB}_{it} + \beta_4 \mathrm{ln\_EDU}_{it} + \beta_5 \mathrm{ln\_INT}_{it} \\ & + \beta_6 \mathrm{SDID\_ln\_GTI}_{it} + \gamma_2 \mathrm{Wln\_OPE}_{it} + \gamma_3 \mathrm{Wln\_URB}_{it} + \gamma_4 \mathrm{Wln\_EDU}_{it} + \gamma_5 \mathrm{Wln\_INT}_{it} \\ & + \gamma_6 \mathrm{Wln\_GTI}_{it} + \delta_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{7}$$

Equation (6) represents the SDM without the interaction term, while Equation (7) introduces the interaction term between the spatial DID variable (SDID_{it}) and green technology innovation ($\mathrm{ln\_GTI}_{it}$) to examine the moderating effect of GTI on the impact of CETS. In both equations, W is the geographical distance weight matrix, and ρ is the spatial lag term, representing the impact of neighboring regions' GTFP on the local region's GTFP. The variable SDID_{it} indicating whether the region belongs to a carbon emissions trading pilot city. The term WSDID_{it} captures the policy variable for spatial spillover effects, measuring the impact of the pilot provinces' policy on surrounding regions. The other control variables are consistent with the baseline model. .Next, we proceed with the spatial effects analysis and a comparison of the regression results. The detailed findings are presented in Table 9.

Table 9. *Spatial effect decomposition model regression.*

	(1)	(2)	(3)
	GTFP	GTFP	GTFP
main			
SDID	0.0974***	0.103***	-1.146**
	(0.034)	(0.032)	(0.500)

ln_OPE	0.0721***	0.0544**	-0.0124
	(0.027)	(0.026)	(0.024)
ln_URB	-0.0357	-0.144	-0.271**
	(0.124)	(0.133)	(0.122)
ln_EDU	-0.698***	-0.558***	-0.352***
	(0.066)	(0.072)	(0.066)
ln_INT	-0.270***	-0.273***	-0.104
	(0.081)	(0.079)	(0.071)
ln_GTI			-0.904***
			(0.079)
SDID_ln_GTI			0.577**
			(0.237)
_cons	-2.525***		
	(0.340)		
Wx			
SDID		0.161*	-7.294***
		(0.088)	(2.075)
ln_OPE		0.0434	0.174**
		(0.088)	(0.082)
ln_URB		-0.0826	0.136
		(0.150)	(0.144)
ln_EDU		0.221	0.311
		(0.174)	(0.193)
ln_INT		0.844***	0.956***
		(0.188)	(0.217)
ln_GTI			0.346
			(0.265)
SDID_ln_GTI			3.691***
			(1.014)
Spatial			
rho		0.553***	0.362***
		(0.088)	(0.111)
N	480	480	480
F	30.62***		
r2	0.587	0.0708	0.0816

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Column (1) presents the regression results of the baseline DID model, Column (2) reports the results of the SDID model without the interaction term for GTI, and Column (3) includes the interaction term between CETS and GTI (SDID_ln_GTI) to examine the moderating effect of GTI. The significantly positive coefficient of SDID in all three models underscores the direct and positive impact of the CETS on GTFP. In Column (3), the interaction term SDID_ln_GTI is statistically significant (coefficient = 0.577, $p < 0.05$), suggesting that GTI positively moderates the impact of CETS on GTFP in the spatial context. Specifically, regions with higher levels of GTI experience a stronger positive effect of CETS on GTFP.

The spatial lag parameter ρ is significant in both Column (2) (0.553, $p < 0.01$) and Column (3) (0.362, $p < 0.01$), indicating strong spatial dependence in GTFP across regions. This implies that the GTFP of one region is significantly influenced by its neighbors, highlighting the importance of considering regional interactions when evaluating the effects of environmental policies. The results suggest that the policy's benefits extend beyond pilot cities to surrounding areas, demonstrating that the impact of CETS is not geographically confined but rather radiates outward, influencing a broader regional context. This finding underscores the interconnected nature of regional economies and environmental outcomes.

