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Exploring the Impact of 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. This article calculates the green total factor productivity (GTFP) based on the SBM-DDF model and uses the entropy method and principal component analysis to calculate the digital economy index. We use panel data from 282 Chinese cities to test the driving effect of the digital economy on green total factor productivity. The study results show that the digital economy significantly increases GTFP, and the heterogeneity of this impact is further explored. We also explored the mechanism of the digital economy in promoting green. 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

1. Introduction

Digital economy, based on digital technologies, the internet, and the data used, encompasses the goods and services facilitated by digital platforms and networks, which can be traced back to the 1990s, and governments can economy access to prosperity for the 21st Century [1]. In China, the digital economy began in the early 2000s. It rapidly grew in the following years, including some significant milestones: the first 3G network in 2006, the "Internet Plus" strategy in 2013, the "Made in China 2025" plan, and the Digital Currency Electronic Payment (DCEP) in 2020. China's digital economy has been on an upward trend from 2000 to 2020. During Xi Jinping's Era, China had a new approach to global economic governance by digital transformation [2]. As an emerging economy, the digital economy plays a vital role in national economic development and GDP, employment rates, and changes in industrial structure [3]. The incorporation of digital technology and data elements has improved the productivity of enterprises [4,5]; the digital economy accelerates information dissemination, increases the speed of innovation, broadens the scope of innovation [6,7], and shocks the labour market, significantly changes skill structure [8–10]. China has recognized the importance of the digital economy and experienced a new phase characterized by medium-to-high growth and a focus on innovation and global competitiveness. Digitalization is an essential economic model that affects the country's sustainable development in the future [11–13].

Total factor productivity (TFP) is a reference standard used in economics to measure economic efficiency. It is primarily used to denote that part of an economic activity that cannot be explained by the amount of input (e.g., capital, labour). Green total factor productivity (GTFP) is based on traditional total factor productivity and adds environmental factors. GTFP is defined as a productivity measurement framework incorporating input variables such as capital, energy, and labour, economic benefits representing desired output, and environmental pollution representing undesired output [14], comprehensively considering resource and environmental constraints and the input constraints of traditional TFP. Therefore, GTFP can effectively reflect the sustainability of economic development [15–17]. Besides, World Bank public data reveals that China's primary energy intensity in 2015 was 81 % higher than Japan's, while it was 24 % higher than the United States', indicating a relatively

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serious energy waste in China. Accordingly, severe environmental pollution and energy waste have restricted the development of China's green economy [18,19]. GTFP is a comprehensive efficiency considering economic growth, energy consumption and environmental pollution [20]. The digital economy effectively improves resource utilization, upgrades industrial structure and optimizes economic structure through digital information and knowledge. It is considered a vital development engine of GTFP [21,22]. Therefore, thorough research on the relationship between the digital economy and GTFP can contribute to a greener development path for China, where economic growth can be maintained while balancing environmental performance and energy saving and enlightening other countries to achieve green development.

Existing literature on this topic covers various aspects. Canh and Thanh [23] have argued that the digital economy is multidisciplinary in the qualitative research literature. Qualitative research emphasizes that the digital economy is multidisciplinary and arises from the practical application of information and communications technology (ICT). The evolution of the digital economy is closely linked to technological production models and organizational governance structures, which have been shaped by technological change and governance adjustments since the Industrial Revolution [24]. The digital economy also offers new areas for modern technology.

To some extent, the digital economy allows SMEs to shift from traditional operating activities to digitalization through its impact on innovation performance [25–27]. The regulatory system, empowerment management and industrial restructuring of the digital economy have also received researchers' attention [28] as the impact of the labour market, especially changes in the skill structure [9,10,29]. The digital economy drives innovation in economic research data and methods [30,31]. The strategic management literature mainly focuses on the impact of the digital economy on management operations. By reducing the cost of transmitting and copying information, the digital economy has brought pressure and new challenges to traditional companies [32,33].

However, there are several areas for improvement in the existing literature. Firstly, there needs to be a scientific index system in quantitative research to accurately measure the current state of digital economy development. Secondly, more attention needs to be given to the relationship between GTFP and the digital economy, which could be a crucial driver of innovation for GTFP. Thirdly, many scholars analyze GTFP within Solow's framework using the perpetual inventory method to simulate capital stock, but these methods have inherent limitations.

