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Study on the Impacts of City Digital Economy on Green Total Factor Productivity

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Abstract

Based on existing studies of the digital economy and green total factor productivity, combined with sustainable development, network effect theory, information asymmetry theory and new economic geography, this paper analyzes the impact mechanism of the digital economy on green total factor productivity. Using the entropy weight method, this study measures the digital economy development of 280 prefecture-level cities in China from 2013 to 2022. The super-efficient SBM-GML model is used to calculate green total factor productivity and its spatiotemporal trends. Fixed effects and spatial Durbin models are constructed to test the impact empirically. Results show that: (1) China's urban digital economy has been improving overall with a converging gap between cities, but significant regional heterogeneity still exists. (2) Urban green total factor productivity shows a fluctuating upward trend, driven by technological progress and efficiency changes, but their synergy is not yet formed. (3) The digital economy significantly promotes green total factor productivity with regional and developmental heterogeneity, especially in coastal areas and high-productivity regions. It functions through upgrading industrial structure and improving human capital.

Keywords: Digital economy, Green total factor productivity, Super-efficiency SBM-GML, Spatial Durbin Model.

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1. Introduction

High-quality development is the primary task in comprehensively building a modern socialist country, and promoting green and low-carbon economic and social development is a key link in achieving high-quality development. The Third Plenary Session of the 20th Central Committee of the Communist Party of China emphasized "accelerating the comprehensive green transformation of economic and social development," and pursuing green development has become the main goal of economic development planning for the country and governments at all levels. How to improve the efficiency of urban green economy is one of the core issues in fully implementing Xi Jinping's economic thought and Xi Jinping's ecological civilization thought, and achieving high-quality development. As China's economy enters a new normal of innovation-driven development, the digital economy has gradually become an important support for promoting high-quality economic development. According to statistics from the China Academy of Information and Communications Technology, the added scale of China's core digital economy industries reached 12.7 trillion yuan in 2023, accounting for 9.9% of GDP. Therefore, in recent years, how to effectively utilize the digital economy to promote China's high-quality development and improve the efficiency of urban green economy has become an important topic widely discussed by the government and all sectors of society.

The digital economy, powered by cutting-edge technologies like big data, cloud computing, and artificial intelligence, is injecting new momentum into high-quality development. Research on the digital economy primarily focuses on theoretical frameworks, indicator measurement, and its economic benefits and governance challenges. The term "digital economy" was first coined by Tapscott, later expanded upon by Negroponte in his seminal work Being Digital, which posits that digital existence - a paradigm shift driven by digitization, informatization, and networking - has fundamentally transformed human production and living patterns. Currently, the digital economy is undergoing rapid evolution and deep integration with the national economy. Its dynamic nature makes defining its essence particularly challenging (Sutherland & Jarrahi, 2018). In terms of measurement methodologies, there currently exists no authoritative indicator to quantify the development level of the digital economy. Regarding economic benefits, the digital economy has catalyzed the emergence of digital trade, achieved deep integration with the real economy, driven technological innovation and industrial chain upgrading, optimized resource allocation, and accelerated sustainable economic development (Pan et al., 2022). It has gradually become a key driver of economic growth and a vital force in national economic development. However, challenges such as monopolies and the digital divide persist in its development, necessitating improvements in governance systems.

In the pursuit of high-quality economy, the traditional measure of economic growth, total factor productivity, is not enough to describe the economic factors. Some scholars have included environmental factors and energy factors in the traditional total factor productivity analysis. (Estache et al., 2004; Ming-Xu Wang et al., 2018), and it is used as the input factor of production function to study the efficiency of input and output.Some scholars argue that traditional productivity measurement methods, which only consider capital and labor while neglecting environmental and energy factors, tend to overestimate production efficiency. They propose incorporating these environmental and energy factors into the calculation of total factor productivity (TFP), which they term as green TFP (Ke-Liang Wang et al., 2020). Since the introduction of Green Total Factor Productivity (GTFP), its measurement methodologies have been continuously refined. Research on GTFP measurement primarily employs both parametric and non-parametric approaches (Chao Feng, 2017). Compared with traditional DEA models, the non-expected output SBM model effectively avoids radial and angular bias issues, offering greater flexibility. Research on factors influencing green total factor productivity (TFP) has primarily focused on environmental regulations, industrial structure upgrading, technological progress, and urbanization.

