sustainability

MDPI

Article

Does Smart City Construction Decrease Urban Carbon Emission Intensity? Evidence from a Difference-in-Difference Estimation in China

Eryu Zhang [1], Xiaoyu He [1,*] and Peng Xiao [2]

[1] School of Finance and Public Administration, Anhui University of Finance and Economics, Bengbu 233030, China
[2] School of Business, Anhui University, Hefei 230601, China
* Correspondence: hxy@aufe.edu.cn; Tel.: +86-17730019990

Abstract: Climatic changes and environmental pollution caused by traditional urban development models have increased due to accelerated urbanisation and industrialisation. As a new model of urban development, smart city construction relies on digital technology reform to achieve intelligent urban governance, which is crucial for reducing carbon emission intensity and achieving regional green development. This paper constructs a multi-period DID model based on panel data from 283 cities from 2007 to 2019 to explore the impact of smart city construction on urban carbon emission intensity. This study found that smart city construction decreased urban carbon emissions intensity significantly and decreased carbon emissions per unit GDP in pilot areas by 0.1987 tonnes/10,000 CNY compared to that in non-pilot areas. According to a heterogeneity analysis, the integration of smart city developments could decrease carbon emission intensity in northern China's cities and resource-based cities significantly but had an insignificant influence on carbon emission intensity in southern China's cities and non-resource-based cities. The reason for this finding is that northern cities and resource-based cities have a higher carbon emission intensity and enjoy more marginal benefits from smart city construction. Based on an analysis of the influencing mechanisms, smart city construction can decrease urban carbon emission intensity by stimulating green innovation vitality, upgrading industrial structures, and decreasing energy consumption. These research conclusions can provide directions for urban transformation and low-carbon development, as well as a case study and experience for countries that have not yet established smart city construction.

Keywords: smart city; carbon emission intensity; difference-in-difference

check for updates

Citation: Zhang, E.; He, X.; Xiao, P. Does Smart City Construction Decrease Urban Carbon Emission Intensity? Evidence from a Difference-in-Difference Estimation in China. *Sustainability* **2022**, *14*, 16097. https://doi.org/10.3390/su142316097

Academic Editors: Tim Walmsley, Florian Schlosser and Benjamin Hung Yang Ong

Received: 27 October 2022
Accepted: 29 November 2022
Published: 1 December 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

With the continuous progress in urbanisation and industrial civilisation, production activities mainly based on fossil energy sources have led to a constant rise in carbon emissions, posing significant challenges to the ecosystem and economic development [1]. The emission of greenhouse gases such as carbon dioxide (CO_2) increases global air temperature and extreme weather. Burma's Cyclone Nargis, melting glaciers at the North Pole, and other extreme weather events are all highly related to carbon emissions [2,3]. In 2015, at the 21st United Nations Climate Change Conference held in Paris, 197 state parties around the world signed the Paris Agreement, which explicitly states its goal to 'try to control the global average temperature rise within 2 °C of the pre-industrial level in the current century and try to control within 1.5 °C [4,5]. As a responsible developing country, China plays a significant role in mitigating global climate change and participating in global environmental governance. In September 2020, at the 75th United Nations General Assembly, President Xi Jinping committed to a goal of 'carbon peaking' before 2030 and 'carbon neutrality' before 2060 in China. Therefore, clarifying the influencing factors of carbon emissions and seeking ways to reduce carbon emission intensity are not only critical topics in environmental economics research, but also the springboard for countries around the world to formulate environmental policies and achieve low-carbon economic development.

Carbon emission intensity refers to the CO_2 emission volume per unit of gross domestic product (GDP). It reflects the mutual relationship between pollutants and economic growth and is an important index for evaluating sustainable economic development [6]. The existing literature on the influencing factors of carbon emission intensity is relatively extensive, listing environmental regulation [7,8], the fiscal and taxation system [9,10], urbanisation [11,12], FDI [13,14], international trade [15,16], etc., as factors. The impact of urbanisation on carbon emissions is significant. However, the existing research on the relationship between the promotion or inhibition of urbanisation and carbon emissions is still inconclusive. On the one hand, urbanisation can promote industrialisation and increase the energy consumption demand, leading to extensive carbon emissions [17,18]; furthermore, with the increase in population density, urban management faces greater pressure [19]. On the other hand, with the development of urbanisation, the scale effect of public goods and the accumulation effect of human capital can improve the efficiency of energy use and create conditions for technological advances, thereby reducing the intensity of carbon emissions [20,21].

Some scholars have ignored the differences in urbanisation brought about by different urban development models and the key role of new urban development models in reducing carbon emission intensity [22,23]. The traditional urban development model blindly pursues the development speed of urbanisation, ignoring the development quality. The high-investment and high-energy consumption development model significantly increased environmental pollution, especially that in the form of carbon emissions [24]. Is the traditional urban development model unable to eliminate the climate effects? In the era of intelligence and digitalisation, the implementation of a new urban governance model could be the key for countries around the world to fulfil their environmental protection responsibilities and establish a new competitive advantage [25,26]. With the emerging disadvantages of the traditional urban development model, an increasing number of countries have begun to explore new models. Scholars have also begun to study the economic and social effects of these new urban development models, such as smart cities, confirming the positive impact of smart cities on environmental pollution control [27], enterprise technology innovation [28], energy efficiency improvement [29], and the advancement of various industrial structures [30]. However, few scholars have investigated the impact of smart-city-based urban development models on urban carbon emission intensity.

As a new urban development model, the smart city, proposed by IBM in 2010, refers to making full use of information and communication technology to obtain, analyse, and integrate various key data from the urban operation core system to intelligently respond to various needs, including people's livelihood, environmental protection, public security, and urban services, and create a better urban life. China's smart city pilot policy, which was initiated in 2012 and aimed at changing the traditional urban development model through digital technological reform, realised the refined and intelligent management of cities, and created opportunities for both innovations and green development [31]. This policy is conducive to decreasing resource consumption, eliminating urban diseases, and realising the sustainable development of cities. Therefore, does smart city construction decrease carbon emission intensity? Are there differences in the carbon emission reduction effect of smart city construction among different cities? What is the influencing mechanism of smart city construction on carbon emission intensity? The answers to these questions have important theoretical and practical significance for exploring new urban governance models and realising low-carbon urban development.

Therefore, this paper, considering China's smart city pilot policy as a quasi-natural experiment, uses the double-difference method (DID) to explore the effect of smart city construction on carbon emission intensity. The main contributions of this study include the following. (1) The research perspective of this study differs from that of existing studies, which mainly focused on the influences of the traditional urban development model on carbon emission intensity. This study integrates smart city construction and environmental governance into the same research framework to explore the causal relationship between smart city construction and carbon emission intensity. (2) Concerning the research methods, urban carbon emission intensity might be influenced by non-policy factors that change with time and may have endogenous problems. In this study, other factors are separated from policy factors through the quasi-natural experiment provided by smart city construction, thus avoiding endogenous problems. (3) This study explores the multiple influencing effects of smart cities on carbon emission intensity theoretically and empirically, based on Schumpeter's theory of innovation and innovation-driven theory, which enriched the research.

The remainder of this paper is organised as follows. Section 2 provides a literature review. Section 3 introduces the research method and data. Section 4 is the empirical study of the influences of smart city construction on carbon emission intensity and details the robustness test carried out. Section 5 provides an analysis of heterogeneity. Section 6 analyses and tests the influencing mechanism. Finally, Section 7 summarises the research conclusions and proposes policy suggestions.

