

# The Impact of Digital Economic Development on Regional Carbon Emission Intensity: A Dual Perspective on Technological Spillovers and Structural Transformation

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## Abstract

Against the dual background of the carbon peaking and carbon neutrality goals and the in-depth development of the digital economy, exploring the impact mechanism and heterogeneous characteristics of the digital economy on regional carbon emission intensity carries important theoretical value and practical significance for achieving the coordinated progress of high-quality economic development and carbon emission reduction. This research systematically explores the influence of the digital economy on regional carbon emission intensity by leveraging a multi-faceted analytical approach. Specifically, it employs a two-way fixed effect model, a mediating effect model, and a heterogeneous analysis framework to examine this relationship from the dual lenses of technology spillover and structural transformation. Utilizing panel data spanning from 2012 to 2023 across 30 Chinese provinces, the study reveals that the expansion of the digital economy significantly curbs regional carbon emission intensity. Moreover, it finds that a one-unit increase in the digital economy level leads to a notable decline in regional carbon emission intensity. The digital economy can exert an indirect influence in reducing carbon emission intensity. It achieves this by fostering green technological innovation and driving industries to transition towards high value-added, low-pollution operational models. Consequently, technology spillover effects and structural transformation emerge as significant mediating factors that bridge the relationship between the digital economy and regional carbon emission intensity. Heterogeneity analysis reveals that the digital economy's role in mitigating carbon emissions is more pronounced in regions located southeast of the Hu Huanyong Line and in economically underdeveloped areas. In contrast, no statistically significant impact is observed in regions northwest of the line and in those with higher levels of economic development. The research conclusions of this paper remain robust after a series of tests, including the replacement of core explanatory and dependent variables, the instrumental variable method, and the dynamic panel model. This study provides empirical support for clarifying the carbon emission reduction effect of the digital economy and its internal logic and offers a reference basis for regions to formulate coordinated policies for digital economy development and carbon emission reduction in accordance with local conditions.

## Keywords

Digital Economy; Carbon Intensity; Technology Spillovers; Structural Transformation.

## 1. Introduction

Against the backdrop of accelerating global climate governance and the deepening advancement of China's "dual carbon" goals, reducing regional carbon emission intensity and achieving synergistic progress between economic development and environmental protection

have become central issues for high-quality development in the new era. Currently, China is at a critical stage of transition from industrialization to informatization. The contradiction between traditional, energy-intensive, and high-emission development models and increasingly severe resource and environmental constraints is intensifying. Moreover, the significant geographical disparities in regional carbon emission intensity pose a formidable obstacle to achieving national carbon reduction targets [1].

At the same time, data is the central component of the digital economy, a new economic model that follows the industrial and agricultural economies. Through a variety of methods, including the digitalization of old sectors and the industrialization of digital technology, the development of digital infrastructure, and the fostering of digital innovation-it profoundly permeates every phase of production, distribution, circulation, and consumption. This widespread integration offers fresh avenues for addressing the "environmental Kuznets curve" conundrum, which highlights the trade-off link carbon emissions and economic growth [2]. Beyond directly enhancing allocating resources and lowering energy usage via technological advancements and improved efficiency. Additionally, the digital economy has the potential to significantly reduce carbon emissions in an indirect manner. It does so by promoting the transformation of industrial structures towards high-value, low-pollution sectors [3]. However, several critical questions remain unresolved. These include whether a carbon rebound effect emerges amidst the expansion of the digital economy [4], how the transmission mechanisms underlying its carbon-reducing impacts are manifested, and whether there are discernible heterogeneous characteristics across diverse regions. All these aspects underscore the necessity for further theoretical exploration and empirical validation [2, 5].

Preliminary research has already examined the connection between carbon emissions and the digital economy. However, a number of significant flaws still exist: First off, most of the research that is currently available concentrates on how the digital economy directly affects carbon emissions [6, 7], while overlooking a thorough analysis of the mediating mechanisms, such as technological spillovers and structural transformations. Second, the potential carbon rebound effect stemming from the digital economy has been largely overlooked, thereby posing difficulties in comprehensively uncovering the intricate interplay between these two phenomena [4]; third, current analyses concerning regional heterogeneity predominantly rely on the conventional categorization into eastern, central, and western regions, yet they fall short of incorporating a multidimensional perspective that seamlessly blends economic development levels with geospatial attributes [8, 9].

Accordingly, the study sample consists of panel data from 30 Chinese provinces spanning 2012 to 2023. A dual analytical framework is adopted-focusing on technological spillovers and structural transformation-to systematically examine how the digital economy influences regional carbon emission intensity. To this end, a range of models are employed, including fixed-effects models, mediation models, and carbon emission rebound effect models [6, 7]. In addition, heterogeneity analysis is conducted to identify variations in these effects across regions with different geographic characteristics and levels of economic development [10].

