Analysis of SO_2 Emission Reduction Effect of Smart City Construction Based on a Multi-period DID Model

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Abstract. Along with the acceleration of urbanization and industrialization, the problem of environmental pollution in China has become increasingly prominent, putting forward new requirements for city construction. In 2012, the Chinese government proposed to build smart cities. This policy not only strengthened the urban informatization construction, but also provided valid solutions for China's environmental governance. However, there is little literature about the effect of smart city construction on pollution emission. Based on this, this paper used panel data from 284 cities in China during 2003–2019 to evaluate the effect of smart city construction on SO_2 emissions by constructing a multi-period DID model. The findings are as follows: (1) The smart city construction could significantly reduce the emission of SO_2 and the conclusion was robust. (2) There was a temporal hysteresis in the response of SO_2 emissions to the smart city construction, and SO_2 emissions began to decrease significantly in the third year after smart city construction. (3) Industrialization could significantly increase SO_2 emissions, while opening up to the outside world and the concentration of population could significantly decrease SO_2 emissions.

Keywords: Multi-period DID, Smart City, SO_2, PSM-DID.

1. Introduction

1.1. Background

With the deepening of reform and opening-up in China, the proportion of industrial production and urban population have risen dramatically, accelerating urbanization and industrialization. The expansion of urban consumer groups and the stimulation of consumption potential contributed greatly to the economic growth. However, the rapid economic development has led to serious industrial pollution, followed by the decline in quality of life and wellbeing, the environmental deterioration, and some other problems. "Urban disease" has become increasingly prominent in China. Taking SO_2, a common industrial pollutant, as an example, from 1995 to 2010, the total amount of SO_2 emissions had increased from 14.05 million tons to 18.64 million tons, with a growth rate of 32.7%. Moreover, SO_2 is a significant health and environmental hazard. Long-term exposure to high concentrations of SO_2 can damage the respiratory system, decrease immune function and even cause cancer. What's worse, when the content of SO_2 in the atmosphere exceeds the standard, it can form acid fog and sulfuric acid rain, doing harm to soil, water and forests.

In order to effectively mitigate residents' health problems and environmental deterioration caused by pollution discharge, the reform of urban construction was imperative. At the end of 20th century, building model cities of environmental protection was put forward, emphasizing reduction of main pollution. What's more, with the advancement of IT, represented by big data, blockchain and artificial intelligence, smart city was proposed as a brand-new city construction pattern. In 2012, the government of China announced the first batch of pilot cities. Thus, China began to explore smart city construction, and launched two batches of pilot cities successively in 2013 and 2014. Compared with the previous two traditional construction patterns, smart city construction focuses on the application of IT and aims to promote the intelligent development of enterprises, accelerate new-type urbanization, reduce pollution emissions and improve residents' quality of life. It can be said that smart city is crucial to alleviating "urban disease", while taking high-quality development into account.

1.2. Literature review

The idea of smart city was derived from the "Smart Earth", which was put forward by IBM in 2010. Smart city construction is able to promote industrial upgrading, enhance city operation performance and transform the city intelligently via the next-generation of IT, including blockchain, 5G network and big data. Meanwhile, the construction concept of smart city is people-oriented, which is a new model of harmonious development of economy, society and nature. The ultimate goal is to achieve sustainable economic growth, improve the quality of life and the utilization efficiency of resources and environment.

Smart city is a new model of urban construction, which can effectively deal with "urban disease" caused by traditional urban construction mode and has triggered the upsurge of researches on the smart city. After reviewing the existing literature, this paper found that relevant researches mainly focused on the following four aspects to investigate the effect of smart city construction.

The first was the economic driving effect of smart city construction. Compared with areas without smart city pilot projects, smart city construction could promote the economic development [1]. In addition, via the application of modern information technology, smart city construction could promote regional economic development by optimizing resource allocation, improving economic agglomeration level and promoting industrial structure upgrading. Its role was enhanced with the improvement of urban human capital, the reduction of government intervention, and the development of financial services [2]. The second was the impact on production factors and production efficiency. Smart city construction could improve urban total factor productivity via three mechanisms: promoting technological innovation and improving economic agglomeration [3]. By using the multi-period DID method, some scholars found that smart city construction could significantly improve the green total factor productivity of enterprises, and this conclusion remained robust after considering the endogeneity [4]. The third was the impact on industrial structure. Smart city construction had significantly positive effects on the upgrading and rationalization of industrial structure [5]. Some scholars found that smart city construction could contribute to urban innovation, financial services development and foreign direct investment in the process of promoting industrial structure upgrading [6]. The fourth was the impact on urban innovation. Smart city could stimulate the enterprise innovation vitality, which could be effectively enhanced by promoting regional innovation ability and easing financing constraints [7].

