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Evaluating the Impact of Smart City Policy on Carbon Emission Efficiency

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Abstract: Smart city policy (SCP) is crucial to addressing climate change and achieving sustainable urban development with low carbon emissions. The purpose of this paper is to investigate the mechanisms through which smart city policies have an impact on carbon emission efficiency (CEE). In terms of research methodology, we construct a quasi-natural experiment on smart city policies in China and use the time-varying DID approach to study this issue. The DEA method was used to measure the CEE. For the data sample, panel data from 281 cities in China between 2007 and 2020 was used in this study. The findings are as follows: ① SCP has a significant impact on CEE. This conclusion remains valid after introducing parallel trend tests, placebo tests, and other robustness tests. ② The mechanism test result reveals that SCP has a positive impact on urban CEE through three main channels: promoting industrial upgrading, increasing public environmental attention, and enhancing marketization. ③ The analysis of heterogeneity reveals that the impact of SCP on CEE is noticeable in cities that belong to well-developed economic regions with a lower intensity of environmental regulations, higher levels of green finance, and fewer official changes. This research contributes to the existing literature on the environmental assessment of SCP and offers valuable policy insights for cities to tackle climate change and sustainable urban planning.

Keywords: smart city; carbon emission efficiency; environmental assessment; sustainable urban development; urban planning

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1. Introduction

As human economic activities continue to expand and globalization accelerates, the severity of global climate change and environmental issues is increasing. It is crucial to address the challenges of reducing energy consumption, improving carbon emission efficiency, and promoting sustainable urban development while pursuing economic growth [1,2]. Achieving a green and low-carbon development model is a pressing global concern [3,4]. In order to combat the pressing issues of climate change and environmental pollution, the United Nations has implemented the 2030 Agenda for Sustainable Development. Furthermore, during COP27 in 2022, the UN established a set of practical agreements aimed at reducing carbon emissions. Meanwhile, China has taken strategic action to reduce carbon emissions, pledging to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 [5,6].

Smart cities are considered an important policy practice to reduce urban carbon emissions and achieve sustainable urban development [7]. It refers to the intelligent management and transformation of a city's infrastructure, public services, government governance, business operations, and residents' lives through the usage of advanced information and communications technology (ICT), big data, the Internet of Things (IoT), and cloud computing [8–11]. The European Commission considers energy, transport, and ICT to be the core elements of smart city construction. For example, Francesco Russo et al. found that smart cities are the main path to pursuing sustainability goals in mobile planning tools [12]. Additionally, Paola Panuccio found that smart planning is an important tool in the pursuit of urban sustainability in complex territorial systems, based on the Italian case study [13]. The ultimate purpose of a smart city is to create more sustainable and efficient urban environments [14].

Since the 1990s, numerous countries and regions, such as the European Union, the United States, and Singapore, have implemented smart city projects. In 2012, China launched its own nationwide smart city program, with over 100 cities approved as national smart city pilot cities in 2012, 2013, and 2014. These initiatives have yielded valuable policy experience for the study of smart cities.

In recent years, scholars have conducted many studies on sustainable development. The research covers several aspects, including ecosystem services, the circular economy, climate change, and the interaction between social development and natural ecology. For instance, Yan et al. examined the main EU nations' energy efficiency using panel data collected between 2010 and 2018 and found that countries with higher ecological security outperformed others in terms of energy efficiency [15]. Moreover, Lagodiienko et al. found that the external economic activity of enterprises has an important role in sustainable development based on Ukrainian data [16].

Academics have also conducted extensive research on smart cities and carbon emission issues. Research on smart cities is conducted in three main aspects: theoretical research, practical research, and methodological research. Theoretical research focuses on the conceptual connotation, explanatory framework, and functional role of smart cities [17–19]. Practical research includes the digital economy, green innovation, and communication technology [20–22]. Methodological research encompasses policy evaluation, practical case studies, and development trend research [23–25]. Research on carbon emissions has focused on identifying the factors that influence carbon emissions, developing effective measurement methods, and evaluating the performance of carbon emissions [26–29].

The current body of literature serves as a strong foundation for this paper, however, there is a noticeable gap in research regarding the effect of smart city policy (SCP) on carbon emissions, particularly in terms of how these policies can improve carbon emission efficiency (CEE). So, can SCP, a sustainable urban development policy that is widely used around the world, have an impact on CEE? What is the mechanism of its impact? What are the factors associated with this impact on cities? Therefore, this paper builds on previous research to propose our research topic, which is to evaluate the impact of smart city policies on carbon emission efficiency. The research goal is to explore how smart city policies affect carbon emission efficiency and give constructive policy recommendations for improving urban energy use efficiency and promoting sustainable urban development. The research tasks of this paper are three: first, to construct a quasi-natural experiment on the impact of smart city policies on carbon emission efficiency based on China's smart city construction experience using the time-varying DID method; second, to measure urban carbon emission efficiency based on the DEA model; and third, to identify the action channels of smart city policies on carbon emission efficiency.

This paper offers a unique contribution to the existing studies by highlighting three distinct aspects that have not been previously explored. Firstly, from a research perspective, this paper presents a quasi-natural experiment on SCP using practical experience from China. It investigates the impact of SCP on CEE, providing empirical evidence to enrich the literature on SCP evaluation and improve CEE. Secondly, this paper employs two different measurement methods to assess CEE. The baseline model uses SBM-DEA, while the robustness test utilizes EBM-DEA. This approach helps to prevent any bias in the estimation results that may have arisen from relying solely on a single measurement method, as was done in prior studies. Lastly, from an analytical perspective, the mechanism of action is examined through three aspects: promoting industrial upgrading, increasing public environmental attention, and enhancing marketization. To analyze the heterogeneity of policy impact, four perspectives are selected: regional differences among cities, environmental regulation intensity, green finance level, and official change cycles. This approach offers a fresh analytical perspective for evaluating the impact of SCP on CEE and provides theoretical guidance for the scientific construction of SCP.