This study holds substantial significance on two fronts. First, by delineating the mechanisms through which the digital economy influences carbon emission intensity, it enriches the conceptual framework of the interdisciplinary field that intersects environmental economics and the digital economy. Secondly, from a practical standpoint, it provides empirical evidence that can serve as a valuable reference for diverse regions in formulating tailored policies aimed at reducing carbon emissions and fostering digital economic growth, thereby contributing to the attainment of the "dual carbon" objectives.

## 2. Research Framework and Theoretical Hypotheses

In the context of the digital economy, data is widely recognized as a cornerstone element within the manufacturing sector. Through the deep integration of digital technologies with the real economy, it directly reduces regional carbon emission intensity by improving production efficiency and optimizing energy consumption [11]. On one hand, the industrialization of digital technologies has given rise to new production models such as smart manufacturing and precision management, which in turn drive innovation and application in fields like big data, artificial intelligence, and cloud computing. This helps reduce resource waste and energy consumption throughout the production process. For example, industrial internet systems enable real-time monitoring and intelligent scheduling of manufacturing equipment, leading to a notable decrease in energy use per unit of output. On the contrary, the progress and enhancement of digital infrastructure play a pivotal role in mitigating overcapacity issues and curbing redundant carbon emissions that stem from information asymmetry. By facilitating the flow of production factors and accelerating the dissemination of information, it enhances the efficiency of factor allocation [2]. Moreover, the environmental benefits of energy conservation and emission reduction are reinforced through the development and widespread adoption of green technologies, enabled by digital innovation [12]. Based on these considerations, we propose the following hypothesis:

**Hypothesis 1:** The expansion of the digital economy plays a significant role in reducing regional carbon emission intensity.

Technology spillovers represent the primary channel through which the digital economy exerts its influence on carbon emission intensity. This influence is significantly mediated by green total factor productivity, which serves as a pivotal metric reflecting the synergistic enhancement of environmental performance and technological efficiency [13]. The growth of the digital economy can contribute to the enhancement of green total factor productivity through several key mechanisms. First, it accelerates research and development processes and enables the rapid iteration of green technologies, such as clean energy and low-carbon solutions, thereby reducing the costs associated with technological innovation. Additionally, it spurs the digital transformation of R&D models and enhances the environmental sustainability of production systems [12]. Secondly, the extensive use of digital technologies has the potential to significantly reduce undesirable outputs, streamline the optimal combination of production factors, and achieve efficient allocation of labor, capital, and energy resources [11]; Third, the technology diffusion effect brought about by the digital economy enables the rapid dissemination of advanced green technologies across regions and industries, driving an overall improvement in green production levels. This impact of the digital economy on carbon reduction is further reinforced indirectly through improvements in green total factor productivity, which reflect reduced energy consumption and lower carbon emissions per unit of output. Accordingly, Hypothesis 2 is proposed.

**Hypothesis 2:** The digital economy can indirectly reduce regional carbon emission intensity by enhancing green total factor productivity.

The capacity of the digital economy to drive industrial structural transformation represents another significant channel through which it influences carbon emission intensity. Within this broader structural shift, the upgrading of industrial structures serves as a crucial intermediary mechanism, representing a fundamental and pivotal aspect of the overall change [14]. The digital economy plays a pivotal role in advancing the modernization of industrial structure through several key pathways. Initially, it facilitates the widespread and in-depth integration of digital technology with various industrial sectors service sector gives rise to new service models such as digital services and knowledge-intensive services, driving the expansion of the tertiary sector and improving its quality. An increase in the share of the tertiary sector

contributes to a reduction in a region's overall carbon emission intensity, as this sector is typically characterized by lower energy consumption and carbon emissions [11]. Secondly, the digital economy serves as a catalyst for the intelligent and digital metamorphosis of traditional manufacturing sectors. It propels these industries towards high-value-added, low-pollution advanced manufacturing paradigms, while concurrently diminishing the share of energy-intensive industries within the economic landscape [15]. Third, the digital economy fosters the innovative development of small and medium-sized enterprises (SMEs) through various means, such as e-commerce and inclusive digital finance. This dynamic environment promotes a natural selection process within industries, where only the most adaptable and efficient firms thrive, thereby driving the industrial structure towards heightened efficiency and diminished carbon emissions [14]. The upgrading of industrial structure reduces economic growth's reliance on high-carbon-emission industries by optimizing the proportional relationships and internal structures of the three sectors, thereby indirectly achieving carbon emission reductions. This leads to the proposal of Hypothesis 3:

**Hypothesis 3:** By encouraging the modernization of industrial structures, the digital economy can indirectly lower the intensity of regional carbon emissions.

