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Exploring the Impact of the Digital Economy on Green Total Factor Productivity—Evidence from Chinese Cities

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Abstract: The digital economy promotes economic development, industrial upgrading, and environmental protection. In this study, we calculated green total factor productivity (GTFP) based on the SBM-DDF model and used the entropy method and principal component analysis to calculate a digital economy index. We used panel data from 282 Chinese cities to measure the driving effect of the digital economy on green total factor productivity. The study results show that the digital economy significantly increases GTFP. We then assessed the heterogeneity of this impact. We also explored the mechanisms by which the digital economy promotes green development and found that the digital economy can indirectly increase industrial production efficiency by promoting innovation in green technologies.

Keywords: digital economy; innovation; green technologies; green total factor productivity

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1. Introduction

A digital economy, based on digital technologies, the Internet, and the use of data, encompasses commerce in goods and services facilitated by digital platforms and networks. The development of digital economies can be traced back to the 1990s, when governments across the world began to promote access to digital commerce to secure future prosperity for their populations [1]. In China, the digital economy began in the early 2000s and grew rapidly in the following years. Significant milestones in this development included the introductions of the first 3G network in 2006, the "Internet Plus" strategy in 2013, the "Made in China 2025" plan in 2015, and Digital Currency Electronic Payment (DCEP) in 2020. China's digital economy has been on an upward trend since 2000. During the era of Xi Jinping, China pursued a new approach to global economic governance through digital transformation [2]. The digital economy is crucial for national economic development, including GDP growth, high levels of employment, and changes in industrial structure [3]. The integration of digital technology and data components has also enhanced the efficiency of businesses [4,5]. Furthermore, the digital economy has accelerated information dissemination, increased the speed of innovation, and broadened the scope of innovation [6,7]. It has also brought profound changes in the labor market, with significant changes in skill structures [8–10]. China has acknowledged the significance of the digital economy and has undergone a distinct phase characterized by medium-to-high growth and a focus on innovation and global competitiveness. In short, digitalization is now an essential economic model that will affect the sustainable development of China—and all other countries—in the years ahead [11–13].

Total factor productivity (TFP) is a reference standard used in economics to measure economic efficiency. It is primarily used to denote the proportion of economic activity that cannot be explained by amounts of input (e.g., capital and labor). Green total factor productivity (GTFP) incorporates both conventional total factor productivity and environmental variables. GTFP is a productivity measurement methodology that encompasses input variables such as capital, energy, labor, and economic benefits as desired output, and environmental damage as undesirable output [14]. GTFP thoroughly takes into account the input restrictions of conventional TFP, as well as resource and environmental constraints. As a result, GTFP can more accurately depict the durability of economic growth [15–17]. According to publicly available data from the International Energy Agency (IEA), in 2015, China's primary-energy intensity exceeded that of Japan by 81% and that of the United States by more than 25%. This indicates that China has a significant issue with energy waste. Indeed, high levels of energy waste and environmental pollution have hindered the growth of China's green economy [18–20]. GTFP is a complete efficiency metric that takes into account environmental pollution, energy consumption, and economic growth [21]. The digital economy effectively improves resource utilization, resulting in an upgraded industrial structure and a better optimized economic structure through digital information and knowledge. It is considered a vital development engine of GTFP [22–24]. To sustain economic growth while prioritizing environmental performance and energy conservation, and, at the same time, inspire other countries to achieve sustainable development, comprehensive research on the relationship between the digital economy and GTFP should be conducted to help China take a greener development path. Previous studies have considered various aspects of this topic. According to Canh and Thanh [25], the qualitative research literature supports the idea that the digital economy is multifunctional. Qualitative research has highlighted the transdisciplinary nature of the digital economy which results from the pragmatic utilization of information and communications technology (ICT). Technology production models and organizational governance structures, which have been impacted by governance modifications and technology advancements since the Industrial Revolution, are closely interconnected with the advancement of the digital economy [26], which also offers new areas for modern technology.

