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Energy and Environment Impact of Carbon Credit on Emission Reduction in China

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Abstract. Carbon credits serve as emission reduction certificates for projects that reduce GHG emissions, while carbon emission trading policies serve as a market-based carbon trading mechanism. This study is based on a quasi-natural experiment of carbon emission trading pilot programs in multiple regions of China. Using panel data from 30 provinces from 2005 to 2021, it examines the direct impact of carbon trading policies on carbon emission intensity. The policy effect was tested using a DID model, supplemented by a series of tests to verify the model's stability, and the heterogeneity of emission reduction in each pilot area was analyzed using the synthetic control method. The study found that carbon emissions trading policies work synergistically to reduce SO_2 and $PM_{2.5}$ emissions, but have little effect on nitrogen oxides. The carbon trading system has significant potential for carbon emission reduction in China, but it needs to strengthen price signals and market mechanisms to improve its effectiveness.

1 Introduction

Addressing severe climate change has become a global challenge, and mitigating GHG emissions has become a consensus among countries. Since the early 1990s, the international community has been seeking a mechanism for jointly addressing climate change. The signing of the Kyoto Protocol is an important milestone in the evolution of international climate governance, as it quantifies GHG emission reduction quotas and timelines[1]. The Kyoto Protocol introduced three market-based emission reduction mechanisms, among which the CDM (Clean Development Mechanism) allows developed and developing countries to implement emission reduction projects and obtain emission reduction credits[2].

As the world's largest carbon emitter, China proposed the dual carbon goal at the United Nations General Assembly in 2020: to peak carbon emissions before 2030 and achieve carbon neutrality before 2060. Based on the dual carbon objectives, China has been conducting carbon emission trading pilot programs in multiple provinces and cities since 2011[3]. From 2013 to 2014, seven provinces and cities established carbon trading systems based on their regional industrial structure, energy consumption characteristics, and carbon emission situation, and launched carbon trading market. The Fujian carbon market was launched in 2016[4].

Within the framework of China's carbon emissions trading market system, this study treats carbon trading policies as a quasi-natural experiment and constructs a DID model of carbon intensity in pilot areas by analyzing panel data using Stata software. This model studies the direct emission reduction effects of carbon trading policies and their driving mechanisms:(1) Examines three factors—carbon trading policy, carbon price, and trading volume, to quantitatively assess their impact on carbon emission intensity.(2) Analyzes the emission reduction pathways of carbon trading from the perspectives of energy consumption and pollutants.(3) The results and the heterogeneity of the study area were verified using the synthetic control method.

2 Literature Review

In theory, carbon emission trading systems (ETS) can reduce carbon intensity by internalizing environmental externalities and through the incentive effect of market-based regulation[5]. Porter Hypothesis[6] argues that environmental protection and economic development are not simply contradictory; reasonable environmental regulations can stimulate technological innovation and improve production efficiency, and partially or completely offset the negative costs of environmental regulations. According to the study of panel data on Chinese enterprises by Wang et al[7], mandatory environmental policies or energy consumption constraints will increase enterprises' green innovation investment and patent output after a certain lag period. Based on an understanding of Porter's hypothesis, a stable and predictable carbon price will incentivize enterprises to increase investment in green technologies, thereby improving energy efficiency and achieving sustained emission reductions, ultimately resulting in benefits for both the environment and the economy.

Marginal emission reduction cost (MAC) represents the additional cost required to reduce emissions by one unit under given conditions. The principle of cost minimization states that, under a given overall emission

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reduction target, equalizing the marginal emission reduction costs of different emission reduction entities (enterprises, factories, or sectors) can achieve the target at the lowest overall social cost[8]. ETS is one of the institutional tools for minimizing costs. By assigning prices to carbon emission rights and allowing trading between different emission sources, it automatically transmits price signals among participating entities, thereby driving marginal costs towards convergence. Similarly, the initial allocation method of quotas does not change long-term efficiency, but it does affect income redistribution and short-term behavior. MAC can vary significantly between industries and firms: some emission reduction measures can be effective within a lower cost range (such as energy efficiency improvements), while others are more costly in the initial stages (such as carbon capture and storage). Therefore, practical design must balance the strength of price signals with market stability.