2. Theoretical Analysis and Research Hypothesis

As a typical representation of a new urban development mode, smart city construction not only plays an important role in facilitating urban green development [32,33], stimulating the innovation of cities [34,35], and promoting enterprise development [36,37], but also has positive effects on the energy transition of cities. According to Schumpeter's innovation theory, a smart city can be understood as a comprehensive innovation system integrating technological innovation, product innovation, market innovation, resource allocation innovation, and organisational innovation [38]. Further combining Porter's innovation-driven theory, the five major innovations [39], which can effectively collaborate with specialised production factors and information-sharing mechanisms, promote digital information technology innovation, promote smart industry clusters, and expand the ecological scenario of clean industry applications, thereby reducing carbon emissions. Specifically, the construction of smart cities provides two guarantees, namely, elements and systems, for reducing carbon emission intensity. On the one hand, the construction of a smart city integrates data elements, information technology developments, new information infrastructure, and other production factors to transform traditional industries into advanced ones, providing guarantees for reducing carbon emission intensity. On the other hand, the formation and effective output of intelligent innovation systems, such as digital information knowledge innovation, technological innovation, and management system innovation, provide an institutional guarantee for reducing carbon emission intensity.

In addition, smart city construction can indirectly affect urban carbon emission intensity by stimulating green innovation vitality, promoting industrial structure advances, and reducing energy consumption. Firstly, technological progress, especially green technological progress, effectively decreases carbon emission intensity [40,41]. Smart cities view data with both green and technological attributes as the core production elements, and the technological progress brought about by a smart city is indubitably green, low-carbon, energy-saving, and emission-reducing [42]. Therefore, smart cities facilitate green technological progress and promote the economic transition to a low-carbon energy system. Secondly, the primary aim of smart city construction is to optimise urban digital infrastructure. This not only facilitates the development of a new digital industry, but also accelerates the integration and reconstruction of the traditional manufacturing industry and digital technology, thus decreasing the dependence of industrial development on high-carbon energy sources, facilitating the industrial structural transition to digital and low-carbon models, decreasing energy consumption and carbon emission per unit output [43], and facilitating the urban transition to low-carbon energy sources. Finally, based on mass data sources and strong digital technologies, smart city construction can largely break spatial and temporal constraints on traditional knowledge and technological exchange [44] and develop new technologies, industries, and business states (e.g., energy storage technology, new energy sources, and intelligent traffic), which are closely related to energy production and consumption, decrease energy consumption, and can help realise low-carbon energy source development. To this end, we tested the following hypotheses:

Hypothesis 1. *Smart city construction decreases urban carbon emission intensity.*

Hypothesis 2. *Smart city construction reduces the urban carbon emission intensity by promoting green technology innovation, upgrading industrial structure, and improving energy efficiency.*

3. Research Design

3.1. Benchmark Model

IBM put forward the concept of a 'smart planet' for the first time in 2008, which further highlighted smart cities as a critical paradigm in development strategy. China officially launched smart city construction in 2012. The first batch of pilot areas included 90 prefecture-level (county-level) cities. The second and third batches were established in 2013 and 2014. Smart city construction was reported for the first time in 2015 and noted in the report of the 19th National Congress of the Communist Party of China in 2017, together with technology power, network power, traffic power, and a digital China. As a national strategic measure, smart city construction in China is exogenous to carbon emissions and plays an important role in facilitating the informatisation and intelligent development of pilot cities. Hence, smart city construction was viewed as a quasi-natural experiment in this study, and its carbon emission reduction effect was evaluated using the DID method. As smart cities were expanded batch-wise, the following multiperiod DID model was constructed with reference to Beck et al.'s [45] study:

$$Carbon\_pgdp_{it} = \beta_0 + \beta_1 Policy_{it} + \beta_2 Controls_{it} + \eta_t + \gamma_i + \varepsilon_{it} \tag{1}$$

where i refers to the city, t indicates the year, and *Carbon_pgdp* denotes the urban carbon emission intensity. *Policy*, a dummy variable, refers to the pilot policy of a smart city and is the intersection between the policy dummy variable (Treat) and time dummy variable (Post). If the city is a pilot area for a smart city, Treat = 1; otherwise, Treat = 0. If the city is included in the scope of the smart city at t, Post = 1; otherwise, Post = 0. Controls refer to the set of control variables. η_t is the time fixed effect, γ_i is the urban fixed effect, and ε_{it} is the random disturbance term. The regression coefficient (β_1) of Policy in the model was of particular significance in this study, and it reflects the influences of smart city construction on urban carbon emission. If $\beta_1 < 0$ and it is significant, the smart city indeed has a carbon emission reduction effect.

3.2. Variables

The explained variable is the carbon emission intensity. Previous studies generally estimated urban carbon emissions according to the consumption of natural gas, liquefied petroleum gas, and electric power [46]. Nevertheless, the carbon emissions produced by other energy-consuming industries are not included; thus, the estimation results are slightly lower than the actual value. For this reason, with reference to the study of Chen et al. [47], the total carbon emissions of cities in China were deduced based on two sets of night light data (DMSP/OLS and NPP/VIIRS) provided by the National Aeronautics and Space Administration (NASA). Considering the significant differences in numerical values between these two sets of night light data, the particle swarm optimisation–backpropagation (PSO-BP) algorithm was applied to adjust the two sets of night light data and guarantee the uniformity of the data. Finally, total carbon emissions were normalised by the GDP of prefecture-level cities, and the carbon emission intensity of different regions was calculated. The average carbon emission intensities of cities in China from 2007 to 2019 are shown in Figure 1. The spatial distribution of urban carbon emission intensity is shown in Figure 2 (only distributions for 2007, 2011, 2015, and 2019 are shown). It was found that: (1) given the variation trend, the average carbon emission intensity of cities in China from 2007 to 2019 generally presented a decreasing trend, except for a small increase in 2019. (2) With respect to spatial features, urban carbon emission intensity in China was basically 'high in north and low in south', and regions with heavy carbon pollution were concentrated in northeast China and northern China.

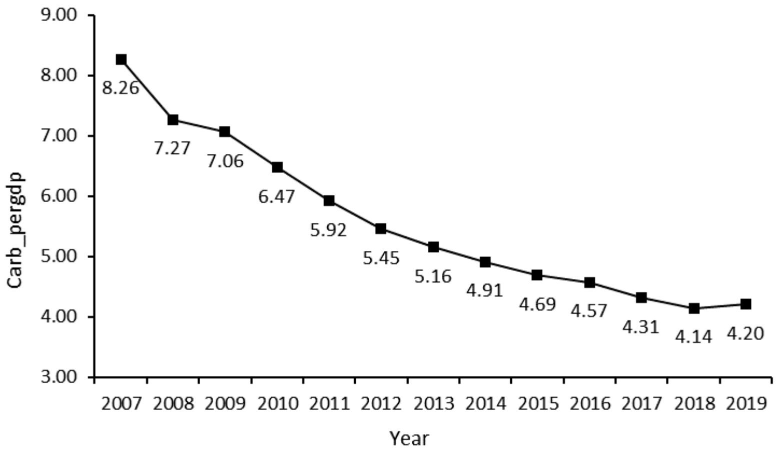

Figure 1. Carbon Emission Intensity of Cities in China during 2007–2019.