This article aims to make the following contributions. First, conduct a multidisciplinary comprehensive study of the digital economy, including infrastructure, industrial scale, and local finance, rather than just focusing on the Internet industry. Second, this article uses principal component analysis as an objective weighting method to construct scientific indicators to measure the development of the digital economy. Third, this paper uses the dual method production function to accurately calculate GTFP [34], avoiding the limitations of capital stock estimation.

In this article, we use a linear model to explore the impact of the digital economy on green total factor productivity, and the heterogeneity of this impact is further explored. Measuring the green total factor productivity of 282 cities over 2011-2019 makes up for relevant research at the city level. It provides a factual basis for the country's current situation of high-quality economic development from the urban level.

2. Mechanism Analysis

2.1. Digital Economic Index

The digital economy has provided new impetus for enhancing GTFP and promoting economic development. First, the digital economy enhances social participation in innovation, innovation power and the pool of innovative talent by increasing the openness of the economy, optimizing the industrial structure and expanding market potential, which in turn increases R&D investment and R&D activities bring about green innovations that create economic value while reducing resource consumption and the environmental cost of economic development, thereby enhancing GTFP [35–37]. Second, the digital economy has increased the use and development of intelligent technologies such as artificial intelligence, cloud computing and the Internet of Things, optimizing the use of

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resources, lowering the cost of growth, and increasing the efficiency of energy use and city operations, thereby increasing GTFP [38,39]. In addition, the digital economy itself is constantly innovating to promote green technologies, for example, by promoting renewable energy innovations to reduce carbon emissions, production technology innovations to reduce the demand for finite resources, and green finance innovations to increase investment in sustainability and finance green total factor productivity [40]. Therefore, this paper proposes that the digital economy promotes GTFO through green innovation.

Based on the definition of the connotation of the digital economy and the availability of data, drawing on relevant research and referring to the digital economy development report, the first-level indicators of the digital economic index are divided into three aspects: digital economic carrier, industry digitization and digital industrialization (see Table 1). At present, the subjective weighting method and the objective weighting method are mainly used. Considering that the subjective weighting method is too subjective, this article uses the entropy weight method to measure 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 centres
		Cloud platforms
Industry digitization	Industrial digitalization	Computers per 100 people in industrial enterprises
		Proportion of Industrial Applications 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

Economic growth theory based on Solow residuals usually only considers traditional capital and labour factors in input variables while ignoring resource and environmental constraints [41,42]. Therefore, this article considers resource and environmental factors in the construction of the green total factor productivity index system and treats resources and environment as endogenous variables that affect economic development. The selected indicator data comes from China Statistical Yearbook, China Industrial Statistical Yearbook, China Energy Statistical Yearbook and China Environmental Statistical Yearbook.

The input indicators selected in this article are (1) Labor input, which reflects the number of employees. This article uses the number of employees in urban units at the end of the year to express it: (2) Capital investment, which reflects the level of capital investment in the production process. This article uses fixed asset investment to express it; (3) Energy Input is one of the characteristic variables that reflects green production [43]. This article uses total energy consumption to express it.

The selected output indicators in this article are as follows: (1) Expected Output, represented by the Real GDP (Gross Domestic Product) from 2011 to 2019, using 2011 as the base year; (2) Non-Expected Output, which is another characteristic variable highlighting green production [20]. This study represents it by three indicators: industrial wastewater discharge, industrial sulfur dioxide emissions [44], and industrial smoke (dust) emissions.

2.3. Measurement and Analysis Methods

Assuming n input factors for k decision units: $x = (x_1, \dots, x_n) \in R_n^+$, the expected output for m period: $y = (y_1, \dots, y_n) \in R_m^+$, and i no-expected output: $d = (d_1, \dots, d_n) \in R_i^+$, the input-output expression for stages$(t = 1,2, \dots T)$: (x_k^t, y_k^t, d_k^t), the definition of current production possibility set:

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

Due to the utilization of current data to determine the production frontier, denoted as $P^t(x^t)$, there is a potential for technological regression. Consequently, we employ the aggregate of inputs and outputs across different periods as the reference set. This approach mitigates computational errors arising from the incommensurability of distinct production boundaries across different periods, thereby enhancing the comparability of efficiencies. This is expressed as:

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

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 is computed using Data Development Analysis (DDF). Recognizing the significance of slack variables, this paper, based on the global production possibility set, adopts the approach of Fukuyamah and Weber [45] [52]. SBM-DDF is defined as:

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

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

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; S_i^d denotes the slack variable for non-expected output. As shown in Formula (3.15), SBM-DDF measures the weighted sum of slack variables, with a higher value of D_v^G indicating lower efficiency.

