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Original Paper

Does the China Emission Trading Schem (CETS) Affect Carbon Abatement and Atmospheric Pollutant Reduction?

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Abstract

China Emissions Trading Scheme (CETS) is a market-based approach that promotes emission reduction activities by allocating carbon emission permits and allowing firms to exchange these emission rights in the market. Once CETS play a positive role, it will bring huge carbon abatement and atmospheric pollutant reduction effects. Therefore, this research adopted the time-varying Difference-in-Differences method to construct panel data with 30 provinces in China from 2008 to 2018 as samples to study the role of CETS in carbon abatement and atmospheric pollutant reduction. Four main conclusions emerged from this study. Firstly, the CETS pilot has a significant impact on carbon abatement and the reduction of PM10, SO2 and NO2 concentrations. Secondly, the CETS pilot has a long-term impact on carbon abatement and a relatively short-term effect on the reduction of PM10, SO2 and NO2 concentrations. Thirdly, the CETS pilot has no significant effect on reducing carbon emission intensity. Fourthly, through the regional heterogeneity test, this research found that the intervention of CETS is more significant in carbon abatement and atmospheric pollutant reduction in the northern region than in the southern region of China. The results of this research will help to provide scientific reference for the improvement of government policies.

Keywords

China Emissions Trading Scheme (CETS), Carbon Abatement, Atmospheric Pollutant Reduction, Policy Evaluation

1. Introduction

1.1 Research Background

China is currently the largest developing country and emitter of carbon dioxide globally (Shi, Xu, & Sun, 2022). With rapid economic development, accelerated industrialization and urbanization, energy consumption and greenhouse gas emissions have increased significantly. Carbon dioxide is the main greenhouse gas, which is a major contributor to climate change. In recent years, the increasing risks of global climate change, including adverse weather conditions, rising sea levels and declining biodiversity, have already had a dramatic impact on human society and the natural environment.

In addition to the impact on climate, carbon emissions have direct and indirect effects on atmospheric quality (Wang et al., 2019). Typically, carbon emissions are accompanied by other hazardous substances, such as suspended particles, nitrogen oxides and sulphur oxides. These pollutants can have a direct adverse influence on atmospheric quality. Moreover, carbon emissions can react with other gases in complex chemical reactions, which may lead to the production and dispersion of different pollutants and indirectly affect atmospheric quality.

It is thus evident that carbon emissions have a substantial influence on climate change and atmospheric pollution. To address this issue, several carbon-cutting initiatives have been implemented by the Chinese government. The most crucial strategy is the China Emission Trading Scheme (CETS). Negative externality issues, such as environmental pollution caused by carbon emissions, result from economic production activities (Cong & Wei, 2010). Coase (1972) argued that if the borders between the property rights of public goods can be clearly defined, then the market may effectively resolve negative externalities. This provides the most direct theoretical basis for the pilot of CETS.

CETS is a market approach that promotes emission reduction activities by generating carbon emission permits and allowing firms to swap these emission rights on the market. The specific method is that the government can set different carbon emission quotas according to the different emission profiles of various industries and enterprises. Enterprises are required to purchase enough emission permits to cover their actual emissions. If their emissions exceed emission permits, they are required to purchase additional permits or make an effort to emission reduction. Such a market mechanism allows the price of carbon emission rights to float freely according to supply and demand, incentivizing enterprises to take more emission abatement measures. In addition, the government imposes penalties on enterprises that do not meet the emission requirements and sets up an incentive mechanism for enterprises that actively use clean technologies to reduce emissions.

In 2011, the pilot CETS was planned to be started by 7 provinces and municipalities: Beijing, Tianjin, Shanghai, Guangdong, Hubei, Chongqing, and Shenzhen. 7 provinces and municipalities officially opened their online carbon emission trading in 2013. As the 8th emission trading scheme pilot region, Fujian Province introduced the CETS in 2016. In July 2021, CETS was officially implemented by the whole country (Wang, Ma, & Tang, 2022). The establishment and intervention of CETS marks an important step in China's response to climate change and emission reduction and also provides useful experience and reference for the development of the global carbon market.

The Paris Climate Agreement, which aims to improve national activities to reduce carbon emissions internationally, was approved during the 2015 Paris Climate Change Conference (Schleussner et al., 2016). The signing and entry into force of the Paris Climate Agreement marks the consensus and action of the global community on climate change and provides an important legal framework and policy guidance for the global response to climate change. Given this, at the 75th United Nations General Assembly, the Chinese authorities proclaimed that it will implement practical measures to achieve Carbon Peak by 2030 and to achieve Carbon Neutral status by 2060 (Chen & Lin, 2021). This demonstrates the tenacious resolve to address climate change and environmental pollution. CETS is an exemplary eco-friendly mechanism and once it plays a positive role, it will bring about a huge carbon abatement and atmospheric pollutant reduction effect. Therefore, exploring the utility of the pilot CETS will assist the Chinese authorities in defining the path for enhancing relevant policies and strengthening its capacity to address environmental issues. In particular, researching the effects of CETS on carbon abatement and atmospheric pollutant reduction will provide a scientific reference for China to achieve Carbon Peak and Carbon Neutral status on schedule, promote the progress of ecological civilization, and improve the government's policies.

Although pilot CETS has made significant progress since 2011, there are still some questions and controversies that need to be confirmed. Whether the pilot CETS has been effective in carbon abatement and how effective it has been in atmospheric pollutant reduction needs to be studied in depth. Moreover, whether there is regional heterogeneity in the role of CETS also needs to be explored. Therefore, the research questions are proposed. Using empirical methods to assess the effectiveness of pilot CETS on carbon abatement. Using empirical methods to assess the effectiveness of pilot CETS on atmospheric pollutant reduction. Studying whether the utility of pilot CETS has regional heterogeneity.

1.2 Literature Review

The existing literature on CETS is divided into two main categories. The first type is evaluating the carbon abatement effect of CETS. The majority of the literature has found that pilot emission trading schemes can reduce carbon emissions. The European Union Emission Trading Scheme (EU ETS) is the world's largest carbon emissions trading market and one of the first carbon markets to be implemented in the world. It was launched in 2005 and covers all EU member states, and it controlled about 46% of total carbon emissions in the EU (Shi, Xu, & Sun, 2022). Korea's Emissions Trading System (KETS) is a market mechanism established by the South Korean government to reduce greenhouse gas (GHG) emissions. Launched in 2015, KETS focused on emissions reductions in the energy, industrial, and transport sectors. The intervention of KETS has forced companies to change the way they manage energy efficiency and reduce GHG emissions (Suk & Jeong, 2017). According to Chen and Lin (2021), CETS is also a useful method for reaching carbon-neutral status because it helps reduce emissions and encourage energy conservation. In addition to having a direct impact on carbon neutrality, Wang, Huang, and Liu (2022) contended that CETS could also have an indirect influence on reaching a carbon-neutral status by modifying the structure of the industry, adopting carbon-cutting policies, fostering the popularize of low-carbon culture, increasing urban green space and reducing energy consumption. Tao and Goh (2023) argued that the market-oriented CETS significantly reduces the total amount of carbon emission at the national level, however, it has spatial heterogeneity effects at the regional and local levels. Ren and Liu (2023) argued that in addition to significant spatial heterogeneity, the utility of pilot CETS in the 8 provinces and municipalities included effects on green innovation and the economy, with the intensity of these effects changing over time.

