

Smart Governance and Carbon Emission Reduction: Evidence from Chinese Cities

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Abstract

This paper examines how smart governance affects urban carbon emissions using panel data from 296 Chinese cities over 2017–2023. We conceptualize smart governance as comprehensive institutional capacity encompassing value orientation, system application, and institutional-technological support. Employing two-way fixed effects, instrumental variables, and double machine learning, we find that a one-unit increase in the smart governance index reduces emissions by 0.85 percent, equivalent to approximately 330,000 tons of CO₂ annually. All three dimensions independently contribute to reductions. Mechanism analysis reveals smart governance operates by increasing government innovation support (raising science and technology expenditure share by 0.18 percentage points) and accelerating industrial upgrading toward less carbon-intensive sectors. Effects exhibit substantial heterogeneity, proving most pronounced in eastern cities, large cities (1–5 million population), and non-old industrial base cities. These findings suggest digital governance transformation constitutes a viable emission reduction strategy when complemented by appropriate infrastructure and institutional conditions.

JEL Classification: Q54, Q58, R11, O33, H76

1 Introduction

Climate change represents one of the most pressing challenges confronting humanity in the twenty-first century. In response, countries worldwide have committed to ambitious carbon reduction targets through international agreements such as the Paris Agreement. China, as the world's largest developing economy and carbon emitter, pledged in 2020 to achieve carbon peak by 2030 and carbon neutrality by 2060, the so-called “dual carbon” goals (Liu, et al., 2022). These commitments have fundamentally transformed urban emission reduction from a purely engineering-technical challenge into a problem of governance capacity. As digital tools, including government data aggregation, online regulation, and algorithm-assisted decision-making, become embedded in urban operational systems, smart governance is reshaping how governments identify problems, allocate resources, and execute organizational functions, with profound implications for environmental outcomes (Gil-Garcia, et al., 2016). Simultaneously, the energy demands of digital infrastructure construction and system maintenance continue to rise (Jones, 2018). The net effect of smart governance on carbon emissions therefore requires rigorous empirical evidence and mechanistic explanation at the urban scale.

Understanding how digitalization affects environmental outcomes has become a central question in both academic research and policy circles, yet the existing literature faces critical limitations that constrain both theoretical understanding and practical guidance. While studies have documented associations between various forms of digitalization and environmental performance (Dong, et al., 2022, Yigitcanlar & Kamruzzaman, 2018), they predominantly employ broad, poorly differentiated concepts such as “digital economy,” “informatization,” and “smart cities” without clearly delineating what constitutes governance transformation as distinct from technological infrastructure deployment (Meijer & Bolívar, 2016). This conceptual imprecision obscures whether environmental benefits arise from digital hardware itself or from changes in how governments exercise authority, manage information, and coordinate action. Moreover, although researchers have proposed various mechanisms linking digitalization to emission reductions, including enhanced monitoring, improved energy efficiency, and accelerated innovation (Guo, et al., 2024), these explanations typically receive limited empirical scrutiny and are examined in isolation rather than as potentially interacting pathways within broader governance systems (Kitchin, 2014). The literature particularly lacks systematic evidence on how digital governance might operate through indirect channels such as fiscal resource reallocation and structural economic transformation (López, et al., 2011), despite theoretical reasons to expect such effects.

To address these gaps, we conceptualize smart governance, following the framework employed in recent smart governance index research, as a comprehensive governance capability comprising three dimensions: value orientation, system application, and institutional-technological support (Scholl & Scholl, 2014). Using panel data from 296 Chinese prefecture-level and above cities spanning 2017 to 2023, we systematically examine the impact of smart governance on urban carbon emissions. Our empirical analysis yields several key findings. First, smart governance significantly reduces urban carbon emissions: a one-unit increase in the smart governance index corresponds to an 0.85% decrease in carbon emissions, equivalent to an annual reduction of approximately 330,000 tons of CO₂, offsetting emissions from roughly 110,000 fuel-powered vehicles. This relationship proves robust across multiple specifications, including instrumental variable estimation and double machine learning approaches (Chernozhukov, et al., 2018). Second, all three dimensions of smart governance (value orientation, system application, and institutional-technological support) exert significant negative effects on carbon emissions, confirming that emission reduction arises from comprehensive governance capacity rather than isolated technological adoption. Third, we identify and empirically validate two principal mechanisms through which smart governance reduces emissions: by enhancing government innovation support (measured by the share of fiscal expenditure allocated to science and technology) and by promoting industrial structure upgrading (measured by the ratio of tertiary to primary-plus-secondary industry output). These mechanisms reveal that smart governance operates not merely through direct regulatory enforcement but by reshaping fiscal priorities and accelerating structural economic transformation. Finally, the carbon reduction effects of smart governance exhibit substantial heterogeneity across urban contexts. Effects prove more pronounced in cities located southeast of the Hu Huanyong Line, non-provincial capital cities, key environmental protection cities, non-old industrial base cities, and cities with strong innovation capacity and high informatization levels, suggesting that the effectiveness of smart governance depends critically on economic development stage, industrial composition, and absorptive capacity (Cohen & Levinthal, 1990).

This paper makes two main contributions to the literature. First, we advance theoretical understanding of the governance-environment relationship by developing an integrated framework that explains how digital governance transformation affects carbon emissions through complementary institutional mechanisms. While ecological modernization theory suggests that environmental improvements can accompany economic development through institutional-technological co-evolution (Mol, et al., 2009), existing research has not clearly articulated how governance capacity translates into environmental outcomes. We synthesize insights from transaction cost economics (Williamson, 1981), principal-agent theory (Jensen & Meckling, 1976), and induced innovation theory (Hicks, 1932) to propose that smart governance operates through both direct regulatory channels and indirect structural channels. The direct channel reduces information asymmetries and coordination costs in environmental enforcement, enhancing regulatory credibility and compliance

incentives. The indirect channels reshape fiscal priorities toward innovation support and accelerate structural economic transformation by reducing institutional barriers and enabling targeted industrial policies. This theoretical framework reconciles previously fragmented perspectives in the literature and provides a more complete conceptualization of how governance institutions shape environmental performance beyond simple monitoring and enforcement functions.

Second, we contribute methodologically by developing a multidimensional measure of smart governance that addresses conceptual ambiguity in previous research. Most existing studies use single indicators such as internet penetration or broadband subscriptions, which fail to reflect the comprehensive governance capabilities determining whether digital tools improve policy outcomes. Our composite index incorporates three dimensions: value orientation (prioritizing green development in policy formulation), system application (integrating digital tools into core governance functions), and institutional-technological support (providing infrastructure and organizational arrangements for effective digital governance). By demonstrating that all three dimensions independently reduce emissions, we show that effective environmental governance requires balanced development across multiple domains rather than narrow technological upgrades (Lemos & Agrawal, 2006, Nam & Pardo, 2011). The heterogeneity analysis reveals that smart governance proves most effective in cities with moderate development levels, diversified economies, and strong innovation ecosystems, suggesting that governance capacity and contextual conditions interact to determine environmental outcomes.