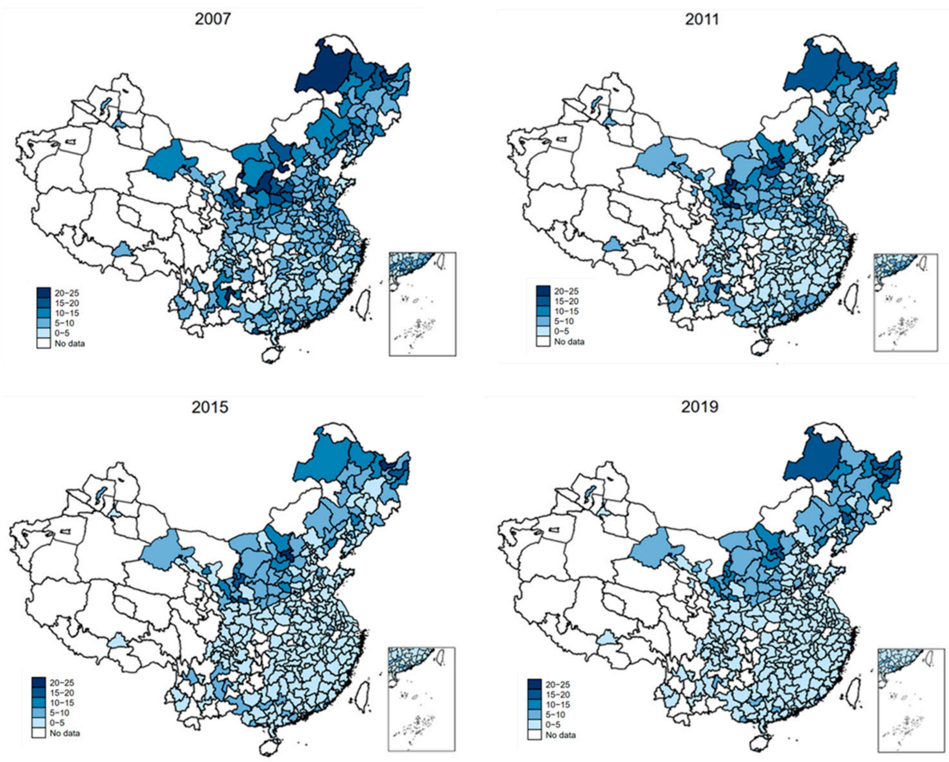

Figure 2. Urban Carbon Emission Intensity in 2007, 2011, 2015, and 2019.

Together with existing studies [48,49], this study further controlled other variables that may influence urban carbon emission intensity to relieve endogenous problems caused by missing variables. These variables included: (1) economic development level (Pgdp), expressed by the logarithm of the actual per capita GDP of a city; (2) population density (Pop), expressed by population per unit area; (3) FDI, expressed by the percentage of actual foreign direct investment in GDP; (4) financial development level (Finc), expressed by the percentage of the balance of deposits and loans of financial institutions at the end of a year in GDP; (5) government support strength (Gtec), expressed by the percentage of fiscal expenditures for technologies in GDP; and (6) urban green land area (Green), expressed by the natural logarithm of urban green land area.

3.3. Samples and Data

The study period lasted from 2007 to 2019. According to research needs, sample data were processed as follows: (1) city samples with significant administrative zoning adjustments during 2007–2019 were eliminated; (2) city samples with extensive missing data for key variables were eliminated. Based on data screening, 3679 samples from 283 cities were finally obtained, including 2132 smart city samples and 1547 non-smart city samples. The approval data for the smart city were collected from the official website of the Ministry of Housing and Urban–Rural Development of the People's Republic of China (MOHURD) and organised manually. Light data were obtained from NASA's CEADs database. Other city-level data were obtained from the China City Statistical Yearbook for the period 2008–2020. Missing data were compensated for with information from provincial statistical yearbooks and urban statistical bulletins. Descriptive statistics of variables are listed in Table 1.

Table 1. Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Carbon_pgdp	3679	5.6028	4.3504	0.4413	45.1543
Policy	3679	0.3381	0.4731	0.0000	1.0000
Pgdp	3679	10.4798	0.6873	4.5951	13.0557
Pop	3679	4.2309	2.9786	0.1757	13.6961
Fdi	3679	1.8728	1.8394	0.0064	8.696
Finc	3679	2.2667	1.1935	0.5600	21.3015
Gtec	3679	0.1353	0.1782	0.0014	1.1169
Green	3679	8.1393	1.0882	3.1355	12.0319

4. Empirical Analysis

4.1. Parallel Trend Test

The premise for the multipoint DID model is that the experimental group and the control group have a consistent variation trend before policy implementation; that is, it should meet the parallel trend test hypothesis, or the DID estimation results are unreliable. Hence, with reference to the work of Du et al. [50], the parallel trend was tested using the event study method. The model setting was:

$$Carbon\_pgdp_{it} = \beta_0 + \sum_{k=-7}^{7} \beta_k Policy_{i,t_0+k} + \beta_2 Controls_{it} + \eta_t + \gamma_i + \varepsilon_{it} \quad (2)$$

where $Policy_{i,t_0+k}$ refers to the year k after the city i was included in the smart city list. The remaining variables have the same meaning as those in Equation (1). The value of β_k, representing the difference in carbon emission intensity between the experimental group and the control group in the year k, is a vital concern of this study. If it is within the interval of $k < 0$, the estimation results of β_k are not significantly different from 0, indicating that the parallel trend test is met; otherwise, it is not met.

The parallel trend test results are shown in Figure 3. Obviously, the estimation results of β_k have no significant difference from 0 before the implementation of the Policy, and it passed the parallel trend hypothesis test. After the implementation of the Policy, there were significant differences in carbon emission intensity between the experimental group and the control group every year after the first year. This preliminarily calculation proved that smart city construction could significantly decrease the carbon emission intensity of pilot cities.

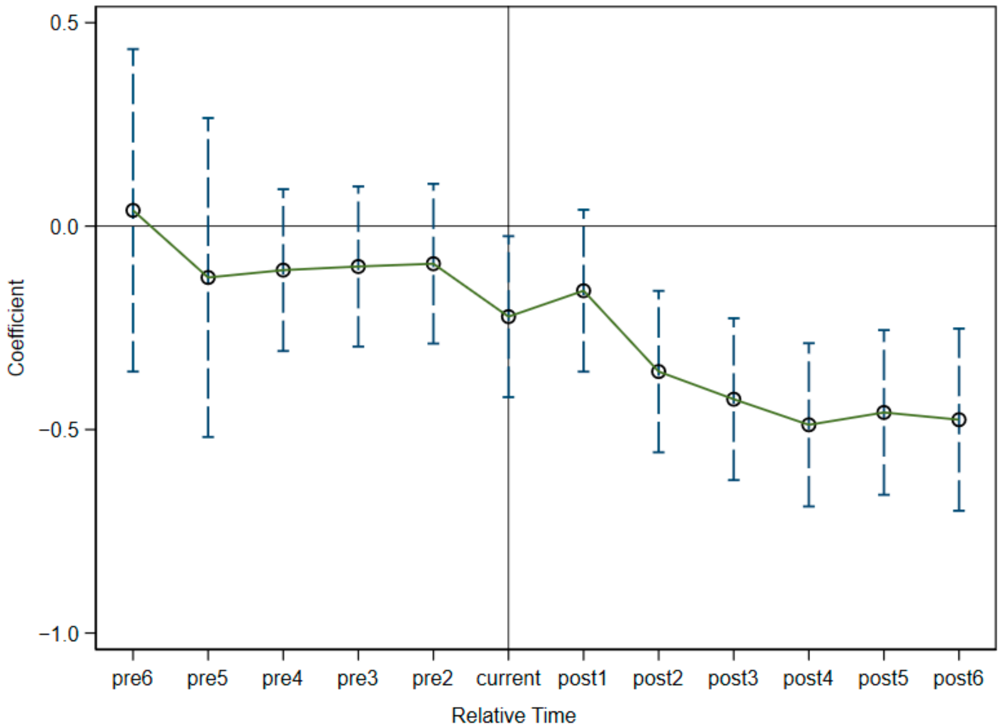

Figure 3. Parallel Trend Test Results.

