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Synergistic effect of carbon emission reduction from regional carbon trading on air pollutant emission reduction

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Introduction: In recent years, with the intensification of climate change, reducing greenhouse gas emissions has become a necessary measure to address climate change. The carbon trading policy, as an effective policy to promote carbon reduction, has been accepted and implemented by many countries.

Method: This study employs the twofold difference approach and synthetic control method to evaluate the impact of carbon trading policies on air pollutant emissions.

Result: Results showed that implementing carbon trading could lead to an average reduction of 54.13 million tonnes of CO₂ annually, alongside decreases of 176.1 thousand tonnes of SO₂ and 112.5 thousand tonnes of NO_x. Among the six pilot regions—Hubei, Guangdong, Shanghai, Beijing, Tianjin, and Chongqing—Hubei exhibited the most significant CO₂ reduction, approximately 66.25 million tonnes. Hubei and Beijing also showed notable synergistic effects for SO₂ reduction. The synergistic emission reduction effect of NO_x was more evident in Chongqing, Shanghai, and Hubei.

Discussion: These findings highlighted the effectiveness of carbon trading in mitigating CO₂ and related air pollutants. To enhance and optimize the carbon trading market, the study recommends increasing the clean energy share in the energy mix, improving market management systems, enforcing reasonable penalties for defaults, and developing tailored carbon trading mechanisms for different industries.

KEYWORDS

regional carbon trading, carbon emission reduction, synergistic emission reduction, synthetic control method, double difference method

1 Introduction

Carbon emissions (CEs) from the agricultural, industrial, service, and transportation sectors have become a major global concern (Abbas et al., 2022; Huang et al., 2024; Solaymani, 2019). Since the Industrial Revolution, the intensification of the greenhouse effect has resulted in more frequent extreme weather events, earthquakes, tsunamis, and other natural disasters. These events pose serious challenges to human survival. According to a report published by the World Meteorological Organization, there has been a 1.2°C increase in the worldwide average temperature in 2020 when compared to the period between 1850 and 1900. Therefore, it is essential to minimize greenhouse gas (GHG) emissions, such as CO₂, in order to adapt to climate change and slow down global warming

(Yang and Yao, 2023). The United Nations Framework Convention on Climate Change was signed by more than 150 countries and the European Economic Community in 1992. At the same time, in order to further limit the GHG emissions of developed countries to curb global warming, the *Kyoto Protocol to the United Nations Framework Convention on Climate Change* was adopted in 1997. The international emissions trading mechanism (IETM), the joint implementation mechanism (JI), and the clean development mechanism (CDM) are the three adaptable cooperation instruments that the Convention developed to minimize GHG emissions (Qi and Han, 2020). Among them, the core of the IETM is to allow developed countries to trade CE credits with each other, and after the construction of the CE trading mechanism, European and American countries have established carbon trade (CT) markets. Moreover, China approved seven pilot regions to establish CT market in 2011 to promote GHG emission reduction (ER) (Hao et al., 2021). Due to the homology between carbon dioxide and atmospheric pollutants (AP), and the fact that their production processes often interact with each other, it is necessary to coordinate and manage them. Therefore, in order to reduce the difficulty of realizing the expected CE reduction effect and to analyze the ER effect of carbon trading policies, it is necessary to analyze in depth the synergistic ER effect of carbon trading policies. This can optimize the carbon trading policy and enhance its synergistic ER effect. Among various statistical methods, difference in differences (DID) and synthetic control method (SCM) are used for impact analysis in multiple fields due to their simplicity and ease of operation.

DID is a statistical method commonly used in policy evaluation and causal inference. It is used to evaluate the causal effects of policies and interventions and has been widely adopted in many fields. Callaway et al. recognized that differences in the program processing effects of identification, estimation, and inference can occur over multiple time periods, therefore, DID was used to identify the parameters of treatment effect. It was demonstrated experimentally that a family causality can be recognized for parameters in a staggered setting. A number of different aggregation schemes were proposed through regression results and used to deal with the heterogeneity of different dimensional effects. Through asymptotic properties it was finally found that the experimentally proposed method was effective in guiding the program to correct reasoning (Callaway and Sant'Anna, 2021). Athey et al. suggested a staggered method to estimate and infer the average treatment impact in a setting with panel data by utilizing difference-in-difference settings. The process analyzed the nature of the given values and quantities from a design perspective. The results demonstrated that the estimates of the standard deviation could be obtained by weighting the mean causality when the dates used were randomly assigned, precisely giving the corresponding numerical variations (Athey and Imbens, 2022). Researchers such as Venkataramani identified the closure of automobile assembly plants as a significant cause of local economic decline. The study synthesized data from the beginning of 1999 to the end of 2016 and found that adjusted counties were more economically impacted compared to manufacturing counties that were not affected by plant closures. County workers died in larger numbers during the 5-year period of plant closures. This side effect indicated that the closure of automobile factories and the irrational use of drugs were the main

reasons for the decline of the local economy (Venkataramani et al., 2020). Fan et al. analyzed the pollution caused by highways on industrial emissions based on data from 2004 to 2016. Multi-period difference modeling was used throughout to address issues related to endogenous nature. Robustness tests proved that the suggested strategy was well-validated and may successfully minimize emissions produced by industrial pollution. Cities with HSR were found to be more polluted compared to other cities (Fan et al., 2020).

SCM is a ubiquitous method for estimating the impact of treatments on individual units in a panel data setup. Ben-Michael et al. proposed augmented SCM as an extension of SCM for cases where preprocessing was not feasible. Experimental results revealed that augmented SCM limited the estimation error of this method under different data generation processes, including linear factor models, and showed how regularization could help avoid overfitting noise (Ben-Michael et al., 2021). An SCM-based analysis was suggested by Tian et al. for a study on the efficacy and timing of a moderate COVID-19 intervention. The findings indicated that the new Crown pneumonia outbreak might be contained by the early application of modest treatments. In the hardest-hit areas, the epidemic worsened the later the intervention was put into place (Tian et al., 2021). An SCM-based computation technique for the straightforward determination of the synthetic jet exciter's momentum coefficient was presented by Liu et al. However, this method was empirically proven to be ineffective at large stall angles (Liu et al., 2020). Cole et al. proposed an SCM-based analytical method for the effect of the Wuhan New Crown Pneumonia blockade on the concentration of four air pollutants. According to the experimental findings, there was no discernible impact of the blockade on the sulfur dioxide concentration (Cole et al., 2020).