2. Conceptual Framework and Mechanisms

We synthesize insights from multiple theoretical perspectives to explain how smart governance affects carbon emissions. Ecological modernization theory provides the overarching framework, suggesting that environmental improvements can accompany economic development through institutional-technological co-evolution rather than requiring growth-environment tradeoffs (Huber, 2008). Within this framework, transaction cost theory and principal-agent theory explain the direct regulatory channel through which smart governance enhances enforcement effectiveness, while induced innovation theory and structural transformation theory illuminate the indirect channels operating through fiscal resource reallocation and industrial upgrading.

2.1 Smart Governance and Urban Carbon Emissions

Smart governance represents an institutional capacity enhancement achieved by embedding digital technology within public administration systems (Dunleavy, et al., 2005). Its impact on carbon emissions operates not through singular technological effects but primarily by transforming three critical elements of environmental governance: information structure, enforcement constraints, and coordination mechanisms.

The three dimensions of smart governance contribute distinctly to emission reduction. Value orientation ensures that green development objectives receive priority in policy formulation and resource allocation, establishing the normative foundation for environmental action. System application integrates digital tools into core governance functions such as emissions monitoring, permit management, and inter-agency coordination, reducing the operational costs of environmental regulation. Institutional-technological support provides the data infrastructure, technical standards, and organizational arrangements that enable sustained governance effectiveness. Together, these dimensions address the fundamental challenges that have historically undermined environmental regulation (Kostka & Mol, 2013).

From an institutional operation perspective, transaction cost theory posits that environmental regulation often fails not due to inadequate rules but because implementation confronts prohibitive costs of information search, monitoring and evidence collection, and cross-departmental coordination (Coase, 2013). Smart governance reduces these transaction costs through data aggregation, process reengineering, and digital coordination platforms, enhancing the continuity and verifiability of regulatory implementation (Cordella & Tempini, 2015). Principal-agent theory indicates that information asymmetry between regulators and firms induces opportunistic behavior and selective compliance, weakening environmental policy effectiveness (Shimshack, 2014). By enhancing the verifiability and traceability of emission information, smart governance increases the probability of detecting violations, thereby raising expected compliance costs through deterrence mechanisms and inducing enterprises to adjust production and emission behaviors (Becker, 1968).

However, these direct regulatory effects may be attenuated in contexts where firms possess superior technical capacity to manipulate digital reporting systems or where regulatory agencies lack personnel trained to interpret complex data outputs. Additionally, the energy consumption associated with digital infrastructure itself may partially offset emission reductions achieved through improved regulation, suggesting the net effect remains an empirical question (Lange, et al., 2020). Accordingly, we propose:

H1: Smart governance significantly reduces urban carbon emission levels through the enhancement of multidimensional governance capabilities including value orientation, system application, and institutional-technological support.

2.2 The Innovation Support Channel

Beyond direct regulatory effects, smart governance can fundamentally reshape technological development trajectories and emission intensity by strengthening government innovation support. Induced innovation theory suggests that policy signals and public resource investments oriented toward environmental objectives can alter the innovation benefit structure facing enterprises, thereby stimulating clean technology development and promoting long-term emission reduction (Acemoglu, et al., 2012, Porter & van der Linde, 1995). Smart governance enhances this process by improving both the quantity and quality of fiscal science and technology expenditures through three interconnected mechanisms.

First, the value orientation dimension elevates green innovation within government priority hierarchies, increasing the likelihood that environmental R&D and energy-saving technological transformation receive budgetary support. Second, the system application dimension enables more precise targeting of fiscal resources through data-driven project selection and performance monitoring, reducing information asymmetries between government agencies and potential

innovation recipients. Third, the institutional-technological support dimension improves transparency and accountability in fund utilization through enhanced disclosure requirements and digital tracking systems, compressing opportunities for inefficient investment and rent-seeking.

Existing research provides support for this mechanism. Halkos and Paizanos (2013) demonstrate that government environmental R&D expenditure significantly reduces private sector innovation costs and market risks, while Lin and Zhu (2019) confirm that fiscal science and technology spending enhances regional green innovation capacity with spatial spillover effects. In the context of digital governance, fiscal expenditure may serve as a bridge amplifying innovation's effect on carbon emission efficiency. Government innovation support can achieve emission reduction by improving energy efficiency, promoting green technological innovation, and guiding industrial upgrading (Sun, et al., 2019).

However, this transmission mechanism depends critically on local absorptive capacity (Griffith, et al., 2004) and the quality of government spending decisions (Rajkumar & Swaroop, 2008). In regions where innovation ecosystems are underdeveloped or where fiscal governance remains weak despite digitalization, increased science and technology expenditure may not translate effectively into emission reductions (Tódtling & Tripl, 2005). The effectiveness of this channel also depends on complementarities between public funding and private sector innovation capabilities (Zúñiga-Vicente, et al., 2014). Based on this reasoning, we propose:

H2: Smart governance indirectly suppresses urban carbon emissions by increasing government innovation support, with effects contingent on local innovation ecosystem development.

2.3 The Structural Transformation Channel

Smart governance may also reduce carbon emissions by accelerating industrial structure transformation from energy-intensive manufacturing toward less carbon-intensive services and high-technology sectors (Hao, et al., 2023). Industrial structure determines the fundamental energy requirements of urban economic activity and constitutes a crucial structural determinant of emission intensity (Zhang, et al., 2014). Smart governance influences industrial composition through two complementary mechanisms.

First, by improving information transparency and analytical capacity, smart governance enables governments to identify high-emission industries and production processes more precisely, thereby increasing constraint intensity through targeted industrial planning, environmental access requirements, and differentiated regulatory enforcement. Relying on big data platforms and enterprise behavioral information, governments can more accurately pinpoint high-energy-consuming and high-emission industries and their critical links, strengthening constraints on high-carbon sectors through multiple policy instruments (Li & Wang, 2022).

Second, smart governance facilitates the development of service industries and knowledge-intensive sectors by reducing institutional transaction costs, streamlining administrative procedures, and improving the quality of public services that these industries require (Goldfarb & Tucker, 2019). By optimizing the business environment and enhancing public service efficiency, smart governance provides more favorable institutional conditions and factor endowments for the development of service industries, the digital economy, and high-technology industries (Ren, et al., 2021). Yin and Song (2023) demonstrate that digital technology penetration from smart city construction transforms production processes in traditional manufacturing while simultaneously promoting modern service industry development.

