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Governing the Green Transition: Evaluating the Synergistic Co-Benefits of China's Environmental Policies

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Abstract

This study provides causal evidence that stringent command-and-control policies can generate environmental co-benefits. We evaluate China's 2013 Air Pollution Prevention and Control Action Plan, a robust place-based intervention designed to improve local air quality, to explore whether it creates synergistic effects for carbon mitigation. Utilizing provincial-level data from 2008 to 2024, our Difference-in-Differences (DID) analysis reveals that the policy produced a statistically significant synergistic coupling effect between the reduction of conventional pollution (SO_2) and carbon emissions (CO_2), effectively increasing the average coordination scores within target regions. We measure this synergy through a novel Coupling Coordination Degree (CCD) index. To further investigate the underlying mechanism, we employ the Logarithmic Mean Divisia Index (LMDI) decomposition, finding that the improvement in synergistic effects stems primarily from the policy's positive impact on energy intensity.

Keywords Atmospheric Pollution Prevention and Action Plan; Coupling Effect; Coupling Coordination Degree (CCD); Difference-in-Differences (DID); Logarithmic Mean Divisia Index (LMDI)

1. Introduction

In the global campaign against climate change, China has established ambitious "dual-carbon" targets, positioning the green and low-carbon transition of its industrial sector as a core national strategy. As the primary engine of economic growth and the principal source of greenhouse gas emissions, the industrial sector's ability to sever its dependence on carbon is a critical determinant of the nation's sustainable future. To address air pollution and foster sustainable development, the Chinese government introduced the Air Pollution Prevention and Control Action Plan(APPCAP) in 2013 as a cornerstone regulatory framework. This national strategy employed a comprehensive ten-measure approach, focusing on industrial restructuring, energy source decarbonization, and the enhancement of scientific innovation to achieve synergistic multi-pollutant reductions. By establishing specific five-year targets (2013–2017) and fostering regional cooperation in priority clusters like Beijing-Tianjin-Hebei, the plan successfully institutionalized a rigorous responsibility allocation and monitoring system. The implementation of APPCAP yielded remarkable results, evidenced by a 22.7% decline in average PM10 concentrations nationwide and significant PM2.5 reductions in key regions, effectively demonstrating that targeted administrative mandates and localized optimization can drive substantial air quality improvements(Song, Li& Lee, 2025). This raises a pivotal

question regarding the efficacy of stringent command-and-control policies: can interventions designed primarily for local air quality improvement generate significant environmental co-benefits for carbon reduction? Specifically, to what extent did 2013 APPCAP, foster a synergistic relationship between the mitigation of traditional pollutants and the reduction of carbon dioxide?

To understand this dynamic, this study moves beyond descriptive analysis to provide causal evidence of policy-induced synergy. While a substantial body of research has explored the correlation between economic activity and emissions, a significant gap remains in systematically identifying whether mandatory pollution targets actually catalyze a "coupling" effect with carbon governance. Many existing studies utilize broad indicators that fail to isolate the specific impact of place-based policies or stop at describing emission trends without delving into the underlying causal mechanisms. This research addresses these gaps by evaluating the APPCAP's impact through a robust Difference-in-Differences (DID) empirical framework, using provincial-level data spanning from 2011 to 2023. This longitudinal approach allows us to isolate the policy's effect from regional economic fluctuations and pre-existing trends.

Central to our analytical framework is the quantification of the synergistic relationship between sulfur dioxide (SO_2) and carbon dioxide (CO_2). We employ a novel Coupling Coordination Degree (CCD) index to provide a rigorous, quantitative measure of how harmoniously these two reduction efforts interact. Unlike traditional decoupling models that offer only qualitative classifications, the CCD index allows us to track the evolution of environmental governance performance in targeted regions versus non-targeted regions. By focusing on this "synergy score," we can determine if the 2013 APPCAP successfully pushed the industrial sector toward a more integrated model of green development, or if pollution control occurred at the expense of carbon efficiency.

This study seeks to open the black box of the policy’s impact by decomposing the drivers of observed changes in industrial carbon emissions. To achieve this, furthermore, we integrate the Logarithmic Mean Divisia Index (LMDI) model, based on an extended Kaya identity, into our causal analysis. This allows us to determine whether the improved synergy identified by the DID model was driven by shifts in economic scale, industrial restructuring, or - as our findings suggest - policy-induced improvements in energy intensity. By identifying these specific transmission channels, the findings offer crucial, evidence-based insights for policymakers. This research demonstrates that targeted command-and-control air quality policies can indeed serve as a linchpin for broader industrial decarbonization, providing a blueprint for more precise and effective environmental policy integration in the "dual-carbon" era.

2. Literature Review

The performance evaluation of Pollution Control (PC) and Carbon Reduction (CR) remains a cornerstone of environmental economics as researchers seek to balance industrial growth with ecological limits. Early research in this field primarily relied on

