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The Impacts of Smart City Construction on Carbon Total Factor Productivity: Empirical Evidence from China

Abstract: *Today, low-carbon development and smart city pilots are prevalent. Against this backdrop, an urgent need exists to clarify the impact of smart city construction (SCC) on low-carbon development. However, studies on the low-carbon development effects of SCC remain scarce. Therefore, this in-depth study focuses on China, the world's largest developing country, to examine the role of SCC in promoting low-carbon development. First, we calculate the carbon total factor productivity (CTFP) of 182 prefecture-level cities in China using the slacks-based global Malmquist–Luenberger index. Second, to empirically examine the impact of SCC on CTFP, we employ a multi-period difference-in-difference (DID) model and a machine learning–based propensity-score matching DID (PSM-DID) model. The results reveal that SCC significantly enhances CTFP and low-carbon technological efficiency, while its impact on low-carbon technological progress is nonsignificant. Mechanism tests indicate that SCC can improve CTFP through the following three channels: green technological innovation, industrial structure upgrading, and resource allocation. Heterogeneity tests indicate that all three batches of SCC improve CTFP, and that the positive effect of the third batch is greater than that of the first and second batches. Furthermore, the CTFP promotion effect of SCC is stronger in megacities and cities in the Central region. Finally, we propose relevant policy implications.*

Keywords: *Smart city construction (SCC); carbon total factor productivity (CTFP); difference-in-difference (DID); machine learning PSM-DID; heterogeneity*

I Introduction

Global warming has emerged as a formidable challenge facing human society, with carbon dioxide (CO_2) emissions serving as the key influencing factor. As of May 2022, a total of 127 countries worldwide had either proposed or were preparing to articulate carbon neutrality goals.[1] Under the constraints imposed by CO_2 emission reduction, a prevailing global consensus has been reached regarding low-carbon development. Furthermore, the key to boosting economic low-carbon development lies in promoting carbon total factor productivity (CTFP).

CTFP incorporates carbon emissions as an undesirable output into the measurement framework of total factor productivity (TFP), which actually gauges TFP under CO_2 emission constraints (Wang et al., 2022). In contrast to traditional TFP assessments, CTFP offers a more objective evaluation of economic growth performance under carbon emission constraints, with its magnitude being closely linked to the prospects of economic sustainability.

As the world's largest developing country, China faces an increasingly severe carbon emissions challenge. From 2000 to 2021, energy-related CO_2 emissions surged from 3.328 to 10.523 billion tons, with an average annual growth rate of 5.64%.[2] As the largest emitter of CO_2, China has committed to reaching its carbon peak by 2030 and carbon neutrality by 2060. To accomplish this dual carbon goal while ensuring stable economic growth, China must urgently enhance its CTFP.

As urbanization advances, cities have emerged as crucial vehicles for economic growth and carbon emissions as well as drivers of low-carbon development in all countries (Dong et al., 2022). Against this backdrop, the concept of smart city construction (SCC) has arisen. Many developed countries have taken the lead in

[1] Data source: https://www.cikd.org/detail?docId=1538692320059240449.
[2] Data source: BP statistical review of world energy 2022.

formulating SCC policy, where a strong emphasis is placed on not only overall economic growth but also energy conservation, environmental improvement, and the promotion of sustainable economic development. For instance, in European countries, 33% of SCC programs prioritize green ecology in their construction endeavors (Beretta, 2018).

Similar to the global trend, China is also promoting low-carbon development through SCC. The country first proposed the National Smart City Pilot Program in 2009 and subsequently released lists of pilot cities in three batches. As of the time of writing, over 700 Chinese cities are either planning or actively constructing smart cities. SCC effectively alleviates the conflict between CO_2 emissions and economic growth, thus promoting CTFP. First, SCC facilitates the accelerated application of information and communication technologies (ICTs), such as the Internet, big data, and artificial intelligence; optimizes resource allocation (Chu et al., 2021); and improves energy efficiency and other factors (Weber and Cabras, 2017), thereby boosting CTFP. Moreover, SCC contributes to knowledge spillovers (Delitheou et al., 2019), rapid green technological innovation, and CTFP enhancement. Furthermore, smart cities optimize industrial structures and propel low-carbon growth (Wang et al., 2022). However, existing research on the impact of SCC on CTFP is scarce. Therefore, the present study seeks to fill this research gap.

Specifically, this study aims to investigate the impact of SCC on CTFP. We first employ the slacks-based measure and global Malmquist–Luenberger (SBM-GML) index to calculate CTFP for 182 cities in China from 2007 to 2018. Then, we use a multi-period difference-in-difference (DID) model and a machine learning–based propensity-score matching DID (PSM-DID) model to empirically examine the effect of smart city pilot construction on CTFP. The research findings from the multi-period DID model demonstrate a significant positive effect of SCC on CTFP. Moreover, regression results for the decompositions of CTFP reveal that SCC improves low-carbon technological efficiency; however, its impact on low-carbon technological progress is nonsignificant. Mechanism tests indicate that SCC can boost CTFP by promoting green technological innovation, upgrading industrial structures, and optimizing resource allocation. Furthermore, heterogeneity tests demonstrate significant city-level heterogeneities in the impact of SCC on CTFP. This study holds crucial significance for the global community, particularly developing countries, regarding the use of SCC to promote low-carbon development.

The marginal contributions of this study are as follows:

First, distinct from existing literature, which has focused on SCC's impact on factors such as economic growth, productivity, carbon emissions, pollution emissions, and green TFP considering pollution emission constraints, this study focuses on CTFP under CO_2 emission constraints. This focus enables a more accurate assessment of the impact of SCC on low-carbon development.

Second, while existing literature has often used logit regression combined with nearest-neighbor matching for PSM, this study adopts a random forest model to obtain propensity scores. It further conducts model training to achieve more precise matching results, which enhance the reliability of the regression results through the selection of more accurate experimental and control groups.

Third, while previous literature has primarily employed intermediate variables, such as technological innovation (Jiang et al., 2021), industrial structure (Wang et al., 2022), technological progress, and government subsidies (Liu et al., 2023) to examine the mechanism of SCC's impact on economic development, this study adds resource allocation as an external mechanism variable. Thus, it provides a valuable supplement to the existing literature.

Lastly, in contrast to the existing literature, which has mainly analyzed the economic and environmental effects of the first and second batches of smart city pilot projects (Xin and Qu, 2019; Jiang et al., 2021), this study investigates the heterogeneous impact of the first, second, and third batches of SCC on CTFP.

The remainder of the paper is structured as follows: Section 2 presents the literature review; Section 3 provides a theoretical analysis; Section 4 outlines the model, variables, and data; Section 5 interprets the regression results; and lastly, Section 5 presents the study's conclusions and implications.

II Literature Review

This section presents a review of the relevant literature. The literature relevant to the research topic can be categorized into the following two main groups: the effects of SCC and the measurement and driving factors of CTFP.

Regarding the effects of SCC, existing studies have primarily focused on the economic and environmental effects of SCC (Song et al., 2022). In terms of economic effects, SCC exerts positive effects on economic equity (Lara et al., 2016), production efficiency (Peng et al., 2017), innovation (Caragliu and Del Bo, 2019), and economic growth (Visvizi et al., 2018; Sergi et al., 2019). It also drives regional employment, lowers production costs, and enhances urban development (Luo et al., 2021; Min et al., 2022), thereby fostering high-quality development (Chen et al., 2022). Concerning environmental effects, SCC promotes energy efficiency (Yu and Zhong, 2019), accelerates resource recycling (Liu et al., 2023), and reduces emissions of pollutants, such as CO_2 (Yigitcanlar and Kamruzzaman, 2018; Qian et al., 2023), haze (Feng and Hu, 2022), SO_2 (Shen et al., 2023), and NO_2 (Chen, 2023). To further clarify the impact of SCC on sustainable growth, studies have analyzed the effect of SCC on green TFP, which considers wastewater, SO_2, and solid waste to be undesirable outputs (Jiang et al., 2021; Wang et al., 2022).