3 Model Description

3.1. DID Model Construction

Data from 2005 to 2021 from 30 provinces in China were selected as the research object. The 30 provinces were divided into experimental and control groups based on whether they were carbon emission trading pilots. The experimental group included seven provinces: Shanghai, Beijing, Guangdong, Tianjin, Hubei, Chongqing, and Fujian, while the control group consisted of the remaining 23 provinces. The pilot programs for China's carbon trading rights policy in pilot provinces mainly started at the end of 2013 and the beginning of 2014, so 2013 was selected as the year of policy impact.

Based on the research on the difference-in-differences principle by Bacon[9]. Construct the DID models, expressed as follows:

$$lnCI_{it} = \beta_0 + \beta_1 policy_{it} * post_{it} + \beta_X X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

$$lnCI_{it} = \beta_0 + \beta_2 lnprice_{it} * post_{it} + \beta_X X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

$$lnCI_{it} = \beta_0 + \beta_3 lnvolume_{it} * post_{it} + \beta_X X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{3}$$

Where, $lnCI_{it}$ represents the logarithm of the carbon emission intensity of province i at time t; X_{it} represents the selected control variables, including economic development level, industrial structure, urbanization level, degree of openness to the outside world, population size, and environmental protection investment; $policy_{it}$ is the policy dummy variable, indicating whether it is a pilot area for carbon trading rights policy, with a value of 1 if it is a pilot area and 0 otherwise; $post_{it}$ is a time dummy variable, representing the time of policy implementation, with a value of 1 if t is in or after the year of policy impact, and 0 otherwise; in models 2 and 3, $lnprice_{it}$ and $lnvolume_{it}$ are continuous explanatory variables, $lnprice_{it}$ represents the logarithmic value of carbon trading price in province i's carbon market at time t, which is expressed as the logarithmic value of the annual average carbon transaction price in this paper; $lnvolume_{it}$ represents the logarithmic value of the annual total transaction volume in province i's carbon market; $policy_{it}*post_{it}$, $lnprice_{it}*post_{it}$, and $lnvolume_{it}*post_{it}$ are interaction terms of the dummy variables. μ_i and γ_t represent the individual fixed effect and time fixed effect, respectively, and ε_{it} represents the error term. β_0 is the constant term of the equation, i.e., the intercept; β_1, β_2, and β_3 are the coefficients of the three model interaction terms, respectively. β_1, β_2, and β_3 characterize the impact of carbon trading policies, carbon trading prices, and carbon trading scale on carbon intensity before and after policy implementation; β_X represents the coefficient of the control variable, reflecting the marginal impact of the control variable on carbon intensity, and is used to eliminate potential confounding factors.

In the models, *lnCI* (carbon emission intensity) is the dependent variable, and it is calculated using the logarithmic measure of carbon dioxide emissions per unit of GDP. $policy_{it}*post_{it}$, $lnprice_{it}*post_{it}$, and $lnvolume_{it}*post_{it}$ are the core explanatory variables. Among them, *policy∗post* (carbon emission trading policy) is represented by the interaction term between carbon emission trading policy and time dummy variable; *lnprice∗post* (carbon emission trading rights price) is represented by the interaction term between the logarithm of the annual average transaction price of carbon trading and the time dummy variable; *lnvolume∗post* (carbon emission trading volume) is represented by the interaction term of the logarithm of the annual total carbon trading volume and the time dummy variable. Control variables include *lnpcgdp* (economic development level), using the logarithm of per capita GDP; *ins* (industrial structure), expressed as the proportion of the secondary industry in total GDP; *ur* (urbanization level) is measured by the ratio of urban population to the total population of a region; *fdi* (openness to the outside world), measured by the ratio of foreign direct investment to total GDP; *lnpop* (population size) is a logarithmic measure of the year-end resident population per unit area in each region; *epi* (environmental protection investment) is expressed as a percentage of regional environmental protection public spending relative to total GDP.

3.2 Synthetic Control Method

The synthetic control method is a quasi-experimental method used to assess the dynamic changes of dependent variables in a single or a small number of individuals after a policy intervention. Its core idea is to construct a counterfactual reference group for the intervention group by weighting the individual weight vectors of the control group, thereby estimating the treatment effect[10].