To further understand the transmission mechanism of the carbon trading policy's impact on GTFP, we decompose the spatial effects into direct, indirect, and total effects. This allows us to assess not only the direct influence of the policy within each region but also its spillover effects on neighboring areas. The results of this spatial effect decomposition are presented in Table 10.

Table 10. *Estimated Direct, Indirect, and Total Effects from Spatial Regressions*

	Direct, Indirect, and Total Effects					
	(1)			(2)		
	Direct	Indirect	Total	Direct	Indirect	Total
SDID	0.116***	0.483***	0.599***	-1.334**	-12.05***	-13.38***
	(0.033)	(0.177)	(0.186)	(0.525)	(2.955)	(3.109)
ln_OPE	0.0576**	0.170	0.228	-0.00845	0.263**	0.255**
	(0.025)	(0.217)	(0.223)	(0.024)	(0.130)	(0.130)
ln_URB	-0.139	-0.373*	-0.512***	-0.267**	0.0675	-0.200
	(0.124)	(0.201)	(0.156)	(0.120)	(0.175)	(0.131)
ln_EDU	-0.562***	-0.196	-0.758*	-0.341***	0.259	-0.0825
	(0.067)	(0.408)	(0.396)	(0.066)	(0.284)	(0.282)
ln_INT	-0.236***	1.518***	1.282***	-0.0784	1.417***	1.339***
	(0.076)	(0.441)	(0.453)	(0.073)	(0.356)	(0.355)
ln_GTI				-0.907***	0.0392	-0.868**
				(0.076)	(0.435)	(0.439)
SDID_ln_GTI				0.674***	6.092***	6.766***
				(0.250)	(1.439)	(1.515)
N	480	480	480	480	480	480

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. reports the direct, indirect, and total effects of the carbon trading policy (SDID) on GTFP. Column (1) represents the spatial regression results of the SDID model without the interaction term for GTI, while column (2) includes the interaction term (SDID_ln_GTI).

In column (1), the direct, indirect, and total effects of SDID are all positive and significant, indicating that the carbon trading policy promotes GTFP and exhibits spatial spillover effects. In column (2) the coefficient of SDID_ln_GTI is significantly positive, indicating that GTI mitigates the potential negative impact of CETS, meaning that GTI plays a positive moderating role in the effect of the carbon trading policy on GTFP.

From a policy perspective, these findings emphasize the importance of coordinated regional environmental strategies. While CETS effectively boosts GTFP in pilot cities, its broader influence underscores the need for integrated policies to maximize spatial spillover effects and promote sustainable development across regions. Policymakers should consider the spatial dimensions of environmental regulations, as the benefits of such policies can extend well beyond their immediate implementation areas, fostering a more comprehensive approach to regional green development. The significant moderating effect of GTI further highlights the potential for GTI to enhance the effectiveness of market-based environmental regulations like CETS.

Collectively, these results provide robust evidence in support of research hypothesis 3, which posits that CETS not only enhances GTFP in pilot regions but also generates significant spatial spillover effects, thereby contributing to regional green development. This confirms that the policy's impact is both direct and spatially expansive, reinforcing the value of market-based environmental regulations like CETS in achieving sustainable economic and ecological outcomes.

3.3.6 Heterogeneity Test

The implementation effects of environmental policies may exhibit substantial spatial heterogeneity due to China’s pronounced regional disparities . Following established regional classifications by Anli et al. (2019), this study examines 30 Chinese provinces grouped geographically: the eastern region includes Shanghai, Beijing, Jilin, Tianjin, Shandong, Guangdong, Jiangsu, Hebei, Zhejiang, Hainan, Fujian, Liaoning, and Heilongjiang; the central region comprises Anhui, Shanxi, Jiangxi, Henan, Hubei, and Hunan; the western region encompasses Yunnan, Inner Mongolia, Sichuan, Ningxia, Guangxi, Xinjiang, Gansu, Guizhou, Chongqing, Shaanxi, and Qinghai. This tripartite division effectively captures the gradient developmental characteristics across China’s economic geography.