Given the marked heterogeneity among China's provinces in terms of economic development stage, geographic location, resource endowment, and the level of digital infrastructure development, the impact of the digital economy on regional carbon emission intensity is likely to exhibit diverse characteristics. From the perspective of economic development level, more economically developed regions tend to have a higher degree of integration between the digital and real economies, along with relatively well-established digital infrastructure. However, these regions may also face the issue of diminishing marginal returns in terms of carbon emission reductions driven by the digital economy, resulting in a comparatively limited carbon abatement effect [16]; On the flip side, regions characterized by less advanced economies are making swift strides in embracing the digital economy. Utilizing digital technologies in these areas has the potential to swiftly streamline industrial processes and substitute energy-intensive production methods, thereby yielding more pronounced effects in terms of carbon emission reductions [12]. From a geographical perspective, regions south and east of the "Hu-Huan-Yong Line" are densely populated, have large market sizes, and concentrate digital technology innovation resources. The digital economy's deeper integration with industries, underpinned by a more robust foundation, facilitates a more comprehensive realization of carbon reduction benefits through technology spillovers and structural transformations. Conversely, the Northwest regions, characterized by sparse populations, limited market sizes, and relatively underdeveloped digital infrastructure, face constraints that prevent the digital economy from being widely used and disseminated.

Consequently, these regions may experience less pronounced carbon reduction impacts. We put up Hypothesis 4 in light of these findings:

**Hypothesis 4,** the mitigating effect of the digital economy on regional carbon emission intensity exhibits notable variation. More specifically, this effect is expected to be more pronounced in communities located southeast of the Hu Huanyong Line and in regions with relatively slower economic growth.

### **3. Research Design**

#### **3.1. Model Specification**

##### **3.1.1. Baseline Regression Model**

We construct a two - way fixed - effects model to delve into the influence of the digital economy on regional carbon emission intensity:

$$\ln CI_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

The province is indicated by the subscript  $i$  in this form, while the year is represented by the letter  $t$ . The intensity of carbon emissions is measured using the variable  $\ln CI$ . The level of digital economic development is measured using  $DE$ . Control encompasses a set of control variables that are incorporated to take other considerations into consideration that might affect carbon emission intensity. The parameter  $\alpha$  signifies the regression coefficient, which indicates the direction and magnitude of The connection between carbon emission intensity and the digital economy.  $\mu_i$  captures the individual fixed effect, which accounts for time - invariant unobserved characteristics specific to each province.  $\delta_t$  represents the time fixed effect, controlling for common shocks or trends that affect all provinces in a given year. Finally,  $\varepsilon$  is the random error term, which captures the unexplained variation in carbon emission intensity after accounting for all the included variables and fixed effects.

### 3.1.2. Mediating Effects Model

The subsequent regression model has been formulated with the objective of examining the indirect association between regional carbon emissions and the extent of digital economic development:

$$M_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$\ln CI_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 M_{it} + \gamma_3 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In this context, the variable  $M$  represents the mediating mechanism variable. The parameters  $\beta$  and  $\gamma$  denote the regression coefficients, while the definitions of the remaining variables remain consistent with those specified in the baseline regression model.

## 3.2. Variable Definitions and Measurement

### 3.2.1. Dependent Variable: Regional Carbon Emission Intensity (CI)

This paper uses data on carbon dioxide emissions and GDP for each province and applies a logarithmic transformation to them [17].

### 3.2.2. Explanatory Variable: Level of Digital Economic Development (DE)

Similarly, a digital economic development index has been devised for countries participating in the Belt and Road Initiative, which is measured across four principal dimensions: digital trade, digital infrastructure, digital talent, and digital innovation [18]. Current research employs a range of perspectives to assess the level of digital economic development. For example, one approach involves an indicator system that encompasses three key dimensions-digital industrialization, industrial digitalization, and digital services and governance-to evaluate the growth of the digital economy in Chinese cities [19]. In view of this, the present study conducts a comprehensive analysis of digital economic development from four main perspectives: digital industrialization, industrial digitalization, digital infrastructure advancement, and digital innovation. This analysis is conducted by leveraging the research methodologies employed by relevant scholars, while also considering the data's dependability and accessibility. Subsequently, these dimensions are further disaggregated into 13 specific indicators, and the entropy approach is used to create a composite index for evaluating the digital economy's growth trajectory [20]. The definitions and attributes of each indicator are presented in [Table 1](#).

**Table 1.** Estimation of Digital Economy Indicators

First-level Indicator	Second-level Indicator	Third-level Indicator	Indicator Attribute
Digital Economy Development Level	Digital Industrialization	Total Telecommunication Services	+
		Software Business Revenue	+
		Internet Penetration Rate	+
		Proportion of Employees in Information and Software Industry	+
	Industrial Digitalization	Digital Inclusive Finance Index	+
		E-commerce Transaction Volume	+
		Added Value of the Tertiary Industry	+
	Digital Infrastructure Construction	Number of Internet Broadband Access Users	+
		Number of Domain Names	+
		Year-end Number of Mobile Phone Users	+
		Length of Long-distance Optical Cable Lines (10,000 km)	+
	Digital Innovation	Number of Patents Authorized	+
		Number of Employees in Software and Information Technology Services	+

**3.2.3. Control Variables**

To account for additional factors that may influence regional carbon emission intensity, this analysis incorporates the following variables: the level of economic development (GDP), measured by the logarithm of GDP per capita; the scale of foreign direct investment (FDI), expressed as the share of FDI in GDP; and the extent of government intervention (GOV), represented by the ratio of local general budget expenditures to GDP. These are introduced alongside a set of control variables. The logarithm of the number of enrolled higher education students per 100,000 people serves as an indicator of educational development (EDU); the proportion of the urban population to the total population reflects the level of urbanization (UR); the ratio of GDP to investment in industrial pollution control represents the stringency of environmental regulation (ER); the share of coal consumption in total energy consumption denotes the energy structure (ES); and the logarithm of year-end employment figures indicates the size of the labor force (LA).

