

# The Effect of Digital Governance on Urban Carbon Emission Intensity: Evidence from China's "Information for All"

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**Abstract:** Under the strategic framework of China's dual carbon targets, numerous cities have accelerated efforts toward ecological transformation. Digital governance, as a tool aimed at enhancing public sector efficiency, has seen increasing adoption; however, its direct influence on carbon emissions has yet to be thoroughly assessed through quantitative methods. Drawing on panel data from Chinese cities at the prefecture level and above for the years 2006 to 2021, this paper applies a Difference-in-Differences approach, taking the 2014 launch of the national "Information Benefiting the People" initiative as a quasi-natural experiment. The empirical results indicate that the implementation of the pilot led to a notable reduction in urban carbon emission intensity. These findings are consistent across a range of robustness checks. Further analysis reveals that digital governance contributes to emission reductions primarily by enhancing the effectiveness of environmental regulation. Additionally, heterogeneity tests suggest that the emission reduction effects are more significant in eastern regions, larger urban centers. The study offers evidence-based support for aligning digital transformation with low-carbon urban development.

**Keywords:** Digital Governance; Carbon emissions; Difference-in-Differences; Environmental Regulation

## 1. Introduction

As the climate crisis continues to worsen, promoting low-carbon transitions and curbing greenhouse gas emissions have emerged as pressing objectives for policymakers globally [1]. As the primary spatial units of energy consumption and carbon emissions, cities play a pivotal role in achieving national carbon peaking and neutrality ("dual carbon") goals,

and they are essential drivers of sustainable development. In this process, the government's governance capacity—as the key agent in allocating public resources—largely determines the effectiveness of emission reduction policies. In recent years, the rise of digital governance has injected new institutional momentum and technical tools into urban environmental management, emerging as a key factor influencing cities' carbon governance performance [2].

Digital governance, also referred to as e-government, entails the use of digital technologies, and artificial intelligence to restructure administrative processes, improve policy tools, and enhance governance efficiency [3]. It represents a profound transformation from traditional governance models and offers new opportunities for more effective and responsive environmental regulation [4,5]. On one hand, digital tools empower governments with enhanced capabilities to collect and analyze information, enabling real-time and granular monitoring of urban carbon emissions in terms of structure, intensity, and spatial distribution—thereby providing robust data support for policy formulation. On the other hand, digital platforms facilitate information sharing and coordination across government departments, breaking through long-standing barriers such as "information silos" and fragmented oversight, and advancing the transition from "extensive" to "precise" and "intelligent" carbon governance [6].

At the urban level, digital governance affects carbon mitigation through several mechanisms. First, it improves the efficiency of environmental regulation. Traditional regulatory approaches often face limitations such as staffing shortages, delayed enforcement, and high monitoring costs, making it difficult to include high-emission enterprises in regulatory frameworks. By leveraging digital platforms, governments can

access real-time emissions data, identify abnormal activities, and dynamically allocate enforcement resources, thereby achieving a full-cycle regulatory loop—from early warning to real-time intervention and post-event accountability—which significantly enhances policy responsiveness and enforcement effectiveness [7,8].

Second, digital governance enables the intelligent upgrade of green public services and infrastructure. Under this framework, systems such as smart transportation, intelligent power grids, green buildings, and energy monitoring networks have been developed and optimized [9,10]. These initiatives are often spearheaded and operated by the government and form the technical backbone of low-carbon urban operations. For example, smart traffic systems help alleviate congestion and reduce vehicle emissions, while intelligent energy systems improve the efficiency and integration of renewable energy through dynamic scheduling, thereby indirectly lowering total urban emissions.

Third, digital governance promotes public participation and policy transparency. Digital platforms are not only tools for administration but also serve as communication bridges. Governments can use platforms such as cloud-based or mobile e-government systems to release carbon data, environmental policies, and regulatory updates—enhancing transparency and public oversight [11]. Meanwhile, the public can report environmental issues or engage in green lifestyle practices through these platforms, fostering a broader system of participatory governance and enhancing environmental awareness [12]. This inclusive approach is vital in encouraging individuals and enterprises to adopt emission-reducing behaviors in their daily operations [13].

Additionally, digital platforms enhance the feasibility and precision of green incentive mechanisms. Governments can tailor policy instruments—such as carbon quota allocations, green credit policies, and subsidies—based on real-time emissions, historical carbon intensity, and firms' reduction performance. This dynamic and differentiated approach strengthens both the incentive and fairness of policy implementation, encouraging technological innovation and sustainable transitions in the private sector [14].

