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Research on the Impact of Smart City Construction on Urban Carbon Emission Reduction Effect

——Based on Hefei City, Anhui Province

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ABSTRACT

Realizing a dual-carbon city is an inherent requirement for promoting high-quality economic development and the construction of ecological civilization. The double difference method was used to empirically test the impact of Hefei's smart city policy on carbon emission reduction from 2006 to 2019. The results show that smart city construction significantly reduces urban carbon emission intensity and improves energy utilization efficiency. Based on this, relevant suggestions are put forward, such as formulating long-term, phased construction plans, aiming to promote green and low-carbon development of cities and achieve dual carbon goals.

KEYWORDS

Smart city; Double difference; Carbon reduction effect; Low-carbon development

1. INTRODUCTION

Global warming has led to accelerated melting of glaciers, rising sea levels, floods and other problems. As a major greenhouse gas emitter and a developing country, China has always regarded reducing greenhouse gas emissions and promoting green and low-carbon economic development as an important task. As the main body of emission reduction actions, cities need to improve the quality of urban construction and explore ways to improve carbon emission efficiency, which have become key issues that many Chinese cities need to solve urgently.

As the core carrier of China's new urbanization strategy, smart cities systematically promote the innovation of urban governance systems and the reconstruction of industrial ecology through the in-depth application of new generation information technologies such as the Internet of Things, big data, and artificial intelligence. Its essential characteristics are reflected in the collaborative innovation of multiple dimensions such as data-driven intelligent infrastructure systems, digital planning and management platforms, intelligent public service networks, and modern industrial ecosystems . It reflects the essential requirements of cities moving towards green, low-carbon and sustainable development, and is of great significance to urban low-carbon development [3]. Hefei's smart city construction project can not only improve the efficiency of urban governance, but also reduce carbon emissions through energy system optimization, technological innovation-driven, industrial structure upgrading, and policy mechanism innovation [5].

2. LITERATURE REVIEW

There is still limited research in the existing literature on the relationship between smart city construction and carbon emission efficiency. In-depth exploration of its mechanism and impact effect can not only fill this research gap, but also provide a theoretical basis for understanding the role of smart cities in improving carbon emission efficiency. Empirical research by Shi Daqian and other scholars (2018) shows that smart city construction has effectively promoted the transformation and upgrading of urban development models through the innovative application of digital information technology. The results of the study showed that this transformation process significantly reduced the emission levels of industrial "three wastes" (sulfur dioxide, wastewater and solid waste), confirming the positive impact of digital technology empowerment on environmental governance [1]. Zhao et al. (2022) found based on a spatial econometric model that the intelligent transportation system not only directly reduces CO_2 emissions in the transportation sector, but also indirectly suppresses carbon emissions in non-transportation sectors through industrial linkage effects [1]. The research of Tang Jun et al. (2022) shows that energy system optimization in smart city construction can significantly reduce carbon emissions. This conclusion was verified through a quasi-natural experiment of the synthetic control method. The construction of a smart energy system significantly improved the city's carbon emission reduction performance through a dual mechanism: on the one hand, it promoted the transformation of the energy structure towards a cleaner direction, and on the other hand, it improved the efficiency of energy conversion and utilization. Empirical results show that this policy intervention has led to a statistically significant downward trend in per capita carbon emissions in the pilot cities [1].

This study uses a double difference model and empirically analyzes the impact of smart city construction on urban carbon emissions based on panel data from Hefei. The results not only provide a strong empirical basis for the carbon reduction effect of smart city construction, but also enrich theoretical research in the field of smart cities and low-carbon development. By revealing the relationship between smart city construction and carbon emission efficiency, this study provides theoretical support for the planning and construction of future smart cities, which will help promote the development of cities in a green, low-carbon and sustainable direction.