In summary, the parallel trend hypothesis has not been fully validated by existing studies using the DID method, which results in biased estimates of the policy effects of DID. At the same time, overfitting the data during the preprocessing stage of constructing the synthetic control group poses a problem. This affects the model's ability to generalize and the robustness of the estimation results. Therefore, in order to analyze the synergistic emission reduction (SER) effect of AP, the study analyzed the ER effect by DID and SCM. Air pollution is taken into consideration when analyzing China's present CT strategy, which serves as a guide for improving the regional carbon trading (RCT) system. The average treatment effect and path of collaborative ER in pilot carbon markets are analyzed using DID, and the theoretical model of the carbon market collaborative ER mechanism is empirically validated. Then, SCM is used to analyze the SER effects of APs in various pilot carbon markets. When conducting empirical analysis, the study utilizes non pilot areas (PAs) to synthesize PAs and determine the weights of each province and city in the composite control group. The determination of weights aims to minimize the mean square prediction error. A virtual control group, called a "synthetic control," is constructed by assigning different weights and linearly combining them. To verify the robustness of the results, the study also conducts a placebo test by shuffling the groups.

The study is broken up into four sections. The first section will give a quick overview of the previous research on DID and SCM. The second section will design an empirical study on the SER effect of RCT. The third section will analyze the results of the study. The

fourth section is a discussion, which will explain and elaborate on the research results. The fifth section will summarize the full study.

2 Empirical study design of the synergistic emission reduction effect of regional carbon trading

In order to study the synergistic effect of regional CE trading on reducing APs and promoting low-carbon development of enterprises, an empirical model based on DID and SCM is designed and analyzed.

2.1 Design of empirical models

DID is a particularly useful technique for evaluating the effects of policies since it can mostly avoid the endogeneity issue and has a simplified model configuration. In the meantime, DID's model setup is more scientific. It can estimate the effects of policies more accurately than the usual approach because it establishes a dummy variable that indicates whether or not the policy occurred before performing a regression. DID is used under the following conditions: (1) Parallel Trend Hypothesis: in the absence of a policy intervention, the trends in the outcome variables of the treatment and control groups should be parallel. (2) Ideally, the assignment of treatment and control groups should be randomized to reduce selection bias. (3) Its necessary to have sufficient time points and groups to estimate policy effects. Its robustness is tested by changing the model settings or using different estimation methods to verify the robustness of the results. The principle of DID as follows: Assuming there are two regions, one implementing a certain policy as the experimental group and the other as the control group. Prior to the policy intervention time point, the two districts exhibit parallel patterns; however, following the policy intervention, the experimental group's path diverges. In a continuous data timeframe, the figure shows the impact of a non-targeted policy on the experimental and control groups at each time point following the policy intervention. The impact is represented in blue. The effect of a focused policy is represented in green. To obtain the effect of the target policy, only two differencing is required. The DID modeling formula is shown in Equation 1.

$$Y_{it} = \alpha_0 + \alpha_1 du + \alpha_2 dt + \alpha_3 du \cdot dt + \varepsilon_{it} \quad (1)$$

In Equation 1, α_0 denotes the effect of the control group before the implementation of the target policy. α_1 denotes the difference between the experimental and control groups, and α_2 denotes the difference between the experimental group before and after policy implementation (PI). α_3 denotes the interaction term regression coefficient, which captures the net effect of PI. du denotes the grouping dummy variable (Denton et al., 2022; Bhaktikul et al., 2021; Wu et al., 2022). To examine the impact of RCT on AP emissions, the effect of the CT market policy can be analyzed using the DID model. Now, taking the time of CT PI as the cut-off point, the change of air pollution emissions before and after the PI can be obtained by subtracting the AP emissions before and after the PI. However, since there are many factors influencing AP emissions in

practice, the effects of other influencing factors on AP emissions need to be eliminated. Therefore, when evaluating the impact of the RCT policy on AP emissions, it is necessary to perform two differentials according to pilot/non-pilot cities and before/after the policy in order to exclude other influencing factors. The formula for calculating the changes in regional CO₂ and AP emissions before and after the implementation of the RCT policy is shown in Equation 2.

$$\Delta P_i = P_{i,1} - P_{i,0} \quad (2)$$

In Equation 2, ΔP_i represents the change in CO₂ and AP emissions in region i . $P_{i,1}$ denotes the AP emissions of region i after the PI, and $P_{i,0}$ denotes the AP emissions of region i before the PI. Equation 3 calculates the effect of the RCT policy on the variation of CO₂ and AP emissions.

$$\Delta \Delta P_i = \frac{1}{N_1} \sum_{N_1} (\Delta P_i | X_i = 1) - \frac{1}{N_2} \sum_{N_2} (\Delta P_i | X_i = 0) \quad (3)$$

In Equation 3, $\Delta \Delta P_i$ denotes the effect of the policy on CO₂ and AP emissions in region i . X_i denotes the regional dummy variable, which takes the value of 1 for pilot regions and 0 for non-pilot regions. The DID model for the SER effect of the RCT policy is shown in Equation 4.

$$P_{i,t} = \alpha + \beta_1 \cdot CM_{i,t} + \sum \beta_2 Z_{i,t} + u_i + u_t + \varepsilon_{i,t} \quad (4)$$

In Equation 4, $P_{i,t}$ denotes CO₂ and AP emissions of region i in year t , and α is a constant term. β_1 denotes the core explanatory variables and $CM_{i,t}$ denotes the double difference term for the pilot cities of the RCT policy. $Z_{i,t}$ denotes control variables and u_i denotes fixed differences across regions. u_t denotes time fixed effects and $\varepsilon_{i,t}$ denotes the error term of the model. Although DID model can assess the effects of RCT policies, it is difficult to reflect the SER effects of individual pilots. Therefore, the study uses SCM to investigate the SER effects of each pilot. The SCM only needs to find a potential control group that is highly similar. Then, it can construct a virtual control group by assigning different weights to several test units similar to the test group. The virtual group formed by this set of weights is called a "synthetic control." The applicable conditions for SCM are as follows: (1) Before PI, it is necessary to find or construct a control group similar to the treatment group. (2) The data from the control and treatment groups must be comparable to ensure the validity of the comparison. (3) There must be sufficient data to accurately estimate the weights of the control group. Assume that the CE of several regions since year T is known, where region 1 is a pilot region and all regional regions are non-pilot regions (Pan et al., 2021; Eyuboglu and Uzar, 2020; Nokhrina et al., 2022; Mordue et al., 2020; Yang et al., 2021). The suppression effect of RCT policy on CO₂ and AP emissions is shown in Equation 5.

$$\alpha_{it} = Y_{it}^I - Y_{it}^N \quad (5)$$

In Equation 5, α_{it} represents the suppression effect of RCT policies on CO₂ and AP emissions. Y_{it}^I denotes the CO₂ and AP emissions of region i in the case of CT in period t . Y_{it}^N denotes the CO₂ and AP emissions of region i in period t without CT. Since the AP emission environments are basically the same in each region without initiating the RCT policy, the differences are negligible.