Regarding the measurement and driving factors of CTFP, TFP has always been a key indicator in explaining economic growth (Solow, 1956). However, traditional TFP does not account for undesirable outputs and thus fails to assess true economic performance (Färe et al., 1989). Therefore, Chung et al. (1997) incorporate environmental pollutants as undesirable outputs and construct the Malmquist–Luenberger index to calculate environmental TFP under pollution emission constraints. This index, also known as green TFP, addresses the shortcomings of traditional TFP and has been widely used.

As the issue of CO_2 emissions has become increasingly prominent, academia has started to treat CO_2 emissions as an undesirable output for measuring environmental TFP under CO_2 emission constraints (Gao et al., 2021; Liu et al., 2021), which is also known as total factor carbon productivity (Bai et al., 2019; Du and Li, 2019; Lin et al., 2022) or CTFP (Wang et al., 2022). Moreover, studies have explored the impact of various factors on CTFP, such as technological innovation (Wang et al., 2021; Wu et al., 2022), economic structure (Zhang and Lin, 2018), human capital (Wang et al., 2021), environmental regulations (Li et al., 2022), carbon trading (Yu et al., 2022), industrial intelligence (Wang et al., 2022), and green finance (Chen et al., 2023).

Notably, however, existing literature has the following drawbacks:

First, it has focused on analyzing the impact of SCC on economic growth, productivity, carbon emissions, pollutant emissions, energy efficiency, and green TFP under pollution emission constraints. However, scarce research has specifically studied the effect of SCC on CTFP, which means that the impact of SCC on low-carbon development cannot be accurately identified.

Second, in the PSM process, most studies have used logit regression combined with nearest-neighbor matching. However, the flexibility of the matching process is insufficient and it fails to effectively address issues related to self-selection.

Third, previous studies have primarily adopted factors such as technological innovation (Jiang et al., 2021), industrial structure (Wang et al., 2022), technological progress, and government subsidies (Liu et al., 2023) as mediating variables to explore the effects of SCC. Thus, they have neglected an analysis of other transmission mechanisms, such as resource allocation.

Fourth, the literature has mainly analyzed the economic and environmental effects of SCC from the second batch (Xin and Qu, 2019) and the first batch (Jiang et al., 2021). Doing so cannot reveal the differentiated impact of SCC on CTFP between different batches of SCC.

III Theoretical Analysis

This section constitutes a theoretical analysis. Section 3.1 provides smart city policies across various countries, including China's smart city pilots. Section 3.2 conducts the influencing mechanisms of SCC on CTFP.

A. Policy background

Since IBM proposed the concept of smart cities in 2008, SCC has attracted worldwide attention. SCC integrates artificial intelligence, big data, cloud computing, and other advanced ICTs across various sectors, including enterprise production, government governance, and residents' daily lives. More specifically, through the incorporation of AI devices into infrastructure, transportation systems, pipelines, rivers, and natural environments, smart cities can constantly monitor their operational status in real time. They effectively analyze and integrate urban operational data, providing valuable feedback and decision-making support to city management departments. SCC represents a collective endeavor by governments worldwide to optimize urban operations and enhance management practices.

Moreover, SCC has drawn significant attention in many countries. For instance, in 2005, the European Union initiated the "i2010" program, and in 2006 it launched the Smart Cities Network Building project. Following this, European countries have tailored smart city plans to suit their specific developmental goals. Notably, the United Kingdom launched the "Digital Britain" plan with the vision of transforming London into a digital capital. In Germany, SCC primarily revolves around energy conservation and environmental protection, emphasizing the application of the Green City PPP construction model. Since 2000, Japan has expedited its ICT strategy, making strides in informatization through initiatives like "e-Japan," "U-Japan," and "I-Japan." (Su et al., 2022). Similarly, Singapore has made significant progress with the implementation of its "Smart Nation 2015" plan. This involves effectively incorporating digital technologies into critical areas, such as e-governance, financial services, production and sales, and education and learning. In the United States, collaboration between IBM and Dubuque City has resulted in the digitization of public resources for addressing residents' needs and societal challenges. These collective efforts demonstrate the global commitment to SCC and the use of digital technologies to enhance various aspects of urban life.

In 2012, China issued the "Notice on the Launch of the National Smart City Pilot Work," which explicitly recognized the vital role of SCC in advancing intelligent, eco-friendly, and low-carbon urbanization development. The first batch of smart cities, initiated in 2012, comprised 90 cities, counties, and districts. The second batch, initiated in 2013, comprised 83 cities and districts along with 20 counties and towns. Subsequently, in 2014, the third batch encompassed 13 counties and districts as well as 79 cities. In 2021, both the central and local governments in China emphasized the prioritization of SCC in the "14th Five-Year Plan" for future development. At present, over 700 cities in China are actively planning or undergoing SCC projects. Therefore, the significant contribution of SCC to China's low-carbon development is becoming increasingly apparent.

B. Influencing mechanism

In essence, CTFP stands for TFP under the constraints of carbon emissions. Therefore, SCC can boost CTFP through the combined promotion of productivity growth and carbon emission reduction.

Regarding productivity growth, SCC facilitates the widespread adoption of ICT, which enhances the allocation efficiency of production factors (Xu and Yang, 2022), thereby ultimately promoting productivity. Furthermore, smart cities serve as attractive destinations for high-tech and foreign enterprises, thus fostering economies of scale that increase capacity utilization and expedite knowledge spillover effects. Consequently, efficiency and the technological level are increased and productivity is elevated.

Concerning carbon emission reduction, SCC leverages ICT to conduct real-time monitoring of urban areas, which enables the precise implementation of environmentally friendly products and clean production technologies in the energy and manufacturing sectors. This fundamental integration improves resource use efficiency and fosters proactive measures against energy use and carbon emissions, thereby enhancing CO_2 prevention and control measures in urban businesses. Additionally, SCC expedites the transition toward greener and more digitized practices, which significantly contribute to reduced carbon emissions (Ferrara, 2015); ultimately, this propels low-carbon development. Thus, we propose the following hypothesis (H):

H1: SCC promotes productivity growth and carbon reduction, leading to an overall improvement in CTFP.

Moreover, SCC serves as a catalyst for the development of ICT applications and inclusive digital finance, which facilitate improved access to funding for enterprises and offer financial support for green technological innovations (Arora, 2018). Furthermore, the low-carbon goal of SCC must be supported by green technological innovations in green product design, green materials, and clean energy. This will provide broad application scenarios and market opportunities for green technological innovation, thus guiding the flow of capital to the field of green technological innovation. Such innovation plays a key role in enhancing production processes and improving the use efficiency of production factors, ultimately increasing productivity. Moreover, green technological innovation in areas such as clean energy can accelerate the substitution of fossil fuels with clean energy as well as reduce carbon emissions, thus increasing CTFP. Accordingly, we propose the following hypothesis:

H2: SCC enhances CTFP by promoting green technological innovation.

In addition, SCC plays a pivotal role in expediting the adoption of new energy and information materials, which in turn propels the development of information-based infrastructures and modern industries (e.g., the information, research and development [R&D], and design sectors). In effect, this fosters the flow of production factors across industries, reduces resource idleness, mitigates structural imbalances, and facilitates industrial structure upgrading. Noteworthily, the process of industrial structure upgrading yields "structural dividends" (Peneder, 2003), which drive the shift of production factors from less efficient sectors to more efficient ones, which leads to the improved use efficiency of energy and other factors as well as less carbon emissions, ultimately increasing CTFP. Accordingly we propose the following hypothesis:

H3: SCC enhances CTFP by promoting industrial structure upgrading.

