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Original Research

The Impact of Digital Economy on Total Factor Carbon Productivity: Empirical Analysis Based on Spatial and Mediating Effects

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Abstract

The digital economy has been considered a powerful weapon in addressing global warming. However, the "win-win" effect of the digital economy on economic development and carbon reduction is still unclear. With China's provincial panel data from 2012 to 2019, this paper intends to explore the direct and spatial effects of the digital economy on total factor carbon productivity (TFCP), further revealing the influencing mechanism from the perspective of energy intensity. The results show that the digital economy contributes to boosting TFCP and this conclusion is robust after adopting some robustness tests and solving the endogeneity problem. Moreover, the impact of the digital economy on TFCP has significant positive spillovers. Finally, the digital economy can significantly boost TFCP through reducing the energy intensity. Considering the regional heterogeneity, the impact of the digital economy on TFCP is significantly positive in Mid-Eastern China, however, the impact is not significant in other areas. The above findings provide strong policy guidance for the region to boost the digital economy and TFCP comprehensively, thus stimulating the green transition of the economy.

Keywords: digital economy, total factor carbon productivity, spatial spillover effect, mediating effect, heterogeneous effect

Introduction

Climate change and its environmental impacts have become a worldwide topic [1]. Global warming is one of the most concerning climate issues, which results from the growing concentration of greenhouse gases in the atmosphere [2]. Unfortunately, the greenhouse effect not only poses a great threat to natural resources but also harms public health, which has an adverse effect on ecological sustainability and human survival [3, 4]. China, the biggest carbon emitter, has been committed to achieve the "carbon peak" by 2030 and "carbon neutrality" by 2060 [5, 6]. Given that China is a developing country, reducing carbon emissions may inevitably compromise its economic development goals [7]. Notably, total factor carbon productivity (TFCP) is a specific embodiment of decoupling between economic development and carbon emissions. Hence, it is feasible and practical for developing countries to achieve green and low-carbon development through boosting TFCP [8, 9].

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In this digitalization era, the digital economy supported by the advanced technologies has developed rapidly, which has a crucial marginal utility [10]. Notably, the significant enhancement of the digital economy has introduced a new production factor, that is, data resources. Undoubtedly, the magnification and multiplication effects of new production factor play a prominent role in boosting economic development [11, 12]. Not only does the digital economy help to boost new industries and models, but also it is conductive to accelerating the process of industrial digitalization and digital industrialization [11]. The boom of the digital economy, therefore, is becoming a significant impetus for China's economic development [13]. In terms of its environmental impact, the digital economy is believed to provide a solid basis for environmental management [14, 15]. More importantly, the digital economy has gradually penetrated in the environmental domain and played an essential role in coping with thorny environmental issues. Considering the importance of the digital economy for green and sustainable development, China has formulated some digital economy development policies, such as "Made in China 2025", "Internet +," and "Digital China." These strategies are beneficial to integrate the digital economy with economic and ecological fields and realize sustainable economic development. Significantly in this post-epidemic era, realizing high-speed and green development has become a more critical topic [9].

Given that the digital economy has become an essential support for energy conservation and carbon reduction, it is worth studying the impact of the digital economy on green and low-carbon development. Therefore, this paper intends to investigate the relationship between the digital economy and TFCP, further revealing its spillover and mediating effects. The marginal contributions of this study can be summarized as the following two aspects. (1) Although existing studies abound in examining the relationship between the digital economy and carbon emissions, few studies focus on the "win-win" effect of the digital economy on economic development and carbon reduction. Therefore, this paper innovatively incorporates the digital economy and TFCP into the same research framework, exploring the impact of the digital economy on green and low-carbon development. (2) This paper not only aims to explore the direct impact of the digital economy on TFCP, but also intends to reveal its spatial and mediating effects on TFCP to enrich existing research framework. Specifically, this paper examines the spatial spillover effect of the digital economy on TFCP and further reveals the in-depth mechanism of the impact of the digital economy on TFCP from the perspective of energy intensity, which is of great importance to boost green economy effectively.

The remainder of this paper is as follows: Section 2 shows the literature review and theoretical assumptions. Section 3 presents the methods and materials. Section 4 lists the empirical results. Section 5 summarizes the main conclusions and policy guidance.