Except for the above four research focuses, scholars also did research on the environmental protection effects of smart city pilot projects, confirming the positive impact on decreasing carbon emission intensity [8], reducing haze pollution [9], and improving urban ecological total factor energy efficiency [10]. However, few scholars have investigated the influence of smart city construction on SO_2 emissions. Based on this, this paper used panel data from 284 cities in China from 2003 to 2019 to evaluate the effect of smart city construction on SO_2 emissions via the multi-period DID method.

2. Model and data

2.1. Model description

China officially launched the smart city pilot project in 2012. The second and third batches were set up in 2013 and 2014 respectively. As smart city construction was a national strategic measure in China, it was exogenous to SO_2 emissions. Hence, this paper viewed smart city construction as a quasi-natural experiment. Due to the inconsistency in the time of smart city construction, this paper constructed a multi-period DID model with the dual fixed-effects to evaluate the effect of smart city construction on SO_2 emissions.

$$SO_2 = \beta_0 + \beta_1 Policy + \alpha X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \quad (1)$$

Where i denotes the city, t denotes the year, SO_2 refers to SO_2 emissions. *Policy* is a dummy variable of the intersection between the smart city pilot policy and the construction time. β_1 is the

effect of the smart city construction. β_0 is a constant term. X_{it} refers to the set of control variables, including the economic development level (*Pgdp*), the industrialization level (*Industry*), the degree of opening-up (*Open*), the urban innovation level (*Patent*), the environmental regulation intensity (*Green*), and the concentration of population (*Population*). α refers to the coefficients of control variables. γ_t represents the year fixed effect, and μ_i represents the city fixed effect, and ε_{it} is the random disturbance term.

2.2. Variables

The explained variable is the amount of SO_2 emissions. SO_2 is one of the main pollutants causing environmental pollution. As SO_2 mainly comes from industrial pollution sources, industrial SO_2 emissions was selected as the proxy variable to evaluate the amount of SO_2 emissions.

The key explanatory variable is smart city construction (*Policy*). The experimental group samples selected were the three batches of pilot cities established in 2012, 2013 and 2014 respectively. Other non-pilot cities served as the control group. The sample size of the experimental group is 103. For the pilot city, the value of *Policy* was 1 in the year and years after the implement of smart city pilot policy. For other cities and years, the value of *Policy* was 0.

The following factors are taken into account in this paper to scientifically evaluate the causality between SO_2 emissions and the smart city construction. Firstly, according to the Environmental Kuznets Curve, the economic development level would affect pollution emissions [11]. Therefore, the economic development level (*Pgdp*) was added into control variables, expressed by per capita GDP. In addition, industrialization also affected pollution emission [12]. A large part of SO_2 came from the combustion of traditional industrial enterprises. Thus, the industrialization level (*Industry*) was added into control variables, expressed by the proportion of secondary industry production value. And, according to the "pollution refuge hypothesis" and "pollution halo hypothesis", open-door to the world could impact pollution emission [13-14]. Thus, the degree of opening-up (*Open*) was introduced into control variables, expressed by import and export volume. Moreover, innovation could reduce environmental pollution via enhancing the optimization and upgrading of industrial structure and reducing energy intensity [15]. Therefore, the city innovation level (*Patent*) was added to reflect whether or not technological innovation provided effective support for reducing pollution emission, represented by the number of green patents obtained per 10,000 people. Furthermore, environmental regulation played a significant role in reducing pollution [16]. So, the environmental regulation intensity (*Green*) was introduced, represented by green coverage rate of built-up areas. Finally, urban population concentration was conducive to the reduction of SO_2 emissions via improving the degree of industrial specialization and reducing the treatment cost of productive pollutants [17]. Thus, the concentration of population (*Population*) was added, expressed by permanent population.