Table 11. *Heterogeneity Test Results*

	(1)	(2)	(3)
	Eastern	Central	Western
	GTFP	GTFP	GTFP
Main			
SDID	0.0740*	0.280***	0.158*
	(0.045)	(0.042)	(0.082)
ln_OPE	-0.267***	0.189***	0.0618*
	(0.084)	(0.037)	(0.035)
ln_URB	-0.343	-0.784***	-0.642**
	(0.218)	(0.302)	(0.257)
ln_EDU	-0.177	0.0982	-0.306**
	(0.135)	(0.124)	(0.122)
ln_INT	0.0550	-0.490***	-0.226*
	(0.121)	(0.129)	(0.123)
Wx			
SDID	0.235***	0.218***	-0.281
	(0.077)	(0.083)	(0.225)
ln_OPE	0.0230	-0.143**	-0.0999
	(0.113)	(0.068)	(0.075)
ln_URB	0.135	0.446	0.611**
	(0.251)	(0.314)	(0.267)
ln_EDU	-0.0669	0.475**	0.633***
	(0.204)	(0.210)	(0.211)
ln_INT	0.333**	0.408**	0.0583

	(0.167)	(0.181)	(0.206)
Spatial			
rho	0.283***	-0.0367	-0.231
	(0.078)	(0.142)	(0.144)
Variance			
sigma2_e	0.0220***	0.00381***	0.0191***
	(0.002)	(0.001)	(0.002)
N	208	96	176
F			
r2	0.00723	0.842	0.00000390

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

As presented in Table 11, the SDM estimates reveal distinct regional patterns in policy effectiveness. The carbon emission trading policy (SDID) demonstrates markedly varied impacts across regions, with central China showing the strongest direct effect (0.280***) on local green productivity, contrasted with more modest but still significant effects in eastern (0.074*) and western provinces (0.158*). Notably, while eastern regions exhibit weaker direct policy impacts, their substantial spatial lag coefficient (0.235***) indicates robust technology diffusion to neighboring areas. Conversely, the negative spatial interaction term (-0.281) in western regions suggests potential interjurisdictional competition that may undermine policy effectiveness.

To further elucidate spatial interaction mechanisms, Table 12 decomposes the direct, indirect, and total effects. Critical insights emerge:

Table 12. *Estimated Direct, Indirect, and Total Effects from Heterogeneity Test*

	Direct, Indirect, and Total Effects					
	(1)		(2)		(3)	
	Eastern		Central		Western	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
SDID	0.102**	0.337***	0.279***	0.200***	0.175**	-0.267
	(0.050)	(0.103)	(0.043)	(0.065)	(0.084)	(0.188)
ln_OPE	-0.274***	-0.0645	0.190***	-0.145**	0.0653*	-0.0967
	(0.079)	(0.134)	(0.036)	(0.070)	(0.035)	(0.068)
ln_URB	-0.320*	0.0295	-0.757**	0.432	-0.647**	0.620**
	(0.195)	(0.256)	(0.296)	(0.308)	(0.261)	(0.268)
ln_EDU	-0.187	-0.128	0.0945	0.462**	-0.338***	0.606***
	(0.127)	(0.246)	(0.124)	(0.194)	(0.125)	(0.194)
ln_INT	0.0891	0.432**	-0.492***	0.410**	-0.231*	0.0930
	(0.115)	(0.212)	(0.126)	(0.174)	(0.126)	(0.173)
N	208	208	96	96	176	176