Literature Review and Theoretical Assumptions

Literature Review

In terms of TFCP, its measurement is a heated field in the academia. Some academics build an input-output system to analyze the impact of production factors on TFCP comprehensively [16, 17]. On one hand, some scholars apply the stochastic frontier analysis (SFA) to evaluate the environmental efficiency, which needs setting the production function before analysis [18, 19]. On the other hand, the data envelopment analysis (DEA) is more widely used to measure the environmental efficiency [20, 21], including the global Malmquist-Luenberger [9], global super efficiency Epsilon-Based method [22], directional distance functions [23], and non-directional distance functions [7, 24, 25]. After measuring TFCP, some scholars attempt to find its affecting factors. Previous research has examined the influence of urbanization [18], industrial structure [26], technological innovation [25], digital finance [7], and digital investment [9].

In terms of the digital economy, Tapscott firstly introduced the concept of the digital economy, a socioeconomic model driven by digital technologies [27]. However, unfortunately, there has yet to be a consensus on the concept of the digital economy in both academia and industry. From a narrow perspective, the digital economy consists of ICT, digital technologies, and digital data [28]. Comparatively, from a broad perspective, some scholars insist that the digital economy involves both digital technologies and the digitalization of traditional technologies and industries [29]. Subsequently, many researchers attempted to measure the level of digital economy. In the Chinese context, most academics build an evaluation system to calculate the digital economy index through the entropy method, whereas an accepted indicator system for calculating the regional digital economy is still lacking. Different researchers select various indicators to build an evaluation system. Specifically, Li et al. established an index system including three sub-indictors: the informatization, internet, and digital transaction development [30]. Also, considering the availability of city-level data, Zhang et al. built a comprehensive index system consisting of three sub-indicators: fundamentals of digital industry, digital innovation capability, and digital application degree [22].

Since the digital economy includes essential factors affecting energy consumption and carbon emissions, pioneers have investigated the environmental effects of the digital economy from multiple perspectives [31], especially in the field of carbon reduction. In fact, substantial studies have examined the impact of the digital economy on carbon emissions; however, scholars still disagree with their nexus. Firstly, some researchers consider that the digital economy leads to more carbon emissions. Constructing a well-rounded input-output framework, Zhou et al. confirmed that the carbon contribution of digital economy is becoming more and more prominent [32]. Also, Zhang et al. concluded that the digital economy development increases carbon emissions [22]. Secondly, some scholars argue that the digital economy development is beneficial to cut carbon emissions. Based on mechanism analysis, Zhu et al. found that the digital economy is conductive to carbon reduction through promoting technological innovation and upgrading industrial structure [33]. Yu et al. also concluded that the digital economy helps to lower carbon emissions [34]. Moreover, Zhang et al. confirmed that the digital economy plays an essential role in green development. Finally, some academics insist that the nexus between the digital economy and carbon emissions is nonlinear [35]. Considering the spatial effects, Li and Wang found that the digital economy's direct and indirect impacts on carbon emissions show an inverted U-shaped nexus [36].

In summary, although some academics have investigated the relationship between the digital economy and carbon emissions, few studies consider the impact of the digital economy on economic development and carbon reduction. Some pioneers have explored this research topic. Applying China's provincial data from 2009 to 2019, Han et al. found that the digital economy development plays a significant role in boosting TFCP [37]. Likewise, Liu et al. used China's provincial data from 2011 to 2019 and confirmed the significant positive direct and spillover relationship between the digital economy and TFCP [38]. Consequently, it is worth studying the impact of the digital economy on TFCP. Employing China's provincial data from 2012 to 2019, this paper aims to study the direct and spatial effects of the digital economy on TFCP and further reveal its impact mechanism, thus providing theoretical support for green economic development in developing countries.