The remainder of the article is structured as follows: Section 2 is the policy background and mechanism analysis. Section 3 displays the research design. Section 4 presents the benchmark analysis of SCP on CEE. Section 5 is the robustness test. Section 6 outlines the heterogeneous analysis of SCP. The following Section 7 draws on the mechanism analysis. The final section gives the conclusions and policy implications.

2. Policy Background and Mechanism Analysis

2.1. Policy Background

Numerous countries have already embarked on practical explorations of smart city construction. One such example is the Intelligent Transportation System (ITS) project, launched by the city of Seattle in 1996, aimed at resolving the issue of urban traffic congestion. The ITS project uses intelligent transportation technology to dynamically monitor and analyze traffic flow, optimizing carbon emissions by reducing traffic congestion and improving traffic efficiency. Another instance is the Songdo International Business District (SIBD) project, implemented in Incheon, South Korea, in 2003, which investigated the potential of urban science and technology parks and sought to optimize their operational efficiency. One of the features of the SIBD project is the adoption of green building design principles. The project involves the extensive use of energy-efficient equipment and technologies in the main buildings. High-efficiency lighting systems, solar panels, and geothermal energy are used in buildings to reduce energy consumption and carbon emissions. Additionally, in 2009, the Amsterdam Smart City (ACS) project was launched by the city of Amsterdam in the Netherlands. This project developed an open data sharing platform that facilitates data sharing and applications to improve the efficiency of city management and the quality of life of residents. Similarly, the 'Virtual Singapore' (VS) project aims to build a large-scale 3D city model and a multidimensional data collaboration platform based on the concept of data-driven digitization. The goal of this project is to improve the efficiency of city operations. A common feature of the ACS and VS projects is the use of big data and smart technologies to collect and analyze a variety of urban data to support data-based decision-making. This helps identify areas with high energy consumption and carbon emissions and develop corresponding emission reduction measures.

The development of smart cities in China was officially initiated in 2012 with the announcement of the *Notice on National Smart City Pilot Work* (NNSCPW) and the *National Smart City Pilot Index System* (NSCPIS) by the Chinese Ministry of Housing and Urban-Rural Development. This policy practice marked the beginning of smart city construction in China. NNSCPW and NSCPIS mainly provide guidelines for the direction of urban carbon reduction in four aspects: urban infrastructure protection, green building, urban intelligent management, and sustainable industrial development. Furthermore, the construction direction and target for smart city construction have been indicated in two documents: *Several Opinions on Promoting Information Consumption to Expand Domestic Demand* (SOPICEDD) from 2013 and the *National New Type Urbanization Plan (2014–2020)* (NNTUP) from 2014. SOPICEDD and NNTUP point out that information infrastructure construction and information consumption are the focus of smart city construction. Information-driven smart city construction based on information can promote sustainable urban development and efficient allocation of energy use. Meanwhile, the following release of two documents, namely *Guidance on Promoting the Healthy Development of Smart Cities* and *Guidance on the Construction and Application Implementation of the Smart City Standard System and Evaluation Index System*, has established evaluation standards and operational guidelines for the development of smart cities. This provides a unified analytical framework for scientifically evaluating the efficiency of urban operations, measuring energy consumption, and identifying carbon emissions footprints. Notably, in 2017, the inclusion of smart city construction in the report of the 19th National Congress of the Communist Party of China marked the formal recognition of smart cities as a national strategy and top-level design.

Following this, the Chinese government issued a series of guidance documents to promote the integration and development of smart cities with various industries. This indicates that the construction of smart cities is moving towards specialization and sophistication.

During the development process of SCP, it became evident that these policies have a direct impact on carbon emissions. As environmental issues continue to escalate, improving CEE has become a key focus of SCP. As a result, it is crucial to investigate the impact of SCP on CEE and explore the mechanisms behind this impact.

2.2. Mechanism Analysis

2.2.1. SCP Can Improve CEE by Promoting Industrial Upgrading

The effect of industrial upgrading can be observed in three main areas: the aggregation of industrial factors, the transformation of traditional industries, and the development of emerging industries. In terms of the aggregation of industrial factors, SCP aims to optimize industrial layout and enhance industrial agglomeration, resulting in efficient allocation and utilization of resources [21]. By sharing infrastructure, technical resources, and talents, enterprises in industrial agglomeration areas can reduce production costs and improve economic efficiency [30]. Industrial agglomeration not only facilitates the formation of the scale effect but also reduces energy consumption and carbon emissions during transportation by optimizing the supply chain and logistics [31]. Furthermore, the synergic effect and technological innovation brought by industrial agglomeration can promote the development and application of green production technologies, enhancing the efficiency of energy utilization and carbon emissions in the production process. In terms of the transformation of traditional industries, the SCP aims to promote technological transformation in traditional industries by introducing advanced energy-saving and low-carbon technologies, thereby reducing energy consumption and carbon emissions [32]. To achieve this, the policy offers R&D support, financial subsidies, and tax incentives to reduce the cost of renovation and stimulate the reform motivation of enterprises. The policy not only encourages enterprises to reduce carbon emissions but also aims to improve their efficiency by implementing clean production standards, carbon emission quotas, and market mechanisms. This can be achieved through the adoption of intelligent, networked, and environmentally friendly production methods, which can help traditional industries achieve their goals of high efficiency, low carbon emissions, and environmental protection [33]. In terms of the development of emerging industries, the SCP aims to optimize and upgrade the economic structure by supporting the development of emerging industries such as new energy, clean technology, and green building [34]. These low-carbon industries have high added value and environmental performance, which can effectively reduce carbon emission intensity [35]. The smart city policies offer financial support, talent training, market development, and other measures to attract companies to invest in emerging industries. This leads to an increase in the proportion of emerging industries in the economy, resulting in a significant improvement in CEE. Additionally, the development of emerging industries drives the green transformation of related industrial chains, creating a low-carbon industrial ecology.

