

Article

Policy Coordination Effects of APPCAP and ETS on Pollution and Carbon Reduction

Na Liu ^{1,*}, Siyue Yang ² , Xinwei Gao ³ and Ruirui Yang ³¹ International Business School, Qingdao Huanghai University, Qingdao 266427, China² School of Public Policy and Administration, Northwestern Polytechnical University, Xi'an 710072, China; siyueyang@nwpu.edu.cn³ School of Economics and Management, China University of Petroleum (East China), Qingdao 266580, China; glxgxw@163.com (X.G.); b22080008@s.upc.edu.cn (R.Y.)

* Correspondence: liun14@qdhc.edu.cn; Tel.: +86-18227592249

Abstract: Coordinated control of pollution and carbon reduction is an imperative choice for China's overall transition towards sustainability. However, China's environmental policies often treat pollutants and CO₂ separately, potentially resulting in imbalanced pollution and carbon reduction. Since several cities are not only critical cities for the Air Pollution Prevention and Control Action Plan (APPCAP) policy but also pilot cities for the Carbon Emissions Trading Scheme (ETS), this study aims to examine the extent to which the policy coordination of APPCAP and ETS can influence air pollutants and CO₂ emissions. Using panel data from 2011 to 2019 for China's 231 prefecture cities, we compare the pollution and carbon reduction effects of separate and coordinated policy implementation of APPCAP and ETS via the difference-in-differences (DID) model and the causal forest model. Research shows that (1) the policy coordination of APPCAP and ETS has significantly reduced both air pollutants and CO₂ emissions in dual-policy pilot cities. For non-dual pilot cities, the separate implementation of APPCAP or ETS only exerts significant unilateral effects. (2) Enhancing government supervision, weakening the relationship between government and enterprises, and raising enterprises' green innovation capabilities are the main mechanisms through which policy coordination can significantly influence pollution and carbon reduction. (3) The combined implementation impacts of APPCAP and ETS are more evident in pollution-intensive cities and cities with weak carbon-peaking trends. Our research inspires the development of a collaborative system of pollution reduction and carbon reduction policies.



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Keywords: air pollution prevention and control action plan; carbon emissions trading scheme; policy coordination; pollution and carbon reduction

1. Introduction

Since atmospheric pollutants and greenhouse gases basically originate from the same source and process [1], the coordinated control of pollution reduction (PR) and carbon reduction (CR) has become an indispensable choice for countries with high pollution dependence or high carbon emissions, such as China, India, Brazil, South Africa, Russia, and the like. However, air pollution control and carbon reduction policies are more often implemented independently in these countries, which is prone to unbalanced or unsynchronized PR and CR. The challenges these countries encounter when coordinating PR and CR policies are often related to their respective economic structures, policy priorities, technical capabilities, and social acceptance. For example, India faces the problem of insufficient funds and technology; Brazil has great difficulty in reducing deforestation and methane emissions; Russian policies mostly on controlling industrial waste gas and air pollution; and the country lacks CR measures, despite its heavy reliance on fossil fuels. Fortunately, a few countries and cities, such as several provinces and cities in China (Beijing, Guangdong), have tried dual-policy pilots for PR and CR. Consequently,

employing China as the subject of study to explore the synergistic effects of PR and CR policies can provide empirical evidence for policy improvement of other high-pollution and high-carbon-emitting countries around the world.

China's PR and CR policies are in the transitional stage from separation to coordination, and the establishment of dual-policy pilots is an effective strategy to complete this transition. The "Air Pollution Prevention and Control Action Plan" (APPCAP), a typical representative of PR policies, was officially released by China's State Council in September 2013. Meanwhile, the "Carbon Emissions Trading Scheme" (ETS), a typical representative of CR policies, was also carried out in 2013. Theoretically, APPCAP and ETS implemented independently should have cross-cutting co-benefits on CR and PR, considering air pollutants and CO₂ often have the same origin. However, there is a "seesaw" effect in the PR and CR control processes. For example, using desulfurization technology to reduce SO₂ emissions may increase the energy consumption of the coal burning process and generate new CO₂ emissions [2,3]. Perhaps relying solely on a single policy is far from controlling environmental pollution and climate change collaboratively but must count on policy coordination [4].

Existing research has conducted rich discussions on the effects of single policy implementation. The APPCAP and the "Three-Year Action Plan to Win the Blue-Sky Defense War" have been proven to reduce atmospheric pollutants emissions significantly [5–8], but their reduction effects on CO₂ emissions are not necessarily apparent [9]. Still, the implementation effect of ETS on PR and CR lacks consistent conclusions [10–13]. For PR, Dong et al. [11] demonstrated that ETS had improved air quality, while Shao et al. [13] concluded that ETS did not exert a collaborative-governance effect on SO₂ emissions in non-key environmental protection and energy-oriented cities. For CR, Xuan et al. [10] confirmed that ETS could significantly reduce CO₂ emission intensity. However, Wen et al. [12] held that ETS had little impact on industrial CO₂ emissions, and Dong et al. [11] showed the policy did not significantly affect China's overall carbon emissions intensity but instead increased CO₂ emissions in neighboring cities.

While there is a substantial body of literature on policy coordination, studies specifically addressing the coordination between APPCAP and ETS policies remain limited. Policy coordination is the systematic collaboration between public and private organizations to ensure adequate public policy delivery without duplication or service gaps [14]. Most studies indicate that combining multiple policies is more effective than implementing them individually. For example, Chang et al. [15] stated that coordination of tradable green certificates (TGCs) and ETS promotes low-carbon transition in the energy sector; Xian et al. [16] demonstrated that under the cooperative control scenario of CR policies and PR policies, CO₂ emissions will peak in 2028, and the 2 °C carbon emission target will be basically achieved by 2050; Li et al. [17] verified that the synergy of green policies in terms of content, departments, and types has a very significant effect on PR; Nie et al. [18] reported that policy coordination might successfully align the objectives and strategies of energy policies and facilitate the growth of entities within the energy system. Sepehriar and Eslamipour [19] proved that the quantity of CO₂ emissions could be regulated through the coordination between carbon tax and carbon trading policies. However, the coordination effect of multiple policies is not necessarily superior to separate implementation effects due to possible overlap or conflict among policies. Li et al. [20], for instance, revealed that the combined implementation effect of the Emission Rights Trading and the Emission Tax Policy was not consistently higher than that of separate implementation, with penalty cost being the key determinant. Another piece of evidence is that the CR effect produced by the coordination of the ETS and the green power policy is weaker than that of using the green power policy alone [21].

The majority of research highlights the necessity for synergy between PR and CR policies via qualitative analysis, but there are few quantitative analyses. Wang et al. [22] believed that the coordination between command-and-control policies and ETS policy was indispensable, along with reducing policy overlap to avoid possible policy conflicts.

Duan et al. [23] revealed that institutional vested interests might be the most crucial reason for insufficient synchronization between ETS policy and other policies. Stoerk et al. [24] showed that the Clean Development Mechanism (CDM) credits might limit the conception of ETS markets. From a quantitative perspective, Peng et al. [25] found that the ETS policy has a more significant effect on improving intra-city green innovation cooperation in cities with high command-and-control environmental regulation intensity.

Two research gaps can be identified based on existing studies. First, most articles have tested the PR and CR effects of APPCAP and ETS, but there is no unified conclusion on APPCAP's CR effects and ETS's PR/CR effects. Second, relevant literature exploring the policy coordination effects of APPCAP and ETS only remains at the qualitative analysis level and needs more quantitative research. Therefore, our objective is to address these deficiencies by evaluating the PR and CR effects of APPCAP and ETS implemented individually and collaboratively, associated with further mechanisms and heterogeneity analysis.

Marginal contributions are as follows: Initially, we compare the PR and CR impacts of APPCAP and ETS implemented separately and collaboratively, expanding existing literature on dual-policy pilot studies. Then, we further assess the mechanisms of policy coordination in three aspects: government supervision, government-enterprise relations, and corporate green innovation, adding a more systematic perspective to the mechanisms analysis of environmental policies. Finally, we dig out the heterogeneity of policy coordination in cities characterized by differing pollution densities and distinct carbon-peaking trends, offering enlightenment for the government to carry out heterogeneous measures for different areas.

