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ARTICLE

Smart City Construction and Urban Green Development: An Analysis from the Perspectives of Industrial Structure and Technological Progress

Diandian Zhang *, Haiqiao Wu

School of Public Administration and Policy, Shandong University of Finance and Economics, Jinan 250014, China

ABSTRACT

As an innovative urban development model, smart cities have become a pivotal strategy for fostering green, efficient, and sustainable urban growth, epitomizing efficiency, intelligence, and sustainability. Investigating the impact of the smart city pilot policy on urban green development not only deepens our understanding of smart city construction but also further supports urban green development. This study utilizes panel data from 191 Chinese cities (2008-2022) and employs a DID model and a mediating effect model to analyze the influence of smart city construction on urban green development. The smart city pilot policy significantly and positively impacts urban green development, a finding that remains robust across various tests. The direct influence of the smart city pilot policy on urban green development is seen in three key areas: resources, environment, and technology. Mechanism tests indicate that the smart city pilot policy promotes urban green development via two primary pathways: industrial structure upgrading and technological progress. The impact shows clear heterogeneity, having a significant effect on non-resource-based cities and small cities. The study proposes several policy recommendations, including promoting the digitalization and informatization level of industries, strengthening the guidance and regulation of smart city construction and technological innovation, and establishing a regional coordination mechanism.

Keywords: Urban Green Development; Smart City; DID; Mediating Effect

*CORRESPONDING AUTHOR:
Diandian Zhang, School of Public Administration and Policy, Shandong University of Finance and Economics, Jinan 250014, China; Email: zhangdd@sdufe.edu.cn

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1. Introduction

Cities are pivotal to modernization, continuously improving living conditions by meeting diverse human needs. Yet rapid urbanization has generated global challenges - environmental pollution [1,2], traffic congestion [3], resource depletion [4], and the urban heat-island effect - that critically undermine urban sustainability [5]. Tackling these issues is now central to global urban-development agendas. The State Council of China issued the "National New-Type Urbanization Plan (2014–2020)," which explicitly calls for the construction of smart, green, and human-centered cities, promoting a development model that is intensive, innovative, integrated, harmonious, and sustainable. In this context, smart cities have emerged as a key model for fostering sustainable urban development, characterized by efficiency, intelligence, and sustainability. Green development, one of the core principles of sustainable development, emphasizes the harmonious balance between economic growth and environmental conservation. In the development of smart cities, green development is integrated throughout the process, influencing urban planning, infrastructure construction, energy utilization, and environmental governance.

The conception of the Smart City dates back to IBM's "Smart Planet" initiative in 2008, which proposed a new social development model. This concept was later integrated into urban planning. Globally, smart cities are emerging as a response to urbanization and a means to elevate living standards. Often equated with "digital", "intelligent", or "knowledge-based" cities, they leverage information and communication technologies to foster scientific growth, efficient governance, and a higher quality of life. By collecting transparent, comprehensive data and ensuring secure transmission and effective processing, these cities optimize operations, enhance public services, and cultivate low-carbon ecosystems [6,7]. As technology rapidly advances and the information society emerges, smart cities have become a key focus for future urban planning.

Smart cities development exemplifies a paradigm for tackling the ecological and governance challenges of rapid urbanization [8]. It centers on leveraging technology to enhance quality of life, improve service delivery, and optimize resource use [9]. Smart cities encompass not only information technology but also concentrate on more efficient resource utilization and reduced emissions [10]. Yigitcanlar et al. [11,12] empirically analyzed the relation between urban smart levels and carbon dioxide emissions, revealing a nonlinear connection that remains stable over time. Witkowski [13] contends that IoT, big-data analytics, and cloud computing allow firms to optimize scale and quality, boosting efficiency while cutting logistics and transaction costs and curbing pollution—underscoring the growing scholarly interest in the smart-city–green-development nexus. Chinese researchers, integrating technological, humanistic, structural, and environmental perspectives, broadly concur that smart-city initiatives markedly elevate urban green performance. Using a difference-in-differences design, Zhang and Gao [14] show that the pilot policy upgrades regional manufacturing via technological innovation and improved resource allocation. Mo and Wu [15] argue that as urban development progresses, the green development impact of new smart cities becomes more pronounced, with clear stages and variations in its effects.

Though existing studies on the relationship between smart city construction and urban green development offer valuable insights, there are still areas that need further exploration and refinement. First, the indicators used to assess urban green development levels need further optimization and enhancement. Second, the mechanisms by which smart city construction impacts urban green development require further investigation. As a key government strategy to advance smart city development, the policy effects and impact mechanisms of the smart city pilot program have attracted significant attention. Therefore, examining the influence of the smart city pilot policy on urban green development not only deepens our understanding of smart city construction but also further supports urban green development.

