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The Impact of the Digital Economy on Low-Carbon Total Factor Productivity: Evidence from Chinese Cities

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Abstract: *Based on panel data from 279 prefecture-level cities in China from 2011 to 2020, this study employs the Undesirable Output-Super Efficiency SBM model to measure the level of Low-Carbon Total Factor Productivity (CTFP), the empirical analysis reveals the spatiotemporal heterogeneous impact of the digital economy on CTFP. The core findings of this research are as follows: First, the development of the digital economy has a significant promoting effect on CTFP, but there exists certain spatial and temporal heterogeneity. Specifically, the enhancing effect of the digital economy on urban CTFP is more pronounced in central and western cities than in eastern cities; stronger in southern cities compared to northern cities; and higher in low-carbon pilot cities than in non-pilot cities, the promoting effect of the digital economy on CTFP shows a periodic attenuation trend corresponding to the Five-Year Plans for National Economic and Social Development. Based on the above findings, this study proposes the following policy recommendations: establishing a hierarchical and categorized digital infrastructure system, implementing region-specific digital decarbonization pathways, and enhancing digital environmental governance mechanisms.*

Keywords: *Digital Economy, CTFP, SBM Model*

1. Introduction

Against the backdrop of China's "Dual Carbon" goals, coordinating economic growth with green transformation has become a central issue. The digital economy—defined by data as a critical factor, modern information networks as its main carrier, and the integration of information and communication technologies—has rapidly evolved as a major economic form following agricultural and industrial economies, providing new momentum for addressing this challenge. According to the Digital China Development Report (2024), the value-added of China's core digital economy industries accounted for 10% of GDP in 2024, with mobile IoT users reaching 2.656 billion, generative AI patents representing 61.5% of the global total, and total data production growing by 25% year-on-year to 41.06 ZB. Through its enabling and driving effects, the digital economy has become a crucial force in boosting CTFP [1-2], making research on its impact essential for promoting high-quality growth and sustainable development in China.

Throughout the entire chain from production to consumption, the digital economy plays an active role in reducing carbon emissions and improving energy efficiency, laying the foundation for a green, low-carbon economy. Firstly, it generates direct effects by optimizing resource allocation and enhancing energy efficiency. Digital technologies such as the Internet of Things and big data are integrated into energy systems and production processes, enabling more precise monitoring, scheduling, and management—thereby reducing energy consumption per unit output and carbon emission intensity at the source [3-4]. Secondly, the digital economy significantly lowers the cost and barriers to knowledge acquisition, talent mobility, and collaborative R&D, facilitating green technology innovation and promoting the development, diffusion, and application of advanced emission reduction technologies, which in turn drives the improvement of carbon total factor productivity [5-6].

The impact of the digital economy on carbon total factor productivity exhibits complex spatial spillover effects and significant regional heterogeneity. Research shows that the development of the digital economy not only enhances local CTFP but also generates positive spatial spillover effects on neighboring regions through technology diffusion and industrial chain linkages. Moreover, this

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facilitating effect is more pronounced in regions with advanced digital infrastructure, higher levels of human capital, and more developed financial markets, suggesting that the "digital divide" may exacerbate imbalances in green development across regions [2]. Based on data from the power industry, it has been found that digital transformation improves total factor productivity through optimized resource allocation and technological progress, with more substantial effects observed in enterprises with a higher share of clean energy [7-8].

In summary, existing research has laid a foundation for understanding the impact of the digital economy on carbon total factor productivity, yet several limitations remain: 1) Most current studies rely on provincial-level data, with limited use of more granular city-level administrative samples. 2) Traditional measures of total factor productivity often fail to incorporate environmental and resource constraints, making them inadequate for assessing green and low-carbon development. 3) While many studies consider spatial heterogeneity, few delve into temporal heterogeneity in depth. The marginal contributions of this study are as follows: First, using micro-level city data, it incorporates energy consumption and carbon emissions into the accounting framework and applies an Undesirable Output-Super Efficiency SBM model to measure carbon-inclusive total factor productivity (CTFP). Second, it integrates the digital economy and low-carbon development within a unified analytical framework to examine the influence of the digital economy on CTFP, incorporating spatiotemporal heterogeneity tests.