single-target indices, such as the Environmental Quality Index, to reflect the multidimensional nature of regional pollution (Latif, 2022; Liu et al., 2022). More recently, scholars have shifted toward more holistic frameworks, employing the ecological footprint to quantify the long-term sustainability of natural capital use (Hassan et al., 2023; Abakah et al., 2023). With the emergence of China's "dual carbon" goals, the analytical focus evolved from independent assessments toward a "dual-system" perspective. Central to this transition is the CCD index, which moves beyond raw emission volumes to document the spatially uneven synchronization between air pollutants and CO_2 (Nie & Lee, 2023). Recent empirical evidence suggests that while China's national coordination levels are trending upward, the landscape is marked by significant spatial imbalances. Studies indicate a "high in the south/east and low in the north/west" layout, where coastal regions demonstrate stronger synergy due to advanced industrial structures, while inland areas exhibit distinct beta-convergence and "Matthew Effects" (Nie & Lee, 2023; Yi et al., 2022). Beyond static coordination, current research explores the "synergy degree" from a directional optimization perspective. Innovative measurement frameworks evaluate the proximity between actual mitigation paths and optimal benchmarks, identifying that the reduction of carbon intensity - rather than mere volume control - is the primary catalyst for achieving high-level coordination (Tu et al., 2025). The theoretical scope of synergy is also expanding to incorporate broader ecological elements. The development of the "Pollution-Carbon-Ecology" triple-synergy index represents a significant advancement, as it integrates ecosystem services into the carbon-pollution nexus to address the systemic neglect of natural capital in traditional governance (Wang et al., 2025). This coordinated transition is frequently driven by external policy shocks. Evidence from China's Five-Year Plans demonstrates that stringent administrative mandates can force a "win-win" outcome for polluting industries by incentivizing energy substitution and green technological innovation (Zhu et al., 2023). Although such gains may occasionally incur short-term costs in industrial output, they are essential for breaking the "Club Convergence" of high-emission intensity (Chen et al., 2023). Collectively, these studies emphasize that achieving a sustainable "dual-system" requires localized, place-based interventions that move beyond isolated pollutant control toward an integrated governance path.

Hypothesis 1: The implementation of the 2013 APPCAP significantly enhances the synergy between conventional air pollutants (SO_2) and greenhouse gas (CO_2) emission controls.

Moreover, a burgeoning body of literature investigates whether specific policy instruments can achieve the "win-win" goal of simultaneous PC and CR. Two primary schools of thought have emerged regarding the mechanisms of policy impact. The first focuses on market-based instruments, such as China's carbon emissions trading system, which has been shown to decrease total carbon emissions while yielding air quality co-benefits (Chen et al., 2022; Dong et al., 2022). The second focuses on stringent command-and-control policies, most notably the APPCAP. This national strategy employed phased quantitative targets and concrete regulatory measures to

significantly improve overall air quality, particularly through the reduction of PM2.5 and SO_2 concentrations across 338 Chinese cities (Feng et al., 2019). Beyond atmospheric metrics, the health dividends of such mandates are substantial; decomposition analysis reveals that APPCAP-induced air quality improvements prevented tens of thousands of pollution-attributable deaths, although more ambitious frameworks are required to sustain these gains toward 2030 (Yue et al., 2020).

The effectiveness of APPCAP is further validated by rigorous DID and PSM-DID evaluations, which confirm that the policy exerted a significant negative impact on fine particulate matter even when accounting for the overlapping effects of carbon trading schemes (Yu et al., 2022). These administrative mandates do not merely act as environmental constraints but also reshape the corporate landscape. Evidence indicates that APPCAP can enhance enterprises' economic and social performance by incentivizing technological innovation and optimizing resource allocation, suggesting a synergy between ecological protection and industrial development (Li, 2021). The role of green innovation is particularly critical in this transition. City-level data suggests that heterogeneous green innovations - ranging from environmentally sound technologies to administrative reforms - significantly bolster carbon emission performance through industrial structure upgrades and the promotion of foreign direct investment (Xu et al., 2021). As Wang et al. (2022) identified, mandatory pollutant charges and localized air quality targets force industrial upgrades that inadvertently reduce carbon footprints. This confirms that "key treatment in key areas" yields robust co-benefits for both air pollutants and CO_2, positioning administrative mandates as powerful drivers of institutional and technical synergy.

$$TFP_{it} = \theta(Exposure_i \times PostBSDW_t) + \beta LCCP_{it} + \gamma_i + \delta_t + \epsilon_{it}$$

Hypothesis 2: As a robust policy intervention and command-and-control policy, the 2013 APPCAP exerts a significant positive causal impact on the CCD within the targeted regions.

Beyond measuring outcomes, the literature seeks to identify the specific factors that inhibit or promote carbon reduction, typically through two methodological lenses. Researchers frequently use Efficiency Frameworks, specifically DEA-based models like the advanced SBM model, which treat environmental pollutants as undesirable outputs to measure green total factor productivity (Dong et al., 2022; Yang et al., 2020). To understand the underlying drivers of these efficiency gains, the standard approach utilizes the Kaya Identity and LMDI decomposition to attribute emission changes to factors like energy structure or economic activity (Yang et al., 2020). By integrating multi-layer LMDI with clustering techniques, scholars have uncovered a critical "tug-of-war" in China’s industrial transition: while rising GDP per capita acts as a powerful expansionary force pushing emissions higher, improvements in energy intensity serve as the primary mitigating force (Wen & Li, 2020).