2. Research Hypotheses

Accelerated urbanization confronts cities with acute resource shortages and environmental degradation. Green development is now essential for sustainable urban growth, rendering the green transition of urban models imperative. The smart-city pilot policy leverages next-generation information technologies to reshape urban development, foster multidimensional green growth, and elevate overall urban sustainability. Intelligent methods are pivotal in urban planning and construction. Strategically planned functional zones shorten travel distances, cutting energy use and carbon emissions. Smart transportation systems monitor traffic in real time, easing congestion, reducing vehicle emissions, and improving air quality [16]. Smart grids collect and analyze instantaneous energy data, enabling precise allocation and minimizing transmission and utilization losses. Meanwhile, intelligent environmental monitoring tracks air quality continuously, rapidly detects pollution sources, and supplies actionable data for governance. By integrating these measures, the smart city pilot policy accelerates urban green development [6]. In conclusion, the smart city pilot policy drives urban green development by collaborating across various sectors. Based on this, the following hypothesis is proposed:

Hypothesis 1: *The smart city pilot policy contributes to enhancing urban green development.*

A well-organized, balanced industrial structure is crucial for effectively coordinating resource management, environmental protection, and economic development [17,18]. The smart city pilot policy presents both opportunities and challenges for urban development. Smart cities prioritize the use of next-generation information technologies to enhance resource allocation efficiency and quality of life, while also bolstering urban resilience, sustainability, and climate change adaptation [19]. By leveraging advanced technologies such as big data, the Internet of Things, and cloud computing, smart cities foster the development of emerging industries, including the digital economy, intelligent transportation, and smart energy, thereby optimizing the industrial structure. These emerging industries, characterized by high added value, low pollution, and low energy consumption, drive the greening and high-end development of urban industrial structures. Smart city development also significantly advances the greening of traditional industries. For instance, integrating industrial Internet and intelligent manufacturing technologies into production processes can reduce energy consumption and environmental pollution, leading to a green upgrade of the industrial structure. In summary, smart cities play a pivotal role in optimizing and upgrading urban industrial structures through technological innovation, industrial enhancement, and optimized resource allocation, providing substantial support for urban green development. Based on this, the following hypothesis is proposed:

Hypothesis 2: *The smart city pilot policy contributes to urban green development by optimizing the industrial structure.*

Technological progress is a core driver of urban green development, and the smart city pilot policy fosters a conducive environment for technological innovation and progress [16]. On one hand, policy guidance and support encourage businesses to invest more in green technology research and development, accelerating the introduction and application of new technologies. Technological innovation can significantly improve manufacturing resource and energy efficiency, while reducing pollution emissions [20]. For instance, in the energy sector, smart grid technology enhances energy distribution and usage efficiency, reducing energy waste, losses, and carbon emissions. The use of digital design and intelligent manufacturing technologies allows for precise control of production processes, reducing defects and raw material consumption, while simultaneously improving product quality and added value. Additionally, the smart city pilot policy facilitates the deep integration of information technology with traditional industries, enhancing production efficiency, optimizing resource allocation, and significantly reducing waste and environmental pollution in manufacturing. Through the creation of information-sharing platforms and innovation networks, enterprises can more easily access and adopt new technologies, boosting the region's overall technological capabilities. This diffusion of technology helps bridge the technological gap between enterprises, improving the overall green development level of urban industries. Based on this, the following hypothesis is proposed:

Hypothesis 3: *The smart city pilot policy fosters urban green development through technological progress.*

Urban development imbalances are a notable feature of China's economy and society. As the smart city pilot policy is implemented, varying urban forms may lead to different effects [21]. The 2012 smart city pilot - covering 90 cities - revealed wide disparities in economic development, industrial structure, infrastructure, resource endowments, innovation capacity, and policy intensity, all of which shape the inputs and outcomes of smart city initiatives. Non-resource cities, with diversified and dynamic economies, generally enjoy steadier growth and derive greater benefits from the pilot, whereas resource-dependent cities, weighed down by legacy extraction and processing, confront ecological degradation and pollution that can dampen the policy's impact. Based on this, the following hypothesis is proposed:

Hypothesis 4: *The influence of the smart city pilot policy on urban green development is heterogeneous.*

3. Materials and Methods

3.1. Selection of Variables

3.1.1. Explained Variables

Based on the "Green Development Indicator System" published on the Chinese government website in 2016 and drawing from previous studies, this research develops an evaluation system for urban green development, incorporating three dimensions: environmental governance, growth quality, and green living (as shown in **Table 1**). The overall score for urban green development is calculated using the entropy method.

Table 1. The Evaluation Indicators for Urban Green Development Level.