2. Theoretical Foundation and Research Hypotheses

2.1 Basic Mechanisms

The digital economy enhances urban carbon total factor productivity (CTFP) through dual pathways: technological empowerment and application-driven effects. Specifically, in terms of technological empowerment, digital infrastructure—such as 5G, the Internet of Things (IoT), and cloud computing—significantly reduces the costs of knowledge acquisition and collaborative innovation, providing strong support for the development and diffusion of green technologies, thereby directly shifting the production frontier outward [5]. Regarding application-driven effects, IoT technologies in digital industries enable real-time monitoring and precise regulation of energy consumption and carbon emissions, while digital inclusive finance alleviates financing constraints and directs capital more efficiently toward green innovation projects, substantially improving resource allocation efficiency[2]. Based on this, we propose Hypothesis 1:

Hypothesis1: The digital economy can significantly promote urban carbon total factor productivity.

2.2 Heterogeneous Mechanisms

The carbon productivity enhancement effect of the digital economy is not uniformly distributed but is significantly moderated by regional characteristics and policy environments. From a regional perspective, eastern China—benefiting from well-established digital infrastructure and agglomeration of high-tech industries—exhibits stronger technological empowerment effects. In contrast, northeastern, central, and western regions rely more on application-driven effects through digital upgrading of traditional industries [9]. Moreover, significant differences in energy structure, industrial composition, and marketization levels between northern and southern cities lead to varying impacts of the digital economy, particularly in southern cities.

Furthermore, policy environment and economic planning play critical roles. Low-carbon pilot cities, with stricter environmental regulations and incentive mechanisms, demonstrate a notable "policy-technology" synergistic effect with digital technologies. Meanwhile, cities that explicitly emphasize the deep integration of digital and green transformation in their national economic and social development plans provide a more favorable institutional environment for industrial green upgrading[10]. Accordingly, we propose Hypothesis 2:

Hypothesis2: The impact of the digital economy on synergistically promoting carbon reduction, pollution control, green expansion, and economic growth is heterogeneous.

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3. Specification, Variable analysis and data acquisition

3.1 Model Specification

3.1.1 Non-Desirable Output - Super-Efficiency SBM Model

This study evaluates the carbon total factor productivity of China's industrial sectors by integrating Tone's super-efficiency approach with a methodology for handling undesirable outputs[11]. The standard SBM model with undesirable outputs yields efficiency values that are less than or equal to 1, making it unable to further evaluate or compare efficient decision-making units (DMUs) with efficiency scores exceeding 1[12-13]. To simultaneously account for both undesirable outputs and super-efficiency, this paper draws on methods from representative scholars[14], and constructs a super-efficiency SBM model that incorporates undesirable outputs. The model is specified with inputs (capital, labor, energy), a desirable output (GDP), and an undesirable output (carbon emissions). The constructed model is as follows:

$$\rho = \min_{\lambda,\bar{x},\overline{y^g},\overline{y^b}} \frac{\sum_{i=1}^{m} \frac{\overline{x_t}}{x_{io}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{\overline{y_r^g}}{y_{ro}^g} + \sum_{k=1}^{s_2} \frac{\overline{y_k^b}}{y_{ko}^b}\right)} \tag{1}$$

$$\begin{aligned} s.t. X &\geq \sum_{\substack{j=1 \\ j\neq 0}}^{L} \lambda_j x_j \\ \overline{Y^g} &\leq \sum_{\substack{j=1 \\ j\neq 0}}^{L} \lambda_j y_j^g \\ \overline{Y^b} &\leq \sum_{\substack{j=1 \\ j\neq 0}}^{L} \lambda_j y_j^b \end{aligned} \tag{2}$$

$$\begin{aligned} &\overline{X} \geq x_o, \overline{Y^g} \leq y_o^g, \overline{Y^b} \geq y_o^b \\ &\overline{Y^g} \geq 0, \overline{Y^b} \geq 0, \;\; L \leq e\lambda \leq \mu, \lambda_j \geq 0 \end{aligned} \tag{3}$$

$$\begin{aligned} \overline{x_t} &= x_{io} + s^{-}(i = 1,\ldots,m) \\ \overline{y_r^g} &= y_{ro}^g - s^g(r = 1,\ldots,s_1) \\ \overline{y_k^b} &= y_{ro}^b - s^g(r = 1,\ldots,s_1) \end{aligned} \tag{4}$$

In this equation, $\overline{x}$, $\overline{y_r^g}$, and $\overline{y_k^b}$ represent the projected input and output values of the evaluated unit, while x_{io}, y_{ro}^g, and y_{ko}^b are the corresponding original values.