3. STUDY DESIGN

3.1. Model Construction

Smart city construction is a policy implemented in many cities in China. In order to scientifically evaluate the impact of smart city pilot policies on carbon emission efficiency, this study uses the double difference method to systematically examine the carbon emission reduction effect of smart city construction and its internal mechanism by comparing the dynamic changes in carbon emission efficiency between the experimental group (pilot city) and the control group (non-pilot city) before and after the implementation of the pilot policy [1]. The specific model is constructed as follows:

$$\ln carbon_{it} = \beta + \beta_0 smart_{it} + \beta_1 controls_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$

The subscripts iand t represent the city and year respectively, i represents Hefei City, Anhui Province; carbon represents urban carbon emissions, which is logarithmically processed as lncarbon; smart is the core explanatory variable, $\mathrm{smart}_{\mathrm{it}} = \mathrm{policy}_{\mathrm{i}}\mathrm{year}_{\mathrm{t}}$, is the interaction term between smart city pilot and implementation time, and takes a value of 0 or 1. If the city tis established as a smart city pilot in the year or later , it is 1, otherwise it is 0 i [1]; $controls_{it}$represents other control variables that have an impact on the explained variable, namely, urban carbon emission efficiency; $\mu_i$represents the city fixed effect, $\gamma_t$represents the time fixed effect, and ε_{it}represents the random disturbance term [10]. β_0It represents the net emission effect of smart city construction on urban carbon emission efficiency, which is also the estimated coefficient that this paper focuses on. If the coefficient is significantly negative, it indicates that smart city construction has effectively reduced carbon emission intensity and improved urban carbon emission efficiency [1]. If the coefficient is not significant or positive, it indicates that smart city construction has not achieved the expected results in emission reduction. This parameter directly measures the actual contribution of smart city policies to low-carbon development.

3.2. Variable Selection

The explained variable is in the form of the natural logarithm of carbon emission intensity, where carbon emission intensity is defined as the amount of carbon dioxide emissions generated per 10,000 yuan of GDP. Given the limitations of energy consumption data at the prefecture-level, this study uses the measurement method proposed by Feng and Rui (2017) for calculation. The specific calculation formula is as follows [2]:

$$\mathrm{carbon} = \mathrm{C_u} + \mathrm{C_P} + \mathrm{C_t} = \mu\mathrm{E_u} + \upsilon\mathrm{E_p} + \tau(\eta \times \mathrm{E_t})$$

Among them, carbon represents the total carbon emissions of the city; C_u, C_p, C_t represents the carbon emissions generated by natural gas, liquefied petroleum gas and total social electricity E_u, E_p, E_t consumption in the city; represents the natural gas, liquefied petroleum gas and total social electricity consumption data of the city over the years [9]. ηrepresents the proportion of coal-fired power generation in the total power generation. This paper uses the coal-fired power ratio data published in the "China Electric Power Yearbook" over the years as the basis to measure the proportion of coal-fired power generation in the city's power structure. μ, ν, τ represents the greenhouse gas emission coefficients of natural gas, liquefied petroleum gas and coal-fired power generation, and their values are $2.1622\mathrm{kg/m^3}, 3.1013\mathrm{kg/m^3}, 1.3023\mathrm{kg/(kw}$ ·h) [3].

The core variable is the interaction term between smart city pilot and implementation time, $\mathrm{smart_{it}} = \mathrm{policy_i year_t}$, which takes a value of 0 or 1, if the city $\mathrm{i}$was established as a smart city pilot tin , then it is tin and later $\mathrm{smart_{it}} = 1$, otherwise it is 0 [1].

Control variables. In order to explore the various factors that affect carbon emissions, we referred to relevant literature and selected the following seven key indicators: 1. Economic development level (lnpgdp). The natural logarithm of per capita regional GDP is used as an indicator to measure the level of economic development. This indicator reflects the overall scale of regional economic activities and the average economic status of residents. 2. Population size (lnpop). This paper uses the natural logarithm of the total population at the end of the year to measure this indicator. This indicator helps us understand the possible impact of population size on carbon emissions. 3. Administrative land area (lnarea). This paper uses the logarithm of the administrative land area to measure the geographical size of the region. 4. Fiscal self-sufficiency rate (czzjl). This paper uses the ratio of public fiscal revenue to fiscal expenditure to measure this indicator. This indicator reflects the fiscal autonomy of local governments and their dependence on external funds. 5. Urban infrastructure level (lnroad). This paper uses the logarithm of per capita paved road area to measure this indicator. This indicator helps to evaluate the impact of urban infrastructure construction on carbon emissions [2]. 6. Urban greening level (lvhua). This paper uses the greening coverage rate of built-up areas to measure this indicator. 7. Financial development level (fd). This paper uses the ratio of the balance of various RMB loans of financial institutions to GDP to measure this indicator [6].