Lastly, SCC can increase the efficiency of innovation, promote the precise application of low-carbon technologies (Xue et al., 2023), accelerate the flow of capital and labor in the factor market, alleviate factor mismatch, improve the efficiency of resource allocation (which can alleviate the contradiction between economic growth and carbon emissions), and promote low-carbon development. According, we propose the following hypothesis:

H 4: SCC enhances CTFP through optimizing resource allocation.

Based on the above analysis, Figure 1 illustrates the influencing mechanism of SCC on CTFP.

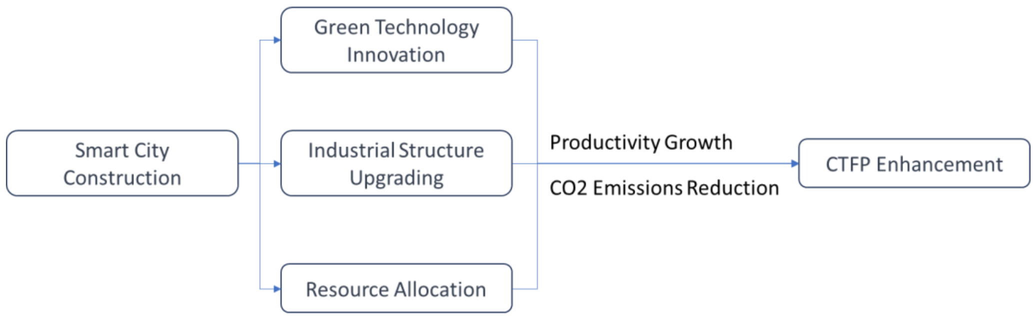

FIGURE 1 INFLUENCING MECHANISM OF SCC ON CTFP

IV Research Design

This section introduces model, variables and data. Section 4.1 constructs regression models. Section 4.2 and 4.3 describes variables and data, respectively.

A. Model

In 2012, China officially planned the first batch of smart city pilots, followed by the approval of the second and third batches in 2013 and 2014, respectively. This study considers the smart city pilot a quasi-natural experiment and uses the multi-period DID method to assess the impact of SCC on CTFP.

First, two dummy variables – treat and post – are constructed: *treat* = 1 represents smart cities, the treatment group, while *treat* = 0 represents non-smart cities, the control group. Furthermore, *post* denotes the policy shock, where *post* = 1 indicates the period after the implementation of a smart city pilot, while *post* = 0 indicates the period before the implementation. The coefficient of the interaction term, $did_{i,t} = treat \times post$, represents the impact of SCC on CTFP.

During the selection of the experimental and control groups, cities that only implement policies at the district and county levels are excluded to avoid underestimating the carbon reduction effect. Cities with significant data gaps are also excluded. Ultimately, the treatment and control groups comprise 77 and 105 cities, respectively.

The multi-period DID regression model is specified as follows:

$$CTFP_{it} = \beta_0 + \beta_1 treat \times post + \Sigma_{i=1}^{n} \gamma_i X_{it} + v_t + \mu_i + \varepsilon_{it} \tag{1}$$

Furthermore, to address sample selection bias, this study employs machine learning for PSM. Subsequently, the PSM-DID method is used to tackle endogeneity problems and identify the policy treatment effect. The model is as follows:

$$CTFP_{it}^{PSM} = \beta_0 + \beta_1 treat \times post + \Sigma_{i=1}^{n} \gamma_i X_{it} + v_t + \mu_i + \varepsilon_{it} \tag{2}$$

where *CT*FP represents the CTFP, and its calculation process is detailed in the following section; *X* represents the control variables; v_t denotes time-fixed effects; μ_i represents city-fixed effects; and ε represents the disturbance term.

Then, following Wang and Zhong (2023), we investigate the impact of SCC on the mediating variables to identify the mediating mechanism:

$$Med_{i,t} = \beta_0 + \beta_1 treat \times post + \Sigma_{i=1}^{n} \gamma_i X_{it} + v_t + \mu_i + \varepsilon_{it} \tag{3}$$

If β_1 is significant, SCC can influence CTFP through the intermediate variables.

B. Variables

Dependent variable—CTFP is the dependent variable, and CO_2 emissions are chosen as the undesirable output and incorporated into the environmental TFP calculation framework. The SBM directional distance function and GML index are used to calculate CTFP.

Production possibility set: In this study, each city is treated as a decision-making unit to construct the best practice frontier for all cities in each period. Each city is represented by N types of input factors $x = (x_1, \dots, x_N) \in R_N^+$ to produce M types of "good" outputs $y = (y_1 \dots y_M) \in R_M^+$ and I types of "bad" outputs $b = (b_1 \dots b_I) \in R_I^+$. We assume the period to be denoted as t = 1, 2,...,T and each city to be denoted as k = 1, 2,...,K. Therefore, the input and output values of city k at period t can be denoted as $(x^{k,t},\ y^{k,t},\ b^{k,t})$

Following Chung et al. (1997), the production possibility set is calculated as follows:

$$(4) \qquad P^t(x^t) = \{(y^t,\ b^t):\ \sum_{k=1}^{K} w_k^t y_{km}^t \geq y_{km}^t,\ \forall m;\ \sum_{k=1}^{K} w_k^t b_{ki}^t = b_{ki}^t, \forall i;$$

$$\sum_{k=1}^{K} w_k^t x_{km}^t \leq x_{kn}^t, \forall n; \sum_{k=1}^{K} w_k^t = 1, w_k^t > 0, \forall k$$

where w_k^t represents the weight of each cross-sectional observation, and $\sum_{k=1}^{K} w_k^t = 1$ and $w_k^t > 0$ indicate variable returns to scale (VRS) in the production technology. To calculate the GML index, following Oh (2010), $P^t(x^t)$ is replaced by the global production possibility set $P^G(x)$ as follows:

$$(5) \qquad P^G(x) = \{(y^t, b^t): \sum_{t=1}^{T} \sum_{k=1}^{K} w_k^t b_{ki}^t = b_{ki}^t, \forall i;$$

$$\sum_{t=1}^{T} \sum_{k=1}^{K} w_k^t x_{kn}^t \leq x_{kn}^t, \sum_{k=1}^{K} w_k^t = 1, w_k^t \geq 0, \forall k\}$$

Global SBM directional distance function: Following Fukuyama and Weber (2009), this function is defined as follows:

$$(6) \quad S_V^G\left(x^{t,k^t}, y^{t,k^t}, b^{t,k^t}, g^x, g^y, g^b\right) = max_{s^x, s^y, s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M+1}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \sum_{i=1}^{I}\frac{s_i^b}{g_i^b}\right)}{2}$$

$$s.t. \sum_{t=1}^{T} \sum_{k=1}^{K} w_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \forall n; \sum_{t=1}^{T} \sum_{k=1}^{K} w_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m;$$

$$\sum_{t=1}^{T} \sum_{k=1}^{K} w_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall i$$

$$\sum_{k=1}^{K} w_k^t = 1, w_k^t \geq 0, \forall k; s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i$$

Here, x^{t,k^t}, y^{t,k^t}, and b^{t,k^t} represent the input, good output, and bad output vectors for period *t* and city *k*, respectively; g^x, g^y, and g^b represent the direction vectors for input reduction, good output increase, and bad output reduction, respectively; and s_n^x, s_m^y, and s_i^b represent the slack vectors for inputs, good outputs, and bad outputs, respectively.