The principle is that for the carbon emission intensity of $j+1$ regions in period t (T=1, 2...T), one region is the treatment group, i.e., the pilot province for carbon trading. Assume that the implementation time of the policy pilot program in province i is t=T_0 ($1 \le T_0 \le T$), then let the carbon intensity of province i as a non-policy pilot and the policy pilot in period t be represented as C_{it}^E and C_{it}^N, respectively. When $t \le T_0$, province i is not affected by the carbon trading emission rights policy, and $C_{it}^E = C_{it}^N$;

When $t \geq T_0$, the carbon emission trading policy has an impact on province *i*. Its emission reduction effect is expressed as:

$$\tau_{it} = C_{it}^N - C_{it}^E \quad (4)$$

Where τ_{it} represents the total emission reduction effect of province *i* in period *t*.

Based on the parametric regression factor model proposed by Abadie and Gardeazabal[11], C_{it}^N is estimated.

$$C_{it}^N = \beta_i X_i + \lambda_i U_i + \gamma_t + \varepsilon_{it} \quad (5)$$

Where X_i represents the selected control variables, including *lnpcgdp*, *ins*, *ur*, *fdi*, *lnpop*, and *epi*; β_i represents the coefficients of the control variables; λ_i represents the common factor variables that are difficult to observe; U_i is the individual fixed effect; and ε_{it} represents the error term.

3.3 Mechanism Testing Model

To examine the emission reduction effect of carbon emission trading policies at energy level and the environmental synergistic emission reduction level, the following new mechanism models (6, 7, and 8) are constructed to explore the identification of influencing mechanisms:

$$Mec_{it} = \alpha_0 + \alpha_1 policy_{it} * post_{it} + \alpha_X X_{it} + \mu_i{}' + \gamma_t{}' + \varepsilon_{it}{}' \quad (6)$$

$$Mec_{it} = \alpha_0 + \alpha_2 lnprice_{it} * post_{it} + \alpha_X X_{it} + \mu_i{}' + \gamma_t{}' + \varepsilon_{it}{}' \quad (7)$$

$$Mec_{it} = \alpha_0 + \alpha_3 lnvolume_{it} * post_{it} + \alpha_X X_{it} + \mu_i{}' + \gamma_t{}' + \varepsilon_{it}{}' \quad (8)$$

In this model, *Mec* is the mechanism variable. In analyses involving energy and environmental synergistic emission reduction, the respective explained variables replace this mechanism variable. α_0 is the constant term in the model equations, α_1, α_2, and α_3 are the coefficients of the three model interaction terms, and α_X represents the coefficients of the control variables. μ_i' and γ_t' represent the individual fixed effect and time fixed effect, respectively, and ε_{it}' represents the error term. The remaining parameters in models 6, 7, and 8 are represented in the same way as in models 1, 2, and 3, respectively.

The energy-level mechanism variable uses energy intensity as an indicator. The environmental synergistic emission reduction mechanism variables are represented by the logarithm of regional sulfur dioxide emissions ($lnSO_2$), the logarithm of nitrogen oxide emissions ($lnNO_X$), and the average concentration of PM2.5 (*PM2.5*), with the unit of *PM2.5* being $\mu g/m^3$.

4 Simulation Results and Discussion

4.1. Model Robustness Test

To ensure the robustness of the model, it is necessary to first perform a robustness test on the model to guarantee the reliability of the regression results.

Fig.1 shows that the true estimates for the event years before the policy implementation fluctuated around 0, and the confidence intervals all covered the zero axis, further proving that there was no significant difference in the changes in carbon intensity between the experimental group and the control group before the policy implementation, and passed the parallel trend test.

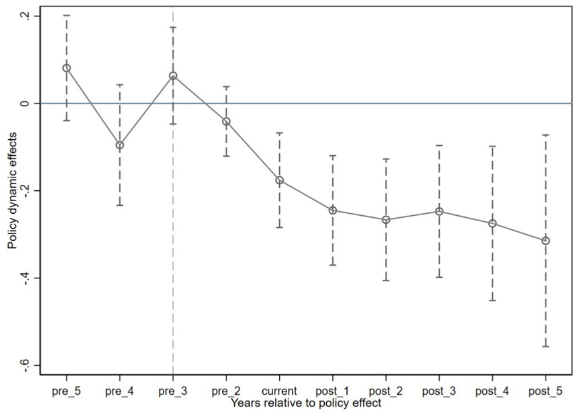

Fig. 1. Parallel Trend Dynamic Effect Test Chart.