2. Policy Background and Hypothesis Formulation

APPCAP, aiming to improve air quality, was officially released by China's State Council in September 2013 and implemented until the end of 2017, with the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta as crucial implementation areas. It is noticeable that there are no specific CR goals in APPCAP to force local governments to reduce CO₂ emissions, which can restrain the synergic emission reduction technological efficiency change [26]. For cities that are highly dependent on energy-intensive industries, APPCAP is particularly restrictive, such as Tangshan (Hebei), a major steel town. For cities like Shenzhen, characterized by a high proportion of service industries and high-tech industries, APPCAP can promote the development of green cities, such as the electrification of buses.

Integrating PR measures with CR policies is crucial to mitigate the "seesaw" effect between the reduction of air pollutants and the increase of CO₂ emissions [27]. The "Carbon Emissions Trading Scheme" (ETS), targeting CO₂ emissions reduction, has been carried out since 2013. Shenzhen took the lead in implementing the ETS in June 2013, followed by Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong in around 2014, and Fujian in 2016. For cities like Wuhan (Hubei), dominated by energy-intensive industries, the ETS policy increases the carbon emission compliance costs of enterprises, forcing them to adopt energy-saving and emission-reduction measures. For cities like Shanghai, characterized by a predominance of the digital economy and service industry, ETS policy mainly develops green finance and carbon asset management through the carbon trading system. It is observable that 12 cities are not only pilot cities for ETS but also key cities for APPCAP, providing a realistic basis for evaluating the effectiveness of the coordinated implementation of the two policies.

As a command-and-control policy, APPCAP mainly puts external pressure on highly polluted enterprises through a "top-down" approach, thereby forcing them to make a green transformation. Tang et al. [28] revealed that state-owned enterprises were crucial transmission channels for command-and-control policies. Meanwhile, state-owned enterprises are also the main emitters in China's carbon market since they almost monopolize energy supply and have a strong influence on national policy formulation [29]. Therefore, APPCAP may promote the role of ETS in CR through state-owned enterprises or other media of government intervention [30]. Considering that the ETS and APPCAP can complement

each other during their joint implementation process, this paper believes that the policy coordination of APPCAP and ETS can significantly reduce air pollutants and CO₂ emissions simultaneously. We put forward Hypothesis 1 as follows:

H1: Policy coordination of APPCAP and ETS can significantly reduce air pollutants and CO₂ emissions.

Combined with the “Porter Hypothesis” [31] and China’s social capital theory [32], the transmission mechanism of the policy implementation can be divided into three parts: the upper end from the government supervision, the middle end from government-enterprise relations, and the lower end from enterprises’ green innovation. Details are as shown in Figure 1.

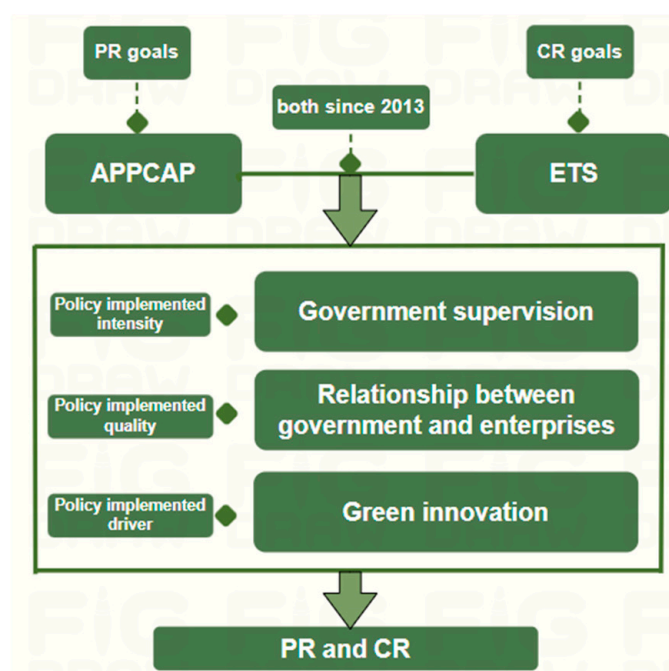


Figure 1. Mechanism framework for policy coordination.

Government supervision, which determines the policy implementation intensity, takes the upper end. Many studies have proven that the higher the government supervision level, the more conducive it is to strengthening the effectiveness of emission reduction initiatives. For instance, European nations have predominantly implemented more rigorous environmental legislation, motivated by social, technical, and regional collaboration aspects [33]. For China, Chu et al. [34] tested that horizontal transfer payment and regional environmental supervision could ensure China’s air pollution governance is sustainable. Zeng et al. [35] demonstrated that Central Environmental Protection Inspection could mitigate local pollution emissions and improve green transformation. Environmental oversight has a function comparable to air pollution in terms of carbon reduction. Although China’s perfect ETS has not yet been formed [36], Pan et al. [37] revealed that strict government supervision in ETS tended to boost the carbon trading market’s efficiency and enhance enterprises’ total factor productivity. Quite a few studies have confirmed that ETS’s CR effect is more evident in areas with stringent enforcement of environmental regulations or solid legal supervision [38,39]. Considering that both the ETS and the APPCAP include the provision of “strengthening environmental supervision”, dual-policy pilot cities will be subjected to environmental supervision from both PR and CR aspects. In this scenario, pilot cities are inclined to decrease CO₂ emissions and air pollutants simultaneously. According to this, Hypothesis 2 is suggested in the following manner.

H2: *Policy coordination of APPCAP and ETS can significantly reduce air pollutants and CO₂ emissions by enhancing government supervision.*

The relationship between government and enterprises deserves the middle end, with the policy implementation quality being affected by it. An honest government-enterprise partnership could benefit both enterprises and the government's development, but the relationship can easily develop into a government-enterprise collusion under China's political system. For example, the long tenure of critical local government officials tends to enhance the probability of government-enterprise collusion [40]. Revolving around environmental conservation, Hu and Shi [41] found that cities with government-enterprise collusion had an 11.3% increase in SO₂ emissions compared with cities without collusion. When heavily polluting enterprises face stringent pressures to reduce emissions, they may seek to evade substantial pollution control costs through collusion with local governments, undermining the effectiveness of ETS and APPCAP policies. However, in cities implementing both APPCAP and ETS, the higher collusion costs associated with dual policy enforcement could mitigate the likelihood of such collusion. Furthermore, China's anti-corruption campaigns could incentivize companies to enforce environmental laws strictly and decrease pollutants and CO₂ emissions [42]. Hypothesis 3 is proposed in light of the analysis provided above.

H3: *Policy coordination of APPCAP and ETS can significantly reduce air pollutants and CO₂ emissions by weakening the relationship between government and enterprises.*

Enterprises' green innovation is the primary stimulus for reducing emissions, determining whether a company has higher emission reduction technology. For OECD countries, green innovation can significantly improve their environmental quality and is an effective mechanism for environmental policies to play a role [43]. When the emission reduction technology of enterprises becomes increasingly advanced, it will help break through the existing "seesaw" effect of "pollution reduction and carbon increase" or "carbon reduction and pollution increase" [27], which will provide a pronounced reduction in both pollutants and greenhouse gases. Most studies have concluded that environmental policies can stimulate technological advancement or green innovation. For instance, Brunel [44] showed that environmental policies could boost the application of foreign green technologies; Liu et al. [45] found that ETS policy had the potential to motivate an increase in enterprises' green innovation patent numbers. Still, there are some researchers holding different opinions. Chen et al. [46] discovered that the percentage of green patents in China had been considerably decreased by ETS policy; Yao et al. [47] demonstrated that the effect of ETS policies on green innovation differed depending on the area; several studies showed a U-shaped relationship between environmental regulatory tools and green innovation [48,49]. Perhaps the progress of green innovation in enterprises is not apparent in the short term, but it can be enhanced with direction from market and non-market regulations. Enterprises governed by a single policy may reduce output rather than invest in green innovation to meet emission reduction targets [46]. In contrast, the simultaneous implementation of APPCAP and ETS provides dual incentives from market and non-market mechanisms, encouraging enterprises to adopt long-term strategies that enhance green innovation and strengthen the technological synergy between PR and CR. Hypothesis 4 is below.

H4: *Policy coordination of APPCAP and ETS can significantly reduce air pollutants and CO₂ emissions by raising the green innovation capabilities of enterprises.*

3. Materials and Methods

3.1. Sample Selection

The difference-in-differences (DID) method estimates causal relationships in quasi-experimental settings by comparing changes over time between a treatment group (exposed to the policy) and a control group (not exposed). It helps isolate the policy's impact by accounting for both observed and unobserved time-invariant factors. DID also reduces biases from selection effects, making it a reliable method for analyzing causal impacts in non-randomized studies. Thus, we apply the DID method to analyze the policy coordination effect between APPCAP and ETS. A total of 64 cities are key implemented cities for APPCAP issued in September 2013 (recorded as 2014, considering September is approaching the end of the year), while 45 cities for the ETS in total.