While the digital economy and green development have become prominent research areas in academia, existing literature predominantly focuses on provincial-level or regional data, with limited attention to urban studies. As an economic model driven by next-generation information technologies, the digital economy can facilitate urban green transformation through multiple pathways. Therefore, investigating the extent and mechanisms of its impact on urban green total factor productivity holds significant importance.

In view of this, this paper adopts data from 280 prefecture-level cities in China from 2013 to 2022 for research. The first innovation is to supplement the previous research scope, which was mostly focused on provincial or a single urban agglomeration, and then adopts a multi-dimensional analytical approach to the study area. From multiple perspectives such as the overall, regional, and development level, the spatiotemporal evolution characteristics, dynamic change processes, and spatial differences of cities are analyzed to reveal the distribution characteristics and sources of efficiency disparities, explore the underlying mechanisms of efficiency differences, and provide a certain basis for precise regulation of regional green development. The second innovation is that previous scholars, when measuring green total factor productivity, typically used the total electricity consumption of a city to measure energy input. Considering that energy input is not only generated by electricity consumption, this study estimates urban energy consumption by using nighttime lighting data and constructs an energy accounting model, which is more comprehensive and more accurately reflects the factual performance of green development levels.

2. Theoretical Analysis and Research Hypotheses

2.1 The Direct Impact of Digital Economy on Green Total Factor Productivity

Your text goes here. The digital economy directly impacts green total factor productivity. On one hand, environmental regulations incentivize technological innovation, while digital applications enhance production efficiency, reduce resource waste and emissions, and improve urban environmental quality and green development. On the other hand, advancements in big data and internet technologies expand public participation in environmental governance, enabling government agencies to monitor pollution sources and corporate compliance in real time, thereby ensuring effective environmental oversight. Based on these observations, this paper proposes the following hypothesis.

H1: The digital economy has a significant direct impact on green total factor productivity.

2.2 The Indirect Impact of Digital Economy on Green Total Factor Productivity

2.2.1 Upgrading of the Industrial Structure

Industrial restructuring has reduced energy consumption in traditional sectors while facilitating the transition of labor-and capital-intensive industries to mid-to-high-end sectors. This transformation has also spurred the rise of technology-intensive and digital emerging industries, which helps reduce energy consumption and enhance the overall energy efficiency of production factors. As China transitions to a high-quality economic development phase, the digital economy, as a key driver of economic growth, should fully leverage its positive role in integrating the digital and real economies, advancing industrial restructuring, and ultimately improving the overall energy efficiency of production factors.

On one hand, the digital economy will drive the upgrading of traditional industrial structures and enhance green total factor productivity. As the digital economy develops, digital technologies will be progressively applied to traditional industries, facilitating the modernization of production equipment, reducing manufacturing costs, and minimizing redundant production processes. Simultaneously, production factors will shift from inefficient sectors to high-efficiency ones, compelling traditional industries to transition toward green and intelligent operations, thereby reducing energy consumption and improving green total factor productivity. On the other hand, the digital economy will foster the growth of emerging industries and further boost green total factor productivity. The integration of the digital economy with high-tech and digital industries will make them more technology-intensive and digitally characterized. Beyond their environmental benefits of low pollution and low emissions, the application of digital technologies will strengthen their technological advantages, enhancing green total factor productivity, promoting social innovation, and accelerating the transition to a green and low-carbon society. This leads us to propose the second hypothesis.

H2a ∶ Digital Economy Promotes Urban Green Total Factor Productivity by Upgrading Industrial Structure.