3.3. Data Source and Description

The research sample is the panel data of Hefei City from 2006 to 2024. The data comes from the Anhui Province Statistical Yearbook, the Hefei City Statistical Yearbook , and the Urban and Rural Statistical Yearbook. In the process of data processing, we encountered some missing data. We performed linear interpolation estimation on the missing values to ensure the integrity of the data and solve this problem. The descriptive statistics of the variables are shown in Table 1.

Table 1. Descriptive statistics of variables

Variable Symbols	Variable Name	Mean	Standard Deviation	Minimum	Maximum
lncarbon	Urban carbon emission intensity	17.49	0.88	16.38	18.89
$smart_{it}$	Smart city construction	0.33	0.49	0.00	1.00
lngdp	Economic Development Level	11.03	0.59	9.85	11.78
lnarea	Administrative area land area	9.21	0.22	8.86	9.35
czzjl	Financial self-sufficiency rate	0.71	0.05	0.63	0.82
lnroad	Urban infrastructure level	2.83	0.08	2.67	2.97
lvhua	Urban greening level	40.31	3.34	32.58	45.32
fd	Financial Development Level	1.60	0.22	1.32	2.17
lnpop	Population size	6.50	0.21	6.15	6.69

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Benchmark Regression

Table 2. Benchmark regression results

variable	lncarbon	
	(1)	(2)
smart	- 0.2942 * (-1.997)	-0.2281 * (-0.799)
Constant term	2.622 *** (9.738)	9.282 *** (5.230)
Control variables	No	Yes
Year fixed effects	Yes	Yes
R-squared	0.730	0.960

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, and the t-values are in brackets.

Table 2 shows the baseline regression results of the impact of smart city construction on carbon emissions. Model (1) only controls for the year fixed effect and does not include other control variables; while model (2) controls for the year fixed effect and further adds a series of control variables [8]. The results of the two regression models in Table 2 are both significantly negative at the 10% level, indicating that the urban carbon emission intensity is significantly reduced under the construction of smart cities. Further regression analysis in column (2) shows that the estimated coefficient of smart city construction on carbon emission intensity is -0.2281, indicating that smart city construction significantly reduces carbon emission intensity by 22.81% [2]. The construction of smart cities promotes innovation in production methods and improvements in management methods, and uses information technology to achieve real-time monitoring and management of urban pollution emissions, thereby effectively improving the urban environment and promoting the efficient operation of cities. This result highlights the actual effect of the policy, indicating that the construction of smart cities has played a positive role in low-carbon governance, and is highly consistent with the green and low-carbon development goals advocated by smart city construction.

4.2. Robustness Test

4.2.1. Parallel trend test

Before using the double difference method, the parallel trend hypothesis must be tested first. To this end, the event study method can be used to set the following test equation [2], as follows:

$$\text{carbon} = \alpha + \sum_{k=12}^{5} \beta_k \, \text{smart}_{\text{it}} + \gamma X_{it} + \mu_{\text{i}} + \gamma_{\text{t}} + \varepsilon_{it}$$

The value range of k is -12≤k≤5. This paper selects the first 12 years and the last 5 years of smart city construction for parallel trend testing. The parallel trend test is mainly to estimate the coefficients $\beta_k$and examine the changes in the coefficients in each period before and after the implementation of the policy. These coefficients can accurately capture the dynamic impact of the smart city pilot policy on the urban carbon emission efficiency. The results of the parallel trend test using model (2) are shown in Figure 1. In each time period before the implementation of the policy, the trend of carbon emission intensity changes in the treatment group and the control group remained consistent, and the coefficient was not significant, satisfying the parallel trend premise of the double difference method [1]. After the implementation of the policy, it showed a gradual impact - no significant effect was produced in the first two years, and a stable emission reduction effect did not begin to appear until the third year. This dynamic effect analysis shows that the carbon emission reduction effect of smart city construction has a lag period of about two years, after which a sustained inhibitory effect gradually emerges. This result not only verifies the premise of the DID model, but also reveals the time lag characteristics of policy effects, providing an empirical basis for the formulation of long-term and sustainable smart city construction plans.