Since China's nationwide CO₂ trading market officially launched trading on 16 July 2021, research on dual-policy pilots after 2021 no longer has a realistic basis. Furthermore, the sudden COVID-19 epidemic in 2020 caused a significant drop in China's industrial production and energy demand that year, and the carbon and pollution emission levels were also significantly affected. Thus, we selected urban data from 2011 to 2019 as the research sample. After excluding cities with missing data, the final panel dataset comprises 231 cities, including 62 in the APPCAP experimental group, 45 in the ETS experimental group, and 12 in the policy coordination experimental group. The specific experimental groups are listed in Table 1.

Table 1. Sample selection.

Experimental Group	Province	City
APPCAP implemented in 2014	Beijing	Beijing
	Shanghai	Shanghai
	Tianjin	Tianjin
	Anhui	Lu'an, Ma'anshan, Suzhou, Anqing, Huangshan, Bozhou, Huainan, Tongling, Bengbu, Hefei, Chizhou, Fuyang, Huaibei, Wuhu, Chuzhou, Xuancheng
	Guangdong	Guangzhou, Huizhou, Shenzhen, Foshan, Jiangmen, Zhongshan, Zhuhai, Zhaoqing, Dongguan
	Jiangsu	Suqian, Nanjing, Wuxi, Changzhou, Lianyungang, Taizhou, Suzhou, Nantong, Yangzhou, Xuzhou, Huai'an, Yancheng, Zhenjiang
ETS implemented in 2013	Hebei	Baoding, Handan, Shijiazhuang, Cangzhou, Zhangjiakou, Langfang, Hengshui, Xingtai, Tangshan, Qinhuangdao
	Zhejiang	Wenzhou, Jinhua, Taizhou, Huzhou, Hangzhou, Zhoushan, Ningbo, Lishui, Quzhou, Shaoxing, Jiaxing
	Guangdong	Shenzhen
	Beijing	Beijing
ETS implemented in 2014	Tianjin	Tianjin
	Shanghai	Shanghai
	Chongqing	Chongqing
	Guangdong	Zhongshan, Huizhou, Zhanjiang, Guangzhou, Shaoguan, Qingyuan, Foshan, Zhuhai, Jieyang, Dongguan, Jiangmen, Yangjiang, Yunfu, Shantou, Zhaoqing, Chaozhou, Meizhou, Maoming, Shanwei
ETS implemented in 2016	Hubei	Xiaogan, Jingzhou, Yichang, Shiyan, Huanggang, Suizhou, Xiangyang, Xianning, Huangshi, Ezhou, Jingmen, Wuhan
	Fujian	Ningde, Longyan, Quanzhou, Fuzhou, Nanping, Zhangzhou, Sanming, Putian, Xiamen

Notes: 12 dual-policy pilot cities are in bold.

3.2. Variables and Data Sources

3.2.1. Dependent Variables

- Comprehensive emissions of urban air pollutants (POLL). POLL is the sum of urban sulfur dioxide (SO₂), smoke dust (PM), and nitrogen oxide (NO_x) emission equivalents, and the conversion factors of SO₂, PM, and NO_x are 0.95, 0.95, and 2.18, respectively, which are derived from the “Environmental Protection Tax Law of the People’s Republic of China”.
- Per capita air pollutant emissions (PERPO). PERPO is the ratio of POLL to the city’s registered population in that year.
- Urban CO₂ emissions (CE). CE data are gained from the China Carbon Accounting Database (CEADs), using the IPCC sub-sector emission accounting method (45 production and two residential departments).
- Per capita CO₂ emissions (PERCE). PERCE is the ratio of CE to the city’s registered population in that year.

3.2.2. Core Independent Variables

The cross-multiplication term of policy and time dummy variables is the core explanatory variable. The policy dummy variable is 1 if it is in the experimental group and 0 otherwise. The time dummy variable values 0 if it is before the policy implementation year and 1 otherwise. In this paper, we name DID1 to represent the core explanatory variable for testing the APPCAP policy effect, DID2 for testing the ETS policy effect, and DID for testing the policy coordination effect.

3.2.3. Mechanism Variables

- Government supervision (GS). The logarithm of the number of urban environmental administrative penalty cases is used to capture GS.
- Relationship between government and enterprises (ZS). Referring to Wang et al. [50] and Feng [51], ZS is measured by multiplying the “government-market relationship” value at the provincial level by the proportion of urban GDP to provincial GDP.
- Enterprises’ green innovation (GI). Following Chen et al. [43], this paper uses the number of green inventions obtained by the city to measure GI.

3.2.4. Control Variables

This project needs to control seven factors, including (1) urban economic development level (PGDP), captured by logarithmic regional per capita GDP [52]. (2) Population size (PEOP), expressed as the logarithm of the city’s registered population at the end of the year [53]. (3) Industrial structure (TS), measured by the ratio of the city’s tertiary industry’s added value to the secondary industry’s added value [54]. (4) Environmental investment (EI), represented by adding up the six investment amounts of “sewage treatment”, “sludge treatment”, “recycled water utilization”, “landscape”, “city appearance and environmental sanitation”, and “garbage treatment” and taking a logarithm [55]. (5) Science and technology expenditure (RD), measured by the ratio of urban science and technology expenditure to urban GDP [56]. (6) Industrialization level (IL), represented by the logarithmic number of industrial enterprises above the designated size in the city [57]. (7) Green finance index (GF), calculated using the entropy weight method to weight indicators such as urban green credit, green insurance, green investment, green bonds, green support, green funds, and green equity and sum up [58].

Table 2 illustrates the theoretical connections between dependent and independent variables.

Table 2. Theoretical connections between variables.

Dependent Variables	Independent Variables	Expected Direction of Impact
Pollution: POLL and PERPO Carbon: CE and PERCE	DID	Negative for both Pollution and Carbon
	DID1	Negative for Pollution, indeterminacy for Carbon
	DID2	Indeterminacy for both Pollution and Carbon
	PGDP	Positive
	PEOP	Positive
	TS	Negative
	EI	Negative
	RD	Negative
	IL	Positive
	GF	Negative

3.2.5. Data Sources

Urban CO₂ emission data come from the “Carbon Emission Inventory of 290 Chinese Cities from 1997 to 2019” in the Carbon Emission Accounts & Datasets (CEADs). GS data are collected from the China Law Retrieval System (<https://www.pkulaw.com/law?isFromV5=1>, accessed on 9 November 2023). ZS data are obtained from China’s provincial marketization index database. GI data is obtained from the National Intellectual Property Database. EI data come from the China Urban Construction Statistical Yearbook (2012~2020). Other variable data come from the China Urban Statistical Yearbook (2012~2020).

3.3. Baseline Model

We aim to test the effects of the APPCAP and ETS implemented separately and collaboratively. The baseline DID model is shown in (1), and we use STATA 17 software to obtain the results.

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_i \times \text{After}_t + \lambda \sum \text{Controls}_{it} + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

In model (1), Y_{it} represents all explained variables, including POLL, PERPO, CE, and PERCE; Controls_{it} indicates control variables; μ_i and v_t represent individual fixed effects and time fixed effects, respectively; and ε_{it} denotes the random disturbance term.