4.2. Benchmark Regression Results

The DID estimation based on Model (1) is shown in Table 2. Specifically, Column (1) presents the univariate regression results based on the least-squares method. Column (2) presents the univariate regression results based on the dual fixed- effects model. Columns (3) and (4) added the control variables based on Column (1) and Column (2). According to the results, the coefficients of Policy were smaller than 0, and they were at least significant at the 5% level, irrespective of whether a city, year fixed effect, or control variable was introduced. Given the specific coefficients of Column (4) and other fixed factors, smart city construction decreased the carbon emission per unit GDP in pilot regions by 0.1987 tonnes/10,000 CNY compared to in non-pilot regions. This demonstrates that smart city construction plays a vital [31] role in the actual practices of carbon peaking and carbon neutrality. Hypothesis 1 is thus confirmed.

With respect to control variables, Pgdp, Pop, and Green had significantly negative influences on carbon emission intensity. FDI and Gtec had negative, but not significant, influences on carbon emission intensity. Finc had significantly positive influences on carbon emission intensity at the 1% level.

4.3. Robustness Test

4.3.1. Placebo Test

As some unobservable factors may cause errors in the regression results, a placebo test was performed with reference to the work of Chetty et al. [51]. The placebo test was performed as follows. Some cities were chosen randomly as the pseudo-test group, and the remaining cities were chosen as the pseudo-control group. A year was chosen randomly for the pseudo-test group, thus enabling the estimation of the obtained pseudo-samples and the error regression coefficients. Finally, the above process was cycled 500 times, leading to 500 error coefficients. The probability distribution of error coefficients is shown in Figure 4. The error coefficients were all near the null value and had a normal distribution. The true estimation coefficient in this study was -0.2451, which is shown to be an abnormal value in Figure 4. This conformed to the expectation for the placebo test. In other words, there were no other unobservable factors that may have significantly influenced the regression results, and the benchmark regression conclusions were robust.

Table 2. Benchmark Regression results.

Variable	(1)	(2)	(3)	(4)
	Carbon_pgdp	*Carbon_pgdp*	*Carbon_pgdp*	*Carbon_pgdp*
Policy	−1.7102 ***	−0.2947 ***	−0.8153 ***	−0.1987 **
	(0.1469)	(0.0933)	(0.1563)	(0.0898)
Pgdp			−0.8823 ***	−1.8985 ***
			(0.1328)	(0.1504)
Pop			−0.3409 ***	−0.2269 ***
			(0.0260)	(0.0732)
Fdi			−0.0025	−0.0283
			(0.0391)	(0.0238)
Finc			0.2939 ***	0.3142 ***
			(0.0611)	(0.0462)
Gtec			−0.4681	−0.2046
			(0.4755)	(0.2959)
Green			−0.2549 ***	−0.3363 ***
			(0.0905)	(0.0777)
_cons	6.1491 ***	8.2632 ***	18.0115 ***	29.8233 ***
	(0.0854)	(0.0861)	(1.1912)	(1.5931)
Adj. R^2	0.0355	0.4591	0.1497	0.5084
N	3679	3679	3679	3679
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

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

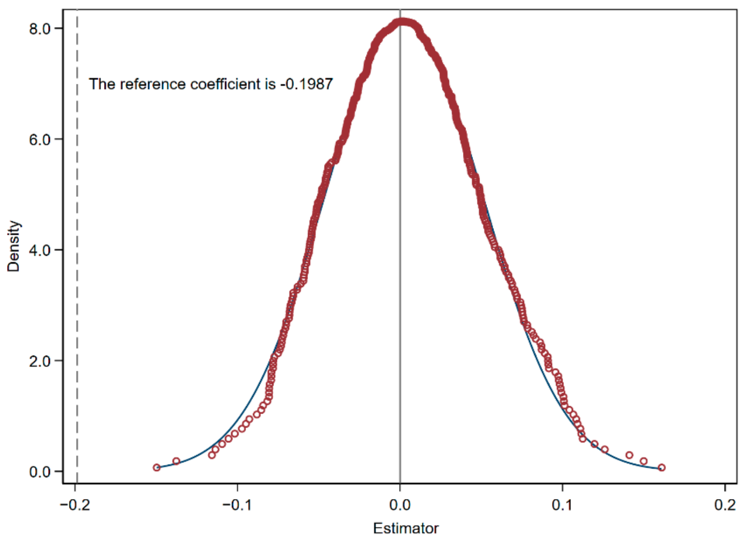

Figure 4. Placebo Test Results.

4.3.2. Placebo Test

De Chaisemartin and D' Haultfoeuille [52] and Baker et al. [53] found a heterogeneity processing effect is likely to occur during policy evaluation when the multiperiod DID method is used, which is attributed to differences in time points of policy processing. This can further lead to errors in two-way fixed effect (TWFE) estimation. Essentially, TWFE is equal to the weighted average of the processing effects of all individuals in the data:

$$TWFE = E\left(\sum_{(gt):D_{gt}=1} W_{gt}\Delta_{gt}\right) \quad (3)$$

where $\Delta_{g,t}$ and $W_{g,t}$ are the policy effect and its weight for the smart city g at year t after smart city construction, respectively. Since W_{gt} might be negative, the *TWFE* might be negative, although the sum of the total processing effect weights is 1. To eliminate such a possibility, the heterogeneity processing effect was tested in this study by the external order of 'twowayfeweights' in the Stata software with reference to the work of De Chaisemartin and D' Haultfoeuille [42]. If the heterogeneity processing robustness approached 1 and deviated from 0, it passed the heterogeneity processing effect test; otherwise, there was a significant error in evaluating the entrepreneurship effect of 'broadband China' based on the multiperiod DID method. The results show that the heterogeneity processing robustness index was 0.8633, indicating that there is no heterogeneity processing effect in the present study.

4.3.3. PSM-DID

As preferences might be given to regions with unique characteristics (e.g., a high economic development level), when choosing smart cities, the pilot cities were not chosen via random selection, causing errors in the regression results. To decrease systematic differences between the experimental group and control group, the propensity score matching–difference-in-difference (PSM-DID) method was applied for secondary regression. Specifically, the radius-matching method and the chosen covariables were consistent with the control variables. The results are shown in Column (1) of Table 3. The regression coefficient of the core explanatory variable Policy was significantly negative at the 5% level, indicating that smart city construction indeed can significantly decrease carbon emission intensity. The benchmark regression conclusions are robust.