However, the impact of digital governance on emissions reduction is not uniform. Its effectiveness is shaped by factors such as digital infrastructure quality, institutional capacity, enforcement strength, and data-sharing mechanisms. In particular, small and medium-sized cities and resource-dependent regions often face a “capability trap” marked by underdeveloped digital systems, weak governance structures, and poor emissions control. Therefore, it is necessary to empirically examine the mechanisms and contextual boundaries of digital governance across different types of cities to inform more nuanced and effective policy design.

In conclusion, digital governance functions not only as a tool for administrative modernization, but also as a strategic instrument for advancing low-carbon urban transitions. By enhancing regulatory effectiveness, streamlining public service delivery, encouraging civic engagement, and enabling more precise allocation of resources, it introduces fundamental changes to the framework of urban carbon governance. As digital technologies become further integrated into governance systems, their potential to support emissions reduction efforts is expected to increase. Going forward, policy attention should center on strengthening digital infrastructure, fostering institutional coordination, and upgrading technological capacity to simultaneously promote urban sustainability and environmental quality.

Against this backdrop, this study examines the role of digital governance in reducing urban carbon emissions by leveraging China's National Pilot Policy of Information Benefit for the People (NPIB) as a quasi-natural experiment. Since its inception, the policy has been implemented in 80 cities across 31 provinces. After excluding nine cities due to insufficient data, 71 are retained in the treatment group. Utilizing panel data from 283 prefecture-level and above cities spanning from 2006 to 2021, and employing a Difference-in-Differences (DID) estimation strategy, this paper provides a comprehensive empirical investigation into the effect of digital governance on urban carbon intensity and explores the underlying mechanisms through which these effects are realized.

## 2. Research Hypotheses

### 2.1 Digital Governance and Urban Emission Reduction

As a key engine for technological advancement and green transformation, digital technologies have played an increasingly important role in fostering synergy between pollution control and carbon emission reduction [15]. On the one hand, digital tools promote data sharing and integration across governmental departments, breaking long-standing information silos and improving both resource management efficiency and governance capacity. At the same time, digital public services—such as online approval systems—streamline administrative procedures, reduce transaction costs, and enhance resource allocation efficiency, thereby contributing to reduced energy waste and carbon emissions [16].

On the other hand, digital technologies also serve as critical enablers of environmental regulation. Through the application of big data and cloud computing, governments can monitor energy use and pollution emissions with greater accuracy and timeliness, enhancing the scientific basis and effectiveness of environmental oversight. Moreover, digital platforms increase policy transparency and open up new avenues for public participation, encouraging market actors and civil society to play active roles in the low-carbon transition. The promotion of green practices such as remote work and virtual meetings also contributes to low-carbon development and sustainable urbanization [17].

Based on these considerations, we propose the following hypothesis:

H1: Digital governance contributes to urban carbon emission reduction.

### 2.2 Mechanism of Digital Governance: Environmental Regulation

Digital governance enhances both the precision and transparency of environmental regulation, thereby improving the implementation effectiveness of environmental policies. Prior research has shown that digital governance—through technologies such as big data and artificial intelligence—enables dynamic and real-time monitoring of pollution sources, corporate emissions, and environmental quality, strengthening

government capacity and efficiency in regulatory enforcement. Digital platforms allow for the continuous collection and analysis of environmental data, enabling regulators to rapidly detect excessive emissions or illegal activities and increasing the deterrent effect of policy enforcement [18]. In addition, under strengthened regulatory frameworks, governments have adopted policy instruments such as green subsidies and tax incentives to actively support the development of low-carbon technologies and clean energy. These measures reduce the costs of innovation and facilitate the deployment of green technologies, further lowering carbon emissions. Environmental regulation also raises environmental awareness among both firms and the general public, advancing carbon governance toward more institutionalized and participatory forms. As a result, a broader social consensus around green development can emerge. Through a combination of regulatory constraints and incentive mechanisms, environmental regulation provides robust institutional support for achieving urban carbon reduction goals.

Based on this mechanism, we propose the second hypothesis:

H2: The application of digital governance strengthens environmental control, thereby reducing the carbon intensity of cities.