The principle of the placebo test is to use random sampling in the research sample and obtain results through a large number of repeated experiments, thereby comparing the results with the actual policy effect. The sample included 119 samples from 7 provinces that implemented carbon emission trading policies. Therefore, 119 samples were randomly selected from the total 510 samples as a virtual experimental group. This selection process was repeated 1000 times to obtain the kernel density and p-value distribution of the placebo test.

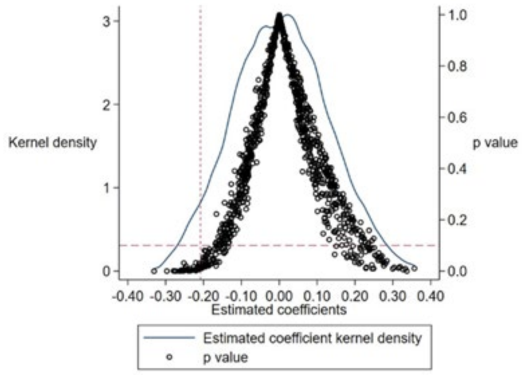

Fig. 2. Placebo Test Results of Kernel Density and P-value Distribution.

As shown in Fig.2, the kernel density curves of the estimated coefficients generally fit a normal distribution, demonstrating that the results of the randomized virtual experiment are statistically reliable, with no obvious outliers or systematic biases. The estimated coefficients of the randomly selected virtual experimental group are concentrated near 0, far from the true value of the policy effect regression coefficient (-0.208), meaning that the observed policy effect is very weak or non-existent under random conditions. The p-values of the coefficients are mostly above the horizontal dashed line (p>0.1), indicating that the policy effect of the randomly sampled virtual experimental group is not significant. Therefore, the robustness of the model is proven.

4.2. Policy, Pricing and Volume Effects for Carbon Emissions Trading

Table 1 shows the benchmark regression results for models 1, 2, and 3. The results show that, regardless of the presence or absence of control variables, *policy∗post* (policy effect coefficient), *lnprice∗post* (carbon trading price effect coefficient), and *lnvolume∗post* (carbon trading volume effect coefficient) are all significantly negative at the 1% confidence level. Therefore, the carbon emissions trading policy has a substantial emission reduction effect; Meanwhile, driven by the market, higher carbon trading prices and the scale of carbon trading also contribute to emission reduction.

Table 1. Benchmark Regression Results of Models.

Variable	Explained variable: ***lnCI***					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
policy∗post	-0.268*** (-7.55)			-0.208*** (-4.60)		
lnprice∗post		-0.079*** (-6.96)			-0.064*** (-4.38)	
lnvolume∗post			-0.017*** (-6.63)			-0.011*** (-3.51)
lnpcgdp				-0.988*** (-6.73)	-0.981*** (-6.65)	-0.995*** (-6.67)
ins				-0.177 (-0.54)	-0.221 (-0.68)	-0.230 (-0.70)
ur				2.065*** (3.41)	1.879*** (3.03)	2.165*** (3.44)
fdi				-0.103 (-0.16)	0.044 (0.07)	-0.022 (-0.03)
lnpop				-0.423 (-1.64)	-0.438* (-1.74)	-0.508* (-1.95)
epi				-0.125 (-0.07)	0.521 (0.28)	0.388 (0.21)
_cons	0.653*** (70.63)	0.648*** (69.96)	0.646*** (69.53)	12.261*** (5.37)	12.376*** (5.47)	12.750*** (5.49)
N	510	510	510	510	510	510
R^2	0.949	0.949	0.948	0.957	0.957	0.957

Note: ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% statistical levels, respectively. The values in parentheses are t-values. The same applies to the following benchmark regression tables.

4.3. Regional Emission Reduction Heterogeneity

To performed a weighted fitting of the carbon emission intensity in the seven pilot areas of the carbon emission trading policy to generate a trend comparison chart of the actual and synthetic regional carbon emission intensity. When the synthetic value can track the actual value well before the policy is implemented, i.e., the difference is small, it indicates that the fitting quality is good. When the actual carbon intensity of the pilot areas is lower than its synthetic value after the policy is implemented, it can be interpreted as the carbon trading emission rights policy having a significant emission reduction effect on the region. As shown in Fig.3, the synthetic effects of the carbon trading pilot programs in Tianjin and Hubei were good, with Hubei showing good emission reduction results and Tianjin showing less significant results. The synthetic effects of the carbon trading pilot programs in Chongqing and Fujian were moderate, with Chongqing showing good emission reduction results and Fujian's results being less significant. The synthetic effects of the carbon trading pilot programs in Shanghai, Beijing, and Guangdong were poor.