Although the GML productivity index can compensate for the infeasibility issue in linear programming of ML productivity index, a single GML indicator cannot address the radial angle problem. Therefore, this paper employs the GML productivity index method based on SBM-DDF.

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$$GML_t^{t+1} = \frac{1+\overrightarrow{D_v^G}(x^t,y^t,d^t;g^x,g^y,g^d)}{1+\overrightarrow{D_v^G}(x^{t+1},y^{t+1},d^{t+1},g^x,g^y,g^d)} = GEC_t^{t+1} \times GTC_t^{t+1}$$

$$GEC_t^{t+1} = \frac{1+\overrightarrow{D_v^t}(x^t,y^t,d^t;g^x,g^y,g^d)}{1+\overrightarrow{D_v^{t+1}}(x^{t+1},y^{t+1},d^{t+1};g^x,g^y,g^d)}$$

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

In this context, $\overrightarrow{D_v^G}(x^t,y^t,d^t;g^x,g^y,\ g^d)$ represents the SBM-DDF dependent on the global production possibility set $P^G(x)$; $\overrightarrow{D_v^G}(x^t,y^t,d^t;g^x,g^y,\ g^d)$ and $\overrightarrow{D_v^G}(x^{t+1},y^{t+1},d^{t+1};g^x,g^y,\ g^d)$ take all inputs and outputs during the sample period as reference, ensuring the transitivity of GML. GML greater than 1 indicates an increase in green total factor productivity, GML less than 1 indicates a decrease in green total factor productivity, and GML equal to 1 indicates stability in green total factor productivity; GEC measures the degree to which DMU approaches the production possibility frontier, GTC measures changes in the production possibility frontier. When both GEC and GTC are more significant than one or less than 1, they indicate an increase in technical efficiency and a decrease in technological progress.

2.4. Empirical Model

First, we employ the 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. μ_i denotes city-specific fixed effects, θ_t represents year-specific fixed effects, and ε_{it} represents the random error term.The model is formulated as follows:

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

Then, we develop a transmission mechanism model to investigate the transmission mechanism of the digital economy on GTFP. We use regression analysis to estimate the effect of the independent variable on green innovation and the effect of green innovation on the dependent variable. Suppose both the effect of the independent variable on green innovation and the effect of green innovation on the dependent variable are significant. In that case, green innovation is conducive to promoting GTFP in the digital economy. TI stands for green innovation, measured by the number of green patent applications. The model is formulated as follows:

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

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

2.5. Data Sources and Variables Descriptive Statistics

This article uses the entropy weight method to measure the digital economic index (DEI)， a productivity index method based on SBM-DDF. Science expense (Sciexp) can promote the innovation-driven development of cities, attract high-level talents to join and enhance cities' competitiveness, innovation, and attractiveness [46,47]. Foreign direct investment (Fdi) stimulates the upgrading of the digital economy in local industries by bringing in new capital and advanced technologies [48]. Economic development (Lngdp) was expressed as the growth speed of regional GDP. The relation between public finance budget expenditure (Govfin) and GDP (Fingdp) was measured by Govfin*100/ Fingdp. The Proportion of tertiary industry (Tzgdp), cities' public finance budget expenditure (Govfin), number of urban green patent applications (Apply), and number of urban green patents granted (Author) all promote changes to the digital economy [49]. The indicator (Yangziriver) determines whether the city is in the Yangtze River Delta region.

All data for these indicators were from China Cities Statistical Yearbook. Due to the partially missing city data, some cities are deleted in this article, and 2,538-panel data for 282 cities from 2011 to 2019 are finally obtained. The descriptive statistics of each variable are presented in Table 2.

Table 2. Descriptive statistics for variables.

