

Article

Unlocking Synergies: How Digital Infrastructure Reshapes the Pollution-Carbon Reduction Nexus at the Chinese Prefecture-Level Cities

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Abstract

In the context of global climate governance and the green transition, digital infrastructure serves as a critical enabler of resource allocation in the digital economy, offering strategic value in tackling synergistic pollution and carbon reduction challenges. Using panel data from 280 prefecture-level cities, this study employs a multiperiod difference-in-differences (DID) approach, leveraging smart city pilot policies as a quasinalatural experiment, to assess how digital infrastructure affects urban synergistic pollution-carbon mitigation (SPCM). The empirical results show that digital infrastructure increases the urban SPCM index by 1.5%, indicating statistically significant effects. Compared with energy and income effects, digital infrastructure can influence this synergistic effect through indirect channels such as the energy effect, economic agglomeration effect, and income effect, with the economic agglomeration effect accounting for a larger share of the total effect. Additionally, fixed-asset investment has a nonlinear moderating effect on this relationship, with diminishing marginal returns on emission reduction when investment exceeds a threshold. Heterogeneity tests reveal greater impacts in eastern, nonresource-based, and environmentally regulated cities. This study expands the theory of collaborative environmental governance from the perspective of new infrastructure, providing a theoretical foundation for establishing a long-term digital technology-driven mechanism for SPCM.

Keywords: digital infrastructure; synergistic effects; carbon mitigation; multiperiod DID; fixed-asset investment



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1. Introduction

The increasing impacts of climate change and pollution underscore the critical importance of emission reduction for sustainable development. With rapid industrialization and urbanization, China has become one of the world's leading sources of pollutant and carbon emissions, facing immense pressure to curb emissions. As cities serve as key actors in environmental governance, identifying scientifically sound and effective strategies to advance SPCM at the urban level holds significant strategic importance for fostering green and sustainable socioeconomic development in China.

Against this backdrop, smart cities leverage policy guidance and resource integration to drive urban digital and intelligent transformation based on digital infrastructure development, offering new pathways and models for sustainable urban development. In recent years, smart city initiatives have proliferated globally. For example, in 2009, the United

States embarked on smart city initiatives aimed at enhancing urban energy efficiency and environmental governance through digital technologies. Similarly, in 2005, the European Union implemented the i2010 strategy, seeking to improve urban operational efficiency by advancing communication technologies and building next-generation networks.

As the critical enabler of smart city development, digital infrastructure holds significant potential for enhancing urban operational performance, resource efficiency, and environmental governance capacity. However, key questions remain: How does digital infrastructure influence urban SPCM? What are the underlying mechanisms driving this relationship? Addressing these questions—by systematically examining whether digital infrastructure can achieve synergistic pollution-carbon reduction, clarifying its operational mechanisms, and mapping its impact pathways—is vital for advancing urban emission reduction and fostering sustainable urban development.

The literature has extensively examined SPCM and its contributing factors. Studies have confirmed that atmospheric pollutants and greenhouse gases share common sources and formation pathways [1], indicating that measures to reduce carbon emissions simultaneously decrease air pollution concentrations, thereby revealing inherent synergistic effects between pollution abatement and carbon mitigation. The literature primarily examines three key influencing dimensions: policy effects [2–4], technological effects, and structural effects [5–7]. Coordinated pollution-carbon policies, green technology innovation, and industrial and energy structure adjustments are key drivers of synergistic emission reductions.

Building upon existing research, this study identifies several critical gaps that warrant further exploration. While prior studies have examined the impact of digital infrastructure on SPCM from perspectives such as industrial development [8] and environmental regulation [9], few have specifically investigated this relationship under smart city policies or systematically elucidated the underlying mechanisms involved. Furthermore, although numerous studies have assessed the influence of digital infrastructure on urban SPCM, most lack rigorous causal identification and fail to incorporate multidimensional policy evaluations from heterogeneous perspectives. The current study addresses these limitations by employing robust endogeneity controls and comprehensive robustness tests, with a particular emphasis on deciphering the mechanistic pathways through which digital infrastructure enhances urban SPCM. These findings offer valuable empirical insights for advancing urban green and sustainable development.

Using panel data from 280 Chinese cities (2007–2022), this study examines the causal effect of digital infrastructure on urban SPCM. We measure SPCM performance via Super-SBM modeling and then apply multiperiod DID to assess the direct governance effects of digital infrastructure. Furthermore, mediation effect models are applied to uncover the operational pathways through which digital infrastructure influences urban SPCM. Our findings reveal a significant single-threshold effect of fixed-asset investment levels on this relationship, demonstrating that when investment surpasses a critical threshold, digital infrastructure's governance effect on SPCM becomes attenuated. Finally, we conduct comprehensive heterogeneity analyses to explore how geographic location, resource endowments, and environmental regulations differentially shape the effectiveness of the digital infrastructure in achieving SPCM.

Our work makes three principal contributions to the extant research. First, adopting a novel infrastructure perspective, it thoroughly investigates the transmission mechanisms through which digital infrastructure facilitates urban SPCM, thereby enriching the theoretical framework of collaborative environmental governance. Second, through mechanistic examination, the study explores how digital infrastructure influences urban SPCM within the context of smart city pilot policies, significantly expanding upon previous research

in this domain. Finally, building on urban characteristics, we examine the heterogeneous SPCM governance impacts of digital infrastructure across city types, providing multidimensional policy recommendations.

The paper proceeds as follows: Section 2 reviews the relevant literature, and Section 3 develops our theoretical framework, analyzing the impact mechanisms of digital infrastructure through direct effects and indirect channels. Section 4 details the econometric model and data. Section 5 presents the empirical results of the impacts of the digital infrastructure on the SPCM. Section 6 discusses findings in relation to existing research, and Section 7 concludes with policy implications.

2. Literature Review

2.1. *Influencing Factors of SPCM*

Building upon the co-origin hypothesis of carbon and pollution, greenhouse gases and atmospheric pollutants predominantly originate from extensive fossil fuel consumption, exhibiting similar emission characteristics that lend significant theoretical and practical value to collaborative research on pollution and carbon reduction. Scholars have primarily employed coupling coordination models and composite indicator approaches to measure SPCM performance. For example, Zhu et al. (2024) employed a coupling coordination model, which revealed improvements in the SPCM in the Yangtze River Delta, with an increase in high-synergy cities and a reduction in regional disparities [10]. Similarly, Abdullah and Usman (2022) adopted composite indicators to demonstrate significant synergistic mitigation potential between carbon and pollution reduction in the construction and transportation sectors [11]. The literature has focused predominantly on investigating mechanistic pathways and implementation strategies for achieving effective SPCM.

Current studies highlight three key pathways for pollution-carbon cogovernance: technological mitigation pathways, structural mitigation pathways, and policy coordination pathways [12]. With respect to technological and structural approaches, Dong et al. (2024) demonstrated that corporate green technology innovation significantly enhances resource utilization efficiency while simultaneously reducing both pollution and carbon emissions [13]. Liu et al. (2024) further established that shifting from traditional fossil fuels to cleaner energy sources through energy structure optimization effectively mitigates greenhouse gas and atmospheric pollutant emissions [14]. In the policy domain, initiatives such as low-carbon city pilot programs [15] and comprehensive big data experimental zones [16] have had positive impacts on coordinated pollution-carbon reduction. The academic consensus represented in the literature recognizes technological and structural mitigation pathways [17,18] as the two most critical approaches, with their synergistic effects having gained substantial empirical validation.

2.2. *Environmental Dividends of Digital Infrastructure*

The application of digital infrastructure has significant potential in facilitating both pollution and carbon emission reduction processes. The convergence of big data and AI technologies offers novel capabilities for tracking pollutants and controlling carbon emissions [19]. Digital platforms and analytical tools enable the effective integration and sharing of emission data [20], optimizing management systems and substantially improving urban environmental quality. With respect to pollution mitigation, Zou et al. (2023) employed a difference-in-differences (DID) approach leveraging China's broadband strategy, revealing that network infrastructure development significantly reduces environmental pollution, with particularly pronounced effects on particulate matter reduction [21]. Complementing these findings, Li et al. (2025) employed spatial Durbin models, showing that digital

infrastructure reduces local emissions while creating positive spillovers. contribute to environmental improvements in neighboring cities [22].

With respect to carbon mitigation, Song et al. (2024) analyzed China's provincial panel data and demonstrated that digital infrastructure effectively reduces regional carbon emissions while exhibiting notable regional heterogeneity and spatial spillover effects [23]. Using urban panel data, Zhang et al. (2023) reported an inverted U-shaped relationship between digital infrastructure and carbon intensity [24]. Their findings suggest that carbon emission intensity may initially increase during the early stages of digital infrastructure deployment but subsequently significantly decrease as the infrastructure matures and becomes more sophisticated.

2.3. Influence of the Digital Infrastructure on the SPCM

The literature classifies the impact of digital infrastructure on emission control into three primary mechanisms. Studies have demonstrated that digital infrastructure optimizes industrial structures and enhances resource utilization efficiency, thereby simultaneously advancing both pollution abatement and carbon mitigation [25]. Zhang et al. (2025) verified that digital infrastructure significantly strengthens SPCM effects through its dual capacity to promote technological innovation and advance digital financial development [5]. Complementing these findings, Liang et al. (2025) revealed that digital infrastructure substantially reduces urban carbon emission intensity while generating measurable spatial spillover effects to surrounding regions [26].