3.1.2 Benchmark Regression Model

To empirically examine the impact of digital economy development on low-carbon total factor productivity (CTFP), we establish the following benchmark regression model:

$$GTFP_{it} = \beta_0 + \beta_1 digital_{it} + \gamma X_{it} + \delta_i + \varphi_t + \varepsilon_{it} \tag{5}$$

$GTFP_{it}$ represents the low-carbon total factor productivity of city i in year t; $digital_{it}$ denotes the digital economy development level of city i in year t; X_{it} signifies the vector of control variables; β_0 indicates the constant term; β_1 and γ represent the coefficients of corresponding variables; δ_i captures city-specific fixed effects; φ_t accounts for time-specific effects; ε_{it} stands for the random error term.

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3.2 Variable analysis and data acquisition

3.2.1 Dependent Variable: Low-Carbon Total Factor Productivity (CTFP)

Capital input, labor input, and energy input are selected as input indicators; GDP and carbon emissions are designated as the desirable output and undesirable output, respectively. Carbon total factor productivity is measured using the super-efficiency SBM model. As shown in Table 1.

Table 1 Indicator System for Carbon Total Factor Productivity.

Primary indicators	Secondary indicators
Input indicators	Capital input
	Labor input
	Energy input
Output indicators	Desired output: GDP
	Undesirable output: Carbon Emissions

3.2.2 Core Explanatory Variable: Digital Economy

With reference to relevant studies on the digital economy[15–16], an indicator system for assessing the level of digital economy development was constructed based on three dimensions: digital infrastructure, digital industry development, and digital financial inclusion. The principal component analysis (PCA) method was employed for measurement, as shown in Table 2.

Table 2 Comprehensive Evaluation Indicator System for Digital Economy.

Criterion layer	Indicator layer	Indicator description(Units)
Digital infrastructure	Broadband internet infrastructure	Number of international internet users(Households)
	Mobile internet infrastructure	Number of mobile phone users (households)
Digital industry development	Development of the information industry	Number of employees in information transmission, Computer services, and Software industry (Tens of Thousands of People)
	Output of the telecommunications industry	Total volume of telecommunications services (Ten Thousand Yuan)
Digital inclusive finance	Coverage breadth	Index of coverage breadth for digital inclusive finance
	usage depth	Index of usage depth for digital inclusive finance
	Degree of digitalization	Index of digitalization degree for digital inclusive finance

Drawing on existing scholarly work, the control variables were defined as follows: the level of industrial development is represented by the proportion of the secondary and tertiary industries in GDP [17]; the urbanization level is measured by the proportion of urban population to the total population [2]; the financial development level is indicated by the ratio of financial institution loan balances to GDP[6]; scientific research input is expressed as the proportion of R&D expenditure in GDP [5]; and the GDP deflator was applied to remove the impact of price changes, thereby accurately reflecting the real economic development level[10].

3.2.3 Data Sources

Taking into account data availability and continuity, this study utilizes a panel of 279 prefecture-level cities in China from 2011 to 2020 as the research sample. Cities such as Tongren, Hami, Chaohu, Shigatse, Nyingchi, Shannan, and Hong Kong, Macao, and Taiwan were excluded due to data unavailability or administrative mergers and adjustments. Data were primarily drawn from the China City Statistical Yearbook (2012–2021), China Statistical Yearbook for Regional Economy (2012–2021), China Environmental Statistical Yearbook (2012–2021), and China Urban Construction Statistical Yearbook (2012–2021), as well as municipal statistical yearbooks, national economic and social development bulletins, official statistical websites, the CEIC database, and the WIND database. Missing values were supplemented using linear interpolation. Descriptive statistics are presented in Table 3.

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Table 3 Descriptive Statistics.