Therefore, $Y_{it}^I = Y_{it}^N$ before RCT is not carried out. If the regional dummy variables are introduced into the calculation of the realistic values of CO₂ and AP emissions in the pilot regions, the formula is shown in Equation 6.

$$Y_{1t} = Y_{1t}^N + X_{1t}\alpha_{1t} \quad (6)$$

In Equation 6, Y_{1t} represents the realistic values of CO₂ and AP emissions in the pilot region. After starting the RCT, only the CO₂ and AP emissions in the pilot region when no more CTs are conducted are required to be calculated to obtain the actual CT market treatment effect in the pilot region. The SCM calculation formula is shown in Equation 7.

$$\sum_{j=2}^{J+1} w_j Y_{jt}^N = u_t + \theta_t \sum_{j=2}^{J+1} w_j z_j + \lambda_t \sum_{j=2}^{J+1} w_j u_j + \sum_{j=2}^{J+1} w_j \varepsilon_{jt} \quad (7)$$

In Equation 7, w_j denotes the vector of weights of the SCM, and the sum of the weights is 1. θ_t denotes the unknown parameter, and z_j denotes the control variable that is not affected by the RCT policy. u_j denotes area fixed effects and $J+1$ denotes the number of observed areas. The suppression effect of RCT policy on CO₂ and AP emissions is obtained from Equation 7.

$$Y_{1t}^N - \sum_{j=2}^{J+1} w_j Y_{jt}^N = \theta_t \left(z_1 - \sum_{j=2}^{J+1} w_j z_j \right) + \lambda_t \left(u_1 - \sum_{j=2}^{J+1} w_j u_j \right) + \sum_{j=2}^{J+1} w_j (\varepsilon_{1t} - \varepsilon_{jt}) \quad (8)$$

When Equation 8 satisfies certain conditions, there exists a weight vector such that its value tends to zero. Therefore, $\sum_{j=2}^{J+1} w_j^* Y_{jt}^N$ can be used as an unbiased estimator of CO₂ and AP emissions in the pilot region without CT. At this point, the policy effects of the CT market are shown in Equation 9.

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}^N \quad (9)$$

In Equation 9, $\hat{\alpha}_{1t}$ denotes the unbiased estimator of the CT market policy effect in the pilot region. w_j^* denotes the vector of weights for the control group.

2.2 Variables and data sources

In conducting the empirical analysis of the SER effect of RCT policies, the study takes China as an example. The data used are obtained from the National Bureau of Statistics, Wind database, China Urban Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, Environmental City Statistical Bulletin, and National Economic Development and Statistical Bulletin. Since the RCT PAs include not only cities but also provinces, the study uses municipal panel data from 2010 to 2017 and provincial panel data from 2007 to 2017. In addition, in order to avoid interference, the study excludes the data related to the second RCT policy pilot regions (Zhang and Umair, 2023; Okafor et al., 2022; Deng and Shangguan, 2021; Shi et al., 2023). The data analysis software used in the experiment is EViews. The explanatory variables of the study contain CO₂

emissions, SO₂ emissions, and NO_x emissions. SO₂ and NO_x are chosen as the objects of SER because the emission data of SO₂ and NO_x are more sufficient and homologous to CO₂ compared with those of airborne particulate matter, O₃, and other pollutants. The control variables selected for the study include *per capita* GDP, industrial structure, urbanization rate, population density, and energy consumption. These control variables are chosen to ensure that the model's estimated results accurately reflect the impact of carbon trading policies on SER effects while controlling for other factors that could affect the outcome variables. The selection of the variables controlled above is based on their impact on regional CEs. The National Bureau of Statistics, local statistical yearbooks, environmental statistics bulletins, and other sources provided the SO₂ and NO_x emissions. Due to the lack of a uniform calculation method for CO₂, the study calculates provincial CO₂ emissions using the IPCC National GHG Inventory Guidelines and the China Energy Statistics Yearbook. Additionally, Equation 10 displays the calculating formula.

$$CO_2 = \sum_{q=1}^8 E_q \times S_q \quad (10)$$

In Equation 10, E_q denotes the consumption of energy in category q and S_q denotes the CO₂ emission factor corresponding to the eight FF. The study uses electricity consumption, CO₂ emission coefficients, natural gas, raw coal, and LPG consumption, as well as electricity consumption to calculate municipal CO₂ emissions. Equation 11 provides the calculation formula. This is because it is difficult to obtain complete energy consumption data at the municipal level.

$$CO_2 = \sum_{q=1}^3 E_q \times S_q + E_e \times S_e \quad (11)$$

In Equation 11, E_e denotes urban electricity consumption, and S_e CO₂ electricity emission factor, which is derived from the baseline emission factor published by the National Grid. As the CT market in each region confirmed that the opening time is not consistent, the Shenzhen market was opened in June 2013, the earliest. The Chongqing market was opened in June 2014, the latest. Therefore, for the convenience of calculation, the study choose 2014 as the launch time of the RCT policy. In addition, due to the large overlap in location and data between Shenzhen and Guangdong Province, and the relatively close opening time of the CT market, the two are combined for the study. In the actual study, since AP emissions are not only affected by RCT policies, but also by the total energy effect, population, economic development effect and industrial results (Shi et al., 2023; Li et al., 2023; Zhang et al., 2021). Therefore, to reduce the estimation error of the ER effect, the study includes other control variables in the DID and SCM models. These variables includes *per capita* GDP, industrial structure, urbanization rate, *per capita* energy consumption, population density, environmental protection financial expenditures, and *per capita* sewage costs. Since the environmental Kuznets curve theory suggests that CO₂ emissions and economic growth have an inverted U-shaped relationship, the study includes the quadratic term of GDP *per capita* in DID and SCM (Xia and Yang, 2022; Kreibich and Hermwille, 2021). While in the DID and SCM models

TABLE 1 Data are descriptive statistics.