4. Results and Discussion

4.1. Descriptive Statistical Analysis

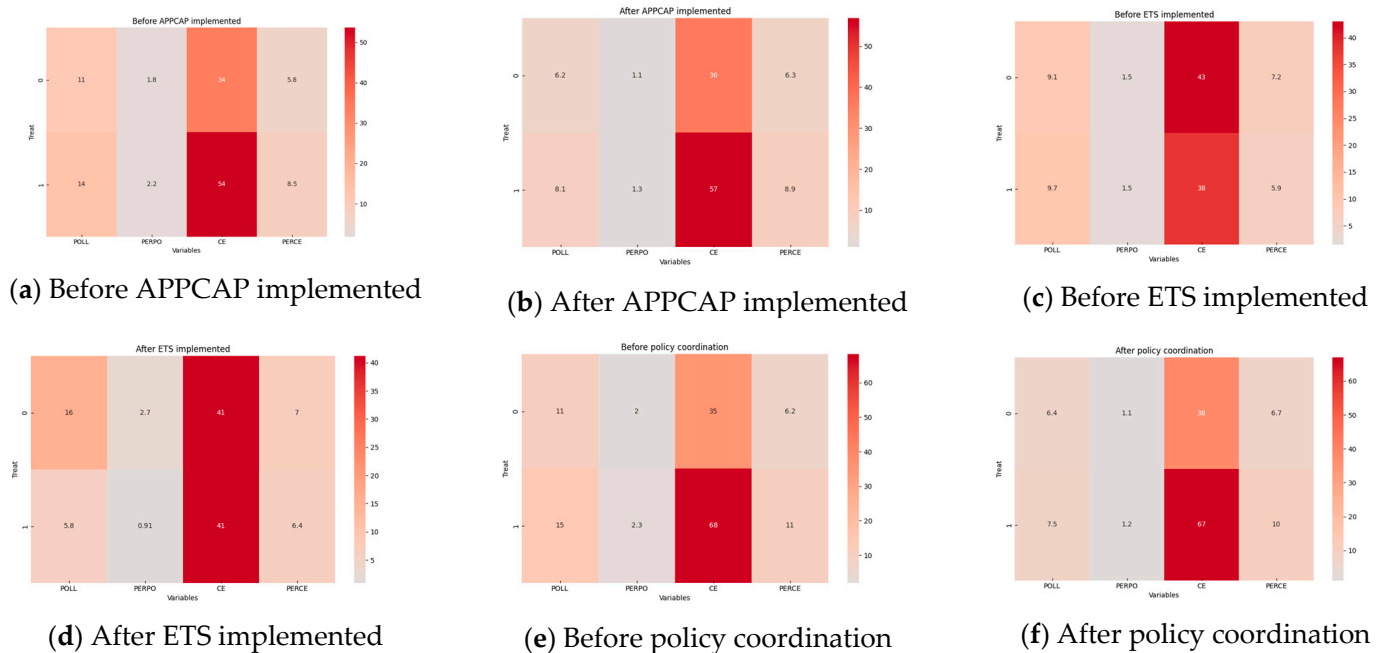
Three sets of research samples will be used to assess the effects of APPCAP and ETS separately and collaboratively. Table 3 displays the descriptive statistics. Figure 2 compares the mean of pollution and carbon emissions of the experimental (Treat = 1) and control (Treat = 0) groups before and after the policy.

There are 1836 samples for studying the effect of APPCAP policy, and the mean values of POLL, PERPO, CE, and PERCE are 8.363 (tons), 1.399 (tons/10,000 people), 41.626 (million tons), and 6.929 (million tons/10,000 people), respectively. A total of 2079 samples are selected to verify the effect of implementing the ETS alone, associated with the mean values of POLL, PERPO, CE, and PERCE being 8.767, 1.462, 42.392, and 7.037. There are only 1089 samples to study the effects of dual-policy pilots, and the standard deviations of the four dependent variables of this group are larger than those of the first two groups of samples, showing that the data distribution of the sample of the dual-policy pilot is more discrete.

Table 3. Descriptive statistics.

	APPCAP		ETS		Policy Coordination	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
POLL	8.363	9.935	8.767	10.502	8.209	8.782
PERPO	1.399	1.571	1.462	1.68	1.426	1.486
CE	41.626	46.742	42.392	45.27	40.151	44.851
PERCE	6.929	7.515	7.037	7.284	6.926	7.65
CI	2.473	3.213	2.598	3.401	2.843	3.854
PGDP	10.812	0.576	10.794	0.566	10.795	0.589
PEOP	5.915	0.696	5.937	0.677	5.78	0.734
TS	1.009	0.578	0.999	0.565	1.073	0.702
EI	9.905	2.741	9.881	2.735	9.749	2.729
RD	0.004	0.004	0.003	0.004	0.003	0.004
IL	6.776	1.035	6.755	1.01	6.447	1.049
GF	0.33	0.099	0.327	0.097	0.31	0.112
GS	2.194	2.292	2.233	2.295	2.099	2.224
ZS	0.744	1.25	0.717	1.185	0.812	1.441
GI	119.68	421.159	112.622	398.623	126.163	511.645

Notes: The sample size of APPCAP is 1836, 2079 for ETS, and 1089 for policy coordination.

**Figure 2.** The pollutants and CO₂ emissions of the experimental and control groups before and after the policy.

From Figure 2a,b, we can observe that the mean of POLL and PERPO in both the experimental and control groups decreased significantly after the APPCAP implementation, while the mean of CE and PERCE increased. Figure 2c,d show that the mean of CE and PERCE of the experimental group increased slightly after ETS implementation. However, Figure 2e,f reveal that the coordinated implementation of APPCAP and ETS leads to lower mean values for the four dependent variables in the experimental group, indicating a significant reduction in air pollutants and carbon emissions.

4.2. Results of Baseline Model

The regression results of the policy effects of APPCAP and ETS implemented separately and simultaneously are shown in Tables 4 and 5.

Table 4. Individual effects of APPCAP and ETS policy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	APPCAP				ETS			
	POLL	PERPO	CE	PERCE	POLL	PERPO	CE	PERCE
DID1	−1.470 ** (−2.41)	−0.177 * (−1.78)	−0.262 (−0.19)	−0.132 (−0.57)				
DID2					1.561 ** (2.10)	0.300 ** (2.45)	−2.735 * (−1.83)	−0.497 * (−1.95)
PGDP	2.585 *** (2.74)	0.553 *** (3.61)	−6.237 *** (−2.96)	−1.173 *** (−3.25)	2.863 *** (2.79)	0.598 *** (3.54)	−7.165 *** (−3.47)	−1.308 *** (−3.71)
PEOP	−0.298 (−0.10)	−0.171 (−0.35)	−1.688 (−0.25)	−1.657 (−1.42)	−0.628 (−0.19)	−0.205 (−0.38)	2.796 (0.42)	−0.957 (−0.84)
TS	0.815 (1.37)	0.158 (1.64)	−4.594 *** (−3.45)	−0.805 *** (−3.53)	0.889 (1.40)	0.174 * (1.66)	−4.521 *** (−3.52)	−0.789 *** (−3.60)
EI	0.00480 (0.07)	0.00201 (0.18)	−0.224 (−1.44)	−0.0432 (−1.61)	−0.0345 (−0.46)	−0.00433 (−0.35)	−0.187 (−1.25)	−0.0363 (−1.42)
RD	60.42 (1.29)	9.699 (1.28)	5.751 (0.06)	1.482 (0.08)	36.91 (0.72)	6.152 (0.73)	33.36 (0.32)	5.996 (0.34)
IL	2.203 ** (2.48)	0.342 ** (2.37)	3.597 * (1.81)	0.666 * (1.96)	1.671 * (1.76)	0.261 * (1.67)	3.396 * (1.78)	0.631 * (1.94)
GF	5.554 (0.86)	1.461 (1.39)	0.415 (0.03)	−0.407 (−0.17)	3.815 (0.55)	1.117 (0.98)	−2.962 (−0.21)	−1.011 (−0.43)
CITY	Y	Y	Y	Y	Y	Y	Y	Y
YEAR	Y	Y	Y	Y	Y	Y	Y	Y
_CONS	−29.44 (−1.45)	−5.488 * (−1.66)	95.56 ** (2.11)	25.20 *** (3.25)	−25.09 (−1.13)	−4.917 (−1.34)	81.35 * (1.82)	22.94 *** (3.00)
R ²	0.290	0.302	0.0498	0.0481	0.273	0.279	0.0500	0.0486
N	1836	1836	1836	1836	2079	2079	2079	2079

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table 5.** Coordination effects of APPCAP and ETS policy.