2.2.2 Human Capital Level

First, the digital economy has accelerated the accumulation of human capital, thereby driving high-quality urban economic development. In this regard, the high penetration and value of the digital economy have transformed traditional production methods and industrial models. Furthermore, the growth of emerging industries has led to fundamental changes in the demand for human capital, requiring more highly skilled workers. Consequently, shifts in market demand have compelled the labor market to enhance skills, elevating the overall level of human capital in the region. The application of the internet and big data has also provided more sophisticated and convenient technological means for disseminating educational information, breaking down spatial barriers to knowledge, technology, and other information. This has optimized the skill, educational, and knowledge structures of the workforce, thereby improving labor productivity.

In addition, a higher level of human capital has become a driving force for the high-quality economic development of China's cities. Meanwhile, with the improvement of human capital, the matching of high-skilled material capital and high-level labor has led to higher labor productivity and the quality development of China's economy. Therefore, we propose the third hypothesis.

H2b: The digital economy promotes the green total factor productivity of cities by improving the level of human capital

3. Research Design

3.1 Sample Selection and Data

The research object of this paper is 280 prefecture-level cities in China, and cities with unavailable or insufficient data were excluded during sample selection. The study period selected for this paper is 2013-2022, and a two-way fixed effects model was used to systematically examine the impact of the digital economy on urban green total factor productivity. The research data mainly come from the "China City Statistical Yearbook", "China Science and Technology Statistical Yearbook", Peking University Digital Finance Research Center, CNRDS database, and the National Economic and Social Development Statistical Bulletin, with some missing data supplemented by interpolation methods.

3.2 Variable Selection and Processing

3.2.1 Dependent variable: Green Total Factor Productivity (GTFP)

The super-efficiency SBM model can effectively assess the relative efficiency of decision-making units, but the values derived from this model are only applicable to static conditions. Economic development is dynamic, and the analysis of economic laws must transcend the limitations of static evaluation (Sun et al., 2024). In 2010, Oh developed the GML index by integrating global estimation techniques with the ML index. Since then, the GML productivity index has been widely adopted by scholars worldwide (Chen et al., 2026; Zhu et al., 2023).

Based on this analysis, this paper adopts a method combining the super-efficient SBM model with the GML index to measure the green total factor productivity level of 280 prefecture-level cities in China, and the input-output indicators are selected as shown in Table 1.

Table 1: Measurement index of green total factor productivity

Indicator Type	First-level Indicator	Second-level Indicator
Input Indicator	Capital	Number of Employed Persons
	Labor	Fixed Capital Stock
	Energy	Urban Light Intensity
Output Indicator	Desirable Output	Gross Regional Product (GRP)
	Undesirable Output	Industrial Wastewater Discharge
		Industrial Sulfur Dioxide Emissions
		Industrial Smoke (Dust) Emissions

3.2.2 Explanatory variable: Digital Economy Development Level (Dig)

As a subjective weighting approach, the Analytic Hierarchy Process (AHP) is prone to randomness and uncertainty in weight distribution due to subjective factors. When evaluating indicators with significant interactions or nonlinear relationships, principal component analysis and factor analysis may produce distorted evaluation models, compromising the interpretability and accuracy of results. The entropy weighting method, by quantifying the dispersion of indicator data, effectively overcomes the limitations of subjective weighting methods influenced by human factors, as well as the challenges of linear dimensionality reduction in handling nonlinear relationships (Liu et al., 2024). Based on a systematic comparative analysis of the aforementioned methods, this study adopts the entropy weight method as the evaluation tool to systematically assess the digital economy development levels of various cities. The specific measurement indicators are presented in Table 2.

Table 2: Digital economy development level evaluation index system

First-level Indicator	Second-level Indicator	Third-level Indicator
Digital Economy Development Level	Digital Infrastructure	Number of internet users per 10,000 people
		Number of mobile phone users per 10,000 people
	Digital Industry Development	Proportion of employees in information transmission, computer services and software industry
		Per capita telecom business volume
	Digital Innovation Capacity	Number of digital economy patent applications
		Science and technology expenditure
	Digital Inclusive Finance	Digital inclusive finance index

3.2.3 Control variables

To mitigate potential biases from omitted variables and more accurately assess the net effect of the digital economy on urban green total factor productivity, this study controls for the following variables, with their names and measurement indicators listed in Table 3.