Dimension	Indicator	Unit of Measurement
Environmental Governance	Harmless treatment rate of domestic waste	%
	Total investment in pollution source control	Ten thousand yuan
Growth Quality	Proportion of tertiary industry in regional gross product	%
Green Living	Greening coverage rate in developed areas	%
	Per capita green space area	Square meters per person

3.1.2. Core Explanatory Variable

The core explanatory variable in this study is Treat*Time. Specifically, Treat is assigned values based on the list of smart cities established in 2012, as published in relevant documents by the Ministry of Housing and Urban-Rural Development of the State Council of China. Time is assigned values based on the time nodes of the establishment of smart cities, and the multiplication of the two yields the core explanatory variable Treat*Time.

3.1.3. Control Variables

In addition to the core explanatory variable, several other factors may influence the level of urban green development and must be controlled for. These include urbanization (urb), economic development (eco), human capital (hum), infrastructure (inf), level of openness (ope), and industry agglomeration (agg) (see **Table 2**).

Table 2. Control Variables.

Name	Description of Variable
Urbanization	Sum of the proportion of employment population in the secondary and tertiary industries
Economic Development	The real per capita GDP
Human Capital	Number of college students per ten thousand people
Infrastructure	The completed investment in urban environmental infrastructure construction
Level of Openness	Ratio of the actual total foreign investment used to GDP
Industry Agglomeration	Number of large-scale industrial enterprises

3.1.4. Mediating Variables

Based on the theoretical analysis presented earlier, the following indicators are selected as mediating variables in this study: (1) Industrial structure upgrading (structure), which typically results from the combined effects of factors such as technological progress, policy guidance, capital investment, and improvements in human resource quality, is represented by the ratio of the added value of the tertiary industry to that of the secondary industry. (2) Technological progress (progress), encompassing the invention and promotion of new products, the improvement of production processes, and the application of new energy sources and materials, is measured by expenditure on science and technology.

3.2. Data Sources and Descriptive Statistics

In December 2012, the Ministry of Housing and Urban-Rural Development of the State Council of China officially issued two documents: the "Interim Measures for the Administration of National Smart City Pilots" and the "Pilot Indicator System for National Smart Cities (Districts, Towns) (Trial)." These documents marked the official launch of the national smart city pilot program. The first batch of national smart city pilots comprised 90 cities, including 37 prefecture-level cities, 50 districts (counties), and 3 towns. To ensure the objectivity and authenticity of the research results and the availability of data, this study excluded cities that were designated as pilot areas in 2013 and 2014, as well as those where the pilot program was only implemented at the district or county level. Ultimately, panel data from 191 prefecture-level cities across China were selected. Of these, the 29 cities that implemented the smart city pilot program in 2012 were classified as the treatment group, while those that did not participate in the program were considered the control group (a total of 162 cities).

This study compiles panel data from 191 Chinese prefecture-level cities over a 15-year span from 2008 to 2022. Data for the dependent variable, mediator variable, and control variables are sourced from the China Statistical Yearbook, the China Urban Database, the EPS Database, provincial and municipal statistical yearbooks, and the National Bureau of Statistics website. Missing data, accounting for less than 5%, are imputed based on linear trends. Descriptive and econometric analyses are conducted using Stata 17 (64-bit), with two-way fixed-effects regression tests executed via the reghdfe command to account for individual and time effects. **Table 3** presents descriptive statistics for the explained variable (urban green development level, UGD), the core explanatory variable (Smart City Pilot Policy, Treat*Time), mediating variables (industrial structure upgrading, structure; technological progress, progress), and control variables (urbanization, urb; economic development, eco; human capital, hum; infrastructure, inf; level of openness, ope; industry agglomeration, agg).

Table 3. Descriptive Statistics.

Variable Name	Abbreviation	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Urban Green Development Level	*UGD*	2672	0.787	0.416	0.043	2.532
Smart City Pilot Policy	*Treat*Time*	2865	0.111	0.315	0.000	1.000
Industrial Structure Upgrading	*structure*	2864	0.987	0.449	0.139	5.650
Technological Progress	*progress*	2864	−0.117	0.500	−1.975	1.732
Urbanization	*urb*	2671	4.732	1.164	−0.211	8.347
Economic Development	*eco*	2865	10.662	0.648	4.595	13.056
Human Capital	*hum*	2674	97.907	6.803	0.000	127.210
Infrastructure	*inf*	2673	11.643	1.674	3.555	15.920
Level of Openness	*ope*	2244	0.302	0.287	0.000	2.944
Industry Agglomeration	*agg*	2864	6.792	1.051	3.296	9.536

3.3. Methods

3.3.1. Benchmark Model

The smart city pilot policy implemented by China in 2012 can be considered a quasi-natural policy experiment. To evaluate its effects, the Difference-in-Differences (DID) method is usually used to construct the benchmark regression model presented in Equation (1), which explores the influence of the smart city pilot policy on urban green development levels:

$$UGD_{it} = \mu_i + \lambda_t + \alpha Treat_{it} * Time_{it} + \Sigma\, \beta_i x_{iit} + \varepsilon_{it} \quad (1)$$

where i denotes the city, and t denotes the year. UGD represents the urban green development level; Treat is a dummy variable for grouping; Time is a time dummy variable; x is a set of control variables; individual effects are denoted by μ_i, time effects by λ_t, and ε_{it} represents the random error.