2.2.2. SCP Can Improve CEE by Raising Public Environmental Attention

The public environmental concern effect of smart city policies is mainly reflected in three aspects: raising environmental awareness, promoting green consumption, and influencing policy implementation. From the perspective of raising environmental awareness, SCP aims to increase public awareness of environmental protection through enhanced environmental education and public participation [36]. A highly environmentally conscious public is more likely to adopt a low-carbon lifestyle, which includes green travel, energy savings, and waste reduction. Moreover, improving environmental awareness helps to create a positive social atmosphere and encourages enterprises to fulfill their social responsibility by paying attention to carbon emission issues, thus improving CEE [37]. From the perspective of promoting green consumption, SCP aims to encourage environmentally conscious consumption by promoting green products and services as well as establishing green labeling and certification systems. This approach has proven effective in reducing carbon emissions as consumers opt for energy-efficient home appliances, clean energy, and public transportation [38]. From the perspective of influencing policy implementation, SCP enables the government to obtain real-time information and policy recommendations on carbon emissions by creating a data analysis platform to analyze, evaluate, and monitor data related to public environmental concerns [39]. This information helps the government adjust policy direction and measures in a timely manner, optimize resource allocation, and achieve CEE.

2.2.3. SCP Can Improve CEE by Increasing Marketization

The marketization effects of SCP are mainly reflected in three aspects: improving resource allocation efficiency, stimulating innovation-driven development, and promoting carbon emissions trading. Regarding improving resource allocation efficiency, the SCP aims to efficiently allocate and utilize resources through market-oriented operations, optimize industrial layouts, guide capital investment, and adjust energy structures [40]. As part of this goal, the policy encourages the development of clean and renewable energy sources to reduce reliance on high-carbon energy. Additionally, the policy not only encourages the adoption of circular economy and green development strategies but also introduces market competition mechanisms to stimulate the growth of the renewable energy market. Thus, it helps reduce resource waste and improve CEE. Regarding stimulating innovation-driven development, the SCP aims to enhance talent competition and innovation development mechanisms through market-based approaches. It supports investments in research and development, talent training, and technological innovation to stimulate innovation. The policy promotes healthy competition, reduces costs and energy consumption, and fosters green technology innovation and research [41]. Additionally, it encourages the research and application of clean, low-carbon, and energy-saving technologies to reduce carbon emissions. Regarding promoting carbon emissions trading, the SCP encourages businesses to engage in the trading of carbon emission rights by creating a carbon emission trading market and quota system [42]. This approach facilitates a market-based allocation of carbon emissions, which incentivizes companies to reduce their carbon emissions and improve their CEE. Consequently, enterprises can use market-based trading to buy or sell carbon emission rights, which can help them achieve their carbon emission reduction targets. Additionally, the carbon emission trading market can aid in the rational allocation of resources and ultimately reduce the overall cost of carbon emission reduction.

3. Research Design

3.1. Multiple Time-Varing DID Model

This paper utilizes the three batches of Chinese smart city construction lists released by the Ministry of Housing and Urban-Rural Development (MHUD) in 2012, 2013, and 2014 to construct a quasi-natural experiment for Chinese smart city policy. The selected cities for smart city construction are considered the treatment group, while the cities not selected are the control group. Following the classical methodology [43,44], a multiple-time-varying DID model is used to identify the policy impact of smart city construction on urban carbon emission efficiency.

$$Eff_{Carbon_{i,t}} = \alpha + \beta Smart_{Policy_{i,t}} + \gamma Controls + CityFE + YearFE + \varepsilon_{i,t} \quad (1)$$

In the above Equation (1), Eff_{Carbon} denotes the efficiency of urban carbon emissions; $Smart_{Policy}$ denotes the smart city policy; $Controls$ denotes the control variables; $CityFE$ denotes control of city fixed effects; $YearFE$ denotes control of year fixed effects; ε denotes the random disturbance term. The estimated coefficient β measures the average difference in carbon efficiency before and after being subjected to smart city policy implementation.

3.2. DEA Model and CEE

Data envelopment analysis (DEA) is a method that uses linear programming to evaluate the relative efficiency of decision units in a multi-input, multi-output system. This method is widely used in efficiency evaluation and is one of the common models used to calculate carbon emission efficiency. In addition, the DEA model, as a non-parametric method, has also been widely used in urban system planning [45]. However, the traditional DEA model ignores the measurement error caused by the slack variables. To overcome this problem, Tone introduces a non-radial and non-angular SBM model based on the measurement of slack variables, which solves the slackness problem of the traditional DEA model. It is worth noting that the model cannot further differentiate and rank the efficiency of multiple decision-making units (DMUs) with efficiency values equal to 1 (effective frontier surface). Consequentially, Tone proposes a super-efficient SBM model that combines the super-efficiency model with the SBM model. The model incorporates undesirable output variables, corrects slack variables, and could be able to decompose multiple decision units with an efficiency value of 1. This enables comparison and ranking among efficient decision units and improves the accuracy of the model. Therefore, the super-efficiency SBM-DEA model, considering non-desired outputs, is chosen to measure urban carbon emission efficiency in this paper. The model is set as follows:

$$Min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\overline{x_i}}{x_{ij}}}{\left[\frac{1}{S_1+S_2}\left(\sum_{q=1}^{S_1} \frac{\overline{y_q^w}}{y_{qj}^w} + \sum_{q=1}^{S_2} \frac{\overline{y_q^b}}{y_{qj}^b}\right)\right]}$$

$$s.t.\begin{cases} \overline{x} \geq \sum_{j=1,\neq k}^{n} \varnothing_j x_j \\ \overline{y^w} \leq \sum_{j=1,\neq k}^{n} \varnothing_j y_j^w \\ \overline{y^b} \geq \sum_{j=1,\neq k}^{n} \varnothing_j y_j^b \\ \overline{x} \geq x_k, 0 \leq \overline{y^w} \leq \overline{y_k^w} \\ \overline{y^b} \geq y_k^b, \varnothing \geq 0 \end{cases} \tag{2}$$

In the above model: ρ denotes the Eff_{Carbon}; n denotes the numbers of city decision units; m denotes the numbers of city inputs; S_1 denotes the numbers of city desirable outputs; S_2 denotes the numbers of city undesirable outputs; x_{ij} denotes city inputs; y_{qj}^w denotes city desirable outputs; y_{qj}^b denotes city undesirable outputs; $\overline{x_i}$ denotes the slack variable of city inputs; $\overline{y^w}$ denotes the slack variable of city desirable outputs; $\overline{y^b}$ denotes the slack variable of city undesirable outputs; x_k denotes the maximum city inputs; $\overline{y_k^w}$ denotes the maximum slack variable of city desirable outputs; $\varnothing$ denotes the model vector weighting.