Another type is to assess the utility of CETS on other variables. Various literatures also concluded that CETS is beneficial to other factors. For instance, energy efficiency has greatly increased as a result of CETS, and robustness tests confirm this finding (Xie, Guo, & Zhao, 2023). In 8 high-carbon-emitting industries, CETS has a positive impact on the quality of green technology innovation (Qin & Xie, 2023). CETS can also significantly improve the level of environmental responsibility of companies in the pilot region by enhancing corporate environmental protection investment (Chen, 2023). According to Yang, Jiang & Pan (2020), CETS intervention not only achieves emission reduction and environmental protection but also promotes the expansion of employment. CETS interventions, in particular, favour income growth and job creation in rural areas. This means that CETS is integrating ecological protection with rural poverty alleviation, which may benefit poverty alleviation efforts in the provinces included in CETS (Zhang & Zhang, 2020). In particular, the influence of atmospheric pollutant reduction has been studied by many scholars. Evaluating atmospheric pollutants' decreasing effect in Guangdong Province, Cheng et al. (2015) concluded that the CETS had the synergistic benefit of reducing emissions of NO2 and SO2 by 11.7% and 12.4%, respectively. According to Liu, Woodward and Zhang (2021), PM2.5 concentrations decreased by 4.8% after CETS was implemented, and this decrease was greatest in the summer. The reduction in PM2.5 concentrations could have prevented 23,363 deaths and saved US$41.38 billion in GDP annually. In addition to the direct improvement in atmospheric quality, CETS can indirectly affect carbon emission and atmospheric quality by changing the innovative capacity of the municipality and the location choices of local industries (Dong et al., 2022). Sun and Cao (2023) stated that, while CETS can improve city atmospheric quality, regional heterogeneity tests revealed that CETS only improved city atmospheric quality in eastern and central China.

1.3 Research Gap

Existing research, however, still has shortcomings. Firstly, most of the attention in the previous literature on the carbon abatement effects of CETS has been limited to pure carbon emissions, while neglecting to focus on the relationship between economic growth and carbon emissions. Secondly, when studying the effect of CETS, most of the previous literature only focused on the investigation of the carbon abatement effect, however, the investigation of the atmospheric pollutant reduction effect was relatively small. Third, even though the past literature has paid attention to the atmospheric pollution reduction effect, the selected measurement indicators are insufficient, which seems to be a common problem. For example, some studies only selected AQI (Air Quality Index) as a single indicator to measure atmospheric quality. Furthermore, several earlier studies neglected the gradual nature of pilot CETS and roughly assigned the time when different provinces were included by the CETS to the same year. However, the truth is that different provinces joined the pilot policy in different years.

Therefore, the objective of this research is to fill these research gaps. Analyse whether pilot CETS plays a role in both carbon abatement and atmospheric pollutant reduction. Firstly, to comprehensively measure the carbon abatement and atmospheric pollutant reduction effect, this research will add more indicators. Furthermore, to analyse the dynamic and multi-period policy effect, the empirical research method will be improved.

2. Method

2.1 Model Seletion

Difference-in-Differences model (DID) is a common method applied in econometrics and policy evaluation. Huang and Yi (2023) used a traditional DID approach in their study of the role of Low-carbon policy pilots and CETS pilots in prefecture-level cities.

The principle of the DID model is shown in Table 1. The specific method is to select a control group without policy intervention and a treatment group with policy intervention. The net time effect can be obtained by subtracting the pre-policy time trend from the post-policy time trend of the control group. The time effect and the policy effect can be obtained by subtracting the pre-policy time trend from the post-policy time trend of the treatment group. Thus, the net effect of policy can be obtained by subtracting the difference in the control group from the difference in the treatment group.

Table 1. Principle of DID Model

	Pre-intervention	Post-intervention	Difference	Effects
Control group	C_1	C_2	C_2-C_1	Time effect
Treatment group	T_1	T_2	T_2-T_1	Time effect + Policy effect
			(T_2-T_1) - (C_2-C_1)	Policy effect

The time-varying DID model extends the time dimension by considering the effects before and after the intervention of the policy as well as focusing on multiple time points of the policy intervention, which is more in line with the characteristics of the gradual intervention of CETS. Lin and Huang (2022) explored the relationship between the intervention of CETS and the carbon abatement effect through the time-varying DID model. Sun and Cao (2023) adopted the time-varying DID model in their study of the effects of CETS on urban atmospheric quality. Therefore, this research referred to the research method of those researchers, adopting time-varying DID to test the carbon abatement effect and atmospheric pollutant reduction effect of CETS. The function of the time-varying DID model was constructed as the following equation (1). Term Y_{it} represents explained variables. Term $treat_i \times post_{it}$ is the core explanatory variable. Term X_{it} represents control variables. Term λ_i represents individual-fixed effect. Term μ_t represents the time-fixed effect. Term ε_{it} represents random disturbance. Term β_1 measures net policy effect.

$$Y_{it} = \beta_0 + \beta_1 \cdot treat_i \times post_{it} + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

The DID method has two assumptions. The first is the parallel trend assumption. The trends of the treatment and control groups before the policy intervention should be parallel, which means the trends of the treatment and control groups before the policy intervention should be similar. If there exist trend differences between the treatment and control groups before the policy intervention, the effect estimates obtained by the DID method may be inaccurate. The second is the exogeneity assumption. The policy intervention for the treatment group is exogenous, which means whether the treatment group is included in the policy pilot does not depend on the characteristics of the treatment group itself, but mainly on the allocation mechanism of the policy. If the policy allocation to the treatment group is correlated with its characteristics, then the estimation results of the DID method may suffer from endogeneity problems. Whether a province is included in the CETS pilot region purely depends on the planning of the policy. The CETS pilot policy is therefore consistent with the exogeneity assumption. In addition to these two key assumptions, the DID method needs to control for other potential influences to maintain the accuracy and robustness of the estimation results. Therefore, in this research, robustness tests need to be conducted, which are mainly in the form of parallel trend tests and placebo tests.

2.2 Sample Selection

Table 2. Sample Selection

	Pilot time	Provinces
Treatment group	2013	Beijing, Tianjin, Shanghai, Guangzhou, Hubei, Chongqing
	2016	Fujian
Control group		Heilongjiang, Jilin, Liaoning, Inner Mongolia, Jiangsu, Zhejiang, Anhui, Henan, Hebei, Jiangxi, Hainan, Shandong, Qinghai, Ningxia, Shanxi, Hunan, Guangxi, Sichuan, Guizhou, Yunnan, Shannxi, Gansu, Xinjiang

This research had two main considerations in the selection of the research sample. First, in terms of province selection, the 6 provinces that were included in the CETS pilot in 2013 (Beijing, Tianjin, Shanghai, Guangdong, Hubei, and Chongqing) and the 7th province that was included in the CETS pilot in 2016 (Fujian) were selected as the treatment group. Shenzhen, which joined the CETS pilot in 2013, belongs to Guangdong province, so it was not considered separately in this research. The control group consisted of the remaining 23 provinces (Tibet, Hong Kong, Macau, and Taiwan were excluded due to missing data). The sample selection is shown in Table 2. Second, in terms of period, from 2008 to 2018 was chosen to cover the 5 years before and after the time of CETS intervention.