Cities that adopted the smart city pilot policy in 2012 are classified as the treatment group, whereas those that did not are classified as the control group. A policy dummy variable is assigned a value of 1 for pilot areas and 0 for non-pilot areas. Additionally, a time dummy variable is set at 1 for 2012 and subsequent years, and 0 for earlier years.

3.3.2. Mediating Effects Model

To further examine the impact mechanism of the smart city pilot policy on urban green development levels, this paper addresses potential estimation biases that may arise from the traditional step-by-step regression approach in mediation effect models. Drawing on Jiang's suggestions for improving mediating effect tests [22], we construct the following mediating effect model based on Model (1):

$$structure_{it} = \mu_i + \lambda_t + \gamma Treat_{it} * Time_{it} + \Sigma\, \Phi_i x_{iit} + \varepsilon_{it} \quad (2)$$

$$progress_{it} = \mu_i + \lambda_t + \eta Treat_{it} * Time_{it} + \Sigma\, \tau_i x_{iit} + \varepsilon_{it} \quad (3)$$

Where structure and progress represent the mediating variables. According to the testing criteria, when conducting the mediating effect test, if the regression coefficient α in Model (1) is significant, and the coefficient γ in Model (2) or η in Model (3) is also significant, it suggests that the core explanatory variable's regression coefficients are all significant, indicating the presence of a mediating effect.

4. Results

4.1. Benchmark Regression

Table 4 displays the benchmark regression results, assessing the impact of the smart city pilot policy on urban green development levels. Column (1) excludes control variables, whereas Columns (2)–(7) incrementally include control variables. All models account for individual and time fixed effects. The regression results indicate that, in the absence of control variables, the coefficient of Treat*-Time is 0.068 and statistically significant at the 1% level. This suggests that, compared to cities that did not implement the smart city pilot policy, cities that did saw a significant improvement in their level of green development post-2012. After progressively adding control variables in Columns (2)–(7), the coefficient of Treat*Time changed slightly but remained significantly positive. These results suggest that the implementation of the smart city pilot policy significantly enhanced urban green development levels.

Table 4. Benchmark Regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	UGD	*UGD*	*UGD*	*UGD*	*UGD*	*UGD*	*UGD*
*Treat*Time*	0.068***	0.068***	0.063***	0.061***	0.061***	0.054***	0.054***
	(4.787)	(4.741)	(4.449)	(4.257)	(4.259)	(3.902)	(3.922)
urb		0.000	0.000	0.000	0.000	0.000	0.000
		(1.002)	(0.605)	(0.696)	(0.706)	(1.037)	(1.057)
eco			−0.070***	−0.068***	−0.068***	−0.073***	−0.039**
			(−5.420)	(−5.335)	(−5.333)	(−5.188)	(−2.504)
hum				−0.003***	−0.003***	−0.001	−0.001

Table 4. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	UGD	***UGD***	***UGD***	***UGD***	***UGD***	***UGD***	***UGD***
				(−2.942)	(−2.950)	(−0.781)	(−0.778)
inf					−0.001	−0.004	−0.004
					(−0.299)	(−0.918)	(−0.804)
ope						−0.049***	−0.030**
						(−3.317)	(−2.028)
agg							−0.064***
							(−5.271)
_cons	0.114***	0.113***	0.771***	1.007***	1.020***	0.961***	1.013***
	(3.432)	(3.401)	(6.127)	(6.755)	(6.537)	(5.008)	(5.308)
N	2672	2672	2672	2672	2672	2244	2244
Individual Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2. Parallel Trends Test

The parallel trend assumption asserts that, before policy implementation, the outcome variables of the treatment and control groups should follow the same trend of change. To test this, an event study approach is applied. The year 2012, when the policy was implemented, serves as the base period, and period -1 is excluded to prevent perfect collinearity. The estimation results are shown in **Figure 1**. Before the policy implementation, the estimated urban green development level did not significantly differ from 0, fluctuating around it. This suggests that there was no significant difference between the treatment and control groups before the policy, thus satisfying the parallel trend assumption. After the policy implementation, it is observed that various measures were not fully operational in the initial phase, resulting in no significant immediate effects. This can be interpreted as a time-lag effect of policy implementation. However, when considering the overall trend, the smart city pilot policy still appears to have a potential positive impact on urban green development levels.