Consequently, in the selection of indicators, the number of urban labor forces employed, the stock of urban fixed capital investment, and coal consumption are used as input indicators. Regional GDP is the desired output. Urban CO_2 emissions are used as undesirable outputs. Finally, the indicators are brought into the SBM-DEA model to measure CEE.

3.3. Variable Selection

Explained variables: CEE (Eff_{Carbon}). In this paper, the SBM-DEA model [46] based on non-desired outputs is used to measure the CEE. Meanwhile, in order to ensure the robustness of the results, the EBM-DEA model [47] is also used in this paper to measure the CEE in the robustness test.

Explanatory variables: SCP ($Smart\_Policy$). In this paper, we consider SCP as a quasi-natural experiment and construct interaction terms for the city dummy variable and the policy implementation time dummy variable to characterize the policy treatment effect of smart city policy. Specifically, if a city is classified as a smart city, let $Smart_{Policy} = 1$, otherwise take the value 0.

Control variables. In this paper, the following control variables are selected based on existing studies to consider other possible factors that may affect CEE: ① Urban economic development level (*economy*) is expressed by the logarithm of GDP per capita. ② Urban information infrastructure level (*infrastructure*) is expressed by the logarithm of the number of international internet users. ③ Urban financial development level (*finance*) is expressed by the logarithm of the balance of deposits and loans of financial institutions at the end of the year. ④ Urban environmental pollution intensity (*pollution*) is expressed by the logarithm of industrial sulfur dioxide emissions.

3.4. Data Description

The base data for this paper is the panel data of 281 cities in China from 2007 to 2020. The data sources are the China Statistical Yearbook, the China Urban Statistical Yearbook, and the China Environmental Statistical Yearbook. For data processing, linear interpolation was used to fill in individual missing values according to local government websites and statistical bulletins. The descriptive statistics of the main variables in this paper are shown in Table 1.

Table 1. Descriptive statistics.

Variables	N	Mean	SD	Min	Max
eff_carbon	3633	0.363	0.177	0.0713	1.484
economy	3628	10.52	0.685	4.595	13.06
finance	3633	17.15	1.198	13.82	21.69
infrastructure	3351	13.04	1.111	5.468	17.76
polution	3591	10.08	1.284	0.693	13.43
baidu index	3633	24.61	27.05	0	174
IU index	3633	6.479	0.359	5.517	7.657
marketization index	3633	10.95	2.697	3.351	19.69

4. Benchmark Analysis

Table 2 presents the regression results for the impact of SCP on CEE. Column (1) displays the estimation results without considering control variables or fixed effects. In Column (2), we observe the estimation results without considering control variables but controlling for city and year fixed effects. Finally, Column (3) shows the estimation results that consider the control variables as well as city and year fixed effects. According to the regression results, the coefficient of the *smart_policy* is positively significant at the 1% level in both scenarios. This indicates that SCP has an elevated effect on CEE of about 3.72% without considering control variables and fixed effects. In the case where only city-fixed effects and time-fixed effects are considered, the SCP boost to CEE is about 2.04%. Accordingly, the net policy effect of SCP on CEE improvement is 1.61% after excluding the confounding factors of city, time, and other variables. This suggests that SCP has a strong impact on CEE, indicating its robustness. Therefore, implementing SCP can greatly enhance CEE.

Table 2. Benchmark regression estimates.

Variables	(1)	(2)	(3)
smart_policy	0.0372 ***	0.0204 ***	0.0161 ***
	(5.802)	(3.157)	(2.616)
economy			0.0868 ***
			(3.456)
finance			0.0200
			(0.852)
infrastructure			−0.0191 ***
			(−2.590)

Table 2. *Cont.*

Variables	(1)	(2)	(3)
pollution			−0.0162 ***
			(−3.902)
City FE	NO	YES	YES
Year FE	NO	YES	YES
Observations	3633	3633	3329
R-squared	0.010	0.692	0.754

Notes: *** denotes significant at the 1% level.

5. Robustness Test

5.1. Parallel Trend Test

The multiple time-varying DID model assumes that there are no significant differences between the experimental and control groups prior to the implementation of the policy. In other words, the policy sample must satisfy parallel trends. Table 3 presents the hypothesis test results for the parallel trend analysis of SCP. The *policy_year* variable denotes the relative year of policy implementation, with *pre** indicating the period before policy implementation, *post** indicating the period after policy implementation, *policy_test* indicating the policy effect test coefficient, and *current* indicating the baseline period of policy implementation. Table 3 shows that the coefficients for the policy effect test were not significant or negative prior to the implementation of SCP. This indicates that there was no significant difference between the control and experimental groups before the policy was put in place. Therefore, the research sample passed the parallel trend hypothesis test.

Table 3. Parallel trend test.