The emission reduction effect of industrial upgrading operates as a structural dividend: factor reallocation from low-productivity, high-energy-consuming sectors toward high-productivity, low-energy-consuming sectors reduces energy consumption per unit output (Peneder, 2003). This factor reorganization can diminish energy consumption at the source. Research further indicates that industrial structure upgrading generates spatial spillover effects, promoting both local carbon emission reduction and potentially driving emission reduction in surrounding areas, with emission reduction efficiency varying across regions at different development stages (Cheng, et al., 2018).

However, this mechanism faces important limitations. In old industrial base cities with entrenched heavy industry and substantial sunk costs, smart governance may prove insufficient to overcome path dependencies and carbon lock-in effects (Unruh, 2000). Additionally, the emission reduction benefits of service sector growth depend on the specific composition of service activities; energy-intensive services such as data centers may offset gains from traditional service sector expansion (Belkhir & Elmeligi, 2018). These considerations suggest:

H3: Smart governance indirectly suppresses urban carbon emissions by promoting industrial structure upgrading, with effects stronger in cities with diversified economic structures and weaker carbon lock-in.

3. Research Design

3.1 Empirical Specification

To examine the effect of smart governance on urban carbon emissions, we estimate the following two-way fixed effects model:

$$\ln\text{CO}_{2it} = \alpha_0 + \alpha_1 \text{sg}_{it} + \alpha_2 \text{Controls}_{it} + \delta_i + \mu_t + \varepsilon_{it}$$

1

where $\ln\text{CO}_{2it}$ denotes the natural logarithm of carbon dioxide emissions in city i during year t . The variable sg_{it} represents the smart governance index for city i in year t , our primary explanatory variable of interest. The coefficient α_1 captures the elasticity of carbon emissions with respect to smart

governance capacity. A negative and statistically significant estimate of α_1 would indicate that improvements in smart governance reduce urban carbon emissions.

The vector Controls_{it} includes covariates that may confound the relationship between smart governance and emissions: economic development level (per capita GDP), labor structure (share of secondary sector employment), population urbanization rate, infrastructure development (highway density per capita), real estate investment intensity, environmental sanitation capacity (household waste treatment rate), and industrial energy consumption. These controls account for variation in emissions driven by economic structure, urbanization dynamics, and energy use patterns. City fixed effects δ_i absorb time-invariant heterogeneity across municipalities, while year fixed effects μ_t control for common temporal shocks affecting all cities. Standard errors are clustered at the city level to address potential serial correlation within cities.

3.2 Variable Construction

Dependent Variable. Our primary measure of carbon emissions is $\ln\text{CO}_{2it}$, the natural logarithm of total carbon dioxide emissions at the prefecture level. To assess robustness across alternative emission metrics, we construct two supplementary measures: $\ln\text{PopCO}_2$, per capita carbon emissions (total emissions divided by permanent resident population), and $\ln\text{LandCO}_2$, land-averaged carbon emissions (total emissions divided by built-up area). These three indicators characterize urban emission performance from complementary perspectives—scale, population efficiency, and spatial intensity—providing comprehensive measurement of environmental outcomes.

Primary Explanatory Variable. The smart governance index (sgi) derives from the "China Smart Governance Index 2025" published by Renmin University of China. This composite measure reflects the digitalization and intelligence level of urban governance across multiple dimensions. The index employs the "PSSS" evaluation framework, incorporating three constituent dimensions: value orientation (vos), which captures whether green development objectives are prioritized in policy formulation; system application (sas), which measures the integration of digital tools into core governance functions such as emissions monitoring and inter-agency coordination; and institutional-technological support (itss), which assesses the data infrastructure, technical standards, and organizational arrangements enabling effective digital governance. The index is constructed using the entropy method to weight these components, yielding a comprehensive measure that distinguishes smart governance capacity from simple technology adoption.

Mechanism Variables. We examine two transmission channels through which smart governance may affect emissions. Government innovation support (fisc) is measured as the ratio of science and technology expenditure to total local fiscal expenditure. This variable captures the extent to which governments allocate fiscal resources toward innovation activities, including R&D subsidies, technology platforms, and green technology development. Regions with higher smart governance capacity typically demonstrate stronger strategic foresight in identifying bottlenecks in green technological innovation and directing public investment accordingly. Industrial structure upgrading (ais) is measured as the ratio of tertiary sector value added to the sum of primary and secondary sector value added. This variable reflects the shift of economic activity from energy-intensive manufacturing toward less carbon-intensive services and high-technology sectors. Smart governance may accelerate this structural transformation by reducing institutional transaction costs, improving the business environment, and enabling more precise identification and regulation of high-emission industries.

Control Variables. To minimize omitted variable bias, we include seven city-level controls identified as potential confounders in prior research. Economic development level (pgdp) is measured by per capita GDP (in ten thousand yuan), capturing the scale of economic activity and income levels that influence energy consumption patterns. Labor structure (psi) is the share of employment in the secondary sector, reflecting the degree of industrial concentration. Population urbanization (uop) is the ratio of urban to permanent residents, representing agglomeration effects and infrastructure demands associated with urban density. Infrastructure development (infra) is highway mileage per capita (kilometers per ten thousand residents), characterizing transportation network sophistication. Real estate investment (rei) is the natural logarithm of completed real estate development investment, proxying for construction activity and fixed capital formation. Environmental sanitation level (hwd) is the household waste treatment rate, indicating municipal service capacity and environmental management quality. Industrial energy consumption (elec) is the natural logarithm of industrial electricity use, directly measuring energy intensity in manufacturing. Table 1 provides detailed definitions for all variables.

Table 1
Variable definition

Variable	Name	Defination
<i>lnCO₂</i>	Carbon emissions	The natural logarithm of carbon dioxide emissions in prefecture-level cities
<i>lnPopCO₂</i>	Carbon emissions per capita	The natural logarithm of carbon dioxide emissions per in prefecture-level cities
<i>lnLandCO₂</i>	Carbon emissions per unit of land	The natural logarithm of (Carbon dioxide emissions / Built-up area) in prefecture-level cities
<i>sgi</i>	Smart governance	Smart Governance Index
<i>vos</i>	Value objective	Second level of the Smart Governance Index
<i>sas</i>	System application	Second level of Smart Governance Index
<i>itss</i>	Institutional technical support	Second level of the Smart Governance Index
<i>fisc</i>	Government innovation support	Fiscal expenditure on science and technology / Total fiscal expenditure
<i>ais</i>	Industrial structure upgrading	The value added of the tertiary industry / The value added of the primary industry and the secondary industry
<i>pgdp</i>	Economic development level	Per capita of GDP
<i>psi</i>	Labor force structure	The proportion of employees in the secondary industry
<i>uop</i>	Population urbanization	Urban population / resident population
<i>infra</i>	Infrastructure	Highway mileage / permanent population
<i>rei</i>	Real estate investment	The natural logarithm of the completed investment in real estate development
<i>hwd</i>	Environmental hygiene level	Household waste treatment rate
<i>elec</i>	Industrial energy consumption	The natural logarithm of industrial electricity consumption

[Table 1 would appear here]

3.3 Data and Sample

Our analysis employs a balanced panel of 296 Chinese prefecture-level and above cities spanning 2017 to 2023, yielding 2,072 city-year observations. The smart governance index is obtained from the "China Smart Governance Index 2025" report published by Renmin University of China. Carbon dioxide emissions data are extracted from the Emissions Database for Global Atmospheric Research (EDGAR), with GIS software used to match emission estimates to Chinese administrative boundaries at the prefecture level. City-level socioeconomic indicators are compiled from the China City Statistical Yearbook, China Statistical Yearbook, local statistical bulletins, and the EPS database. Per capita GDP is expressed in ten thousand yuan at current prices. Infrastructure is measured in kilometers per ten thousand persons.