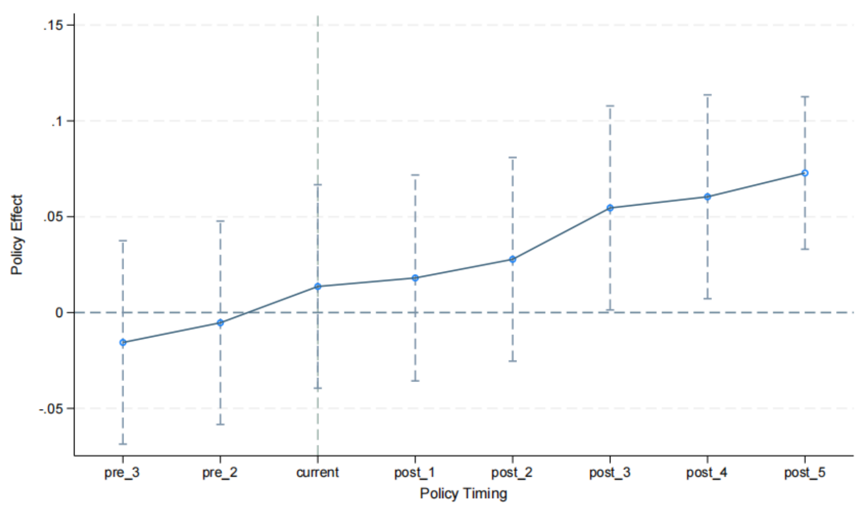

Figure 1. Parallel Trends Test.

4.3. Robustness

4.3.1. Placebo Tests

The placebo test examines whether the observed policy effects are influenced by random factors or data biases by simulating random policy interventions. Using Stata software, this study generates 500 random treatment and control groups based on the implementation of the smart city pilot policy. It then calculates 500 virtual regression coefficients and their corresponding p-values. The distribution of these estimated coefficients is plotted (see **Figure 2**). The results show that the estimated coefficients of the fictitious difference-in-differences term are distributed around zero, approximating a normal distribution, with the mean far from the true value. This suggests that the influence of the smart city pilot policy on urban green development is reliable, and the main conclusions are robust.

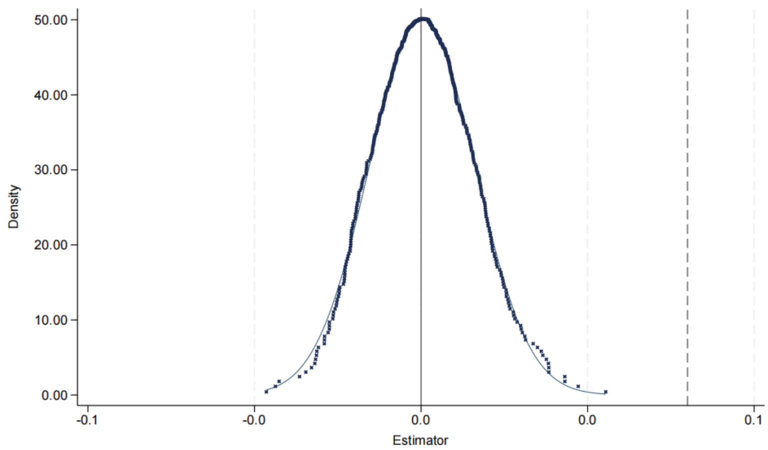

Figure 2. Placebo Tests.

4.3.2. Propensity Score Matching Test

To further ensure an accurate assessment of the true impact of the policy and control for potential confounding factors, propensity score matching (PSM) is employed to find a control group with minimal differences from the treatment group. The sample is processed using PSM, as shown in **Table 5**. After matching, the standard deviations of the control variables between the treatment and control groups are significantly reduced, with all absolute values falling below 10%. Furthermore, the p-values for all control variables are insignificant, indicating that the PSM effect is satisfactory.

Table 5. Results of the Propensity Score Matching.

Variable	Matching	Mean		Standard Deviation	t	p-value
		Treatment Group	Control Group			
urb	U	5.443	4.650	77.2	10.25	0.000
	M	5.443	4.650	6.8	0.77	0.441
eco	U	11.07	10.507	99.3	13.03	0.000
	M	11.07	11.045	4.3	0.51	0.611
hum	U	99.544	97.554	40.9	4.42	0.000
	M	99.544	99.557	−0.3	−0.20	0.840
inf	U	12.364	11.505	54.4	7.63	0.000
	M	12.364	12.266	6.2	0.67	0.501
ope	U	0.3755	0.2935	28.8	4.13	0.000
	M	0.3755	0.3545	7.4	0.76	0.448
agg	U	7.0865	6.7872	31.4	4.33	0.000
	M	7.0865	7.0804	0.6	0.07	0.945

4.3.3. Shortening the Sample Period

In the robustness tests, we shortened the sample period to verify the reliability and stability of the research conclusions. The original sample period, which covered 2008 to 2022, was shortened to 2009 to 2020 to exclude potential abnormal data fluctuations and other disturbances that may arise over a longer period. Utilizing the matched sample, the difference-in-differences (DID) method is employed for estimation, with the results displayed in Column (2) of **Table 6**. Column (3) shows that the regression results remain significant within the shortened sample period, and the coefficient of the core explanatory variable Treat*Time is close to that of the benchmark regression (Column (1)). This indicates that even with a shorter sample period, the policy effect remains stable in terms of both strength and direction. A series of tests confirms that the smart city pilot policy has a significant positive impact on urban green development.