Recent studies emphasize that the effectiveness of administrative mandates in reducing carbon intensity is often mediated by green technology innovation. Evidence suggests a non-linear relationship where environmental regulation triggers significant

technological spillover, positioning green technology as a vital mediator that facilitates the transition toward low-carbon production (Yang et al., 2020). This transition is closely tied to the energy system's evolution, as the development of renewable energy significantly reduces carbon intensity by indirectly improving energy use efficiency (Liu et al., 2024). In the context of global climate modeling, strict environmental policy measures represent an essential strategy for managing energy balances. High levels of policy stringency are associated with reduced energy intensity and better management of natural resources, a trend observed across diverse economic cohorts from G7 to BRICS countries (Degirmenci et al., 2025; Wang & Tian, 2025). The interaction between policy stringency and energy end-uses suggests that integrating digital and renewable technologies enhances the monitoring and optimization of energy systems. Empirical estimates indicate that carbon emission indicators and the energy intensity level of primary energy are negatively related to policy stringency, implying that stricter regulations are necessary to reverse the adverse effects of resource depletion (Tian & Khan, 2025). In countries with significant fiscal capacity, environmental policy instruments that combine R&D support for clean technologies with stringent emission standards are particularly effective in accelerating the green energy transition (Degirmenci et al., 2025). Collectively, these findings provide a robust theoretical foundation for the hypothesis that the improvement in coordination between pollution and carbon systems under APPCAP is primarily driven by the structural reduction of energy intensity and the incentivized adoption of sustainable energy practices.

Hypothesis 3: The improvement in the CCD induced by the 2013 APPCAP is primarily driven by the structural reduction of energy intensity.

3. Methodology

The methodology of this study follows a multi-stage quantitative framework designed to test a central hypothesis through a primary econometric model. The analytical core relies on two distinct yet complementary methods: the LMDI Model and the CCD Model. These tools are used to measure the primary explanatory variable, specifically the synergistic state between pollution reduction and carbon mitigation. By using this dual-method approach, the study ensures that the empirical findings are robust and reliable.

To maintain a precise focus, the synergistic system is strictly limited to the two dimensions of SO_2 and CO_2. Other non-target pollutants, such as industrial wastewater, are deliberately excluded from this analysis. This narrow scope allows for a clear examination of whether the policy significantly improves the level of synergistic governance between SO_2 and CO_2. It also helps determine if such an improvement can be explained through changes in energy intensity. Using this structured path, the research aims to uncover the specific ways in which environmental mandates drive coordinated results across different types of emissions.

3.1 Measurement of Industrial Pollution and Carbon Emission Reductions

The initial step is to accurately quantify the total emissions of both SO_2 and CO_2. Subsequently, we calculate the reduction amounts relative to a fixed baseline year. These calculated reduction volumes, which reflect the intensity of environmental governance, serve as the foundational variables for the subsequent synergy analysis. Following established literature(Hoffmann, Muttarak& Peisker, 2022), To ensure consistency between the indicator system and the research objectives, both the SO_2 and CO_2 subsystems utilize emission intensity as the core indicator, with per capita indicators serving as a robustness supplement.

$$SO2_{int,it} = \frac{SO2_{it}}{GDP_{it}}, CO2_{int,it} = \frac{CO2_{it}}{GDP_{it}} \quad (1)$$

$$SO2_{pc,it} = \frac{SO2_{it}}{POP_{it}}, CO2_{pc,it} = \frac{CO2_{it}}{POP_{it}} CO_2 \quad (2)$$

These expressions define two types of emission intensity indicators. $SO2_{int,it}$ and $CO2_{int,it}$,it represent emission intensity per unit of economic output, meaning the amount of SO_2or CO_2 emissions produced per unit of GDP for object i at time t. $SO2_{pc,it}$ and $CO2_{pc,it}$ represent per capita emissions, meaning the amount of SO_2 or CO_2 emissions per person, calculated by dividing total emissions by population (POP). Here, $SO2_{it}$ and $CO2_{it}$ are the total emissions of sulfur dioxide and carbon dioxide, GDP_{it} is the gross domestic product, and POP_{it} is the population for object i at time t.

3.2 Coupling Coordination Degree Model

Regarding the measurement of the CCD, we employ the Entropy Weight Method (EWM) to determine the objective weights of the indicators. To ensure comparability across dimensions and eliminate the influence of different units and scales, the raw data are first subjected to normalization according to the following formulas:

$$z_{ijt} = \frac{max(x_j) - x_{ijt}}{max(x_j) - min(x_j) + \varepsilon} \quad (3)$$

$$p_{ijt} = \frac{z_{ijt}}{\sum_i z_{ijt}} \quad (4)$$

$$E_j = -\frac{1}{\ln n} \sum_i p_{ijt} \ln p_{ijt} \quad (5)$$

$$w_j = \frac{1 - E_j}{\sum_j (1 - E_j)} \quad (6)$$

$$U_{it}^{SO2} = \sum_{j \in SO2} w_j \, z_{ijt}$$

(7)

$$U_{it}^{CO2} = \sum_{j \in CO2} w_j \, z_{ijt}$$

(8)

Where x_{ijt} is the original value of indicator j for object i at time t; $max(x_j)$ and $min(x_j)$ are the maximum and minimum values of indicator j across all objects, and ε is a small positive constant used to avoid division by zero. z_{ijt} is the normalized value obtained by scaling the original data, typically transforming it so that different indicators become comparable; p_{ijt} is the proportion of object i under indicator j after normalization. E_j is the entropy of indicator j, measuring how dispersed the values are; w_j is the weight assigned to indicator j, where indicators with greater variability receive higher weight;U1 and U2 represent the evaluated scores of the SO_2 and CO_2 subsystems, respectively, derived from the entropy weight method.