2.3 Variable Selection

2.3.1 Explained Variables

To measure the effect of carbon abatement, this research referred to the method of Dong et al. (2022) and selected carbon emissions (CE_{it}) and carbon emission intensity (CEI_{it}) as the explained variables. Carbon emission is the total annual carbon emissions of each province. Carbon emission intensity is a measure of the relationship between economic growth and carbon emissions and was calculated by dividing the total annual carbon emissions of a province by the GDP of the province for that year in this research.

To measure the effect of atmospheric pollutant reduction, Liu, Woodward and Zhang (2021) selected $PM_{2.5}$ as the explained variable. To include suspended particulate matter with larger particle sizes, the concentration of suspended particulate matter (PM_{10}) with particle size less than or equal to 10 microns was used as the explained variable in this research. Nitrogen dioxide and sulphur dioxide are major pollutants in the atmosphere (Cheng et al., 2015). Therefore, this research added sulphur dioxide concentration (SO_2) and nitrogen dioxide concentration (NO_2) as explained variables as well.

2.3.2 Explanatory Variable

Term did ($treat_i \times post_{it}$) is the core explanatory variable. Term $post_{it}$ denotes the time dummy variable. When t ≥ policy time, $post_{it}$= 1. When t < policy time, $post_{it}$= 0. Term $treat_i$ denotes the province dummy variable. If the province is included in the CETS, $treat_i$ = 1, representing the treatment group, otherwise, $treat_i$= 0, representing the control group. The coefficient β_1 represents the net policy effect of CETS.

2.3.3 Control Variables

To preserve the accuracy and reliability of the research results, this research added 4 control variables. The first one is GDP per capita (*pgdp*). The degree of economic development of each province also affects the province's carbon and atmospheric pollutant emissions, and the more economically developed the province should have higher emissions. This research referred to the methodology of Sun and Cao (2023), which used provincial GDP per capita as an indicator of the level of economic development of the province.

The second is population size (*pop*), specified as the resident population of each province at the end of each year. Population is a critical factor that affects carbon emissions and atmospheric pollutant emissions (Dong et al., 2022). Typically, an increase in population leads to an increase in carbon and atmospheric pollutant emissions. This research referred to the methodology of Shi, Xu and Sun (2022) and also included it as one of the control variables.

The third is the level of industrialization level (*industry*). Typically, higher levels of industrialization lead to higher carbon and atmospheric pollutant emissions. Referring to Shi, Xu and Sun (2022), this research measured the level of industrialization by dividing the value added of the secondary industry by GDP.

The fourth control variable is the investment in environmental protection (*invest*). In general, the more the government spends on environmental protection, the better the environmental governance will be. This research referred to the methodology of Sun and Cao (2023) to include government environmental expenditure as one of the control variables.

2.4 Data Collection

The data of *CE* and *CEI* for each province in each year were obtained from the China Carbon Accounting Database. The data of PM_{10}, SO_2 and NO_2 concentrations for each province in each year were obtained from annual provincial data published by the National Bureau of Statistics. The data of GDP per capita, population, industrialization level and investment in environmental protection for each province in each year were obtained from the China Economic and Social Big Data Research Platform. The list of all variables and data sources is shown in Table 3.

Table 3. Variables List

Variables	Notation	Description	Sources
Explained Variables	*CE*	Carbon Emission	China Carbon Accounting Database
	CEI	Carbon Emission Intensity	
	PM_{10}	Concentration of PM_{10}	National Bureau of Statistics
	SO_2	Concentration of SO_2	
	NO_2	Concentration of NO_2	
Explanatory Variable	*did*	$Treat_i \times Post_{it}$	
Control Variables	*pgdp*	GDP per capita	China Economic and Social Big Data Research Platform
	pop	End-of-year resident population	
	industry	Industrialization level	
	invest	Investment in environmental protection	

2.5 Research Hypotheses

Prior to the empirical analysis, this research proposed a series of hypotheses based on model construction and variable selection:

H1: CETS intervention has a significant impact on carbon abatement and carbon emission intensity reduction.

H2: CETS intervention has a significant impact on the reduction of PM_{10}, SO_2 and NO_2 concentrations.

H3: The long-term operation of CETS will lead to a continuous carbon abatement effect, which will also have a long-term impact on the reduction of atmospheric pollutant concentration.

H4: After CETS intervention, regional differences will affect the CETS effect in different regions.

The verification of these hypotheses was carried out by different analysis methods, among which H1 and H2 were verified by baseline regression analysis, H3 was verified by parallel trend test and policy dynamic effect analysis, and H4 was verified by regional heterogeneity test.

3. Results and Findings

3.1 Descriptive Statistics

Table 4 presents the statistical characteristics of carbon emissions, carbon intensity and atmospheric pollutant concentration changes in 30 provinces in China before and after the intervention of CETS.

Table 4. Descriptive Statistics

Variables	Unit	Obs	Mean	SD	Min	Median	Max
CE	million tons	330	347.407	279.120	32.119	257.475	1650.244
CEI	tons/yuan	330	4.076	3.418	0.879	2.867	19.030
PM_{10}	μg/m^3	330	94.261	38.084	6.000	92.500	237.000
SO_2	μg/m^3	330	53.945	29.499	6.000	46.000	165.000
NO_2	μg/m^3	330	81.100	44.217	9.000	69.500	247.000
pgdp	thousand yuan	330	44.957	24.787	9.600	39.616	140.211
pop	million people	330	45.310	27.673	5.540	38.370	123.480
industry	%	330	43.038	8.132	16.545	44.322	61.960
invest	billion yuan	330	2.147	2.057	0.036	1.494	14.165

3.2 Baseline Regression Results

Based on the selected models and variables, this research constructed the following 5 regression equations (2), (3), (4), (5) and (6).

$$CE_{it} = \beta_0 + \beta_1 \cdot treat_i \times post_{it} + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{2}$$

$$CEI_{it} = \beta_0 + \beta_1 \cdot treat_i \times post_{it} + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{3}$$

$$PM_{10\,it} = \beta_0 + \beta_1 \cdot treat_i \times post_{it} + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{4}$$

$$NO_{2\,it} = \beta_0 + \beta_1 \cdot treat_i \times post_{it} + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{5}$$

$$SO_{2\,it} = \beta_0 + \beta_1 \cdot treat_i \times post_{it} + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{6}$$

The results of the baseline regression are shown in Table 5. Doing the baseline regression this research considered the two cases, not adding control variables and adding control variables. The column (1) below each explained variable shows the results without considering the control variables, and the column (2) shows the results considering the control variables.

In the first case, no control variables were considered. According to the baseline regression results, the coefficients of the interaction term *did* are significantly negative at the 10% level when *CE*, PM_{10}, SO_2 and NO_2 are the explained variables. The coefficient of the interaction term *did* is not significant at the 10% level when *CEI* is the explained variable.