Variables	Sample size	average value	Standard deviation	Minimum value	Maximum value
GTFP	2790	0.5144	0.1951	0.1604	1.3749
digital	2790	0.5596	0.1426	0.0879	1.7652
industry	2790	1.0253	0.5778	0.1136	5.3482
urb	2790	0.5538	0.1479	0	1
pgdp	2790	10.7298	0.5659	8.8416	13.0557
tech	2790	1.488	2.8624	0.0103	31.5868
capital	2790	2.3064	1.2083	0.5009	21.3015
trade	2790	2.2308	1.1564	0	5.522

4. Empirical Results and Analysis

4.1 Analysis Results of the Benchmark Regression Model

Table 4 presents the baseline regression results. Column (1) shows the results without control variables. After gradually incorporating control variables in Columns (2) to (5), the regression coefficient of the digital economy remains positive and significant. In Column (5), the regression coefficient of the digital economy's impact on carbon total factor productivity is 0.4293, which is significant at the 1% level, indicating that the digital economy has a significantly positive promoting effect on carbon total factor productivity (CTFP).

Table 4 Benchmark Regression Analysis.

Variables	(1) CTFP	(2) CTFP	(3) CTFP	(4) CTFP	(5) CTFP
digital	0.4086***	0.4090***	0.4146***	0.4246***	0.4293***
	(7.9150)	(7.9323)	(8.0312)	(8.0125)	(8.0961)
industry		-0.0466***	-0.0466***	-0.0345*	-0.0337*
		(-2.6487)	(-2.6517)	(-1.8486)	(-1.8112)
urb			0.1766*	0.1381	0.1339
			(1.8402)	(1.4273)	(1.3845)
pgdp				0.1062***	0.1104***
				(3.7642)	(3.9033)
tech				0.0070*	0.0071*
				(1.8444)	(1.8602)
capital				0.0197***	0.0195***
				(2.7183)	(2.6957)
trade					0.0240*
					(1.8690)
Constant	0.2411***	0.2749***	0.1826***	-0.9653***	-1.0659***
	(7.3365)	(7.8059)	(2.9802)	(-3.1796)	(-3.4588)
Observations	2, 790	2, 790	2, 790	2, 790	2, 790
R-squared	0.0570	0.0596	0.0609	0.0683	0.0696
Number of id	279	279	279	279	279

Note: *, **, and***indicate significance levels of 10%, 5%, and 1%, respectively. Numbers in parentheses are t-statistics. This applies to all subsequent tables.

4.2 Spatiotemporal Heterogeneity Analysis

4.2.1 Examinating Spatial Heterogeneity

According to the standard classification of China's four major geographic regions, the cities are divided into eastern, central, western, and northeastern areas. The heterogeneity test results for these regional groupings are shown in Table 5. While the digital economy exhibits a certain enhancing effect on CTFP across all regions, its impact demonstrates notable regional variations, with a more pronounced effect observed in central and western cities. This stronger influence in central and western cities may be attributed to their role in undertaking industrial relocation from eastern regions, where digital technologies significantly enable and substitute traditional resource-intensive industries. In northeastern

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cities, the effect may stem from the digital transformation of equipment manufacturing and heavy industries in these traditional industrial bases. Eastern cities, dominated by high-tech and advanced manufacturing sectors, also experience a measurable—though comparatively moderated—improvement in low-carbon total factor productivity through digital economy development.

Table 5 Regression Results of the Four Major Regions.

Variables	(1)	(2)	(3)	(4)
Regions	Eastern Cities	Central Cities	Western Cities	Northeastern Cities
digital	0.3474***	0.5107***	0.5129***	1.1402**
	(4.0506)	(3.6968)	(4.2141)	(2.4119)
Controlled variable	Control	Control	Control	Control
Region fixed	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-0.7810	-0.2289	-1.9206**	-0.9187
	(-1.3596)	(-0.3044)	(-2.5017)	(-0.5284)
Observations	860	790	800	340
R-squared	0.0758	0.1055	0.0775	0.1076
Number of id	256	271	266	199

