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Can low-carbon transition reduce industrial pollution emissions? --Evidence from Low Carbon City Pilots in China

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ABSTRACT

Achieving a synergistic effect of carbon emission and pollution reduction is important to China. However, whether the low-carbon transformation measures can simultaneously achieve the reduction of industrial pollution remains unclear. This paper takes the low-carbon city pilots as a quasi-natural experiment, combining the time-varying difference in difference (DID) model and the spatial Durbin model to explore whether the low-carbon city policy can reduce industrial SO_2 emissions. The results show that the low-carbon city policy significantly reduces local industrial SO_2 emissions, but raises the emissions of neighboring cities. For the mechanism, the low-carbon city policy promotes green technology innovation to reduce industrial SO_2 emissions. In addition, low-carbon city policy shows a spatial spillover effect by influencing local industrial enterprises and foreign direct investment to transfer to non-pilot cities.

Keywords: Low-carbon city pilots; carbon emission and pollution reduction synergies; quasi-natural experiments; spatial spillovers

1. INTRODUCTION

Countries around the world have put forward low-carbon transformation goals against climate change[1]. China, as a major energy consumer, has actively responded to climate change by proposing the goal of carbon peaking and carbon neutrality. Low-carbon city pilot policy is an important initiative for China's low-carbon transition [2]. The pilots were established to promote sustainable urban development[3]. After the policy was implemented, pilot cities began to promote structural changes, especially in high-carbon-emitting industries. The high carbon emission industries are frequently characterized by high pollutant emitting[4]. Therefore, promoting a low-carbon transition has the potential to simultaneously reduce industrial pollution. Currently, China attaches great importance to promoting the synergy of pollution and carbon reduction [5].

Studies have been conducted on whether the low-carbon transition can realize the synergistic effect of reducing pollution emissions. Many scholars believe that the measures to promote low-carbon transition are conducive to reducing pollution. Scholars take environmental regulations as quasi-natural experiments and use the DID model to test whether the low-carbon transition policy can realize the synergistic effect of pollution reduction[6–8]. This approach solves the endogeneity problem to a certain extent. However, the low-carbon transition policy not only has impacts on the local market but also on the pollution emissions of neighboring cities through industrial transfer[9,10]. To address this, many scholars have researched the spatial spillover effects of environmental regulations[11,12]. The spatial spillover effects are generally generated through the transfer of polluting enterprises and technological progress. Combining the DID and spatial effect model can be used to explore whether low-carbon measures can achieve the synergistic effect of reducing pollution[13,14].

This paper takes the launching of the first and second batches of low-carbon city pilots to test the impact of the low-carbon city policy on SO_2 emissions. We examine the spatial effects and mechanisms in terms of the exit of enterprises, the transfer of foreign investment, and the innovation of green technology. We aim to provide useful insights for realizing the synergistic effect of carbon emission and pollution reduction.

2. DATA SOURCE AND EMPIRICAL MODEL

2.1 Data source

This is a paper for the international conference on energy, ecology and environment 2023 (ICEEE2023), Aug. 14-18, 2023, London, UK.

This paper collects city-level data in China from 2007-2016, sourced from the statistical yearbooks of Chinese cities. Cities with missing values are excluded. In addition, spatial spillovers at the city level generally affect neighboring cities, so spatially non-neighboring cities are excluded. Totally 268 cities with 10 years of data are selected in this study. Referring to the government's "Notice on the Pilot Work of Low-Carbon Provinces, Regions and Cities" issued in 2010, the first batch of pilots included both provinces and cities, which accounted for about 54.16% of the country's total carbon emissions. The second batch of pilots was announced at the end of 2012, including 33 cities. In 2017, the third batch of low-carbon pilot cities was announced. However, due to data constraints, they were not included in the analysis. The experimental and control groups were identified, as shown in Fig. 1, with pilot cities included in blue and not included in green.

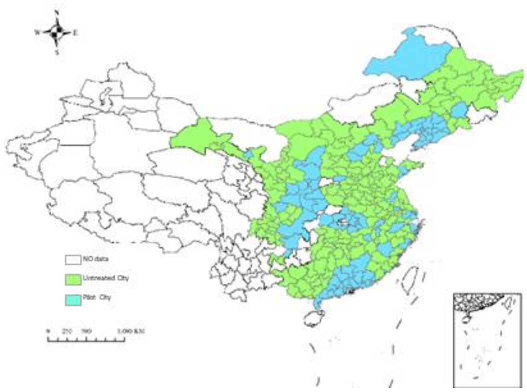

Fig. 1 Low-carbon city pilot cities and cities in the control group

2.2 *DID model and spatial effect model*

State the objectives of the work and provide an adequate background, avoiding a detailed literature survey or a summary of the results.