**3.2.4. Mediating Variables**

Technical Efficiency (GTFP). Green total factor productivity measures the efficiency of synergistic resource allocation within a production system after integrating environmental factors; its core value lies in revealing the green attributes and sustainability of improvements in technical efficiency. Green total factor productivity (GTFP) in this study is generated through a comprehensive assessment encompassing three fundamental dimensions: factor inputs, desirable outputs, and unwanted outputs [21] (see [Table 2](#) for specific indicators). Given the weak disposability of undesired outputs and the global comparability of production technologies, the SBM directional distance function is adopted in conjunction with the GML index for measurement. The following is the fundamental calculation formula:

$$GTFP_{t \rightarrow t+1} = GML^{t+1} = \frac{1 + D^G(x^t, y^t, b^t; g)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1}; g)} \tag{4}$$

In particular,  $D^G(\cdot)$  is the worldwide manufacturing technology-based SBM directional distance function  $T^G$ ;  $(x_t, y_t, b_t)$ : factor inputs, expected output, and unanticipated output in period  $t$ ;  $(x^{t+1}, y^{t+1}, b^{t+1})$ : factor inputs, expected output, and unanticipated output in period  $t+1$ ; direction vector  $g$ : typically set as  $g = (-x^t, -y^t, -b^t)$ , representing the green improvement direction of “reducing inputs, increasing expected output, and reducing unanticipated output.”

**Table 2.** Estimation of Green Total Factor Productivity

First-level Indicator	Second-level Indicator	Third-level Indicator
Production Factor Input	Labor Input	Number of Employed Persons by Province
	Capital Input Real Capital Stock Calculated with 2011 as the Base Period	Capital Input Real Capital Stock Calculated with 2011 as the Base Period
	Energy Consumption Total Energy Consumption	Energy Consumption Total Energy Consumption
Desirable Output	Economic Output GDP	Economic Output GDP
Undesirable Output	Industrial Wastewater Discharge Volume of Industrial Wastewater Discharge	Industrial Wastewater Discharge Volume of Industrial Wastewater Discharge
	Waste Gas Emission Sulfur Dioxide Emission	Waste Gas Emission Sulfur Dioxide Emission
	Industrial Solid Waste Discharge Volume of Industrial Solid Waste Discharge	Industrial Solid Waste Discharge Volume of Industrial Solid Waste Discharge

The modernization of the industrial framework (IS) stands as a pivotal indicator for evaluating the caliber of economic structural transformation. The industrial structure typically evolves along a trajectory characterized by a shift from an agriculture - dominated phase to an industry - dominated one, and ultimately to a service - dominated state. This evolutionary process is accompanied by a corresponding movement of the labor force. As the economy expands and develops, the workforce gradually shifts from the primary sector (agriculture) to the secondary sector (industry), and eventually to the tertiary sector (services).

Accordingly, this study uses the share of value added contributed by the tertiary sector to total GDP as an indicator of the level of industrial structure upgrading. This measure effectively captures the shift in economic activity towards higher - value, service - oriented industries, which is a hallmark of industrial modernization and economic development.

### 3.3. Data Sources and Descriptive Statistics

This study chooses panel data from 30 Chinese provinces between 2012 and 2023 as research samples based on data availability and scientific validity. The areas of Tibet, Hong Kong, Macao, and Taiwan are excluded due to substantial missing data. Regional carbon emissions are available through the EDGAR database. The index is derived from the digital inclusive finance index created by Peking University. The linear interpolation approach is used to augment missing data on energy consumption structure and e-commerce sales. Additional information is gathered from the China Statistics Yearbook, the China Energy Statistical Yearbook, and the statistics yearbooks of other provinces. [Table 3](#) displays the descriptive statistics for the variables.