GML index in reference to Oh (2010): The GML index based on the SBM directional distance function is calculated as follows:

(7) $$GML_t^{t+1} = \frac{1+S_V^G(x^t,y^t,b^t;g)}{1+S_V^G(x^{t+1},y^{t+1},b^{t+1};g)}$$

The GML_t^{t+1} index bein equal to 1, greater than 1, or less than 1 indicates that the CTFP remains unchanged, increases, or decreases from period *t* to *t*+1, respectively. The GML_t^{t+1} index can be further decomposed into the product of a low-carbon technology efficiency index and a low-carbon technology change index, which are denoted as CEC_t^{t+1} and CTC_t^{t+1}, respectively. Their decomposition is presented as follows:

(8) $$GML_t^{t+1} = GEC_t^{t+1} \times GTC_t^{t+1}$$

(9) $$CEC_t^{t+1} = \frac{1+S_V^t(x^t,y^t,b^t;g)}{1+S_V^{t+1}(x^{t+1},y^{t+1},b^{t+1};g)}$$

(10) $$CTC_t^{t+1} = \frac{1+S_V^G(x^t,y^t,b^t;g)/1+S_V^t(x^t,y^t,b^t;g)}{1+S_V^G(x^{t+1},y^{t+1},b^{t+1};g)/1+S_V^{t+1}(x^{t+1},y^{t+1},b^{t+1};g)}$$

CEC_t^{t+1} and CTC_t^{t+1} indices greater than 1 indicate efficiency improvement and technological progress from period *t* to *t*+1. When the indices are less than 1, this signifies a decline in efficiency and technological regression from period *t* to *t*+1.

Inputs and outputs: We select the following inputs and outputs for measuring CTFP: The desirable output is represented by the real gross domestic product (GDP) at 2007 constant prices, while the undesirable output is represented by CO_2 emissions. Capital input is represented by the logarithm of the capital stock, which is calculated using the perpetual inventory method, while labor input is represented by the logarithm of the total number of employees. Considering the availability of data, energy input is represented by industrial electricity consumption.

Mediating variables—Green technological innovation is represented by the number of green technology innovation patents (*Pergreenpat*) and the quality of green technology innovation (*Pergreeninv*), where *Pergreenpat* and *Pergreeninv* are represented by the number of green patent applications and number of green invention applications per 10,000 people, respectively. Industrial structure upgrading is represented by industrial structural rationalization (*struc*), which is measured using the Theil index. Lastly, resource allocation (*ra*) is measured by the level of regional scientific and technological expenditures.

Control variables—The control variables are as follows: population size (*lnpop*, measured by the logarithm of urban population), economic development level (*lnpgdp*, measured by the logarithm of real per capita GDP), industrial structure (*is*, measured by the proportion of value added from the secondary industry to GDP), urbanization (*urban*, represented by the proportion of the nonagricultural population among the total population), energy consumption structure (*es*, represented by the ratio of coal consumption to total energy consumption), level of opening up (*open*, measured by the proportion of total imports and exports to GDP), and R&D investment (*rd*, measured by the ratio of regional R&D expenditure to GDP).

Data—CO_2 emissions data are obtained from the CEADs database, while data for other variables are sourced from the *China City Statistical Yearbook*, the *China Energy Statistical Yearbook*, and the *China Population and Employment Statistical Yearbook*. Thus, balanced panel data for 182 prefecture-level cities from 2007 to 2018 are obtained.

TABLE 1— DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max
CTFP	2184	1.019	0.311	0.063	11.256
lnpop	2184	5.815	0.673	2.898	7.138
lnpgdp	2184	10.44	0.643	4.595	12.46
is	2184	50.05	9.898	17.72	90.97
urban	2184	32.68	21.95	4.350	100.0
es	2184	0.094	0.139	0.005	4.176
open	2184	16.89	35.58	0.001	813.4
rd	2184	0.004	0.007	0.001	0.134

V Empirical Results

This section discusses empirical results, including baseline regression results, machine learning–based PSM-DID regression results, parallel trend test, placebo test, mechanism analysis and heterogeneity analysis.

A. Baseline regression results

From Models (1) and (2) in Table 2, the coefficients of *treat* × *post* (*did*) are significantly positive at the 1% level. This indicates that SCC can significantly enhance CTFP, thus confirming **H1**. According to H1, SCC boosts productivity growth and inhibits carbon emissions, thereby improving CTFP. Regarding the decomposition term, SCC significantly enhances CEC, while its impact on CTC is nonsignificant. The results indicate that the positive impact of SCC on CTFP is mainly due to it promoting low-carbon technological efficiency rather than low-carbon technological progress.

TABLE 2 — MULTI-PERIOD DID REGRESSION RESULTS

	(1)	(2)	(3)	(4)
	CTFP	CTFP	CEC	CTC
did	0.073***	0.159***	0.195***	0.010
	(4.452)	(6.313)	(5.679)	(0.819)
lnpop		0.010	−0.184	0.143**
		(0.106)	(−1.342)	(2.307)
lnpgdp		0.026	−0.013	0.008
		(0.901)	(−0.239)	(0.431)
is		−0.001	−0.005*	0.004***
		(−0.674)	(−1.897)	(3.168)
urban		0.000	0.002*	−0.000
		(0.641)	(1.812)	(−1.299)
es		0.010	0.029	−0.006
		(0.333)	(0.620)	(−0.219)
open		0.000***	0.000*	−0.000
		(2.910)	(1.797)	(−0.380)
rd		0.707	0.187	0.754
		(0.712)	(0.154)	(1.302)
_cons	1.004***	0.686	2.400**	−0.085
	(134.652)	(0.959)	(2.317)	(−0.188)
Adj. R-squared	0.0086	0.1371	0.0625	0.3478
Urban-fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year-fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
N	2,184	2,184	2,184	2,184

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

B. Machine learning–based PSM-DID regression results

Generally, propensity-score estimation uses logistic regression (LR). The use of LR to estimate propensity scores and achieve covariate balance typically involves an iterative process through the addition of interaction terms and nonlinear transformations of explanatory variables until an acceptable covariate balance is achieved (Lee et al., 2009). However, this process does not guarantee an improved covariate balance. Therefore, this study adopts a machine learning approach for PSM, which effectively captures nonlinear patterns and automatically selects features with the most significant impact on the results; thus, this approach avoids the manual feature selection process. This enables relationships to be more accurately captured between features and potential nonlinear relationships and interactions to be identified (Whata & Chimedza, 2022); thus, more precise matching results can be provided. The results are presented in Figure 2:

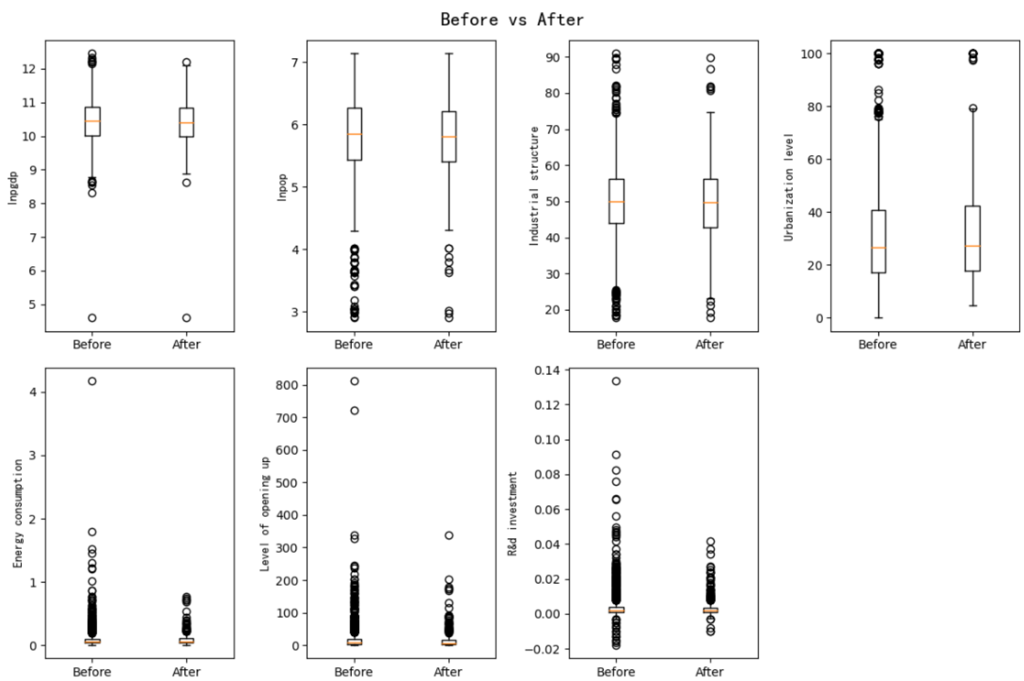

FIGURE 2 MACHINE LEARNING PSM RESULTS

Propensity scores are obtained using the random forest algorithm, and then machine learning models are trained and predicted. Thus, a highly matched combination between the treatment and control groups is achieved. Based on this, a regression analysis is conducted, the results of which are presented in Table 3:

TABLE 3 —MACHINE LEARNING PSM-DID REGRESSION RESULTS

	(1) CTFP	(2) CEC	(3) CTC
did	0.188***	0.202***	0.048
	(4.280)	(2.650)	(1.115)
_cons	0.649	3.322	−0.358
	(0.473)	(1.501)	(−0.238)
Adj R-squared	0.2577	0.1921	0.4005
Urban-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
N	400	400	400

Note: The estimated results of control variables are shown in the Table A1 of Appendix A.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

In PSM, the use of machine learning algorithms offers stronger modeling capabilities, automatic feature selection, fault tolerance, and robustness. With a higher matching quality achieved after we train the machine learning model, the coefficient of *variation* is 0.188, significant at the 1% level. This indicates that smart cities can indeed enhance CTFP.

C. Parallel trend test

Before we implement smart city pilot policies, the changes in CTFP between pilot cities and nonpilot cities should be similar. Therefore, it is necessary to verify the existence of parallel trends in CTFP. The test results are presented in Figure 3:

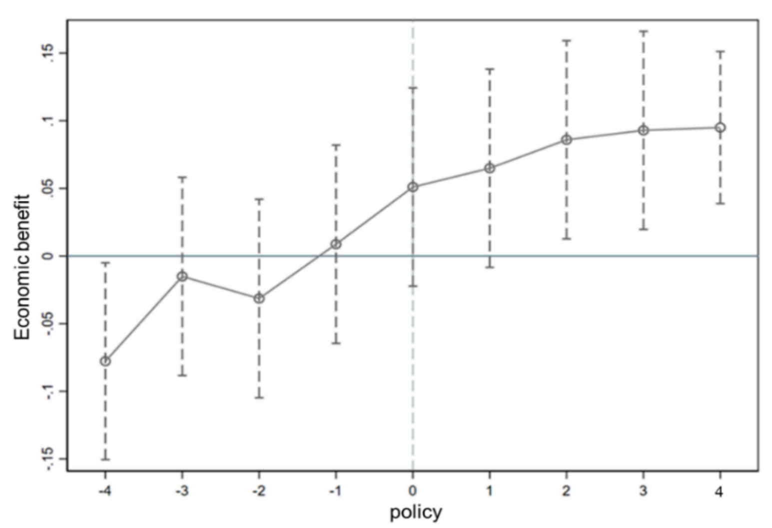

FIGURE 3 PARALLEL TREND TEST RESULTS

According to Figure 3, before the implementation of smart city policies, the values of CTFP were distributed around zero and were nonsignificant. This indicates that the treatment and control groups exhibited similar growth trends in CTFP. After the policy implementation, the effects of relevant policies do not exhibit immediate significance but rather a certain lag. Approximately 2 years after the policy's implementation, both the treatment group and the control group experience significant changes and an increase in CTFP.

D. Placebo test

To examine whether the regression results are influenced by random factors and omitted variables as well as to avoid the impact of unobservable factors on the baseline regression analysis, this study randomly selects new cities as the treatment group and conducts placebo tests. Randomly selected cities from the sample are used to represent a fictitious treatment group, and then a regression is performed again. This process is repeated 1,000 times, resulting in 1,000 regression coefficients and assumed values. The kernel density distribution and *t* values are depicted in Figure 4.

The mean of the coefficients is close to 0, which aligns with the expectations of the placebo test. Therefore, the estimation results are not biased due to omitted variables, which further validates the robustness of the baseline regression results.

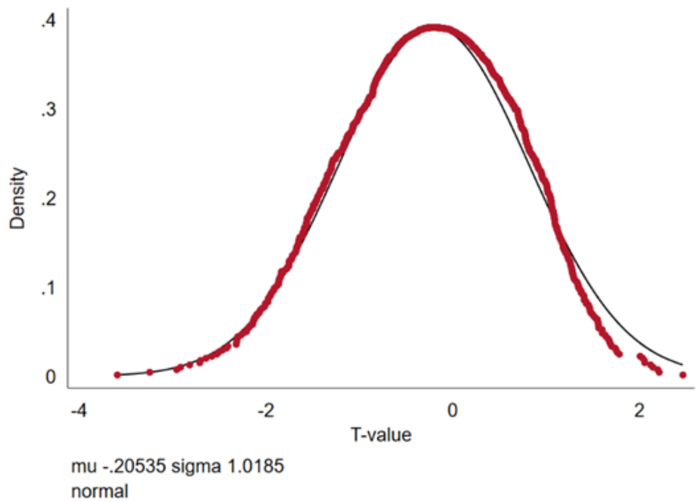

FIGURE 4 PLACEBO TEST RESULTS

E. Mechanism analysis

As described in Section 3.2, SCC influences CTFP by promoting green technological innovation, upgrading industrial structures, and improving resource allocation. These mechanisms are further examined in Table 4:

TABLE 4— MECHANISM TEST RESULTS

	(1) pergreenpat	(2) pergreeninv	(3) struc	(4) ra
did	0.719**	0.419**	0.046*	1.1e+05**
	(2.522)	(2.483)	(1.875)	(2.515)
cons	−8.103	−2.134	0.140	−6.2e+05
	(−1.452)	(−0.694)	(0.185)	(−0.553)
Urban-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
N	395	395	400	400

Note: The estimated results of control variables are shown in the Table A2 of Appendix A.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

The coefficients of *pergreenpat*, *pergreeninv*, *struc*, *and ra* are significantly positive, indicating that SCC can enhance CTFP through promoting green technological innovation, upgrading industrial structure, and optimizing resource allocation. Thus, H2, H3, and H4 are validated. In other words, green technology innovation, industrial structure upgrading, and resource allocation are crucial channels through which SCC promotes CTFP.