2.3 Section of material and methods

The DID model is widely used in policy evaluation to estimate the causal effects by comparing the differences before and after the policy intervention. The implementation of the low-carbon city pilot can be regarded as a quasi-natural experiment. Since the policy pilots are implemented in batches, this paper uses a time-varying DID model for estimation with the following basic settings:

$$y_{it} = \beta_0 + \beta_1 DID_{it} + \sum_{s=1}^{n} \beta_s x_s + \mu_i + \delta_t + \varepsilon_{it}$$

y_{it} is the dependent variable. DID_{it} is the term representing the policy effect, taking 0 before a city becomes a pilot and 1 after it becomes a pilot. x is the control variable. β is the estimated coefficient. μ_i is the city fixed effect. δ_t is the time fixed effect. ε_{it} is the error term.

The spatial model is combined with a DID model:

$$y_{it} = \rho W y_{it} + \beta_1 DID_{it} + \beta_2 W \times DID_{it} + \gamma_1 X + \gamma_2 WX + \mu_i + \delta_t + \lambda W \varepsilon_{it}$$

W is the spatial weight matrix, which is set as the adjacency matrix. The existence of connecting boundaries in the city is taken as 1, otherwise, it is taken as 0, and normalized. The ρ, β, γ, λ are estimated coefficients. Equation (2) is the general form of the spatial-DID model. when ρ=β2=γ2=0, the model is the spatial error DID model (SEM-DID); when β2=γ2=λ=0, the model is the spatial autocorrelation DID model (SAR-DID); when λ=0, it is the spatial Durbin double difference model (SDM-DID).

2.4 Description of variables

To explore the impact of low-carbon city pilots on industrial pollution, we select industrial SO_2 emissions as the dependent variable, denoted as *SO2* The independent variable is *DID*, whose coefficient represents the policy effect. This paper also adds control variables, including: per capita gross domestic product (*PGDP*); the proportion of the secondary industry in GDP (*second*), which represents the industrial structure; the number of industrial enterprises with fixed assets over 5 million CNY, denoted as *inQ*; the total population, which is denoted as *pop*; and the per capita investment in fixed assets, which is denoted as *fix*. To further test the mechanism, this paper also collects data on intermediary variables, respectively: the number of foreign direct investment enterprises (*FDI*), representing foreign direct investment; and the number of green innovation patents authorized per 10,000 people (*patent*), representing green technological innovation. The descriptive statistics of the variables are shown in the table 1:

Table 1 Descriptive statistics of variables

	N	Mean	SD	Min	Max
SO2	2680	56491	55146	759	682922
DID	2680	0.192	0.394	0	1
PGDP	2680	39735	30211	99	467749
second	2680	49.68	10.21	14.95	85.08
pop	2680	448.5	314.6	18.14	3392
fix	2680	28208	23072	958.6	219393
inQ	2680	1352	1788	20	18792
FDI	2639	124.0	367.0	0	4773
patent	2616	0.380	0.866	0	15.18

3. RESULTS AND DISCUSSION

3.1 Baseline regression

To verify whether low carbon cities policy can reduce SO_2 emissions, we conduct the OLS regression and the two-way fixed-effects regression, and the results are shown in columns (1) and (2) of Table 2. The coefficients of the DID are negative, which indicates that the pilot policy reduces the emissions. However, the results of the two-way fixed effects model are not significant, indicating that the model may have estimation bias. The previous analysis shows that the low-carbon city pilot not only affects the local economic structure but also affects the neighboring cities, so the spatial measurement model is further considered in columns (3)-(6). We compare the three spatial models of SAR, SDM, and SEM and test them to determine the specific form of the spatial model Column (3) is the spatial autoregressive model and column (4) is the spatial error model. Both the LR test and Wald test results indicate that the spatial Durbin model is better for estimation. Therefore, we use the two-way fixed effects spatial Durbin model as the regression model.

Table 2 Baseline regression

	(1) SO2	(2) SO2	(3) SO2	(4) SO2
DID	-8284.4***	-3799.2	-3663.6*	-3548.4*
	(2332.3)	(2094.2)	(1753.1)	(1751.0)
W*DID				
_cons	-60944.9***	85373.7***		
	(4938.3)	(18654.8)		
Controls	Yes	Yes	Yes	Yes
Time	No	Yes	Yes	Yes
City	No	Yes	Yes	Yes
Random	No	No	No	No
Hausman				
LR test			4.66*	4.16*
Wald			4.67*	4.90*
N	2680	2680	2680	2680
R^2	0.306	0.869	0.125	0.124

Note: Robust standard errors in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

3.2 Robustness test

The basic assumption of the DID model is that the treatment and control groups had a similar trend before the implementation of the policy. We conduct a parallel trend test to ensure the robustness of the results. Based on the principle of the event study method, the test is conducted according to the following formula based on SDM-DID:

$$y_{it} = \rho W y_{it} + \sum_{j=-6}^{6} \alpha_j D_j + \sum_{j=-6}^{6} \varphi_j W D_j + \gamma_1 X + \gamma_2 W X + \mu_i + \delta_t + \varepsilon_{it}$$

where D_j is a set of dummy variables. When j>0, it represents the j year after the start of the pilot. When j <0, it represents the $|j|$ year before the start of the pilot. The results are shown in Fig. 2, where the estimated coefficients are not significant in years before the implementation of the policy, indicating that there is no significant difference in the trend of the treatment group and the control group before the implementation of the policy.

