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Analysis of the carbon reduction effect of smart city construction

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Abstract

The construction of smart cities has a significant impact and involves many aspects. This article collects data from prefecture-level cities from 2009 to 2019 and explores the impact of smart city construction on carbon emissions through the staggered DID. Research has shown that the implementation of smart cities can reduce carbon emissions and improve the urban environment.

Keywords: Smart city construction; Carbon emission; staggered DID

1. Introduction

With the rise of new generation information technology such as artificial intelligence, blockchain, cloud computing and big data, digital technology is being deeply integrated into the trend of economic and social development from various fields and in all aspects. The Chinese government has responded to the trend by proposing the construction of smart cities in a graded and classified manner, using new generation information technology to reshape the city operation and development mode. The policy was officially released in 2012 as the "Notice on National Smart City Pilot Work", while three batches of cities have embarked on the pilot project since 2012. It has not only improved the living conditions and production methods of residents, but also catalyzed the digitalization process of urban enterprises [1] , and can stimulate regional entrepreneurial vitality and effectively improve the quality of urban economic development [2] . Along with this, China strives to reach peak carbon dioxide emissions by 2030 and carbon neutrality by 2060, and for this reason, literature is focusing on the impact of smart city construction on carbon emissions and their productivity. Huang et al. [3] argued that smart city construction reduces the intensity of urban carbon emissions

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and promotes low-carbon development mainly by accelerating industrial structure upgrading, enhancing carbon absorption capacity and improving energy use efficiency. Chu et al. [4] analyzed the effects of smart city construction on pollutant emissions and found that smart city construction significantly reduced urban industrial wastewater and exhaust gas emissions. Guo et al. [5] found that there is an inverted U-shaped relationship between energy efficiency and per capita carbon emissions, and that most Chinese cities have now crossed the inflection point, and smart city construction has reduced per capita carbon emissions by improving energy use efficiency and achieving energy saving and emission reduction. From the perspective of carbon productivity, Song T et al. [6] suggested that smart city construction can improve urban carbon productivity through technological progress, industrial structure upgrading, and energy structure optimization, despite the time lag effect. Shi et al. [7] found that smart city construction uses modern information technology to promote the innovation of urban development model and reduce urban environmental pollution. Xu et al. [8] argued that the policy by strengthening environmental regulation and promoting green technology innovation, the policy can reduce CO_2 emissions from industrial firms in China to 23%.

From the perspective of emitting pollutants, smart city construction reduces traffic congestion by creating a smart transportation system, while the use of bike-sharing, car-sharing and other green short-distance transport reduces transport carbon emissions and achieves sustainable transport [9][10]. Also, the use of Internet of Things can change the way we manage our environment by facilitating the integration of spatial and temporal information, reducing waste of resources and energy, learning how to improve energy use efficiency and further reducing greenhouse gas emissions by monitoring vehicle emissions in real time [11]. In terms of the impact path, smart city construction promoted by innovation will produce technology effect, configuration effect and structure effect, and these three effects will be reflected in environmental protection, which will produce the result of continuously reducing environmental pollution [7]. In addition, smart city construction can also integrate data related to natural resource management, expand the construction of cross-sector and cross-industry natural resource function models, and provide more efficient service support for natural resource industry management thus achieving the goal of energy saving and emission reduction[5]. But focusing on production, the use of new technologies will accelerate the productivity of enterprises and improve their production [12], then the internal energy generated by the enterprise and the power loss will be further increased, and the increased energy consumption of this part will generate more carbon emissions. At the same time information technology as an innovative factor, by replacing the traditional factors to obtain higher output with lower inputs, is conducive to product innovation in the production sector and the development of new markets. And the efficiency of energy saving and emission reduction through digital technology enhancement is lower than the rate of its market scale expansion [13], which can cause energy consumption to be further expanded and carbon emissions to surge. Therefore, it is important to investigate how smart cities will affect carbon emissions. In order to accurately identify the carbon emission reduction effect, this paper uses panel data of 285 prefecture-level cities in China except Tibet to study the carbon emission reduction effect of smart cities through the staggered DID approach, extending the literature in related fields. Moreover, this paper draws on the research of Wu and Guo [14], and innovatively includes the indirect carbon emissions caused by the use of electricity and heat into carbon emissions, which not only calculates the carbon emissions of each city more accurately but also makes the identification of the carbon emission reduction effect more convincing.

2. Data

2.1. Variable selection and statistical data

1) Selection of explanatory variable

This item is indicated by the distinction between the experimental and control groups referring to the study by Shi et al.[7]. The prefecture-level cities that only included a district or county in the pilot list were excluded, and the cities that were piloted in different batches in 2012, 2013, and 2014 were distinguished. A value of 1 indicates that the city has already started and implemented the smart city pilot, while a value of 0 indicates that the city isn’t included in the smart city pilot list or included but not yet in the implementation year.