Following the normalization process, the measurement of the CCD is conducted through a three-step procedure to quantify the interaction between the SO_2 and CO_2 subsystems. First, we calculate the Coupling Degree, which reflects the strength of the interaction between the two subsystems without necessarily indicating the quality of that coordination:

$$C_{it} = \frac{2\sqrt{U_{it}^{SO2} U_{it}^{CO2}}}{U_{it}^{SO2} + U_{it}^{CO2}},$$

(9)

Second, to integrate the overall level of development of the two systems, we calculate the Comprehensive Coordination Index :

$$T_{it} = \alpha U_{it}^{SO2} + \beta U_{it}^{CO2}$$

(10)

In this study, α and β represent the assigned weights for each subsystem. Given that pollution abatement and carbon reduction are considered equally significant under current "dual-carbon" and environmental protection policies, we set α=β= 0.5. Finally, to address the potential limitation where the coupling degree might be high even if both subsystems are at a low level of development, the Coupling Coordination Degree is calculated as follows:

$$CCD_{it} = \sqrt{C_{it} \times T_{it}}$$

（11）

The value of CCD ranges between 0 and 1. A higher value of CCD indicates a more optimized state of synergy and coordination between the reduction of SO_2 and CO_2 emissions.

3.3 Decomposition of Driving Factors using the LMDI Model

The final step is to decompose the changes in total industrial carbon emissions to identify and quantify the contribution of key driving factors, using the LMDI method

based on an extended Kaya identity (Kaya, 1989). We decompose total industrial carbon emissions (C) as follows:

$$C = CI \times EI \times AF \times PF \quad (12)$$

Where CI typically represents carbon intensity, EI is energy intensity, for example, energy use per unit of output, AF is an activity or economic scale factor, and PF reflects population or scale-related factors.

Then, the change in total carbon emissionsis additively decomposed into the effects of these driving factors:

$$\Delta C = \Delta C_{CI} + \Delta C_{EI} + \Delta C_{AF} + \Delta C_{PF} \quad (13)$$

This means the overall change in emissions is attributed to changes in carbon intensity, energy intensity, activity level, and population

$$L(a,b) = \frac{a-b}{\ln a - \ln b} \quad (14)$$

where *L(a,b)=(a−b)/(lna−lnb)* is the logarithmic mean function. The function $L(a,b)$is the logarithmic mean, used to ensure a smooth and consistent decomposition even when values change proportionally. It serves as a weighting term in the decomposition formulas. So the specific formulas for effect in our model are:

$$\Delta C_{EI} = L(C_t, C_0)\ln\left(\frac{EI_t}{EI_0}\right) \quad (15)$$

3.4 Dinference - in Difference Model

The dependent variable in this study is CCD. The key independent variable is APPCAP in DID indicator, which equals 1 if city i initiated the low-carbon city development program in year t and 0 otherwise.

We estimate the following equation:

$$CCD_{it} = \alpha + \beta APAP_{it} + \delta Controls_{it} + ind_i + v_t + \varepsilon_{it}$$

where i and t denote industry and year dimensions respectively, APPCAP represents 2013 Air Pollution Action Plan, Controls represents the control variables, ind_i and v_t capture industry-specific and time-specific fixed effects, ε_{it} denotes the idiosyncratic error term.

4. Data Sources

The implementation of this research relies on a comprehensive provincial-level panel dataset covering 30 Chinese provinces from 2008 to 2024, yielding a total of 510 province-year observations. To rigorously evaluate whether "pollution reduction" and

"carbon mitigation" can be improved synchronously under the dual constraints of "carbon neutrality" and environmental governance, this study utilizes the 2013 Atmospheric Pollution Prevention and Action Plan as a quasi-natural experiment. Given that the 2013 Plan exhibits distinct regional differentiation in its execution, it provides a robust identification strategy for assessing policy synergistic effects. Consequently, the policy shock is set at the year 2013, with the treatment group defined as the provinces belonging to the Beijing-Tianjin-Hebei cluster (Beijing, Tianjin, and Hebei), the Yangtze River Delta (Shanghai, Jiangsu, Zhejiang, and Anhui), and the Pearl River Delta (Guangdong, and excluding Hong Kong and Macao), while the remaining provinces constitute the control group.

The empirical analysis employs a DID framework with dual fixed effects, incorporating both province and year fixed effects to control for time-invariant regional characteristics and temporal shocks, respectively. To ensure the reliability of statistical inference, standard errors are clustered at the provincial level. The underlying dataset integrates multi-source environmental, energy, and macroeconomic data necessary for emission reduction measurement and LMDI decomposition. Specifically, industrial SO_2 emissions and macroeconomic variables - including gross industrial value-added and regional gross domestic product - are sourced from the National Bureau of Statistics (NBS) provincial database. CO_2 emission data are derived from the Mendeley Provincial CO_2 Inventory and Carbon Monitor China's daily emission records, while terminal energy consumption data across various types are compiled to facilitate a granular analysis of energy intensity and structural shifts.

Based on a comprehensive review of existing literature, we systematically constructed the following indicator framework as Table 1, to capture the multifaceted dimensions of environmental policy impacts:

<please insert table 1 here>

Table1 Variable Definitions

No.	Variable	Definition / Description
	Core Variables	
1	ccd	Coupling Coordination Degree
2	SO_2_10k_ton	SO_2 Emissions (10,000 tons)
3	CO_2_mt	CO_2 Emissions (Million tons)
4	did	Policy Interaction Term (Difference-in-Differences)
	Control Variables	
5	agri_share	Share of Agricultural Sector
6	g_resident_pop_10k	Growth Rate of Resident Population
7	hotel_share	Share of Hotel and