The concept of the digital economy represents a historical stage in economic development. It has emerged from the evolution of the information and Internet economies. In 1996, Tapscot first introduced the concept of the digital economy, defining it as an economic system characterized by the continuous application of computer information technology. The digital economy can be understood in both broad and narrow terms. Broadly speaking, it refers to economic activities that utilize knowledge and digital information as production factors, employing information technology and networks to optimize macroeconomic structures and enhance economic efficiency. Narrowly defined, the digital economy involves activities extracted from traditional economic operations, such as the production, consumption, and distribution of goods or digital services.

China's understanding of the digital economy has continued to deepen. In 2016, the "G20 Digital Economy Development Cooperation Initiative" emphasized that the digital economy, based on digital information and knowledge, utilizes modern information technology and networks to promote the optimization of economic structures and improve economic efficiency. The "China Digital Economy Development White Paper (2021)" released by the China Academy of Information and Communications Technology proposed that there are several aspects to the digital economy, including industrial digitization, digital industrialization, digital value creation, and digital governance. Among these, digital industrialization may be seen as the foundation of the digital economy; it includes perception, represented by intelligent communication devices; connection, represented by wireless networks; integration, represented by the Internet of things and artificial intelligence; as well as digital applications. Industrial digitization refers to the innovative integration of new technologies with traditional industries; this may be evidenced in new forms of business models.

As Internet technology advances, the strain on old business models continues to increase. Recent research has indicated that the digital economy allows SMEs to shift from traditional operating activities to digitalization through its impact on innovation performance [27–29]. The regulatory system, empowerment management, and the industrial restructuring of the digital economy have also garnered the interest of researchers in recent years [30]. Studies on the effects of the digital economy of the labor market may also be found in the literature, especially changes in skill structures [9,10,31]. The digital economy fosters innovation in the collection and analysis of economic research data and methodologies [32,33]. The strategic management literature is mostly concerned with the influence of the digital economy on management operations. The digital economy has brought new pressures and new challenges to established firms by decreasing the expenses associated with transmitting and duplicating information [34,35].

However, there are several areas of research in which further studies may be of value. First and foremost, in quantitative research, it is imperative to establish a scientific index system that can precisely gauge the present condition of digital economy advancement. Secondly, it is imperative to prioritize the examination of the correlation between GTFP and the digital economy, as this has the potential to significantly stimulate innovation for GTFP. Thirdly, although a number of scholars have employed Solow's framework to examine GTFP, utilizing the perpetual inventory method to mimic capital stock, this method involves inherent limitations.

In the study described in this paper, we sought to make the following contributions: First, we conducted a multidisciplinary comprehensive study of the digital economy, including infrastructure, industrial scale, and local finance, instead of just focusing on the Internet industry. Second, we employed principal component analysis as an unbiased weighting technique to create scientific indicators for assessing the progress of the digital economy. Third, we used the dual-method production function to accurately calculate GTFP [36], thus avoiding the limitations of capital stock estimation.

In this study, we employed a linear model to investigate the influence of the digital economy on green total factor production. The model was also used to assess the variability of this influence. By measuring the green total factor productivity of 282 cities over the 2011–2019 period, we obtained a substantial body of new research evidence which is relevant at the city level. The findings reported here provide a factual basis for assessing the current situation of high-quality economic development in China at the urban level.

2. Mechanism Analysis

2.1. Digital Economic Index

The digital economy has provided a new impetus for the enhancement of GTFP and the promotion of economic development. First, by opening up the economy, improving the industrial structure, and increasing the market potential, the digital economy has enhanced social engagement in invention, boosted innovation capacity, and expanded the pool of innovative individuals. This, in turn, has boosted R&D investment and led to the development of green innovations which generate economic value with a lower consumption of resources and reduced environmental cost, thereby increasing GTFP [37–39]. Second, the digital economy has bolstered the utilization and advancement of sophisticated technologies such as artificial intelligence, cloud computing, and the Internet of things. This has resulted in the optimization of resource utilization, reduction in the cost of expansion, and enhancement of energy efficiency and urban operations, again increasing GTFP [40,41]. Furthermore, the digital economy continues to advance, supporting the development of environmentally friendly technologies; these include renewable energy innovations which reduce carbon emissions, production technology innovations which reduce the demand for finite resources, and green finance innovations which increase investment in sustainability and finance green total factor productivity [42,43]. In short, the digital economy fosters GTFO (green transformation for organizations) by means of green innovation.