2) Selection of Explained variable

There are many variables related to carbon emissions, and the main measures are divided into two. One type is based on the natural gas, liquefied petroleum, and electricity consumed by the city [15], but this method may miss other types of energy consumption; the other type uses two sets of DMSP/OLS Data provided by NASA based on the PSO-BP algorithm to adjust and invert the two sets of nighttime lighting data [16]. However, such algorithms often fail to obtain accurate results and even result in errors. This paper draws on Wu and Guo [14] of the study, not only accounting for carbon emissions generated by direct energy consumption, but also including indirect carbon emissions caused by the use of electrical and thermal energy. This method can calculate carbon emissions more comprehensively and make the study of the impact of smart cities on carbon emissions more accurate, as the direct and indirect carbon emissions due to digitization in the process of smart city construction are highly variable. To solve the problem of inaccurate measurement results due to large standard deviation, the carbon emissions calculated in this part are logarithmized.

3) Control variables

The following variables are included in the control variables after considering many contributing factors of carbon emissions: 1. economic development level, the logarithmic form of urban GDP per capita (*agdp*); 2. population density, which is calculated by taking the logarithm of the number of people per administrative area (*peo*); 3. R&D investment intensity, the ratio of local budget expenditure on science and technology to regional GDP (*rd*); 4. Degree of Openness , the proportion of real foreign investment in each city to GDP (*fdi*); 5. financial development level, the proportion of the balance of loans of financial institutions in each city to GDP (*fin*); 6. Industrial structure, the proportion of value added in the secondary industry to GDP (*sec*); 7. Urbanization level, the composition of the resident population in cities and towns than the resident population in the city (*city*); 8. According to the environmental Kuznets curve, there is an inverted U-shaped relationship between the level of environmental pollution and the level of economic development. Therefore, the result of taking the logarithm of the square of economic development level (*agdp2*) is added.

The panel data of 285 cities from 2009 to 2019, except Tibet, are obtained from the China Urban Statistical Yearbook and the statistical yearbooks of each province. Some of the prefecture-level cities have missing data in some years, and this paper uses interpolation to fill them in, and finally obtains the balanced panel data of 285 prefecture-level cities in China for 11 years from 2009-2019. The following are the descriptive statistics of each variable.

Table 1. Descriptive statistics of each variable

Variable	obs	Mean	Standard Deviation	Min	Max
fin	3117	0.950	0.678	0.132	17.356
fdi	3118	0.278	0.410	0.000	13.975
rd	3119	0.003	0.003	0.000	0.063
peo	3132	434.677	340.277	4.97	2759.139
sec	2895	47.766	10.816	10.68	89.75
agdp	3057	48106.13	33119.09	99	467749
co	3125	861.716	1452.263	8.305	22861.19
city	3126	53.247	15.422	18.492	100

2.2. Model construction

In this paper, the carbon emission effects of smart city pilots are evaluated using the staggered DID method. The implementation of the smart city pilot policy in China may not only lead to differences in carbon emissions in the same pilot city before and after the implementation of the policy, but may also lead to differences between pilot and non-pilot cities at the same point in time, so it is considered as a "quasi-natural experiment". Since the policy was implemented in three different cities in 2012, 2013, and 2014, a staggered DID was used for the evaluation, and the following model was constructed:

$$\boldsymbol{co_{ct}} = \boldsymbol{\alpha_1} + \boldsymbol{\beta_1 TD_{ct}} + \boldsymbol{\gamma_1 Z_{ct}} + \boldsymbol{\delta_c} + \boldsymbol{\mu_t} + \boldsymbol{\varepsilon_{ct}} \tag{1}$$

where the explained variable $\boldsymbol{co_{ct}}$ are the carbon emissions of city c in year t; the core explanatory variable $\boldsymbol{TD_{ct}}$ are dummy variables, which reflect whether city c implemented the smart city urban pilot policy in year t. It takes the value of 1 if the policy was implemented, otherwise, it is zero; $\boldsymbol{\delta_c}$ and $\boldsymbol{\mu_t}$ denote the city fixed effects and year fixed effects, respectively; $\boldsymbol{\varepsilon_{ct}}$ is considered as the random disturbance terms affecting the carbon emissions of the city;

$\boldsymbol{\beta}_1$ is the estimated coefficient of the double difference, which measure the the effect of city pilot on urban carbon emissions; $\boldsymbol{Z}_{ct}$ represents a series of control variables affecting urban c carbon emissions in year t.