The second category of studies presents alternative perspectives, with Mao et al. (2024) demonstrating that computing infrastructure development may increase energy consumption and associated carbon emissions, potentially undermining pollution and carbon reduction objectives [27]. Similarly, Nie et al. (2025) indicated that during initial construction phases, digital infrastructure expansion may generate additional pollution and carbon emissions due to technological limitations and regional disparities [28,29]. A third perspective reveals complex nonlinear relationships, where some scholars identify U-shaped effects of digital infrastructure on emission reduction, whereas others observe inverted U-shaped patterns in these environmental impacts.

While existing studies have extensively discussed the role of digital infrastructure in pollution reduction and carbon mitigation separately, significant gaps remain in understanding its mechanisms for achieving synergistic governance of these dual objectives. This research context makes investigating how digital infrastructure facilitates urban SPCM particularly valuable, as it not only enriches the theoretical framework of collaborative environmental regulation but also provides practical insights for achieving sustainable development goals.

3. Policy Background and Research Hypotheses

3.1. Policy Background

The rapid advancement of global urbanization has intensified urban challenges, including traffic congestion, environmental degradation, and resource scarcity, positioning smart city development as a pivotal strategy to address these multidimensional issues. By integrating IoT, big data analytics, and AI technologies, smart city programs enhance intelligent urban management through precision governance approaches. China's national smart city program was formally institutionalized in 2012 when the MOHURD issued interim administrative measures for national smart city pilot projects, initiating the first batch of 90 pilot cities at the prefectural and county levels. This was subsequently expanded through additional batches implemented in 2013 and 2014. Current official statistics indicate that the Ministry has approved 290 cities as designated smart city pilots to date. These

systematically implemented pilot projects are projected to exert substantial and enduring impacts across multiple dimensions of China's socioeconomic development trajectory. The spatial distribution of the smart city pilot zones is presented in Figure 1.

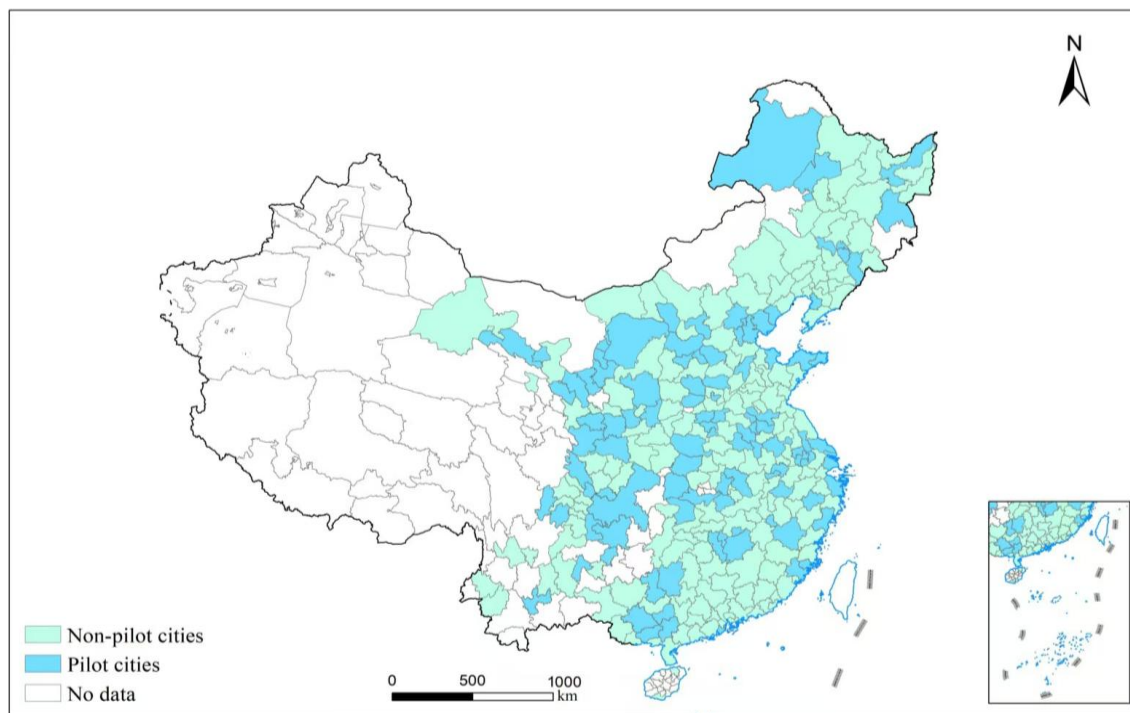


Figure 1. Geographical allocation of smart cities pilots.

3.2. Research Hypothesis

3.2.1. Analysis of Direct Effects

The development of digital infrastructure significantly contributes to enhancing urban SPCM, which is manifested primarily across three dimensions: digital production, digital governance, and digital lifestyles. In terms of digital production, the incorporation of cloud computing, AI, and other digital applications—supported by digital infrastructure—into enterprise production and management has driven the transition toward digitalized production management systems [30,31]. This shift helps reduce excessive resource consumption and pollutant emissions during production and management processes. By enabling enterprise digital transformation and fostering industrial digitization, digital infrastructure improves resource utilization efficiency and reduces pollution emissions [32], directly contributing to urban green development.

From the perspective of digital governance, the adoption of digital infrastructure, such as information technologies, digital platforms, and intelligent tools, significantly enhances information flow [21,33], facilitating efficient communication and collaboration among governments, businesses, the public, and other stakeholders. This strengthens interconnections and interactions between governance entities, leading to optimized resource allocation and improved urban environmental governance efficacy. With respect to digital lifestyles, digital infrastructure provides the public with convenient tools and platforms. The proliferation of internet and social media platforms has made dissemination and access to environmental information easier [34], enabling the public to obtain such information more efficiently. This accessibility helps raise environmental awareness among citizens, thereby advancing urban emission reduction efforts.

Hypothesis 1. *Digital infrastructure can help promote urban SPCM.*

3.2.2. Analysis of Energy Effects

Digital infrastructure enhances energy utilization efficiency through the integration, transfer, and application of resources via information technologies and communication networks—a critical pathway for achieving urban synergistic pollution-carbon mitigation. On the production front, through real-time monitoring of industrial energy consumption [35], digitalized energy systems allow enterprises to accurately detect inefficiencies and improve energy utilization patterns [36,37]. This operational refinement directly reduces both pollutant discharges and carbon emissions. Simultaneously, smart sensor networks, IoT systems, and big data analytics platforms generate high-precision energy consumption and environmental monitoring data [38]. Such technological capacities allow for scientifically informed designs of urban transport and energy infrastructure, improving energy efficiency while furthering emission reduction objectives.

Hypothesis 2. *Digital infrastructure facilitates urban SPCM through enhanced energy utilization efficiency.*

3.2.3. Analysis of Economic Agglomeration Effects

Digital infrastructure dismantles information flow barriers and significantly enhances information circulation efficiency, enabling interfirm resource integration and collaborative innovation [39]. This capability attracts enterprise agglomeration, fostering industrial clusters that generate economic agglomeration effects. Such spatial concentration facilitates both production scale economies and centralized pollution control, improving environmental governance efficiency through optimized resource utilization. Furthermore, economic agglomeration promotes shared access to innovative equipment, advanced technologies, and managerial expertise among colocated firms [40], effectively reducing innovation costs and stimulating collaborative innovation. This sharing mechanism activates technology diffusion and knowledge spillover effects [41], increasing regional innovation capacity and ultimately advancing synergistic pollution-carbon mitigation governance.

Hypothesis 3. *Digital infrastructure promotes urban SPCM through economic agglomeration effects.*

3.2.4. Analysis of Income Effects

Digital infrastructure development significantly enhances average labor productivity and fosters the growth of value-added industries [42], whereas telecommuting and on-line platforms expand employment opportunities [43], collectively contributing to urban economic development and increased household incomes. The increase in per capita disposable income further facilitates urban SPCM through two complementary pathways: consumption structure transformation and corporate product innovation. With respect to consumption patterns, higher disposable incomes drive a shift from subsistence-oriented food expenditures to development-focused service consumption, encompassing education, healthcare, and cultural activities [44,45]. This structural transition reduces material resource intensity and correspondingly decreases emissions.

From the innovation perspective, elevated incomes strengthen green consumption preferences, with higher income demographics demonstrating greater willingness to pay premium prices for environmentally friendly products and services [46]. This market dynamic incentivizes firms to pursue technological innovation, develop sustainable offerings, and minimize their environmental footprint, thereby significantly improving urban environmental quality.

Hypothesis 4. *Digital infrastructure promotes urban SPCM through income effects.*

3.2.5. Analysis of Threshold Effects

The capital-intensive nature of digital infrastructure, which encompasses broadband deployment and data center construction, makes fixed-asset investment a critical metric of development scale and intensity, which in turn affects its pollution–carbon mitigation performance. In the initial development phase, increased investment levels extend the scale and spatial reach of digital infrastructure, thereby strengthening its positive environmental impacts [37,47]. However, as investment continues to grow and digital infrastructure approaches saturation, its marginal contribution to pollution and carbon reduction gradually diminishes [48,49]. When investment exceeds a certain threshold, the environmental benefits derived from digital infrastructure begin to weaken. Consequently, beyond optimal investment levels, additional funding may no longer effectively enhance the synergistic pollution–carbon mitigation effects.