	N	MAX	MIN	MEAN	p50
GTFP	2,538	1.243	0.806	0.997	0.996
Sciexp	2,538	4.334e+06	753	100,930	26,566
Tzgdp	2,538	83.50	10.20	40.97	40.20
Govfin	2,538	835,154	1,678	40,287	26,809
Fdi	2,538	2.050e+07	0	598,789	154,231
Fingdp	2,538	13.64	7.426	10.26	10.20
Lngdp	2,538	19.76	14.11	16.57	16.46
Szjj3	2,538	0.552	0.0102	0.0938	0.0853
Szjj4	2,538	6.374	-1.234	-0.0110	-0.121
DEI	2,538	1.243	0.806	0.997	0.996
Yangziriver	2,538	1	0	0.383	0
Apply	2,538	24,472	0	536.0	106.5
Author	2,538	11,615	0	292.9	65

3. Empirical Analysis and Results

3.1. Results of Baseline Regression

Before conducting a panel data regression analysis, we need to determine whether to use a fixed or random effects model. Based on the Hausman test, AIC criterion and R^2 measure, the fixed effect model with a better fitting effect can be selected for analysis. As shown in column (2) in Table 3, the regression coefficient of the digital economy on GTFP is 0.059, indicating that the negative impact of the digital economy on green total factor productivity is significant. The result of this study confirms that the development of the digital economy has a green value and helps to promote the green and high-quality development of the regional economy, which is in line with the concept of "promoting green development and harmonious coexistence between human beings and nature" put forward by the Twentieth National Congress.

Table 3. Baseline Regression analysis (BRA).

	DEI		
	(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***

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		(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, * p<0.1.

3.2. Robustness Test

Considering the differences in the merits and demerits of each digital economy indicator measurement method, this article reconstructs the digital economy indicators based on principal component analysis. As shown in column (3) of Table 4, the digital economy still significantly enhances GTFP. Therefore, the conclusion is robust.

Table 4. Heterogeneity analysis.

	GTFP				
	Yangziriver	**Non-Yangzi**	**East**	**West**	**Medium**
	(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	1,566	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, * p<0.1.

3.3. Heterogeneity Analysis

Drawing on the research [44], we categorize 282 cities into the Yangtze River Economic Zone (YRED) and non-YRED cities for heterogeneity analysis. As can be seen from columns (1) and (2) in Table 4, the economic gap between YRED cities and non-YRED cities has further widened, and there is a "digital divide" between cities. Further, we categorize the cities into East, West, and Central. The results of the heterogeneity analysis show that the digital economy significantly contributes to the green economic growth of cities in the eastern region rather than in the western and central regions. It may be due to the relatively low level of digital economy development and the relatively lagging infrastructure development in the central and western regions and non-YRED cities, which affect the development and application of the digital economy and, thus, GTFP growth. Second, the relatively small market size in the central and western regions and non-YRED cities may limit the development and application of the digital economy, thus affecting economic growth.

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3.4. Analysis of Impact Mechanisms

This article examines the impact mechanism of the digital economy on GTFP from the perspective of green innovation by adopting the mediation effect model. As shown in Table 6, the digital economy positively affects green innovation, which is significant at the 1% level. Green innovation also contributes to GTFP, which is significant at the 1% level. Therefore, the digital economy affects GTFP through green innovation. This indicates that the digital economy promotes green technological innovation, makes traditional industries intelligent and digital, reduces energy consumption and pollutant emissions, and then enhances the level of green GTFP. Columns (3) and (4) of Table 5 use the number of green patents granted as a measure of green innovation to test the impact mechanism's robustness; the coefficients are still significant, and the robustness passes. Further, we measured by the Sobel test that the Proportion of green innovation in the digital economy affects GTFP that is mediated:26%. Goodman-1 (Aroian) has a z-value of 2.184 and a p-value of 0.230, which is significant at the 5% level.

Table 5. Mechanisms for the impact of the digital economy on GTFP.

	(1)	(2)	(3)	(4)
	a1	a2	b1	b2
VARIABLES	Apply	gmlddfgml	Author	gmlddfgml
Szjj3	7,750.294***		3,074.472***	
	(379.469)		(189.835)	
Apply		0.001**		
		(0.000)		
Author				0.001**
				(0.000)
Govfin	0.031***	-0.000	0.015***	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Fdi	-0.000*	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Fingdp	-890.440***	-0.007	-390.644***	-0.007
	(87.077)	(0.005)	(43.561)	(0.005)
Tzgdp	-14.536***	-0.000	-7.475***	-0.000
	(2.823)	(0.000)	(1.412)	(0.000)
lngdp	115.226	0.014***	39.400	0.015***
	(72.809)	(0.004)	(36.424)	(0.004)
Constant	6,375.485***	0.830***	3,077.951***	0.831***
	(1,184.639)	(0.062)	(592.632)	(0.062)
Observations	2,538	2,538	2,538	2,538
R-squared	0.952	0.131	0.956	0.130
Yearfix	YES	YES	YES	YES
Idfix	YES	YES	YES	YES