## 3. Research Design

### 3.1 Model Specification

This study employs a Difference-in-Differences (DID) model to identify the causal effect of digital governance on urban carbon emissions. The baseline specification is as follows:

$$\ln CO_{2it} = \alpha_1 + \beta Treat_{it} \times Post_{it} + \gamma(1)X(it) + Year_t + City_i + \xi(it) \quad (1)$$

where  $\ln CO_{2it}$  denotes the logarithm of carbon emission intensity in city  $i$  at year  $t$ , serving as the dependent variable that captures the level of emission reduction at the urban scale. The key explanatory variable is the interaction term  $Treat_{it} \times Post_{it}$ , where:  $Treat_{it}$  is a binary variable equal to 1 if city  $i$  is designated as a pilot city under the National Pilot Program for Information Benefiting the People (NPIB) in year  $t$ , and 0 otherwise;  $Post_{it}$  is a time dummy variable that equals 1 for the post-policy

implementation period and 0 for the pre-policy period. The coefficient  $\beta$  on the interaction term captures the average treatment effect of digital governance, proxied by the NPIB policy, on urban carbon intensity—this is the primary parameter of interest.

To enhance estimation reliability and address potential omitted variable bias, the model incorporates both city fixed effects and year fixed effects to control for time-invariant city characteristics and unobserved macroeconomic shocks over time, respectively. In addition, a set of time-varying control variables  $X_{it}$  is included to account for other urban factors potentially influencing carbon emissions. These controls include: the natural logarithm of total population ( $\ln POP$ ), the level of urban digital development ( $UDDL$ ), and the logarithm of environmental regulatory intensity ( $\ln ER$ ). Table 1 presents the descriptive statistics of the variables.

**Table 1. Definition and Descriptive Statistics of Main Variables**

Variable	Variable Description
$\ln CO_2$	Logarithm of urban carbon emission intensity
$Treat$	Cities participating in digital governance are assigned a value of 1, otherwise 0
$Post$	Time dummy variable, 0 before policy implementation and 1 after implementation
$\ln POP$	The logarithm of the total urban population
$UDDL$	Urban digital development level
$\ln ER$	Logarithm of environmental regulation

### 3.2 Data Sources

The data used in this study are primarily drawn from authoritative Chinese statistical sources, including the *China Statistical Yearbook*, *China Regional Economic Statistical Yearbook*, *China Urban Statistical Yearbook*, and various provincial and municipal statistical yearbooks from 2006 to 2021. Based on these sources, we applied the following data processing procedures:

To ensure consistency and availability of control variables, cities with severe data deficiencies were excluded from the sample.

For variables with minor missing values, linear interpolation was used to fill gaps.

After cleaning and processing, we constructed a balanced panel dataset covering 283 prefecture-level and above cities in China over the period 2006–2021.

## 4. Empirical Results

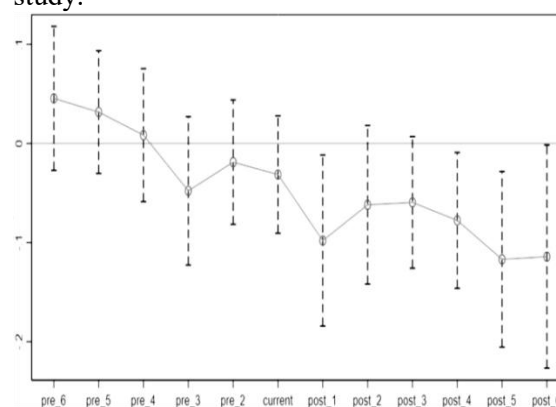
### 4.1 Parallel Trend Test

A key identification assumption of the DID methodology is the *parallel trends assumption*—that is, in the absence of the policy intervention, the treated (pilot) and control (non-pilot) cities would have followed similar trends in carbon emission intensity. To verify this assumption, we conduct an event study-based parallel trend test using 2014, the launch year of the NPIB policy, as the baseline.

As shown in Figure 1 (not included here), when using urban carbon emission intensity as the dependent variable, the estimated coefficients for the pre-treatment period are statistically insignificant. This indicates that, prior to the implementation of the NPIB policy, there were no significant differences in the trends of carbon emission intensity between pilot and non-pilot cities, thereby validating the parallel trend assumption.

Notably, starting from the third year after the policy implementation, the estimated coefficients become significantly negative. This suggests that pilot cities experienced a statistically significant decline in carbon emission intensity relative to non-pilot cities. In other words, following the NPIB rollout in 2014, treated cities began to outperform the control group in reducing carbon intensity.