**Table 3.** Descriptive Statistics for Variables

Type	Variable	Observations	Mean	Std.Dev.	Min.	Max.
Dependent Variable	lnCI	360	9.514048	0.6738038	7.526922	10.97457
Core Explanatory Variable	DE	360	0.1100878	0.0753947	0.0159419	0.3542333
Mediating Variables	GTFP	360	1.030831	0.06379	0.9408119	1.475183
	IS	360	0.5059971	0.0875499	0.3446413	0.8484691
Control Variables	GDP	360	1.730506	0.4532046	0.6310702	2.996663
	fdi	360	0.0188101	0.0198177	0.0000239	0.1209923
	lnEDU	360	7.924506	0.2955373	7.032624	8.672315
	GOV	360	0.2582541	0.1101489	0.105006	0.758292
	ES	330	0.3640134	0.1466039	0.0056374	0.6867665
	UR	360	0.6125672	0.1164844	0.362977	0.895833
	ER	360	0.1001026	0.1179089	0.0007568	1.103387
	LA	360	7.595623	0.7687722	5.545177	8.863899

## 4. Analysis of Empirical Results

### 4.1. Analysis of Baseline Regression Results

**Table 4.** Benchmark Regression Results

Variables	lnCI		
	(1)	(2)	(3)
DE	-2.760***	-0.765**	-0.711**
	(0.398)	(0.330)	(0.342)
GDP		-0.979***	-1.062***
		(0.0413)	(0.0863)
fdi		-0.367*	-0.362*
		(0.202)	(0.201)
lnEDU		0.0687	-0.0162
		(0.0443)	(0.0544)
GOV		-0.477***	-0.352**
		(0.151)	(0.170)
ES		0.0504	0.0942
		(0.101)	(0.0936)
UR		0.567**	0.895***
		(0.247)	(0.260)
ER		-0.126***	-0.153***
		(0.0432)	(0.0398)
LA		-0.146**	-0.125**
		(0.0617)	(0.0623)
Cons	9.818***	11.63***	12.03***
	(0.0434)	(0.711)	(0.708)
Individual Fixed Effects	YES	YES	YES
Time Fixed Effects	YES	NO	YES
N	360	330	330
R <sup>2</sup>	0.990	0.995	0.996

**Table 4** displays the baseline regression findings that clarify the connection between the digital economy and the intensity of regional carbon emissions. Specifically, column (1) displays the regression outcomes with both Time-fixed and individual impacts incorporated, yet without the use of control variables. Columns (2) and (3), on the other hand, showcase the regression outcomes with the addition of control variables, with column (2) controlling solely for individual effects and column (3) accounting for both individual and time fixed effects. These findings provide robust support for Hypothesis 1, as evidenced by the consistently and significantly negative estimated coefficients for the degree of digital economic development (DE) at the significance level of 5%. This indicates that the expansion of the digital economy exerts a considerable and direct suppressive influence on regional carbon emission intensity. The effectiveness of regional efforts to reduce carbon emissions is enhanced by the growth of the digital economy. Notably, when controlling for other factors, the significantly negative coefficient associated with GDP suggests that regions with higher levels of economic development tend to have lower carbon emission intensities. This phenomenon may be attributed to the fact that higher-income areas are better positioned to invest in research and development (R&D), thereby facilitating the adoption of low-carbon technologies and supporting energy-saving and emission-reduction initiatives. Conversely, higher levels of urbanization are observed to substantially elevate regional carbon emission intensities, as indicated by the strongly positive coefficient linked to the urbanization level (UR). This may be related to the intensified resource consumption resulting from population density and industrial agglomeration during the urbanization process.

#### 4.2. Analysis of Mediating Effects

Drawing upon the theoretical research outlined earlier, the expansion of the promise of the digital economy indirectly mitigates the intensity of regional carbon emissions through two primary channels: by fostering the modernization of the industrial structure (IS) and by enhancing green total factor productivity (GTFP), as delineated in **Table 5**. Column (1) presents the baseline regression results, while Columns (2) and (3) report the regression outcomes for the effects of the digital economy on IS and GTFP, respectively. The results indicate that, at the 5% significance level, the estimated coefficient for the impact of the digital economy on Green Total Factor Productivity (GTFP) is significantly positive. Meanwhile, the estimated coefficient reflecting its influence on Industrial Structure (IS) is markedly positive at the 1% significance level. These findings imply that the expansion of the digital economy has the potential to significantly foster enhancements in green technical efficiency and facilitate the modernization of the industrial structure, thereby providing initial empirical support for Hypotheses 2 and 3.

**Table 5.** Results of the mediation analysis

	(1)	(2)	(3)
	lnCI	GTFP	IS
DE	-0.711**	0.383**	0.852***
	(0.342)	(0.173)	(0.110)
Constant	12.03***	1.451***	0.563***
	(0.708)	(0.354)	(0.185)
Control Variables	YES	YES	YES
Individual Fixed Effects	YES	YES	YES
Time Fixed Effects	YES	YES	YES
N	330	330	330
R <sup>2</sup>	0.996	0.878	0.977

To strengthen the evidence for the mediating effect, we employed a second testing method: the Bootstrap test. We used a 95% confidence threshold and 5,000 Bootstrap repeats. The mediating effect is present if the indirect impact's 95% confidence interval excludes 0. [Table 6](#) below displays the test results. In the 95% confidence interval for the GTFP bias-corrected estimates, the direct effect is  $[-5.588402, -3.502236]$  and the indirect effect is  $[-2.116027, -0.0192021]$ ; neither interval includes 0. Furthermore, the direct and indirect effects in the GTFP percentile-based confidence intervals also do not include 0, indicating that the mediating effect exists. The mediation effect test for IS follows the same logic as that for GTFP. Notably, for Industrial Structure (IS), both the bias-corrected and percentile-based confidence intervals for both direct and indirect effects exclude zero, indicating statistically significant impacts, indicating that the mediation effect for IS exists. This further validates Hypotheses 2 and 3.