F. Heterogeneity analysis

Heterogeneity in batches—The first, second, and third batches of smart city pilots in China were implemented in 2012, 2013, and 2014, respectively. To explore whether the CTFP promotion effects of different batches of smart city pilots have been homogeneous, this study proceeds to investigate the impacts of the three batches of SCC on CTFP. To ensure the reliability of the regression analysis, only other cities in the provinces where the treatment group smart cities are located are selected as the control group. Table 5 presents the regression results:

TABLE 5 —REGRESSION RESULTS OF DIFFERENT SCC BATCHES

	2012	2013	2014
	CTFP	CTFP	CTFP
did	0.096***	0.181***	0.215***
	(3.059)	(4.410)	(5.851)
R-squared	0.1204	0.1058	0.2422
Urban-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
N	1,500	1,260	912

Note: The estimated results of control variables are shown in the Table A3 of Appendix A.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

According to Table 5, each batch of smart city pilots has significant positive effects on CTFP. The coefficients of *did* for the first, second, and third batches are 0.096, 0.181, and 0.215, respectively, all of which are significant at the 1% level. This further confirms the positive effect of SCC on CTFP. Moreover, the third batch of smart city pilots has the largest positive impact on CTFP, followed by the second batch, while the first batch has the smallest impact. Compared with the first batch, the second and third batches of pilot smart cities have the advantage of being able to learn from the experience of other cities' policy pilots, and they implement smart city policies more accurately based on their own comparative advantages. This can more effectively promote CTFP.

Heterogeneity in location and urban scale—Due to the uneven development policies and diverse location conditions, significant regional disparities exist in low-carbon development in China (Figure 5). Therefore, regional heterogeneities may exist in the impact of SCC on CTFP.

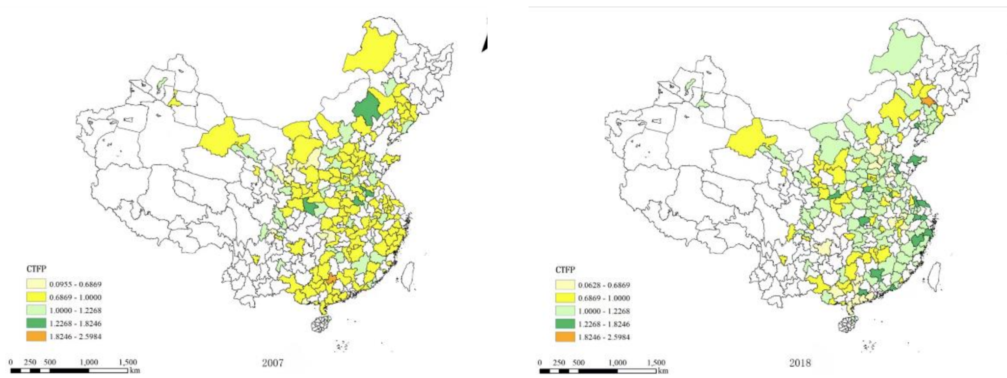

FIGURE 5 CTFP IN 2007 AND 2018 IN CHINA

First, cities are divided into the following three regional groups: the Eastern, Central, and Western regions. Then, regressions are conducted to examine the regional heterogeneity in the influence of SCC on CTFP. Columns 1–3 in Table 6 present the results:

TABLE 6— HETEROGENEITY REGRESSION RESULTS

	Urban Location Heterogeneity			Urban Scale Heterogeneity	
	Eastern	Central	Western	Megacities	Other Cities
	(1)	(2)	(3)	(4)	(5)
	CTFP	CTFP	CTFP	CTFP	CTFP
did	0.156^{***}	0.192^{***}	0.167^{*}	0.185^{***}	0.106^{**}
	(3.864)	(5.858)	(1.731)	(6.144)	(2.514)
Urban-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
N	912	864	408	1,740	444

Note: The estimated results of control variables are shown in the Table A4 of Appendix A.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

In the samples from the Eastern, Central, and Western regions, the coefficients of *variation* are 0.156, 0.192, and 0.167, respectively, all of which are significant at the 1%, 1%, and 10% levels. Therefore, SCC can promote CTFP in China's three major regions. Moreover, the effect of SCC is most significant in the Central region. This may be due to the fact that the Central region benefits from knowledge spillovers and industrial migration from Eastern cities, enabling it to improve CTFP more effectively through SCC. While an increase is found to have occurred in the level of innovation in the Eastern region (Wang & Deng, 2022), due to diminishing marginal returns, the positive impact of SCC on CTFP in said region is relatively smaller. The Western region has clearer latecomer advantages, and the cost and risk of SCC are lower; thus, a significant improvement in CTFP is achieved.

Second, the economic and environmental effects of SCC vary by city size. Therefore, this study classifies cities with a population of over 2 million as megacities and those below 2 million as Other cities before performing grouped regressions (Columns 4–5 in Table 6).

The coefficient of *did* for the megacities is 0.185, which is significant at the 1% level, while the coefficient of *did* for the Other cities is 0.106, which is significant at the 5% level. This suggests that the impact of SCC on CTFP is more pronounced in megacities. The reason could be that the SCC in megacities reflects more prominent knowledge and technological spillover effects, which contribute to CTFP growth.

VI Conclusion and Implications

A. Conclusion

In this era of low-carbon development and the prevalence of smart city pilots, it is necessary to identify the impact of SCC on low-carbon development. However, little is known about the causal relationship between SCC and CTFP. This study employed multi-period DID and machine learning PSM-DID methods to empirically investigate the impacts of SCC on CTFP in Chinese cities. The key findings are as follows:

First, SCC was found to have significantly increased CTFP and low-carbon technological efficiency; however, its impact on low-carbon technological progress is nonsignificant.

Second, mechanism tests indicated that SCC enhances CTFP by promoting green technological innovation, upgrading industrial structure, and optimizing resource allocation.

Third, heterogeneity tests demonstrate that all three batches of SCC promote CTFP, and the promotion effect of the third batch is larger than that of the first and second batches. Moreover, the positive impact of SCC on CTFP is more significant in the Central region and megacities.

B. Policy implications

Based on the abovementioned conclusions, the following policy implications are proposed:

First, importance should be attached to the vital role of the pilot smart city policy in promoting low-carbon development. Furthermore, ICT technologies such as big data and cloud computing should be used to monitor possible energy and carbon emission problems in the city in real time, accelerate the digital transformation and low-carbon transformation of enterprises, and strengthen the CTFP promotion effect of smart cities.

Second, smart cities' role in driving technological innovation should be promoted, resource allocation should be optimized, the industrial structure should be upgraded, technological efficiency should be improved, a favorable market environment should be created, and the channels for smart cities to improve CTFP should be smoothed.

Finally, SCC must be adapted to local conditions. The Eastern regions and megacities of China should leverage their strong economic foundation to assume a leading role in the construction of smart cities. Furthermore, the Central regions should fully utilize their favorable geographical advantages and absorb the experience of SCC in the East. Moreover, Western regions can fully strengthen the positive effect of SCC on CTFP through special government transfer payments.

REFERENCES

Arora, R. U. 2018. "Financial sector development and smart cities: The Indian case." Sustainable Cities and Society, 42, 52-58.

Autor, D. H. 2003. "Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing." Journal of Labor Economics, 21(1), 1-42.

Bai, C., Du, K., Yu, Y., & Feng, C. 2019. "Understanding the trend of total factor carbon productivity in the world: Insights from convergence analysis." Energy Economics, 81, 698-708.

Beretta, I. 2018. "The social effects of eco-innovations in Italian smart cities." Cities, 72, 115-121.

Caragliu, A., & Del Bo, C. F. 2019. "Smart innovative cities: The impact of Smart City policies on urban innovation." Technological Forecasting and Social Change, 142, 373-383.

Chen, J. 2023. "Mitigating nitrogen dioxide air pollution: The roles and effect of national smart city pilots in China." Energy, 263, 125652.

Chen, J., Abbas, J., Najam, H., Liu, J., & Abbas, J. 2023. "Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China." Journal of Cleaner Production, 382, 135131.

Chen, Y., Huang, D., Liu, Z., Osmani, M., & Demian, P. 2022. "Construction 4.0, Industry 4.0, and Building Information Modeling (BIM) for sustainable building development within the smart city." Sustainability, 14(16), 10028.