	(1)	(2)	(3)	(4)
	Policy Coordination			
	POLL	PERPO	CE	PERCE
DID	−2.288 * (−1.66)	−0.291 * (−1.74)	−7.267 ** (−2.25)	−1.328 ** (−2.31)
PGDP	0.876 (0.70)	0.295 ** (2.07)	−9.839 *** (−3.35)	−1.794 *** (−3.43)
PEOP	−1.635 (−0.29)	−0.0230 (−0.04)	12.44 (0.95)	0.620 (0.27)
TS	0.768 (1.12)	0.170 *** (2.75)	−4.070 ** (−2.53)	−0.754 *** (−2.63)
EI	−0.0305 (−0.33)	−0.00345 (−0.26)	−0.369 * (−1.70)	−0.0705 * (−1.82)
RD	46.32 (0.73)	7.582 (1.16)	22.39 (0.15)	5.213 (0.20)
IL	2.955 *** (2.64)	0.444 ** (2.36)	6.137 ** (2.34)	1.105 ** (2.37)
GF	12.53 (1.45)	2.497 ** (2.02)	−16.86 (−0.83)	−3.150 (−0.87)
CITY	Y	Y	Y	Y
YEAR	Y	Y	Y	Y
_CONS	−8.920 (−0.27)	−4.770 (−1.17)	41.01 (0.54)	16.73 (1.24)
R ²	0.280	0.621	0.0448	0.0464
N	1089	1089	1089	1089

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Given that the implementation of APPCAP policy is approaching the end of 2013, the APPCAP's policy time node is set to 2014 in the DID model. Columns (1) to (4) in Table 4 report the APPCAP policy effect on POLL, PERPO, CE, and PERCE. The results indicate that DID1 is significantly negatively correlated with atmospheric pollutants, with coefficients of -1.47 ($p < 0.05$) for POLL and -0.177 ($p < 0.1$) for PERPO. This suggests that APPCAP dramatically improves air quality but does not have a significant impact on reducing CO₂ emissions. As can be seen from Table 1, the ETS policy was implemented in different regions in 2013, 2014, and 2016. Therefore, we adopt the progressive DID model to estimate the effect of ETS. Columns (5) to (8) present the impact of the ETS policy on POLL, PERPO, CE, and PERCE. DID2 is negatively related to CE (-2.735 , $p < 0.1$) and PERCE (-0.497 , $p < 0.1$), but it has a significant promotion impact on POLL and PERPO, denoting that the ETS policy significantly affects CR, not PR.

Considering that 12 cities are dual-policy pilot cities from Table 1, we select these 12 cities as the experimental group and cities that implement neither APPCAP nor ETS as the control group to examine the policy coordination effects, with the policy node being 2014. Table 5 shows the corresponding regression results. The coefficients of DID are all significantly negative for POLL, PERPO, CE, and PERCE, which are -2.288 ($p < 0.1$), -0.291 ($p < 0.1$), -7.267 ($p < 0.05$), and -1.328 ($p < 0.05$), successively. This means the simultaneous implementation of APPCAP and ETS can greatly enhance collaborative pollution and carbon reduction governance.

The study suggests that the separate implementation of APPCAP and ETS results in significant but unilateral effects, overlooking the importance and long-term benefits of CO₂ and air pollution co-management. When APPCAP and ETS are implemented collaboratively, they can effectively complement each other during their joint implementation process, and the reduction effects on POLL, PERPO, CE, and PERCE are all significant. Therefore, our H1 is supported.

4.3. Robustness Checks

Five techniques—the parallel trend test, changing to Propensity Score Matching (PSM)-DID model, changing to the double/debiased machine learning model, shortening time window, and the placebo test—are used for robustness checks to validate the validity of the primary findings.

4.3.1. Parallel Trend Test

Considering that our research objects include two policies, this paper conducts parallel trend tests on three scenarios: APPCAP alone, ETS alone, and policy coordination. We use the event study approach to evaluate the parallel trend. Regressions are performed after one period is eliminated to avoid complete collinearity. Final results are plotted as shown in Figures 3–5.

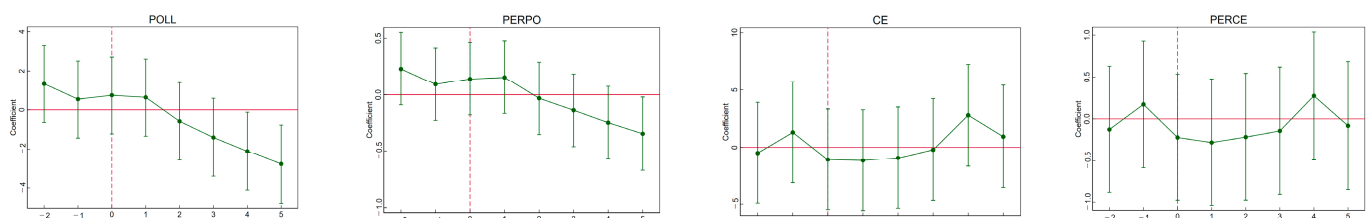


Figure 3. Parallel trend test for APPCAP policy.

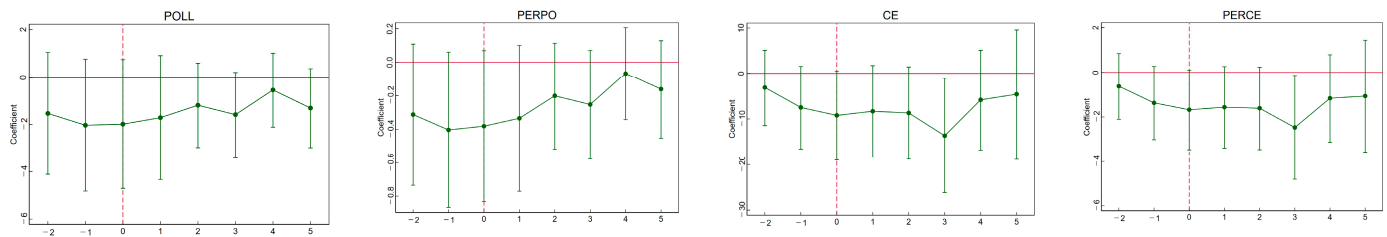


Figure 4. Parallel trend test for ETS policy.

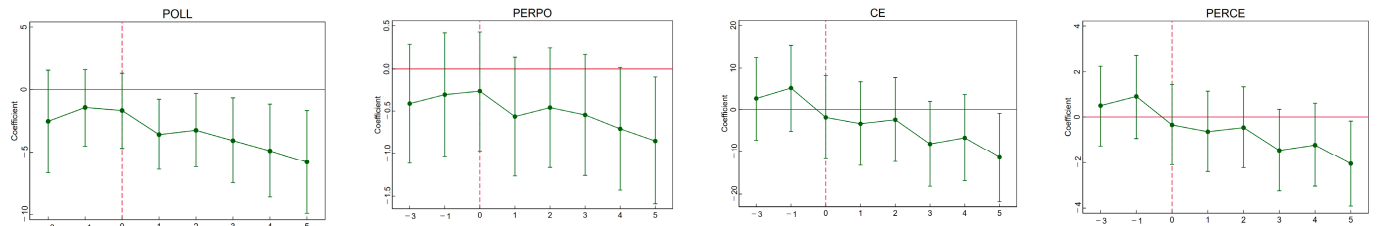


Figure 5. Parallel trend test for policy coordination.

Figures 3–5 show that the regression coefficients of all dependent variables before the policy node are insignificant in all scenarios. Notably, the regression coefficients of POLL, PERPO, CE, and PERCE are significantly negative after the policy coordination node. POLL exhibits the most pronounced performance, significantly decreasing in each period after the policy node. PERPO, CE, and PERCE only decrease significantly in individual periods after the policy node. This means that the simultaneous implementation of the APPCAP and ETS policy in 2014 had a significant impact on both PR and CR. In sum, all three scenarios meet the parallel trend requirements regarding POLL, PERPO, CE, and PERCE.

4.3.2. PSM-DID Model

Considering that the dual-pilot cities may not be randomly generated, we employ a combined method of propensity score matching and difference-in-differences (PSM-DID) for regression analysis. Specifically, the caliper matching method is applied, with a caliper criterion of 0.0143, which is less than 0.25 times the standard deviation of the propensity score. The results are shown in Table 6. It can be seen that the sign and significance of the regression coefficients are consistent with the results in Table 5, proving the reliability of the research conclusion.

Table 6. Regression results after changing to PSM-DID model.

	(1)	(2)	(3)	(4)
	POLL	PERPO	CE	PERCE
DID	−2.639 *	−0.327 *	−7.676 ***	−1.350 ***
	(−1.96)	(−1.71)	(−2.68)	(−2.67)
Controls	Y	Y	Y	Y
CITY	Y	Y	Y	Y
YEAR	Y	Y	Y	Y
_CONS	−7.491	−8.330	−150.2	−15.27
	(−0.26)	(−1.56)	(−1.45)	(−0.79)
R ²	0.812	0.807	0.923	0.919
N	692	692	692	692

Note: * $p < 0.1$, *** $p < 0.01$.

4.3.3. Double/Debiased Machine Learning Model

It should be pointed out that the DID method relies on strong assumptions in its functional form, making it less suitable for handling non-linear relationships between variables or high-dimensional data. Machine learning methods effectively address the functional form limitations of traditional econometric approaches. Accordingly, this study

employs the double/debiased machine learning (DDML) model for robustness checks. Depending on its “partial linear model” and support vector machine algorithm, we set up 500 decision trees and set the sample split ratio of cross-fitting to 1:4. Obtained results are shown in the columns (1) to (4) of Table 7. It is noted that the signs and significance of the regression coefficients of POLL, PERPO, CE, and PERCE are correlated with the basic regression results, indicating that the original conclusion is robust.