The differences in policy effectiveness among pilot regions may be attributed to variations in policy design and economic conditions. Beijing and Shanghai have the highest GDP per capita among all provinces in China, and their tertiary industries account for a large proportion of their GDP. Beijing's energy consumption structure has a low proportion of coal, which is significantly different from most other provinces that rely on coal-fired power generation[12], and Shanghai has a relatively high level of foreign investment. Furthermore, Beijing is the capital of China, and its systems differ somewhat from those of other provinces and regions. Guangdong is one of China's most important manufacturing and exporting provinces, currently boasting the highest GDP among all provinces, and its industrial structure and economic development level are among the best. Therefore, it is difficult to fit these three provinces well. Industry coverage and industrial structure are also crucial: regions with a higher proportion of high-emission industries may have greater emission reduction potential, which may explain why

Hubei and Chongqing have achieved good emission reduction results.

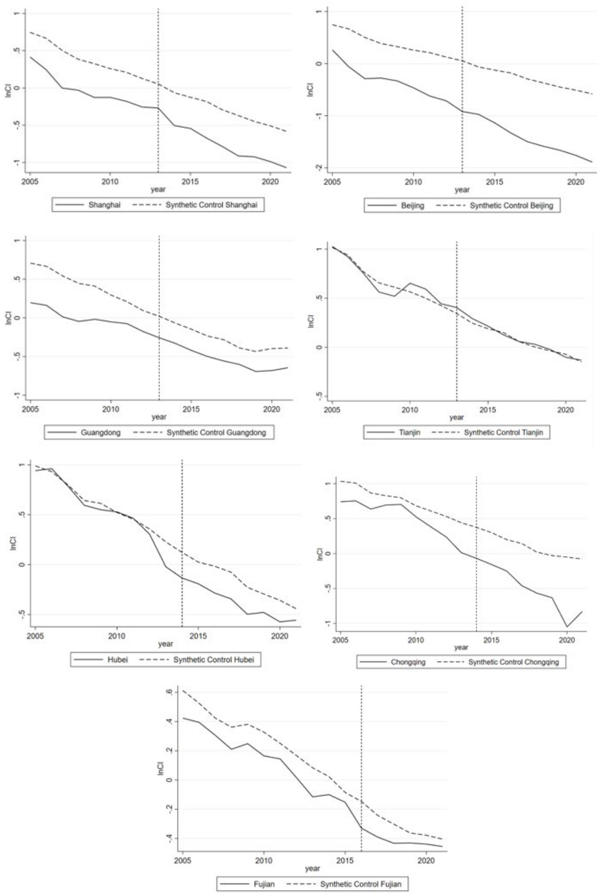

Fig. 3. Comparison of Synthesized and Actual Carbon Intensity Values in Pilot Provinces.

4.4. Energy and Environmental Impact Analysis

Use energy intensity as a mechanism variable to examine the mechanism by which carbon emission trading policies reduce emissions through energy use pathways. As shown in Table 2, this indicates the implementation of the carbon emission trading rights policy and, to some extent, the increase in carbon trading prices contribute to a decrease in energy intensity and a reduction in coal consumption per unit of GDP, and can promote energy efficiency upgrades and fuel structure optimization, thereby promoting emission reduction in pilot areas. This proves that the carbon emission trading rights policy can promote emission reduction by optimizing the energy structure.

Table 2. Energy-level Mechanism Test Regression Results.