To address distributional concerns, we apply several data transformations. Real estate investment and industrial energy consumption are logarithmically transformed to reduce right skewness and stabilize variance. For variables exhibiting severe positive skew (*fisc*, *ais*, *elec*, *uop*), we apply 1% bilateral winsorization to limit the influence of extreme values. Missing observations are imputed using linear interpolation where gaps occur within a city's time series. Variance inflation factors (VIFs) are computed to assess multicollinearity; the mean VIF of 2.10 and maximum individual VIF below 10 indicate that collinearity does not pose a substantive concern for coefficient estimation. Descriptive statistics for all variables are reported in Table 2.

Table 2
Descriptive statistics

	Variable	N	Mean	SD	Min	Max
Explained variables	<i>lnCO₂</i>	2072	16.9737	0.9872	14.1349	19.5453
	<i>lnPopCO₂</i>	2072	11.1613	0.8614	8.9208	13.8490
	<i>lnLandCO₂</i>	2072	7.5536	1.3683	1.4668	10.3849
Explanatory variables	<i>sgi</i>	2072	64.3327	3.8957	53.2967	79.9718
	<i>sas</i>	2072	26.1267	2.0810	21.2385	33.2025
	<i>vos</i>	2072	19.5108	1.0482	15.8359	24.5804
	<i>itss</i>	2072	18.6952	1.3141	15.6799	25.0167
Mechanism variables	<i>fisc</i>	2072	0.0190	0.0203	-0.0001	0.1780
	<i>ais</i>	2072	0.9836	0.4570	0.2947	5.6007
Control variables	<i>pgdp</i>	2072	6.7591	3.6880	1.1693	26.4699
	<i>psi</i>	2072	38.8793	14.2776	2.0000	83.0000
	<i>uop</i>	2072	0.6449	0.2707	0.1711	3.2576
	<i>infra</i>	2072	1.6102	1.8892	0.1075	39.3429
	<i>rei</i>	2072	14.4809	1.4666	5.9269	17.8182
	<i>hwd</i>	2072	98.6955	4.8913	29.0000	100.0000
	<i>elec</i>	2072	13.7503	1.0989	8.0226	16.32947

[Table 2 would appear here]

The sample covers the critical period following China's acceleration of smart city initiatives and encompasses substantial variation in both governance capacity and emission trajectories. The mean smart governance index is 64.33 with a standard deviation of 3.90, indicating meaningful cross-sectional heterogeneity. Carbon emissions exhibit considerable variation, with log emissions ranging from 14.13 to 19.55, corresponding to a roughly 180-fold difference between the lowest and highest emitting cities. This variation provides sufficient statistical power to identify the effects of governance capacity on environmental outcomes while controlling for confounding factors.

4. Results

4.1 Baseline Estimates

Table 3 presents baseline estimates of the effect of smart governance on urban carbon emissions. Column 1 reports results from a specification including only city and year fixed effects, without additional controls. The estimated coefficient on the smart governance index is -0.0074, significant at the 1 percent level, indicating that a one-unit increase in smart governance corresponds to a 0.74 percent reduction in carbon emissions. Column 2 incorporates the full set of control variables described in Section 3.2. The coefficient estimate becomes slightly larger in absolute magnitude at -0.0085 and remains highly significant, suggesting that the negative relationship between smart governance and emissions is not confounded by observable city characteristics such as economic development, urbanization, or industrial structure.

Table 3
Baseline Estimates of Smart Governance Effects on Carbon Emissions

	(1)	(2)	(3)	(4)	(5)
	<i>lnCO2</i>	<i>lnCO2</i>	<i>lnCO2</i>	<i>lnCO2</i>	<i>lnCO2</i>
<i>sgi</i>	-0.0074***	-0.0085***			
	(0.0028)	(0.0028)			
<i>vos</i>			-0.0160**		
			(0.0064)		
<i>sas</i>				-0.0095*	
				(0.0052)	
<i>itss</i>					-0.0120**
					(0.0047)
<i>Controls</i>	No	Yes	Yes	Yes	Yes
<i>City</i>	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2072	2072	2072	2072	2072
<i>adj. R2</i>	0.197	0.204	0.221	0.239	0.203
<i>Note:</i> This table presents two-way fixed effects estimates of Eq. 1. The dependent variable in all columns is the natural logarithm of total CO₂ emissions. Column 1 includes only city and year fixed effects. Column 2 adds the full vector of control variables: per capita GDP, secondary sector employment share, urbanization rate, infrastructure, real estate investment, waste treatment rate, and industrial electricity consumption. Columns 3 through 5 replace the composite smart governance index with its three constituent dimensions: value orientation, system application, and institutional-technological support. All specifications include city and year fixed effects. Standard errors clustered at the city level are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.					

The magnitude of this effect is economically meaningful. Given that the average Chinese city emitted approximately 38.9 million tons of CO₂ in 2023, a one-unit improvement in smart governance (roughly one standard deviation given the index's distribution) would reduce annual emissions by approximately 330,000 tons. To contextualize this reduction, it equals the combined annual emissions of approximately 110,000 gasoline-powered passenger vehicles, assuming 2.99 tons of CO₂ per vehicle annually, or the energy consumption of a medium-sized industrial park. This emission reduction represents about 0.85 percent of mean city-level emissions, a substantial effect given that the dual carbon goals require aggregate emission reductions of similar or larger magnitude sustained over multiple decades.