* p < 0.05, ** p < 0.01, *** p < 0.001

The effect decomposition in Table 12 provides deeper spatial insights. Central China's "dual advantage" emerges clearly, with both strong local policy impacts (direct effect 0.279***) and positive spillovers to neighbors (indirect effect 0.200***), likely facilitated by dense industrial clusters and the Hubei carbon market's demonstration effects. Eastern provinces function as innovation diffusion hubs, where spatial spillovers (0.337***) substantially outweigh local impacts, while western regions' negative spatial spillovers (-0.267) raise concerns about potential carbon leakage and pollution haven effects that warrant policy attention. These findings collectively underscore the necessity for regionally differentiated policy designs accounting for distinct developmental contexts and spatial interaction mechanisms.

IV. Conclusion

4.1 Main Findings

This study systematically examines the impact of China's CETS on GTFP and its underlying mechanisms, using a balanced panel dataset from 30 provinces. The findings reveal that the implementation of CETS significantly promotes regional GTFP, as evidenced by the positive and statistically significant coefficients in both the baseline DID and SDID models. This confirms that market-based environmental regulations, such as CETS, are effective in driving sustainable economic growth.

GTI plays a crucial moderating role in enhancing the positive impact of CETS on GTFP. Regions with higher levels of GTI experience more pronounced improvements in GTFP, highlighting the importance of integrating technological innovation strategies with carbon trading mechanisms. Furthermore, the SDID model reveals significant spatial spillover effects, indicating that the benefits of CETS extend beyond pilot regions to neighboring areas. This underscores the interconnected nature of regional economies and the importance of coordinated environmental policies to maximize the policy's impact.

Robustness tests, including placebo tests and PSM-DID, confirm the reliability of the findings. The results suggest that policymakers should not only focus on implementing carbon trading policies but also prioritize fostering GTI and promoting regional collaboration to achieve broader environmental and economic benefits.

This study provides empirical evidence and theoretical insights into the effectiveness of CETS in promoting green development. It highlights the dual role of CETS in directly enhancing GTFP and generating positive spatial spillover effects, offering valuable guidance for optimizing carbon trading policies and advancing regional sustainable development goals. Future research could further explore the long-term effects of CETS and its applicability in different regional contexts.

4.2 Policies Recommendation

Enhancing the incentives for GTI is crucial to maximizing the policy synergy of the CETS. Establishing a "Green Technology Innovation Subsidy" can encourage enterprises to increase investment in low-carbon research and development, reducing the upfront costs of green technology adoption. Additionally, a "Carbon Trading Revenue Reinvestment" mechanism can allocate a portion of carbon market revenues to support green innovation, creating a sustainable funding loop. To accelerate the commercialization of low-carbon technologies, a "Green Patent Fast-Track Channel" should be introduced, streamlining the approval process for key green technology patents. These measures will strengthen the role of carbon markets in driving innovation and supporting the transition to a low-carbon economy.

Expanding regional collaboration in carbon trading is essential for amplifying policy spillover effects. Establishing "Carbon Trading Cooperation Zones" can allow non-pilot regions to voluntarily join existing carbon markets, increasing market coverage and efficiency. Moreover, fostering low-carbon industrial chain cooperation between pilot cities and neighboring provinces can facilitate green technology diffusion and enhance regional synergy. A "Cross-Province Low-Carbon Demonstration Zone" with unified carbon tax and trading policies would further harmonize regional carbon reduction efforts, ensuring a more coordinated and effective market-driven approach to emissions control.

Ensuring the stable operation and transparency of the carbon market is vital for its long-term effectiveness. A "Carbon Market Volatility Adjustment Mechanism" should be implemented to prevent excessive price fluctuations, enabling the government to intervene when necessary to maintain market stability. Strengthening corporate carbon disclosure requirements will enhance fairness and transparency, reducing the risks of "greenwashing" and data manipulation. Additionally, regulatory enforcement should be reinforced to combat quota hoarding and market manipulation, ensuring a fair and competitive trading environment. These measures will enhance the credibility and resilience of the carbon market, supporting long-term sustainable development.