No.	Variable	Definition / Description
		Catering Industry
8	ln_gdp_100m_yuan	Log of Total GDP (100 Million Yuan)
9	ln_gdp_pc	Log of GDP per Capita
10	ln_industrial_100m_yuan	Log of Industrial Value-added (100 Million Yuan)
11	ln_other_industry_100m_yuan	Log of Value-added of Other Industries (100 Million Yuan)
12	ln_pop	Log of Total Population
13	ln_realestate_100m_yuan	Log of Real Estate Value-added (100 Million Yuan)
14	ln_urban_pop_10k	Log of Urban Population (10,000 persons)
15	realestate_share	Share of Real Estate Industry
16	retail_share	Share of Wholesale and Retail Industry
17	sec_share	Share of Secondary Industry
18	third_share	Share of Tertiary Industry
19	urban_rate	Urbanization Rate

5. Empirical Results and Analysis

5.1 CCD Results

The temporal evolution of the Coupling Coordination Degree (CCD) between SO_2 and CO_2 systems across 30 Chinese provinces from 2008 to 2024 reveals a transformative shift from structural imbalance to high-level synergistic governance. The empirical results indicate that the coordination level has undergone a distinct three-stage progression, reflecting the increasing integration of environmental and climate policy frameworks in China.

<please insert table 2 here>

Table 2 SO_2-CO_2 Coupling Coordination Degree (2008–2024)

Year	Mean	Min	Max	N	Coordination Level

Year	Mean	Min	Max	N	Coordination Level
2008	0.0000	0.0000	0.0000	30	Serious Imbalance
2009	0.0000	0.0000	0.0000	30	Serious Imbalance
2010	0.0105	0.0000	0.3145	30	Serious Imbalance
2011	0.0000	0.0000	0.0000	30	Serious Imbalance
2012	0.2866	0.0000	0.4085	30	Moderate Imbalance
2013	0.4317	0.0000	0.5545	30	Near Coordination
2014	0.5006	0.0000	0.6521	30	Near Coordination
2015	0.5526	0.0000	0.7233	30	Near Coordination
2016	0.6713	0.0000	0.8093	30	Primary Coordination
2017	0.7128	0.0000	0.8298	30	Primary Coordination
2018	0.7459	0.0000	0.8581	30	Primary Coordination
2019	0.7614	0.0000	0.8787	30	Primary Coordination
2020	0.7751	0.0000	0.8982	30	Primary Coordination
2021	0.8288	0.3806	0.9135	30	High Coordination
2022	0.8309	0.4997	0.9234	30	High Coordination
2023	0.8348	0.5347	0.9223	30	High Coordination
2024	0.8461	0.5933	0.9265	30	High Coordination

According to Table 2, the historical evolution of the SO_2 and CO_2 synergistic system can be divided into distinct phases that highlight the transition from fragmented pollution control to integrated environmental governance. During the initial phase from 2008 to 2011, the system remained in a state of serious imbalance. This suggests that efforts to reduce industrial pollutants and mitigate carbon were largely disconnected during this time. Environmental regulations focused mainly on

end of pipe treatments for specific pollutants, which failed to create significant benefits for carbon reduction. A slight improvement was noted shortly after as the system moved into a state of moderate imbalance, marking the very early stages of integrated environmental management.The period following 2013 serves as a major turning point in the study. Following the start of the Atmospheric Pollution Prevention and Action Plan, the level of coordination rose sharply and entered the near coordination range. This upward trend continued through the mid 2010s as the system reached primary coordination. The steady growth in this coordinated state offers early evidence that the 2013 policy worked effectively. It suggests that specific pollution mandates successfully triggered a synergistic effect. Furthermore, the steady rise in the lowest coordination values across various provinces during these years indicates a convergence effect, where regions that previously lagged behind began to adopt more integrated strategies.In the final phase from 2021 to 2024, the synergistic state reached high coordination. This stage is marked by a significant increase in the lower limits of coordination, ensuring that every province moved past the threshold of imbalance. This stabilization at a high level aligns with the strategic shift toward dual carbon goals and the deep decarbonization of the industrial sector. Ultimately, the transition from serious dysfunction to high level coordination confirms the main hypothesis that environmental policy shocks can successfully encourage a synchronized management system for both traditional pollutants and greenhouse gases. This is achieved primarily through the optimization of energy structures and the reduction of energy intensity (Huang et al., 2023).

<please insert figure 1 here>

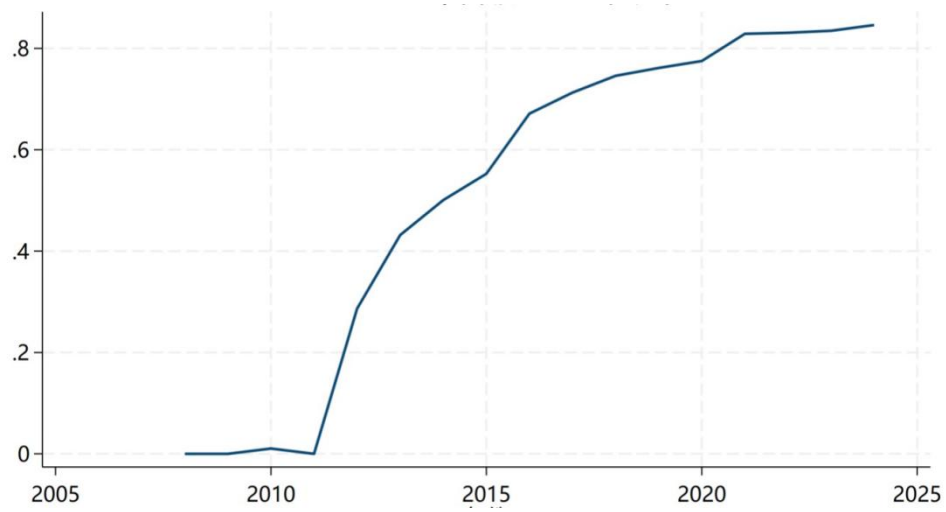

Figure 1 Temporal Trajectory of CCD

According to Figure 1, the temporal trajectory of the CCD from 2008 to 2024 reveals a distinct structural break that warrants further empirical investigation. As illustrated in the trend analysis, the synergistic relationship between SO_2 and CO_2 remained at a stagnant, low-level equilibrium prior to 2012, characterized by a persistent state of serious imbalance. However, a visible inflection point emerged

following the year 2013, after which the CCD values entered a phase of rapid and sustained growth. This chronological alignment provides a preliminary indication that the 2013 Atmospheric Pollution Prevention and Action Plan may have served as a critical external shock, successfully shifting the industrial system toward a more synchronized governance path(Huang et al., 2018).