Policy_Year	Policy_Test	Policy_Year	Policy_Test
pre5	−0.0079	*post3*	0.0030 **
	(−0.652)		(2.351)
pre4	−0.0134	*post4*	0.0110 *
	(−1.084)		(1.867)
pre3	−0.0105	*post5*	0.0149 **
	(−0.843)		(2.197)
pre2	−0.0106	*post6*	0.0273 **
	(−0.798)		(2.169)
Current	0.0143	*post7*	0.0306 *
	(1.213)		(1.801)
post1	0.0020 *	*post8*	0.0487 *
	(1.766)		(1.883)
post2	0.0055 *		
	(1.858)		
Observations	3633	Observations	3633
R-squared	0.693	R-squared	0.693

Notes: * denotes significant at the 10% level; ** denotes significant at the 5% level; The values in parentheses are the *t*-statistics of the parameters.

5.2. Placebo Test

To exclude bias in the estimation results of this paper due to the chance factors of policy sample setting, a placebo test was conducted. This study employs a placebo test by randomly selecting a sample of cities from the test area of the smart city policy. Additionally, the bootstrap method is utilized to perform 500 iterations of the random process to simulate the model and derive the model estimation results. Moreover, the paper presents a kernel density distribution plot of the estimated coefficients measuring the impact of SCP on CEE. The placebo test plots for the randomized policy sample are presented in Figure 1, respectively.

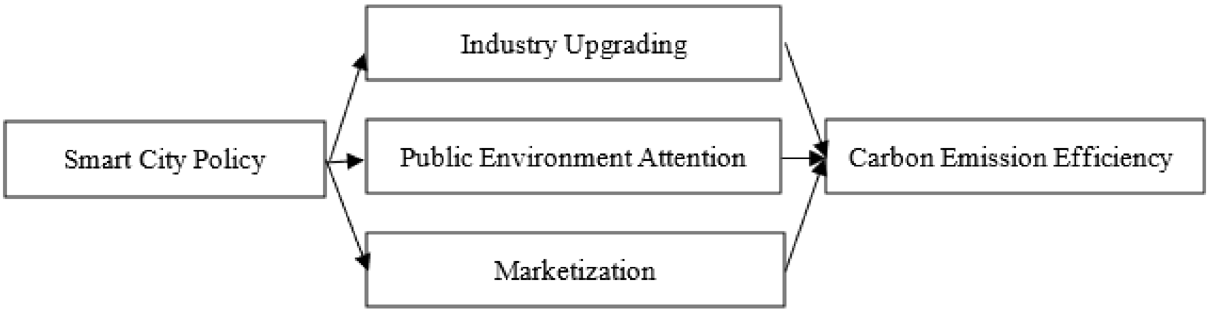

Figure 1. The mechanism effect of SCP on CEE.

Figure 2 displays a normal distribution of the estimated coefficients, where the mean value is insignificant and close to 0. Additionally, most of the *p*-values are higher than 0.1. Notably, the true estimated coefficient of SCP (0.0161) falls within the small probability range of the kernel density plot of the coefficients for the placebo test shown above. In other words, the impact of SCP on CEE is not a random occurrence. Therefore, the results presented in this paper remain reliable and valid.

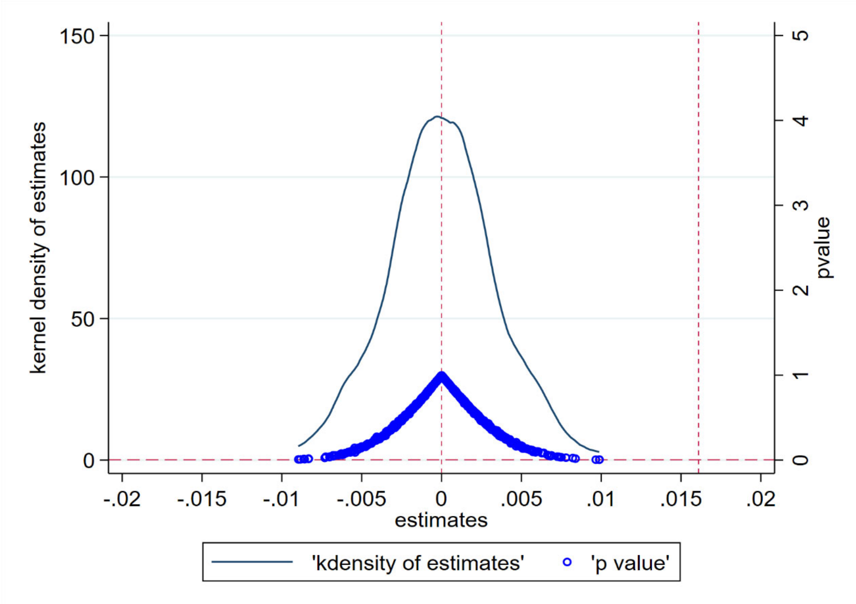

Figure 2. SCP placebo test.

5.3. Other Robustness Tests

To enhance the credibility and dependability of the findings in this research paper, we conducted four additional robustness tests: ① In order to exclude any interference caused by the different measurement methods of explanatory variables, the EBM-DEA model is used to estimate CEE, replacing the estimation obtained through the SBM-DEA model; ② Winsorizing at the 1% level for continuous variables involves excluding the effect of sample extremes to ensure that the analysis is not skewed by outliers; ③ To account for possible omitted variables that may affect CEE, two additional variables are included in the model: government fiscal intervention (*gfi*) and science and technology expenditure (*ste*). ④ In order to exclude the interference of model estimation errors due to policy lags, the explanatory variables are lagged separately in one and two periods using a lagged period model.

The results of the four robustness tests are presented in Table 4. The estimated coefficients remain largely consistent in direction and significance with the original benchmark model. Hence, the model findings in this paper are robust.

Table 4. Other Robustness Tests Estimation.