Based on the definition of the digital economy and the availability of data, drawing on relevant research, and referring to the digital economy development report, the primary indicators of the digital economic index may be divided into three aspects: digital economic carrier, industry digitization, and digital industrialization (see Table 1). Currently, the subjective weighting method and the objective weighting method are the primary approaches utilized. For the present study, we judged that the subjective weighting method was simply too subjective; we, therefore, used the entropy weight approach to quantify the digital economic index (DEI).

Table 1. Digital economic index system.

Primary Indicators	Secondary Indicators	Definitions
Digital economic carrier	Traditional infrastructure	Internet users per 100 people Mobile phone users per 100 people
	Digital infrastructure	Mobile phone base stations Big data centers Cloud platforms
Industry digitization	Industrial digitalization	Computers per 100 people in industrial enterprises Proportion of industrial applications using Internet
	Service industrial digitalization	Digital financial inclusion level E-commerce transaction volume E-government platforms
Digital industrialization	Industry type	Top 100 Internet companies Listed companies in the intelligent manufacturing industry
	Industry scale	Telecommunications and postal services revenue Software and information services revenue Computer and other electronic equipment manufacturing revenue

2.2. Green Total Factor Productivity

The economic growth theory based on Solow residuals usually only considers traditional capital and labor factors in input variables while ignoring resource and environmental constraints [44,45]. In the present study, therefore, we considered resource and environmental factors in the construction of the GTFP index system, and we treated resources and the environment as endogenous variables that affect economic development. The selected indicator data were obtained from the China Statistical Yearbook, the China Industrial Statistical Yearbook, the China Energy Statistical Yearbook, and the China Environmental Statistical Yearbook.

The input indicators used in the present study were as follows: (1) labor input, reflecting the number of employees, as expressed by the numbers of employees in urban units at the end of the year; (2) capital investment, reflecting the level of capital investment in the production process, as expressed by levels of fixed-asset investment; and (3) energy input, one of the variables most characteristic of green production [46], as expressed by total energy consumption.

The selected output indicators were as follows: (1) expected output, as expressed by real GDP (gross domestic product) between 2011 and 2019, using 2011 as the base year; and (2) non-expected output, another characteristic variable highlighting green production [21], as expressed by three indicators: discharges of industrial wastewater, emissions of industrial sulfur dioxide [47], and emissions of industrial smoke (dust).

2.3. Measurement and Analysis Methods

Assuming n input factors for k decision units: $x = (x_1, \ldots, x_n) \in R_n^+$, the expected output for period m: $y = (y_1, \ldots, y_n) \in R_m^+$, i non-expected output: $d = (d_1, \ldots, d_n) \in R_i^+$, and the input–output expression for stage $\mathrm{s}(t = 1, 2, \ldots, T)$: $\left(x_k^t, y_k^t, d_k^t\right)$, the definition of the current production possibility was set as follows:

$$P^t\left(x^t\right) = \left\{\left(y^t, d^t\right) : x \text{ can produce}\left(\mathrm{y}^\mathrm{t}, \mathrm{d}^\mathrm{t}\right)\right\}$$

Due to the utilization of current data to determine the production frontier, here expressed as $P^t\left(x^t\right)$, there is potential for technological regression. Consequently, we employed an aggregate of inputs and outputs across different periods as the reference set. This approach was adopted to mitigate computational errors arising from the incommensurability of distinct production boundaries across different periods, thereby enhancing the comparability of efficiencies. This is expressed as follows:

$$P^G(x) = \left\{ \left(y^t, d^t\right) : \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t y_{km}^t \geq y_{km}^t, \forall m; \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t d_{ki}^t = d_{ki}^t, \forall i; \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t x_{kn}^t \leq x_{kn}^t, \forall n; \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t = 1, Z_k^t \geq 0, \forall k \right\}$$

In this context, Z_k^t represents the weight in period t. The conditions $\sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t = 1, Z_k^t \geq 0$ indicate variable returns to scale.