Columns 3 through 5 decompose the overall smart governance effect by examining each of the three constituent dimensions separately. When value orientation serves as the explanatory variable, the coefficient is -0.0160 and statistically significant at the 5 percent level, indicating that cities prioritizing green development in policy planning and institutional arrangements experience significantly lower emissions. The system application dimension yields a coefficient of -0.0095, significant at the 10 percent level, demonstrating that integration of digital tools into operational governance functions (emissions monitoring, permit management, inter-agency coordination) contributes to emission reductions. The institutional-technological support dimension produces a coefficient of -0.0120, significant at the 5 percent level, confirming that data infrastructure, technical standards, and organizational capacity enable effective environmental governance. All three dimensions exert independent negative effects on emissions, supporting the conceptual framework that smart governance operates through comprehensive capacity enhancement rather than isolated technological adoption. The magnitudes are roughly comparable across dimensions, though value orientation exhibits the largest point estimate, suggesting that policy priorities may be particularly consequential for environmental outcomes.

The control variable coefficients, though not the primary focus, align with theoretical expectations. Economic development exhibits a positive relationship with emissions, consistent with the scale effect of economic growth. The coefficient on secondary sector employment share is also positive, reflecting higher energy intensity in manufacturing relative to services. Real estate investment and industrial electricity consumption both show positive associations with emissions, as expected given their direct connections to construction activity and energy use. These patterns suggest that the model captures fundamental determinants of urban carbon emissions, lending credibility to the smart governance estimates.

4.2 Robustness Checks

Although the baseline specification controls for numerous potential confounders and includes two-way fixed effects, several concerns about identification remain. The relationship between smart governance and emissions could be confounded by reverse causality if cities experiencing emission reductions become more willing or able to invest in digital governance systems. Omitted variables (such as political leadership characteristics, environmental activism, or unmeasured aspects of industrial composition) might simultaneously influence both governance capacity and environmental performance. This section presents multiple robustness exercises designed to address these concerns and probe the sensitivity of our findings to alternative specifications and estimation approaches.

4.2.1 Dynamic Specification

We first examine whether the baseline results are robust to including lagged dependent variables, which control for emission dynamics and persistence. Column 1 of Table 4 incorporates the first lag of log emissions as an additional regressor. The lagged dependent variable enters with a coefficient of 0.6425, highly significant, confirming substantial persistence in emission levels. Despite this autoregressive structure, the smart governance coefficient remains negative at -0.0059 and statistically significant at the 5 percent level, though somewhat attenuated relative to the baseline estimate. This pattern suggests that smart governance reduces emissions even after accounting for historical emission trajectories and short-run dynamics.

Table 4
Robustness Checks: Dynamic Specification and Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>lnCO2</i>	<i>lnCO2</i>	<i>sgi</i>	<i>lnCO2</i>	<i>sgi</i>	<i>lnCO2</i>
<i>sgi</i>	-0.0059**	-0.0069**		-0.0709**		-0.0410*
	(0.0024)	(0.0033)		(0.0327)		(0.0213)
<i>L.lnCO2</i>	0.6425***					
	(0.0420)					
<i>L.sgi</i>		-0.0063*				
		(0.0033)				
<i>IV</i>			0.0623***		0.8225***	
			(0.0145)		(0.2408)	
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>City</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1776	1776	1645	1645	2702	2702
<i>adj. R2</i>	0.560	0.290	0.639	0.127	0.608	0.273
<i>F</i>			13.250		11.696	
<i>Note:</i> This table presents robustness checks addressing endogeneity concerns. Columns 1 and 2 incorporate lagged terms: column 1 includes the lagged dependent variable; column 2 includes lagged smart governance. Columns 3 through 6 report two-stage least squares estimates using two instrumental variables. Columns 3 and 4 use the interaction of 1984 post office business volume and year. Columns 5 and 6 employ a Bartik-style share-shift instrument constructed from initial broadband penetration and national governance trends. First-stage results appear in columns 3 and 5; second-stage results in columns 4 and 6. Cragg-Donald Wald F-statistics test weak instrument concerns. All specifications include city and year fixed effects and the full vector of controls. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.						

Column 2 examines whether lagged smart governance affects current emissions, which would be consistent with delayed policy implementation or gradual behavioral responses. The specification includes both contemporaneous and first-lagged smart governance. The lagged governance term enters negatively at -0.0063, significant at the 10 percent level, indicating that prior-period governance improvements continue to suppress emissions. The contemporaneous effect of -0.0069, significant at the 5 percent level, remains similar in magnitude to the baseline, suggesting that governance improvements produce relatively immediate emission reductions, with effects that persist over time. The presence of both contemporaneous and lagged effects implies that the full impact of governance enhancement unfolds gradually, consistent with mechanisms operating through fiscal reallocation and structural transformation that require time to materialize.

4.2.2 Instrumental Variable Estimation

To address potential endogeneity more directly, we employ two-stage least squares estimation with two distinct instrumental variables that plausibly satisfy the exclusion restriction while remaining correlated with smart governance.

Historical Communication Infrastructure. Our first instrument exploits historical variation in communication infrastructure that predates contemporary governance systems and emission patterns (Nunn & Qian, 2014). Following Wu et al. (2021), we construct the interaction between 1984 post office business volume and year as an instrument. The logic underlying this instrument is straightforward: regions with well-developed postal and telecommunications infrastructure in the early reform period (when environmental concerns were minimal and industrialization patterns differed markedly from the present) subsequently became natural locations for digital infrastructure deployment as information technology advanced. The 1984 measure satisfies relevance because early communication networks predict contemporary digital capacity. It plausibly satisfies exclusion because communication infrastructure from four decades ago is unlikely to directly affect current industrial emissions except through its effect on digital governance adoption. Historical postal development occurred in an era when environmental regulation was nascent and China's industrial structure was fundamentally different, making direct effects on contemporary emissions implausible.

Share-Shift Instrument. Our second instrument follows the Bartik (1991) shift-share logic as formalized by Goldsmith-Pinkham et al. (2020). We construct the instrument as the interaction between each city's 2017 share of internet broadband users (the initial "share") and the mean smart governance level across all other cities nationally in each year (the "shift"). This instrument isolates variation in local governance stemming from national technological trends rather than city-specific factors that might correlate with emission trajectories. The share component reflects predetermined digital infrastructure from the initial period, while the shift component captures aggregate technological progress driven by national policy and innovation. Because the instrument excludes own-city governance from the national average, it removes potentially endogenous local variation while retaining exogenous variation from nationwide digital transformation.

Columns 3 through 6 of Table 4 report two-stage least squares estimate. Columns 3 and 5 present first-stage results for the two instruments respectively. Both instruments exhibit strong positive relationships with smart governance: the historical communication instrument yields a coefficient of 0.0623, highly significant, while the share-shift instrument produces a coefficient of 0.8225, also highly significant. The Cragg-Donald Wald F-statistics are 13.250 and 11.696 respectively, both comfortably exceeding the conventional threshold of 10 for weak instrument concerns proposed by Stock and Yogo (2005), indicating that the instruments possess sufficient predictive power.