These results provide empirical support for the validity of the DID model employed in this study.



**Figure 1. Parallel Trend Chart of Carbon Emission Intensity**

**Table 2. Benchmark Regression Results**

Variables	(1)	(2)
	$\ln CO_2$	
$Treat \times Post$	-0.1056*** (-6.00)	-0.0645*** (-3.67)
$\ln POP$	—	0.0055 -0.07
$UDDL$	—	0.009686
$\ln ER$	—	-0.0832*** (-8.69)
$City\ FE$	Yes	Yes
$Year\ FE$	Yes	Yes
$Constant$	-8.4095*** (-1,844.46)	-9.4090*** (-19.48)
$Observations$	4528	4528
$R-squared$	0.867	0.873

Note: The values in brackets are robust t-statistics, \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < .1$ .

Columns (1) and (2) of Table 2 report the estimated effects of the NPIB policy on urban carbon emission intensity, without and with control variables, respectively. In both specifications, the coefficient of the key interaction term ( $Treat \times Post$ ) is significantly negative at the 1% level, and the estimated magnitudes are highly consistent across the models. This indicates that the policy implementation significantly contributed to urban carbon emission reduction.

Notably, the coefficient reported in Column (2) is -0.0710, indicating that, after accounting for other influencing variables, the implementation of the NPIB pilot policy is associated with an average decrease of approximately 7.10% in urban carbon emission intensity. This result offers robust empirical evidence in support of Hypothesis H1.

## 5. Further Analysis

### 5.1 Robustness Check

To mitigate concerns regarding omitted variable bias and unobserved heterogeneity, a placebo (or falsification) test is conducted to further validate the robustness of the baseline results. This method is instrumental in confirming that the estimated treatment effect can be genuinely attributed to the NPIB policy intervention rather than to random fluctuations or spurious associations.

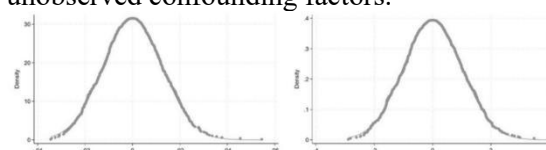
In the placebo design, 71 cities are randomly selected to form a pseudo-treatment group, while the remaining 212 cities serve as the

placebo control group. The DID model is then re-estimated using the same specification as in Equation (1), incorporating city and year fixed effects along with other control variables.

This process is repeated 1,000 times to generate a counterfactual distribution of the DID interaction term ( $Treat \times Post$ ). For each iteration, both the estimated coefficient and its corresponding t-statistic are recorded, and the resulting distribution is visualized using kernel density plots.

As illustrated in Figure 2, the placebo coefficients and their t-values are tightly clustered around zero, suggesting that the random assignment of treatment status yields no systematic impact on urban carbon intensity. This reinforces the inference that the policy effect observed in the main analysis is unlikely to be driven by random chance.

Overall, the placebo test strengthens the credibility of the identification strategy and supports the conclusion that the observed effects of the NPIB policy are not the result of unobserved confounding factors.

**Figure 2. Placebo Test Results**

Note: (1) Regression coefficient kernel density plot of urban carbon emission intensity. (2) T-value kernel density plot of urban carbon emissions.

### 5.2 PSM-DID Estimation

Table 3 reports the estimation outcomes derived from the Propensity Score Matching combined with Difference-in-Differences (PSM-DID) approach. When urban energy efficiency serves as the dependent variable, the estimated coefficients for digital governance remain consistently positive and statistically significant at the 1% level across all matching algorithms. Likewise, when the dependent variable is urban carbon emission intensity, the estimated coefficients remain significantly negative at the 1% threshold.

These results suggest that, even after correcting for potential selection bias stemming from the non-random assignment of treatment, the effect of digital governance on carbon mitigation remains both robust and statistically significant. This further reinforces

the credibility of the baseline DID estimates and underscores the reliability of the study's empirical strategy.

**Table 3. PSM-DID Results Comparison**

Variables	k-nearest neighbor	Caliper matching	Mahalanobis matching	Kernel matching
	(1)	(2)	(3)	(4)
	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$
<i>Treat</i> × <i>Post</i>	-0.0657*** (-3.74)	-0.0657*** (-3.74)	-0.0645*** (-3.67)	-0.0657*** (-3.74)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	-9.8442*** (-21.76)	-9.8442*** (-21.76)	-9.4090*** (-19.48)	-9.8442*** (-21.76)
<i>Observations</i>	4522	4522	4528	4471
<i>R-squared</i>	0.873	0.873	0.873	0.873

Note: The values in brackets are robust t-statistics, \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < .1$ .