Theoretical Assumptions

In this digital epoch, the digital economy has been dramatically integrated with life and production and contributed to achieving low-carbon transformation, thus helping to TFCP improvement. With reference to existing literature, the impacts of the digital economy on TFCP can be manifested in three aspects. Firstly, the digital industrialization, represented by information technology and digital services, is friendly to environmental sustainability due to its green attributes. There is no doubt that the digital industries are much greener than traditional ones, which exerts more favorable impact on green development [39]. Secondly, industrial digitalization, supported by the digital technologies and data resources, has gradually integrated with the conventional industries, which helps these industries to transform into an environmental-friendly stage while maintaining high-speed output growth [40]. Finally, the carbon trading market, relying on digital innovation and application, helps to promote green technology innovation. Weng and Xu revealed that the boom of the digital economy is conductive to coping with thorny problems that obstruct the development of carbon emission trading market [41]. Therefore, motivated by the significant environmental effects of digital economy, some academics conducted empirical research to analyze their relationship and confirmed that the digital economy can significantly improve TFCP [22, 37, 38]. In summary, this paper puts forth the hypothesis 1:

H1. The digital economy development contributes to enhancing TFCP.

The spatial effects of the digital economy on TFCP may be summarized as the following three points. Firstly, the boom of the digital economy contributes to speed up the flow of information and human capital and cultivate new industries, which improves the resource allocation efficiency in a specific area and its neighboring areas [31]. Secondly, the development of the digital economy breaks through the space-time boundary of traditional transactions and promotes the regional collaboration strategies through the spatial flow of information and digital technologies [22]. Finally, because of the collaboration and interaction between local and adjacent governments [42], local governments may inevitably formulate similar but competitive policies for the digital economy development, which can also explain its spatial spillover effect. In short, this paper puts forward the hypothesis 2:

H2. The impact of the digital economy on TFCP has positive spillover effects.

Since the digital economy has developed rapidly, the penetration of the digital economy in enterprises plays a critical role in reducing the energy intensity (EI) through promoting green technology innovation and introducing new production factor [43]. Moreover, the digital economy development can help the enterprises transform to a greener production stage and increase the output of unit energy, which contributes to TFCP improvement. In the Chinese context, based on the provincial panel data from 2012 to 2019, Guo et al. concluded that there is significant negative relationship between the digital economy and EI [44]. In addition, applying the panel data of 277 cities from 2011 to 2019, Zhang et al. found that the digital economy is conductive to boosting carbon emission performance through lowering the EI [22]. Therefore, this paper proposes the hypothesis 3:

H3. The development of the digital economy can boost TFCP through reducing EI.

Materials and Methods

Measurement of Total Factor Carbon Productivity

This paper employs the non-radical directional distance function (NDDF) to measure TFCP. The NDDF, proposed by Zhou et al. [45], is a relatively new DEA model and overcomes the limitation in measuring efficiency by considering the proportion of expected and unexpected outputs. It is set in the following form:

$$\overrightarrow{ND}(K, L, E, Y, C;\ \boldsymbol{g}) = sup\{\boldsymbol{\omega}^T\boldsymbol{\beta}: [(K, L, E, Y, C) + \boldsymbol{g} \cdot diag(\boldsymbol{\beta})] \in T\} \tag{1}$$

where $\boldsymbol{\omega}^T = (\omega_K, \omega_L, \omega_E, \omega_Y, \omega_C)^T$ represents the weight vector of input and output, $\boldsymbol{g} = (g_K, g_L, g_E, g_Y, g_C)$ denotes the directional vector of input and output, and $\boldsymbol{\beta} = (\beta_K, \beta_L, \beta_E, \beta_Y, \beta_C)^T \geq 0$ is the slack variable, measuring the inefficiency of input and output. Specifically, this paper considers the capital stock (K), energy consumption (E), and labor (L) as inputs, GDP (Y) as desirable output, and carbon emissions (C) as undesirable output. Moreover, following the practice of Zhang and Choi [46], the calculation results can be solved by linear programming as follows:

$$\begin{aligned}
&\overrightarrow{ND}(K, L, E, Y, C;\ \boldsymbol{g}) = max(\omega_K\beta_K + \omega_L\beta_L + \omega_E\beta_E + \omega_Y\beta_Y + \omega_C\beta_C)\\
&s.t.\ \textstyle\sum_{n=1}^{N}\lambda_n K_n \leq K + \beta_K g_K\\
&\textstyle\sum_{n=1}^{N}\lambda_n L_n \leq L + \beta_L g_L\\
&\textstyle\sum_{n=1}^{N}\lambda_n E_n \leq E + \beta_E g_E\\
&\textstyle\sum_{n=1}^{N}\lambda_n Y_n \geq Y + \beta_Y g_Y\\
&\textstyle\sum_{n=1}^{N}\lambda_n C_n = C + \beta_C g_C\\
&\lambda_n \geq 0,\ n=1,2,\ldots,N\\
&\beta_K, \beta_L, \beta_E, \beta_Y, \beta_C \geq 0
\end{aligned} \tag{2}$$

where the weight and directional vectors can be set in different ways. Given that there are three inputs, one desirable output, and one undesirable output, this paper sets the weight vector to $\boldsymbol{\omega}^T = (1/9, 1/9, 1/9, 1/3, 1/3)^T$ and the directional vector to $\boldsymbol{g} = (-K, -L, -E, Y, -C)$, which is based on previous studies [45-47]. Following existing literature [45, 48], this paper describes the TFCP as the average efficiency, therefore, it can be formulated as follows:

$$\mathrm{TFCP} = \frac{1/4[(1-\beta_K^*)+(1-\beta_L^*)+(1-\beta_E^*)+(1-\beta_C^*)]}{1+\beta_Y^*} \tag{3}$$

where β_K^*, β_L^*, β_E^*, β_Y^*, and β_C^* are the optimal solution to Eq. (2). The efficiencies are between 0 and 1. Specifically, the closer the TFCP is to 1, the higher the TFCP is.

Measurement of Digital Economy

This paper measures the digital economy level through the improved entropy method. Firstly, the threshold method is used to standardization. Considering that all indicators are positive indicators, this paper applies the following formula:

$$x_{ij} = \frac{v_{ij} - min(v_{ij})}{max(v_{ij}) - min(v_{ij})} \times k + q \tag{4}$$

where v_{ij} is the original data of the j-th indicator in the i-th province. x_{ij} is the standardized data. k and q can be set based on the transformed data distribution interval. Given that all data would be logarithmically processed before empirical analysis, the interval is set between 1 and 2, therefore, k and q are both taken as 1. However, with the panel data of China's provinces, the traditional entropy method fails to capture the dynamic features of the digital economy. This paper, therefore, applies the improved entropy method to make the digital economy index comparable across the year. Unlike the conventional method, the improved one considers the time dimension. This paper sets 2012 as the baseline year and standardizes the data with the following equation:

$$x_{ijt} = \frac{v_{ijt} - min(v_{ij1})}{max(v_{ij1}) - min(v_{ij1})} + 1 \tag{5}$$

where v_{ij1} denotes the original data of the j-th indicator of the i-th province in the baseline year. After standardizing, the measurement indicators can be comparable between years. The maximum and minimum scores in the non-baseline year, notably, may be greater than two or less than one, reflecting the dynamic changes of the digital economy. Finally, after obtaining the entropy value and weight, this study calculates the digital economy (DE) index as follows:

$$\mathrm{DE_{it}} = \textstyle\sum_{j=1}^{20} \mathrm{x_{ijt}} * \mathrm{w_j},\ i=1, 2, \ldots, 30, j=1, 2, \ldots, 20, t=1, 2, \ldots, 8. \tag{6}$$

where w_j denotes the weight of j-th indicator and DE_{it} represents the level of the digital economy in the i-th province and t-th year. Obviously, the larger the DE index, the higher the digital economy level.

Model Construction

Motivated by the STIRPAT model framework, this study constructs the benchmark model to study the effect of the digital economy on TFCP.

$$\mathrm{lnTFCP_{it}} = \alpha_0 + \alpha_1 \mathrm{lnDE_{it}} + \gamma \mathrm{lnX_{it}} + \eta_i + \nu_t + e_{it} \tag{7}$$

where $TFCP_{it}$ and DE_{it} denote the level of TFCP and the digital economy in province i in year t. X_{it} represents a set of the control variables, such as population and affluence. If the core coefficient α_1 is significantly positive, the promotion effect of the digital economy on TFCP is identified. γ are the coefficients of control variables. η_t and ν_t are the individual fixed and time fixed effects. e_{it} denotes the random perturbation term. α_0 is the constant term.