Table 7. Regression results after changing to the double/debiased machine learning model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	POLL	PERPO	CE	PERCE	POLL	PERPO	CE	PERCE
DID	−2.570 *	−0.380 *	−22.10 ***	−2.622 **	−2.141 **	−0.279 *	−6.452 ***	−1.189 ***
	(−1.70)	(−1.67)	(−2.67)	(−2.38)	(−1.98)	(−1.73)	(−2.98)	(−3.15)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
CITY	Y	Y	Y	Y	Y	Y	Y	Y
YEAR	Y	Y	Y	Y	Y	Y	Y	Y
_CONS	1.978 ***	0.311 ***	12.03 ***	1.830 ***	−6.228	−5.163	163.9 **	32.73 ***
	(7.75)	(7.48)	(9.22)	(8.52)	(−0.24)	(−1.14)	(2.54)	(2.72)
Algorithm	svm	svm	svm	svm	-	-	-	-
N	1089	1089	1089	1089	968	968	968	968

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3.4. Shortening Time Window

To eliminate the possible impact of the “Three-Year Action Plan for Winning the Blue-Sky Defense” implemented in 2018 on the decrease of pollutants [59], this paper shortens the research time window to 2011~2018; that is, data in 2019 are deleted and regressed again. The results gained are presented in the columns (5) to (8) of Table 7. It shows that the significant decline in total and per capita emissions of air pollutants and CO₂ has been achieved by policy coordination between APPCAP and ETS. These findings sustain H1 again and thus confirm that our previous results are reliable.

4.3.5. Placebo Test

With the policy dummy variable unchanged, the basis for dividing the time dummy variable is advanced from 2014 to 2013, forming a new key explanatory variable DID3 and bringing it into the DID model for regression (other variable data remain unchanged). If significant effects appear during the placebo period, it suggests that factors other than the policy may be influencing the outcomes, questioning the validity of causal interpretations. Table 8 presents the findings, demonstrating that the DID3 regression coefficients on all dependent variables are insignificant when the policy node time is advanced by 1 year. Therefore, the placebo test is passed, and the policy coordination effects are attributable to the actual policy intervention rather than spurious correlations or unaccounted trends.

Table 8. Placebo test for the policy coordination effects of APPCAP and ETS.

	(1)	(2)	(3)	(4)
	POLL	PERPO	CE	PERCE
DID3	−1.979	−0.286	−4.518	−0.844
	(−1.31)	(−1.14)	(−1.27)	(−1.33)
Controls	Y	Y	Y	Y
CITY	Y	Y	Y	Y
YEAR	Y	Y	Y	Y
_CONS	−6.887	−4.208	58.20	19.76
	(−0.21)	(−0.78)	(0.76)	(1.45)
R ²	0.279	0.294	0.0414	0.0429
N	1089	1089	1089	1089

4.4. Mechanism Analysis

Section 2 has constructed the mechanism framework of policy coordination effects, mainly covering government supervision, the relationship between government and enterprises, and enterprises' green innovation. To verify these three mechanism variables' validities, we next use empirical studies to see if policy coordination can impact them significantly. The regression findings are displayed in Table 9. The mediating routes are valid if their corresponding regression coefficients are significant.

Table 9. Mechanism analysis results.

	(1)	(2)	(3)
	GS	ZS	GI
DID	1.770 *** (7.50)	−0.257 *** (−4.60)	3.891 *** (10.25)
Controls	Y	Y	Y
CITY	Y	Y	Y
YEAR	Y	Y	Y
_CONS	−26.97 *** (−4.85)	2.311 * (1.76)	−46.41 *** (−5.19)
R ²	0.771	0.181	0.226
N	1089	1089	1089

Note: * $p < 0.1$, *** $p < 0.01$.

In Table 9, the coefficient 1.770 ($p < 0.01$) in column (1) captures the effect of policy coordination on GS, indicating that government supervision is significantly enhanced under the joint implementation of APPCAP and ETS. Meanwhile, the policy coordination has considerably weakened ZS, with a substantially negative coefficient (−0.257, $p < 0.01$). Column (3) demonstrates the notable rise of GI (the coefficient of DID is 3.891, $p < 0.01$), stating that APPCAP and ETS conjointly improve the enterprises' green innovation capabilities. It is concluded that both APPCAP and ETS tend to play a crucial role in increasing environmental penalties, deterring government-enterprise collusion, and forcing companies to produce more green patents.

In order to verify the robustness of the mechanism test, we estimate the regression coefficient by randomly sampling 500 times and draw the confidence interval distribution diagram of 500 coefficients (Figure 6). It can be seen from Figure 6 that the regression coefficients obtained by 500 random samplings are all positive, and the confidence intervals do not include 0, indicating that the coefficients have passed the significance test.

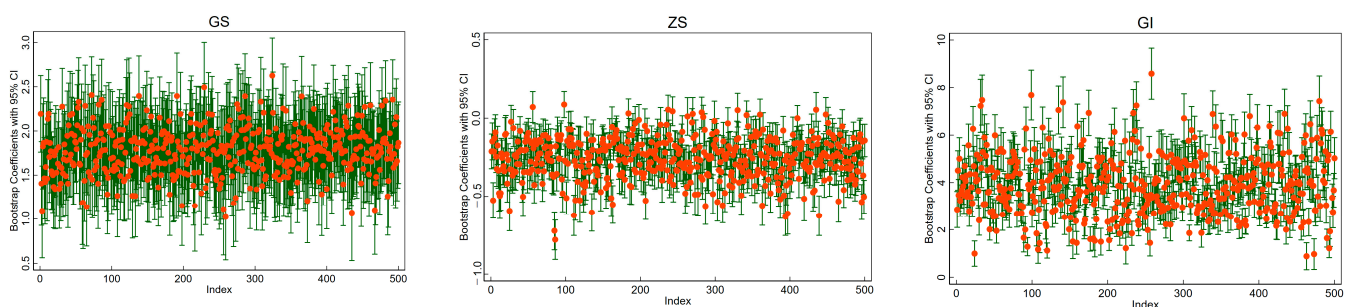


Figure 6. Confidence interval distribution chart of regression coefficients. The red points represent the regression coefficient estimates after each sampling, and the green vertical line represents the 95% confidence interval of the regression coefficient obtained from each sampling.

Conceptual and empirical research discussed above indicates that intensifying government supervision, restraining the relationship between government and enterprises, and reinforcing enterprises' green innovation are major pathways through which policy

coordination is capable of reducing CO₂ and pollutant emissions. Therefore, H2, H3, and H4 are all supported.

4.5. Heterogeneity Analysis

The joint management of pollution and carbon reflects China's pursuit of a balance in achieving "environmental protection" and "carbon peaking and neutrality". However, it is crucial to acknowledge that the pilot regions exhibit varying foundations and initial conditions for PR and CR initiatives, which may substantially affect the efficacy of APPCAP and ETS policies. This paper next analyzes the heterogeneity of policy coordination in two aspects: pollution intensity and carbon-peaking trend.

4.5.1. Pollution Intensity

According to the Multi-resolution Emission Inventory for China, power and industry are China's main emission sectors of CO₂, SO₂, and PM [60]. For instance, in steel-producing cities like Anshan or Shijiazhuang, where the steel industry dominates, emission-reduction policies may encounter slower implementation and less immediate impact compared with regions with more diverse or cleaner industries (Shenzhen, for example). Therefore, how does policy coordination perform in regions with different pollution intensities? To clarify this question, this paper next evaluates the differences in the policy coordination effects in cities with different pollution intensity levels.

First, we separate the study sample of 1089 into two subsamples based on whether there are listed firms in the six highly polluting sectors located in the city in that year, which include power, steel, non-ferrous metals, building materials, petroleum processing, and chemicals industry. Then, data in the two sub-samples are regressed according to model (1), respectively. Table 10 presents the acquired findings.

Table 10. Policy coordination effects under different pollution intensity levels.