Hypothesis 5. *The enhancement effect of the digital infrastructure on the urban SPCM exhibits threshold characteristics contingent on fixed-asset investment levels.*

The conceptual framework of the study is visualized in Figure 2. To address climate change and environmental degradation, our research systematically examines the direct effects, indirect transmission mechanisms, and threshold characteristics of digital infrastructure on urban SPCM. This investigation establishes both a theoretical framework and actionable pathways for building green and sustainable urban development systems.

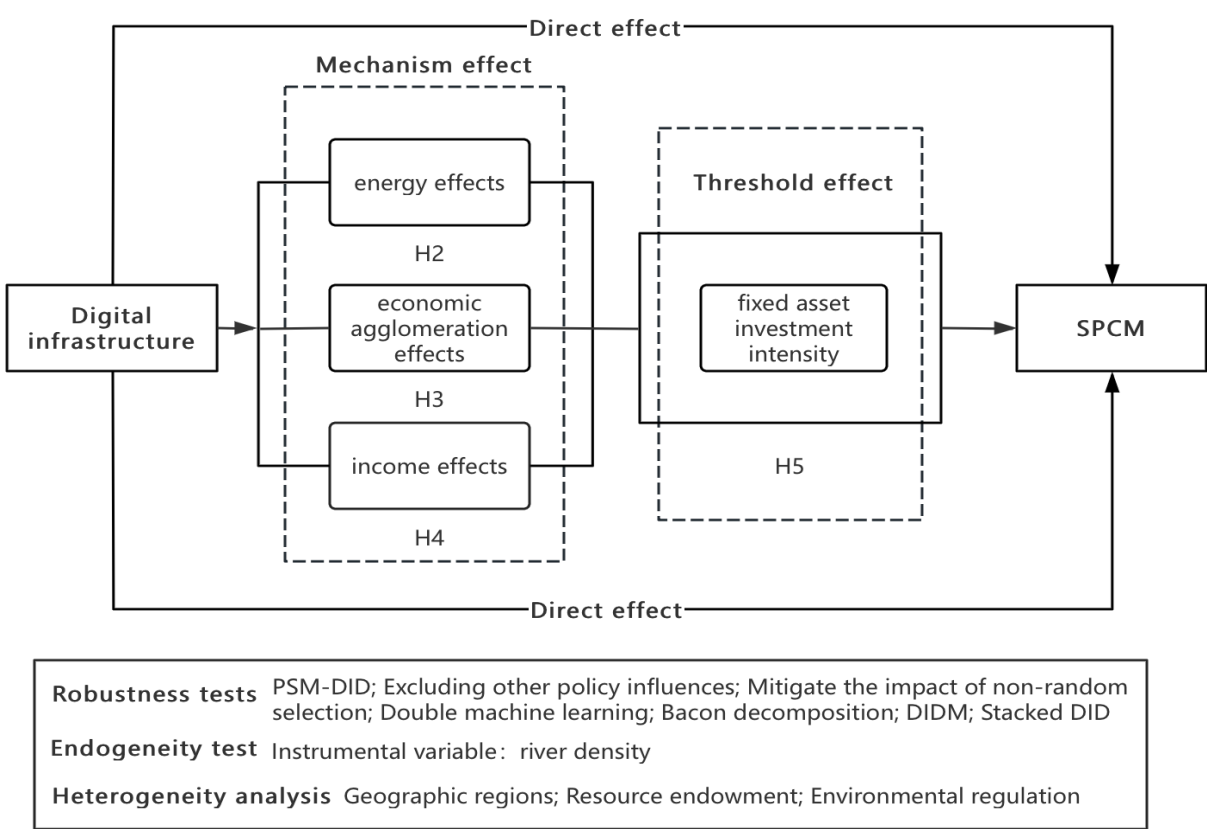


Figure 2. Analytical framework.

4. Research Design

4.1. Sample Selection and Data Sources

This study analyzes data from 280 Chinese prefecture-level cities. Considering the availability of data, the observation interval is from 2007 to 2022. The smart city pilot list

was compiled from three batches of official announcements by China's MOHURD. This method is used to reduce the carbon reduction collaborative efficiency of carbon dioxide emission data from the global emissions EDGAR database for atmospheric research. Other data were obtained from China city statistical yearbooks, China environmental yearbooks, China environmental statistical bulletins, and China city construction statistical yearbooks.

4.2. Model Design

4.2.1. Benchmark Model

Given that, years may show different trends. It is necessary to include year fixed effects to control the characterizing factors that change with the year but not with the individual. Similarly, since each city has its own characteristics and its pollution emission and carbon emission levels are different, it is necessary to include city fixed effects to control for potential characteristics that change with individual cities, forming two-dimensional fixed effects.

$$SPCM_{it} = \alpha_0 + \beta_1 DID_{it} + \beta_2 X_{it} + u_i + v_t + \varepsilon_{it} \quad (1)$$

In the above formula, the SPCM represents synergistic pollution and carbon mitigation. β_1 captures the policy treatment effect as the core explanatory variable's coefficient. If it is significantly positive, digital infrastructure can significantly promote urban SPCM. X refers to a series of control variables, u is the city fixed effect, v is the year fixed effect, and ε is the random disturbance term. Unless otherwise specified, the same applies to other models.

4.2.2. Threshold Effect Model

Adopting the fixed-asset investment level (fix) as a threshold variable, this study constructs a single-threshold regression model:

$$SPCM_{it} = \delta_1 post_{it} I(post_{it} \leq Y_1) + \delta_2 post_{it} I(post_{it} > Y_1) + \mu X_{it} + u_i + v_t + \varepsilon_{it} \quad (2)$$

where Y_1 is the threshold value. $I(\cdot)$ is the indicator function, and the value is 1 if the parenthesis condition is true; otherwise, the value is 0.

4.3. Definition of Key Variables

4.3.1. SPCM

This study adopts the Super-SBM model, which eliminates radial and directional biases while incorporating slack variables, to measure the SPCM. The evaluation index system for the SPCM is constructed across three dimensions: input indicators, including urban energy consumption, year-end employment, and fixed capital stock; desirable outputs, represented by real GDP; and undesirable outputs, comprising concentrations for pollution efficiency and emissions for carbon efficiency.

The fixed capital stock is calculated via the perpetual inventory method with the formula $K_t = \frac{I_t}{P_t} + (1 - \delta_t)K_{t-1}$, where K_t denotes the fixed capital stock in period t (with the base-year stock calculated as 2006 fixed-asset investment divided by 10%), I_t represents fixed-asset investment in period t , P_t stands for the fixed asset price index in period t (proxied by the urban consumer price index), and δ_t is the depreciation rate set at 9.6%.

Urban energy consumption is estimated by first calculating the correlation coefficient between provincial-level nighttime light data and energy consumption and then applying this coefficient to city-level nighttime light data to derive city-level energy consumption. The emission data are obtained from EDGAR, with the original point data converted to

raster format via R software 4.4.3 and subsequently aggregated by region. Under the constant returns to scale (CRS) assumption, the Super-SBM model is specified as follows:

$$\begin{aligned} \rho = \min & \frac{\frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{\frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{rk}} + \sum_{k=1}^{q_2} \frac{s_t^{y-}}{y_{tk}} \right)} \\ \text{s.t.} & \sum_{j=1, j \neq k}^n x_{ij} \lambda_j - s_i^- \leq x_{ik} \\ & \sum_{j=1, j \neq k}^n y_{rj} \lambda_j - s_r^+ \geq y_{rk} \\ & \sum_{j=1, j \neq k}^n y_{tj} \lambda_j - s_t^{y-} \leq y_{tk} \\ & 1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{rk}} + \sum_{k=1}^{q_2} \frac{s_t^{y-}}{y_{tk}} \right) > 0 \\ & \lambda, s^-, s^+ > 0, \sum_{j=1, j \neq k}^n \lambda_j = 1 \end{aligned} \quad (3)$$

In Equation (3), ρ for the SPCM, n represents the number of decision-making units, m and q_1, q_2 represent the number of elements in the input, expected output and unexpected output, respectively, x_{ik}, y_{rk}, y_{tk} represents the vectors of the input, expected output and unexpected output, respectively, and s_i^-, s_r^+, s_t^{y-} represents the corresponding relaxation variables. The input factors and the desired output and nondesired output indicators selected for this study are summarized in Table 1.

Table 1. Evaluation index system for the SPCM.

Types	Primary Indicators	Secondary Indicators
Input	Labor Capital Energy	Urban employment year-end Fixed capital stock Urban energy consumption
Expected output	GDP	Each city's gross domestic product
Unexpected output	CO ₂ Air pollutant emissions	Each city's annual carbon dioxide emission PM _{2.5} concentration

Based on the measured SPCM, this study further illustrates the spatiotemporal distribution of this efficiency in Figure 3. In 2010, before smart city policy implementation, the overall synergistic performance in terms of pollution and carbon reduction across pilot regions remained relatively low. By 2014, following the policy's enactment, the governance levels for both pollutant emissions and carbon emissions in these regions improved. The data for 2018 and 2022 demonstrate that several years after policy implementation, the coordinated governance capacity in the pilot areas significantly strengthened. Overall, from 2010 to 2022, cities exhibited a positive trend in the SPCM, with both carbon mitigation and pollution control achieving notable progress.