Table 3: Description of Control Variables

	Variable Name	Symbol	Description
Control Variables	Government Intervention	Gov	Fiscal expenditure / Gross Regional Product
	Financial Development Level	FDL	Total deposits and loans / Gross Regional Product
	Openness Level	OE	Total import and export of goods / Gross Regional Product
	Urbanization Rate	Urb	Urban permanent population / Total population
	Infrastructure Level	IQL	Logarithm of highway mileage

3.2.4 Mediating variables

Industrial Structure Upgrading (IS). As the industrial structure transitions from traditional primary and secondary sectors to high-value-added tertiary industries, resources are increasingly directed toward technology-intensive, low-carbon, and high-efficiency sectors. This effectively enhances overall resource allocation efficiency and drives sustained growth in green total factor productivity. To scientifically measure the extent of industrial structure upgrading, we adopt the approach proposed by Ma (2021), using the ratio of the combined value-added of the secondary and tertiary industries to the regional GDP as the metric (Ma Dongdong, 2021). Human Capital Level (HCL). As a core element of digital economy development, human capital enables highly skilled workers to significantly enhance energy efficiency and reduce pollution emissions in production processes through effective application of IoT and AI technologies, thereby driving green transformation. Following the methodology of Wang Shaohua et al. (2023), this is measured by the ratio of students enrolled in regular higher education institutions per million population (Wang Shaohua et al., 2023).

3.3 Model Construction

3.3.1 Baseline Regression Model

To test the aforementioned hypothesis, we construct a benchmark model for the digital economy's impact on GTFP.

$$lnGTFP_{i,t} = \alpha_0 + \alpha_1 lnDig_{i,t} + \alpha_2 lnX_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \tag{1}$$

Here *i* denotes the province, *t* the year, *GTFP* the green total factor productivity, *Dig* the digital economy development level. *X* represents a series of control variables, including government intervention (*Gov*), financial development level (*FDL*), openness to the outside world (*OE*), urbanization rate (*Urb*), and infrastructure level (*IQL*). α0 is the constant term, μi the individual fixed effect，νt the time fixed effect, εi,t the random disturbance term.

3.3.2 Baseline Regression Model

The preceding analysis demonstrates that industrial structure upgrading and human capital level constitute the three pivotal pathways through which the digital economy influences the enhancement of green total factor productivity. This study introduces two mediating variables—industrial structure upgrading (*IS*) and human capital level (*HCL*)—and employs a mediation effect model to investigate the underlying mechanisms of the digital economy's impact on green total factor productivity. The specific model framework is presented as follows:

$$lnMed_{i,t} = \gamma_0 + \gamma_1 lnDig_{i,t} + \gamma_2 lnX_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \tag{2}$$

$$lnGTFP_{i,t} = \beta_0 + \beta_1 lnDig_{i,t} + \beta_2 lnMed_{i,t} + \beta_3 lnX_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \tag{3}$$

In this formula, Med serves as an intermediary variable, encompassing industrial structure upgrading (*IS*) and human capital level (*HCL*).

4. Empirical Results and Analysis

4.1 Baseline Regression Analysis

The regression results indicate that the digital economy's coefficient remains significantly positive at the 1% level when only the city and year fixed effects are controlled. After progressively introducing other control variables, the coefficient still maintains a significant positive value at the 1% level, with estimated values ranging from 0.468 to 0.527. The coefficient magnitude remains stable and the significance is robust, demonstrating that the digital economy exerts a stable and significant positive impact on urban GTFP. This finding aligns with theoretical expectations, thereby validating Hypothesis 1.