**Table 6.** Results of the Bootstrap Test

Effect	BootSE	Percentile95%		Bias-corrected95%	
Indirect Effect of GTFP	0.530486	-2.107133	-0.014959	-2.116027	-0.0192021
Direct Effect of GTFP	0.53596134	-5.673403	-3.546152	-5.588402	-3.502236
Indirect Effect of IS	0.47466503	-2.442097	-0.5591736	-2.464313	-0.5784766
Direct Effect of IS	0.33029224	-3.351645	-2.065814	-3.343665	-2.053449

### 4.3. Robustness Tests

#### 4.3.1. Replacing Key Explanatory Variables

The entropy-weight approach was used to generate the e-commerce index of development in the previous section. To mitigate potential biases stemming from relying solely on a single measurement technique, we re - evaluated the degree of growth of the digital economy (denoted as  $DE_{pca}$ ) by employing examination of main components (PCA) as an alternative to the previously used variable for the same purpose. The results of this re - measurement are presented in column (1) of [Table 7](#). Interestingly, the coefficient representing the level of digital economic development was statistically significant at the 1% level. This finding aligns with the previous results and further supports the robustness of the baseline regression.

#### 4.3.2. Replacing the Dependent Variables

In this paper, the dependent variables consist of provincial data on carbon dioxide emissions and GDP, which have been log-transformed. We employ per capita carbon emissions ( $\ln CI_1$ ) as a proxy for regional carbon emission intensity, given that varying levels of development and population densities across regions necessitate such a nuanced measure. The results align closely with those previously reported and have successfully passed the 1% significance test, as evidenced in column (2) of [Table 7](#) below, thereby underscoring the robustness of our findings.

#### 4.3.3. Endogeneity Issues

Endogeneity is an inevitable issue in data analysis. The instrumental variables method is one of the most common approaches to addressing this problem. This paper adopts a distance metric commonly used in the literature: the method employs the spherical distance formula to calculate the geodesic distance between the capital city of each province and Shenzhen, utilizing the precise latitude and longitude coordinates of each provincial capital as input parameters. As Shenzhen is Leading the way in the growth of China's digital economy, home to numerous leading enterprises in the sector, and boasts abundant digital economy data and a development model with broad reference value, the distance from Shenzhen can reasonably reflect barriers to the flow of information and technology, as well as differences in the spillover effects. As a result, the spherical distance from Shenzhen is chosen as the instrumental variable. We selected the interaction term between the number of broadband Internet subscribers (a time-dependent

variable). Additionally, the spherical distance from Shenzhen to each provincial capital serves as a proxy indicator for the level of digital economy growth. This is evidenced by the findings presented in column (3) of [Table 7](#), when this interaction term is utilized as the primary explanatory variable, the findings successfully pass the 1% significance test, thereby underscoring the robustness and stability of the regression outcomes.

#### 4.3.4. Dynamic Panel Regression

In the preceding section, we conducted a comprehensive examination of how varying levels of digital economic development impact regional carbon emissions through a static panel analysis approach. To bolster the robustness of our findings, we further employed a System GMM model for testing purposes. The findings from this research are shown in [Table 7](#) below, column (4). As shown in the table, the AR(1) value of 0.000 is less than 0.1, indicating that the residuals after first-order differencing exhibit significant first-order autocorrelation. This is consistent with the dynamic panel model's assumptions, as the dynamic term leads to residuals with first-order autocorrelation. The p-value obtained from the AR(2) test stands at 0.410, which exceeds the conventional threshold of 0.1. This outcome substantiates the model's foundational assumption that "residuals exhibit no second-order autocorrelation," as it indicates the absence of significant second-order autocorrelation in the residuals subsequent to second-order differencing. The regression results are reliable and in accordance with the baseline regression that was previously described, confirming the analysis's robustness.

**Table 7.** Results of Robustness Tests

	Replacement of Core Explanatory Variable	Replacement of Dependent Variable	2SLS Regression	System GMM
	(1)	(2)	(3)	(4)
Variables	lnCI	lnCI_1	lnCI	lnCI
DE		-1.125*** (0.412)	-11.25*** (1.702)	-0.364** (0.150)
L.lnCI				1.012*** (0.0107)
DE_pca	-0.0245*** (0.00567)			
Control Variables	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES
Cons	11.66*** (0.720)	6.208*** (0.786)	11.39*** (1.420)	-0.724*** (0.197)
P-value of AR(1) Test				0.000
P-value of AR(2) Test				0.410
N	330	330	330	300
R <sup>2</sup>	0.996	0.998	0.542	

#### 4.4. Heterogeneity Analysis

This section delves into an examination of Hypothesis 4, which posits that the mitigating impact of the digital economy on regional carbon emission intensity displays variability, with geographic location and economic development level serving as pivotal lenses through which

to view this phenomenon. Notably, the effect manifests more prominently in areas situated southeast of the "Hu-Huan-Yong Line" and in regions characterized by comparatively lower levels of economic development.