Variable	Symbol	Observations	Unit	Mean value	Variance	Min	Max
Carbon dioxide	CO ₂	308	Megaton	297.72	194.69	19.40	768.39
Sulfur dioxide	SO ₂	308	Ten thousand tonnes	60.93	43.36	0.47	182.75
Nitrogen oxide	NO _x	308	Ten thousand tonnes	61.45	42.76	4.01	180.12
<i>per capita</i> GDP	pgdp	308	Ten thousand yuan/Person	3.99	2.25	1.05	13.61
Urbanization rate	rcpop	308	%	58.12	21.11	31.59	169.55
Density of population	popd	308	Ten thousand people/km ²	462.75	695.73	7.64	3890.86
Industrial structure	sec	308	%	42.95	8.87	16.89	61.95
Environmental protection fiscal expenditure	ergov	308	%	3.03	1.08	0.84	6.73
Per capita discharge fee	ppwf	308	Yuan/Person	17.61	13.39	1.55	3890.86
Energy structure	rcoal	308	%	43.68	15.46	4.41	72.41
Per capita energy consumption	ene	308	Tonnes/People	3.48	3.05	0.22	15.85

for SO₂ and NO_x, *per capita* emissions costs are introduced to minimize the interference of regional pollution reduction policies. Additionally, the study uses dummy variables to eliminate the interference of fixed effects because DID must take into account time fixed effects and regional fixed effects, which will cause bias in the estimate results. The indicator system consists of the dependent variable, core explanatory variable, and control variable, with the dependent variables including CO₂, SO₂, and NO_x. When analyzing the ER and SER effects of RCT policies, the study standardizes various types of data to avoid heteroscedasticity issues. In addition, to verify the SER effect of carbon trading policies, the study also introduces energy structure in the analysis, which is represented by the proportion of coal in the conversion of energy to standard coal. The descriptive statistics of the data are shown in Table 1.

According to Table 1, the smallest and maximum percentages of coal in the energy structure are 4.41% and 72.41%, respectively, with a mean value of 43.68%. The average amount of energy consumed per person is 3.48 tonnes, with minimum and greatest values being 0.22 tonnes and 15.85 tonnes, respectively.

3 Empirical analysis and optimization suggestions on the synergistic emission reduction effect of regional carbon trading

3.1 Empirical analysis of the synergistic emission reduction effect of regional carbon trading

The average treatment impact of AP abatement and the abatement effect of individual pilots are examined using DID and SCM, respectively, to examine the SER effect of the RCT policy. Before conducting the analysis, the study uses the trend observation method to perform a parallel trend test. This test is important for verifying that the trends of the experimental and control groups are parallel when using DID. Table 2 displays the DID analysis results.

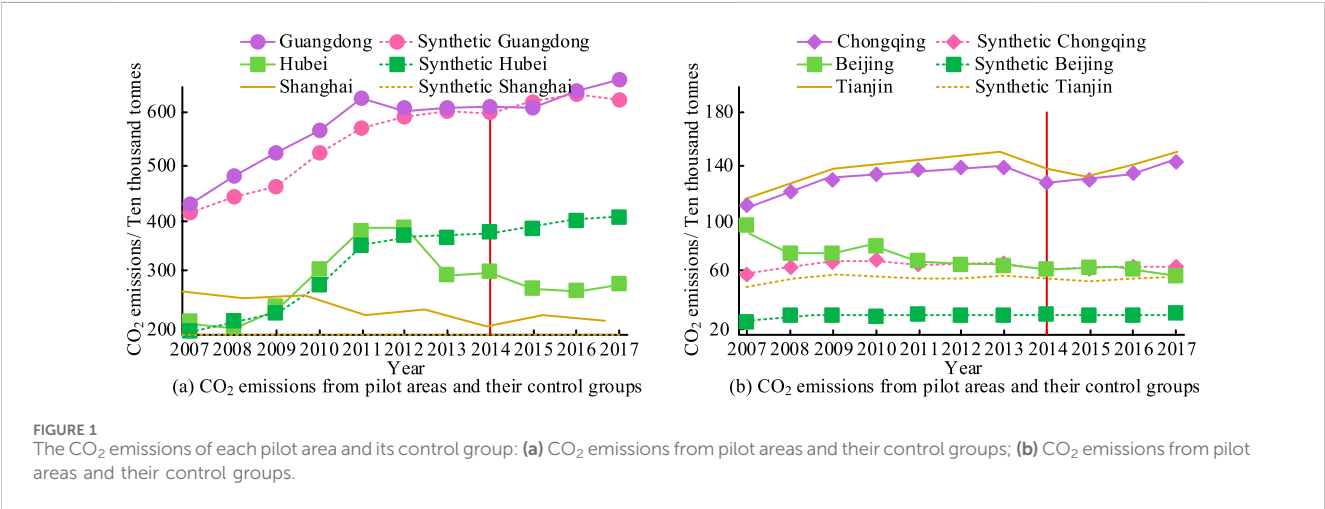
As shown in Table 2, the implementation of CT policy can reduce CO₂ emissions by 54.13 million tonnes per year on average, and reduce SO₂ and NO_x by 176, 100 tonnes and 112, 500 tonnes each. Among the control variables of CO₂ emissions, the coefficient of GDP *per capita* is 44.40, indicating that CO₂ emissions are positively related to economic growth. The coefficient of industrial structure is 1.96, which indicates that the higher the production ratio of secondary industry, the higher the CO₂ emission. The coefficient of urbanization rate is −0.78, meaning that the quantity of CE decreases with increasing urbanization rate. The coefficient of GDP *per capita* for SO₂ emissions is −7.39, indicating a negative correlation between economic growth and SO₂ emissions. With a correlation of 0.63 for NO_x emission related to urbanization rate, it can be concluded that NO_x emissions increase with urbanization rate. This is because urbanization accelerates, leading to a significant increase in the number of vehicles in cities and, consequently, an increase in NO_x emissions from transportation. Urbanization often accompanies industrialization. Industrial production processes, especially those involving fossil fuels, can generate large amounts of NO_x emissions. Power plants and factories are two examples of industrial facilities that emit large amounts of NO_x. The study uses a placebo test to confirm the reliability of the findings. The study uses the non-pilot regions to synthesize the pilot regions, excludes the provinces and municipalities containing the second batch of pilot regions, and establishes the weights of the provinces and municipalities in the synthetic control group. This allows the study to investigate the mitigating effects of CT policies on individual pilots. In determining the weights, the goal is to minimize the mean square prediction error. After the weights are determined, the counterfactual control group can be synthesized according to the weights. The CO₂ emissions of each pilot region and its control group are shown in Figure 1.

In Figure 1a, among the three pilot regions of Hubei, Guangdong, and Shanghai, Guangdong has the highest fit with its control group. Among them, Hubei's CO₂ emissions before 2014 are similar to its control group. Moreover, after 2014, CO₂

TABLE 2 The DID analysis results.