### 5.3 Policy Exclusion Test

To rule out the potential confounding effects of other contemporaneous policies, this study considers the possible influence of the National Big Data Comprehensive Pilot Zones, the Broadband China Pilot Policy, and the Smart City Pilot Policy. A sensitivity analysis was conducted using the sample data prior to the implementation of these policies.

Given that the pilot areas of the above policies partially overlap with the treatment cities in both time and region, the sample was refined by excluding cities involved in these

overlapping pilot programs to ensure the purity and accuracy of the estimation results. As shown in Table 4, even after removing cities participating in the aforementioned pilot policies, the coefficient of the interaction term *Treat* × *Post* remains significantly negative at the 1% level.

This result provides strong evidence that, after controlling for potential interference from other major digital policies, the positive effect of digital governance on urban carbon reduction remains robust and statistically significant.

**Table 4. Policy Exclusion Test**

Variables	National Big Data Comprehensive Pilot Zone	Broadband China Pilot Policy	Smart City Pilot Policy
	(1)	(2)	(3)
	$\ln CO_2$	$\ln CO_2$	$\ln CO_2$
<i>Treat</i> × <i>Post</i>	-0.0729*** (-3.68)	-0.0527** (-2.03)	0.130468
<i>Controls</i>	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Constant</i>	-10.0553*** (-20.18)	-9.6178*** (-17.81)	-8.9223*** (-11.12)
<i>Observations</i>	3744	3824	2160
<i>R-squared</i>	0.865	0.857	0.865

Note: The values in brackets are robust t-statistics, \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < .1$ .

## 6. Mechanism Analysis

### 6.1 Mechanism Verification

To further uncover the underlying mechanism, this study examines the pathway through which digital governance affects carbon intensity, with a particular focus on environmental regulation as a mediating variable. The detailed regression outcomes are reported in Table 5.

### 6.2 The Role of Environmental Regulation

In Column (1) of Table 5, where environmental regulation is treated as the dependent variable, the coefficient of the interaction term *Treat* × *Post* is estimated at 0.2164 and is statistically significant at the 1% level. After incorporating control variables in Column (2), the coefficient decreases to 0.1410, yet remains positively significant at the 1% level. These results indicate that digital

governance enhances the effectiveness of environmental regulation, thereby reducing urban carbon intensity.

Consequently, digital governance optimizes both the design and execution of environmental regulation, indirectly contributing to the achievement of urban carbon reduction goals. This finding confirms the validity of Hypothesis H2.

**Table 5. Testing the Mediating Effect Path**

Variable	lnER	
	(1)	(2)
<i>Treat×Post</i>	0.2164*** (6.52)	0.1410*** (4.19)
<i>Controls</i>	No	Yes
<i>City FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Constant</i>	-10.0485*** (-1,215.88)	-10.0842*** (-12.01)
<i>Observations</i>	4528	4528
<i>R-squared</i>	0.868	0.872

Note: The values in brackets are robust t-statistics, \*\*\*p < 0.01, \*\*p < 0.05, \* p < .1.

## 7. Heterogeneity Analysis

Although the preceding robustness tests confirm the positive impact of digital governance on urban carbon emission reduction, such effects may vary depending on geographic location, urban development scale, and resource endowment. To further explore how digital governance functions across different urban contexts, this section investigates the heterogeneity of its effects from multiple perspectives.

### 7.1 Regional Heterogeneity

Given China's pronounced regional differences, the impact of digital governance on carbon emissions may vary across geographic areas. The eastern, central, and western regions exhibit substantial disparities in terms of economic maturity, technological infrastructure, resource endowments, and policy implementation environments.

Regression outcomes, reported in Columns (1) to (3) of Table 6, reveal that digital governance is associated with a statistically significant decline in carbon intensity in eastern cities. However, the effects are not significant in the central or western regions. The relatively advanced economic conditions, well-established ICT infrastructure, and strong

innovation capacity in the eastern region provide favorable conditions for the adoption of low-carbon technologies and the enhancement of emissions reduction performance.