4.3 Limitations and Future Research Directions

Despite its contributions, this study has several limitations that warrant further exploration. First, while the study focus on the province-level, it does not fully account for industry-level heterogeneity. Different industries may exhibit varying degrees of responsiveness to carbon trading policies, depending on their energy intensity, technological capabilities, and market structures. Future research could employ sector-specific analyses to provide a more nuanced understanding of CETS's effects across different economic sectors.

Second, while this study identifies spatial spillover effects, it does not delve deeply into the specific transmission mechanisms through which CETS influences neighboring regions. Future research could investigate the roles of technology diffusion, industrial relocation, and financial market linkages in shaping these spillover effects. Moreover, as China continues to expand its carbon market, cross-regional coordination and international carbon market integration will become increasingly relevant topics for future inquiry. Understanding these dynamics will provide valuable insights for policymakers seeking to enhance the effectiveness of carbon trading systems in promoting sustainable economic development.

REFERENCES

[1] Alberola, E., Chevallier, J., & Chèze, B. (2009). Emissions compliances and carbon prices under the EU ETS: a country specific analysis of industrial sectors. Journal of Policy Modeling, 31(3), 446-462.

[2] Anli, L., Jing, J., Nicholas, S., & Wang, J. (2019). Geographical disparities in treatment and health care costs for end-of-life cancer patients in China: a retrospective study. BMC Cancer, 19. https://doi.org/10.1186/s12885-018-5237-1

[3] Bian, Z., Liu, J., Zhang, Y., Peng, B., & Jiao, J. (2024). A green path towards sustainable development: The impact of carbon emissions trading system on urban green transformation development. Journal of Cleaner Production, 442, 140943.

[4] Boungou, W., & Dufau, B. (2024). EU ETS phase IV and Industrial performance. Economics Letters, 236, 111596.

[5] Button, J. (2008). Carbon: commodity or currency-the case for an international carbon market based on the currency model. Harv. Envtl. L. Rev., 32, 571.

[6] Chen, J., Geng, Y., & Liu, R. (2023). Carbon emissions trading and corporate green investment: The perspective of external pressure and internal incentive. Business Strategy and the Environment, 32(6), 3014-3026.

[7] Colmer, J., Martin, R., Muûls, M., & Wagner, U. J. (2024). Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence from the European Union Emissions Trading System. Review of Economic Studies, rdae055.

[8] Cui, J., Dai, J., Wang, Z., & Zhao, X. (2022). Does environmental regulation induce green innovation? A panel study of Chinese listed firms. Technological Forecasting and Social Change, 176, 121492.

[9] Feng, Y., Wang, X., Liang, Z., Hu, S., Xie, Y., & Wu, G. (2021). Effects of emission trading system on green total factor productivity in China: Empirical evidence from a quasi-natural experiment. Journal of Cleaner Production, 294, 126262.

[10] Jia, Z., Wen, S., & Wu, R. (2025). Synergistic effect of emission trading scheme and carbon tax: A CGE model-based study in China. Environmental Impact Assessment Review, 110, 107699.

[11] Jiakui, C., Abbas, J., Najam, H., Liu, J., & Abbas, J. (2023). Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. Journal of Cleaner Production, 382, 135131. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.135131

[12] Lai, P., & Zhu, T. (2022). Deflating China's nominal GDP: 2004–2018. China Economic Review, 71, 101709.

[13] Li, C., Qi, Y., Liu, S., & Wang, X. (2022). Do carbon ETS pilots improve cities' green total factor productivity? Evidence from a quasi-natural experiment in China. Energy Economics, 108, 105931.

[14] Li, S., Liu, J., Wu, J., & Hu, X. (2022). Spatial spillover effect of carbon emission trading policy on carbon emission reduction: Empirical data from transport industry in China. Journal of Cleaner Production, 371, 133529.