Subsequently, the optimal solution may be computed using data development analysis (DDF). For the present study, recognizing the significance of slack variables, and, on the basis of the global production possibility set, we adopted the approach of Fukuyamah and Weber [48]. SBM-DDF was defined as follows:

$$\vec{D}_v^G\left(x^{t,k}, y^{t,k}, d^{t,k}; g^x, g^y, g^d\right) = \max \frac{\frac{1}{N}\sum_{n=1}^{N} \frac{s_n^x}{g_n^x} + \frac{1}{M+1}\left[\sum_{m=1}^{M} \frac{s_m^y}{g_m^y} + \sum_{i=1}^{I} \frac{s_i^d}{g_i^d}\right]}{2}$$

$$\text{s.t.} \begin{cases} \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t y_{km}^t - S_m^y = y_{km}^t, \forall m \\ \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t d_{ki}^t + S_i^d = d_{ki}^t, \forall i \\ \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t x_{kn}^t + S_n^x = x_{kn}^t, \forall n \\ \sum_{t=1}^{T} \sum_{k=1}^{K} Z_k^t = 1; Z_k^t \geq 0, \forall k \\ S_m^y \geq 0, \forall m; S_i^d \geq 0, \forall i; S_n^x \geq 0, \forall n \end{cases}$$

In this context, g^x represents the directional vector for input reduction; g^y represents the directional vector for expected output increase; g^d represents the directional vector for non-expected output reduction; S_n^x denotes the slack variable for input; S_m^y denotes the slack variable for expected output; and S_i^d denotes the slack variable for non-expected output. As shown in formula, SBM-DDF measures the weighted sum of slack variables, with higher values of D_v^G indicating lower levels of efficiency.

Although the GML productivity index can compensate for the infeasibility issue in the linear programming of the ML productivity index, a single GML indicator cannot address the radial angle problem. In the present study, therefore, we employed the GML productivity index method based on SBM-DDF.

$$GML_t^{t+1} = \frac{1+\vec{D}_v^G\left(x^t, y^t, d^t; g^x, g^y, g^d\right)}{1+\vec{D}_v^G\left(x^{t+1}, y^{t+1}, d^{t+1}; g^x, g^y, g^d\right)} = GEC_t^{t+1} \times GTC_t^{t+1}$$

$$GEC_t^{t+1} = \frac{1+\vec{D}_v^t\left(x^t, y^t, d^t; g^x, g^y, g^d\right)}{1+\vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, d^{t+1}; g^x, g^y, g^d\right)}$$

$$GTC_t^{t+1} = \frac{\left[1+\vec{D}_v^G\left(x^t, y^t, d^t; g^x, g^y, g^d\right)\right] / \left[1+\vec{D}_v^t\left(x^t, y^t, d^t; g^x, g^y, g^d\right)\right]}{\left[1+\vec{D}_v^G\left(x^{t+1}, y^{t+1}, d^{t+1}; g^x, g^y, g^d\right)\right] / \left[1+\vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, d^{t+1}, g^x, g^y, g^d\right)\right]}$$

In this context, $\vec{D}_v^G\left(x^t, y^t, d^t; g^x, g^y, g^d\right)$ represents the SBM-DDF dependent on the global production possibility set $P^G(x)$; and $\vec{D}_v^G\left(x^t, y^t, d^t; g^x, g^y, g^d\right)$ and $\vec{D}_v^G\left(x^{t+1}, y^{t+1}, d^{t+1}; g^x, g^y, g^d\right)$ take all inputs and outputs during the sample period as reference, ensuring the transitivity of GML. A GML value of greater than 1 indicates an increase in green total factor productivity, a GML value of less than 1 indicates a decrease in green total factor productivity, and a GML value equal to 1 indicates stability in green total factor productivity. GEC measures the degree to which DMU approaches the production possibility frontier, and GTC measures changes in the production possibility frontier. When

GEC and GTC values are both greater than 1, or when they are both less than 1, this indicates an increase in technical efficiency and a decrease in technological progress.