Table 6. The Results of PSM-DID and Shortening the Sample Period.

	(1)	(2)	(3)
	UGD	***PSM-DID***	***UGD***
*Treat*Time*	0.054***	0.046***	0.0504***
	(3.922)	(3.446)	(3.3365)
urb	0.000	−0.001	0.0042
	(1.057)	(−0.139)	(0.9104)
eco	−0.039**	0.033**	−0.0346*
	(−2.504)	(2.018)	(−1.7948)
hum	−0.001	−0.001	0.0008
	(−0.778)	(−0.978)	(0.5816)
inf	−0.004	−0.005	0.0045
	(−0.804)	(−1.128)	(0.8218)
ope	−0.030**	−0.044***	−0.0207
	(−2.028)	(−3.031)	(−1.3965)
agg	−0.064***	−0.024**	−0.0513***
	(−5.271)	(−1.974)	(−4.0973)
_cons	1.013***	−0.009***	0.6971***
	(5.308)	(−11.607)	(3.1216)
N	2244	2242	1864
Individual Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3.4. Endogeneity

When exploring the relationship between the smart city pilot policy and urban green development, bidirectional causality between the two could trigger endogeneity issues, which might undermine the accuracy and reliability of the research results. To address this, the total volume of postal and telecommunications services in the region is used as an instrumental variable for endogeneity testing. Typically, regions with higher volumes of postal and telecommunications services have efficient information transmission and developed communication networks, which provide a strong foundation for smart city construction and correlate highly with the smart city pilot policy. As an objective reflection of the scale of information and communication activities, the total volume of postal and telecommunications services is an exogenous factor, independent of other random disturbances affecting urban green development, thus satisfying the exogeneity requirement.

The endogenous variable Treat exists in the form of an interaction term (Treat*Time), so the actual endogenous variable in this study is the interaction term Treat*-Time. When using instrumental variables for analysis, the instrumental variable corresponding to the interaction term Treat*Time is set as IV*Time. In the first stage of regression, the instrumental variable IV is multiplied by the variable Time to construct the interaction term IV*Time, which is then introduced into the regression model to rigorously test the relevance of the instrumental variable. The regression results are shown in **Table 7**. As indicated by the first-stage regression results in Column (1), the coefficient of the instrumental variable interaction term "IV*-Time" exhibits significant statistical characteristics. In the second-stage regression results of Column (2), the coefficient of the core explanatory variable Treat*Time remains significantly positive. This suggests that after successfully addressing endogeneity, the positive impact of the smart city pilot policy on urban green development remains significant, confirming that the benchmark regression results are not due to sample selection bias.

Table 7. Endogeneity.

	(1)	**(2)**
	UGD	***UGD***
*IV*Time*	0.025***	
	(5.108)	
*Treat*Time*		1.425**
		(2.186)
urb	−0.001	0.019
	(−0.270)	(1.331)
eco	−0.045***	0.050
	(−2.908)	(0.906)
hum	−0.001	0.009
	(−0.400)	(1.569)
inf	−0.003	−0.005
	(−0.640)	(−0.501)
ope	−0.021	−0.080*
	(−1.392)	(−1.906)
agg	−0.063***	−0.065**
	(−5.204)	(−2.278)
_cons	1.018***	−0.681
	(5.358)	(−0.740)
N	Yes	Yes
Individual Effects	Yes	Yes
Time Effects	2241	2241

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4. Moderating Effects

To further explore the mechanisms of influence, industrial structure upgrading and technological progress are set as mediating variables. This study follows Jiang's recommendation for the two-step method in mediating effect analysis to effectively elaborate and verify the proposed mechanisms [22].

Table 8 presents the mediating effect results. Column (2) indicates that the regression coefficient for the impact of smart city construction on industrial structure upgrading is positive and significant at the 1% level, suggesting that smart city initiatives can boost industrial structure upgrading. Column (3) shows that the regression coefficient for the impact of smart city construction on technological progress is positive and significant at the 5% level, indicating that smart city initiatives can enhance technological progress. This suggests that smart city pilot policy contributes to urban green development by optimizing the industrial structure, thereby confirming Hypothesis 2, and through technological progress, thus confirming Hypothesis 3.

Table 8. Moderating Effects.