2.3. Data description

This paper selected 284 cities in China as research samples and the study period was 2003-2019. The data were collected from China City Statistical Yearbook, National Bureau of Statistics, National Intellectual Property Office, China City Database and provincial Statistical Yearbook. Descriptive statistics of relevant variables are listed in Table.1.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
SO_2	4828	4.9429	5.6807	0.0002	68.316
Policy	4828	0.1512	0.3583	0	1
Pgdp	4828	3.6982	2.9357	0.1891	20.349
Industry	4828	0.4657	0.1132	0.1139	0.9097
Open	4828	0.7305	2.8453	0.0001	34.122
Patent	4828	0.0955	0.3041	0	5.0888
Green	4828	0.3524	0.1219	0.0059	0.9525
Population	4828	441.14	311.85	16.37	3416.0

3. Empirical results

3.1. Benchmark regression results

This paper used the multi-period DID method based on the dual fixed-effects to estimate equation (1). The estimation results are shown in Table 2 Column (1) only took the smart construction as the only explanatory variable. The regression results show that the smart city construction reduced SO_2 emissions by 3.797, and it was significant at the 1% level. This influence might be caused by the smart city pilot project or the omission of relevant variable. In column (2), in addition to the *Policy*, the dual fixed-effects were added. The influence of smart city construction on SO_2 decreased, compared with column (1), but it was still significantly negative at 1% level. Column (3) introduced control variables on the basis of column (2). The smart city construction significantly reduced SO_2 emissions by 1.2005 at the 1% level. This demonstrates that the smart city construction decreased SO_2 emissions.

Table 2. Benchmark regression results

Variable	*SO_2*			PSM-DID
	(1)	(2)	(3)	(4)
Policy	-3.7974***	-1.2781***	-1.2005***	-1.2599***
	(0.1566)	(0.1629)	(0.1575)	(0.1588)
Pgdp			0.0177	0.0122
			(0.0375)	(0.0387)
Industry			5.6677***	5.7969***
			(0.8188)	(0.8298)
Open			-0.4748***	-0.4695***
			(0.0466)	(0.0464)
Patent			-0.6853**	-0.6191**
			(0.2775)	(0.2782)
Green			1.0892**	0.9152*
			(0.5060)	(0.5192)
Population			-0.0085***	-0.0088***
			(0.0016)	(0.0016)
The dual fixed-effects	No	Yes	Yes	Yes
N	4828	4828	4828	4828

Note: *, ** and *** indicate significance at the 10%, 5% and 1% significance levels, respectively. Values in parentheses are standard deviations.

With respect to control variables, the regression coefficient of *Pgdp* was positive but not significant. *Industry* had significantly positive impacts on SO_2 emissions. As fossil fuel combustion of industrial enterprises was the main source of SO_2, the higher the industrialization level was, the more SO_2

emissions there would be. *Open* had significantly negative influences on SO_2 emissions at the 1% level. This indicated that there existed a "pollution halo" effect which meant the advanced clean technology mastered by multinational companies spread to China in the process of foreign investment, so as to have a favorable impact on the environment. *Patent* had significantly negative influences on SO_2 emissions at the 5% level, indicating that green patents provided technical support for decreasing the emission of SO_2. *Green* had significantly positive impacts on SO_2 emissions at the 5% level, indicating that the current environmental regulation intensity was insufficient. *Population* had significantly negative influences on SO_2 emissions at the 1% level. According to previous studies, urban population concentration could reduce SO_2 emissions by promoting industrial specialization and reducing the treatment cost of pollution.

3.2. Parallel trend test

There is an important premise for multi-period DID model: Before smart city construction, the variation trends of the experimental group and the control group should be consistent; that is the model should meet parallel trend test hypothesis. In this paper, the method shown in Figure 1 was adopted to conduct parallel trend test.

The figure showed that the regression coefficients of *Policy* were not significant before the smart city construction. This indicated that, before smart city construction, the variation trends of samples were parallel and the difference was slight.