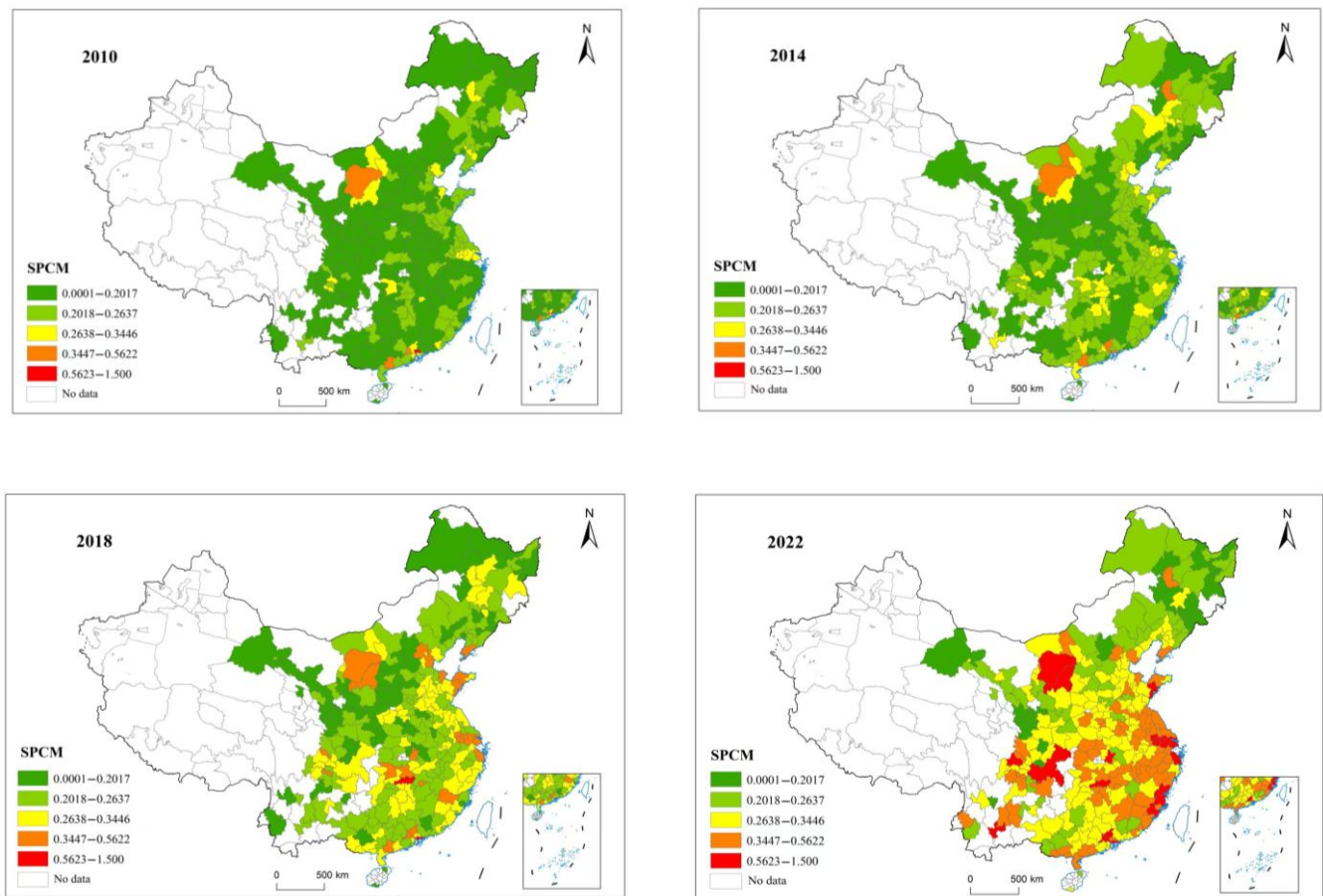


Figure 3. Spatiotemporal evolution of the urban reduction in pollution and carbon in China.

4.3.2. Digital Infrastructure

The core explanatory variable (DID) is a dummy variable of the smart city pilot policy, consisting of a group dummy variable (Treat) and an annual dummy variable (Post). This variable is assigned a value of 1 only when the city is on the pilot list after the policy implementation; otherwise, it is assigned a value of 0. The smart city pilot policy has been in place for 14 years since its implementation, providing sufficient time coverage and data granularity to use this policy as a proxy variable for digital infrastructure.

4.3.3. Control Variables

A range of variables that may influence the SPCM are controlled for in the empirical model [10,29,39,50]. Population density (pop) is measured by the resident population per urban area. Educational attainment (edu) is represented by the ratio of education expenditure to general government fiscal expenditure. Environmental regulation (env) is measured by the comprehensive utilization rate of general solid waste. Mobile phone penetration (mobile) is measured as the average number of mobile phones per capita. The financial development level (fin) is indicated by the ratio of year-end financial institution deposit balances to regional GDP. The informatization level (inf) is captured through the ratio of per capita telecommunications business volume to per capita GDP. The employment structure (emp) is measured as the proportion of tertiary industry employment in total employment. Fixed-asset investment intensity (fix) is represented by the ratio of fixed-asset investment to regional GDP. Industrial structure upgrading (ind) is calculated as the weighted average of the proportion of value added by the three industries to regional GDP. Healthcare capacity (hosp) is measured by the number of hospital beds per 100 inhabitants. Technological capacity (sci) is quantified as the logarithm of total patent applications.

4.3.4. Mechanism Variables

This study investigates the mechanistic pathways through which digital infrastructure influences urban SPCM via three distinct channels: the energy effect (energy), the economic agglomeration effect (eagg), and the income effect (income) [42,51,52]. The energy effect is operationalized using GDP per unit of energy consumption. Economic agglomeration effects are measured by GDP per capita, whereas income effects are quantified through disposable income per capita.

4.3.5. Threshold Variable

This study employs the fixed-asset investment level (fix) as the threshold variable. Digital infrastructure development requires substantial capital investment, where fixed-asset investment intensity reflects a region's financial commitment to digital infrastructure construction and serves as a proxy for its development maturity. Table 2 provides the formal definitions of all the primary variables.

Table 2. Variable definitions.

Types	Variables	Symbols	Definitions
Independent variable	Digital infrastructure	DID	Virtual variable of smart city pilot policy
Dependent variable	Synergistic efficiency in pollution reduction and carbon mitigation	SPCM	Superefficiency model calculation
Control variables	Population density	pop	Resident population per urban area
	Educational attainment	edu	Education expenditure/general government expenditure
	Environmental regulation	env	Comprehensive utilization rate of industrial solid waste
	Mobile phone penetration rate	mobile	Mobile subscriptions per capita
	Financial development level	fin	Year-end financial institution deposits/GDP
	Informatization	inf	Per capita telecom revenue/per capita GDP
	Employment structure	emp	Number of tertiary industry workers/total employment
	Fixed-asset investment intensity	fix	Fixed-asset investment/GDP
	Industrial structure upgrading	ind	$1 \times \text{primary sector} + 2 \times \text{secondary sector} + 3 \times \text{tertiary sector shares of GDP}$
	Healthcare capacity	hosp	Hospital beds per 100 inhabitants
Mechanism variables	Technological capacity	sci	log of total patent applications
	Energy effect	energy	GDP per unit of energy consumption
	Economic agglomeration effect	eagg	GDP per capita
	Income effect	income	Disposable income per capita

The descriptive statistics for all the study variables are reported in Table 3. We employed linear interpolation for limited missing values and excluded cases with substantial missing data to maintain result reliability. The cleaned dataset exhibits no significant data gaps, with all the variables demonstrating numerically and economically plausible values.

Table 3. Descriptive statistics of the main variables.

Variables	Obs.	Mean	Std.Dev	Min	Max
SPCM	4480	0.228	0.099	0.035	1.147
DID	4480	0.227	0.419	0.000	1.000
pop	4480	5.757	0.914	1.574	8.100
edu	4480	0.180	0.042	0.018	0.377
env	4480	79.06	23.28	0.240	156.6
mobile	4480	0.979	0.776	0.063	10.17
fin	4480	0.985	0.606	0.112	7.450
inf	4480	0.039	0.068	0.001	3.372
emp	4480	54.57	13.48	9.910	99.42
fix	4480	0.749	0.489	0.00	8.635
ind	4480	2.286	0.146	1.831	2.836
hosp	4480	0.435	0.178	0.098	1.377
sci	4480	808.7	613.9	1.000	2.276
energy	4480	4.933	3.442	0.001	46.77
eagg	4480	7.116	1.317	2.349	12.00
income	4480	1.528	1.024	0.165	22.79

5. Empirical Test and Analysis

5.1. The Impact of the Digital Infrastructure on the SPCM

Table 4 presents the estimated results of the synergistic effects of digital infrastructure on urban pollution reduction and carbon emission reduction. As shown in Table 4, column (1) lists the results with control variables included and without the fixed effects of cities and years. The coefficient of DID is 0.023, which is significant at the 1% level. After adding the urban fixed effect in column (2), the coefficient still remains significantly positive. In column (3), after individual fixed effects and annual fixed effects are simultaneously incorporated, digital infrastructure has a statistically significant positive effect on the synergistic effect of urban pollution reduction and carbon emission reduction. In an economic sense, the results in column (3) show that digital infrastructure can significantly increase a city's SPCM by 1.5%, and the empirical results support Hypothesis 1.