While the graphical evidence suggests a strong temporal correlation between the policy implementation and the improvement in coordination levels, descriptive statistics alone are insufficient to isolate the causal effect of the mandate. The observed upward trend could be influenced by concurrent macroeconomic shifts, autonomous technological progress, or pre-existing regional development trajectories. Therefore, to rigorously identify the treatment effect of the 2013 Plan and to rule out potential confounding factors, it is essential to transition from trend observation to a formal econometric framework. The following section employs a Difference-in-Differences (DID) model with dual fixed effects to provide a more robust causal estimation of the policy's impact on the SO_2- CO_2 synergistic state.

5.2 DID Baseline Regression Results

The baseline regression results indicate that the 2013 Atmospheric Pollution Prevention and Action Plan significantly enhanced the synergistic governance of SO_2 and CO_2. Across all empirical specifications, the policy interaction term (did) remains positive and statistically significant, confirming that the quasi-natural experiment successfully triggered a coordinated reduction in both conventional pollutants and greenhouse gas emissions.

<please insert table 3 here>

Table 3 Baseline DID

Variables	(1)	(2)	(3)
did	0.0809*	0.2132***	0.0663*
	(-0.0482)	(-0.0376)	(-0.0358)
Province Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	No	Yes
Joint Significance of Controls (p-value)	0.0000***	0.0000***	0.0007***
N	510	510	510
R^2	0.7685	0.919	0.969

Note: Standard errors clustered at the provincial level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

According to Table 3, the following analysis reorganizes the baseline regression results and the economic logic of the 2013 policy using a semi-formal academic style

and straightforward language.The initial estimation in Model 1, which does not include fixed effects, shows a positive correlation between the 2013 APPCAP and the coordination of SO_2 and CO_2 management. However, this preliminary result likely suffers from bias because it fails to account for the natural differences between regions (Maji et al., 2018). When province fixed effects are introduced in Model 2, both the size and the statistical significance of the policy's impact increase substantially. This shift highlights the importance of controlling for permanent regional factors such as geographical location, natural resource availability, and historical industrial bases. Once these baseline differences are filtered out, the active role of the policy in key regions becomes much more evident. The 2013 Plan effectively pushed these high-emission areas to move away from fragmented pollution control toward a more integrated governance framework.Model 3 provides the most rigorous results by incorporating dual fixed effects. By controlling for year-specific events, the model separates the actual impact of the 2013 Plan from broader national trends like economic fluctuations or general technological progress. The results remain statistically significant, and the high R-squared value indicates that the model captures nearly all the variation in coordination levels. The slight reduction in the effect size compared to Model 2 suggests that the year fixed effects correctly absorbed common temporal trends that might have previously inflated the perceived policy effect. From an economic perspective, these findings support the co-benefit theory of environmental regulation. Since SO_2 and CO_2 are both created when fossil fuels are burned in the industrial sector, they are essentially joint products. The significant improvement in the coordination degree suggests that the 2013 Plan did more than just promote end-of-pipe solutions like desulfurization equipment.Instead, the strict mandates appear to have encouraged deeper structural changes. These include improvements in energy efficiency and the optimization of energy consumption patterns, both of which reduce the carbon footprint alongside traditional pollutants. This confirms that targeted environmental policies can successfully create a synchronized governance mechanism. The transition of the industrial system toward a high-level coordination state is driven by the internal logic of the policy. By raising the costs of high-intensity energy use, the 2013 Plan forced firms in the regulated regions to adopt cleaner production methods. This systemic shift addresses both pollution reduction and carbon mitigation goals at the same time, providing a strong empirical foundation for further analysis of the energy intensity channel (Feng, 2019; Zhang et al., 2021).