After adding 4 control variables, the baseline regression was performed again. According to the regression results, the coefficients of the interaction term *did* are found to be significantly negative at the 1% level when *CE*, SO_2 and NO_2 are used as explained variables. When PM_{10} is used as an explained variable, the coefficient of the interaction term *did* is significantly negative at the 5% level. However, the coefficient of the interaction term *did* remains insignificant at the 10% level when *CEI* is the explained variable

Table 5. Baseline Regression Results

Variables	*CE*		*CEI*		PM_{10}		SO_2		NO_2	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
did	-97.928*	83.265***	0.349	0.154	-13.956*	-12.511**	-9.098*	-8.965***	-13.927*	13.582***
	(-2.54)	(-3.30)	(1.80)	(0.82)	(-2.30)	(-2.54)	(-2.11)	(-3.13)	(-2.16)	(-3.16)
pgdp		-1.393		0.009		-0.239		-0.170		-0.261
		(-0.85)		(1.30)		(-1.04)		(-1.06)		(-1.09)
pop		3.404		0.042*		0.577		0.963**		1.414**
		(0.84)		(2.57)		(1.14)		(2.14)		(2.11)
industry		-9.126		-0.007		-1.163		-1.023		-1.512
		(-1.01)		(-0.34)		(-0.95)		(-1.20)		(-1.18)
invest		-3.718		0.032		-1.675**		-0.772		-1.154
		(-0.66)		(0.88)		(-2.22)		(-1.45)		(-1.45)
Constant	359.573***	666.918	4.033***	2.001	95.995***	134.045*	55.076***	64.756	82.830***	98.011
	(74.94)	(1.18)	(167.09)	(1.82)	(127.46)	(1.80)	(102.70)	(1.21)	(103.45)	(1.22)
Observations	330	330	330	330	330	330	330	330	330	330
R-squared	0.910	0.916	0.981	0.982	0.863	0.871	0.908	0.918	0.909	0.918
Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

According to the baseline regression results, it is found that the results of the model with the addition of 4 control variables are better than the results of the model without the addition of control variables, both in terms of the overall fitting effect of the model and the significance of the variables. Therefore, this research adopted the regression results after adding control variables.

Different from the research hypothesis, the baseline regression results show that CETS does not play a significant role in carbon emission intensity, which means that the intervention of CETS does not affect the control of carbon emissions per unit of production. However, through the establishment of property rights, CETS significantly contributes to carbon abatement and atmospheric pollutant reduction. Specifically, the intervention of CETS resulted in carbon emissions decreased by 83.265 million tons, PM_{10} concentration decreased by 12.511 μg/m^3, SO_2 concentration decreased by 8.965 μg/m^3, and NO_2 decreased by 13.582 μg/m^3.

3.3 Parallel Trend Test and Policy Dynamic Effects

The basic premise for adopting the DID approach is the assumption of parallel trends. That is, without the intervention of the policy on the treatment group, there should be no systematic difference in the changing trend of the outcome variables between the treatment group and the control group over time. To conduct a formal test of ex-ante parallel trends, this research referred to the method of Shi, Xu and Sun (2022), employing the research framework of event analysis to develop the following 4 regression equations (7), (8), (9) and (10) to assess the dynamic effects of CETS.

$$CE_{it} = \sum_{j=-5}^{5} \beta_j D_j + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{7}$$

$$PM_{10\,it} = \sum_{j=-5}^{5} \beta_j D_j + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{8}$$

$$SO_{2\,it} = \sum_{j=-5}^{5} \beta_j D_j + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{9}$$

$$NO_{2\,it} = \sum_{j=-5}^{5} \beta_j D_j + \gamma' \cdot X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{10}$$

D is the interaction term between the year dummy variable and the treatment group variable. Where D_0 is the dummy variable for the year the CETS was introduced. When $-j < 0$, D_j is a dummy variable for the year before the CETS was introduced. When $j > 0$, D_j is a dummy variable for the year after CETS was introduced. Since CETS was not introduced in all treatment group provinces at the same time, D_0 represents different years for different provinces. The regression results are shown in Table 6.

To see the parallel trends and the dynamic effects of the policy more clearly, four figures were drawn below, Figures 1, 2, 3 and 4. Figures 1, 2, 3 and 4 report the magnitude of the estimated parameters ($\beta_{-5}, \beta_{-4}, \beta_{-3}, \beta_{-2}, \beta_{-1}, \beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) and the corresponding 95% confidence intervals. If the 95% confidence interval of the estimated parameter, represented by the vertical grey dotted line, intersects the horizontal solid line of 0, it means that the estimated coefficient of the dummy variable fails the significance test at the 5% level.

It can be found that the estimated coefficients ($\beta_{-5}, \beta_{-4}, \beta_{-3}, \beta_{-2}, \beta_{-1}$) of the dummy variables for the 5 years before the introduction of CETS fail the significance test at the 5% level when *CE*, PM_{10}, SO_2 and NO_2 are used as the explained variable. This precisely verifies that the treatment group included in the CETS pilot and the control group not included in the CETS pilot satisfy the parallel trend assumption. In other words, the trends of the treatment and control groups before the intervention of CETS were similar. Therefore, the significant decrease in *CE*, PM_{10}, SO_2 and NO_2 in the treatment group relative to the control group after the intervention of CETS is a result of the CETS intervention and not a result of ex-ante differences.

The estimated coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) of the post-CETS dummy variables, when *CE* is used as an explained variable, pass the significance test at the 5% level of significance and are significantly negative up to 5 years after CETS intervention. When PM_{10}, SO_2 and NO_2 are used as explained variables, the estimated coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) of the post-CETS dummy variables are significantly negative at the 5% level within 3 years after CETS intervention and do not show significance at the 5% level starting from 4 years after CETS intervention. When SO_2 and NO_2 are used as explained variables, although the estimated coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) of the post-CETS dummy variables are significantly negative at the level of 10% in the fourth year after CETS intervention, they are no longer significant at the level of 10% after the fifth year after policy implementation.

Policy dynamic effects show that CETS has a long-term impact on carbon abatement, and the impact on carbon abatement is still significant 5 years after CETS implementation. However, different from the research hypothesis, the impact of CETS on atmospheric pollutant reduction is relatively short-term. CETS has a significant emission reduction effect at the level of 5% within 3 years after its implementation, but its effect on atmospheric pollutant reduction is no longer obvious from the 4th year after CETS intervention.

Table 6. Regression Results for Parallel Trend Test and Policy Dynamic Effects

	(1)	(2)	(3)	(4)
Variables	*CE*	PM_{10}	SO_2	NO_2
pre_5	36.41	-0.532	1.814	2.961
	(32.55)	(7.462)	(5.765)	(8.701)
pre_4	26.48	2.673	0.878	1.327
	(29.18)	(6.331)	(5.221)	(7.772)
pre_3	10.57	2.272	-0.440	-0.562
	(21.49)	(4.303)	(3.676)	(5.704)
pre_2	-8.938	-0.835	-2.162	-3.244

	(13.26)	(2.923)	(2.405)	(3.681)
current	-62.04**	-15.77***	-8.973***	-13.17***
	(26.17)	(4.687)	(2.763)	(4.110)
post_1	-76.57**	-18.35***	-11.67***	-17.47***
	(30.51)	(5.513)	(3.488)	(5.209)
post_2	-81.03**	-17.60***	-11.38***	-17.28***
	(32.13)	(5.779)	(3.731)	(5.604)
post_3	-91.95***	-15.04**	-9.123**	-14.21**
	(33.04)	(7.145)	(3.767)	(5.617)
post_4	-98.68***	-5.821	-6.937*	-10.90*
	(34.04)	(6.916)	(4.018)	(5.973)
post_5	-108.5***	-5.443	-5.842	-9.227
	(36.79)	(7.040)	(4.153)	(6.173)
Constant	356.7***	95.82***	55.07***	82.81***
	(4.039)	(0.894)	(0.599)	(0.905)
Observations	330	330	330	330
R-squared	0.910	0.865	0.908	0.909