Table 4: Baseline regression results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	lnGTFP	**lnGTFP**	**lnGTFP**	**lnGTFP**	**lnGTFP**	**lnGTFP**
lnDig	0.468***	0.487***	0.475***	0.474***	0.525***	0.527***
	(15.756)	(16.611)	(13.581)	(13.358)	(14.031)	(14.175)
lnGov		-0.278***	-0.273***	-0.274***	-0.162***	-0.137***
		(-8.030)	(-7.712)	(-6.918)	(-3.393)	(-2.882)
lnFDL			0.031	0.031	0.075	0.093*
			(0.648)	(0.637)	(1.531)	(1.929)
lnOE				0.002	0.007	0.004
				(0.129)	(0.495)	(0.312)
lnUrb					-0.667***	-0.969***
					(-4.192)	(-5.728)
lnIQL						-1.406***
						(-4.855)
cons	-0.738***	-0.967***	-1.011***	-1.009***	-2.010***	1.859***
	(-13.059)	(-16.029)	(-11.009)	(-10.799)	(-17.348)	(2.969)
Individual Fe	Y	Y	Y	Y	Y	Y
Year Fe	Y	Y	Y	Y	Y	Y
N	2800	2800	2800	2800	2800	2800
R^2	0.180	0.180	0.185	0.185	0.190	0.191

4.2 Robustness checks

The robustness test of the regression results is carried out under the condition of lagging core explanatory variables and tail-trimming of 1% and 5% on the sample. The test results show that the estimated coefficients of digital economy remain significantly positive, which indicates that the empirical results of this paper are robust.

Table 5: Robustness Test Results

Variables	(1) lnGTFP	(2) lnGTFP	(3) lnGTFP
lnDig	0.527***	0.543***	0.595***
	(14.18)	(13.09)	(14.35)
lnGov	-0.137***	-0.135**	-0.117**
	(-2.88)	(-2.56)	(-2.42)
lnFDL	0.093*	0.085	0.065
	(1.93)	(1.53)	(1.25)
lnOE	0.004	0.004	0.001
	(0.31)	(0.27)	(0.06)
lnUrb	-0.969***	-0.985***	-1.005***
	(-5.73)	(-5.45)	(-5.83)
lnIQL	-1.406***	-1.431***	-1.275***
	(-4.85)	(-4.30)	(-4.26)
cons	1.859***	1.946***	1.703***
	(2.97)	(2.74)	(2.65)
Individual Fe	Y	Y	Y
Year Fe	Y	Y	Y
R^2	0.191	0.191	0.188

5. Further analysis

5.1 Heterogeneity Analysis

5.1.1 Regional heterogeneity

China is divided into coastal and inland regions. According to the results in columns (1) and (2) of Table 6, the impact of the digital economy on green total factor productivity is more pronounced in coastal areas. The reasons for this difference may be as follows: First, compared to inland regions, coastal areas have a more solid development foundation and a higher level of digital technology application, which enables the digital economy to play a greater role in driving growth in coastal areas. Second, coastal areas possess more high-quality resources and advanced industrial clusters than inland regions, creating more favorable conditions for the development of the digital economy. In contrast, inland regions have relatively abundant resources and a more homogeneous industrial structure, which to some extent limits the improvement effect of the digital economy on green total factor productivity. Third, coastal areas have greater advantages in talent attraction and technological innovation capabilities compared to inland regions. The development of coastal areas has attracted a large number of talents, forming a clustering effect of economic development and innovation. In contrast, inland regions have a lower talent density and a more widespread phenomenon of talent outflow.

5.1.2 Quantile Heterogeneity in Digital Economy

To further explore the relationship between the digital economy and green total factor productivity, this study conducts an in-depth analysis of the digital economy at two quantile points: 0.25 and 0.75. The results from columns (3) to (5) in Table 6 demonstrate that in cities below the 0.25th percentile, the digital economy's impact on green total factor productivity is statistically insignificant. However, in cities above the 0.25th percentile, the digital economy's effect on green total factor productivity becomes significantly positive at the 1% significance level, with coefficients showing a trend of increasing initially and then decreasing. This indicates a nonlinear promotion effect of the digital economy on green total factor productivity. The potential reasons include: In regions with lower digital economy levels, energy consumption remains inherent during the technological and industrial upgrading process, and resource allocation efficiency optimization has not reached its maximum potential. After surpassing the 25th percentile, regional digital economies enter a mature phase, where the penetration and adoption of digital technologies, along with public environmental awareness, have significantly improved.