Table 4. Results of benchmark regression.

Variables	Dep.Var.:SPCM		
	(1)	(2)	(3)
DID	0.023 *** (0.007)	0.015 *** (0.006)	0.015 *** (0.006)
Constant	−0.266 *** (0.074)	−2.604 *** (0.469)	−1.549 *** (0.382)
Controls	YES	YES	YES
Year FEs	NO	NO	YES
City FEs	NO	YES	YES
Obs.	4480	4480	4480
Adjusted R ²	0.346	0.640	0.704

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote robust standard errors.

On the basis of data from 2007 to 2022, this paper analyzes the data of 280 prefecture-level cities in China by constructing a DID model and concludes that digital infrastructure can promote the synergistic effect of pollution reduction and carbon reduction in cities, which is consistent with the research results of Zhang et al. (2025) and Li et al. (2025) [5,22].

Digital infrastructure development offers strategic potential for urban pollution–carbon coreduction in the current digital transformation era. Digital infrastructure enables the precise monitoring and control of resource and energy utilization in both industrial production and government administration [37], facilitating optimal resource allocation and enhancing energy efficiency, which effectively reduces pollutant and carbon emissions. Furthermore, the agglomeration effects and knowledge spillovers generated by digital infrastructure foster interfirm collaborative innovation [53,54], increasing regional innovation capacity to advance green technology development and providing critical support for next-generation pollution–carbon reduction technologies.

5.2. Validity Test of the DID Model

5.2.1. Parallel Trend

The parallel trend assumption is a prerequisite for using a multiperiod DID model, which requires that the experimental group and the control group have the same or similar changing trends before being affected by policy shocks. The results in Figure 4 show that the policy estimation coefficient is not significant before the implementation of the smart city pilot policy but becomes significantly positive after the policy is implemented. This indicates that there was no significant difference between the experimental group and the control group before the implementation of the smart city pilot policy, meeting the parallel trend hypothesis test. These findings suggest that the construction of digital infrastructure

has a significant positive effect on the synergistic effect of pollution reduction and carbon emission reduction.

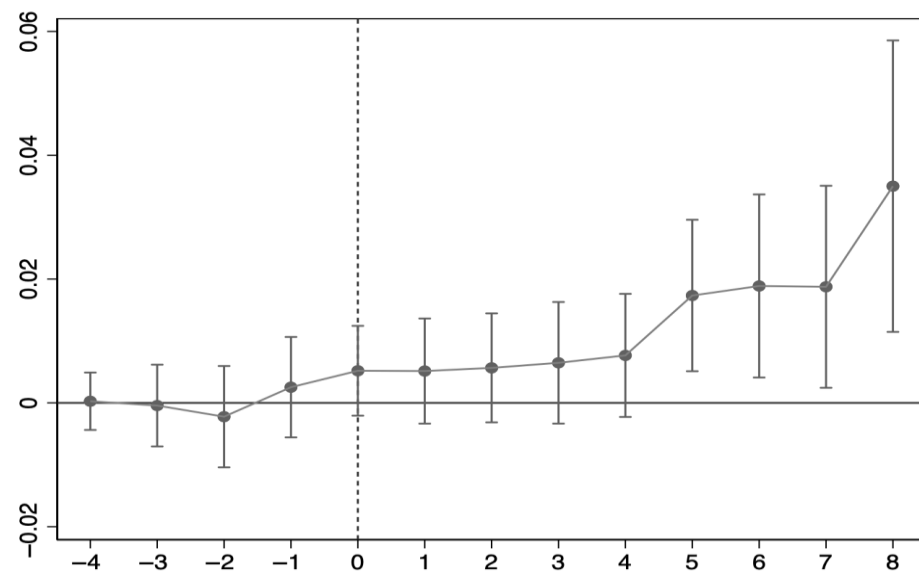


Figure 4. Para-trend test.

5.2.2. Placebo Test

To examine whether the impact of digital infrastructure on the synergy of pollution reduction and carbon emission reduction is caused by undetectable random factors, 60 cities were randomly selected as the intervention group, false pilot variables were artificially constructed, and on the basis of the settings of Model (1), after 500 regressions, the p value distribution and kernel density of the estimated values of the regression coefficients were plotted. The results are shown in Figure 5. The randomly assigned estimated values are concentrated around 0, and the p values of most estimated coefficients are greater than 0.1. The mean of the false estimated coefficients is close to 0, which is much smaller than the true estimated value of 0.015 in the benchmark regression. This finding indicates that the impact of digital infrastructure on the synergy of pollution reduction and carbon emission reduction is genuine and effective, verifying the robustness of the regression results.

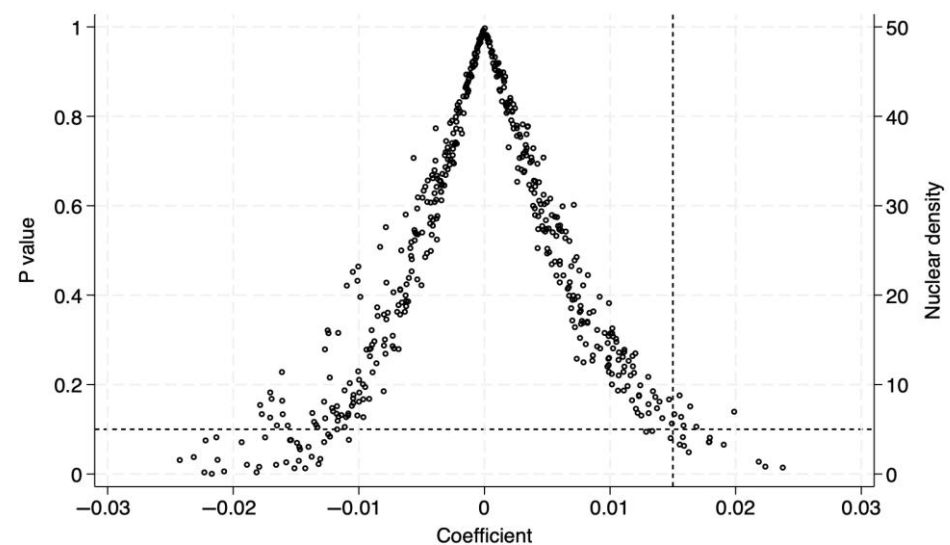


Figure 5. Placebo test.

5.3. Robustness Analysis

5.3.1. PSM-DID

Since the smart city pilot policy does not constitute a strict natural experiment, self-selection bias may arise in evaluating its policy effects. To address this issue, we employ the PSM-DID method for robustness checks. Specifically, we construct a logit model using control variables as covariates and perform propensity score matching through three approaches: nearest-neighbor matching, caliper matching, and kernel matching. The matched samples are then analyzed via the baseline regression model. As shown in Table 5, the coefficients of digital infrastructure remain significantly positive across all specifications, with no statistically significant differences from the baseline regression results. This confirms the robust effect of digital infrastructure in promoting urban SPCM.

Table 5. Results of the PSM-DID estimators.

Variables	Dep.Var.:SPCM		
	Nearest-Neighbor Matching	Caliper Matching	Nuclear Matching
DID	0.015 ** (0.006)	0.015 ** (0.006)	0.017 *** (0.006)
Constant	−1.437 *** (0.344)	−1.437 *** (0.344)	−1.364 *** (0.317)
Controls	YES	YES	YES
Year FEs	YES	YES	YES
City FEs	YES	YES	YES
Obs.	4263	4263	4134
Adjusted R ²	0.706	0.706	0.706

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

5.3.2. Excluding the Impact of Other Policies

During the study period, two potentially confounding policy interventions—the Broadband China Strategy (BCS) pilot launched in 2013 and the National Big Data Comprehensive Pilot Zone (NBDCPZ) initiative implemented in 2016—may influence urban synergistic pollution-carbon mitigation outcomes. To isolate these effects, we incorporate both policy dummies into our baseline regression specification. As Table 6 shows, the digital infrastructure coefficient remains statistically significant and positive after controlling for these concurrent policies, providing robust evidence that digital infrastructure development independently enhances the urban SPCM.

Table 6. Results of other robustness tests.

Variables	Dep.Var.:SPCM		
	Excluding the Impact of Other Policies	Mitigating the Impact of Nonrandom Selection	Winsorize
DID	0.013 ** (0.006)	0.014 *** (0.006)	0.010 ** (0.005)
BCS	0.005 (0.006)		
NBDCPZ	−0.022 *** (0.007)		
Constant	−1.582 *** (0.378)	−2.172 (1.658)	−0.989 *** (0.215)
Controls	YES	YES	YES
Year FEs	YES	YES	YES
City FEs	YES	YES	YES
City × Year	NO	YES	NO
Obs.	4480	4480	4480
Adjusted R ²	0.707	0.704	0.795

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

5.3.3. Mitigating the Impact of Nonrandom Selection

The multiperiod DID approach ideally requires random assignment of treatment and control cities. However, the designation of pilot zones is inherently nonrandom, which may compromise the accuracy of the estimation results. To address this concern, our baseline regression incorporates interaction terms between city characteristics and time trends, effectively controlling for the influence of inherent urban attributes on synergistic pollution–carbon mitigation effects. As Table 6 shows, the coefficient for digital infrastructure remains statistically significant at the 1% level, with a positive sign. This finding confirms the validity of our multiperiod DID approach even after mitigating nonrandom selection concerns, thereby supporting the robustness of our core results.