2.4. Empirical Model

First, we employed a fixed effects model to analyze the impact of the digital economy on green total factor productivity. $GTFP_{it}$ represents green total factor productivity, DEG_{it} represents the level of digital economic growth, and Z_{it} stands for control variables. Additionally, μ_i denotes city-specific fixed effects, θ_t represents year-specific fixed effects, and ε_{it} represents the random error term. The model was formulated as follows:

$$GTFP_{it} = \beta_0 + \beta_1 DEG_{it} + \beta_2 Z_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

We then developed a transmission mechanism model to examine how the digital economy affects GTFP. Regression analysis was employed to quantify the impact of the independent variable on green innovation, as well as the impact of green innovation on the dependent variable. We assumed that the effect of the independent variable on green innovation and the effect of green innovation on the dependent variable were both significant, so that green innovation was, therefore, conducive to promoting GTFP in the digital economy. The term TI was used to represent green innovation, as measured by the number of green patent applications, and the model was formulated as follows:

$$\mathrm{TI}_{it} = \gamma_0 + \gamma_1 DEG_{it} + \gamma_2 Z_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$GTFP_{it} = \alpha\beta_0 + \alpha_1 \mathrm{TI}_{it} + \alpha_2 Z_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

2.5. Data Sources and Descriptive Statistics for Variables

The entropy weight approach was employed in the present study to quantify the digital economic index (DEI). The detailed calculation is shown in Table 1. Science expenditure (Sciexp) indicates the innovation-driven development of cities and their ability to attract high-level talent to enhance their competitiveness, innovation, and attractiveness [49,50]. Foreign direct investment (FDI) indicates the transfer of sophisticated knowledge, technology, and financial resources to stimulate the growth of the domestic digital economy [51]. The development rate of the regional GDP was expressed by economic performance (Lngdp). The relation between public finance budget expenditure (czzc1) and GDP (Fingdp) was measured by Govfin*100/Fingdp. Variables for the proportion of tertiary industry (Tzgdp), the public finance budget expenditure of cities (czzc1), and R&D investment (RD) all indicate the promotion of changes to the digital economy [52]. The variable (Yangziriver) was used to indicate whether or not the city was in the Yangtze River Delta region. The variable (Areacode) was used to indicate the regional location of cities, so that cities in the east had the value 1, central cities had the value 2, and cities in the west had the value 3. A description of these variables is given in Table 2.

Table 2. Description of variables.

Variable Symbol	Variable Meaning	Measurement Method
RD	R&D spending	R&D spending/General financial expenditures
Sciexp	Science expenditure	Urban research spending
FDI	Foreign direct investment	Amount of foreign direct investment
Lngdp	The development rate of regional GDP	Lngdp $= ln(GDP)$
czzc1	Cities' finance budget expenditure	Amount of finance budget expenditure

Table 2. *Cont.*

Variable Symbol	Variable Meaning	Measurement Method
Fingdp	GDP	Gross domestic product
Tzgdp	The proportion of tertiary industry	Tertiary industry/total industry
Yangziriver	Cities in the Yangtze River Delta region	If the city belongs to the Yangtze River Delta region, value is 1; otherwise, value is 0
Areacode	City area code	Cities in the east are 1, cities in the central region are 2, and cities in the west are 3

The data for these indicators were sourced only from the China Cities Statistical Yearbook. Because data for some cities were partially missing, these cities were not included in the present study. Our final dataset consisted of 2538 panels representing 282 cities and covered the years between 2011 and 2019. Table 3 gives descriptive statistics for each variable.

Table 3. Descriptive statistics for variables. Summary statistics.