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

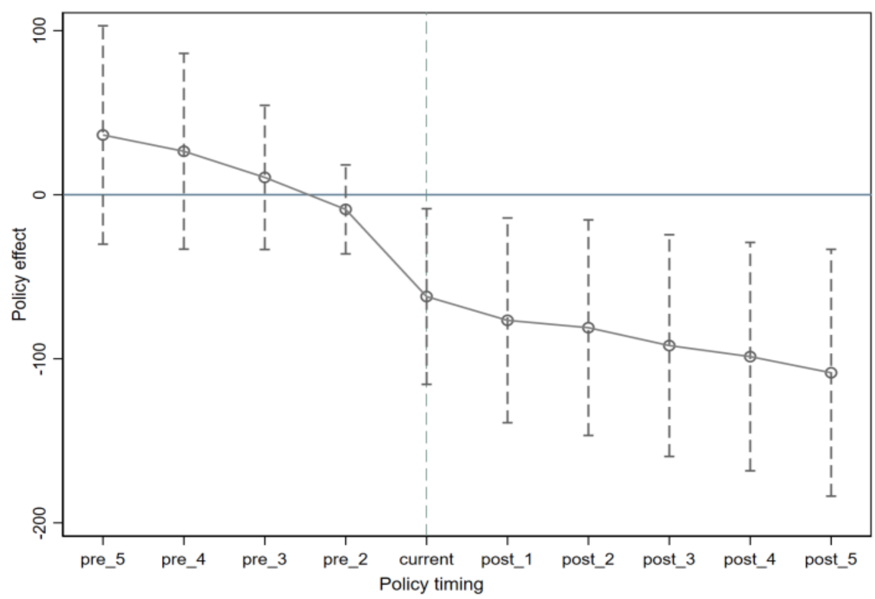

Figure 1. Parallel Trend and Policy Dynamic Effects - *CE*

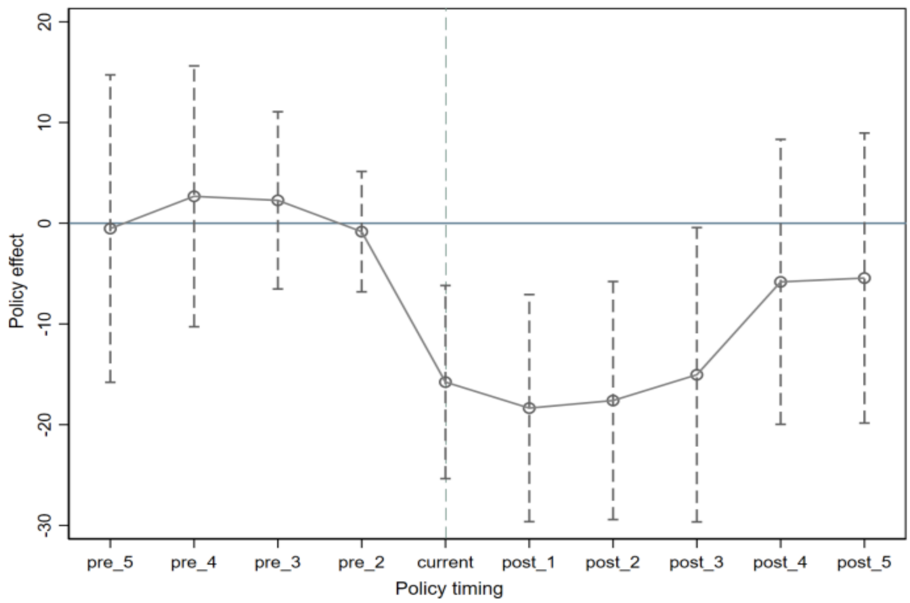

Figure 2. Parallel Trend and Policy Dynamic Effects - *PM_{10}*

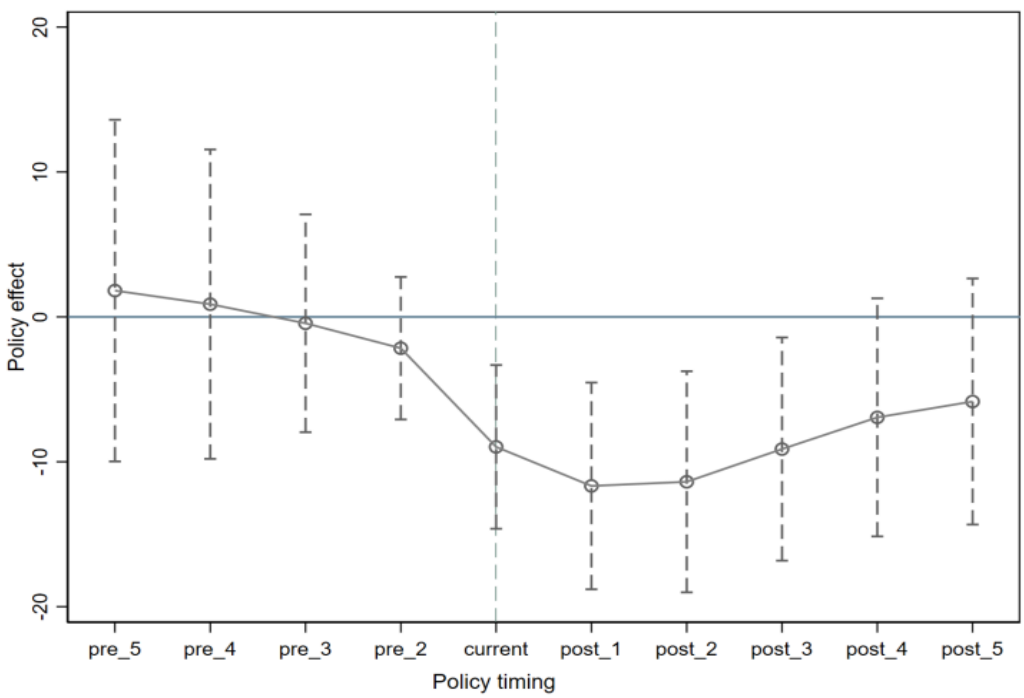

Figure 3. Parallel Trend and Policy Dynamic Effects - *SO_2*

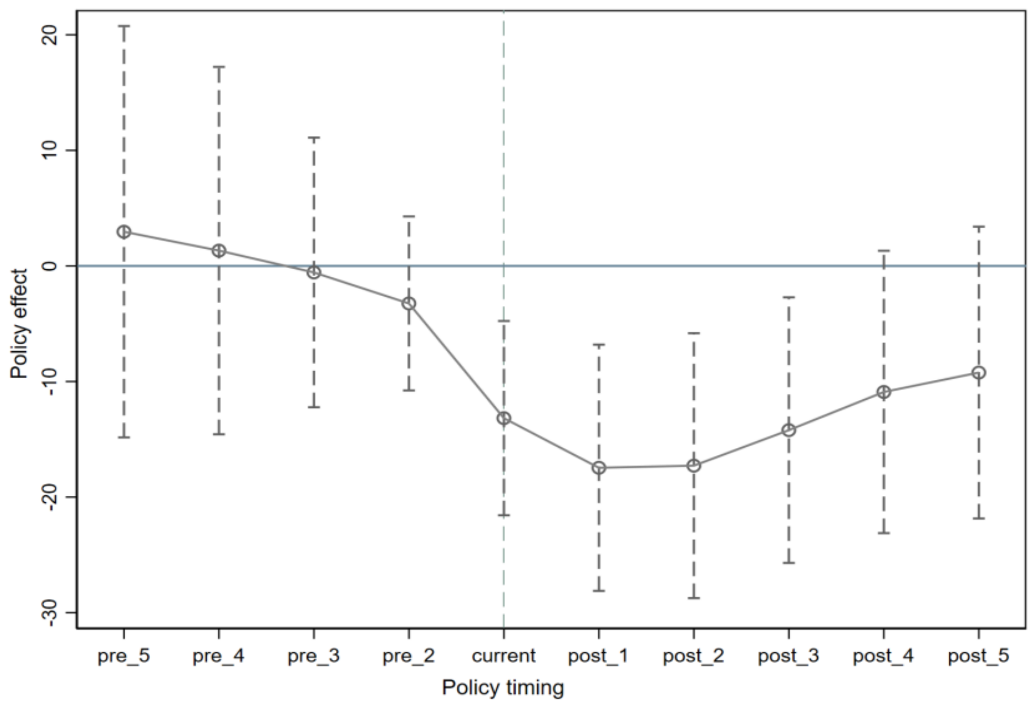

Figure 4. Parallel Trend and Policy Dynamic Effects - *NO_2*

3.4 Placebo Test

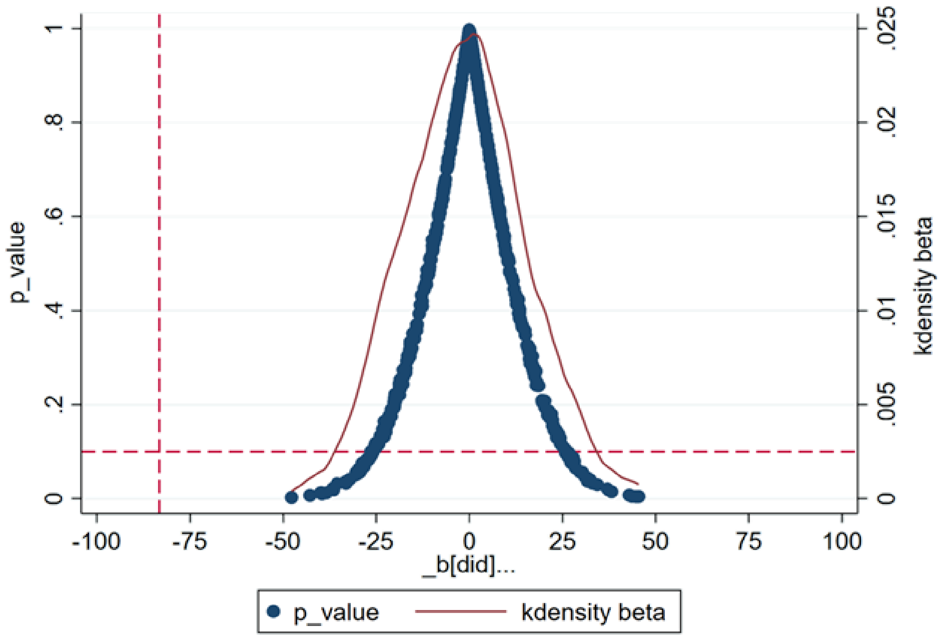

Figure 5. Placebo Test - *CE*

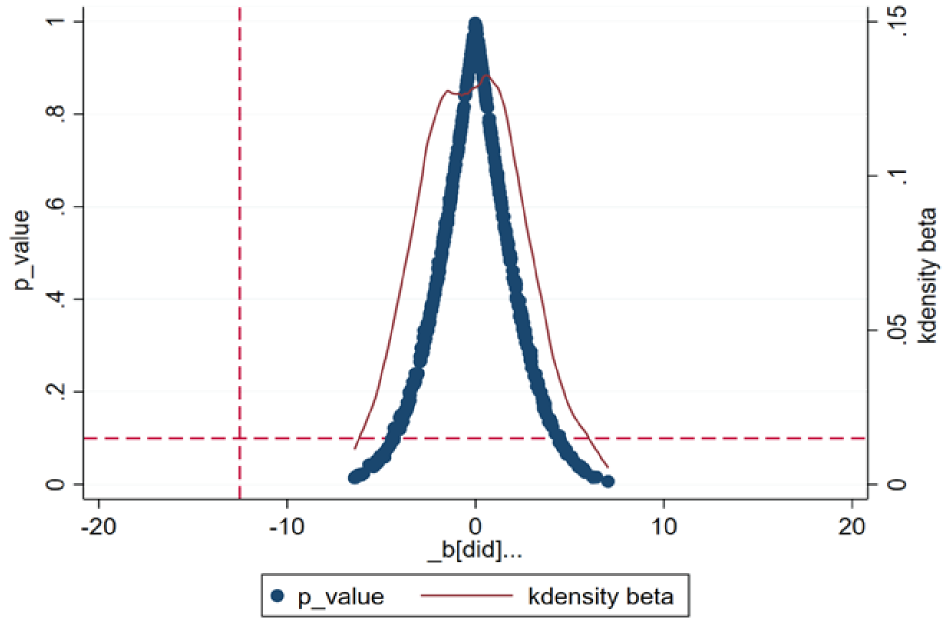

Figure 6. Placebo Test - *PM_{10}*

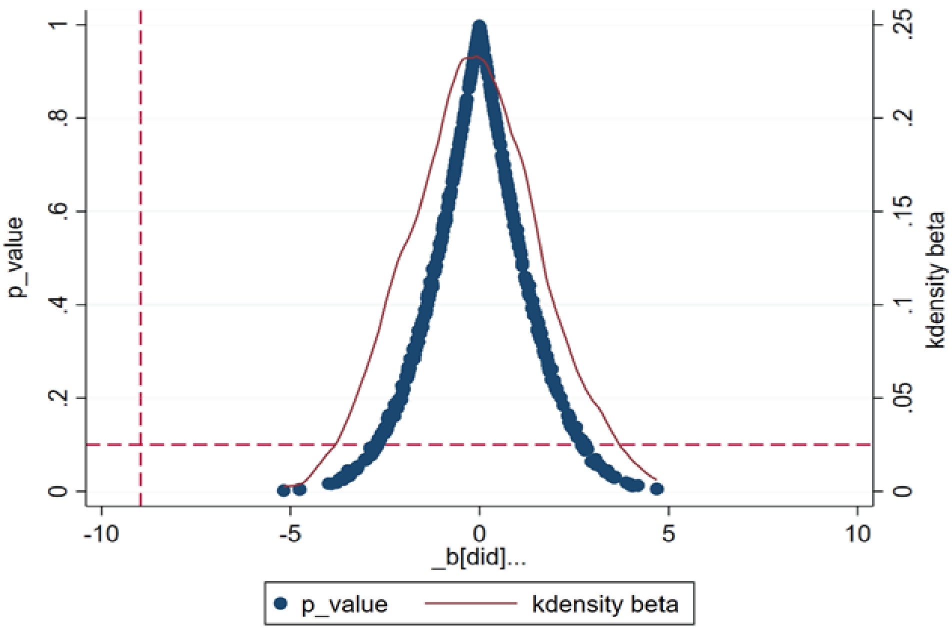

Figure 7. Placebo Test - *SO_2*

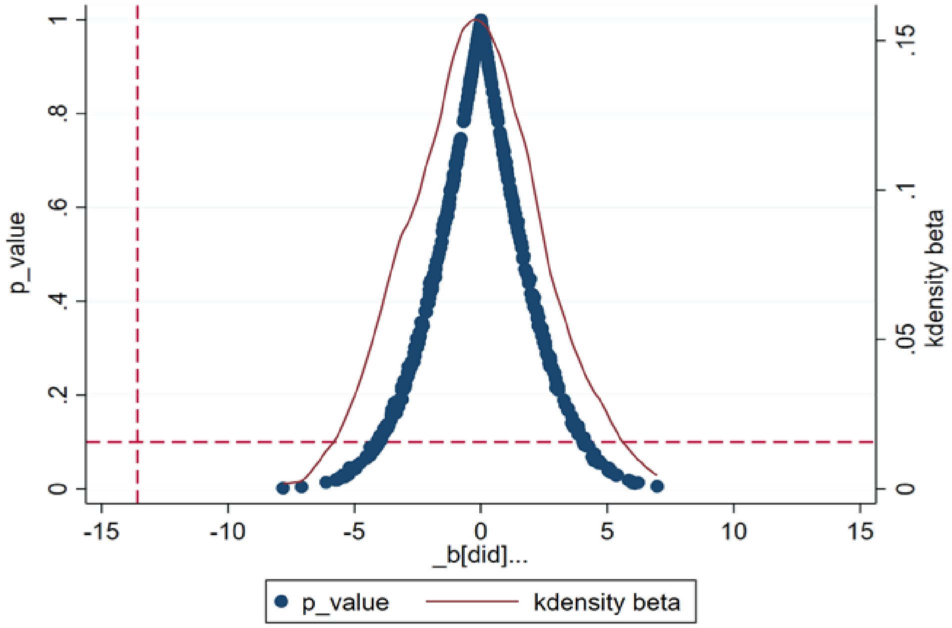

Figure 8. Placebo Test - *NO_2*

Placebo tests can determine whether policy effects are driven by other random factors or by the policy intervention itself (Qin & Xie, 2023). To rule out the possibility that CETS pilot policy effects are confounded by omitted variables, this research conducted a placebo test by randomly selecting the year in which CETS was implemented and randomly selecting the provinces included in the CETS pilot. This is done by randomly selecting the treatment group 500 times and then conducting 500 times baseline regression to obtain the distribution of P-values and the distribution of estimated coefficients. The distribution of the 500 P-values is shown by the blue dots. The distribution of 500 estimated coefficients is shown by the solid red line. The true coefficients are shown by the vertical red dashed line. As shown in Figures 5, 6, 7 and 8. When *CE*, PM_{10}, SO_2 and NO_2 are explained variables, firstly, it is found that