The second-stage estimates, reported in columns 4 and 6, confirm that smart governance reduces emissions when instrumented. Using historical communication infrastructure, the coefficient estimate is -0.0709, significant at the 5 percent level. Using the share-shift instrument, the estimate is -0.0410, significant at the 10 percent level. Both estimates remain negative and statistically significant, though larger in absolute magnitude than the OLS baseline. The larger IV coefficients suggest that measurement error or positive bias from omitted complementary factors may attenuate OLS estimates. Alternatively, the IV estimates may represent local average treatment effects for cities whose governance capacity responds to the instruments (potentially cities with stronger baseline institutional capacity or greater openness to technological adoption) where governance improvements generate larger emission reductions. Regardless of interpretation, the IV results provide reassurance that the negative relationship between smart governance and emissions is not an artifact of reverse causality or omitted variable bias.

4.2.3 Double Machine Learning

Recent econometric research emphasizes that high-dimensional controls and complex functional forms can improve causal inference by flexibly accounting for confounding (Athey & Imbens, 2019; Chernozhukov, et al., 2018). We implement double machine learning (DML), which uses machine learning algorithms to model both the outcome equation and the treatment equation, then combines predictions to produce estimates robust to model misspecification. This approach is particularly valuable when the conditional expectation functions relating controls to outcomes and treatments are unknown and potentially nonlinear.

Columns 1 through 4 of Table 5 report DML estimates under alternative specifications. Columns 1 through 3 employ random forest as the base learner, with K-fold cross-validation using 3, 5, and 8 folds respectively. The smart governance coefficient remains negative and statistically significant across all three specifications, with point estimates ranging from -0.0140 to -0.0145, all significant at least at the 5 percent level. The stability across different cross-validation schemes indicates that results are insensitive to sample partitioning. Column 4 substitutes gradient boosting for random forests while maintaining 5-fold cross-validation. The coefficient estimate is -0.0199, significant at the 1 percent level, slightly larger in absolute magnitude but qualitatively consistent with random forest specifications. The consistency of findings across distinct machine learning algorithms (which make different assumptions about functional form and variable interactions) strongly suggests that the negative governance-emissions relationship is not an artifact of parametric assumptions in the baseline fixed effects specification.

Table 5
Robustness Checks: Machine Learning, Alternative Measures, and Sample Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Kfolds = 3	Kfolds = 5	Kfolds = 8	gradboost	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnCO2</i>
<i>sgi</i>	-0.0140** (0.0058)	-0.0140** (0.0058)	-0.0145*** (0.0056)	-0.0199*** (0.0073)	-0.0098*** (0.0036)	-0.0091** (0.0037)	-0.0119*** (0.0045)	-0.0094** (0.0046)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>City</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2072	2072	2072	2072	2072	2072	1184	1554
<i>adj. R2</i>					0.351	0.313	0.405	0.291
<i>Note:</i> This table presents additional robustness checks. Columns 1 through 4 report double machine learning estimates using different algorithms and cross-validation schemes: random forest with K equals 3, 5, and 8 folds (columns 1 through 3), and gradient boosting with K equals 5 folds (column 4). Columns 5 and 6 replace the dependent variable with per capita emissions and land-averaged emissions respectively. Column 7 excludes the COVID-19 period (2020 through 2022). Column 8 excludes cities in the top quartile of per capita GDP. All specifications include city and year fixed effects and the full vector of controls where applicable. Standard errors clustered at the city level are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.								

4.2.4 Alternative Emission Measures

We assess whether findings depend on the specific measurement of carbon emissions by re-estimating the baseline specification with alternative dependent variables. Column 5 of Table 5 uses per capita emissions (*lnPopCO2*) as the outcome. The smart governance coefficient is -0.0098, significant at the 1

percent level, indicating that governance improvements reduce emission intensity per person. This specification accounts for the possibility that governance effects operate through population dynamics rather than absolute emission reductions. Column 6 employs land-averaged emissions (*lnLandCO2*) as the dependent variable. The coefficient estimate is -0.0091, significant at the 5 percent level, demonstrating that governance reduces spatial emission density. The persistence of negative significant effects across total, per capita, and spatial emission metrics confirms that smart governance genuinely reduces carbon output rather than merely redistributing emissions across population or space.

4.2.5 Sample Restrictions

We examine robustness to alternative sample compositions. Column 7 excludes observations from 2020 through 2022, the COVID-19 pandemic period during which emergency public health measures disrupted normal economic activity and governance operations. Temporary lockdowns reduced emissions through reduced production and mobility, potentially confounding governance effects. Despite removing these atypical years, the coefficient estimate remains negative at -0.0119 and highly significant at the 1 percent level, indicating that the governance-emissions relationship holds under normal operating conditions.

Column 8 restricts the sample to cities outside the top quartile of per capita GDP, thereby excluding the most economically developed cities. This specification tests whether findings are driven by wealthy municipalities with unique characteristics (greater fiscal capacity, stronger environmental preferences, or more advanced industrial structures). The coefficient estimate is -0.0094, significant at the 5 percent level and similar to the full-sample baseline, demonstrating that governance effects extend beyond elite cities to encompass the broader distribution of urban development levels.

Collectively, these robustness exercises demonstrate that the negative relationship between smart governance and carbon emissions is not an artifact of specification choices, estimation methods, or sample composition. The finding persists across dynamic specifications, instrumental variable approaches addressing endogeneity, flexible machine learning estimators relaxing functional form assumptions, alternative emission measures, and restricted samples. This consistency across diverse identification strategies and specifications substantially strengthens confidence in the causal interpretation that smart governance capacity improvements reduce urban carbon emissions.

5. Mechanism Analysis

5.1 Government Innovation Support

The innovation channel through which smart governance may reduce emissions operates by redirecting fiscal resources toward green technology development. Induced innovation theory suggests that policy signals and public resource investments oriented toward environmental objectives can alter the innovation benefit structure facing enterprises, thereby stimulating clean technology development and promoting long-term emission reduction (Gillingham, et al., 2009). Government R&D expenditure reduces private sector innovation costs and market risks associated with clean technology development (Halkos & Paizanos, 2016), directly subsidizing the development of emission-reducing technologies. Public investment in green technology generates knowledge spillovers that benefit firms unable to capture full returns from their own R&D, thereby correcting market failures that lead to underinvestment in environmental innovation.

Smart governance enhances this process through three interconnected mechanisms outlined in Section 2.2. The value orientation dimension elevates green innovation within government priority hierarchies, making environmental R&D and energy-saving technological transformation more likely to receive budgetary support. The system application dimension enables more precise targeting of fiscal resources through data-driven project selection and performance monitoring, reducing information asymmetries between government agencies and potential innovation recipients. The institutional-technological support dimension improves transparency and accountability in fund utilization through enhanced disclosure requirements and digital tracking systems, thereby compressing opportunities for inefficient investment and rent-seeking.