VarName	Obs	Mean	SD	Min	Median	Max
GTFP	2538	0.997	0.019	0.806	0.996	1.243
rd	2538	0.016	0.016	0.001	0.011	0.207
szjj3	2538	0.094	0.051	0.010	0.085	0.552
szjj4	2538	−0.011	0.661	−1.234	−0.121	6.374
sciexp	2538	1.01×10^5	3.09×10^5	753.000	26,565.500	4.33×10^6
fdi	2538	5.99×10^5	1.42×10^6	0.000	1.54×10^5	2.05×10^7
czzc1	2538	10.256	0.730	7.426	10.196	13.635
tzgdp	2538	40.967	9.932	10.200	40.200	83.500
lngdp	2538	16.569	0.909	14.106	16.464	19.760
yangziriver	2538	0.383	0.486	0.000	0.000	1.000
areacode	2538	1.943	0.802	1.000	2.000	3.000

	GTFP	rd	szjj3	szjj4	sciexp	fdi	czzc1	tzgdp	lngdp	yangzi~r	areacode
GTFP	1										
rd	0.089 ***	1									
szjj3	0.165 ***	0.483 ***	1								
szjj4	0.155 ***	0.484 ***	0.969 ***	1							
sciexp	0.109 ***	0.521 ***	0.530 ***	0.482 ***	1						
fdi	0.057 ***	0.443 ***	0.441 ***	0.424 ***	0.791 ***	1					
czzc1	0.075 ***	0.428 ***	0.550 ***	0.521 ***	0.610 ***	0.666 ***	1				
tzgdp	0.120 ***	0.273 ***	0.617 ***	0.625 ***	0.413 ***	0.372 ***	0.526 ***	1			
lngdp	0.077 ***	0.526 ***	0.527 ***	0.527 ***	0.542 ***	0.625 ***	0.885 ***	0.388 ***	1		
yangziriver	−0.0260	0.250 ***	−0.0190	−0.054 ***	0.105 ***	0.106 ***	0.142 ***	−0.053 ***	0.106 ***	1	
areacode	−0.057 ***	−0.346 ***	−0.263 ***	−0.257 ***	−0.209 ***	−0.207 ***	−0.272 ***	−0.244 ***	−0.428 ***	0.110 ***	1

Robust standard errors in parentheses. *** $p < 0.01$.

3. Empirical Analysis and Results

3.1. Results of Baseline Regression

Prior to undertaking a panel data regression analysis, it is necessary to ascertain whether a fixed effects model or a random effects model should be employed. For the present study, a fixed effect model was selected because a better fitting effect was indicated by the Hausman test, AIC criterion, and R2 measure. In the regression analysis shown in Table 4, it can be seen that the coefficient for the digital economy on GTFP is 0.059 in column (2). This indicates a considerable positive effect of the digital economy on GTFP. The findings of this study, therefore, validate the proposition that growth in the digital economy has an environmentally friendly impact and contributes to the advancement of regional economies in a sustainable and eco-friendly manner. This aligns with the ideology of "promoting ecological development and fostering a harmonious coexistence between humans and nature" advocated by the Twentieth National Congress.

Table 4. Baseline regression analysis (BRA).

GTFP	**(1)**	**(2)**	**(3)**
Szjj	0.066 ***	0.059 **	0.004 *
	(0.023)	(0.026)	(0.002)
sciexp		−0.000	0.000
		(0.000)	(0.000)
Govfin		0.000	0.000
		(0.000)	(0.000)
Fdi		−0.000 ***	−0.000 ***
		(0.000)	(0.000)
Fingdp		−0.009 **	−0.009 **
		(0.004)	(0.004)
Tzgdp		−0.0001	−0.0001
		(0.0001)	(0.0001)
Lngdp		0.014 ***	0.014 ***
		(0.004)	(0.004)
Constant	0.990 ***	0.849 ***	0.856 ***
	(0.002)	(0.052)	(0.054)
Yearfix	YES	YES	YES
Idfix	YES	YES	YES
R-squared	0.117	0.132	0.131

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

3.2. Robustness Test

After considering the merits and demerits of each measurement method for digital economy indicators, we constructed digital economy indicators for the present study using principal component analysis. It can be seen from the data in column (3) of Table 5 that the digital economy continues to have a substantial positive impact on GTFP. Hence, the conclusion stated above may be seen as highly reliable.

Table 5. Heterogeneity analysis.