	With HPC	With HPC	With HPC	With HPC	No HPC	No HPC	No HPC	No HPC
	POLL	PERPO	CE	PERCE	POLL	PERPO	CE	PERCE
DID	−5.096 *	−0.679 *	−4.627	−0.844	0.889	0.120	−10.16	−1.847
	(−1.98)	(−1.93)	(−1.34)	(−1.49)	(0.66)	(0.51)	(−1.40)	(−1.46)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
CITY	Y	Y	Y	Y	Y	Y	Y	Y
YEAR	Y	Y	Y	Y	Y	Y	Y	Y
_CONS	−57.52 **	−13.50 ***	−3.499	9.723	169.2 *	24.91	−4.514	5.485
	(−2.21)	(−2.83)	(−0.05)	(0.73)	(1.86)	(1.61)	(−0.01)	(0.08)
R ²	0.443	0.441	0.0881	0.0826	0.188	0.202	0.0462	0.0504
N	571	571	571	571	518	518	518	518

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 illustrates the policy coordination effects on POLL, PERPO, CE, and PERCE under different pollution intensity levels. In the "cities with highly polluting listed companies" group (With HPC), the estimation coefficients of DID are substantially negative for POLL and PERPO but not for CE or PERCE. That is to say, policy coordination only has significant PR effects for groups with HPC. In the sample of cities without highly polluting listed companies (No HPC), it is clear that policy coordination does not profoundly influence the emissions of air pollutants and CO₂, showing that the effects of PR and CR are not significant.

Considering that the above simple sub-sample regression method is not enough to fully present the heterogeneity and changes of policy effects, we next use the causal forest model to estimate the change in policy coordination as the number of heavily polluting listed companies increases. Using the EconML package in Python (Version 3.12.4), we estimate the heterogeneous treatment effects produced by policy coordination under different numbers of heavily polluting listed companies. The linkage relation is shown in Figure 7.

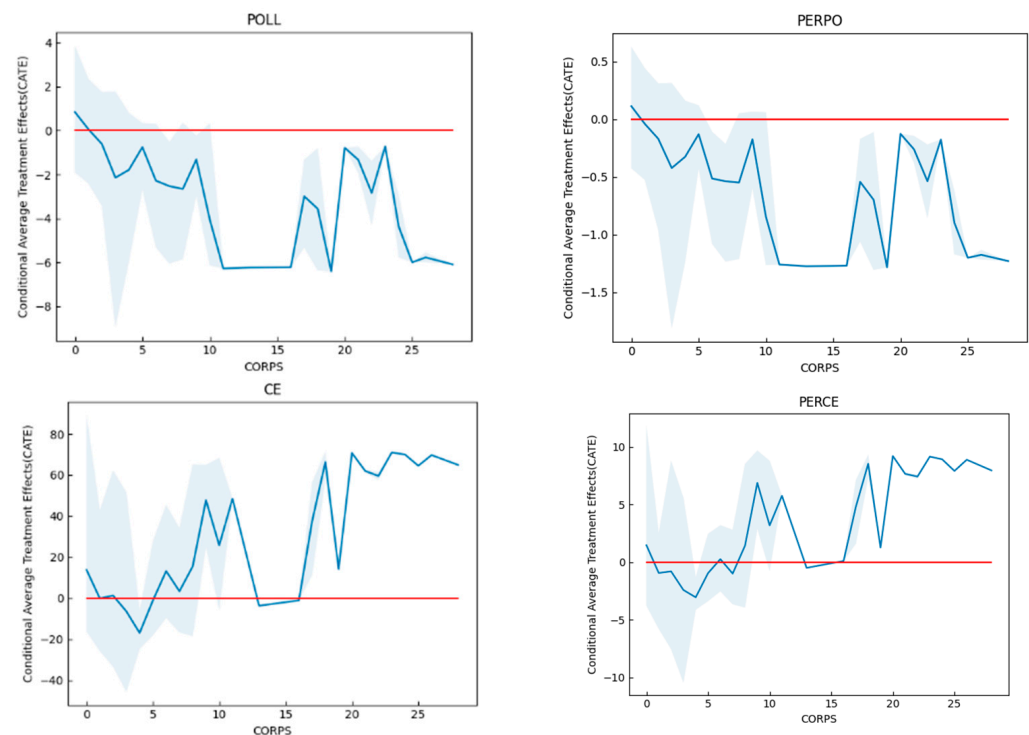


Figure 7. Changes in policy coordination effect with the number of heavily polluting listed companies. The red line represents the baseline value of 0 for the conditional average treatment effects (CATE); the blue line represents the estimated conditional average treatment effects (CATE), and the blue shaded area represents the estimated 90% confidence interval.

It can be seen from Figure 7 that when the number of highly polluting listed companies in the city is 0, both PR and CR effects of policy coordination are not significant (the confidence interval includes 0). As the number of heavily polluting listed companies increases, the simultaneous implementation of APPCAP and ETS policies brings more significant PR effects, especially after there are more than 10 companies. But for carbon emissions, policy coordination can produce some weak CR effects when the number of heavily polluting listed companies is less than 5. However, as the number of companies increases, carbon emissions increase instead of falling, making it a difficult problem for coordinated control of air pollutants and CO₂.

The PR and CR effects of policy coordination vary dramatically among regions with differing pollution levels. In areas with higher pollution levels, the PR effects of policy coordination are more significant.

4.5.2. Carbon-Peaking Trends

According to a research report named “China Provincial Dual Carbon Index 2021–2022” released by the Institute of Public and Environmental Affairs (IPE) (<https://www.ipe.org.cn/reports/Reports.aspx?cid=19477&year=2020>, accessed on 9 October 2024), a public-interest environmental research organization, five provinces (municipalities) are in the “pioneer” stage (greater than or equal to 55 scores) of carbon peaking, namely Beijing, Jilin, Shanghai, Chongqing, and Sichuan. This means that these five provinces (municipalities) are ahead of other provinces in China in terms of “climate ambition”, “low carbon status”, and “CO₂ emission trends”. Cities with better carbon-peaking trends may be more susceptible to the positive impact of APPCAP and ETS policy coordination. To confirm this, we further identify the differences in policy coordination effects on cities in different carbon-peaking stages.

First, the cities included in the study are categorized into two distinct categories based on whether they are in the “pioneer” stage of carbon peaking: Peak and Non-peak.

Then, the two groups are regressed separately according to model (1), and the findings are depicted in Table 11. Furthermore, we still use the causal forest model to draw a trend chart of policy coordination effects with the carbon-peaking index, as shown in Figure 8.

Table 11. Policy coordination effects in cities with different carbon peak trends.

	Non-Peak	Non-Peak	Non-Peak	Non-Peak	Peak	Peak	Peak	Peak
	POLL	PERPO	CE	PERCE	POLL	PERPO	CE	PERCE
DID	−0.852 (−0.52)	−0.118 (−0.44)	−7.984 ** (−2.04)	−1.529 ** (−2.19)	−9.214 *** (−3.52)	−1.115 ** (−2.38)	−3.341 (−0.44)	−0.362 (−0.26)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
CITY	Y	Y	Y	Y	Y	Y	Y	Y
YEAR	Y	Y	Y	Y	Y	Y	Y	Y
_CONS	(−8.76) −23.74	(−9.60) −7.012	(5.22) 83.81	(5.40) 23.64	−21.45 (−1.30)	−4.647 (−1.57)	−192.5 *** (−4.02)	−35.32 *** (−3.99)
R ²	(−0.64)	(−1.15)	(0.94)	(1.49)	0.507	0.408	0.896	0.819
N	0.273	0.295	0.0529	0.0551	207	207	207	207

Note: ** $p < 0.05$, *** $p < 0.01$.