Table 3. Robustness Test Results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	PSM-DID	**Phase I Lag of Control Variables**	**Eliminating Cities with Partial Smart City Construction**	**Eliminating Municipalities and Provincial Capital Cities**	**Traditional DID**	**Elimination of Disturbances by Other Policies**
	Carbon_pgdp	*Carbon_pgdp*	*Carbon_pgdp*	*Carbon_pgdp*	*Carbon_pgdp*	*Carbon_pgdp*
Policy	−0.2822 **	−0.1850 **	−0.2685 ***	−0.1869 *	−0.2327 **	−0.2288 **
	(0.1138)	(0.0733)	(0.1007)	(0.0964)	(0.1033)	(0.0914)
Policy1						−0.0327
						(0.0959)
Policy2						−0.3054 **
						(0.1268)
Pgdp	−1.8203 ***	−1.6007 ***	−1.9019 ***	−1.8413 ***	−1.8565 ***	−1.8998 ***
	(0.1863)	(0.1274)	(0.1664)	(0.1591)	(0.1604)	(0.1506)
Pop	−0.4525 ***	−0.2052 ***	−0.3341 ***	−0.5015 ***	−0.2498 ***	−0.2226 ***
	(0.1059)	(0.0639)	(0.0796)	(0.0967)	(0.0756)	(0.0732)
Fdi	0.0004	−0.0454 **	−0.0134	−0.0244	−0.0512 **	−0.0220
	(0.0301)	(0.0194)	(0.0279)	(0.0267)	(0.0255)	(0.0239)
Finc	0.4330 ***	0.2186 ***	0.2811 ***	0.3900 ***	0.3417 ***	0.3118 ***
	(0.0716)	(0.0505)	(0.0491)	(0.0523)	(0.0498)	(0.0462)
Gtec	−0.4725	−0.6394 **	−0.8609 **	−0.4905	−0.2094	−0.2503
	(0.4423)	(0.2589)	(0.3756)	(0.3436)	(0.3135)	(0.2977)
Green	−0.3343 ***	−0.2408 ***	−0.2422 ***	−0.3300 ***	−0.3377 ***	−0.3415 ***
	(0.0926)	(0.0641)	(0.0870)	(0.0816)	(0.0844)	(0.0777)
_cons	29.5245 ***	25.3383 ***	29.5258 ***	30.1928 ***	29.6290 ***	29.8539 ***
	(1.9771)	(1.3580)	(1.7457)	(1.6795)	(1.7108)	(1.5953)
Adj. R^2	0.4856	0.5394	0.4987	0.5054	0.4920	0.5092
N	2848	3396	3042	3276	3224	3679
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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

4.3.4. Phase I Lag of Control Variables

In the benchmark regression model, there might be a reverse causality between dependent and independent variables, which is not always easily solved. To mitigate possible endogenous problems and accurately estimate the influences of smart city construction on carbon emission intensity, all control variables were lagged for one phase, and then DID estimation was performed again. The results are shown in Column (2) of Table 3. The regression coefficient of Policy was significantly negative at the 5% level, indicating that the benchmark regression conclusions are robust.

4.3.5. Eliminating Cities with Partial Smart City Construction

In smart city construction, some cities may be included in the pilot regions for a county or a district (Pudong New District of Shanghai, Shangcheng District of Hangzhou, and Boye County of Baoding City were included as pilot smart cities). However, this study used urban data, and using these county-level cities as pilot smart cities might have led to the underestimation of the carbon emission reduction effect to some extent. Therefore, cities with partial smart city construction were eliminated. The DID estimation was then performed again. The results are shown in Column (3) in Table 3. The regression coefficients of Policy were significantly negative at the 1% level, showing the benchmark regression conclusions are robust.

4.3.6. Eliminating Municipalities and Provincial Capital Cities

Compared with other prefecture-level cities, municipalities and provincial capital cities might have significant differences in economic scale, resource endowment, and innovation ability, to name a few variables. Therefore, this study eliminated these differences, and the new sample data were estimated again. The results are shown in Column (4) in Table 3. The regression coefficients of Policy were significantly negative at the 10% level, which is consistent with the benchmark regression results. This further proved that the benchmark regression conclusions are robust.

4.3.7. Re-estimation Based on Traditional DID Method

To further verify the robustness of the above research conclusions, the policy effect of the first batch of smart cities in 2012 was investigated, and the influences of smart city construction on carbon emission intensity were re-estimated using the traditional DID method. Specifically, the implementation year of Policy was determined to be 2012, and smart city samples set after 2012 were eliminated. The re-estimated coefficients are shown in Column (4) in Table 3. The regression coefficients of Policy were significantly negative at the 5% level, indicating that smart cities indeed have a carbon emission reduction effect.

4.3.8. Elimination of Disturbances by Other Policies

It was found that the pilot policy of the "Broadband China" strategy (Policy1) implemented in 2014 and the pilot policy of innovative cities (Policy2) implemented in 2012 were closely related to this study. The dummy variables of these policies were added to the benchmark model to control their influences on the estimation results. The results are shown in Column (6) of Table 3. According to the estimation results, the dummy variable coefficient of smart cities was significantly positive, indicating that smart city construction can indeed significantly decrease carbon emission intensity.

5. Heterogeneity Analysis

5.1. Heterogeneity of Urban Locations

From a geology perspective, can smart city construction lead to different policy effects with differences in urban location characteristics? According to existing studies, there are significant differences between eastern China, central China, and western China in terms of economic sources and natural resources. The differences between southern and northern China in environmental pollution are even more significant, being closely related to the heat supply distribution caused by climatic differences. Hence, 283 cities in China were divided into cities in northern China (heat supply) and cities in southern China (no heat supply) to investigate heterogeneous influences of smart city construction on carbon emission intensity under different urban locations. The policy effects of cities in northern China and southern China correspond to Column (1) and Column (2) in Table 4, respectively. According to the regression results, the policy effect of cities in northern China was significantly negative at the 5% level, indicating that smart city construction can indeed significantly decrease carbon emission intensity in cities in northern China. Nevertheless, there was no significant influence of smart city construction on carbon emission intensity in cities in southern China. This might be due to the following reasons. Smart city construction depends on the continuous development of a digital economy. Cities in southern China, represented by Hangzhou and Shenzhen in this study, are far superior to cities in northern China in terms of their popularisation of big data, the Internet of Things (IoT), cloud computing, and other digital technologies. Moreover, southern China presents low carbon emission intensity as it does not require a significant heat supply and there are fewer high-carbon-consuming industries. Hence, smart city construction is only a 'superfluous aspect' in cities in southern China, resulting in a limited marginal effect on low-carbon development. On the contrary, cities in northern China have relatively weak digitalisation implementation and heavy carbon pollution. Smart city construction 'offers timely help' to cities in northern China. It not only accelerates the digital economic development of cities but also significantly contributes to the carbon emission reduction in cities.

Table 4. Heterogeneity Test Results.

Variable	(1)	(2)	(3)	(4)
	Cities in Northern China	**Cities in Southern China**	**Resource-Based Cities**	**Non-Resource Cities**
Policy	−0.2951 **	−0.0399	−0.3615 **	−0.0181
	(0.1434)	(0.1027)	(0.1635)	(0.1030)
Pgdp	−5.8362 ***	−0.3961 **	−1.3017 ***	−2.5239 ***
	(0.2861)	(0.1737)	(0.2329)	(0.2091)
Pop	0.0717	−0.5787 ***	−0.7942 ***	0.0267
	(0.1121)	(0.0871)	(0.1418)	(0.0801)
Fdi	0.0574	−0.0036	−0.0136	0.0131
	(0.0360)	(0.0298)	(0.0522)	(0.0253)
Finc	0.1886 ***	0.6322 ***	0.6014 ***	0.1829 ***
	(0.0540)	(0.1040)	(0.1022)	(0.0484)
Gtec	0.0360	−0.5300 *	−0.6916	−0.5670 *
	(0.5927)	(0.3198)	(0.6489)	(0.3123)
Green	−0.5425 ***	−0.1408	−0.7813 ***	−0.0315
	(0.1217)	(0.0898)	(0.1376)	(0.0902)
_cons	71.7606 ***	12.8950 ***	29.7317 ***	31.7995 ***
	(2.9230)	(1.9099)	(2.3592)	(2.2559)
Adj. R^2	0.5806	0.5492	0.4945	0.5503
N	1586	2093	1456	2223
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

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

5.2. Heterogeneity of City Types

To investigate the differences in the transition to low-carbon sources among smart cities with different levels of resources, city samples were divided into resource-based cities and non-resource-based cities according to the classification standards stipulated by the State Council in the National Sustainable Development Plan for Resource-based Cities (2013–2020). Regression was performed for each group. The policy effects of resource-based cities and non-resource-based cities are listed in Column (3) and Column (4) in Table 4, respectively. According to the regression results, the influence of smart city construction on the carbon emission intensity of resource-based cities was significantly negative at the 5% level, but the carbon emissions of non-resource-based cities were not significantly decreased. These regression results could be explained as follows. Resource-based cities possess abundant energy sources and resources, form resource-type industrial development models based on local resources during the acceleration of industrialisation and urbanisation, and present relatively low industrial digitalisation. Hence, the promotional effect of digital technological development on urban development is significantly lower for resource-based cities than non-resource-based cities. Additionally, with the continuous development and utilisation of precious resources, resource-based cities face the dual pressure of depleting resources and intensifying environmental pollution. Smart city construction brings new opportunities for transition and development and can accelerate industrial and digital industrialisation. The carbon emission intensity is decreased significantly. Non-resource-based cities began the transition to digitalisation very early on, and urban intelligence has reached a relatively high level, accompanied by light carbon pollution, in these cities. Smart cities thus have a slight effect on reducing carbon emissions.