Gas type	CO ₂	SO ₂	NO _x
Index			
CM	−54.13***	−17.61	−11.25
	16.34#	9.07#	10.12#
Per capita GDP ²	−0.05***	—	—
	0.00#	—	—
Per capita GDP	44.40***	−7.39***	−0.41
	8.48#	1.22#	1.45#
Industrial structure	1.96**	1.71***	1.97***
	0.93#	0.31#	0.32#
Urbanization rate	−0.78***	−0.31	0.63**
	0.04#	0.22#	0.29#
Environmental protection financial investment	7.97	−0.60	−3.96***
	4.93#	1.47#	1.44#
Density of population	−0.05	0.02***	0.04*
	0.05#	0.00#	0.03#
Per capita energy consumption	32.96***	1.06**	0.99**
	3.46#	0.52#	0.41#
Per capita discharge fee	—	−0.62***	−0.51***
	—	0.18#	0.18#
Constant term	257.53**	16.06	71.25***
	88.61#	22.62#	27.79#
Area fixation effect	✓	✓	✓
Time fixed effect	✓	✓	✓
R-sq	0.731	0.643	0.612

Note: *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively; # indicates standard error.



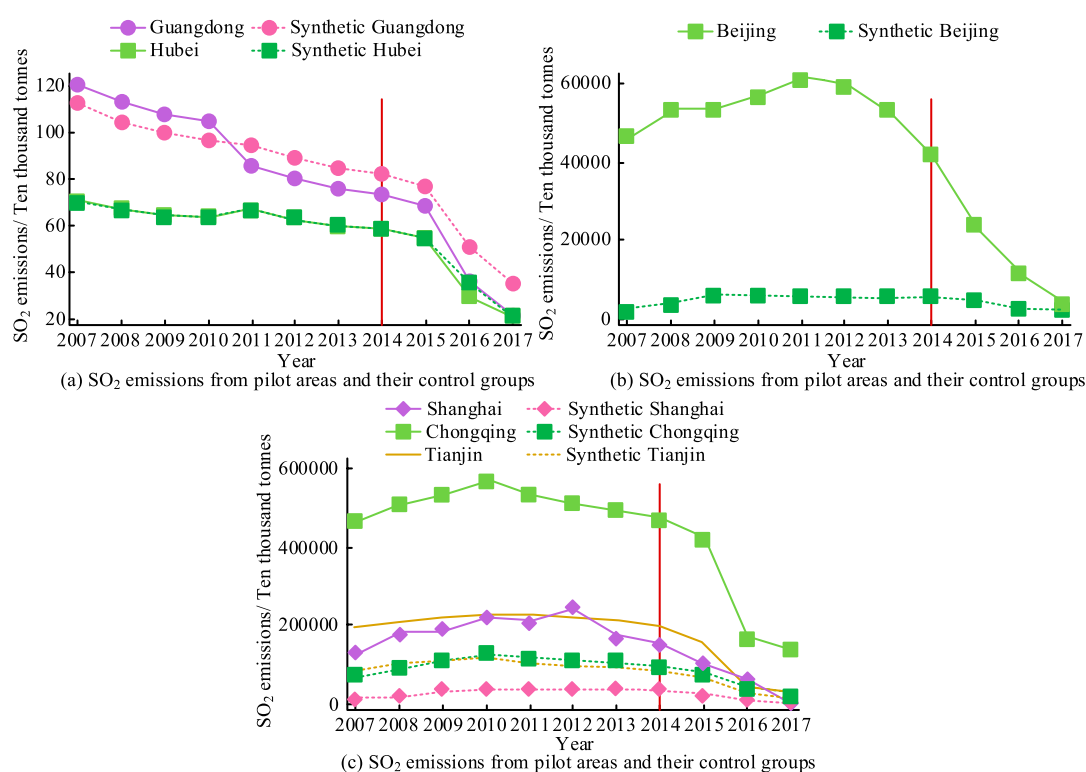


FIGURE 2

SO₂ emissions from each pilot area and its control group: (a) SO₂ emissions from pilot areas and their control groups; (b) SO₂ emissions from pilot areas and their control groups; (c) SO₂ emissions from pilot areas and their control groups.

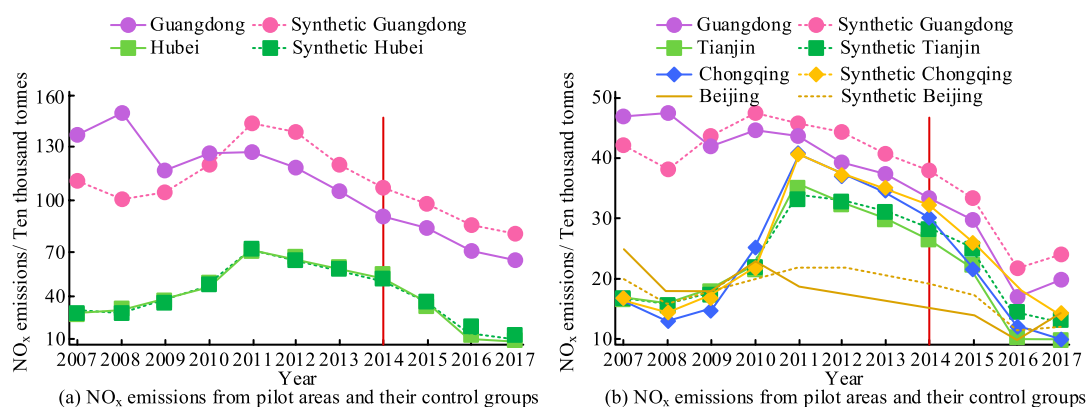


FIGURE 3

NO_x emissions from each pilot area and its control group: (a) NO_x emissions from pilot areas and their control groups; (b) NO_x emissions from pilot areas and their control groups.

emissions decreases significantly, with a reduction of about 66.25 million tonnes. Moreover, Guangdong's CO₂ emission after 2014 is close to that of the control group. Figure 1b shows that, both before and after 2014, Beijing, Tianjin, and Chongqing has CO₂ emissions that are consistently greater than those of their control groups. Additionally, all of the fits are poor, making it impossible to determine the ER effect of the CT policy. According to the aforementioned findings, Hubei Province clearly benefits from

the CT policy's ER effect. Figure 2 displays each pilot region's SO₂ emissions along with those of the control group.