Column 1 of Table 6 examines whether smart governance increases fiscal resources allocated to science and technology. The dependent variable is the ratio of science and technology expenditure to total local fiscal expenditure, which captures government prioritization of innovation activities including R&D subsidies, technology platforms, and green technology development. The coefficient on smart governance is 0.0018, significant at the 1 percent level. This positive relationship indicates that improvements in smart governance lead cities to direct a larger share of fiscal budgets toward innovation support. The quantitative magnitude implies that a one-unit increase in smart governance raises the science and technology expenditure share by approximately 0.18 percentage points, representing a substantial shift in fiscal priorities given that the mean expenditure share is 1.9 percent.

Table 6
Mechanism Analysis: Innovation
Support and Industrial Structure

	(1)	(2)
	<i>fisc</i>	<i>ais</i>
<i>sgi</i>	0.0018***	0.0230***
	(0.0004)	(0.0057)
<i>City</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>N</i>	2072	2072
<i>adj. R2</i>	0.107	0.332

Note: This table presents tests of transmission mechanisms. Column 1 examines government innovation support, measured as the ratio of science and technology expenditure to total local fiscal expenditure. Column 2 examines industrial structure upgrading, measured as the ratio of tertiary sector value added to the sum of primary and secondary sector value added. Both specifications include city and year fixed effects and the full vector of control variables. Standard errors clustered at the city level are reported in parentheses. * Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level.

These findings align with prior empirical work documenting the role of fiscal policy in promoting green innovation. Zhang et al. (2017) confirm that increases in government R&D support significantly enhance regional green innovation capacity and generate spatial spillover effects, thereby reducing carbon emissions over a larger range. In the context of digital governance, fiscal science and technology expenditure may serve as a bridge amplifying innovation's effect on carbon emission efficiency. Government innovation support can achieve emission reduction by improving energy efficiency, promoting green technological innovation, and guiding industrial upgrading. By demonstrating that smart governance systematically increases innovation expenditure, we identify a concrete pathway through which governance capacity improvements translate into the technological conditions necessary for emission reduction. This fiscal channel reveals that smart governance operates not merely through enhanced regulatory enforcement but also through deeper transformations in budgetary priorities that create long-term conditions for technological change.

5.2 Industrial Structure Upgrading

The structural transformation channel through which smart governance may reduce emissions operates by reallocating economic activity from energy-intensive manufacturing toward less carbon-intensive services and high-technology sectors. The emission reduction effect of industrial upgrading operates as a structural dividend: factor reallocation from low-productivity, high-energy-consuming sectors toward high-productivity, low-energy-consuming sectors reduces energy consumption per unit output (Tian, et al., 2019). This factor reorganization can diminish energy consumption at the source.

Smart governance influences industrial composition through two complementary mechanisms outlined in Section 2.3. First, by improving information transparency and analytical capacity, smart governance enables governments to identify high-emission industries and production processes more precisely. Relying on big data platforms and enterprise behavioral information, governments can more accurately pinpoint high-energy-consuming and high-emission industries and their critical links, thereby increasing constraint intensity on high-carbon sectors through multiple policy instruments including targeted industrial planning, environmental access requirements, and differentiated regulatory enforcement.

Second, smart governance facilitates the development of service industries and knowledge-intensive sectors by reducing institutional transaction costs, streamlining administrative procedures, and improving the quality of public services that these industries require. By optimizing the business environment and enhancing public service efficiency, smart governance provides more favorable institutional conditions and factor endowments for the development of service industries, the digital economy, and high-technology industries. Digital platforms reduce bureaucratic friction in business registration, permitting, and regulatory compliance, which disproportionately benefits service firms that rely heavily on smooth government-business interactions.

Column 2 of Table 6 tests whether smart governance promotes structural transformation toward less emission-intensive economic activities. The dependent variable is the ratio of tertiary sector value added to the sum of primary and secondary sector value added, a standard measure of industrial upgrading. The coefficient on smart governance is 0.0230, significant at the 1 percent level. This positive relationship confirms that governance improvements accelerate the shift from manufacturing-dominant to service-dominant economic structures. The effect size indicates that a one-unit increase in smart governance raises the tertiary-to-primary-plus-secondary ratio by approximately 0.023, equivalent to roughly 2.3 percent of the mean ratio of 0.98.

These empirical results are consistent with previous research on digital transformation and industrial upgrading. Chu et al. (2021) demonstrate that digital technology penetration from smart city construction not only transforms production processes in traditional manufacturing but also promotes the development of modern service industries, thereby promoting the evolution of industrial structure from industry-dominated to service-dominated. Research further indicates that industrial structure upgrading can both promote local carbon emission reduction and may drive emission reduction in surrounding areas through spatial spillover effects, with emission reduction efficiency varying across regions at different development stages (Yuan et al. 2016).

The finding that smart governance accelerates this transformation suggests that governance capacity shapes not merely regulatory effectiveness but also the fundamental structure of urban economies, with direct implications for long-run emission trajectories. Together with the fiscal innovation channel, these results reveal that smart governance operates through both technological advancement and structural change, addressing intensive and extensive margins

of emission reduction simultaneously. These indirect pathways may prove more consequential for long-term emission reductions than direct regulatory effects because they alter the underlying conditions that generate emissions rather than merely constraining emission-producing activities.

5.3 Heterogeneous Effects

The baseline estimates impose the restriction that smart governance affects all cities uniformly. This assumption is unlikely to hold if the effectiveness of governance innovations depends on local conditions. Institutional theory emphasizes that governance reforms require complementary capabilities and enabling conditions to generate intended outcomes (Nahapiet and Ghoshal 1998). This section investigates heterogeneity along three dimensions: geographic region, city size, and industrial legacy.

Geographic Variation. Table 7 reports separate regressions for China's four major regions: eastern, central, western, and northeastern. In the eastern region, smart governance coefficients are negative and statistically significant across all emission measures, ranging from -0.0138 to -0.0155 . Coefficients for the central, western, and northeastern regions are smaller and statistically insignificant. This pattern likely reflects differences in digital infrastructure, economic development stages, and industrial composition. Eastern cities possess well-developed digital infrastructure and have largely completed industrialization, facing strong pressure for environmental improvement. Central, western, and northeastern regions face digital divides, economic catch-up pressures, and higher concentrations of heavy industry where emission reductions require fundamental technological change rather than governance optimization alone.