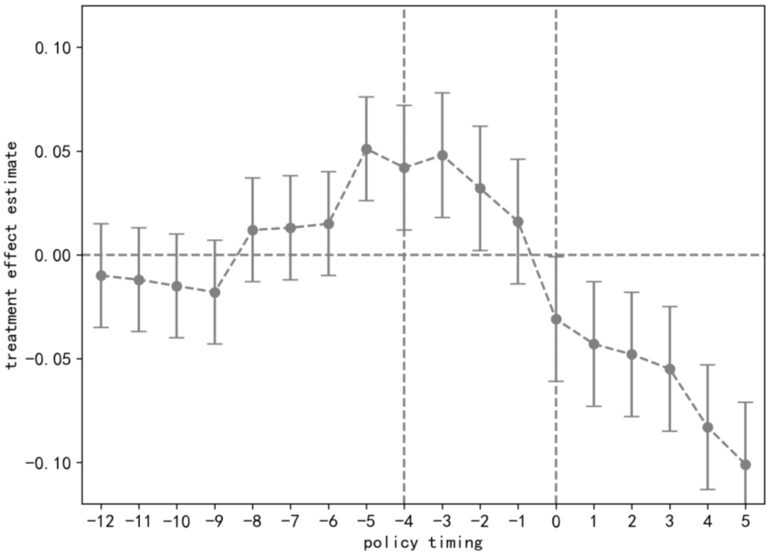

Figure 1. Parallel trend test

4.2.2. PSM-DID

To control the potential selection bias, this study used the propensity score matching double difference method for robustness testing. After processing the samples through the three methods of nearest neighbor matching, radius matching and kernel matching, according to the double difference

(DID) estimation results shown in Table 3, we can draw the following conclusions: Under different matching methods, the regression coefficient of smart city policy remains negative at the 10% significance level, and the corresponding carbon emission reduction effects are 15.37%, 13.43% and 12.34% respectively. This result verifies the reliability of the baseline regression conclusion and shows that after controlling for sample selection bias, smart city construction can still produce significant carbon emission reduction effects. All matching methods passed the balance test, further ensuring the robustness of the research conclusions.

Table 3. PSM-DID regression results

variable	lncarbon		
	Nearest neighbor matching	Radius Matching	Nuclear Matching
smart	- 0.1537 * (- 2.883)	- 0.1343 * (- 1. 785)	- 0.1234 * (- 3.845)
Constant term	2.543 *** (7.667)	3.452 *** (6. 378)	1.456 *** (5. 543)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R-squared	0.601	0.407	0.730

4.2.3. Replacing the Explanatory Variable

In order to verify the reliability of the research conclusions, this study conducted a robustness test by constructing an alternative model and replaced the explained variables with total carbon emissions for re-estimation. The regression results show that when the explained variable is replaced, regardless of whether the control variables are added, the smart city policy has a significant negative impact on carbon emissions. This result is completely consistent with the conclusion of the benchmark regression with carbon emission intensity as the explained variable. The results of the double verification fully confirm that smart city construction can indeed effectively reduce urban carbon emissions levels, and strengthen the credibility and robustness of the research conclusions.

Table 4. Replacement of explained variables

variable	lncarbon	
	(1)	(2)
smart	- 0.2 638 *	-0.2 098*
	(-1.897)	(-0.873)
Constant term	2 .3 2 1 ***	9.178 ***
	(8.73 2)	(5. 1 30)
Control variables	No	Yes
Year fixed effects	Yes	Yes
R-squared	0.7 24	0. 861

5. CONCLUSIONS AND RECOMMENDATIONS

This study uses panel data from Hefei from 2006 to 2019 and adopts the difference-in-difference method to empirically test the impact of smart city policies on carbon emissions. The study found that smart city construction has significantly improved urban carbon emission efficiency, with the carbon emission intensity of pilot cities reduced by an average of 22.81% [9]. It is worth noting that there is a time delay in the manifestation of policy effects. Specifically, the effects are not immediately apparent, but only begin to become gradually apparent in the third year after the policy is implemented. In order to verify the robustness of this effect, we used parallel trend test, PSM-DID analysis and other methods to test, and the research conclusions were verified, confirming the positive role of smart city construction in promoting low-carbon urban development.

Based on this, the following suggestions are put forward: First, formulate long-term, phased construction plans to avoid short-term behavior and ensure the continuity and stability of policies. Second, improve urban infrastructure and public services, increase investment in intelligent infrastructure, such as intelligent transportation systems, green buildings, digital public service platforms, etc., to improve urban operation efficiency, reduce resource waste and pollution emissions; finally, establish a dynamic evaluation system for smart city construction, regularly monitor changes in carbon emission efficiency, and timely adjust policy tools and technical paths to ensure the achievement of emission reduction targets.

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