5.3.4. Reducing the Impact of Extreme Values

To further mitigate potential bias from outliers in the baseline regression, we implement a 1% winsorization on both the dependent variable and all continuous control variables before re-estimating Model (1). As presented in Table 6, the digital infrastructure coefficient remains statistically significant at the 5% level with consistent directional effects compared with the baseline estimates, confirming the robustness of our primary findings.

5.3.5. Dual Machine Learning Model

In the digital economy era, nonlinear relationships between variables are more common, but traditional linear regression assumes linear relationships between variables, and the model setting is biased, making the estimates less robust. Dual machine learning, on the other hand, can effectively eliminate bias and ensure the unbiasedness of the estimated coefficients by constructing a model using residuals. This paper constructs the following dual machine learning model on the basis of the robustness of dual machine learning model validation:

$$\text{SPCM}_{it} = \psi_0 \text{DID}_{it} + g(X_{it}) + U_{it} \quad (4)$$

$$E[U_{it}|X_{it}|\text{DID}_{it}] = 0 \quad (5)$$

$$\text{DID}_{it} = f(X_{it}) + V_{it} \quad (6)$$

$$E[V_{it}|X_{it}] = 0 \quad (7)$$

where ψ_0 is the estimation coefficient of interest in this paper, and the remaining variables are consistent with the reference regression. The difference is that the learning algorithm estimation form of the control variable set is $g(X_{it})$, and Equation (7) indicates that the conditional mean of the random error term is 0. Table 7 shows that the estimated coefficients of the data infrastructure variable are significantly positive, which indicates that the results are robust.

Table 7. Results of the DML tests.

Variables	Dep.Var.:SPCM			
	Random Forest	LASSO Regression	Gradient Lifting	Vector Machine
DID	0.013 *** (0.003)	0.013 *** (0.003)	0.010 *** (0.003)	0.015 *** (0.003)
Constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	−0.000 *** (0.000)
Controls	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
City FEs	YES	YES	YES	YES
Obs.	4480	4480	4480	4480

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

5.3.6. Bacon Decomposition

In multiperiod DID designs, variation in treatment timing across samples may introduce bias in two-way fixed-effects (TWFE) estimators, potentially yielding incorrect treatment effect estimates or even reversed causal interpretations. On this basis, this paper adopts the robust estimators proposed by Borusyak as robust estimators. For multistage DID, the control group consisted of three types: those who had never been treated (Never), those who had been treated before (Late), and those who had been treated before (Early). If early is used as the control group, the traditional estimator may be biased. When the weight of the estimated coefficient of this category is large and contrary to the actual effect of the policy, it will have a very large effect on the result. In this paper, Bacon decomposition is used to test the bias of the estimator, and the results are shown in Table 8. Among them, the late-T vs. early-C category indicates late-T as the treatment group and early-T as the control group. The results show that the coefficient of this category is negative, contrary to the policy effect, but the weight proportion is relatively small (5.5%), indicating that there is no serious bias in the heterogeneous treatment effect and that the results are relatively robust.

Table 8. Bacon decomposition results.

Grouping	Coefficient	Weight
Late T vs. Early C	−0.014	0.055
Treat T vs. Never C	0.011	0.933
Early T vs. Late C	0.450	0.012

Notes: Early indicates the individuals treated first, Late indicates the individuals treated later, Never indicates the individuals never treated, Treat indicates all the individuals treated, T indicates the treatment group, and C indicates the control group.

5.3.7. Multiphase and Multi-Individual DIDM Estimation Subsection

In traditional bidirectional fixed-effect estimation, the heterogeneity of therapeutic effects in the group (class) and time dimensions may lead to biased results. Therefore, this paper adopts a multiperiod and multi-individual DIDM model for robustness testing. The results are shown in Table 9. The results indicate that the average treatment effect of policy conversion is 0.016, which is significantly positive at the 1% level.

Table 9. Results of the heterogeneous treatment effect.

Variables	Dep.Var.:SPCM	
	DIDM	Stacked DID
ATT	0.016 ***	0.017 **
Controls	YES	YES
Year FEs	YES	YES
City FEs	YES	YES

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

We further estimate the dynamic treatment effects of the smart city pilot policy over five pretreatment periods and eight posttreatment periods, with the event study visualization presented in Figure 6. The results demonstrate statistically insignificant policy effects during the pretreatment phase, followed by gradually emerging and statistically significant impacts after policy implementation. These dynamic effect patterns remain fully consistent with our baseline regression estimates, thereby providing additional empirical validation for the robustness of our primary findings.

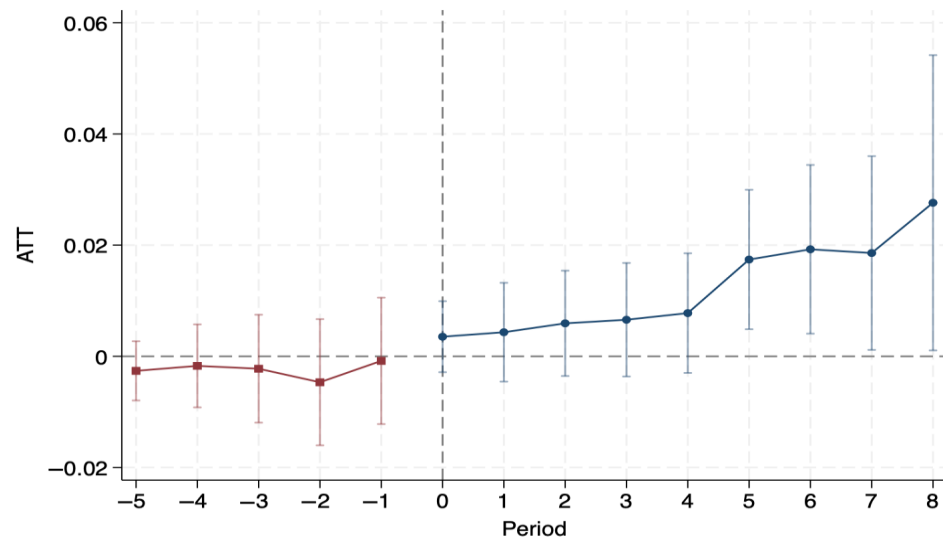


Figure 6. Dynamic effect of DIDM.

5.3.8. Stacked DID Estimation

Given the potential heterogeneity in treatment effects across different pilot cohorts and implementation years, baseline estimates may suffer from bias. To assess the robustness of the policy effects, we construct a stacked dataset by sequentially matching each treatment cohort (cities implementing smart city policies) with control groups drawn exclusively from never-treated cities. This stacked estimation approach mitigates biases inherent in conventional two-way fixed-effects specifications. The results are shown in Table 9. The coefficient of digital infrastructure is significantly positive at the 5% level, indicating that the benchmark regression results are robust.

5.4. Endogenous Test

To address potential endogeneity arising from unobserved omitted variables and non-random selection into smart city pilots, we implement an IV approach using river density as our instrument for digital infrastructure development. The IV estimation results are presented in Table 10. Column (1) reports the first-stage estimates, showing a statistically significant coefficient of 2.527 for the instrument at the 1% level. Column (2) presents the second-stage results, with the digital infrastructure coefficient remaining statistically significant (0.035 , $p < 0.01$). The Kleibergen–Paap F statistic of 18.815 exceeds conventional weak instrument thresholds, confirming the instrument’s validity. These results demonstrate that digital infrastructure has a statistically robust positive effect on urban synergistic pollution–carbon mitigation even after endogeneity concerns are accounted for.

Table 10. Endogenous test.

Variables	First	Second
	DID	SPCM
DID		0.035 *** (0.008)
IV	2.527 *** (4.338)	
Underidentification test	Passed	
Kleibergen–Paap rk Wald F statistic		18.815
Controls	YES	YES
Year FEs	YES	YES
City FEs	YES	YES
Obs.	4480	4480
Adjusted R ²	0.538	0.533

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

5.5. Mechanism Analysis

The regression results in Table 11 show that digital infrastructure can achieve urban SPCM by improving energy utilization efficiency, promoting economic agglomeration and increasing people's disposable income, and the estimated coefficients are all significant at the 1% level.

Table 11. Mechanism test results.

Variables	Energy	Eagg	Income
DID	0.150 *** (0.054)	0.505 *** (0.149)	0.132 *** (0.044)
Constant	−5.168 *** (1.919)	−19.988 *** (5.499)	−15.586 ** (6.510)
Controls	YES	YES	YES
Year FEs	YES	YES	YES
City FEs	YES	YES	YES
Obs.	4480	4480	4480
Adjusted R ²	0.786	0.900	0.956

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

The essence of synergistic pollution-carbon mitigation governance lies in optimizing resource and energy utilization through multistakeholder collaboration to reduce pollution sources and carbon emissions simultaneously. Central to this approach is enhancing energy efficiency as a fundamental pollution prevention strategy at the source. Digital infrastructure applications, including IoT systems, big data analytics platforms, and energy management systems, empower both enterprises and governments to transform traditional production and governance models into digitized operational frameworks [55]. This technological transition reduces excessive resource consumption and pollutant emissions throughout production and administrative processes while significantly improving energy efficiency, thereby facilitating the realization of urban synergistic pollution-carbon mitigation. These findings provide empirical validation for Hypothesis 2.