5.1.3 The Level of Green Total Factor Productivity

This study employs median analysis to categorize regions into high-and low-Green Total Factor Productivity (GTFP) groups, examining the heterogeneous effects of digital economy on green productivity. As shown in Columns (6) and (7) of Table 6, digital economy exerts stronger influence on high-GTFP regions while having limited impact on low-GTFP areas. This regression pattern may stem from three key factors: Regions with lower GTFP typically face challenges including inefficient resource allocation, oversimplified industrial structures, outdated production technologies, and difficulties in economic transformation. These regions struggle to benefit from digital technology spillovers and may experience diminished empowerment effects due to underdeveloped supporting systems, ultimately resulting in weaker impact effects. In contrast, high-GTFP regions possess robust digital infrastructure, abundant high-skilled talent reserves, and mature green industries. They can rapidly integrate digital technologies into production processes, enhancing resource efficiency and reducing pollution through intelligent upgrades. While digital economy impacts these regions are more pronounced, their marginal effects may gradually diminish over time.

Table 6: Heterogeneity Test

Variables	(1) lnGTFP	(2) lnGTFP	(3) lnGTFP	(4) lnGTFP	(5) lnGTFP	(6) lnGTFP	(7) lnGTFP
lnDig	0.445***	0.578***	-0.055	1.017***	0.723***	0.338***	0.622***
	(6.60)	(12.81)	(-0.80)	(9.93)	(5.24)	(7.78)	(12.68)
lnGov	-0.210**	-0.085	-0.242***	-0.207***	-0.531***	-0.061	-0.146***
	(-2.24)	(-1.48)	(-4.29)	(-3.67)	(-4.05)	(-1.23)	(-2.74)
lnFDL	0.278***	-0.056	-0.079	-0.047	0.057	-0.029	0.162***
	(3.73)	(-0.89)	(-1.11)	(-0.78)	(0.55)	(-0.65)	(2.81)
lnOE	0.013	0.021	-0.026*	-0.008	0.042	0.023*	-0.017
	(0.45)	(1.17)	(-1.73)	(-0.47)	(1.16)	(1.84)	(-1.06)
lnUrb	-0.770**	-1.087***	-0.559***	-1.141***	-0.082	-0.621***	-0.953***
	(-2.32)	(-5.17)	(-3.07)	(-6.04)	(-0.19)	(-3.95)	(-5.38)
lnIQL	-1.699***	-1.360***	-2.035***	-1.660***	-0.324	-0.040	-1.012***
	(-4.03)	(-3.28)	(-5.79)	(-4.60)	(-0.69)	(-0.15)	(-3.43)
cons	2.210**	2.061**	2.073***	3.208***	-0.132	-1.411**	1.272**
	(2.45)	(2.26)	(2.67)	(4.02)	(-0.14)	(-2.44)	(1.99)
R^2	0.146	0.096	0.230	0.135	0.132	0.153	0.172

5.2 Mediation Effect Test

The mediation effect analysis demonstrates that the digital economy significantly enhances industrial structure optimization and upgrading. This indicates that faster digital economic growth more effectively drives industrial structure optimization. When mediation variables are included, the digital economy coefficient remains significantly positive, confirming that industrial structure upgrading serves as a key pathway for the digital economy to boost green total factor productivity. Hypothesis 2a is validated. While the digital economy indirectly promotes green total factor productivity growth through human capital enhancement, the mediation effect accounts for only 0.8%. This suggests that although human capital is one of the pathways through which the digital economy enhances green total factor productivity, its contribution remains limited. Consequently, Hypothesis 2b is not supported.