In Figure 2a, both Guangdong and Hubei have better fits. Among them, Guangdong's SO₂ emissions begin to be lower than the control group after 2010. Hubei's SO₂ emissions begin to decline faster than the control group after 2015. Figure 2b shows that after 2014, Beijing's SO₂ emissions all begin to fall more quickly than those of the control group. Nevertheless, because to the poor fit,

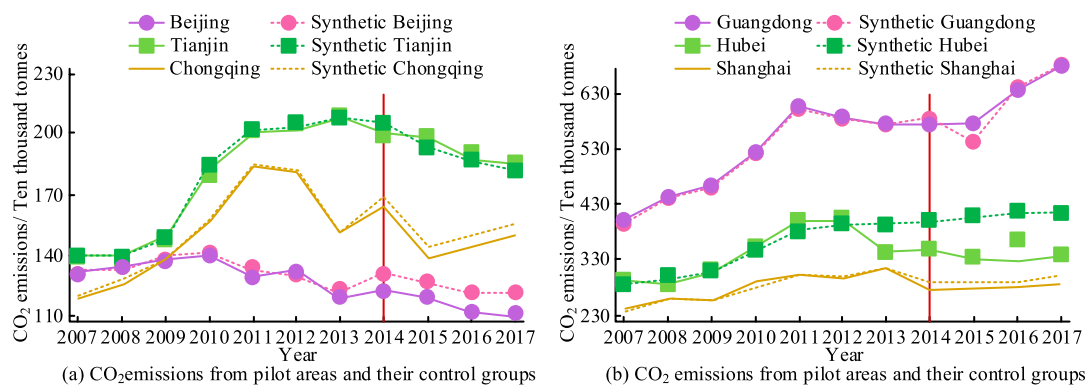


FIGURE 4

The CO₂ emissions of the extended SCM: (a) CO₂ emissions from pilot areas and their control groups; (b) CO₂ emissions from pilot areas and their control groups.

it is not able to assess the SER effect of the CT strategy in the relevant region. In Figure 2c, SO₂ emissions in Shanghai, Tianjin, and Chongqing all started to decrease faster than the control group after 2014, but the fit is poor. Therefore, the SER effect of the CT policy in the corresponding region can not be judged. The above results indicate that the CT policy realizes the SER of SO₂ in Hubei Province with a synergy of about 0.0003. After the implementation of carbon trading policies in 2014, it is worth noting that emissions in various regions did not immediately show significant changes. This is because companies need time to adjust their production processes, invest in new technologies, and change their energy structures. This results in a lag effect in their SER efforts. Meanwhile, CEs in various regions have decreased year by year within 4 years of the implementation of the carbon trading policy, indicating its long-term effectiveness. The NO_x emissions in each PA and its control group are shown in Figure 3.

In Figure 3a, Hubei has a better fit and its NO_x emissions are basically consistent with the control group. Guangdong, on the other hand, starts to emit less than the control group after 2010, and the fit is poor. Therefore, it is difficult to judge the SER effect of its NO_x. In Figure 3b, Tianjin and Chongqing have a better fit, and their NO_x emissions basically start to decrease around 2012, which is earlier than the CT time. The fits of Shanghai and Beijing are poor, and it is difficult to judge their SER effects. The above results indicate that the CT policy realized the SER of NO_x in Hubei, Tianjin and Chongqing. This is because the industrial structure in Hubei, Chongqing, and other areas is primarily heavy industry. This type of industry often involves large amounts of energy consumption and pollutant emissions during the production process. The implementation of carbon trading policies forces high-energy-consuming enterprises to undergo technological transformation and adjust their energy structures to reduce their CE intensity. This directly promotes the coordinated reduction of CO₂ and other APs. Before the implementation of carbon trading policies, the pollution levels in Hubei and Chongqing are relatively high, providing ample opportunity for collaborative ER. Additionally, Hubei and Chongqing have demonstrated exceptional performance in PI, which is another key factor contributing to their substantial SER effect. The local government has demonstrated strong organizational and execution capabilities in promoting and

implementing carbon trading policies. To further explore the SER effect of the CT policy, the study extended the SCM. The CO₂ emissions of the extended SCM are shown in Figure 4.

Figure 4a shows the CO₂ emissions of Beijing, Chongqing, and Tianjin. Emissions in Beijing and Chongqing begin to decline after 2014, with respective reductions of 9.65 and 3.3 million tons compared to the control group. Furthermore, Tianjin's CO₂ emissions are essentially in line with those of the control group. Figure 4b shows that there is little difference in Guangdong's CO₂ emissions before and after the CT policy is put into place. After 2014, CO₂ emissions in Shanghai and Hubei decreased dramatically, by 7.55 million tonnes and 63.7 million tonnes, respectively. The CT policy has obvious ER effects in Beijing, Chongqing, Shanghai, and Hubei. The implementation of carbon trading policies can achieve SERs such as SO₂ and NO_x. This is due to the fact that the energy mix has changed significantly after the implementation of carbon trading policies. With the promotion of carbon trading policies, companies and regions may be encouraged to use clean energy or improve energy efficiency. This would reduce their dependence on fossil fuels. The optimization of this energy structure can simultaneously reduce the emissions of CO₂, SO₂, and NO_x. Technological upgrading is another key driving force for achieving collaborative emissions reduction. The implementation of carbon trading policies has increased pressure on enterprises to reduce emissions. This has prompted them to invest in advanced pollution control technologies, such as flue gas desulfurization and denitrification, to reduce SO₂ and NO_x emissions.

3.2 Suggestions for regional carbon trading market optimization

In recent years, extreme weather and natural disasters have occurred frequently around the world, indicating that it is urgent to address climate change and reduce GHG emissions. According to the above research results, it can be concluded that the energy structure has a significant impact on the SER effect of the carbon trading market. It can be concluded that regions with high coal dependence have significant SER effects after implementing carbon trading policies. It can be concluded that improving the energy

structure, increasing the proportion of clean energy in the energy structure, and gradually phasing out traditional coal fuels can effectively enhance the SER effect. The main measures to improve the energy structure are to promote the construction of smart grids and strengthen the production, storage, sales, and use of clean energy such as photovoltaics and wind power. In regions highly dependent on coal, it is necessary to promote natural gas and biomass energy alternatives, reduce coal dependence, and increase investment in clean energy, such as photovoltaics and wind power, to increase clean energy's proportion in the energy structure. Regions with abundant clean energy resources are encouraged to develop and utilize clean energy, such as small hydropower and geothermal energy. They should also invest in energy storage technologies, such as battery storage and pumped storage, to balance the intermittency of clean energy. In addition, the increase in economic costs caused by carbon trading for enterprises, although temporarily avoided through industrial transfer and output adjustment, cannot guarantee the long-term competitiveness and vitality of enterprises. Therefore, it is necessary to improve the management system of the carbon trading market and formulate reasonable default penalties. This will allow enterprises to operate sustainably, maintain their competitiveness and vitality, and achieve continuous carbon reduction and ER. Finally, the operational mechanism of the carbon trading market itself will determine its SER effect. Therefore, to ensure the SER effect when promoting the carbon trading market, the operating mechanism should be carefully considered. The operating mechanisms of carbon trading markets with a synergy degree greater than 0, such as those in Beijing and Shanghai, should be used as a reference. In addition, different industries have different characteristics. When formulating the operating mechanism of the carbon trading market, it is also necessary to fully consider the characteristics of the emission control industry itself. Based on this, a feedback mechanism is constructed to form a carbon trading market environment with active trading, active participation and effective emission control.