Economic agglomeration yields scale effects that enable infrastructure, technology and resource sharing among firms [56], lowering innovation costs while increasing innovation capacity. The resulting knowledge spillovers facilitate access to innovation resources [57,58], accelerating green technology development and adoption for combined pollution-carbon reduction. Agglomeration further enhances environmental governance efficiency through centralized pollution treatment. These findings provide empirical validation for Hypothesis 3.

An increase in per capita disposable income facilitates urban pollution-carbon reduction through both demand- and supply-side mechanisms. Higher incomes drive consumption patterns toward service-oriented expenditures, stimulating growth in the tertiary sector, which demonstrates characteristically low pollution and energy intensity [59], thereby reducing urban energy consumption and emissions. Furthermore, affluent demographics exhibit stronger environmental consciousness and greater demand for green products [60], creating market pressures that incentivize firms to develop eco-friendly innovations, ultimately lowering both pollutant discharges and carbon emissions. These findings provide empirical validation for Hypothesis 4.

Table 12 presents the effect decomposition results. The mechanism analysis identifies three significant transmission channels: energy effects (contributing 19.02% of total effects), economic agglomeration (eagg) effects (22.11%), and income effects (20.31%). These findings demonstrate that economic agglomeration effects make the most substantial contribution, highlighting their critical role in facilitating the digital infrastructure's promotion of SPCM. However, both energy effects and income effects remain statistically and practi-

cally significant, representing important complementary pathways through which digital infrastructure achieves urban SPCM.

Table 12. Effect decomposition of the digital infrastructure and SPCM.

Transmission Channels	Direct Effect	Energy Effect	Eagg Effect	Income Effect	Total Effect
Absolute contribution	0.015	0.0074	0.0086	0.0079	0.0389
Relative contribution	38.56%	19.02%	22.11%	20.31%	100%

5.6. Threshold Effect Analysis

To examine whether fixed-asset investment levels exhibit threshold effects on synergistic pollution–carbon mitigation, we conduct threshold effect tests with 300 bootstrap replications, with the results presented in Table 13. The analysis reveals a statistically significant single-threshold characteristic for digital infrastructure development at the 95% confidence level. Figure 7 displays the corresponding likelihood ratio function plot, where the estimated threshold value falls within the confidence interval, confirming the validity of the identified threshold.

Table 13. Significance tests for threshold effects.

Threshold Variables	Number of Thresholds	F Value	<i>p</i> Value	Threshold Value
fix	Single sill	109.97	0.000	0.285
	Double sill	25.65	0.150	1.013

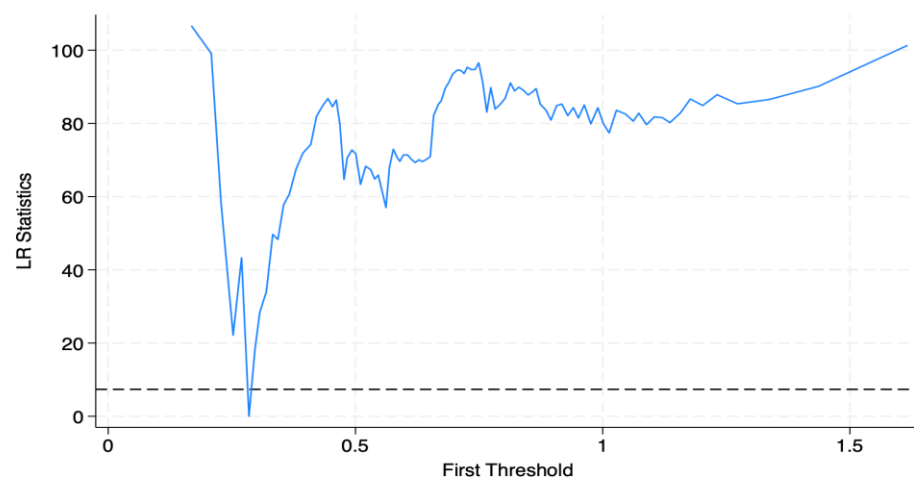


Figure 7. Single-threshold effect estimation for fix.

Table 14 presents the threshold regression results. When fixed-asset investment levels are below the threshold value of 0.285, digital infrastructure has a statistically significant positive coefficient of 0.135 ($p < 0.01$) for the SPCM. However, when investment exceeds 0.285, the coefficient diminishes to 0.011. These results demonstrate a distinct single-threshold characteristic in digital infrastructure promotion by the SPCM, with fixed-asset investment intensity serving as the threshold variable, thereby confirming Hypothesis 5.

Table 14. Estimation results of threshold regression.

Threshold Interval	Regression Result
$\text{fix} \leq 0.285$	0.135 *** (0.041)
$\text{fix} > 0.285$	0.011 ** (0.005)
Adjusted R ²	0.107
Obs.	4480

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

This threshold pattern may stem from differential marginal returns at various investment stages. When fixed-asset investment remains below the threshold (0.285), additional funding expands the scale and coverage of digital infrastructure, thereby increasing its environmental benefits [48,49]. However, as investment surpasses this critical level, infrastructure approaches saturation, and cities achieve optimal resource utilization, causing the marginal contribution of digital infrastructure to SPCM to gradually diminish [29,50]. Consequently, the pollution–carbon reduction effects weaken when investment exceeds the identified threshold.

5.7. Further Discussion: Heterogeneity Analysis

5.7.1. Geographic Regions

Given the substantial regional disparities in economic development, resource endowments, and openness across China, the effect of digital infrastructure on urban SPCM may exhibit substantial heterogeneity. Table 15 presents location-based heterogeneity tests, revealing stark contrasts between the eastern and central-western regions. For eastern cities, the estimated coefficient of 0.042 (significant at the 1% level) reflects their successful smart city initiatives that enhance the capacity of digital infrastructure to provide pollution governance and environmental protection services, thereby improving SPCM efficiency. In contrast, central-western regions show statistically insignificant negative coefficients, likely due to resource constraints, weaker economic dynamism, and limited innovation capacity, which collectively hinder digital infrastructure deployment and consequently impede SPCM achievement.

Table 15. Heterogeneity analysis (1).

Variables	Dep.Var.:SPCM	
	Eastern Region	Central and Western Regions
DID	0.042 *** (0.006)	−0.001 (0.006)
Constant	−2.367 *** (0.543)	−0.479 *** (0.263)
Controls	YES	YES
Year FEs	YES	YES
City FEs	YES	YES
Obs.	1920	2560
Adjusted R ²	0.685	0.758

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

5.7.2. Resource Endowment

The inherent differences in implementation difficulty between environmental governance and carbon reduction inevitably influence how smart city digital infrastructure affects pollution and emission mitigation. Following China’s national sustainable development

plan for resource-based cities (2013–2020), we conduct a comparative analysis between resource-based and nonresource cities to assess how digital infrastructure differentially influences pollution-carbon synergy effects. Table 16 reveals distinct patterns: digital infrastructure development significantly enhances urban SPCM in nonresource cities but has no statistically meaningful impact on resource-based cities.

Table 16. Heterogeneity analysis (2).

Variables	Dep.Var.:SPCM	
	Resource-Based City	Non-Resource-Based City
DID	0.001 (0.006)	0.020 *** (0.007)
Constant	−0.603 (0.375)	−1.558 *** (0.479)
Controls	YES	YES
Year FEs	YES	YES
City FEs	YES	YES
Obs.	1792	2688
Adjusted R ²	0.658	0.746

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

This divergence likely stems from resource cities' ecological challenges, where excessive resource extraction exceeds their environmental carrying capacity, exacerbating ecological damage, pollution, and resource waste, all of which compound governance difficulties. Conversely, nonresource cities demonstrate stronger agglomeration capacities for talent and capital, enabling them to leverage advanced technologies for sustainable development and regional green growth.

5.7.3. Environmental Regulation

Given that environmental protection efforts may differentially affect pollution-carbon synergy across cities, we classify urban areas into environmental priority cities and nonpriority cities on the basis of China's 11th five-year National Environmental Protection Plan issued by the State Council in 2007. As shown in Table 17, environmentally prioritized cities demonstrate markedly stronger SPCM outcomes than their nonpriority counterparts do. This disparity likely stems from three interrelated factors in priority cities: stricter environmental regulations and energy-saving subsidies implemented by local governments, greater resident environmental awareness leading to active participation in conservation initiatives, and a deeper public understanding of pollution-carbon reduction imperatives. Conversely, nonpriority cities face structural constraints, including incomplete environmental legislation and greater reliance on energy-intensive, polluting industries, which currently limits the potential of digital infrastructure to enhance urban SPCM governance.

To address deteriorating air pollution, China implemented two control zone policies starting in 1998. As demonstrated in Table 18, digital infrastructure significantly enhances SPCM within these TCZ cities. This amplified impact stems from the policy's dual mechanisms: first, it compels local enterprises to reduce emissions, driving out low-technology, high-pollution manufacturers through industrial relocation; second, it creates strong incentives for green technology innovation, accelerating corporate environmental upgrading. These combined forces make the contribution of digital infrastructure to urban SPCM particularly pronounced in TCZ regions.

Table 17. Heterogeneity analysis (3).

Variables	Dep.Var.:SPCM	
	Key Environmental Protection Cities	Nonkey Environmental Protection Cities
DID	0.020 ** (0.009)	0.008 (0.006)
Constant	−1.826 *** (0.458)	−0.714 ** (0.206)
Controls	YES	YES
Year FEs	YES	YES
City FEs	YES	YES
Obs.	1744	2736
Adjusted R ²	0.751	0.707

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

Table 18. Heterogeneity analysis (4).