In contrast, central and western regions—characterized by relatively lagging economic development—still rely heavily on energy-intensive and heavy industries. These areas also face constraints such as limited technological reserves and weaker innovation capabilities. As a result, they encounter more practical obstacles in achieving industrial transformation and carbon mitigation, which impedes the effective implementation of digital governance policies in these regions.

**Table 6. Heterogeneity Test**

Variables	lnCO <sub>2</sub>		
	(1)	(2)	(3)
	<i>East</i>	<i>Mid</i>	<i>West</i>
<i>Treat×Post</i>	-0.0737** * (-3.33)	-0.0461 (-1.18)	-0.0446 (-1.51)
<i>Controls</i>	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Constant</i>	-5.9837** * (-6.24)	-10.4977** * (-8.70)	-9.4125** * (-16.30)
<i>Observations</i>	1584	1,344	1,600
<i>R-squared</i>	0.869	0.857	0.897

Note: The values in brackets are robust t-statistics, \*\*\*p < 0.01, \*\*p < 0.05, \* p < .1.

### 7.2 Urban Size Heterogeneity

The effectiveness of the “Information Benefiting People” pilot policy in reducing carbon emissions may differ notably depending on the population scale of cities. Cities with a permanent resident population of one million or fewer are identified as small and medium-sized, while those exceeding one million are classified as large cities and above. Estimation results, as reported in Table 7, indicate that the policy yields significant improvements in energy efficiency and reductions in carbon intensity within large and mega cities. Specifically, the estimated coefficients are 0.2305 and -0.0631, respectively, both statistically significant at the 1% level. However, no significant policy impact is observed among small and medium-sized cities, suggesting a differentiated effect of digital governance

based on urban scale.

This divergence in policy effectiveness may stem from several factors. Large cities typically possess well-developed digital infrastructure, higher levels of informatization, abundant human capital, and a more vibrant innovation ecosystem, all of which create favorable institutional and technological conditions for implementing digital governance initiatives. In comparison, small and medium-sized cities often lag behind in the adoption of digital technologies, talent availability, and supporting infrastructure, which hampers the effective implementation of digital governance measures and undermines their potential impact on carbon reduction.

**Table 7. Results on City Size Heterogeneity**

Variables	lnCO <sub>2</sub>	
	(1)	(2)
	Small and medium-sized cities	Large cities and above
Treat×Post	-0.1924 (-1.52)	-0.0581*** (-3.31)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Constant	-7.4496*** (-3.08)	-9.0994*** (-15.60)
Observations	185	4,341
R-squared	0.91	0.868

Note: The values in brackets are robust t-statistics, \*\*\*p < 0.01, \*\*p < 0.05, \* p < .1.

## 8. Conclusions and Policy Implications

### 8.1 Research Conclusions

Drawing on panel data from 283 prefecture-level and above cities in China covering the period from 2006 to 2021, this study conducts a comprehensive analysis of how digital governance influences urban carbon emissions. The findings suggest that the advancement of digital governance has a significant and positive effect on facilitating green, low-carbon urban development. The impact is particularly evident in cities located in the eastern region, in those with larger populations, and in non-resource-dependent cities.

To reinforce the credibility of these results, a range of robustness checks were performed. These include placebo tests, a combination of propensity score matching with

difference-in-differences (PSM-DID), and controls for other concurrent policy interventions that might confound the estimates. All approaches consistently validate the robustness and reliability of the observed emission-reduction effects. Mechanism analysis further indicates that environmental regulation acts as a key channel through which digital governance contributes to lower carbon emissions, suggesting that digital tools can substantially improve the effectiveness and precision of environmental regulatory efforts at the municipal level.

### 8.2 Policy Recommendations

Improve the Digital Governance Policy Framework. Governments should further strengthen strategic planning and policy support for digital governance. Tailored and forward-looking implementation pathways should be formulated according to the specific development stages, resource endowments, and governance needs of different regions. This will facilitate the effective implementation of related policies and promote the integration of modern urban governance systems with green development goals.

Enhance Environmental Regulation Capacity. Under the digital governance framework, environmental regulation strategies should be dynamically optimized in line with the actual development conditions of cities. This includes increasing the flexibility and diversification of regulatory tools—for example, establishing comprehensive carbon emission accounting and statistical systems, and improving green taxation mechanisms—to ensure the effective enforcement of environmental governance policies, thereby providing institutional guarantees for promoting green and high-quality urban development.

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