4 Discussion

A comprehensive analysis was conducted on the synergistic effect of reducing APs through DID and SCM in RCT policies. The research results indicated that carbon trading policies could not only effectively reduce carbon dioxide emissions, but also synergistically reduced sulfur dioxide and nitrogen oxide emissions. This discovery was consistent with some research results in existing literature. The study by Wei Y et al. showed that the tiered carbon trading policy increased renewable energy consumption by 0.12% and reduced CEs by 0.6% (Wei et al., 2023). The study by Kou P et al. showed that CEs trading had significant synergistic benefits in reducing sulfur dioxide emissions, and this benefit was mainly achieved by reducing fossil energy consumption (Kou et al., 2021). Carbon trading policies achieved coordinated ERs by adjusting the energy structure during implementation. Due to the promotion of carbon trading policies, enterprises and regions tend to increase their use of clean energy and reduce their dependence on high-carbon energy sources, such as coal. The optimization of this energy structure not only reduced CO₂ emissions, but also reduced SO₂ and NO_x emissions. For example,

research in Hubei Province and Chongqing City indicated that the implementation of carbon trading policies led to a significant increase in the use of clean energy in these areas, thereby achieving a coordinated reduction in various pollutants. The uniqueness of the study lies in the following aspects: first, the study not only evaluated the carbon dioxide ER effect of carbon trading policies, but also examined their SER effects on sulfur dioxide and nitrogen oxides. This comprehensive evaluation method provides a more comprehensive perspective for fully understanding the environmental benefits of carbon trading policies. Second, this study conducted a detailed analysis of the ER effects in different pilot regions, revealing the heterogeneity of policies in different regions. This discovery helps to understand the applicability and effectiveness of policies in different economic, social, and environmental contexts, providing a scientific basis for regional differentiated policy design. Through the above research, it has been proven that carbon trading policies can effectively reduce GHG and air pollutant emissions, providing empirical support for the effectiveness of carbon trading policies. This will help promote more regions and countries to adopt similar policy tools to address global climate change and air pollution issues. Although the research results of this article have important enlightening significance, there are also some limitations: first, this study incorporates Shenzhen into Guangdong Province for analysis, which may to some extent affect the accuracy of the results. Future research could consider more detailed regional divisions to obtain more accurate evaluations of policy effectiveness. Second, this study only analyzes the SER effect from a theoretical perspective and do not quantitatively evaluate the policy design mechanism. Future research can further quantify key parameters in policy design, such as carbon prices, quota allocation methods, etc., to more comprehensively evaluate the effectiveness and efficiency of policies.

5 Conclusion

To cope with climate warming and reduce the emissions of GHG and AP, all countries in the world have begun to realize CT policies. Since GHG and AP are homologous, the CT policy is bound to have some effects on the emissions of other APs when promoting carbon ER. In order to explore the SER effect of RCT policy, the study analyzed the SER effect of CT using DID and SCM. The main findings were as follows: Implementing carbon trading policies could significantly reduce annual CO₂ emissions by about 54.13 million tons. These policies also had a synergistic effect on reducing SO₂ and NO_x emissions by 176,100 and 112,500 tons, respectively. Among the six PAs, Hubei Province had the most significant CO₂ ER effect, with a reduction of approximately 66.25 million tons. In addition, Hubei Province and Beijing performed well in coordinating the reduction of SO₂ emissions. Chongqing, Shanghai, and Hubei Province, on the other hand, performed more significantly in coordinating the reduction of NO_x emissions. The above results show that the CT policy can effectively promote the reduction of GHG and AP. It can be inferred that carbon trading PAs can adjust their energy consumption structure by reducing total energy consumption and improving enterprise energy utilization efficiency. Although this will increase

the production costs of enterprises, it can encourage them to promote economic growth through value enhancement and technological innovation compensation, which is the key path for carbon trading mechanisms to bring economic dividends. However, due to limitations in data acquisition, the study is unable to consider all factors that may affect ER. Additionally, incorporating Shenzhen into the Guangdong Province analysis impacts the accuracy of the results. Therefore, in the future, the effectiveness and efficiency of the carbon trading policy will be evaluated more comprehensively by quantifying and evaluating key parameters such as carbon prices and quota allocation methods. At the same time, the study needs to consider the characteristics of more regions and industries, and explore the applicability and effectiveness of carbon trading policies in different contexts.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

QY: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Writing – original draft. SY: Conceptualization, Resources, Software, Supervision, Validation, Visualization, Writing – review and editing.