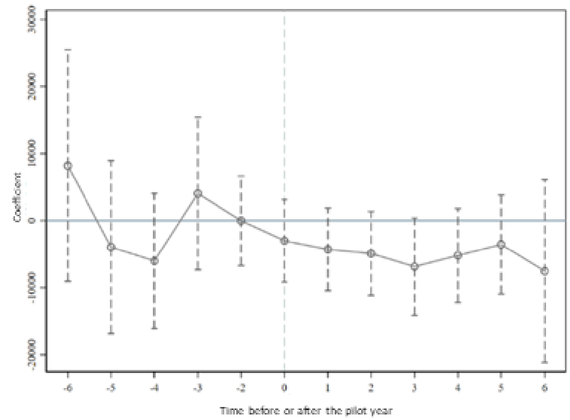

Fig. 2 Parallel trend test

We conduct a placebo test by setting the treatment group randomly repeated 500 times, and the results are shown in Fig. 3. The vertical reference line is the estimated coefficients of the spatial Durbin model, and the horizontal reference line is the P-value of 0.05. The results show that the coefficients are concentrated around 0. The distribution of coefficients' P-values is mostly over 0.05, suggesting that it passes the placebo test.

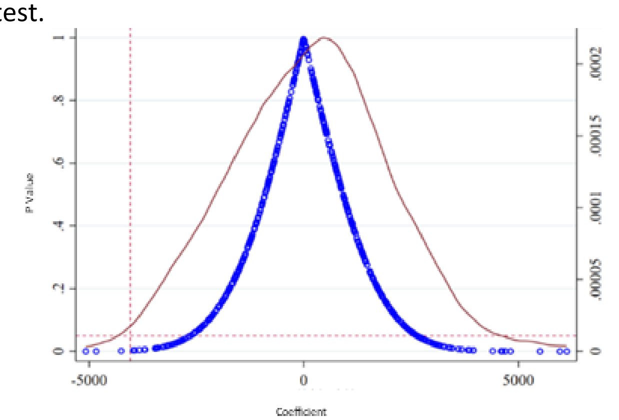

Fig. 3 Placebo test

3.3 Mechanism analysis

We conduct mechanism tests with a mediation effects model. The direct effect coefficient in column (1) is significantly negative, indicating that the pilot policy significantly reduced local industrial enterprises. The indirect effect coefficient is significantly positive, indicating that the pilot policy increased industrial enterprises in neighboring areas. Column (2) shows that the number of industrial enterprises is positively related to industrial SO_2 emissions. Combined with columns (1)-(3), the results indicate that the pilot policy can reduce local SO_2 emissions, but leads to the transfer of industrial enterprises, which increases SO_2 emissions in neighboring places. Columns (4)-(6) test the mediating effect of foreign direct investment. Due to missing data, only two-way fixed effects regression is added. A similar analysis can be applied according to the significance of the coefficients: the pilot policy significantly reduces foreign direct investment, thereby reducing industrial SO_2 emissions. Columns (7)-(9) is the mediating effect of green technology innovation. The results show the pilot policy to promote green technology innovation and thus reduce industrial sulfur dioxide emissions. The above results indicate that the low-carbon city pilot policy can lead to SO_2 reduction mainly through three mechanisms.

Table 3 Mechanism analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	maQ	SO2	SO2	FDI	SO2	SO2	patent	SO2	SO2
did	-245.0***		-4034.6*	-16.65***		-4034.6*	0.235***		-4776.8*
	(36.71)		(1760.0)	(4.904)		(1760.0)	(0.0433)		(2212.9)
inQ		6.100***	5.297***						
		(0.891)	(0.918)						
FDI					50.29*	48.92*			
					(23.13)	(22.98)			
patent								-4356.3*	-3968.7*
								(1840.1)	(1817.7)
W*did	56.32	7051.1*	7783.1*						
	(75.97)	(3593.6)	(3602.3)						
direct	-244.0***	-68.82	-4051.7*						
	(37.74)	(54.47)	(1807.3)						
indirect	63.79*	6784.7*	7585.0*						
	(72.81)	(3335.5)	(3561.0)						
total	-180.2*	6715.9*	3533.3						
	(79.32)	(3305.3)	(3876.6)						
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2680	2680	2680	2639	2639	2680	2616	2616	2616
R^2	0.089	0.143	0.126	0.987	0.871	0.126	0.815	0.868	0.868

Note: Robust standard errors in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively.

4. CONCLUSIONS

This paper focuses on the low-carbon city policy and tests the reduction effect of industrial SO_2 emissions. Combining the time-varying DID model and the spatial Durbin model, we further conduct the robustness tests such as the parallel trend test, and the placebo test. We apply the mediating effect model to test the mechanism The following conclusion is drawn: the pilot low-carbon city can significantly reduce local SO_2 emissions, but has a spillover effect on neighboring emissions. The reason for this is that the pilot policy has led to the withdrawal of industrial enterprises from the local market and their transfer to the neighboring market. The low-carbon city pilots, although intended to reduce carbon dioxide emissions, have also reduced industrial SO_2 emissions by influencing foreign direct investment and green technology innovation, realizing synergies between carbon reduction and pollution reduction.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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