	GTFP				
	Yangziriver	**Non-Yangzi**	**East**	**West**	**Central**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DEI	0.100 ***	0.036	0.059 **	−0.027	0.051
	(0.032)	(0.025)	(0.026)	(0.056)	(0.046)
Govfin	0.000	0.000	−0.000	0.000 *	0.000 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fdi	−0.000 **	−0.000 ***	−0.000 ***	−0.000	−0.000 **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fingdp	−0.006	−0.013 **	−0.026 ***	0.004	−0.011
	(0.007)	(0.006)	(0.008)	(0.009)	(0.009)
Tzgdp	0.000	0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lngdp	0.019 **	0.020 ***	0.029 ***	0.005	0.016 ***
	(0.009)	(0.005)	(0.008)	(0.008)	(0.005)
Constant	0.734 ***	0.799 ***	0.771 ***	0.876 ***	0.833 ***
	(0.164)	(0.076)	(0.120)	(0.130)	(0.104)
Observations	972	1566	891	747	900
R-squared	0.137	0.152	0.198	0.115	0.136
Yearfix	YES	YES	YES	YES	YES
Idfix	YES	YES	YES	YES	YES

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

3.3. Heterogeneity Analysis

Drawing on previous research [47], we categorized 282 cities as either Yangtze River Economic Zone (YRED) cities or as non-YRED cities for the purpose of heterogeneity analysis. As can be seen from columns (1) and (2) in Table 5, the economic gap between YRED cities and non-YRED cities has further widened, and there is a "digital divide" between these two groups of cities. In addition, we categorized the cities as either East, West, or Central, depending upon their regional locations. The results of the heterogeneity analysis results revealed that, in contrast to western and central areas, the digital economy has made a substantial contribution to the green economic expansion of cities in the eastern region. The limited progress in the digital economy and infrastructure development in the central and western regions, as well as non-Yangzi cities, has hindered the growth of the digital economy and, consequently, GTFP growth. In addition, the limited market size in the central and western regions, as well as non-Yangzi cities, may impede the progress and implementation of the digital economy, further impacting economic growth.

3.4. Analysis of Impact Mechanisms

In the present study, we examined the mechanism by which the digital economy impacts GTFP from the perspective of R&D investment using a mediation effect model. Table 6 illustrates how R&D investment is positively impacted by the digital economy, with this relationship being statistically significant at the 1% level. Additionally, R&D investment adds to GTFP, again with significance at the 1% level. We may conclude, therefore, that the digital economy affects GTFP through R&D investment. Further, we measured, by the Sobel test, that the proportion of R&D investment in the digital economy affecting GTFP was around 26%. Finally, we found that Goodman-1 (Aroian) had a z-value of 1.431 and a p-value of 0.153, which was significant at the 5% level.

Table 6. Mechanisms for the impact of the digital economy on GTFP.

Variable	**(1)** **R&D Investment**	**(2)** **GTFP**
rd		0.069 **
		(0.027)
DEI	0.128 ***	
	(0.008)	
caizhengzc	−0.000 ***	0.000 ***
	(0.000)	(0.000)
fdi	0.000 ***	−0.000 **
	(0.000)	(0.000)
czzc1	−0.004 ***	−0.004 ***
	(0.001)	(0.001)
tzgdp	−0.000	0.000 ***
	(0.000)	(0.000)
lngdp	0.008 ***	0.002 **
	(0.001)	(0.001)
Constant	−0.088 ***	0.995 ***
	(0.006)	(0.009)
Observations	2538	2538
R-squared	0.393	0.065
Yearfix	YES	YES
Idfix	YES	YES

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

4. Discussion

4.1. Discussion of the Main Effects

The results of the above empirical analyses reveal that the digital economy has had a positive impact on GTFP, especially in the cities in the Yangtze River Delta region, whereas the impact of the digital economy on GTFP in non-YRD-region cities has been broadly neutral. We may say, then, that the impact of the digital economy on GTFP in China has been characterized by significant regional variation, with a greater impact on cities in the eastern region and less of an impact on cities in western and central regions.