6. Influencing Mechanism Test

Based on the above empirical results, smart city construction decreases urban carbon emission intensity significantly and continues to benefit cities through low-carbon governance. Several questions still remain. What is the mechanism by which smart city construction aids the low-carbon urban transition? In other words, through which key variables do smart cities decrease urban carbon emission intensity? Considering the implementation of smart city construction policy, the specific mechanisms by which smart city construction decreases carbon emission intensity were investigated from the perspectives of green technological innovation, industrial structure advances, and energy consumption levels. With reference to the research of Shi and Wang [54], the direct regression method was used for verification.

Firstly, the green technological innovation effect was verified. The level of urban green innovation was measured using the natural logarithm of application quantity of green invention patents (Lngreen) and green invention patent quantity per 10,000 people (Pgreen). The regression results are shown in Columns (1) and (2) in Table 5. The influences of smart city construction on the level of green innovation were significantly positive at the 5% level, indicating that smart cities could facilitate the reduction in urban carbon emission intensity through the green innovation effect. Secondly, the effect of advanced industrial structures was verified. The proportion of value added by the second largest industrial GDP was used to measure the industrialisation level, while the proportion of the value added by the third largest industrial GDP was used to measure the service industrial development level. The proportion of value added by the third and secondary industrial GDPs was used to measure the optimisation of the industrial structure. The regression results are shown in Columns (3)–(5) in Table 5. The influence of smart city construction on the degree of industrialisation was significantly negative at the 1% level; its influence on the level of service industrial development was significantly positive at the 1% level; and its influence on the optimisation of industrial structure was significantly positive at the 1% level. These results reflect that smart city construction can optimise industrial structure by advancing the traditional manufacturing industry and developing new service industries, thus decreasing urban carbon emission intensity. Finally, the energy consumption reduction effect was verified. Per capita power consumption (Pec) and total power consumption (Lnec) were used as mechanism variables for regression. Power consumption was used to represent resource consumption because urban power consumption in China is mainly dominated by coal power and correlates highly with carbon emission intensity. The regression results are listed in Columns (6) and (7) in Table 5. The influences of smart city construction on per capita power consumption and total power consumption were significantly negative at the 1% level. This indicates that smart city construction decreases energy consumption through technological reform and industrial reform to some extent, thereby decreasing urban carbon emission intensity. Hypothesis 2 is thus confirmed.

Table 5. Influencing Mechanism Test Results.

Variable	(1) Lngreen	(2) Pgreen	(3) Ind2	(4) Ind3	(5) AIS	(6) Pec	(7) Lnec
Policy	0.0697 **	0.3657 ***	−0.6630 ***	0.5187 ***	0.0378 ***	−0.0697 ***	−0.0790 ***
	(0.0313)	(0.0520)	(0.2376)	(0.1968)	(0.0127)	(0.0211)	(0.0258)
Pgdp	0.4548 ***	−0.3367 ***	11.3797 ***	−5.7244 ***	−0.3061 ***	−0.1996 ***	0.3432 ***
	(0.0524)	(0.0872)	(0.3981)	(0.3297)	(0.0213)	(0.0354)	(0.0432)
Pop	0.0084	0.2399 ***	0.2665	−0.0957	0.0051	−0.0073	0.0450 **
	(0.0255)	(0.0424)	(0.1937)	(0.1604)	(0.0104)	(0.0172)	(0.0210)
Fdi	−0.0088	−0.0990 ***	0.0590	0.0551	−0.0072 **	−0.0015	0.0096
	(0.0083)	(0.0138)	(0.0629)	(0.0521)	(0.0034)	(0.0056)	(0.0068)
Finc	0.0079	0.0103	−0.2511 **	0.5880 ***	0.0347 ***	0.0032	−0.0031
	(0.0161)	(0.0268)	(0.1224)	(0.1013)	(0.0066)	(0.0109)	(0.0133)
Gtec	1.0611 ***	3.4313 ***	1.1432	−0.9588	−0.0750 *	0.1006	−0.0965
	(0.1030)	(0.1715)	(0.7830)	(0.6485)	(0.0420)	(0.0695)	(0.0850)
Green	0.1254 ***	−0.0453	0.1575	0.0968	−0.0032	0.0476 ***	0.1158 ***
	(0.0270)	(0.0450)	(0.2056)	(0.1703)	(0.0110)	(0.0183)	(0.0223)
_cons	−3.1395 ***	2.6500 ***	−64.3062 ***	90.4224 ***	3.7424 ***	1.7774 ***	8.1459 ***
	(0.5546)	(0.9234)	(4.2161)	(3.4921)	(0.2259)	(0.3744)	(0.4579)
Adj. R^2	0.7887	0.3075	0.5698	0.7206	0.4927	0.1435	0.6945
N	3679	3679	3679	3679	3679	3679	3679
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

7. Conclusions and Policy Enlightenment

Smart city construction is critical to changing the urban governance model and promoting high-quality economic development. Exploring a smart city's carbon emission reduction effect has theoretical and practical significance for future sustainable urban development. Based on panel data from 283 cities in China during 2007–2019, the causality between smart city construction and urban carbon emission intensity was evaluated using a multiperiod DID method. The results show the following: (1) Smart city construction decreased urban carbon emissions intensity significantly and decreased carbon emissions per unit GDP in pilot areas by 0.1987 tonnes/10,000 CNY compared to that in non-pilot areas. (2) According to the analysis of heterogeneity, smart city construction significantly decreased carbon emissions intensity in cities in northern China and resource-based cities but had insignificant influences on carbon emission intensity in cities in southern China and non-resource-based cities. (3) Based on the analysis of influencing mechanisms, smart city construction could influence urban carbon emission intensity by stimulating green innovation vitality, promoting the advancement of industrial structures, and decreasing energy consumption.

Based on the above conclusions, some insights can be provided for low-carbon urban development. Firstly, the government should continue to increase support for smart city construction, acknowledging construction tasks such as digital infrastructure and smart government as the most critical, provide basic support for sustainable economic and social development, and promote the carbon emission reduction effect of smart city construction to the maximum extent. Moreover, the expansion of smart city pilot policy should be promoted to allow more cities to enjoy its benefits. Secondly, differences in the policy effect of smart city construction in different cities should be considered fully. The government should formulate policy orientations following local resource availability and development status, continue to increase smart city construction in northern China and resource-based cities, and facilitate the implementation of a low-carbon development model. Further, the government should change existing practices in southern China's cities and non-resource-based cities and explore more effective smart city construction models. Finally, it is suggested that the government continues to optimise policy incentives for green innovation, industrial advances, energy-saving practices, and emission reductions. The government must become an 'aggressive government' and offer enterprises a good market environment for green innovation based on new digital technologies, such as 5G, big data, and the industrial IoT. Moreover, the government must increase support for emerging industrial development and provide convenient services and financial support to manufacturing enterprises to promote digital transformation. In general, in the context of urbanisation and industrialisation, countries around the world should learn from this case study on smart city construction and actively explore new urban development models that meet their own development needs.