Variable	Explained variable: *Energy intensity*		
	(1)	**(2)**	**(3)**
policy∗post	-0.020**		
	(-0.61)		
lnprice∗post		-0.015*	
		(-1.70)	
lnvolume∗post			-0.003
			(-1.29)
lnpcgdp	-0.764***	-0.748***	-0.752***
	(-4.81)	(-4.76)	(-4.72)
ins	0.993***	0.993***	0.988***
	(2.93)	(2.91)	(2.90)
ur	-1.422***	-1.595***	-1.525***
	(-3.71)	(-4.09)	(-3.92)
fdi	-1.031**	-0.995**	-1.010**
	(-2.19)	(-2.13)	(-2.16)
lnpop	0.308	0.356*	0.338
	(1.46)	(1.75)	(1.65)
epi	-0.242	-0.167	-0.197
	(-0.11)	(-0.08)	(-0.09)
_cons	7.732***	7.407***	7.504***
	(3.33)	(3.27)	(3.26)
N	510	510	510
R^2	0.938	0.939	0.939

The mechanism model was used to detect different pollutant gases and to test the synergistic emission reduction effect of the carbon emission trading policy. As shown in Table 3, among these three pollutant emissions, the synergistic emission reduction effect of the carbon emission trading policy is mainly reflected in the reduction of sulfur dioxide emissions and PM2.5 concentrations.

Table 3. Environmental Mechanism Test Regression Results.

Variable	Explained variable		
	(1) $lnSO_2$	**(2) lnNOx**	**(3) PM2.5**
policy∗post	-0.314***	-0.066	-3.910***
	(-4.34)	(-1.51)	(-4.26)
lnpcgdp	-0.377*	0.552***	-0.616
	(-1.73)	(3.05)	(-0.24)
ins	0.669	-0.591	-4.513
	(1.28)	(-1.58)	(-0.73)
ur	6.822***	-0.416	-3.273
	(5.24)	(-0.74)	(-0.26)
fdi	-0.105	-0.018	44.836***
	(-0.10)	(-0.03)	(2.60)
lnpop	-1.174***	-0.068	0.067
	(-3.17)	(-0.26)	(0.02)
epi	-2.731	4.000**	-85.957**
	(-0.95)	(2.55)	(-2.44)
_cons	19.010***	7.789***	55.544
	(6.26)	(3.68)	(1.49)
N	510	330	510
R^2	0.955	0.977	0.955

5 Conclusion

China's carbon emissions trading policy has had a significant impact on reducing carbon intensity and promoting emissions reduction in pilot provinces. The market and scale of carbon trading have also played an important role in promoting emissions reduction. The study of emission reduction effects in seven pilot provinces revealed that China's carbon emission trading policy has heterogeneous effects on different regions. In addition, China's carbon emissions trading policy has promoted the reduction of energy intensity, the improvement of energy structure, and the synergistic reduction of environmental pollutants.

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References

1. M. Azad, Open Journal of Social Sciences 2025, **145** (2025). 10.4236/jss.2025.138009
2. Konstantinos Bisiotis, D. Christopoulos, and G. Tzougas, Journal of Forecasting **34**, (2025). 10.1002/for.70054
3. S. Zeng, Q. Fu, F. Haleem, Y. Shen, W. Peng, M. Ji, Y. Gong, and Y. Xu, Humanities and Social Sciences Communications **11**, (2024). 10.1057/s41599-024-03646-6
4. X. Yang, J. Zhang, L. Bi, and Y. Jiang, International Journal of Environmental Research and Public Health **20**, 4421 (2023). 10.3390/ijerph20054421
5. Y. Han, C. Zhe, and X. Liu, Energy Reports **9**, 3787 (2023). 10.1016/j.egyr.2023.02.023
6. M. E. Porter and C. van der Linde, Journal of Economic Perspectives **9**, 97 (1995). 10.1257/jep.9.4.97
7. M. Wang, Y. He, J. Zhou, and K. Ren, International Journal of Environmental Research and Public Health **19**, 6882 (2022). 10.3390/ijerph19116882
8. H. Chen and Y. Wang, Utilities Policy **93**, 101883 (2025). 10.1016/j.jup.2024.101883
9. A. Gupta, Handbook of Environmental and Sustainable Finance 3 (2016). 10.1016/b978-0-12-803615-0.00001-7
10. E. Ben-Michael, A. Feller, and J. Rothstein, Journal of the American Statistical Association **116**, 1789 (2021). 10.1080/01621459.2021.1929245
11. A. Abadie and J. Gardeazabal, American Economic Review **93**, 113 (2003). 10.1257/000282803321455188
12. X. Zhu, J. Che, X. Niu, N. Cao, and G. Zhang, Sustainability **17**, 1364 (2025). 10.3390/su17041364