Variables	(1) EBM-DEA	(2) Winsorization	(3) *gfi*	(4) *ste*	(5) Lag 1 Period	(6) Lag 2 Periods
smart_policy	0.0215 ***	0.0134 **	0.0163 ***	0.0150 **	0.0177 ***	0.0161 **
	(3.812)	(2.274)	(2.667)	(2.435)	(2.783)	(2.562)
economy	0.106 ***	0.123 ***	0.0818 ***	0.0827 ***	0.0673 ***	0.0470 **
	(3.739)	(8.438)	(3.320)	(3.198)	(2.874)	(2.404)
finance	0.0251	−0.00353	0.00911	0.0168	−0.0239	−0.0448
	(1.243)	(−0.175)	(0.375)	(0.730)	(−0.965)	(−1.638)
infrastructure	−0.0147 **	−0.0232 ***	−0.0195 ***	−0.0194 ***	−0.00629	0.00626
	(−2.372)	(−3.297)	(−2.645)	(−2.634)	(−1.058)	(0.913)
pollution	−0.0136 ***	−0.0172 ***	−0.0161 ***	−0.0158 ***	−0.0118 ***	−0.00910 **
	(−3.687)	(−3.702)	(−3.853)	(−3.779)	(−3.070)	(−2.385)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	3329	3329	3329	3329	3028	2731
R-squared	0.755	0.745	0.755	0.755	0.782	0.800

Notes: ** denotes significant at the 5% level; *** denotes significant at the 1% level.

6. Heterogeneity Analysis

6.1. Regional Heterogeneity

Resource dependency theory suggests that the economic growth and development paths of cities often depend on the material resources (natural resources and land resources) and immaterial resources (human resources and technological resources) they possess. The resource endowments of cities in different regions of China vary widely. Cities located in various regions have distinct economic conditions and resources, which consequently impact CEE in diverse ways. Hence, to investigate potential differences in the policy effects of SCP in different regions, we divided our sample of cities into three regions based on the geographical and economic regions in China: eastern, central, and western. We then conducted a group regression test to analyze the policy effects within each region. Table 5 displays the estimated impact of SCP on CEE in the eastern, central, and western regions. The results are shown in columns (1), (2), and (3) for each respective region. The results show that the coefficient estimate of *smart_policy* in the sample of cities in the eastern region is 0.0322 and is significant at the 1% level. However, in the sample of cities in the central and western regions, the coefficient estimates of *smart_policy* are 0.00751 and 0.0106, respectively, and both fail to pass the significance test. The findings show that the impact of SCP on CEE varies across different regions. Specifically, SCP has a significant positive effect on CEE in the eastern region, while its impact on the central and western regions is insignificant. This shows a boosting effect of SCP on the CEE of the eastern regional cities of about 3.2%. One possible explanation for this phenomenon is that cities located in eastern China tend to be more economically developed and have a higher concentration of technology and skilled professionals, which allows them to effectively reduce carbon emissions [48]. Conversely, cities in central and western China may be less economically advanced and have limited access to technology and talent, which could result in less motivation to prioritize carbon reduction efforts.

Table 5. Heterogeneity analysis in different regions.

Variables	(1) East	(2) Central	(3) West
smart_policy	0.0322 ***	0.00751	0.0106
	(3.420)	(0.791)	(0.830)
economy	0.105 ***	0.108 ***	0.0814 *
	(4.569)	(4.109)	(1.683)
finance	0.0159	0.0363	0.0101
	(0.667)	(0.882)	(0.233)

Table 5. *Cont.*

Variables	(1) East	(2) Central	(3) West
infrastructure	−0.00535	−0.0332 ***	−0.0245
	(−0.579)	(−2.599)	(−1.610)
pollution	−0.0181 ***	−0.0163 **	−0.0159 **
	(−3.047)	(−2.346)	(−2.086)
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	1188	1156	985
R-squared	0.800	0.735	0.722

Notes: * denotes significant at the 10% level; ** denotes significant at the 5% level; *** denotes significant at the 1% level.

6.2. Heterogeneity of Government Environmental Regulation

Different cities differ in their economic incentives, environmental enforcement efforts, carbon reduction policy goals, and technological innovation capabilities, thus leading to different government environmental regulation conditions. Disparities in government environmental regulations may result in varied approaches by firms to addressing environmental protection, ultimately influencing the effectiveness of carbon reduction efforts [49]. Therefore, to investigate the potential heterogeneous differences in the policy impact of SCP on cities with varying levels of environmental regulatory intensities, the city sample is divided into two groups based on their respective environmental regulatory intensities: a high intensity group and a low-intensity group. Table 6 displays the estimated impact of SCP on CEE for the two groups of cities. The results indicate that the estimated coefficient of *smart_policy* for cities with low environmental regulation intensity is 0.0297 and statistically significant at the 1% level. In other words, SCP improves the CEE of low-environmental-regulation cities by about 2.97%. However, the estimated coefficient for cities with high environmental regulatory intensity is not significant. This suggests that the high intensity of government environmental regulation has not contributed to the improvement of CEE, while the appropriate relaxation of environmental regulation has contributed to the improvement of the carbon emission situation. Hence, the implementation of strict environmental regulations can lead to a 'crowding-out effect' on regional environmental improvements, as local entities may respond strategically to environmental inspections. On the other hand, relaxed environmental regulations can have a 'compensating effect' on regional environmental improvements, as local entities may focus more on substantive clean technology upgrades to improve CEE.

Table 6. Heterogeneity analysis in different intensity of environmental regulation.

Variables	(1) Low Environmental Regulation	(2) High Environmental Regulation
smart_policy	0.0297 ***	0.00399
	(2.797)	(0.466)
economy	0.0845 ***	0.124 ***
	(3.709)	(5.225)
finance	0.0119	0.0128
	(0.345)	(0.320)
infrastructure	−0.0187	−0.0139 **
	(−1.607)	(−2.452)
pollution	−0.0138 **	−0.0164 ***
	(−2.286)	(−2.998)
City FE	YES	YES
Year FE	YES	YES
Observations	1617	1677
R-squared	0.744	0.830

Notes: ** denotes significant at the 5% level; *** denotes significant at the 1% level.