The spatial error models (SEM), spatial lag models (SLM), and spatial Durbin models (SDM) are usually applied in spatial econometric analysis. Notably, the SDM, a more general method than the SEM or SLM, considers both spatial lag and spatial error [49]. Given that, this paper adopts the SDM to capture the spillover impact of the digital economy on TFCP.

$$\ln \mathrm{TFCP}_{it} = \alpha_0 + \rho \sum_{j=1}^{N} W_{ij} \ln \mathrm{TFCP}_{jt} + \alpha_1 \ln \mathrm{DE}_{it} + \gamma \ln X_{it} + \theta \sum_{j=1}^{N} W_{ij} \ln \mathrm{DE}_{jt} + \eta \sum_{j=1}^{N} W_{ij} \ln X_{jt} + \eta_i + \nu_t + e_{it}$$

$$\varepsilon_{it} = \lambda \textstyle\sum_{j=1}^{N} W_{ij}\, \varepsilon_{jt} + \mu_{it},\ N=30 \tag{8}$$

where ρ and λ are the coefficients of spatial lag and spatial error, respectively. ε_{it} and μ_{it} denote the spatial auto-correlation error and stochastic error. θ and η are the spatial lag coefficients. W_{ij} is the spatial weight matrix, measured by a composite matrix of the geographic inverse distance matrix and adjacent matrix.

To examine the potential mediating mechanism, this paper adopts the three-step model proposed by Baron and Kenny [50].

$$\ln\mathrm{TFCP}_{it} = \alpha_0 + \alpha_1 \ln\mathrm{DE}_{it} + \gamma \ln X_{it} + \eta_i + \nu_t + e_{it} \tag{9}$$

$$\ln\mathrm{EI}_{it} = \beta_0 + \beta_1 \ln\mathrm{DE}_{it} + \gamma \ln X_{it} + \eta_i + \nu_t + e_{it} \tag{10}$$

$$\ln\mathrm{TFCP}_{it} = \varphi_0 + \varphi_1 \ln\mathrm{DE}_{it} + \varphi_2 \ln\mathrm{EI}_{it} + \gamma \ln X_{it} + \eta_i + \nu_t + e_{it} \tag{11}$$

where EI is the mediating variable. Formula (9) examines the impact of digital economy on TFCP, which is consistent with the baseline model. Formula (10) identifies the relationship between the digital economy and mediating variable. Formula (11) introduces the mediating variable in the model and examines the relationship between the digital economy and TFCP again. Specifically, if the coefficient α_1 is significantly positive and β_1 and φ_2 are significantly negative, the mediating effect of EI is confirmed.

Variables and Data

The explained variable is total factor carbon productivity. With reference to Zhang and Liu [7], this paper adopts the NDDF method to measure TFCP. Input indicators include capital, labor, and energy. Capital is represented by the size of fixed asset investment, and this paper calculates it through the perpetual inventory method [9, 51]. Labor is characterized by the total number of employees in the local region [7, 52]. Additionally, energy is measured by the total energy consumption of each province in tons of standard coal [37]. Output indicators include both desired and undesired outputs. Specifically, the desired output is each province's real gross regional product, and the undesired output is each province's CO_2 emissions.

The core explanatory variable is the digital economy. Considering the broad sense of the digital economy and the availability of data, this paper builds a multi-dimensional index system to measure it from four dimensions, including digital infrastructure, digital industrialization, industrial digitization, and digital innovation, respectively. The selection of all indicators is based on existing literature [7, 22]. Furthermore, the improved entropy method is utilized to capture the dynamic changes of the digital economy. The indicators are listed in Table 1.

The mediating variable of this paper is the energy intensity represented by the ratio of total energy consumption to the real GDP. The control variables applied in this paper include population density [7, 53], economic development [9, 18, 54], urbanization level [9, 18, 53, 54], and energy structure [9, 36]. Specifically, the permanent population at the end of the year per square kilometer is employed to measure population density (PD). Per capita real gross domestic product (GDPP) represents economic development. Moreover, the ratio of urban population to the total regional population is used to represent the level of urbanization (UL). The energy consumption structure (ES) is expressed by the proportion of coal consumption in total energy consumption.