the vast majority of P-values obtained based on random samples are above the red horizontal dotted line, which means that the vast majority of P-values are not significant at the 10% level. Secondly, the estimated coefficients obtained based on random samples are all distributed around 0 and the true coefficients (β_{CE} = -83.265, β_{PM10} = -12.511, β_{SO2} = -8.965, β_{NO2} = -13.582) are all independent of the estimated coefficients of random samples. According to the test results, it is found that the mean value of the completely random results approaches 0, and the distribution density curve basically fits the normal curve, so the results passed the placebo test. This shows that the policy effect of CETS is a real effect caused by real existing policies, and the carbon abatement and atmospheric pollutant reduction effects are not confounded by other omitted variables.

3.5 Regional Heterogeneity Test

There are huge geographical differences in China, so the impacts of CETS in different regions of China may also be different. Dong et al. (2022) analysed the regional heterogeneity of CETS by dividing China into East, Central and West when studying the synergistic benefits of CETS on carbon abatement and atmospheric pollution control. Referring to the methodology of that research, this research examined the regional heterogeneity of the impact of CETS in the Northern and Southern of China by dividing the country into Northern and Southern parts. In this research, the sample of 30 provinces was divided into two parts, North and South, using the Qinling Mountains – Huihai River line as a benchmark. The results of the division are shown in Table 7. Based on the samples after the North-South division, the time-varying DID method and baseline regression analyses were conducted again. The results of the baseline regression are shown in Table 8.