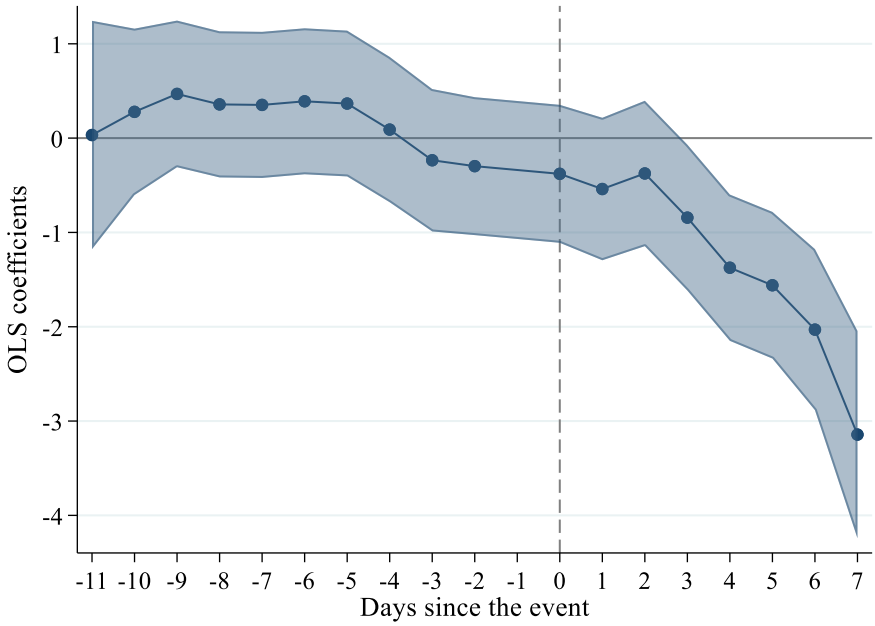


Figure 1. Parallel trend test

From the perspective of dynamic effect, when a city was selected as the pilot city, the regression coefficient of *Policy* was negative and significant at the 5% level in the third year after smart city construction, and was significant at the 1% level in the fourth year. This proved that the smart city construction could reduce SO_2 emissions but there was a temporal hysteresis. The SO_2 emission reduction effect appeared in the third year after the smart city construction.

3.3. Placebo test

Considering that some unobservable factors might cause errors in the estimated results, a placebo test was performed. The internal logic of the placebo test is to generate an error variable, $Policy_{fake}$, that has no impact on the explained variable, to replace the real *Policy*. Because $Policy_{fake}$ is generated randomly, the policy effect, β, is equal to 0. Under this premise, if $\hat{\beta} = 0$, it can be deduced that unobservable factors have no influence on the explained variable is 0; if $\hat{\beta} \neq 0$, it means that unobservable factors do affect the estimated results.

In this paper, the placebo test was performed as follows. Firstly, 123 cities were selected from 284 prefecture-level cities randomly as the experimental group, and other cities served as the control group. Then, *Policy* was randomly selected 500 times to ensure that it had no impact on SO_2 emissions. Then, the regression estimation was carried out according to the multi-period DID method based on the dual fixed-effects. Finally, the distribution of the error regression coefficients was drawn. As shown in Figure 2, the regression coefficients distributed around 0, diverging markedly from the true estimation coefficient (-1.2005, as shown in the dotted line), indicating that unobservable factors barely affect the model. This demonstrated that the conclusions of the benchmark regression had strong robustness.