Due to the data availability, this paper selects the panel data of 30 provinces from 2012 to 2019 as the research samples. The data is mainly collected from China Emission Accounts and Datasets (CEADs), "China Statistical Yearbook", "China Energy Statistical Yearbook", "China Information Technology Statistical Yearbook" and "China Tertiary Industry Statistical Yearbook". The digital finance index is derived from the official data published by the Institute of Digital Finance at Peking University [55]. In addition, the price data is deflated based on the price in 2012, and missing data is filled in by linear interpolation. Finally, this paper takes the natural logarithm of each variable to reduce the heteroscedasticity. The descriptive statistics are listed in Table 2.

Results and Discussion

Relevant Tests

Before estimating the panel regression model, some relevant tests are conducted to select the suitable model. Firstly, this paper adopts the correlation

Table 1. Indicators for measuring the digital economy level.

Main indicator	Primary indicator	Secondary indicator	Tertiary indicator	Unit
Digital Economy	Digital infrastructure	Communication level	Number of mobile phone users per 100 people	%
			Internet penetration rate	%
		Communication capability	Number of Internet domain names	10^4
			Number of Internet broadband access ports	10^4
			Length of fiber optic cable lines	10^4 km
	Digital industrialization	Digital industry	Software business income	10^4 yuan
			Total industrial output value of digital industry	10^6 yuan
		Digital service	Information technology service income	10^4 yuan
			Number of employees engaged in digital industry	10^4
			Total amount of telecommunications business	10^6 yuan
	Industrial digitalization	Enterprise applications	Proportion of enterprises with e-commerce transaction	%
			Number of computers used per 100 people	-
		Inclusive applications	E-commerce transaction amount	10^6 yuan
			Digital financial digitization index	-
			Express delivery volume	10^4
	Digital innovation	Innovation input	Internal expenditure on R&D	10^4 yuan
			Full-time equivalent of R&D personnel	-
		Innovation output	Number of patent applications granted	-
			Number of digital economy enterprises	-
			Number of new product development projects	-

Table 2. Descriptive statistics.

Variable	Abbreviation	Obs	Mean	Standard deviation	Min	Max
Total factor carbon productivity	lnTFCP	240	-0.277	0.238	-0.83	0
Digital economy	lnDE	240	0.467	0.313	0.031	1.910
Energy intensity	lnEI	240	-0.082	0.507	-1.105	1.231
Population density	lnPD	240	5.469	1.296	2.067	8.278
Economic development	lnGDPP	240	1.313	0.386	0.631	2.315
Urbanization level	lnUL	240	4.059	0.195	3.592	4.495
Energy structure	lnES	240	4.404	0.587	0.916	5.506

and multicollinearity tests. Then, the Hausman test is used to test the appropriateness of the fixed effects model. Finally, some diagnostic tests are applied to reveal the characteristics of panel data.

As shown in Table 3, the correlation coefficients of each variable are statistically significant at the significant level of 1%. Especially, there is a strong correlation between the core explanatory variable and explained variable. Furthermore, this paper applies the variance inflation factor (VIF) to test multicollinearity. The results are presented in the first column of Table 3. Notably, the values of VIF for each variable and mean VIF are all less than 10, demonstrating that there is no multicollinearity problem. Then, this paper adopts the Hausman test [56] and the results are shown in Table 4. The null hypothesis that the random effects model is more proper than the fixed effects model is rejected. This paper, therefore, selects the fixed effects

Table 3. Correlation and multicollinearity tests.

Variables	VIF	(1)	(2)	(3)	(4)	(5)	(6)
(1) lnTFCP	-	1.000					
(2) lnDE	1.59	0.496***	1.000				
(3) lnPD	1.76	0.657***	0.491***	1.000			
(4) lnGDPP	5.51	0.593***	0.553***	0.628***	1.000		
(5) lnUL	4.54	0.441***	0.544***	0.527***	0.879***	1.000	
(6) lnES	1.36	-0.496***	-0.388***	-0.352***	-0.493***	-0.437***	1.000
Mean VIF	3.72	-	-	-	-	-	-

Notes: *** signify significance at 1% level.