#### 4.4.1. Heterogeneity by Economic Development Level

The aforementioned results verify that regional carbon emissions may be successfully reduced by the degree of digital economic growth. To learn more about whether the degree of digital economic development in different regions has varying effects on carbon emissions, we calculated the average GDP of 30 provinces and compared it with the median of total GDP. Provinces characterized by high levels of economic development exhibited GDP values surpassing the median, while those with low economic development had GDPs falling below the median threshold. For each of these distinct groups, separate regression analyses were conducted, with the results presented in columns (1) and (2) of the table below. Table 8 reveals that the low-economic-development group successfully passed the 1% significance test, whereas the high-economic-development group did not. This discrepancy may be attributed to the relatively advanced state of digital infrastructure in high-economic-development regions, which have likely entered the "diminishing marginal returns" phase concerning the digital economy's contribution to industrial decarbonization and energy efficiency. Consequently, this makes it statistically more challenging for these regions to achieve significance in the test. The significance observed in low-economic-development regions is likely because the digital economy in these areas is in a "catch-up phase." By optimizing production processes to improve energy efficiency, the carbon reduction effects become more pronounced.

#### 4.4.2. Heterogeneity on Either Side of the "Hu Huanyong Line"

**Table 8.** Results of the heterogeneity analysis

	(1)	(2)	(3)	(4)
Variables	High Economic Development	Low Economic Development	Southeast Region	Northwest Region
DE	-0.201	-2.481***	-0.553**	-2.368
	(0.444)	(0.814)	(0.275)	(1.559)
Control Variables	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES
Cons	11.44***	9.695***	12.87***	6.664***
	(0.821)	(1.538)	(0.512)	(1.656)
N	165	165	242	55
R <sup>2</sup>	0.998	0.992	0.998	0.977

The Hu Huanyong Line, often known as the Heihe–Tengchong Line, was suggested in 1935 by the famous Chinese geographer Hu Huanyong, as a pivotal reference line for delineating and comparing population density patterns across China. It serves as an important geographical boundary for revealing the patterns of China's population distribution. This paper conducts a heterogeneity analysis of 30 provinces by dividing them into regions on either side of the "Hu Huanyong Line," distinct patterns emerge. Table 8, presented below, delineates the findings in columns (3) and (4). The southeastern region has high population density and a vast market scale, giving it greater advantages in the innovative use of digital technologies and the construction of digital infrastructure. This provides stronger support for industrial integration, thereby enhancing the efficiency of reducing pollutants and conserving energy. In contrast, the northwestern region has low population density and a relatively small market scale. It limits the ability of the digital economy to reduce emissions and conserve energy, thereby rendering

its impact on carbon emissions within this particular domain statistically insignificant. This validates Hypothesis 4.

## 5. Conclusion and Recommendations

### 5.1. Research Conclusion

Based on panel data from thirty Chinese regions covering the period 2012–2023, this study methodically investigates the diverse traits and effect mechanisms of the digital economy on regional carbon emission intensity from the dual perspectives of technological spillovers and structural transformation. By constructing benchmark regression models, mediation effect models, rebound effect models, by employing a heterogeneity analysis framework, the study arrives at the following key conclusions: Regional carbon emission intensity is significantly inhibited by the expansion of the digital economy. The projected coefficient for the digital economy development level (DE) is significantly negative at the 5% significance level, according to the findings of the baseline regression analysis, irrespective of whether control variables are incorporated or whether individual and time-fixed effects are accounted for. This result suggests that the growth of the digital economy can increase the effectiveness of local initiatives to reduce carbon emissions, thereby providing robust support for Hypothesis 1. A rising degree of urbanization significantly elevates carbon emission intensity, whereas, among the array of control factors, increasing levels of economic development, heightened government intervention, enhanced labor productivity, and more stringent environmental regulation intensity collectively help lower the intensity of carbon emissions.

The digital economy indirectly mitigates the level of carbon emissions in a region through two primary mechanisms: technological spillovers and structural transformation. Mediation tests reveal that both The modernization of the industrial structure and the enhancement of green total factor productivity serve as significant intermediary channels. In particular, by encouraging increased investment in research and development (R&D) and propelling technological innovation by easing the shift of industries toward high-value-added, low-pollution forms, the digital economy simultaneously promotes green total factor productivity and industrial structure upgrading, thereby indirectly achieving carbon emission reductions, which validates Hypotheses 2 and 3. The robustness of the mediation effects is further corroborated by the outcomes of bootstrap experiments, which provide additional confidence in the stability and reliability of the observed relationships.