Variables	Dep.Var.:SPCM	
	Two Control Zones	Noncontrolled Areas
DID	0.023 *** (0.008)	−0.000 (0.006)
Constant	−2.084 *** (0.520)	−0.428 (0.281)
Controls	YES	YES
Year FEs	YES	YES
City FEs	YES	YES
Obs.	2464	2016
Adjusted R ²	0.743	0.657

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; the values in parentheses denote the standard error.

6. Discussion

This study demonstrates that digital infrastructure can effectively promote urban SPCM, which aligns with the findings of Zhang et al. (2025) and Li et al. (2025) [5,22]. The literature has established empirical evidence supporting the constructive role of digital infrastructure in enhancing environmental governance outcomes. For example, Zou et al. (2023), using China's broadband strategy as a quasinatural experiment, demonstrated that the development of network infrastructure significantly reduces environmental pollution, particularly particulate matter emissions [21]. Similarly, Li et al. (2025) provide evidence that digital infrastructure reduces both local air pollution and generates beneficial spillover effects across neighboring regions [22]. These conclusions provide robust support for our findings.

However, some studies present contrasting perspectives. Mao et al. (2024) reported that the construction of computing infrastructure may lead to increased energy consumption, thereby increasing carbon emissions and potentially hindering pollution and carbon reduction goals [27]. Additionally, Nie et al. (2025) [28] highlighted that the initial phase of digital infrastructure expansion, due to technological limitations and regional disparities [30], could result in elevated pollution and carbon emissions. Therefore, the strategic rollout of digital infrastructure must carefully consider local technological capabilities and regional development conditions to maximize its environmental benefits.

Second, digital infrastructure influences urban SPCM through three primary pathways: energy efficiency improvement, economic agglomeration effects, and income effects. Notably, the economic agglomeration effect contributes most significantly to the overall impact, highlighting the crucial role of economies of scale and collaborative innovation in driving sustainable development. Zhang et al. (2021) demonstrated that industrial

concentration facilitates energy sharing and large-scale application of clean technologies, thereby accelerating low-carbon industrial transformation and promoting carbon emission reduction [41]. These findings align with the literature on the role of digital infrastructure in fostering economic-environmental synergies.

Third, this study identifies a single-threshold effect of fixed-asset investment levels in the relationship between digital infrastructure and the SPCM. When investment exceeds a certain threshold, the marginal benefits for pollution and carbon reduction diminish. This suggests that while substantial investment in digital infrastructure is necessary to promote urban SPCM, beyond this point, additional investment yields progressively smaller environmental returns. This conclusion is corroborated by related research. Wang et al. (2025) examined the threshold effect of digital infrastructure saturation on urban eco-efficiency and reported that when digital infrastructure investment intensity surpasses a critical threshold, its elasticity coefficient for improving urban eco-efficiency decreases [48]. The identified threshold effects reveal that optimizing environmental returns from digital infrastructure requires carefully calibrated scaling of investments and strategic phasing of deployment.

Fourth, the influence of digital infrastructure on urban SPCM displays marked regional variations, with stronger effects in eastern regions, nonresource-based cities, key environmental protection cities, and cities within the two control zones. These differential effects stem from variations in economic development levels, resource endowments, and policy implementation effectiveness. Eastern regions, with their advanced economic and technological foundations, possess greater capacity to harness digital infrastructure for environmental benefits. In contrast, the central and western regions face greater challenges due to resource constraints and weaker innovation capabilities. Similarly, nonresource-based cities, which are less dependent on traditional polluting industries, are better positioned to benefit from digital infrastructure in achieving SPCM. These results highlight the importance of developing differentiated policy interventions that consider the distinct socioeconomic and environmental contexts of various regions and city categories.

7. Conclusions and Policy Implications

7.1. Research Conclusions

Achieving SPCM constitutes a pivotal pathway for sustainable urban development. By utilizing panel data from 280 Chinese prefecture-level cities (2007–2022), this study employs the Super-SBM model to quantify SPCM performance, followed by panel regression, mediation effect, and threshold effect analyses to comprehensively examine the impacts of digital infrastructure, transmission mechanisms, and nonlinear characteristics of the SPCM. The principal findings are as follows: (1) The baseline regression results demonstrate a statistically significant positive coefficient for digital infrastructure at the 1% level, confirming its robust promoting effect on urban SPCM—a conclusion that withstands multiple robustness checks and endogeneity treatments. (2) Energy efficiency gains, economic agglomeration effects, and sustainable income growth emerge as the three primary mechanisms through which digital infrastructure enhances SPCM. (3) Digital infrastructure's impact exhibits a single-threshold effect relative to fixed-asset investment levels, with diminishing marginal returns beyond the threshold. (4) Heterogeneity analysis reveals more pronounced effects in eastern regions, nonresource-based cities, key environmental protection cities, and two control zones.

7.2. Theoretical Contributions

The present research makes three substantial contributions to the literature. First, it adopts a novel infrastructure perspective to thoroughly investigate the transmission

mechanisms through which digital infrastructure facilitates urban SPCM, thereby enriching the theoretical framework of collaborative environmental governance. Second, while previous research has extensively examined the impacts of digital infrastructure on pollution reduction and carbon emission separately, there has been a notable lack of systematic investigations into its synergistic effects on both objectives simultaneously. Furthermore, few studies have explored the mechanisms by which digital infrastructure influences urban SPCM against the backdrop of smart city pilot policies. By analyzing both the direct and indirect effects of digital infrastructure on urban SPCM under these pilot policies, this research substantially expands upon existing knowledge. Third, through comprehensive heterogeneity analysis on the basis of urban characteristics, this study examines variations in the impact of digital infrastructure on SPCM across different city types and discusses the implications of these differences from multiple perspectives. These findings yield practical policy recommendations aligned with the sustainable development needs of various urban settings, providing policymakers with actionable insights to maximize the environmental benefits of digital infrastructure deployment.

7.3. Practical Value

SPCM serves as a fundamental driver of high-quality development and sustainable urban transformation, where digital infrastructure deployment offers a mutually reinforcing solution for both environmental preservation and economic progress. Building upon our empirical findings, we propose three key policy recommendations for global implementation.

National governments, particularly in developing economies, must first formally acknowledge the strategic importance of digital infrastructure in advancing urban SPCM and enabling green economic transitions. This recognition should translate into concrete actions, including the formulation of comprehensive digital infrastructure development plans, the optimization of institutional frameworks to support infrastructure rollout, and the facilitation of multistakeholder collaboration across geographical, administrative, and industrial boundaries. Crucially, governments should establish integrated industry-academia-research partnerships to collectively address technical, financial, and operational challenges throughout digital infrastructure implementation, thereby ensuring its effective contribution to sustainable development goals.

Second, governments should substantially increase investment in digital infrastructure development while actively promoting the integration of intelligent management systems, IoT technologies, and big data analytics into both corporate operations and public administration frameworks. This dual approach will accelerate the digital transformation of enterprises and government entities alike, creating sustainable pathways for long-term pollution and carbon reduction. Concurrently, regional digital economy cooperation platforms should be established to facilitate intercity collaboration, enabling efficient resource sharing and complementary advantage utilization across jurisdictions. On the demand side, businesses must develop digital green consumption platforms that aggregate environmental product information and leverage big data analytics to precisely target consumers with sustainable product recommendations, thereby systematically cultivating green consumption patterns throughout society.

Furthermore, given the nonlinear diminishing returns of fixed-asset investment on digital infrastructure's ability to synergistically enhance urban pollution reduction and carbon mitigation, governments should establish sustained monitoring and evaluation mechanisms. This mechanism should periodically assess the efficacy of digital infrastructure investments and enable dynamic adjustments to funding strategies. Once investment reaches a critical threshold, large-scale allocations toward digital infrastructure should

be progressively scaled back, with priority shifting toward improving digital governance capabilities and advancing technological upgrades.

Finally, given the heterogeneous characteristics of cities, it is essential to formulate targeted policy measures customized to regional particularities. Compared with eastern regions, governments should implement targeted fiscal subsidies and policy incentives to increase digital infrastructure investment in central and western regions, thereby attracting private sector participation. Considering variations in national resource endowments, resource-rich countries should leverage their inherent advantages to drive the digital transformation of traditional industries. In contrast, resource-scarce nations can engage in regional cooperation to share resources and technologies, achieving mutually beneficial complementarity. For regions with relatively weak environmental regulations, stringent enforcement of environmental policies is imperative. The strengthened environmental oversight of enterprises, coupled with the implementation of rigorous environmental standards, can compel firms to pursue green technology innovation and industrial upgrading.

7.4. Research Limitations

This study leaves room for further exploration in several directions. First, with respect to variable measurement, while we employed the superefficiency SBM model to assess the SPCM, future research could develop more appropriate indicators for evaluating the urban SPCM. Second, in terms of mechanism analysis, the current study's mechanism analysis does not account for structural effects; subsequent work could further investigate the structural effects. Third, concerning the research scope, our analysis did not address the spatial spillover effects of digital infrastructure, which warrants deeper examination in future studies. Finally, with respect to sample selection, extending the dataset to cross-national panel data would allow researchers to explore how digital infrastructure influences synergistic pollution–carbon governance across different types of cities in various national contexts.

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