4.2. Discussion of Intermediary Effects

The mediation effect model used in the present study revealed that R&D investment has a positive impact on GTFP. The digital economy enhances GTFP by promoting technological innovation and intelligent production management, with R&D investment playing a financial support role in each case. We may say, then, that the digital economy indirectly increases the level of GTFP through the promotion of R&D investment.

4.3. Discussion of Heterogeneity

The degree of economic development, the robustness of infrastructure, the capacity for technological innovation, and the aggregation of talent in eastern China surpass those in western China. This explains the burgeoning digital economy in eastern China. Conversely, though western China has witnessing substantial advancement in recent years, it still lags behind in the development of the infrastructure and ecosystem necessary for the expansion of the digital economy. The digital economy may be seen as a critical lever in augmenting green total factor productivity (GTFP) by facilitating the exchange of information, enhancing the efficiency of resource allocation, and fostering innovations in green technology. Consequently, the embrace of the digital economy in eastern China may serve to accelerate the enhancement of GTFP. Furthermore, the extent of governmental support for the digital economy and green development significantly influences GTFP improvements. Given its advanced economic stature, the Eastern region frequently secures preferential policies and financial backing, propelling the growth of both the digital economy and green productivity.

5. Conclusions and Implications

In the study reported here, we carried out empirical analyses using panel data from Chinese cities for the years 2011 to 2019 to examine the mechanisms by which the digital economy influences green total factor productivity. Our conclusions may now be stated as follows: (1) The digital economy has the potential to greatly improve the overall efficiency of green production. (2) The digital economy primarily affects green total factor productivity by means of green innovation. Green innovation has a major impact on green total factor productivity in the digital economy. Green total factor productivity may be significantly increased by the use of digital technology, which can also effectively increase production efficiency, lower production input costs, and improve product quality. Green total factor productivity is further improved by the digital economy, which also fosters technical innovation, lowers energy use, and decreases pollutant emissions. (3) In terms of heterogeneity, cities in the Yangtze River Delta and the eastern part of China have achieved notable green economic growth by developing the digital economy, so that there is now a "digital divide" between different regions of China.

In light of these findings, we propose the following recommendations: (1) Recognizing that the digital economy primarily involves the digitization of industries and the adoption of digital technology, the government should enhance its investment in digital infrastructure. It should also actively encourage the deep integration of traditional industries with digital technology, facilitate the transformation and modernization of traditional industries, reduce reliance on energy and the environment, and stimulate the emergence of a new business sector and economy. These measures will enable the simultaneous development of the supply side and demand side. (2) The government should acknowledge and appreciate the significant impact that factor allocation has on the digital economy, eliminate any barriers that impede the movement of money and human resources, and enhance the effectiveness of factor allocation as a new channel of factor flow—the digital platform. (3) The government ought to furnish law-enforcement services to safeguard the advancement of the digital economy and effectively manage the overall circumstances. When promoting the national digital economy plan, it is important to establish precise objectives for the growth of the local digital economy and effectively utilize digital economy policy advice. (4) The government ought to devise a distinct digital economy development strategy. For instance, it is advisable to enforce stronger digital economy policies in underdeveloped cities to facilitate the spread and exchange of digital economy resources and foster collaborative growth across different regions.

6. Study Limitations and Future Research

In this study, we utilized pooled regression analysis to examine the relationships among green total factor productivity (GTFP), green innovation, and the digital economy index. The findings of this study show that the digital economy has a significant positive impact on growth in GTFP. However, the study still has some limitations. First, the data used in this study covered 282 cities in China in the years 2011–2019. Although the sample capacity was sufficient, the lack of data from more recent years may have affected the significance and stability of the results. Second, our analysis lacked a comprehensive assessment of unpredictable variables, such as shifts in policies, trade conflicts, and economic downturns that can have a substantial influence on GTFP. Third, this study employed linear pooled regression. Further research is warranted on whether there exists a more appropriate model to accurately depict the influence of the digital economy on GTFP. Hence, future studies should prioritize augmenting the sample size and modifying the variables, such as investigating additional factors that have a substantial influence on GTFP or examining more scientifically and logically constructed linear models.

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