	(1)	(2)	(3)
	UGD	***Structure***	***Progress***
*Treat*Time*	0.054***	0.116***	0.068**
	(3.922)	(4.278)	(2.471)
urb	0.000	−0.026***	−0.020**
	(1.057)	(−3.031)	(−2.294)
eco	−0.039**	0.246***	0.228***
	(−2.504)	(14.289)	(13.094)
hum	−0.001	0.009***	0.012***
	(−0.778)	(3.229)	(4.396)
inf	−0.004	0.086***	0.071***
	(−0.804)	(9.207)	(7.590)
ope	−0.030**	−0.122***	−0.148***
	(−2.028)	(−4.025)	(−4.830)
agg	−0.064***	−0.286***	−0.291***
	(−5.271)	(−12.649)	(−12.745)
_cons	0.054***	−2.601***	−1.528***
	(3.922)	(−8.771)	(−5.108)
N	2242	2242	2242
Individual Effects	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5. Heterogeneity

The analysis results in the preceding text show that the smart city pilot policy has played a significant role in promoting urban green development. However, whether this role still exists for different types of cities and whether there are differences in its effects are questions that need to be addressed.

Urban resource endowments can influence the efficiency of resource utilization and the industrial structure of economic entities, thus affecting a city's sustainable development [23]. First, we examine the heterogeneity from the perspective of resource endowment. In accordance with the "National Plan for the Sustainable Development of Resource-Based Cities (2013–2020)", the 191 sample cities are categorized into resource-based and non-resource-based cities (with 78 resource-based cities and 113 non-resource-based cities), and grouped regressions are conducted. Columns (1) to (2) of **Table 9** show that the smart city pilot policy has a significant impact on the green development level of non-resource-based cities, while its effect on resource-based cities is not significant.

There may also be differences in this impact across cities of varying sizes. Based on the permanent population in urban areas, the "Notice of the State Council of China on Adjusting the Standards for Classifying City Sizes" categorizes cities by size. According to this classification, cities with a permanent population of less than or equal to 1 million are small cities, cities with populations greater than 1 million but less than or equal to 5 million are large cities, and cities with populations greater than 5 million are megacities. The results in Columns (3) to (5) of **Table 9** show that the smart city pilot policy significantly impacts the green development level of small cities.

Table 9. Heterogeneity.

	(1)	(2)	(3)	(4)	(5)
	Non-Resource-Based	**Resource-Based**	**Small**	**Large**	**Mega**
*Treat*Time*	0.072***	0.022	0.102***	0.008	0.005
	(3.680)	(1.259)	(5.757)	(0.348)	(0.068)
urb	0.010	−0.021***	−0.002	0.008	0.015
	(1.494)	(−3.245)	(−0.509)	(0.537)	(0.380)
eco	−0.019	−0.053***	−0.064***	0.051	0.014
	(−0.609)	(−3.526)	(−3.927)	(1.260)	(0.171)
hum	0.001	−0.001	−0.002*	0.022***	−0.059
	(0.390)	(−0.626)	(−1.673)	(4.006)	(−1.606)
inf	−0.003	0.000	0.005	0.009	−0.027
	(−0.477)	(0.033)	(0.894)	(0.956)	(−1.065)
ope	−0.040**	0.035	0.014	−0.029	−0.138**
	(−2.041)	(1.440)	(0.802)	(−0.847)	(−2.481)
agg	−0.081***	−0.044***	−0.065***	−0.086***	−0.025
	(−4.354)	(−3.002)	(−4.951)	(−3.152)	(−0.378)
_cons	0.625	1.546***	1.309***	−0.801	7.103*
	(1.409)	(7.716)	(6.726)	(−1.259)	(1.871)
N	1335	907	1417	622	203
Individual Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Discussion

Based on panel data from 191 cities over the period from 2008 to 2022, this study employs the DID method to empirically examine the impact of the smart city pilot policy on urban green development levels. The results reveal:

(1) The direct influence of the smart city pilot policy on urban green development is seen in three key areas: resources, environment, and technology. Smart cities optimize water-recycling monitoring, ensure safe gas-system operations, and advance waste reduction through secure data platforms. Real-time environmental monitoring and big-data analytics enable rapid issue resolution, improving urban conditions and social sustainability [24,25]. In terms of technology, data serves as the core resource of smart cities' digital infrastructure. Data, the core asset of digital infrastructure, is processed by sensor-rich, IoT-enabled energy platforms [26]. This fosters the integration of energy networks, the Internet, and IoT, enabling digital supervision and analysis of energy data.

(2) The smart city pilot policy promotes urban green development by optimizing the industrial structure. Empirical evidence shows that smart cities shift from traditional to innovation-driven growth, channeling resources toward high-tech and emerging sectors aligned with the new economic model [27]. The structural dividend hypothesis suggests that adjustments in industrial structure can create "structural dividends" [28], which are critical for enhancing green development efficiency [29]. Upgrading the structure boosts productivity and energy use, steers inputs toward low-carbon technologies, and drives high-precision, green-certified manufacturing, thereby markedly improving urban green efficiency [30]. Consequently, the structural effect of the smart-city pilot policy becomes a key driver of urban green development.