Unlike previously published articles on the relationship between urbanisation and carbon emissions, this paper focuses on the key role of new urban development models in reducing carbon emission intensity. This paper confirms that smart city construction can effectively mitigate carbon emission pollution in the process of urbanisation. This provides a decision-making basis for countries around the world to aid in the control of urban diseases. Due to the different development levels, technological conditions, and resource availability of smart cities, the effects of smart city construction may vary greatly. In the heterogeneity analysis, we only considered the influence of urban locations and city types on the policy effect of smart city construction. In the next step, the interactions between city size, industrial characteristics, transportation conditions, and smart city construction policies will be further analysed. The spatial spillover effect of smart city construction would also be an interesting topic to explore. In addition, can other new urban development models, such as innovative cities, also reduce urban carbon emission intensity? This is a question worthy of further exploration.

Author Contributions: Conceptualization, X.H. and P.X.; methodology, E.Z.; software, E.Z.; validation, X.H., P.X. and E.Z.; formal analysis, P.X.; investigation, X.H., P.X. and E.Z.; resources, P.X.; data curation, X.H.; writing—original draft preparation, E.Z.; writing—review and editing, X.H.; visualization, X.H. and E.Z.; supervision, P.X.; project administration, X.H. and E.Z.; funding acquisition, P.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Major Program of National Social Science Fund of China (grant number 21&ZD096), the Youth Program of National Social Science Fund of China (grant number 19CJY055) and the Key Project of Humanities and Social Sciences Research in Anhui Province (grant number SK2019A0466).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analysed in this study. These data can be found here: https://data.cnki.net/trade/Yearbook/Single/N2022040095?zcode=Z010 (accessed on 26 October 2022).

Acknowledgments: The authors would like to thank the anonymous reviewers for their valuable comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhao, X.; Zhang, X. Research on the Evaluation and Regional Differences in Carbon Emissions Efficiency of Cultural and Related Manufacturing Industries in China's Yangtze River Basin. *Sustainability* **2022**, *14*, 10579. [CrossRef]
2. Bohr, J. Is it hot in here or is it just me? Temperature anomalies and political polarization over global warming in the American public. *Clim. Chang.* **2017**, *142*, 271–285. [CrossRef]

3. Banakar, A.; Montazeri, M.; Ghobadian, B.; Pasdarshahri, H.; Kamrani, F. Energy analysis and assessing heating and cooling demands of closed greenhouse in Iran. *Therm. Sci. Eng. Prog.* **2021**, *25*, 7. [CrossRef]
4. King, L.C.; van den Bergh, J. Potential carbon leakage under the Paris Agreement. *Clim. Chang.* **2021**, *165*, 52. [CrossRef]
5. He, R.; Luo, L.; Shamsuddin, A.; Tang, Q.L. Corporate carbon accounting: A literature review of carbon accounting research from the Kyoto Protocol to the Paris Agreement. *Account. Financ.* **2022**, *62*, 261–298. [CrossRef]
6. Zhu, K.; Tu, M.; Li, Y. Did Polycentric and Compact Structure Reduce Carbon Emissions? A Spatial Panel Data Analysis of 286 Chinese Cities from 2002 to 2019. *Land* **2022**, *11*, 185. [CrossRef]
7. Chen, Q.; Mao, Y.; Morrison, A.M. Impacts of Environmental Regulations on Tourism Carbon Emissions. *Int. J. Environ. Res. Public Health* **2021**, *18*, 12850. [CrossRef]
8. Sun, L.C.; Fang, S. Irrational Carbon Emission Transfers in Supply Chains under Environmental Regulation: Identification and Optimization. *Sustainability* **2022**, *14*, 1099. [CrossRef]
9. Li, H.; Wang, J.; Wang, S. The Impact of Energy Tax on Carbon Emission Mitigation: An Integrated Analysis Using CGE and SDA. *Sustainability* **2022**, *14*, 1087. [CrossRef]
10. Liu, K.; Wang, J.; Kang, X.; Liu, J.; Xia, Z.; Du, K.; Zhu, X. Spatio-Temporal Analysis of Population-Land-Economic Urbanization and Its Impact on Urban Carbon Emissions in Shandong Province, China. *Land* **2022**, *11*, 266. [CrossRef]
11. Zhang, Y.J.; Liu, Z.; Zhang, H.; Tan, T.D. The impact of economic growth, industrial structure and urbanization on carbon emission intensity in China. *Nat. Hazards* **2014**, *73*, 579–595. [CrossRef]
12. Horobet, A.; Popovici, O.C.; Zlatea, E.; Belascu, L.; Dumitrescu, D.G.; Curea, S.C. Long-Run Dynamics of Gas Emissions, Economic Growth, and Low-Carbon Energy in the European Union: The Fostering Effect of FDI and Trade. *Energies* **2021**, *14*, 2858. [CrossRef]
13. Ma, C.Q.; Liu, J.L.; Ren, Y.S.; Jiang, Y. The Impact of Economic Growth, FDI and Energy Intensity on China's Manufacturing Industry's CO_2 Emissions: An Empirical Study Based on the Fixed-Effect Panel Quantile Regression Model. *Energies* **2019**, *12*, 4800. [CrossRef]
14. Du, S.F.; Tang, W.Z.; Song, M. Low-carbon production with low-carbon premium in cap-and-trade regulation. *J. Clean. Prod.* **2016**, *134*, 652–662. [CrossRef]
15. Ren, S.G.; Yuan, B.L.; Ma, X.; Chen, X.H. The impact of international trade on China's industrial carbon emissions since its entry into WTO. *Energy Policy* **2014**, *69*, 624–634. [CrossRef]
16. Guo, Z.H.; Bai, X.X.; Liu, S.H.; Luo, L.N.; Hao, Y.; Lv, Y.Q.; Xiao, Y.F.; Yang, J.Q.; Tian, H.Z. Heterogeneous Variations on Historical and Future Trends of CO_2 and Multiple Air Pollutants from the Cement Production Process in China: Emission Inventory, Spatial-Temporal Characteristics, and Scenario Projections. *Environ. Sci. Technol.* **2022**, *56*, 14306–14314. [CrossRef]
17. Wang, Y.; Li, L.; Kubota, J.; Han, R.; Zhu, X.D.; Lu, G.F. Does urbanization lead to more carbon emission? Evidence from a panel of BRICS countries. *Appl. Energy* **2016**, *168*, 375–380. [CrossRef]
18. Dong, F.; Long, R.Y.; Li, Z.L.; Dai, Y.J. Analysis of carbon emission intensity, urbanization and energy mix: Evidence from China. *Nat. Hazards* **2016**, *82*, 1375–1391. [CrossRef]
19. Krasheninnikov, A.V.; Loktev, D.N.; Soloviev, S.P. Megacity Aerosol Pollution and Atmospheric Electric Field Disturbances. *Izv. Atmos. Ocean. Phys.* **2020**, *56*, 759–772. [CrossRef]
20. Sadorsky, P. The Effect of Urbanization and Industrialization on Energy Use in Emerging Economies: Implications for Sustainable Development. *Am. J. Econ. Sociol.* **2014**, *73*, 392–409. [CrossRef]
21. Pang, Q.; Zhou, W.; Zhao, T.; Zhang, L. Impact of Urbanization and Industrial Structure on Carbon Emissions: Evidence from Huaihe River Eco-Economic Zone. *Land* **2021**, *10*, 1130. [CrossRef]
22. Shi, X.C.; Li, X.Y. Research on three-stage dynamic relationship between carbon emission and urbanization rate in different city groups. *Ecol. Indic.* **2018**, *91*, 195–202. [CrossRef]
23. Li, L.S.; Cai, Y.; Liu, L. Research on the Effect of Urbanization on China's Carbon Emission Efficiency. *Sustainability* **2020**, *12*, 163. [CrossRef]
24. Wang, S.J.; Gao, S.; Huang, Y.Y.; Shi, C.Y. Spatiotemporal evolution of urban carbon emission performance in China and prediction of future trends. *J. Geogr. Sci.* **2020**, *30*, 757–774. [CrossRef]
25. Gren, A.; Colding, J.; Berghauser-Pont, M.; Marcus, L. How smart is smart growth? Examining the environmental validation behind city compaction. *Ambio* **2019**, *48*, 580–589. [CrossRef]
26. Viitanen, J.; Kingston, R. Smart cities and green growth: Outsourcing democratic and environmental resilience to the global technology sector. *Environ. Plan. A* **2014**, *46*, 803–819. [CrossRef]
27. Feng, Y.C.; Hu, S.L. The Effect of Smart City Policy on Urban Haze Pollution in China: Empirical Evidence from a Quasi-Natural Experiment. *Pol. J. Environ. Stud.* **2022**, *31*, 2083–2092. [CrossRef]
28. Wang, J.X.; Deng, K. Impact and mechanism analysis of smart city policy on urban innovation: Evidence from China. *Econ. Anal. Policy* **2022**, *73*, 574–587. [CrossRef]
29. Causone, F.; Sangalli, A.; Pagliano, L.; Carlucci, S. Assessing energy performance of smart cities. *Build. Serv. Eng. Res. Technol.* **2018**, *39*, 99–116. [CrossRef]
30. Jo, S.S.; Han, H.; Leem, Y.; Lee, S.H. Sustainable Smart Cities and Industrial Ecosystem: Structural and Relational Changes of the Smart City Industries in Korea. *Sustainability* **2021**, *13*, 9917. [CrossRef]