6.3. Heterogeneity of Green Finance

Green finance plays a crucial role in driving green technology innovation and has a profound impact on the proliferation and acceptance of clean technologies [50]. Cities with higher levels of green finance typically have access to more investment and financing support for green projects. These funds can be used to promote the development and application of renewable energy, energy efficiency improvements, and carbon reduction technologies. In contrast, cities with lower levels of green finance may face a shortage of funds and difficulty accessing the investment and financing support needed for green projects, thus limiting the implementation of carbon emission reductions. In order to analyze the impact of SCP on CEE in cities with varying levels of green finance, this study categorizes the sample into two groups: cities with low levels of green finance and cities with high levels of green finance. This paper utilizes the entropy value method to compute the green finance index of prefecture-level cities and employs it as a substitute variable to determine the level of green finance in cities based on existing studies. Table 7 displays the regression coefficients for the impact of SCP on CEE for the two city groups. The regression coefficient value for *smart_policy* in the low green finance level city group was −0.00356, which was not significant. However, the regression coefficient value for *smart_policy* in the high green finance level city group was 0.03000 and passed the significance test at the 1% level. Hence, the level of green finance in cities has a significant impact on the effectiveness of SCP in reducing carbon emissions. In terms of policy effects, the SCP has a CEE enhancement effect of about 3% for cities with high green finance levels. It is likely that a favorable green financial environment enables urban entities to have greater financial resources to invest in green innovation, which in turn increases their motivation and capacity for green innovation. As a result, CEE is improved.

Table 7. Heterogeneity analysis in different level of green finance.

Variables	(1) Low Green Finance	(2) High Green Finance
smart_policy	−0.00356	0.0300 ***
	(−0.429)	(2.693)
economy	0.0544 *	0.0885 ***
	(1.858)	(4.377)
finance	0.0725 *	−0.0397
	(1.935)	(−1.504)
infrastructure	−0.00821	−0.0272 *
	(−1.334)	(−1.882)
pollution	−0.00565	−0.0227 ***
	(−0.872)	(−3.639)
City FE	YES	YES
Year FE	YES	YES
Observations	1687	1632
R−squared	0.841	0.740

Notes: * denotes significant at the 10% level; *** denotes significant at the 1% level.

6.4. Heterogeneity of Officer Change

The turnover of officials is a critical component of a city's administrative system. It directly impacts the efficiency of the administration and, consequently, the effectiveness of policies implemented by the city [51]. Changes in officials may lead to policy adjustments and changes, especially in policy measures for environmental protection and carbon emission reduction. If each change of officials is accompanied by policy reformulation or changes, it will affect the planning and investment decisions of enterprises and residents on carbon emission reduction, thus reducing carbon emission efficiency. Hence, to investigate the impact of changes in city officials on the carbon reduction effect of SCP, this study categorizes cities into two groups: those with changes in officials and those without. Referring to existing studies, whether a change in mayor occurs is used as a proxy variable to examine the heterogeneity of change in city officials. Table 8 displays the regression coefficients for both the officer-changed city group and the officer-not-changed city group in columns (1) and (2), respectively. According to Table 8, the coefficient of *smart_policy* for cities without official changes is 0.0183, which is statistically significant at the 5% level. However, for cities with official changes, the value of the *smart_policy* coefficient is 0.00999 and does not pass the significance test. It can be observed that SCP exerts a CEE-enhancing policy effect on office-not-changed cities, with an enhancement effect of 1.83%. The findings indicate that SCP has a positive impact on CEE in cities without official changes but does not result in significant improvements in CEE in cities with official changes. The reason for the importance of a city's principal officials is that they have a significant impact on the policy stability and continuity of the entire city. A stable policy environment enhances governing efficiency and policy effectiveness, which in turn strengthens the policy effect of SCP. This ultimately leads to an improvement in the city's CEE.

Table 8. Heterogeneity analysis in different turnovers of officer change.

Variables	**(1)** **Officer-Not-Changed**	**(2)** **Officerchanged**
smart_policy	0.0183 **	0.00999
	(2.538)	(0.706)
economy	0.0723 ***	0.131 ***
	(2.610)	(4.611)
finance	0.0420	−0.0397
	(1.295)	(−1.146)
infrastructure	−0.0191 **	−0.0194
	(−2.393)	(−1.010)
pollution	−0.0148 ***	−0.0208 **
	(−2.857)	(−2.368)
City FE	YES	YES
Year FE	YES	YES
Observations	2290	1003
R-squared	0.769	0.764

Notes: ** denotes significant at the 5% level; *** denotes significant at the 1% level.

7. Mechanism Analysis

7.1. Industrial Upgrading

According to the mechanism analysis in the previous section, SCP affects CEE through industrial upgrading. This paper utilizes the industrial upgrading index (IU index) as a proxy for the industrial upgrading mechanism and examines the relationship between *smart_policy* and the *IU index* by constructing the interaction term. Table 9 presents the regression results of the industrial upgrading mechanism. In column (1), the regression coefficient of the *smart_policy*IU index* is 0.217 and is statistically significant at the 1% level. The model estimation results show that SCP has led to a 21.7% increase in CEE because of the effect of industrial upgrading. This indicates that the smart city policy promotes carbon efficiency through the industrial upgrading mechanism. Therefore, the industrial upgrading mechanism is validated.

Table 9. Mechanism Analysis of SCP on CEE.

Variables	**(1)** **Industry Upgrading**	**(2)** **Public Environmental Attention**	**(3)** **Marketization**
smart_policy	−0.438 ***	−0.0123	−0.0405
	(−4.647)	(−1.600)	(−1.555)
*smart_policy*IU index*	0.217 ***		
	(4.822)		

Table 9. *Cont.*

Variables	**(1) Industry Upgrading**	**(2) Public Environmental Attention**	**(3) Marketization**
*smart_policy*baidu index*		0.0233 ***	
		(6.220)	
*smart_policy*marketization index*			0.0288 **
			(2.269)
economy	0.0900 ***	0.0875 ***	0.0872 ***
	(3.465)	(3.475)	(3.464)
finance	0.0260	0.0229	0.0183
	(1.106)	(0.980)	(0.781)
infrastructure	−0.0140 **	−0.0114 *	−0.0186 **
	(−1.969)	(−1.656)	(−2.512)
polution	−0.0153 ***	−0.0138 ***	−0.0162 ***
	(−3.711)	(−3.383)	(−3.888)
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3329	3329	3329
R-squared	0.757	0.758	0.755

Notes: * denotes significant at the 10% level; ** denotes significant at the 5% level; *** denotes significant at the 1% level.