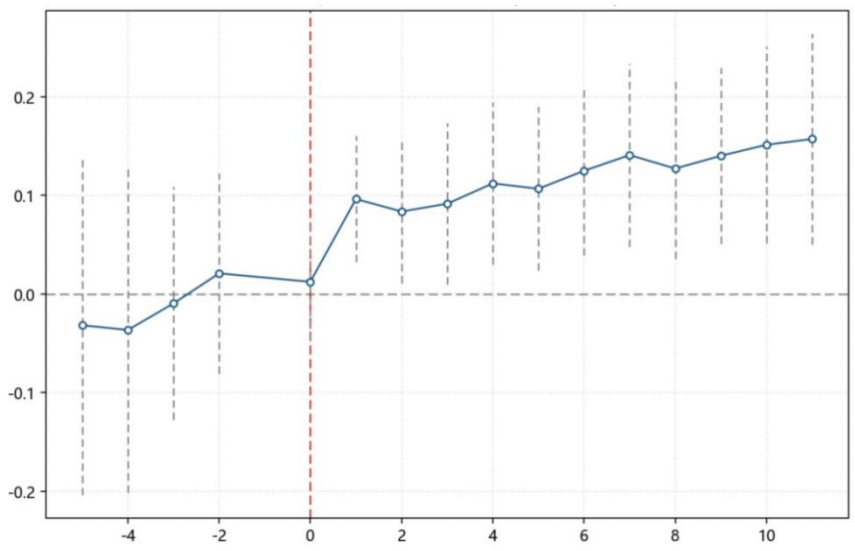

Figure 2 parallel trends test

Figure 2 illustrates the results of the dynamic event study and the parallel trends test, which are used to confirm that the research design is reliable. For the coordination between SO_2 and CO_2, the data shows that before the policy was introduced (2008–2012), the estimated effects were not statistically significant and stayed very close to zero. This lack of a clear trend before the policy is important because it proves that both the treatment and control groups were moving in a similar direction. This rules out the idea that the improvements we see later were simply caused by existing regional differences or older development patterns.After the 2013 Atmospheric Pollution Prevention and Action Plan was put into action, a clear and lasting change occurred. The results for the following years move into positive territory and become more statistically significant over time. This upward trend visually confirms that the policy had a strong and growing impact on improving the coordination between reducing regular pollutants and cutting carbon emissions. Because these positive effects continued long after 2013, it suggests that the policy did not just cause a temporary spike but instead created a long-term shift toward joined-up environmental management.The fact that the "parallel trends" requirement is met provides essential proof that the main results are not biased by other hidden factors. By separating the specific impact of the 2013 mandate from other general changes over time, this test reinforces the conclusion that the move from a state of imbalance to high coordination was a direct result of the government's intervention. These results strengthen the overall findings and provide a solid starting point for looking into how energy intensity played a role, confirming that the policy-driven synergy is a real phenomenon and not just a random statistical result.

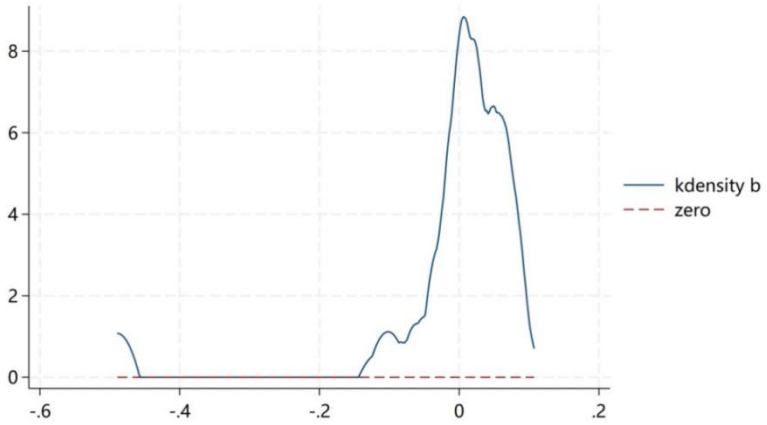

Figure 3 Kernel Density Distribution

Figure 3 illustrates the results of a placebo test, which uses 300 random assignments to check if the model's findings are accidental. The distribution of these random estimates is tightly grouped around zero. This is exactly what should happen in a reliable model: when the policy is assigned to random groups or years in which it didn't actually occur, the effect should be close to zero. This concentration shows that the study's method is not creating "false positives" or fake results. The distribution is mostly balanced, though it has a very slight positive bias. A small number of random tests produced slightly larger positive values, but these are rare and do not change the fact that the overall average is near zero. On the negative side, there are also some scattered results, but these are infrequent and represent the kind of normal variation one expects in any statistical sampling.

A dashed vertical line is placed at zero to serve as a clear reference point. Since the highest point of the curve sits very close to this line, it confirms that the average effect under these fake conditions is approximately zero. This symmetry is a strong sign that the model is working correctly. Overall, the placebo test shows that the study's main results are robust and not driven by random chance or a flawed design, which adds significant weight to the final conclusions.

<please insert table 4 here>

Table 4 Robustness Check

Variables	**Baseline**	**Post-2010 Sample**	**Post-2011 Sample**	**Excluding Pandemic**
did	0.0663*	0.0675**	0.0567**	0.0613*
	-0.0358	-0.0293	-0.0227	-0.035
Controls Joint Significance (p-value)	0.0007***	0.0017***	0.0002***	0.0010***
Province Fixed Effects	Yes	Yes	Yes	Yes

Variables	Baseline	Post-2010 Sample	Post-2011 Sample	Excluding Pandemic
Year Fixed Effects	Yes	Yes	Yes	Yes
N	510	450	420	450
R^2	0.969	0.966	0.9652	0.9682

Note: Standard errors clustered at the provincial level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To further confirm the reliability of the initial findings, this study conducts several sensitivity tests by varying the timeframe and accounting for major external events as Table 4. The goal is to demonstrate that the 2013 Plan's positive impact on SO_2 and CO_2 coordination is a consistent result, not just a product of specific years or unusual disruptions. As shown in the analysis of restricted timeframes, the policy effect remains stable even when the earliest years of the data are removed. When the sample is limited to the period starting from 2010 - focusing more closely on the years around the policy change - the impact actually becomes stronger and more statistically significant. Similar results are found when the data is further narrowed to start from 2011. These tests confirm that the policy's influence is clear and even more pronounced after filtering out older economic noise.

The study also considers the potential impact of the global pandemic. By removing the years affected by COVID-19, the model separates the long-term effects of the 2013 Plan from the temporary industrial slowdowns caused by the virus. Even without these unusual years, the policy's effect stays positive and significant. This proves that the improvement in coordinated governance is due to lasting institutional and technical changes driven by the 2013 mandate, rather than a short-term side effect of a pandemic-related economic dip.