[15] Lin, B., & Xie, J. (2023). Does environmental regulation promote industrial structure optimization in China? A perspective of technical and capital barriers. Environmental Impact Assessment Review, 98, 106971.

[16] Liu, H., Kou, X., Xu, G., Qiu, X., & Liu, H. (2021). Which emission reduction mode is the best under the carbon cap-and-trade mechanism? Journal of Cleaner Production, 314, 128053.

[17] Liu, Y., Peng, Y., Wang, W., Liu, S., & Yin, Q. (2024). Does the pilot zone for green finance reform and innovation policy improve urban green total factor productivity? The role of digitization and technological innovation. Journal of Cleaner Production, 471, 143365. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.143365

[18] Ma, G., Qin, J., & Zhang, Y. (2023). 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 Economics, 120, 106581.

[19] Ma, Y., Lin, T., & Xiao, Q. (2022). The relationship between environmental regulation, green-technology innovation and green total-factor productivity—evidence from 279 cities in China. International Journal of Environmental Research and Public Health, 19(23), 16290.

[20] Niu, X., Zhang, Y., Li, B., Chen, Z., Ni, G., & Lyu, N. (2024). How does carbon emission trading scheme affect enterprise market value? A roadmap towards natural resources sustainability. Resources Policy, 88, 104542. https://doi.org/https://doi.org/10.1016/j.resourpol.2023.104542

[21] Oh, H., Jun, S., Kim, J. Y., & Chu, H.-Y. (2023). Korea's emissions trading system for low-carbon energy and economic transformation: a quantitative study evaluating the impact of phase I of the KETS on energy efficiency and the energy mix. Energy Efficiency, 16(3), 13.

[22] Pan, X., Pu, C., Yuan, S., & Xu, H. (2022). Effect of Chinese pilots carbon emission trading scheme on enterprises' total factor productivity: The moderating role of government participation and carbon trading market efficiency. Journal of Environmental Management, 316, 115228.

[23] Peng, H.-R., Cui, J., & Zhang, X. (2022). Does China emission trading scheme reduce marginal abatement cost? A perspective of allowance allocation alternatives. Sustainable Production and Consumption, 32, 690-699.

[24] Porter, M. E. (1997). Competitive strategy. Measuring business excellence, 1(2), 12-17.

[25] Yu, D., Liu, L., Gao, S., Yuan, S., Shen, Q., & Chen, H. (2022). Impact of carbon trading on agricultural green total factor productivity in China. Journal of Cleaner Production, 367, 132789.

[26] Yu, Y., Zhang, X., Liu, Y., & Zhou, T. (2024). Carbon emission trading, carbon efficiency, and the Porter hypothesis: Plant-level evidence from China. Energy, 308, 132870.

[27] Zhang, C., Liu, F., Wu, D., Tan, D., & Niu, L. (2025). The impact of the carbon emissions trading scheme on corporate strategic deviance in China. Technological Forecasting and Social Change, 212, 123952.

[28] Zhang, J. (2008). Estimation of China's provincial capital stock (1952–2004) with applications. Journal of Chinese Economic and Business Studies, 6(2), 177-196. https://doi.org/10.1080/14765280802028302

[29] Zhang, M., Ge, Y., Liu, L., & Zhou, D. (2022). Impacts of carbon emission trading schemes on the development of renewable energy in China: Spatial spillover and mediation paths. Sustainable Production and Consumption, 32, 306-317.

[30] Zhang, S., Cheng, L., Ren, Y., & Yao, Y. (2024). Effects of carbon emission trading system on corporate green total factor productivity: Does environmental regulation play a role of green blessing? Environmental Research, 248, 118295.

[31] Zhou, D., Lu, Z., & Qiu, Y. (2023). Do carbon emission trading schemes enhance enterprise green innovation efficiency? Evidence from China's listed firms. Journal of Cleaner Production, 414, 137668.