Table 7. Sample Selection for Regional Heterogeneity Test

		Pilot time	Provinces
North	Treatment group	2013	Beijing, Tianjin
	Control group		Heilongjiang, Jilin, Liaoning, Inner Mongolia, Jiangsu, Henan, Hebei, Shandong, Qinghai, Ningxia, Shanxi, Shannxi, Gansu, Xinjiang
South	Treatment group	2013	Shanghai, Guangzhou, Hubei, Chongqing
		2016	Fujian
	Control group		Zhejiang, Anhui, Jiangxi, Hainan, Hunan, Guangxi, Sichuan, Guizhou, Yunnan

Table 8. Baseline Regression Results for Regional Heterogeneity Test

Variables	*CE*		*CEI*		PM_{10}		SO_2		NO_2	
	North	*South*	*North*	*South*	*North*	*South*	*North*	*South*	*North*	*South*
did	-141.6**	-30.72*	0.0569	0.0381	-23.15**	-8.549	-14.65**	-5.172*	-22.44**	-7.533*
	(-3.92)	(-2.87)	(0.22)	(0.16)	(-3.88)	(-1.97)	(-3.65)	(-2.29)	(-3.78)	(-2.23)
pgdp	-1.791	-1.131	0.00715	0.0257	-0.329	0.271	-0.219	-0.0162	-0.327	-0.0124
	(-0.76)	(-1.61)	(0.71)	(1.80)	(-1.07)	(1.03)	(-0.89)	(0.13)	(-0.89)	(-0.07)
pop	16.68	4.374**	0.0861	0.0296	2.427	0.812	1.890	1.242**	2.814	1.823**
	(1.04)	(3.08)	(1.19)	(1.76)	(1.15)	(1.83)	(1.03)	(4.17)	(1.03)	(4.15)
industry	-10.14	4.373	-0.0104	-0.00699	-1.723	2.064**	-1.211	0.789*	-1.789	1.177*
	(-0.98)	(2.09)	(-0.42)	(-0.31)	(-1.25)	(3.19)	(-1.21)	(2.56)	(-1.19)	(2.52)
invest	-10.89	-0.375	-0.00214	0.0596	-2.843*	-0.819	-1.302	-0.651	-1.976	-0.894
	(-1.13)	(-0.09)	(-0.04)	(1.27)	(-2.40)	(-1.06)	(-1.44)	(-1.03)	(-1.46)	(-0.95)
Constant	329.4	-115.2	2.056	0.121	109.5	-60.21	52.09	-50.06*	78.00	-71.23*
	(0.42)	(-1.05)	(0.42)	(0.07)	(1.03)	(-1.30)	(0.61)	(-2.33)	(0.61)	(-2.21)