3. Positive analysis

The double difference method can be used only after the basic premise of parallel trend assumption is satisfied, because it is crude to plot the time trend of the experimental and control groups only by visual observation, so this paper adopts the event-study analysis to test the dynamic effect of the policy implementation, as shown in Fig. 1. The coefficients of the interaction terms in the following figure are insignificant in four years prior to policy implementation and show and annual decline after the third year of the implementation of the system. This not only shows that the experimental and control groups meet the assumption of parallel trends but also indicates that the policy has a time lag effect.

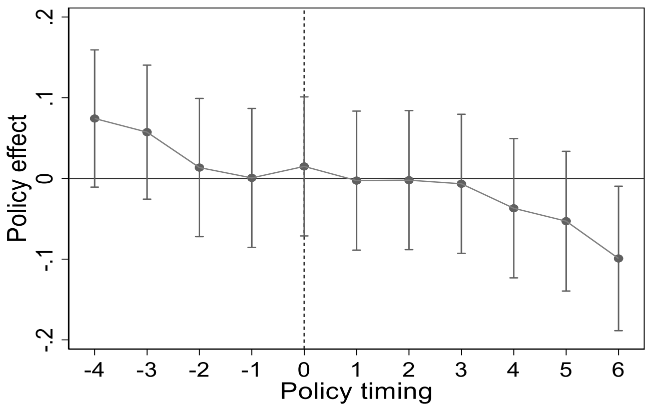

Fig. 1. Results of parallel trend test for smart city construction.

Table 2. Empirical results

lnco	Model 1	Model 2
td	−0.046** (0.021)	−0.048** (0.022)
fin		0.066*** (0.018)
fdi		-0.028* (0.016)
rd		−1.108 (2.737)
lnpeo		0.022 (0.029)
sec		0.01*** (0.002)
lnagdp		−0.146 (0.166)
city		0.003 (0.002)
lnagdp2		0.01 (0.009)
cons	5.81*** (0.017)	5.671*** (0.855)
Adj R-squared	0.938	0.946
Time fixed effects	yes	yes
Urban fixed effects	yes	yes
obs	3135	3135

As a major initiative in urban construction, smart cities use advanced information technology and tools to transform urban operation and governance models, and also have a huge impact on urban environmental issues. In this paper, we use staggered DID to assess the impact of smart city construction on urban carbon emissions with the following results. In Table 2, Model 1 and Model 2 represent the results of the bi-directional fixed effect without the inclusion of control variables and the bi-directional fixed effect with the inclusion of control variables, respectively. The results show that the smart city construction has a significant negative effect on carbon emissions regardless of whether the control variables are added or not, indicating that the smart city construction has a significant effect on carbon emission reduction. Among them, smart city construction significantly reduced carbon emissions by about 5.02% ($e^{0.049} - 1 \approx 0.0502$).

Although potential influencing factors have been controlled for, bias, either overestimation or underestimation, cannot be avoided in the study. To further test the robust of the above results, this paper successively confirms the findings through three methods. Firstly, a temporal placebo test is used to advance the policy implementation time by three years and construct a policy interaction term represented by td_3, the results of which are presented in column (1) of Table 3. td_3 term coefficient is not significant, which indicates that the advanced policy time is not related to carbon emission reduction, and laterally reflects that the construction of smart cities does stimulate carbon emission reduction. Secondly, the results are shown in column (2) of Table 3. td policy interaction term is significantly negative at 5% confidence level, which again verifies the above findings. Thirdly, considering the possible estimation bias caused by data differences, the original data were therefore subjected to tailoring in the analytical study. The results in column (3) of Table 3 show that the construction of smart cities caused regional carbon emission reduction at 10% confidence level.

Table 3. robust test

lnco	(1)	(2)	(3)
td		-0.05^{**}(0.212)	-0.059^{***}(0.02)
td_3	-2.92(5.98)		
Control variables	yes	yes	yes
Control variables with time trend interaction term	no	yes	no
Time fixed effects	yes	yes	yes
City fixed effects	yes	yes	yes
cons	5.565^{***} (0.841)	6.029^{***} (0.952)	5.878^{***} (0.813)
obs	3135	3135	3135

4. Conclusion

In this paper, the carbon reduction effect of smart city construction was studied using the staggered DID method. On average, smart city construction significantly reduces carbon emissions by about 5.02%, which can effectively alleviate a series of problems caused by excessive carbon emissions. Therefore, the construction of smart cities should be further strengthened to solidify the digital foundation, deeply integrate smart technologies, strengthen the R&D and innovation capacity of information technology, upgrade the industrial structure, improve the energy utilization efficiency, and further exert its carbon emission reduction effect.

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