31. Cao, W.B.; Zhang, Y.; Qian, P. The Effect of Innovation-Driven Strategy on Green Economic Development in China-An Empirical Study of Smart Cities. *Int. J. Environ. Res.* **2020**, *16*, 1520. [CrossRef] [PubMed]
32. Qian, Y.; Liu, J.; Cheng, Z.; Forrest, J.Y.L. Does the smart city policy promote the green growth of the urban economy? Evidence from China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 66709–66723. [CrossRef] [PubMed]
33. Jiang, H.; Jiang, P.; Wang, D.; Wu, J. Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. *Sustain. Cities Soc.* **2021**, *69*, 102809. [CrossRef]
34. Caragliu, A.; Del Bo, C.F. Smart innovative cities: The impact of Smart City policies on urban innovation. *Technol. Forecast. Soc. Chang.* **2019**, *142*, 373–383. [CrossRef]
35. Wang, H.Y.; Koblianska, I.I.; Yan, X. Research on Collaborative Innovation Path of Data Resources for Sustainable Development of Smart City. *Int. J. Ecol. Dev.* **2022**, *37*, 26–43.
36. Jnr, B.A.; Petersen, S.A.; Helfert, M.; Guo, H. Digital transformation with enterprise architecture for smarter cities: A qualitative research approach. *Digit. Policy Regul. Gov.* **2021**, *23*, 355–376.
37. Tyas, W.P.; Nugroho, P.; Sariffuddin, S.; Purba, N.G.; Riswandha, Y.; Sitorus, G.H.I. Applying Smart Economy of Smart Cities in Developing World: Learnt from Indonesia's Home Based Enterprises. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *248*, 012078. [CrossRef]
38. Papaioannou, T. Innovation, value-neutrality and the question of politics: Unmasking the rhetorical and ideological abuse of evolutionary theory. *J. Responsible Innov.* **2020**, *7*, 238–255. [CrossRef]
39. Wang, J.L.; Dai, Y.X. The Agglomeration Mechanism of Network Emerging E-Eommerce Industry Based on Social Science. *J. Organ. End User Comput.* **2022**, *34*, 1–16. [CrossRef]
40. Tian, G.L.; Yu, S.W.; Wu, Z.; Xia, Q. Study on the Emission Reduction Effect and Spatial Difference of Carbon Emission Trading Policy in China. *Energies* **2022**, *15*, 1921. [CrossRef]
41. Dong, F.; Zhu, J.; Li, Y.F.; Chen, Y.H.; Gao, Y.J.; Hu, M.Y.; Qin, C.; Sun, J.J. How green technology innovation affects carbon emission efficiency: Evidence from developed countries proposing carbon neutrality targets. *Environ. Sci. Pollut. Res.* **2022**, *29*, 35780–35799. [CrossRef] [PubMed]
42. Gao, K.; Yuan, Y. Is the sky of smart city bluer? Evidence from satellite monitoring data. *J. Environ. Manag.* **2022**, *317*, 115483. [CrossRef] [PubMed]
43. Li, Z.G.; Wang, J. The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. *J. Clean. Prod.* **2022**, *351*, 131570. [CrossRef]
44. Abutabenjeh, S.; Nukpezah, J.A.; Azhar, A. Do Smart Cities Technologies Contribute to Local Economic Development? *Econ. Dev. Q.* **2022**, *36*, 3–16. [CrossRef]
45. Beck, T.; Levine, R.; Levkov, A. Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *J. Financ.* **2010**, *65*, 1637–1667. [CrossRef]
46. Zhou, C.B.; Zhou, S. China's Carbon Emission Trading Pilot Policy and China's Export Technical Sophistication: Based on DID Analysis. *Sustainability* **2021**, *13*, 14035. [CrossRef]
47. Chen, J.D.; Gao, M.; Cheng, S.L.; Hou, W.X.; Song, M.L.; Liu, X.; Liu, Y.; Shan, Y.L. County-level CO_2 emissions and sequestration in China during 1997–2017. *Sci. Data* **2020**, *7*, 391. [CrossRef]
48. Tan, X.J.; Liu, Y.S.; Dong, H.M.; Zhang, Z. The effect of carbon emission trading scheme on energy efficiency: Evidence from China. *Econ. Anal. Policy* **2022**, *75*, 506–517. [CrossRef]
49. Guo, Y.S.; Chen, J.Q.; Shi, F.; Peng, X.P.; Ma, X.J.; Fang, D. The effect of China's carbon emission trading on eco-efficiency: An empirical study at the city level. *Environ. Sci. Pollut. Res.* **2022**, *29*, 84827–84843. [CrossRef]
50. Du, Q.Y.; Yu, H.D.; Yan, C.; Yang, T.L. Does High-Speed Rail Network Access Enhance Cities' Innovation Performance? *Sustainability* **2020**, *12*, 8239. [CrossRef]
51. Chetty, R.; Looney, A.; Kroft, K. Salience and Taxation: Theory and Evidence. *Am. Econ. Rev.* **2009**, *99*, 1145–1177. [CrossRef]
52. De Chaisemartin, C.; D'Haultfoeuille, X. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *Am. Econ. Rev.* **2020**, *110*, 2964–2996. [CrossRef]
53. Baker, A.C.; Larcker, D.F.; Wang, C.C.Y. How much should we trust staggered difference-in-differences estimates? *J. Financ. Econ.* **2022**, *144*, 370–395. [CrossRef]
54. Shi, J.H.; Wang, F. The Effect of High-Speed Rail on Cropland Abandonment in China. *Land* **2022**, *11*, 1002. [CrossRef]