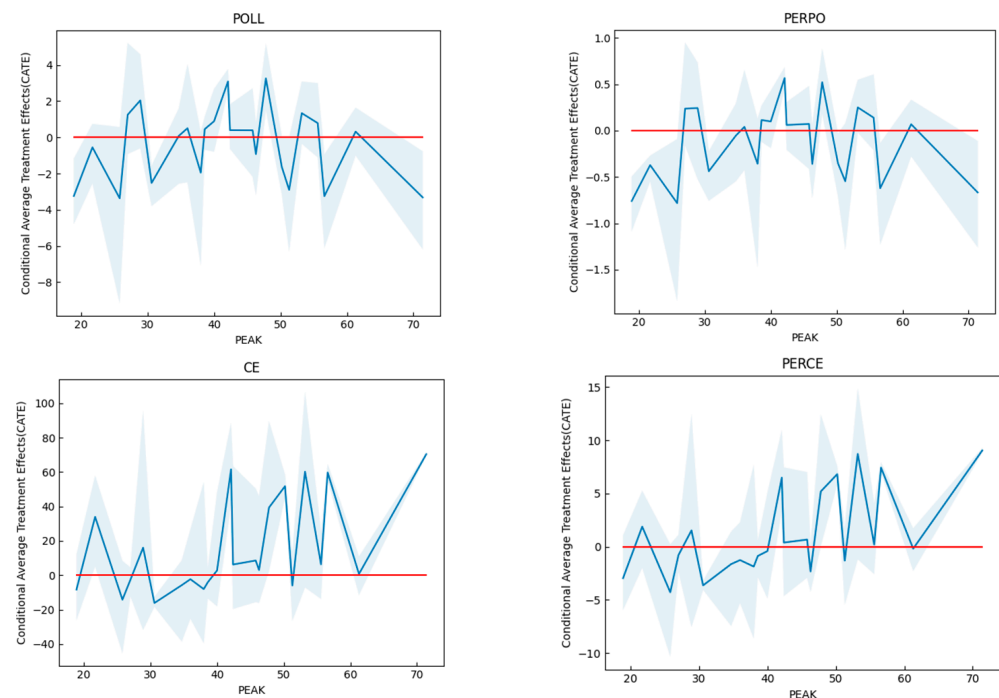


Figure 8. Changes in policy coordination effect with carbon peak index. The red line represents the baseline value of 0 for the conditional average treatment effects (CATE); the blue line represents the estimated conditional average treatment effects (CATE), and the blue shaded area represents the estimated 90% confidence interval.

Table 11 illustrates an apparent difference between the policy effects of Group Peak and Group Non-peak. For Group Non-peak, the policy coordination exerts significant influence on CO₂ emissions reduction, with the coefficients of CE and PERCE being −7.984 and −1.529 correspondingly. For Group Peak, DID is significantly negatively correlated with POLL (−9.214, $p < 0.01$) and PERPO (−1.115, $p < 0.05$).

Compared with split-sample regression, the linkage relationship diagram output by the causal forest model can reflect more information about changes in policy effects. Figure 8 illustrates that policy coordination significantly impacts both PR and CR when the carbon-peaking index is around 30. However, as the index rises, the PR effects surpass the CR effects, suggesting that coordinated governance of PR and CR is more achievable in low carbon-peaking areas. In contrast, in high carbon-peaking areas, policy coordination

primarily drives reductions in air pollutants, likely due to the limited potential for further carbon emission reductions.

5. Discussion

Previous literature has documented the curbing effects of APPCAP or ETS policies on pollutants and CO₂ but often ignores the common pilot cities of these two policies. Rarely, it is confirmed that the APPCAP policy has significantly reduced atmospheric pollutants in ETS policy pilot regions [4]. Still, it did not investigate the policy coordination effects in dual-policy pilot cities. Our paper fills this research gap by conducting a DID regression using 12 dual-policy pilot cities as the experimental group, which can distinguish between the concurrent execution of dual policies and the distinct execution of single policies.

Moreover, few studies focus on the co-benefits of mitigating pollutants and CO₂ emissions brought by environmental policies, and the conclusions drawn are still controversial. For instance, Dong et al. [8] identified the pivotal role of the ETS policy in reducing PM_{2.5} concentration and CO₂ emissions, but there was no significant reduction in CO₂ emission intensity, while Zhou et al. [61] tested that the ETS pilot policy had declined CO₂ emission intensity in a considerable measure. Also, Shao et al. [10] proved that the spatial spillover impact of ETS regulation on cutting pollutant emissions is pessimistic. These inconsistent findings are likely a result of the complex interplay of methodological choices, regional differences, data issues, and the broader economic context in which these pilot policies were implemented. Nevertheless, it is apparent that the majority of studies neglect to account for all policy nodes, resulting in biased estimations of policy effects. Our paper considers all three policy time points of 2013, 2014, and 2016 and uses the progressive DID method to evaluate the ETS policy effects. It is observed that the PR effect of implementing the ETS policy alone is relatively limited, while combining the ETS and APPCAP policies can achieve comprehensive reduction effects.

The study results also provide insights into developing a collaborative PR and CR policy framework. The coordinated implementation of market economy policies has attracted increasing attention from scholars and policymakers lately, such as the coordination of carbon tax and ETS policy, the coordination of Energy Rights Trading and ETS policy, etc. Our research conclusion proves that the coordinated implementation of command-and-control and market economy policies can also bring about coordinated control effects on PR and CR. Different policies have been proven to complement each other, which becomes a policy coordination system optimization direction worth considering.

Furthermore, our findings provide persuasive evidence for encouraging areas with less climate ambition to expedite their transition towards sustainability. The heterogeneity analysis reveals that cities with weak carbon-peaking trends are more likely to achieve coordinated control of PR and CR. However, as the space for pollution alleviation by simple end-of-line treatment measures is gradually narrowing, “PR driven by CR” has become a new focus. Therefore, cities with lower carbon-peaking indexes still need to increase their climate ambitions further and take more source-control measures to reduce atmospheric pollutants and CO₂ emissions simultaneously.

However, some limitations still exist. On the one hand, further refinement of the scale of the data is required. It is hoped that the data acquisition limitations will be overcome and that the data scale can be accurate from the current annual to the monthly level, bringing more precise policy evaluation results. Another point is that this article employs the DID approach to investigate the impacts of policy coordination. Future research is expected to introduce more novel research perspectives to analyze issues related to the coordinated implementation of the two policies.

6. Conclusions

China’s current environmental policy system often treats carbon and pollution separately and devotes insufficient attention to the comprehensive execution of policies to reduce pollution and carbon emissions. Our paper starts from the viewpoint of policy

coordination and explores whether the simultaneous implementation of APPCAP and ETS contributes to integrated governance strategies aimed at reducing pollutants and CO₂ emissions. Using a sample of 231 cities in China from 2011 to 2019, this paper compares the PR and CR impacts of the separate and collaborative implementation of APPCAP and ETS, associated with further mechanism and heterogeneity analysis. The main findings show that the policy coordination of APPCAP and ETS substantially mitigates both air pollution and CO₂ emissions. In contrast, implementing the APPCAP policy alone only substantially reduces air pollutant emissions, and the ETS policy only significantly reduces CO₂ emissions. Meanwhile, improving government supervision, weakening the relationship between government and enterprises, and strengthening green innovation are the principal transmission channels for policy coordination. Furthermore, we also find that policy coordination effects are more evident in pollution-intensive areas and areas with a lower carbon-peaking index.

Three policy implications for the deepening reform of environmental policies are proposed based on the above conclusions. First, it is recommended that the concept of “synchronized management of atmospheric contaminants and greenhouse gas” be added to existing environmental policies. At the same time, it is necessary to explore more aspects of the integrated execution of PR and CR policies, not limited to the dual-pilot perspective. Specifically, China could draw on international best practices, such as the European Union’s “Climate and Clean Air Coalition” (CCAC), which advocates for the simultaneous reduction of short-lived climate pollutants (SLCPs) and carbon emissions. Policymakers should also explore the implementation of sector-specific integrated action plans, similar to the EU’s Green Deal, which simultaneously targets industrial emissions, energy efficiency, and carbon neutrality goals. Second, urban management authorities should enhance environmental penalties, establish the principle of honest government-enterprise relations, and increase financial support for corporate green innovation. For instance, a more stringent system of tiered penalties could be introduced, which escalate based on the severity and frequency of violations, mirroring the graduated penalty systems used in regions like California’s cap-and-trade program. In addition, it is recommended to establish a “green innovation fund” that provides financial incentives and low-interest loans for enterprises investing in sustainable technologies. These financial mechanisms should be similar to the U.S. Green New Deal’s approach of funding green innovation through public–private partnerships, ensuring that businesses are not only penalized for non-compliance but also rewarded for advancing green technologies. Finally, APPCAP and ETS policies in pollution-intensive cities and areas with weak carbon-peaking trends should be strengthened to help these cities attain synchronized management of air pollution and CO₂ emissions. Among them, economically advanced cities should be encouraged to set ambitious targets for carbon neutrality, integrating pollution control with carbon pricing schemes such as carbon taxes or advanced emissions trading systems, similar to those implemented in advanced economies like the UK or Germany. For cities with lower levels of economic development or those heavily reliant on traditional industries, local governments should be empowered to implement a phased approach to policy enforcement, offering compliance assistance and capacity-building programs to help industries adapt to new regulations. This strategy mirrors international models like the “Just Transition” framework in Europe, which provides tailored support to regions dependent on high-pollution industries to ease the economic and social costs of transitioning to a low-carbon economy.

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