Observations	176	154	176	154	176	154	176	154	176	154
R-squared	0.908	0.971	0.984	0.939	0.822	0.951	0.898	0.976	0.899	0.976
Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

From the regression results, when *CE*, SO_2 and NO_2 are the explained variables, the coefficients of the interaction term *did* are significantly negative at the 5% level in northern China, and the coefficients of the interaction term *did* are significantly negative at the 10% level in southern China. Specifically, the intervention of CETS reduced *CE* by 141.6 million tons, SO_2 concentration by 14.65 μg/m^3, and NO_2 concentration by 22.44 μg/m^3 in the pilot region of northern China. The pilot region in southern China reduced *CE* by 30.72 million tons, SO_2 concentration by 5.172 μg/m^3, and NO_2 concentration by 7.533 μg/m^3. When PM_{10} is the explained variable, the coefficient of the interaction term *did* is significantly negative at the 5% level in the northern region, while it is not significant at the 10% level in the southern region. Specifically, the intervention of CETS resulted in a reduction of 23.15 μg/m^3 of PM_{10} concentration in the pilot region of northern China. When *CEI* is used as an explained variable, the coefficient of the interaction term *did* is insignificant in both the northern and the southern regions of China. Overall, the intervention of CETS is more significant in reducing carbon emissions and atmospheric pollutants in the northern region of China.

4. Conclusions, Recommendations and Discussion

4.1 Conclusions

This research adopted the time-varying Difference-in-Differences method to construct panel data with 30 provinces in China from 2008 to 2018 as samples to study the role of CETS in carbon abatement and atmospheric pollutant reduction. The empirical results passed the parallel trend test and placebo test. Four main conclusions were drawn from this research. Firstly, the empirical results show that the pilot of CETS has a significant effect on carbon abatement, PM_{10}, SO_2 and NO_2 concentration reduction. Specifically, carbon emissions decreased by 83.265 million tons, PM_{10} concentration decreased by 12.511 μg/m^3, SO_2 concentration decreased by 8.965 μg/m^3, and NO_2 decreased by 13.582 μg/m^3 after the intervention of CETS. Secondly, CETS has a long-term effect on carbon abatement and has a relatively short-term effect on the reduction of PM_{10}, SO_2 and NO_2 concentrations. Thirdly, the CETS pilot, however, did not have a significant effect on the reduction of carbon emission intensity (carbon emissions per unit of GDP). The reason why economic growth may lead to a stabilisation or even an increase in carbon emissions per unit of GDP is that economic growth may be accompanied by the development of energy-intensive industries, especially in developing countries or emerging markets. Even if the total carbon emissions fall, carbon emissions per unit of GDP may still rise due to the increase in output brought about by economic growth (Shi, Xu, & Sun, 2022). Fourthly, this research found that the intervention of CETS is more significant in reducing carbon emissions and atmospheric pollutants in northern China than in southern China through the regional heterogeneity test. One reason for this is the difference in energy structure between the northern and southern regions. The northern region mainly relies on coal and other high-carbon emission energy sources, while the energy mix in the southern region may include more clean energy sources such as hydro-power, wind power and solar energy. As a result, carbon emissions per unit of production are likely to be higher in the North, and carbon pricing through the CETS may provide a more significant incentive for Northern firms to reduce carbon emissions. The second reason is the difference in industrial structure between the North and South. Northern regions may have a greater concentration of highly polluting and energy-intensive heavy industries and chemical companies, which typically have higher carbon and atmospheric pollutant emissions, and CETS may be more likely to generate greater potential for emission reductions in these industries.

Based on the findings, this research filled in a bit of a research gap. First, unlike the literature that focuses only on the impact of CETS on carbon emissions or only on the impact of CETS on atmospheric quality, this research considered the role of CETS on carbon abatement and atmospheric pollutant reduction at the same time. Second, this research improved the indicators for measuring the abatement effect of carbon and atmospheric pollutants. For example, the carbon emission intensity indicator, which measures the relationship between carbon emissions and economic development, was added, and the suspended particulate matter indicator PM_{10}, which is a larger particle size, was added. Thirdly, unlike the traditional DID, this research used a time-varying DID model that is more in line with the asymptotic characteristics of CETS. In addition, unlike the past literature that studies the regional heterogeneity of CETS by dividing China into East, Middle and West, this research divided China into North and South to explore the heterogeneity of CETS in North and South of China.

4.2 Recommendations

Based on the findings of this research, several suggestions are made for the intervention of CETS. First, given the positive effects of CETS on carbon abatement and atmospheric pollutant reductions, the government should strengthen the intervention of the scheme and gradually expand the scope of the pilot program to cover a wider range of regions and industries.

Second, given the longer-term impact of CETS on carbon abatement, the government and relevant authorities should strengthen regulation and enforcement to ensure that carbon emission reduction targets are consistently met.

Third, considering that CETS will only have a short-term impact on the reduction of atmospheric pollutants, the government should strengthen the monitoring of atmospheric pollutants. For instance, the government should improve emission standards and control requirements for different atmospheric pollutants by targeting different types of atmospheric pollutants.

Fourth, in response to the problem that economic growth may lead to a rise in carbon emissions per unit of GDP, the government should take measures in conjunction with economic policies to promote the development of a green and low-carbon economy, promote the upgrading of the industrial structure, and to reduce the reliance on energy-intensive industries. For instance, the government should provide guidance or subsidies to stimulate green innovation in corporate production. This could simultaneously ensure productivity, reduce carbon emissions and improve atmospheric quality. It is beneficial to achieve a win-win situation for both the economy and the environment in the long run (Xu et al., 2021).

Fifthly, taking into account the differences in energy and industrial structures between the north and the south, the government should implement regionally differentiated policy measures and formulate corresponding emission reduction policies and measures to address the characteristics and needs of different regions, to achieve emission reduction targets more effectively.

4.3 Discussion

Although this research filled some research gaps in previous literature, there are still some problems and deficiencies. First of all, this research covered the period from 2008 to 2018. However, the policy, economic, and technological environments have changed over time, which can affect the robustness of the findings. The policy utility of CETS derived from this research cannot be representative of the policy utility of CETS up to now. Therefore, in future research, covering a longer period can be considered, which is conducive to the study of the long-term effects of CETS.

Second, this research used provincial panel data for 30 provinces, which may lead to the omission of differences in cities within provinces. In addition, data covering only 30 provinces in China may not fully reflect the situation in China as a whole, as China's regional differences are large, and policy intervention and industrial structure may differ significantly in different regions. Therefore, in future research, the use of city-county level data can be considered to more accurately show the impact of CETS pilots on carbon abatement and atmospheric pollutant reduction.

Third, due to the limitation of the sample size of this research, the regional heterogeneity analysis of CETS is sketchy, and this research can only briefly examine the differences in the impact of CETS on the pilot provinces in the North and South. In future studies exploring the heterogeneity analysis of CETS, a more detailed geographical division could be considered, as well as in terms of differences in the level of economic development or industrial structure.

Finally, the research of carbon and atmospheric pollutant emission reduction in this research is limited to the macro level and does not analyse the abatement effects of individual industries or even individual enterprises from the micro level. Therefore, future research can consider focusing on more micro industries or enterprises to deeply explore the abatement effect of the CETS pilot at the micro level.

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