References

- Abbas, A., Waseem, M., Ahmad, R., Khan, K. A., Zhao, C., and Zhu, J. (2022). Sensitivity analysis of greenhouse gas emissions at farm level: case study of grain and cash crops. *Environ. Sci. Pollut. Res.* 29 (54), 82559–82573. doi:10.1007/s11356-022-21560-9
- Athey, S., and Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *J. Econ.* 226, 62–79. doi:10.1016/j.jeconom.2020.10.012
- Ben-Michael, E., Feller, A., and Rothstein, J. (2021). The augmented synthetic control method. *J. Am. Stat. Assoc.* 116, 1789–1803. doi:10.1080/01621459.2021.1929245
- Bhaktikul, K., Aroonsrimorakot, S., Laiphrakpam, M., and Paisantanakij, W. (2021). Toward a low-carbon tourism for sustainable development: a study based on a royal project for highland community development in Chiang Rai, Thailand. *Environ. Dev. Sustain* 23, 10743–10762. doi:10.1007/s10668-020-01083-4
- Callaway, B., and Sant' Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *J. Econ.* 225, 200–230. doi:10.1016/j.econometrics.2020.12.01
- Cole, M. A., Elliott, R. J. R., and Liu, B. (2020). The impact of the Wuhan Covid-19 lockdown on air pollution and health: a machine learning and augmented synthetic control approach. *Environ. Resour. Econ.* 76, 553–580. doi:10.1007/s10640-020-00483-4
- Deng, L., and Shangguan, Z. P. (2021). High quality developmental approach for soil and water conservation and ecological protection on the Loess Plateau. *Front. Agric. Sci. Eng.* 8, 501–511. doi:10.15302/j-fase-2021-1425
- Denton, G., Chi, H., and Gursay, D. (2022). An examination of critical determinants of carbon offsetting attitudes: the role of gender. *J. Sustain Tour.* 30, 1539–1561. doi:10.1080/09669582.2021.1920966
- Eyuboglu, K., and Uzar, U. (2020). The impact of tourism on CO₂ emission in Turkey. *Curr. Issues Tour.* 23, 1631–1645. doi:10.1080/13683500.2019.1636006
- Fan, X., Xu, Y., Nan, Y., Li, B., and Cai, H. (2020). Impacts of high-speed railway on the industrial pollution emissions in China: evidence from multi-period difference-in-differences models. *Kybernetes* 49, 2713–2735. doi:10.1108/k-07-2019-0499
- Hao, X., Wang, J., Sun, P., Shen, D., and Tian, L. (2021). Low-carbon economic operation for integrated energy system considering carbon trading mechanism. *Energy Sci. Eng.* 9, 2064–2078. doi:10.1002/ese3.967
- Huang, Y., Elahi, E., You, J., Sheng, Y., Li, J., and Meng, A. (2024). Land use policy implications of demographic shifts: analyzing the impact of aging rural populations on agricultural carbon emissions in China. *Land Use Policy* 147, 107340. doi:10.1016/j.landusepol.2024.107340
- Kou, P., Han, Y., Qi, X., and Li, Y. (2021). Does China's policy of carbon emission trading deliver sulfur dioxide reduction co-benefits? *Environ. Dev. Sustain.* 24 (5), 6224–6245. doi:10.1007/s10668-021-01699-0
- Kreibich, N., and Hermwille, L. (2021). Caught in between: credibility and feasibility of the voluntary carbon market post-2020. *Clim. Policy* 21, 939–957. doi:10.1080/14693062.2021.1948384
- Li, Y., Dai, J. M., and Zhao, H. (2023). Analysis of collaborative emission reduction of air pollutants and greenhouse gases under carbon neutrality target: a case study of Beijing, China. *Clean Technol. Environ. Policy* 26 (11), 3995–4008. doi:10.1007/s10098-023-02524-0
- Liu, Z., Luo, Z., Zhou, Y., Li, S., and Cheng, P. (2020). Estimation of the momentum coefficient of synthetic jet in flow separation control over an airfoil. *PI Mech. Eng. G-J Aer.* 234, 2050–2061. doi:10.1177/0954410020926656
- Mordue, T., Moss, O., and Johnston, L. (2020). The impacts of onshore-windfarms on a UK rural tourism landscape: objective evidence, local opposition, and national politics. *J. Sustain Tour.* 28, 1882–1904. doi:10.1080/09669582.2020.1769110
- Nokhrina, O. I., Gizatulina, R. A., Golodova, M. A., Proshunin, I. E., Valuev, D. V., Martyushev, N. V., et al. (2022). Alloying and modification of iron-carbon melts with natural and man-made materials. *Metallurgist* 65, 1429–1448. doi:10.1007/s11015-022-01289-z
- Okafor, C. C., Ibekwe, J. C., Nzekwe, C. A., and Ikeotuonye, C. M. (2022). Estimating emissions from open-burning of uncollected municipal solid waste in Nigeria. *AIMS Environ. Sci.* 9, 140–160. doi:10.3934/environsci.2022011
- Pan, Y., Weng, G., Li, C., and Li, J. (2021). Coupling coordination and influencing factors among tourism carbon emission, tourism economic and tourism innovation. *Int. J. Environ. Res. Public Health* 18, 1601. doi:10.3390/ijerph18041601
- Qi, X., and Han, Y. (2020). How carbon trading reduces China's pilot emissions: an exploration combining LMDI decomposition and synthetic control methods. *Pol. J. Environ. Stud.* 29, 3273–3284. doi:10.15244/pjoes/115212

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- Shi, X., Xu, Y., and Sun, W. (2023). Correction to: evaluating China's pilot carbon Emission Trading Scheme: collaborative reduction of carbon and air pollutants. *Environ. Sci. Pollut. Res. Int.* 30 (5), 11357–11358. doi:10.1007/s11356-022-25009-x
- Solaymani, S. (2019). CO2 emissions patterns in 7 top carbon emitter economies: the case of transport sector. *Energy* 168, 989–1001. doi:10.1016/j.energy.2018.11.145
- Tian, T., Luo, W., Tan, J., Jiang, Y., Zhang, H., Pan, W., et al. (2021). The timing and effectiveness of implementing mild interventions of COVID-19 in large industrial regions via a synthetic control method. *Stat. Interface* 14, 3–12. doi:10.4310/20-sii634
- Venkataramani, A. S., Bair, E. F., O'Brien, R. L., and Tsai, A. C. (2020). Association between automotive assembly plant closures and opioid overdose mortality in the United States: a difference-in-differences analysis. *Jama Intern Med.* 180, 254–262. doi:10.1001/jamainternmed.2019.5686
- Wei, Y., Wang, X., Zheng, J. H. J., Ding, Y., and Han, J. (2023). The carbon reduction effects of stepped carbon emissions trading and carbon capture and storage on hybrid wind-PV-thermal- storage generation operating systems. *Environ. Sci. Pollut. Res.* 30 (38), 88664–88684. doi:10.1007/s11356-023-28644-0
- Wu, X., Tian, Z., and Guo, J. (2022). A review of the theoretical research and practical progress of carbon neutrality. *Sustain. Oper. Comput.* 3, 54–66. doi:10.1016/j.susoc.2021.10.001
- Xia, S., and Yang, Y. (2022). Examining spatio-temporal variations in carbon budget and carbon compensation zoning in Beijing-Tianjin-Hebei urban agglomeration based on major functional zones. *J. Geogr. Sci.* 32, 1911–1934. doi:10.1007/s11442-022-2029-y
- Yang, J., Yang, R., Chen, M. H., Xi, J., and Zhi, Y. (2021). Effects of rural revitalization on rural tourism. *J. Hosp. Tour. Manag.* 47, 35–45. doi:10.1016/j.jhtm.2021.02.008
- Yang, Y., and Yao, G. (2023). Fresh agricultural products supply chain coordination considering consumers' dual preferences under carbon cap-and-trade mechanism. *J. Ind. Manag. Optim.* 19, 2071–2090. doi:10.3934/jimo.2022032
- Zhang, Y., and Umair, M. (2023). Examining the interconnectedness of green finance: an analysis of dynamic spillover effects among green bonds, renewable energy, and carbon markets. *Environ. Sci. Pollut. Res.* 30, 77605–77621. doi:10.1007/s11356-023-27870-w
- Zhang, Y., Zhang, H., Fu, Y., Wang, L., and Wang, T. (2021). Effects of industrial agglomeration and environmental regulation on urban ecological efficiency: evidence from 269 cities in China. *Environ. Sci. Pollut. Res.* 28, 66389–66408. doi:10.1007/s11356-021-15467-0