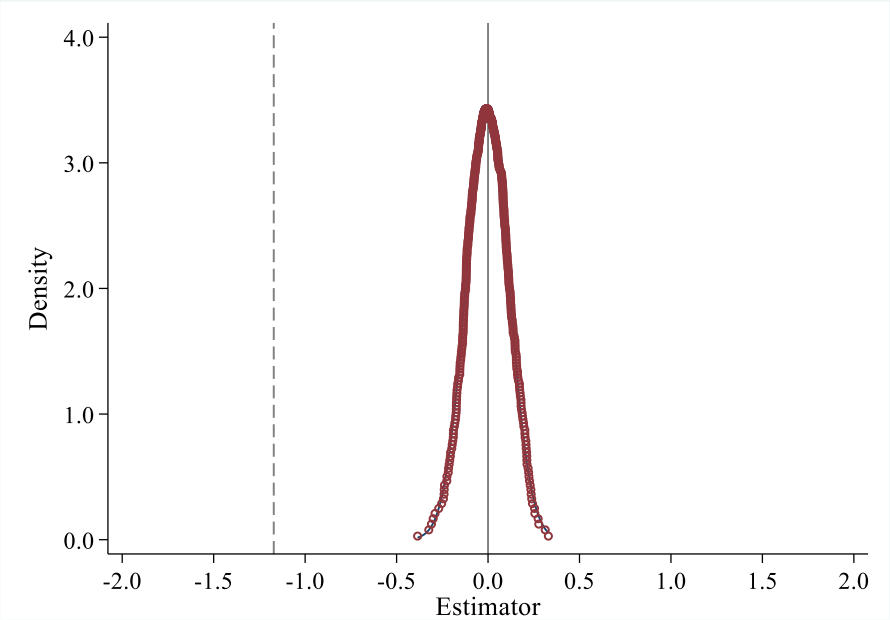


Figure 2. Placebo test

3.4. PSM-DID

As priority might be given to areas with certain unique features, the pilot regions were not selected randomly, indicating that smart city pilot project was essentially a non-randomized experiment. As a result, self-selection bias inevitably existed in the multi-period DID model constructed in this paper. To narrow the gap between pilot cities and non-pilot cities, the propensity score matching-difference-in-difference (PSM-DID) method was applied.

Table 3 shows that the standard bias of most covariates after matching was less than 10%, and significantly less than the bias before matching. Except for the environmental regulation intensity (*Green*), t-statistics of other covariates after matching were not significant, indicating that, after matching, there was no significant difference between the experimental group and the control group.

After matching, 130 samples that didn't satisfy the common support hypothesis were removed. Then, the secondary regression was performed. The results are shown in column (4) of Table.1. Compared with column (3), it could be found that the regression coefficients of *Policy* were both significantly negative at the 1% level and the change was small. This revealed that the conclusions of the benchmark regression had strong robustness.

Table 3. Balance test results of variables before and after PSM

Variable		Mean		%bias	t test	
		Treated	Control		t	$p > \|t\|$
Pgdp	unmatched	5.9764	3.2369	87.7	24.34	0.000
	matched	5.8963	5.8126	2.7	0.46	0.644
Industry	unmatched	0.4691	0.4684	0.7	0.17	0.863
	matched	0.4685	0.4730	-1.6	-0.30	0.768
Open	unmatched	1.2407	0.6210	18	5.50	0.000
	matched	1.2472	1.2614	-0.4	-0.07	0.942
Patent	unmatched	0.2109	0.0720	36.4	11.66	0.000
	matched	0.2117	0.2030	2.3	0.38	0.706
Green	unmatched	0.3910	0.3362	47.6	10.55	0.000
	matched	0.3909	0.4019	-9.5	-2.34	0.019
Population	unmatched	474.28	430.8	12	3.50	0.000
	matched	476.03	494.59	-5.1	-0.91	0.364

4. Conclusions and suggestions

Based on panel data from 284 prefecture-level cities in China during 2003-2019, the causality between the smart city construction and SO_2 emissions was evaluated via the multi-period DID method. The results revealed that smart city construction could effectively reduce SO_2 emissions, but with a temporal hysteresis. This conclusion was robust after several tests.

According to the conclusion, some suggestions can be provided for smart city construction.

Firstly, the construction of smart city infrastructure should be further promoted. The government should help with the promotion of intelligent infrastructure, the development of smart applications. It's also important to promote smart municipal facilities, accelerate the establishment of the Internet of Things perception system, improve the digital level of the city. Secondly, the information technology in smart cities should be further developed. Smart city development depends on the advancement of IT. Therefore, one of the crucial ways to build smart cities is to encourage enterprises to make technological innovations and increase investment in information technology research. On the basis of vigorously developing information technology, the government should help increase the number of enterprises with advanced technology, support the development of low-energy and environment-friendly industries, encourage the upgrading and transformation of enterprises with heavy contamination, and enhance the rationalizing of industrial structure. Thirdly, more innovation-minded personnel should be trained for smart city construction. A host of high-level professionals are needed for developing information technology. Besides providing excellent scientific research environment, the government should also strengthen the training of professionals, refine the personnel training plan, and bring in high-level professionals for technological innovation.

In addition, this paper didn't analyze the heterogeneity and mechanism of the effect of smart city construction on SO_2 emissions. Relevant research can be carried out to investigate the mechanism of pollution reduction effect and heterogeneity concerning smart city pilot projects in the future.

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