Based on the Qinling–Huaihe River boundary, cities are categorized into southern and northern China. As shown in Table 6, the digital economy significantly promotes carbon total factor productivity in both regions, though its effect is more pronounced in southern cities. This disparity can be attributed to the stronger economic foundation, better digital infrastructure, and more active green technology innovation in southern cities, which amplify the low-carbon transition driven by digitalization. In contrast, northern cities—with a higher proportion of traditional industries and greater reliance on coal in the energy mix—experience a slower transition, which constrains the emission reduction potential of the digital economy. In accordance with the Notice on Carrying out Pilot Work for Low-carbon Provinces and Cities (NDRC Document [2010] No. 1587) and the Second Notice on Carrying out Pilot Work for Low-carbon Provinces and Cities (NDRC Document [2012] No. 3760) issued by the National Development and Reform Commission, cities are categorized into low-carbon pilot cities and non-pilot cities. The regression results in Table 6 indicate that the digital economy has a significantly positive impact in both groups, yet the regression coefficient is higher in low-carbon pilot cities. This suggests that the environmental policies in pilot cities—through mandatory emission reduction targets—compel high-energy-consuming enterprises to adopt digital technologies (such as IoT and big data) for refined management and energy-saving upgrades, thereby enhancing carbon total factor productivity.

Table 6 Regression Results of North–South Cities.

Variables	(1)	(2)	(1)	(2)
Regions	*Southern cities*	*Northern cities*	Low-Carbon pilot cities	Non-Low-Carbon pilot cities
digital	0.4474***	0.4070***	0.5182***	0.4519***
	(6.3753)	(4.4682)	(7.1163)	(5.1553)
Controlled variable	Control	Control	Control	Control
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	-1.1432**	-0.8784*	-2.0623***	-0.8586**
	(-2.5554)	(-1.7620)	(-3.6644)	(-2.1044)
Observations	1, 510	1, 280	978	1, 812
R-squared	0.0780	0.0775	0.1117	0.0647
Number of id	279	279	118	210

4.2.2 Examinating Temporal Heterogeneity

Using 2015 as a dividing point, this study finds that the promoting effect of the digital economy on low-carbon total factor productivity (CTFP) exhibits a phased attenuation characteristic. As shown in Table 7, during the 12th Five-Year Plan period (2011–2015)—a phase of rapid and relatively unregulated growth in the digital economy—its positive impact on CTFP was more pronounced, which also coincided with the concentrated release of policy benefits from the first batch of low-carbon pilot initiatives. In contrast, during the 13th Five-Year Plan period (2015–2020), the promoting effect on CTFP slowed, influenced by the diminishing marginal benefits of digital economy expansion and changes in the external environment such as Sino-US trade tensions. These findings indicate that the impact of the digital economy on CTFP is sensitive to policy cycles and vulnerable to external shocks.

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Table 7 Regression Results of Temporal Heterogeneity.

Variables	(3) from 2011 to 2015	(4) from 2015 to 2020
digital	1.0072***	0.3749***
	-6.6919	-6.0537
Controlled variable	Control	Control
Region FE	Yes	Yes
Year FE	Yes	Yes
Constant	0.0074	-2.3689***
	-0.0124	(-3.8223)
Observations	1, 395	1, 674
R-squared	0.0808	0.0538
Number of id	279	279
R-squared	-0.16	-0.145
F	8.831	6.555

5. Conclusions and Recommendations

Based on panel data from 279 prefecture-level and above cities in China (2011–2020), this study constructs an indicator system for carbon total factor productivity (CTFP) and a comprehensive evaluation framework for the digital economy. Using the undesirable output–super efficiency SBM model to measure CTFP, we empirically analyze the heterogeneous impact of the digital economy on CTFP from both spatial and temporal perspectives. The results indicate that the digital economy has a significant promoting effect on CTFP, albeit with notable regional and temporal heterogeneity. Spatially, the effect is stronger in central and western cities than in eastern cities, more pronounced in southern cities than in northern cities, and higher in low-carbon pilot cities than in non-pilot cities. Temporally, the promoting effect exhibits a cyclical attenuation pattern corresponding to China's Five-Year Plans for National Economic and Social Development.

This study proposes the following policy recommendations: First, construct a tiered and categorized digital infrastructure system to guide cities in deploying infrastructure tailored to local conditions—such as promoting industrial Internet in manufacturing hubs, developing green data centers in central and western regions, and advancing new infrastructure like computing power networks in eastern areas. Second, implement region-specific digital carbon reduction pathways by driving digital upgrades in heavy industries, integrating digital technologies with clean energy development, breaking through key technological barriers, and establishing cross-regional cooperation mechanisms. Third, improve digital environmental governance through building smart environmental protection platforms, introducing incentive policies for digital decarbonization, and promoting the digital trading of carbon emission rights.

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