Chui, K. T., Lytras, M. D., & Visvizi, A. 2018. "Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption." Energies, 11(11), 2869.

Chung, Y. H., Färe, R., & Grosskopf, S. 1997. "Productivity and undesirable outputs: a directional distance function approach." Journal of Environmental Management, 51(3), 229-240.

Chu, Z., Cheng, M., & Yu, N. N. 2021. "A smart city is a less polluted city." Technological Forecasting and Social Change, 172, 121037.

Delitheou, V., Meleti, V., & Athanassopoulos, C. G. 2019. "Green economy and smart city." Journal of Reliable Intelligent Environments, 5, 235-240.

Dong, F., Li, Y., Li, K., Zhu, J., & Zheng, L. 2022. "Can SCC improve urban ecological total factor energy efficiency in China? Fresh evidence from generalized synthetic control method." Energy, 241, 122909.

Du, K., & Li, J. 2019. "Towards a green world: How do green technology innovations affect total-factor carbon productivity." Energy Policy, 131, 240-250.

Fare, R., Grosskopf, S., & Kokkelenberg, E. C. 1989. "Measuring plant capacity, utilization and technical change: a nonparametric approach." International Economic Review, 655-666.

Färe, R., Grosskopf, S., & Pasurka Jr, C. A. 2007. "Environmental production functions and environmental directional distance functions." Energy, 32(7), 1055-1066.

Feng, Y., & Hu, S. 2022. "The Effect of Smart City Policy on Urban Haze Pollution in China: Empirical Evidence from a Quasi-Natural Experiment." Polish Journal of Environmental Studies, 31(3).

Ferrara, R. 2015. "The smart city and the green economy in Europe: A critical approach.” Energies, 8(6), 4724-4734.

Fukuyama, H., & Weber, W. L. 2009. “A directional slacks-based measure of technical inefficiency.” Socio-Economic Planning Sciences, 43(4), 274-287.

Gao, Y., Zhang, M., & Zheng, J. 2021. “Accounting and determinants analysis of China's provincial total factor productivity considering carbon emissions.” China Economic Review, 65, 101576.

Guo, M., Xia, M., & Chen, Q. 2022. “A review of regional energy internet in smart city from the perspective of energy community.” Energy Reports, 8, 161-182.

Jiakui, C., Abbas, J., Najam, H., Liu, J., & Abbas, J. 2023. “Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China.” Journal of Cleaner Production, 382, 135131.

Jiang, H., Jiang, P., Wang, D., & Wu, J. 2021. “Can SCC facilitate green total factor productivity? A quasi-natural experiment based on China’s pilot smart city.” Sustainable Cities and Society, 69, 102809.

Kaya, Y., & Yokobori, K. (Eds.). 1997. “Environment, energy, and economy: strategies for sustainability (Vol. 4).” Tokyo: United Nations University Press.

Lara, A. P., Da Costa, E. M., Furlani, T. Z., & Yigitcanlar, T. 2016. “Smartness that matters: towards a comprehensive and human-centred characterisation of smart cities.” Journal of Open Innovation: Technology, Market, and Complexity, 2(2), 1-13.

Lee, B. K., Lessler, J., & Stuart, E. A. 2010. “Improving propensity score weighting using machine learning.” Statistics in medicine, 29(3), 337-346.

Li, X., Shu, Y., & Jin, X. 2022. “Environmental regulation, carbon emissions and green total factor productivity: A case study of China.” Environment, Development and Sustainability, 24(2), 2577-2597.

Lin, B., & Jia, H. 2022. “Does the development of China's high-speed rail improve the total-factor carbon productivity of cities?." Transportation Research Part D: Transport and Environment, 105, 103230.

Liu, D., Zhu, X., & Wang, Y. 2021. "China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors." Journal of Cleaner Production, 278, 123692.

Liu, K., Meng, C., Tan, J., & Zhang, G. 2023. "Do smart cities promote a green economy? Evidence from a quasi-experiment of 253 cities in China." Environmental Impact Assessment Review, 99, 107009.

Luo, J., Wang, Z., & Wu, M. 2021. "Effect of place-based policies on the digital economy: Evidence from the Smart City Program in China." Journal of Asian Economics, 77, 101402.

Oh, D. H. 2010. "A global Malmquist-Luenberger productivity index." Journal of Productivity Analysis, 34, 183-197.

Peneder, M. 2003. "Industrial structure and aggregate growth." Structural Change and Economic Dynamics, 14(4), 427-448.

Peng, H., Bohong, Z., & Qinpei, K. 2017. "Smart city environmental pollution prevention and control design based on Internet of Things." In IOP Conference Series: Earth and Environmental Science (Vol. 94, No. 1, p. 012174). IOP Publishing.

Qian, L., Xu, X., Zhou, Y., Sun, Y., & Ma, D. 2023. "Carbon Emission Reduction Effects of the Smart City Pilot Policy in China." Sustainability, 15(6), 5085.

Sergi, B. S., Berezin, A., Gorodnova, N., & Andronova, I. 2019. "Smart cities and economic growth in Russia. In Modeling Economic Growth in Contemporary Russia (pp. 249-272)." Emerald Publishing Limited.

Shen, Q., Wu, R., Pan, Y., & Feng, Y. 2023. "The effectiveness of smart city policy on pollution reduction in China: New evidence from a quasi-natural experiment." Environmental Science and Pollution Research, 30(18), 52841-52857.

Solow, R. M. 1956. “A contribution to the theory of economic growth.” Quarterly Journal of Economics, 70(1), 65-94.

Song, T., Dian, J., & Chen, H. 2023. “Can SCC improve carbon productivity?—A quasi-natural experiment based on China's smart city pilot.” Sustainable Cities and Society, 92, 104478.

Su, Y., Miao, Z., & Wang, C. 2022. “The experience and enlightenment of Asian smart city development—a comparative study of China and Japan.” Sustainability, 14(6), 3543.

Visvizi, A., Lytras, M. D., Damiani, E., & Mathkour, H. 2018. “Policy making for smart cities: Innovation and social inclusive economic growth for sustainability.” Journal of Science and Technology Policy Management, 9(2), 126-133.

Wang, H., Cui, H., & Zhao, Q. 2021. “Effect of green technology innovation on green total factor productivity in China: Evidence from spatial durbin model analysis.” Journal of Cleaner Production, 288, 125624.

Wang, J., & Deng, K. 2022. “Impact and mechanism analysis of smart city policy on urban innovation: Evidence from China.” Economic Analysis and Policy, 73, 574-587.

Wang, K. L., Pang, S. Q., Zhang, F. Q., Miao, Z., & Sun, H. P. 2022. “The impact assessment of smart city policy on urban green total-factor productivity: Evidence from China.” Environmental Impact Assessment Review, 94, 106756.

Wang, L., Wang, H., Cao, Z., He, Y., Dong, Z., & Wang, S. 2022. “Can industrial intellectualization reduce carbon emissions?—Empirical evidence from the perspective of carbon total factor productivity in China.” Technological Forecasting and Social Change, 184, 121969.

Wang, M., Xu, M., & Ma, S. 2021. “The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity.” Structural Change and Economic Dynamics, 59, 427-441.

Wang, X., Xu, L., Ye, Q., He, S., & Liu, Y. 2022. “How does services agglomeration affect the energy efficiency of the service sector? Evidence from China.” Energy Economics, 112, 106159.

Wang, X., & Zhong, M. 2023. “Can digital economy reduce carbon emission intensity? Empirical evidence from China’s smart city pilot policies.” Environmental Science and Pollution Research, 30(18), 51749-51769.