Across all these model versions, the results remain highly consistent. The high explanatory power of the framework shows that it successfully accounts for differences between provinces and changes over time. The fact that the results are consistently significant across various scenarios confirms that the 2013 mandate was a genuine driver of the joint reduction of SO_2 and CO_2. In short, the shift toward a more coordinated environmental state was fundamentally powered by this specific regulatory intervention.

5.3 LMDI Results

The mechanism analysis utilizing LMDI decomposition provides granular evidence regarding the channels through which the 2013 Atmospheric Pollution Prevention and Action Plan facilitated the synergistic coupling of SO_2 and CO_2. By decomposing the aggregate variation in carbon emissions into the carbon intensity effect (dC_CI), energy intensity effect (dC_EI), economic affluence effect (dC_AF), and population effect (dC_PF), this study isolates the primary determinants of the observed

improvements in the Coupling Coordination Degree (CCD).

LMDI Results

Sample	dC_CI	dC_EI	dC_AF	dC_PF	share_CI	share_EI	share_AF	share_PF
Post-Policy Treatment Group	-3.8484	-24.5364	28.4023	3.0821	0.1356	0.8644	0.0000	0.0000

The decomposition results for the treatment group during the post-policy period reveal a critical empirical finding: energy intensity is the primary driver behind emission reductions. In absolute terms, the contribution of the energy intensity effect reached -24.5364, which significantly outweighs the -3.8484 contributed by the carbon intensity effect. Looking at the relative shares among the factors that helped lower emissions, energy intensity accounted for 86.44% of the downward pressure, while carbon intensity accounted for the remaining 13.56%. This distribution suggests that the 2013 policy shift triggered a major transition toward overall energy efficiency rather than just minor changes in fuel types. The dominance of the energy intensity channel explains why the policy was so effective. The 2013 Plan used strict administrative rules, such as removing inefficient industrial boilers and requiring technical upgrades for high-emission equipment in key regions. Since SO_2 and CO_2 are produced when fossil fuels are burned, reducing the energy used to produce each unit of economic value (GDP) leads to a simultaneous drop in both pollutants. This source-control approach proves much more effective at linking pollution and carbon management than "end-of-pipe" treatments, which often filter out SO_2 without addressing the carbon-heavy nature of the energy being used.

In contrast, economic growth and population increases continued to push emissions upward, contributing 28.4023 and 3.0821, respectively. This indicates that while regional expansion and demographic growth increased total emissions, policy-driven improvements in energy intensity were strong enough to offset a large portion of this growth. The fact that economic and population factors played a negligible role in the reduction category emphasizes that the environmental transition in these regions is driven by efficiency gains rather than economic slowdowns. This provides a clear explanation for the earlier findings, showing that the improved coordination between SO_2 and CO_2 is a direct result of structural shifts in energy efficiency. By requiring industrial sectors to improve production and reduce energy use, the 2013 APPCAP successfully aligned local air quality goals with global climate needs, establishing energy intensity as the primary path for joined-up environmental management.

6. Results and Policy Implications

The empirical evidence presented in this study provides a strong foundation for the argument that strict environmental policies can deliver significant benefits for the atmosphere and the climate. The main analysis shows a positive, statistically significant result for the policy across all tests, confirming that the 2013 Atmospheric Pollution Prevention and Action Plan was a decisive factor in the synchronized governance. This relationship is further supported by the long-term evolution of the coordination level, which underwent a major transformation from a state of serious imbalance before the policy to high coordination by the end of the study period. Such a path highlights a fundamental change in the industrial system, moving away from disconnected pollution control toward an integrated framework for reducing emissions.

The underlying mechanism identified by the LMDI decomposition shows that this improvement in coordination is primarily driven by changes in energy intensity, which accounts for the majority of the factors that help reduce emissions. This identifies efficiency gains at the source, such as the modernization of industrial boilers and the use of energy-saving technologies, as the main engine of the observed synergy. These improvements are more impactful than simple end-of-pipe treatments or minor changes in fuel types. By focusing on energy efficiency, the policy effectively addressed the root causes of both SO_2 and CO_2 emissions, helping to bridge the gap between local air quality goals and global climate targets.

These findings offer important lessons for regional environmental management and the pursuit of dual carbon objectives. The success of the 2013 Plan demonstrates that mandatory interventions can overcome the historical gap between air quality management and carbon reduction by forcing a structural shift in the industrial energy mix. Therefore, future policy frameworks should prioritize the formal integration of regular pollutant targets with greenhouse gas mitigation strategies, moving away from isolated rules that treat air pollution and climate change as separate crises.

Since energy intensity is the main path to achieving high-level coordination, policymakers should increase technical and financial support for industrial energy-saving equipment and accelerate the elimination of inefficient production capacity. Such measures offer the highest returns for both public health and climate stability. Furthermore, the observed closing of the gap in coordination levels across various provinces suggests that spreading integrated management models can effectively reduce regional differences in environmental performance. Ultimately, maintaining high coordination between SO_2 and CO_2 requires a steady focus on optimizing energy systems to ensure that future industrial growth is decoupled from both pollution and carbon-intensive energy use. This integrated approach will be essential as the focus of governance shifts from simple pollution control toward a comprehensive green and low-carbon transition.

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Ethics declarations

Competing interests

The authors declare no competing interests.

Ethical statement

This article does not contain any studies with human participants performed by any of the authors.