Table 7
Heterogeneous Effects by Geographic Region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Eastern cities			Central cities			Western cities			Northeastern cities		
	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>
<i>sgi</i>	-0.0138**	-0.0137**	-0.0155***	-0.0117	-0.0115	-0.0117	-0.0084	-0.0092	-0.0085	0.0069	-0.0011	0.00
	(0.0055)	(0.0054)	(0.0056)	(0.0081)	(0.0082)	(0.0081)	(0.0076)	(0.0075)	(0.0077)	(0.0069)	(0.0077)	(0.0077)
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>City</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	609	609	609	560	560	560	665	665	665	238	238	238
<i>adj. R2</i>	0.463	0.434	0.449	0.323	0.355	0.324	0.334	0.357	0.334	0.315	0.521	0.30

Note: This table presents separate estimates for China's four major geographic regions following National Bureau of Statistics classifications. All specifications include city and year fixed effects and the full vector of controls. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

City Size Variation. Table 8 examines heterogeneity across three city size categories based on urban permanent population. Smart governance coefficients are insignificant for megacities and super-large cities (populations exceeding 5 million), negative and significant for large cities with populations between 1 and 5 million (ranging from -0.0121 to -0.0127), and return to insignificance for small and medium cities (populations below 1 million). This inverted-U pattern suggests that large cities occupy an optimal scale where governance capacity is most productive. These cities possess sufficient resources to develop sophisticated systems yet face manageable operational complexity. Small and medium cities face resource constraints, while megacities confront excessive coordination challenges and rigid energy demands from agglomeration.

Table 8
Heterogeneous Effects by City Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Megacities and super-large cities			Large cities			Small and medium cities		
	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>
<i>sgi</i>	0.0027	0.0025	0.0035	-0.0121**	-0.0127**	-0.0122**	-0.0057	-0.0068	-0.0056
	(0.0058)	(0.0058)	(0.0063)	(0.0056)	(0.0054)	(0.0056)	(0.0050)	(0.0050)	(0.0050)
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>City</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	154	154	154	574	574	574	1344	1344	1344
<i>adj. R2</i>	0.701	0.651	0.609	0.435	0.413	0.432	0.303	0.352	0.304

Note: This table presents separate estimates for three city size categories based on urban permanent population from the seventh national census. Megacities and super-large cities have populations exceeding 5 million. Large cities have populations between 1 and 5 million. Small and medium cities have populations below 1 million. All specifications include city and year fixed effects and the full vector of controls. Standard errors clustered at the city level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Industrial Legacy Variation. Table 9 distinguishes old industrial base cities from other cities. For non-old industrial base cities, smart governance coefficients are negative and significant, ranging from -0.0097 to -0.0111 . For old industrial base cities, coefficients are negative but smaller and statistically insignificant. This heterogeneity reflects carbon lock-in and path dependence. Old industrial bases possess industrial structures with high asset specificity and sunk costs in heavy industry, limiting the effectiveness of governance improvements. Even with enhanced governance capacity, digital tools cannot easily substitute for fundamental technological transformation in steel mills, chemical plants, and coal-fired power generation.

Table 9 Heterogeneous Effects by Industrial Legacy						
	(1)	(2)	(3)	(4)	(5)	(6)
	Old industrial base cities			Non-Old industrial base cities		
	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>	<i>lnCO2</i>	<i>lnPopCO2</i>	<i>lnLandCO2</i>
<i>sgi</i>	-0.0100	-0.0103	-0.0105	-0.0097**	-0.0111***	-0.0103**
	(0.0066)	(0.0066)	(0.0066)	(0.0043)	(0.0042)	(0.0045)
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>City</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	658	658	658	1414	1414	1414
<i>adj. R2</i>	0.336	0.400	0.343	0.333	0.352	0.322

Note: This table presents separate estimates for old industrial base cities and other cities. Old industrial base designation follows the National Old Industrial Base Adjustment and Transformation Plan (2013-2022). All specifications include city and year fixed effects and the full vector of controls. Standard errors clustered at the city level are reported in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

6. Conclusion

This paper investigates the effect of smart governance on urban carbon emissions using panel data from 296 Chinese prefecture-level and above cities spanning 2017 to 2023. We conceptualize smart governance as a comprehensive governance capability encompassing value orientation, system application, and institutional-technological support, and employ multiple identification strategies to estimate its causal impact on emissions.

Our analysis yields three principal findings. First, smart governance significantly reduces urban carbon emissions. A one-unit increase in the smart governance index corresponds to an 0.85 percent decrease in carbon emissions, equivalent to an annual reduction of approximately 330,000 tons of CO₂ or the combined emissions of roughly 110,000 gasoline-powered passenger vehicles. This relationship proves robust across multiple specifications including dynamic panel models, instrumental variable estimation, and double machine learning approaches. All three constituent dimensions of smart governance exert independent negative effects on emissions, confirming that emission reduction arises from comprehensive governance capacity enhancement rather than isolated technological adoption.

Second, we identify and empirically validate two principal mechanisms through which smart governance reduces emissions. Smart governance increases government innovation support, with improvements in governance capacity raising the share of fiscal expenditure allocated to science and technology by 0.18 percentage points. This fiscal reallocation redirects public resources toward green technology development, creating conditions for technological progress that reduces emission intensity. Smart governance also promotes industrial structure upgrading, accelerating the shift from manufacturing-dominant to service-dominant economic structures. These mechanisms reveal that smart governance operates not merely through direct regulatory enforcement but by reshaping fiscal priorities and accelerating structural economic transformation.

Third, the carbon reduction effects of smart governance exhibit substantial heterogeneity across urban contexts. Geographically, effects are concentrated in eastern cities, while remaining insignificant in central, western, and northeastern regions. By city size, effects follow an inverted-U pattern, proving most pronounced in large cities with populations between 1 and 5 million, while remaining insignificant in megacities and small-medium cities. By industrial legacy, effects are significant in non-old industrial base cities but insignificant in old industrial bases. These patterns demonstrate that smart governance effectiveness depends critically on complementary conditions including digital infrastructure, appropriate scale, diversified economic structures, and absence of severe carbon lock-in.

The findings carry important implications for climate policy. The substantial emission reductions associated with smart governance improvements suggest that investments in digital governance infrastructure constitute a viable strategy for achieving carbon reduction targets. However, the heterogeneous effects caution against one-size-fits-all approaches. Policy interventions should be tailored to local conditions, with governance enhancements complemented by investments in digital infrastructure, support for industrial restructuring, and coordination mechanisms appropriate to city scale.

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3 Author Contributions

S.S.: Conceptualization, research design, methodology, data curation, formal analysis, interpretation of results, writing – original draft, and writing – review & editing.

Z.H.: Theoretical analysis, methodology, empirical strategy, validation, and writing – review & editing.

Y.Z.: Research design, resources, supervision, interpretation and discussion of results, and writing – review & editing.

C.W.: Conceptualization, research design, data curation, formal analysis, visualization, writing – original draft, and writing – review & editing.

All authors contributed to the discussion of the results, reviewed the final version of the manuscript, and approved the submitted version.

4 Ethics and Consent to Participate

Not applicable.

5 Data Availability

The data used in this study were obtained from publicly available statistical databases and official government sources. The processed datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

6 Competing Interests

The authors declare that they have no competing interests.

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