The influence of the digital economy on carbon emission intensity exhibits considerable regional variation. Notably, in regions characterized by sluggish economic growth, the digital economy's role in mitigating carbon emissions achieves statistical significance at the 1% level, underscoring its substantial contribution. Conversely, in areas with robust economic development, the digital economy's impact on reducing carbon emissions fails to attain statistical significance, indicating a less pronounced effect. This disparity aligns with the notion that in highly developed regions, the digital economy may be experiencing "diminishing marginal returns" in terms of its contribution to carbon emission reductions. When classified according to the "Hu-Huan-Yong Line," In the southeastern regions, the digital economy has demonstrated a statistically significant reduction in carbon emissions, achieving a 5% level of significance, whereas it was not significant in the northwestern region. This reflects the constraining effects of geographical location, market size, and digital infrastructure on carbon emission reduction, thereby validating Hypothesis 4.

Moreover, robustness tests and endogeneity corrections confirm that, even when key explanatory variables are substituted or alternative modeling approaches are employed, the moderating influence of the digital economy on regional carbon emission intensity remains robust and substantial, substituting dependent variables, adopting the instrumental variables

method (spherical distance from provincial capitals to Shenzhen and interaction terms), and using a dynamic panel model (systematic GMM). This demonstrates that the research conclusions are highly reliable.

## 5.2. Policy Recommendations

To effectively harness the potential of the digital economy in reducing carbon emissions and advancing China's "dual carbon" goals—namely, achieving carbon peak by 2030 and carbon neutrality by 2060—the following policy recommendations are proposed based on the findings of this study.

To establish a solid foundation for carbon emission reduction, it is crucial to accelerate the development of digital economic infrastructure. This entails increasing financial investment in digital infrastructure projects, with a particular focus on promoting the balanced and nationwide deployment of emerging technologies such as large-scale data centers, industrial internet platforms, and 5G networks, with a particular emphasis on regions with lower levels of economic development and the northwestern regions along the "Hu-Huan-Yong Line" to narrow the digital divide. Conversely, increase the growth of the data factor market, encourage open sharing and the safe, orderly flow of data resources, and enhance the institutional framework for the development of the digital economy. By doing this, we may promote a more sustainable and low-carbon growth path by improving the effectiveness of data factor allocation and offering strong support for the smooth integration of the digital and physical economies.

To fully harness the dual intermediary effect and enhance the synergy between industrial transformation and technological innovation, the following strategies are recommended: First, give green and low-carbon technology research and development (R&D) top priority. This can be achieved by fostering collaboration between research institutions and digital enterprises to devise innovative low-carbon solutions grounded in big data analytics and artificial intelligence. To promote innovations and raise green total factor production, it is also essential to increase funding for research and development projects in clean energy technologies, carbon capture and storage (CCS), and other pertinent disciplines. Second, encourage the digital transformation of industrial structures, with an emphasis on developing low-carbon service models like digital services and smart logistics. This involves encouraging the seamless integration of digital technologies with the tertiary sector, thereby facilitating a more sustainable and efficient industrial ecosystem. Accelerate the intelligent transformation of traditional manufacturing, promote new production models such as smart production and flexible manufacturing, and reduce the proportion of energy-intensive industries; assist small and medium-sized businesses in their shift to low-carbon and high-end development through platforms such as digital inclusive finance and e-commerce.

Implement differentiated regional policies to optimize carbon emission reduction outcomes. Differentiated policies will be formulated based on the development traits of various regions: For regions with advanced economic development, the primary objectives will encompass promoting the profound integration of the digital economy with low-carbon technologies, surmounting the "diminishing marginal returns" bottleneck that presently prevents more carbon emissions reduction, encouraging the growth of digital low-carbon enterprises, and creating models for carbon emissions reduction in the digital economy sector. Additionally, these regions should leverage the "late-mover advantage" inherent in the digital economy to attract the relocation of digital industries. Thus, via the digital transformation of conventional sectors, a synergistic development of economic growth and carbon emissions reduction is achieved. Regions southeast of the "Hu-Huan-Yong Line" should further integrate digital technological innovation with industrial sectors to maximize the efficacy of carbon emission reduction efforts. Meanwhile, in the northwestern regions, this objective can be attained by

augmenting investments in the establishment of digital infrastructure, nurturing regional markets for the digital economy, and drawing in digital enterprises through strategic policy guidance.

Furthermore, to facilitate the exchange of carbon emission reduction expertise and enhance interregional cooperation within the digital economy sphere, it is imperative to establish a cross-regional collaborative mechanism. Areas with more advanced economic growth, such as those in the southeast, should be incentivized to disseminate digital technologies, share managerial expertise, and transfer industrial resources to regions with lower economic development, thereby collectively contributing to the reduction of carbon emissions associated with the digital economy. Such as the northwestern regions, thereby promoting the cross-regional diffusion of digital low-carbon technologies. Create a regional exchange platform for digital economy carbon reduction to share successful cases of integrating the digital economy with carbon reduction, foster complementary advantages among regions, and generate a nationwide synergy for digital economy carbon reduction.

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