7.2. Public Environmental Attention

In order to verify the role of public environmental attention in the mechanism, this paper uses the *Baidu index* as a proxy variable for public environmental attention. To measure the public environmental concern of each city, we utilized China's largest Chinese search engine and searched for the term 'environmental protection'. We set the search time and location and used Python web crawler technology to capture the frequency of urban environmental protection words.

Column (2) of Table 9 reports the regression results of the mechanism of action of public environmental attention. It can be shown that the regression coefficient value for the *smart_policy*baidu index* is 0.0233 and is significant at the 1% level. From the results of the estimated parameters of the model, it is easy to conclude that SCP has increased the CEE by 2.33% through the mechanism of public environmental attention. In other words, SCP has a catalytic effect on CEE by increasing public environmental concern. Hence, the public environmental attention mechanism passed validation.

7.3. Marketization

To investigate the impact of SCP on CEE using marketization mechanisms, this study constructs interaction terms between marketization mechanism variables and *smart_policy* and includes them in the benchmark regression. According to previous studies, the *marketization index* is used as a proxy variable for the marketization mechanism to measure the marketization level of each city.

Column (3) of Table 9 reports the regression results for the market-based mechanism. The regression coefficient of the *smart_policy*marketization index* is 0.0288 and is significant at the 5% level. From the results of the Marketization mechanism test, the increase in the level of urban marketization contributes about 2.88% to the CEE. This shows that marketization mechanisms do play a catalytic role in the carbon reduction process of SCP. In other words, the marketization mechanism passed validation.

8. Conclusions and Policy Implications

8.1. Conclusions

This paper evaluates the impact of China's SCP on CEE and its role in promoting green development and sustainable cities. The study uses Chinese city-level data from 2007 to 2020 and a quasi-natural experiment approach, employing a multiple-time-varying DID method. The findings of the study are presented below:

First, SCP significantly improves CEE. From the model estimation results, the implementation of SCP resulted in a 1.61% improvement in CEE after excluding relevant confounding factors. This finding holds after parallel trend tests, placebo tests, and other robustness tests.

Second, there is heterogeneity in the impact of SCP on CEE. In terms of city regions, SCP significantly contributes to CEE in eastern cities while having no impact on western and central cities. In terms of the environmental regulatory intensity of cities, SCP promotes CEE in cities with low environmental regulatory intensity. Additionally, among cities with different levels of green finance, the pilot policy exerts a significant carbon reduction effect in cities with high levels of green finance. Moreover, the implementation of SCP led to a greater improvement in CEE in cities without official changes compared to those with official changes.

Third, SCP acts on CEE through three mechanisms: industrial upgrading, public environmental attention, and marketization. Specifically, the impact of SCP on CEE is positively correlated with industrial upgrading, public environmental attention, and the level of marketization.

To our best knowledge, this study is the first to examine how SCP affects the CEE. Furthermore, we identify the paths (industry upgrading, public environmental attention, and marketization) of action for the policy. The results of this study may provide policymakers with clear operational directions and policy suggestions on how to increase the efficiency of urban carbon emissions.

8.2. Policy Implications

Firstly, Policymakers should prioritize summarizing and promoting the positive effects of carbon reduction in SCP. SCP plays a crucial role in improving energy efficiency, promoting eco-friendly practices, and achieving sustainable and innovative development. Therefore, it is important to leverage the potential of smart city policies to address environmental challenges and promote green growth.

Moreover, to enhance CEE, policymakers must prioritize industrial upgrading, public environmental attention, and marketization in smart city policies. It is crucial to acknowledge the significant role played by these factors and actively create channels for smart city policies to contribute to this goal. Specifically, to drive economic green growth, we recommend promoting the consolidation of industrial elements, fostering new industries while revamping traditional ones, and prioritizing industrial upgrading. Additionally, we suggest increasing public awareness of environmental protection, encouraging green consumption, facilitating access to information, and promoting environmental concerns. To achieve efficient resource allocation, we propose stimulating innovation-driven development, implementing a carbon emission trading system, and enhancing marketization.

Lastly, to ensure effective implementation of SCP, policymakers must consider the varying effects of such policies on different cities. It is crucial to optimize the implementation details and operational guidelines of SCP based on the unique characteristics of each city. City managers should focus on classification management and policy relevance when promoting smart city construction. The first point is to allocate more resources to central and western cities, focusing on improving the CEE of these cities with poor economies and green technologies. The second point is to promote greater autonomy among enterprises and other market players by reducing government administrative intervention in environmental regulation. The third objective is to strengthen the development of urban green finance, increase the funding available for environmental innovation markets, and encourage green innovation. The fourth point is to minimize the turnover of officials in order to maintain policy stability and continuity, ultimately improving the efficiency of policy operations.

8.3. Future Research Perspectives

This paper is the first to investigate the impact of smart city policies on urban carbon emission efficiency. However, there are still some shortcomings. Future researchers can start their research in the following two directions: ① Expand the measurement of carbon emission efficiency indicators. In this paper, when measuring the input indicators of carbon emission efficiency, coal consumption was mainly selected among the fuel types. Other fuel sources, such as natural gas, are not included in the analysis. Scholars can consider more fuel sources in the measurement of input indicators in order to obtain more accurate measurement results. ② Extending the scope of the city sample. The sample of smart city policies in this paper is from Chinese cities, and whether the findings are equally applicable to cities in other developing and developed countries is subject to further validation.

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