Table 7: Mediation Effect Test Result

Variables	(1) lnGTFP	(2) IS	(3) lnGTFP	(4) HCL	(5) lnGTFP
lnDig	0.527***	0.301***	0.237***	0.707***	0.507***
	(14.18)	(14.531)	(7.542)	(15.007)	(15.814)
lnMed			0.495***		-0.269***
			(13.885)		(-8.943)
lnGov	-0.137***	-0.283***	-0.205***	0.479***	-0.035
	(-2.88)	(-16.196)	(-6.749)	(12.043)	(-1.118)
lnFDL	0.093*	0.638***	-0.189***	0.512***	-0.006
	(1.93)	(35.370)	(-5.250)	(12.466)	(-0.658)
lnOE	0.004	0.027***	-0.012	-0.022**	-0.553***
	(0.31)	(5.412)	(-1.413)	(-1.967)	(-5.924)
lnUrb	-0.969***	-0.370***	-0.474***	1.266***	-1.258***
	(-5.73)	(-6.765)	(-5.175)	(10.168)	(-8.496)
lnIQL	-1.406***	0.530***	-1.393***	1.498***	-0.006
	(-4.85)	(6.060)	(-9.536)	(7.524)	(-0.459)
cons	1.859***	-1.578***	2.144***	-6.021***	1.732***
	(2.97)	(-8.349)	(6.751)	(-13.990)	(5.283)
N	2800	2800	2800	2800	2800
R^2	0.191	0.511	0.164	0.535	0.147
mediation effect		0.566***		0.57	
mediation effect proportion		12.6%		0.8%	

6. Conclusion and Policy Implications

Based on data from 280 cities at or above the prefecture level in China from 2013 to 2022, this paper examines the specific impact of the digital economy on urban GTFP. The study finds that the digital economy significantly promotes the improvement of urban GTFP, with industrial structure upgrading playing a mediating role; this improvement effect exhibits significant heterogeneity, being more pronounced in coastal areas, regions with medium-level digital economic development, and high-GTFP cities. Based on this, the paper proposes two major policy recommendations:

First, targeted enhancement of regional green total factor productivity growth momentum to address the insufficient synergy between technology and efficiency. China's GTFP growth lacks coordination mechanisms in technological progress and efficiency changes, with significant inter-regional disparities. Therefore, differentiated strategies should be formulated based on regional characteristics to promote GTFP growth. First, the eastern region should strengthen technological leadership by increasing investment in green technology R&D, establishing national-level green technology centers, and driving technological progress to higher levels. At the same time, it should leverage the advantages of the digital economy to accelerate the industrial application and scenario implementation of green technologies. Second, the central and western regions should capitalize on their efficiency improvement advantages by optimizing industrial structures and resource allocation reforms to release more efficiency dividends. Simultaneously, they should introduce advanced green technologies from the eastern region to compensate for technological progress gaps, gradually forming a dual-wheel drive model of technology and efficiency. Third, the northeastern region should focus on breaking down barriers to technology transfer, deepening institutional and mechanistic reforms to eliminate institutional obstacles to the conversion of technological progress into actual efficiency. It should establish collaborative technology transfer platforms for "industry-university-research" cooperation and utilize digital economy tools to optimize production processes, enhancing the practical application efficiency of technology. Additionally, to address the polarization of GTFP between cities, an inter-city green development cooperation mechanism should be established to promote the cross-regional flow of green production factors.

Second, to deepen the integration of digital economy and green development and enhance their synergistic effects, it is crucial to recognize that the digital economy positively impacts green total factor productivity (TFP), with more pronounced effects in coastal regions and areas with higher green TFP. First, governments should improve digital-green integration infrastructure by accelerating the green transition of new digital facilities like 5G networks and big data centers, providing material support for the digital transformation of green production and services. Second, efforts should focus on promoting digital-green integration through encouraging enterprises to leverage big data and AI to optimize green production processes, develop innovative business models such as smart environmental protection and green supply chain finance, and establish digital-green integration demonstration zones in high-TPF regions to create replicable best practices. Third, differentiated regional policies should be implemented: coastal areas should prioritize supporting high-quality industries integrating digital and green development, while inland regions and areas with lower green TFP should focus on improving foundational data systems for digital-green development. Policy subsidies should also be provided to facilitate cross-regional collaboration in digital and green technologies, thereby narrowing regional development gaps.

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