Weber, G., & Cabras, I. 2017. “The transition of Germany's energy production, green economy, low-carbon economy, socio-environmental conflicts, and equitable society.” Journal of Cleaner Production, 167, 1222-1231.

Whata, A., & Chimedza, C. 2022. “Evaluating uses of deep learning methods for causal inference.” IEEE Access, 10, 2813-2827.

Witkowski, K. 2017. “Internet of things, big data, industry 4.0–innovative solutions in logistics and supply chains management.” Procedia Engineering, 182, 763-769.

Wu, J., Xia, Q., & Li, Z. 2022. “Green innovation and enterprise green total factor productivity at a micro level: A perspective of technical distance.” Journal of Cleaner Production, 344, 131070.

Xin, B., & Qu, Y. 2019. “Effects of smart city policies on green total factor productivity: evidence from a quasi-natural experiment in China.” International Journal of Environmental Research and Public Health, 16(13), 2396.

Xu, G., & Yang, Z. 2022. “The mechanism and effects of national smart city pilots in China on environmental pollution: Empirical evidence based on a DID model.” Environmental Science and Pollution Research, 29(27), 41804-41819.

Xue, F., Zhou, M., & Liu, J. 2023. “Are Cities Saving Energy by Getting Smarter? Evidence from Smart City Pilots in China.” Sustainability, 15(4), 2961.

Yigitcanlar, T., & Kamruzzaman, M. 2018. “Does smart city policy lead to sustainability of cities?.” Land Use Policy, 73, 49-58.

Yu, D., Liu, L., Gao, S., Yuan, S., Shen, Q., & Chen, H. 2022. “Impact of carbon trading on agricultural green total factor productivity in China.” Journal of Cleaner Production, 367, 132789.

Yu, Y., & Zhang, N. 2019. “Does smart city policy improve energy efficiency? Evidence from a quasi-natural experiment in China.” Journal of Cleaner Production, 229, 501-512.

Zhang, G., & Lin, B. 2018. “Impact of structure on unified efficiency for Chinese service sector—A two-stage analysis.” Applied Energy, 231, 876-8.

APPENDIX

TABLE A1 MACHINE LEARNING PSM-DID REGRESSION RESULTS: CONTROL VARIABLES

	(1) CTFP	(2) CEC	(3) CTC
did	0.188***	0.202***	0.048
	(4.280)	(2.650)	(1.115)
lnpop	−0.042	−0.400	0.156
	(−0.185)	(−1.087)	(0.627)
lnpgdp	0.059**	0.011	0.049**
	(2.551)	(0.388)	(2.579)
is	−0.000	−0.000	−0.002
	(−0.074)	(−0.029)	(−0.626)
urban	−0.000	−0.003	0.001
	(−0.381)	(−1.349)	(0.518)
es	−0.163	−0.006	−0.078
	(−0.921)	(-0.022)	(−0.396)
open	0.000	−0.001	0.001
	(0.350)	(−0.323)	(1.298)
rd	0.171	5.414	−4.229
	(0.054)	(1.226)	(−1.431)
_cons	0.649	3.322	−0.358
	(0.473)	(1.501)	(−0.238)
Adj R-squared	0.2577	0.1921	0.4005
Urban fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	400	400	400

Note: This table is a continuation of Table 3.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A2 MECHANISM TEST RESULTS：CONTROL VARIABLES

	(1)	(2)	(3)	(4)
	pergreenpat	pergreeninv	struc	ra
did	0.719**	0.419**	0.046*	1.1e+05**
	(2.522)	(2.483)	(1.875)	(2.515)
lnpop	1.520	0.384	0.053	1.1e+05
	(1.588)	(0.745)	(0.444)	(0.558)
lnpgdp	0.109	0.063	−0.011	2.8e+04
	(0.943)	(0.947)	(−0.926)	(1.167)
is	−0.019**	−0.007	−0.000	192.773
	(−1.996)	(−1.231)	(−0.151)	(0.092)
urban	0.004	0.002	−0.000	926.845
	(0.970)	(1.030)	(−0.605)	(0.994)
es	−1.129	−0.586	−0.125	2.3e+04
	(−1.295)	(−1.285)	(−0.897)	(0.128)
open	−0.023***	−0.013***	0.000	284.249
	(−3.223)	(−3.070)	(0.480)	(0.337)
rd	25.534	13.044	−1.372	−3.0e+06*
	(1.067)	(0.824)	(−1.191)	(-1.719)
_cons	−8.103	−2.134	0.140	−6.2e+05
	(−1.452)	(−0.694)	(0.185)	(−0.553)
Adj R-squared	0.7610	0.6852	0.8792	0.8079
Urban fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	395	395	400	400

Note: This table is a continuation of Table 4.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A3 REGRESSION RESULTS OF DIFFERENT SCC BATCHES： CONTROL VARIABLES

	2012	2013	2014
	CTFP	CTFP	CTFP
did	0.096^{***}	0.181^{***}	0.215^{***}
	(3.059)	(4.410)	(5.851)
lnpop	0.087	−0.051	0.507^{***}
	(0.999)	(−0.313)	(4.261)
lnpgdp	0.038^{**}	0.027	0.330^{***}
	(2.052)	(0.921)	(5.097)
is	−0.002	−0.000	-0.004^{**}
	(−0.829)	(−0.237)	(−2.466)
urban	0.000	-0.001^{*}	−0.000
	(0.795)	(−1.752)	(−0.467)
es	0.011	0.015	0.086
	(0.070)	(0.524)	(0.807)
open	0.000^{***}	0.002	0.003^{**}
	(4.282)	(0.917)	(2.356)
rd	0.694	2.940^{**}	3.824^{***}
	(0.614)	(2.414)	(3.485)
_cons	0.161	1.023	-5.243^{***}
	(0.289)	(0.955)	(−5.247)
Adj R-squared	0.1204	0.1058	0.2422
Urban fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	1500	1260	912

Note: This table is a continuation of Table 5.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A4 HETEROGENEITY REGRESSION RESULTS: CONTROL VARIABLES

	Urban Location Heterogeneity			Urban Scale Heterogeneity	
	Eastern	Central	Western	Megacities	Other Cities
	(1)	(2)	(3)	(4)	(5)
	CTFP	CTFP	CTFP	CTFP	CTFP
did	0.156***	0.192***	0.167*	0.185***	0.106**
	(3.864)	(5.858)	(1.731)	(6.144)	(2.514)
lnpop	−0.944**	0.051	−0.021	−0.045	−0.021
	(−2.317)	(0.348)	(−0.069)	(−0.284)	(−0.204)
lnpgdp	0.087	0.002	0.079**	0.028	−0.046
	(1.380)	(0.010)	(2.056)	(0.934)	(−0.662)
is	0.003	0.002	−0.003	−0.002	0.003
	(1.016)	(0.636)	(−1.076)	(−1.069)	(1.215)
urban	0.000	0.000	−0.004**	0.000	−0.000
	(0.011)	(0.079)	(−2.122)	(0.439)	(−0.097)
es	0.091	0.096	−0.035	0.119	−0.034
	(0.572)	(0.290)	(−1.074)	(1.317)	(−1.106)
open	0.000***	−0.001	−0.001	0.000***	−0.001
	(3.399)	(−1.175)	(−0.227)	(3.283)	(−1.608)
rd	1.644	−1.030	0.838	0.098	5.432**
	(1.328)	(−0.670)	(0.416)	(0.101)	(2.639)
_cons	5.516**	0.565	0.631	1.031	1.439
	(2.442)	(0.257)	(0.347)	(0.924)	(1.389)
Adj R-squared	0.3063	0.2431	0.0209	0.1317	0.1859
Urban fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	912	864	408	1740	444

Note: This table is a continuation of Table 6.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.