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

4. Conclusions and Implications

Based on the panel data of Chinese cities from 2011 to 2019, this paper empirically tests the role mechanism of the digital economy affecting green total factor productivity. This article shows: (1) The digital economy can significantly enhance green total factor productivity. (2) In terms of the mechanism of action, the impact of the digital economy on green total factor productivity is mainly realized through green innovation. (3) In terms of heterogeneity, cities in the Yangtze River Delta and the eastern part of China can achieve incredible green economic growth by developing the digital economy, and there is a "digital divide" between Chinese cities.

Based on the above conclusions, we have these recommendations : (1) Given that the digital economy is mainly manifested in the digitization of industries and digital industrialization, the government should increase investment in digital infrastructure, actively promote the in-depth integration of traditional industries with digital technology, facilitate the transformation and upgrading of traditional industries, reduce the overdependence on energy and the environment, and give rise to a new economy and new forms of business, to achieve synergistic development of the demand side and the supply side. (2) As a new channel of factor flow, the digital platform, the government should give full play to the role of factor allocation in the digital economy, break the barriers to the flow of capital and human factors, and improve the efficiency of factor allocation. (3) The government should provide police protection for the development of the digital economy and coordinate the overall situation. While promoting the digital economy strategy at the national level, it should set specific goals for the development of the local digital economy and give full play to the role of digital economy policy guidance. (4) The government should formulate a differentiated digital economy development strategy. For example, more robust digital economy policies should be implemented for cities with poor development to promote the proliferation and transfer of digital economy resources and synergistic development between regions.

5. Research Limitations and Future Research

Through the pooled regression analysis of GTFP (Green Total Factor Productivity) as an explanatory variable, green innovation as a mediator variable, and the digital economy index as the primary explanatory variable, this study draws the critical conclusion that the digital economy can significantly promote the growth of GTFP. However, the study still has some limitations: first, the applied data in this paper comes from 282 cities in China from 2011-2019, and although the sample capacity is sufficient, the failure to adopt the data of cities in recent years may lead to changes in the significance and stability of the results. Second, it fails to fully consider uncertain factors, such as policy changes, trade frictions, and economic crises, which may significantly impact GTFP. In addition, this study used linear pooled regression, but whether there is a more reasonable model to reflect the impact of the digital economy on GTFP still needs to be further explored. Therefore, future research can focus on increasing the sample capacity and adjusting the variables, including exploring other factors that significantly impact GTFP or exploring more scientific and reasonable linear models.

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References

1. Tapscott, D.; Lowy, A.; Ticoll, D. *Blueprint to the Digital Economy: Wealth Creation in the Era of e-Business*, 1st ed.; McGraw-Hill: New York, NY, USA, 1998; p. 384.
2. Paradise, J. F. China's Quest for Global Economic Governance Reform. Journal of Chinese *Political Science* **2019**, *24*, 471-493.
3. Watanabe, C.; Naveed, K.; Tou, Y.; Neittaanmäki, P. Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. *Technological Forecasting and Social Change* **2018**, *137*, 226–240.
4. Rolle, R. P.; Martucci, V.; Godoy, E. P. Architecture for digital twin implementation focusing on industry 4.0. IEEE Latin America Transactions **2020**, 18(5), 889–898.
5. Huang, J.; Shen, Y.; Chen, J.; Zhou, Y. Regional Digital Economy Development and Enterprise Productivity: A Study of the Chinese Yangtze River Delta. *Regional Science Policy & Practice* **2022**, *14*, 118–137.
6. Curran, D. Risk, innovation, and democracy in the digital economy. *European Journal of Social Theory* **2018**, *21*, 207–226.
7. Nambisan, S.; Wright, M.; Feldman, M. The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy* **2019**, *48*, 103773.
8. Arntz, M.; Gregory, T.; Zierahn, U. The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social Employment & Migration Working Papers* **2016**, *189*, 0_1.