(3) The smart city pilot policy promotes urban green development through technological innovation. Existing research confirms that accelerating technological innovation is a critical policy strategy to improve green development levels. The technological innovations actively

promoted in China have been pivotal in advancing green development [31]. Green-manufacturing innovations drive industrial green growth by cutting energy use and emissions, restructuring energy mixes, and generating knowledge spillovers. Consequently, smart-city-led technological advances will bolster urban sustainability.

(4) Smart city pilots yield heterogeneous impacts on green development. Resource-based cities, historically anchored in natural-resource extraction, confront entrenched barriers to industrial transformation and green innovation [32]. While the pilot policy aims to promote the intelligent and informatized development of cities, resource-based cities face considerable challenges in transitioning from traditional industries to green and sustainable ones. This transition requires substantial time and investment. Non-resource-based counterparts, benefiting from diverse, dynamic economies and steadier growth, integrate the pilot more readily [33]. These cities prioritize upgrading traditional sectors and nurturing high-tech services, leveraging information technologies to raise efficiency and advance green development. Small cities, owing to compact size, experience lower implementation resistance and faster structural adjustment, whereas large and mega-cities - marked by dense populations, intricate industries, and heightened environmental pressures - struggle to roll out uniform policies, delaying visible impacts.

6. Conclusions

Based on the above research conclusions, this article puts forward the following policy suggestions:

Increased investment should be directed toward smart city construction, and the widespread adoption of information technology across industries should be promoted. In particular, traditional industries should be encouraged to utilize big data, the Internet of Things, and other technologies to achieve intelligent transformation, thus improving production efficiency while reducing energy consumption and environmental pollution. Policies should be designed to attract high-tech and green industries to these areas, leveraging smart city advantages to provide a better development environment. Efforts should be made to cultivate and attract talent, offering intellectual support for smart city development and industrial optimization. This includes training professionals skilled in information technology and green development, as well as attracting outstanding domestic and international talent for urban development. A robust evaluation system for industrial structure adjustments should be established to regularly assess changes in the industrial structure and green development under the smart city pilot policy, and to promptly adjust policy directions as necessary.

Government departments should strengthen their guidance and regulation of smart city construction and technological innovation. Increased investment in research and development of smart city-related technologies is essential, with the establishment of specialized research funds to encourage universities, research institutions, and businesses to focus on green technological innovations. A smart city innovation platform should be created to promote cooperation among industry, academia, and research institutions, accelerating the transformation and application of technological advancements. Preferential policies should be introduced to attract technology companies, offering tax exemptions and financial subsidies to those making significant contributions to green technological innovations. A technology innovation evaluation system should be set up to regularly assess technological achievements and green development levels under the smart city pilot policy, adjusting policies as necessary.

Bolster green-development momentum by prioritizing urban innovation. Expand dedicated funds for pilot smart cities to accelerate green-manufacturing R&D and deployment, maximizing its environmental gains. Create innovation-exchange platforms to disseminate technologies across cities and upgrade collective capabilities. On the other hand, institute a regional-coordination framework that enables experience sharing and collaboration among areas with diverse geographies and resource endowments. Policies must account for this heterogeneity through tailored support and evaluation criteria. Prioritize non-resource cities, monitor smart-city progress and green outcomes, and dynamically adjust measures to maintain precision and impact.

The main limitations of this study are as follows: First, the limitations of the indicator system. The evaluation system used to measure urban green development does not comprehensively cover all aspects of green development, such as the value of ecosystem services. Second, while the study focuses on two primary mechanisms - industrial structure upgrading and technological progress - it does not fully explore other potential factors, such as the optimization of social governance structures or the enhancement of public environmental awareness. These factors may also play important roles, but their mechanisms have not yet been fully explored.

Future research will focus on several areas: First, expanding the concept of green development by incorporating more indicators related to ecosystem services for a more comprehensive assessment. The level of smart city construction will also be examined in greater depth, considering improvements in information technology application, the development of intelligent infrastructure, and data sharing. Second, future research will explore additional mechanisms through which the smart city pilot policy affects urban green development. This includes studying the role of social governance optimization in promoting green development, with a focus on policy implementation efficiency and resource allocation effects under various governance models. Further attention will also be paid to the role of public environmental awareness in the implementation process, including public perception and participation in smart city construction and green development.

Author Contributions

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Data Availability Statement

The original data presented in the study are openly available in the China City Statistical Yearbooks and EPS database at https://www.stats.gov.cn/sj/ndsj/ and https://www.epsnet.com.cn/index.html.

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Conflicts of Interest

The authors declare no conflict of interest.

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