 doi:10.20944/preprints202401.0920.v1

9. Frey, C. B.; Osborne, M. A. The future of employment: How susceptible are jobs to computerization? *Technological Forecasting & Social Change* **2017,** *114*, 254–280.
10. Acemoglu, D.; Restrepo, P. Artificial intelligence, automation, and work. *In The economics of artificial intelligence: An agenda*. University of Chicago Press: 2018; pp. 197-236.
11. Jabłoński, M. Value migration to the sustainable business models of digital economy companies on the capital market. *Sustainability (Switzerland)* **2018**, *10*, 3113.
12. Pouri, M. J.; Hilty, L. M. Conceptualizing the digital sharing economy in the context of sustainability. *Sustainability (Switzerland)* **2018**, *10*, 4453.
13. Rosário, A. T.; Dias, J. C. Sustainability and the Digital Transition: A Literature Review. *Sustainability (Switzerland)* **2022**, *14*, 4072.
14. Chen, S.; Golley, J. "Green" productivity growth in China's industrial economy. *Energy Economics* **2014**, *44*, 89–98.
15. Jeon, B. M.; Sickles, R. C. The role of environmental factors in growth accounting. *Journal of Applied Econometrics (Chichester, England)* **2004**, *19*, 567–591.
16. Chen, C.; Lan, Q.; Gao, M.; Sun, Y. Green total factor productivity growth and its determinants in China's industrial economy. *Sustainability (Switzerland)* **2018**, *10*, 1052.
17. Liu, Z.; Xin, L. Has China's Belt and Road Initiative promoted its green total factor productivity？——Evidence from primary provinces along the route. *Energy Policy* **2019**, *129*, 360–369.
18. Zheng, S.; Kahn, M. E.; Sun, W.; Luo, D. Incentives for China's urban mayors to mitigate pollution externalities: The role of the central government and public environmentalism. *Regional Science and Urban Economics* **2014**, *47*, 61–71.
19. Tang, J.; Qin, F. Analyzing the Effect of Local Government Competition on Green Total Factor Productivity From the Market Segmentation Perspective in China—Evidence From a Three-Stage DEA Model. *Frontiers in Environmental Science* **2021**, *9*, 763945.
20. Li, S.; Zhang, W.; Zhao, J. Does green credit policy promote the green innovation efficiency of heavy polluting industries?—empirical evidence from China's industries. *Environmental Science and Pollution Research International* **2022**, *29*, 46721–46736.
21. Deng, H.; Bai, G.; Shen, Z.; Xia, L. Digital economy and its spatial effect on green productivity gains in manufacturing: Evidence from China. *Journal of Cleaner Production* **2022**, *378*, 134539.
22. Guo, J.; Zhang, K.; Liu, K. Exploring the Mechanism of the Impact of Green Finance and Digital Economy on China's Green Total Factor Productivity. *International Journal of Environmental Research and Public Health* **2022**, *19*, 16303.
23. Canh, N. P.; Thanh, S. D. Financial development and the shadow economy: A multi-dimensional analysis. *Economic Analysis and Policy* **2020**, *67*, 37–54.
24. Liu, Y.; Ma, C.; Huang, Z. Can the digital economy improve green total factor productivity? An empirical study based on Chinese urban data. *Mathematical Biosciences and Engineering* **2023**, *20*, 6866–6893.
25. Gaziz, S.; Oteshova, A.; Prodanova, N.; Savina, N.; Bokov, D. O. Digital economy and its role in the process of economic development. *Journal of Security and Sustainability Issues* **2020**, *9*, 1225–1235.
26. Telukdarie, A.; Dube, T.; Matjuta, P.; Philbin, S. The opportunities and challenges of digitalization for SME's. *Procedia Computer Science* **2023**, *217*, 689–698.
27. Jun, W.; Nasir, M. H.; Yousaf, Z.; Khattak, A.; Yasir, M.; Javed, A.; Shirazi, S. H. Innovation performance in digital economy: does digital platform capability, improvisation capability and organizational readiness really matter? *European Journal of Innovation Management* **2022**, *25*, 1309–1327.
28. Liu, B.; Zou, H.; Qin, H.; Ji, H.; Guo, Y. An evolutionary game analysis of digital transformation of multiagents in digital innovation ecosystems. *PloS One* **2023**, *18*, e02890111.
29. Xie, M.; Ding, L.; Xia, Y.; Guo, J.; Pan, J.; Wang, H. Does artificial intelligence affect the pattern of skill demand? Evidence from Chinese manufacturing firms. *Economic Modelling* **2021**, *96*, 295–309.
30. Agrawal, A.; Gans, J.; Golfarb, A. *The economics of artificial intelligence: an agenda*. University of Chicago Press: 2019; pp. 43.
31. Mullainathan, S.; Spiess, J. Machine learning: An applied econometric approach. *The Journal of Economic Perspectives* **2017**, *31*, 87–106.
32. Nuno, G. Change Management in the Digital Economy: Model Proposal. *International Journal of Innovation in the Digital Economy* **2020**, *11*, 37–51.
33. Jesemann, I. Support of startup innovation towards development of new industries. *Procedia CIRP* **2020**, *88*, 3–8.
34. Thijs, T. R.; Victoria, S. The Solow residual, Domar aggregation, and inefficiency: A synthesis of TFP measures. *Journal of Productivity Analysis* **2011**, *36*, 71–77.
35. Li, X.; Liu, J.; Ni, P. The impact of the digital economy on CO2 emissions: A theoretical and empirical analysis. *Sustainability* **2021**, *13*, 7267.
36. Wang, J.; Dong, K.; Dong, X.; Taghizadeh-Hesary, F. Assessing the digital economy and its carbon-mitigation effects: The case of China. *Energy Economics* **2022**, *113*, 106198.

37. Dai, D.; Fan, Y.; Wang, G.; Xie, J. Digital Economy, R&D Investment, and Regional Green Innovation—Analysis Based on Provincial Panel Data in China. *Sustainability* **2022**, *14*, 6508.
38. Zhao, X.; Nakonieczny, J.; Jabeen, F.; Shahzad, U.; Jia, W. Does green innovation induce green total factor productivity? Novel findings from Chinese city level data. *Technological Forecasting and Social Change* **2022**, *185*.
39. Wu, J.; Xia, Q.; Li, Z. Green innovation and enterprise green total factor productivity at a micro level: A perspective of technical distance. *Journal of Cleaner Production* **2022**, *344*, 131070.
40. Javeed, S.A.; Latief, R.; Akram, U. The Effects of Board Capital on Green Innovation to Improve Green Total Factor Productivity. *Sustainability* **2023**, *15*, 10023.
41. Ma, D.; Zhu, Q. Innovation in emerging economies: Research on the digital economy driving high quality green development. *Journal of Business Research* **2022**, *145*, 801–813.
42. Fan, F.; Lian, H.; Liu, X.; Wang, X. Can environmental regulation promote urban green innovation Efficiency? An empirical study based on Chinese cities. *Journal of Cleaner Production* **2021**, *287*, 125060.
43. Chen, C.; Park, T.; Wang, X.; Piao, S.; Xu, B.; Chaturvedi, R. K.; Fuchs, R.; Brovkin, V.; Ciais, P.; Fensholt, R.; Tømmervik, H.; Bala, G.; Zhu, Z.; Nemani, R. R.; Myneni, R. B. China and India lead in greening of the world through land-use management. *Nature Sustainability* **2019**, *2*, 122–129.
44. Zhao, S.; Peng, D.; Wen, H.; Song, H. Does the Digital Economy Promote Upgrading the Industrial Structure of Chinese Cities? *Sustainability* **2022**, *14*, 10235.
45. Fukuyama, H.; Weber, W. L. A directional slacks-based measure of technical inefficiency. *Socio-Economic Planning Sciences* **2009**, *43*, 274–287.
46. Gruber, H. Innovation, skills and investment: A digital industrial policy for Europe. Econ. Politica Ind. **2017**, *44*, 327–343.
47. Xue, Y.; Tang, C.; Wu, H.; Liu, J.; Hao, Y. The emerging driving force of energy consumption in China: Does digital economy development matter? *Energy Policy* **2022**, *165*, 112997.
48. Bobenič Hintošová, A.; Bódy, G. Sustainable FDI in the Digital Economy. *Sustainability* **2023**, *15*, 10794.
49. Jiang, H.; Jiang, P.; Wang, D.; Wu, J. Can smart city construction facilitate green total factor productivity? A quasi-natural experiment based on China's pilot smart city. Sustain. Cities Soc. **2021**, *69*, 102809.