Table 4. Results of diagnostic tests.

Test	Statistic	P value
Hausman test	24.66	0.000
Modified Wald test for GroupWise heteroskedasticity	1507.42	0.000
Wooldridge test for autocorrelation in panel data	26.74	0.000
Frees' test of cross-sectional independence	1.53	0.000

model. Furthermore, as presented in Table 4, this paper successively tests the presence of the heteroskedasticity, autocorrelation, and cross-sectional dependence [57-59]. The results indicate that there exist heteroskedasticity, autocorrelation, and cross-sectional independence. Hence, this paper estimates the two-way fixed effects model with Driscoll and Kraay standard errors to obtain robust results [60]. Finally, the Moran's I index is adopted to conduct spatial correlation test. Table 5 lists Moran's I values and statistic tests of TFCP. The results show that Moran's I statistics are all significantly positive, signifying a positive spatial correlation of TFCP.

Table 5. Moran's I index of TFCP.

Year	Moran's I index
2012	0.407***
2013	0.293**
2014	0.325***
2015	0.315**
2016	0.465***
2017	0.444***
2018	0.501***
2019	0.622***

Notes: ** and *** signify significance at 5%, and 1% level.

Direct Effect

Considering that the digital economy is a comprehensive concept and includes many aspects, this paper attempts to investigate its overall impact on TFCP, further studying its impact at the subdivision level. Consequently, referring to the secondary indicators of the digital economy index, the index is disaggregated into four sub-indicators. Table 6 displays the impact of the digital economy and its sub-indicators on TFCP. The results show that the estimation coefficient of lnDE is significantly positive at the significance level of 1%, signifying that the digital economy contributes to improving TFCP; thus, H1 is verified. The results are consistent with the conclusions drawn by Zhang et al. [22]. Specifically, for every 1% increase in the digital economy, TFCP enhances by 0.230%. As reported in Table 6, all sub-indicators have significant positive effects on improving TFCP. Notably, digital infrastructure exerts the most substantial impact on TFCP, which may because digital infrastructure is the solid foundation for other dimensions. The finding also coincides with the conclusions drawn by Tang et al. [61].

Spatial Effect

Following the practice of Elhorst [49], this paper conducts some model selection tests to choose an appropriate spatial model, including the robust Lagrange multiplier (LM) tests, Hausman tests, LR tests and Wald tests. Table 7 indicates that robust LM tests are rejected at 1% significance level, demonstrating that the spatial

Table 6. Benchmark model results.

Variable	(1)	(2)	(3)	(4)	(5)
	DE	Infrastructure	Digital	Industry	Innovation
lnDE	0.230***				
	(0.0529)				
lnInfrastructure		0.230**			
		(0.0871)			
lnDigital			0.226***		
			(0.0634)		
lnIndustry				0.169***	
				(0.0339)	
lnInnovation					0.138***
					(0.0374)
lnPD	0.491	0.834	0.626	0.517	0.710
	(0.422)	(0.448)	(0.408)	(0.434)	(0.419)
lnGDPP	0.504***	0.409***	0.506***	0.504***	0.519***
	(0.127)	(0.0874)	(0.115)	(0.137)	(0.114)
lnUL	0.953***	0.664***	0.780***	1.036***	0.819***
	(0.0896)	(0.0950)	(0.0826)	(0.0970)	(0.113)
lnES	-0.0721***	-0.0791***	-0.0531***	-0.0776***	-0.0776***
	(0.0183)	(0.0224)	(0.0135)	(0.0184)	(0.0221)
Constant	-7.232**	-7.794**	-7.365**	-7.665**	-7.875**
	(2.651)	(2.453)	(2.434)	(2.763)	(2.642)
Regional fixed	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes
N	240	240	240	240	240
R^2	0.591	0.573	0.587	0.589	0.576

Notes: Figures in () are the Driscoll and Kraay standard errors. *, **, and *** signify significance at 10%, 5%, and 1% level.

models are superior to the static models. Additionally, Table 8 represents the Hausman tests in three fixed effect models. The null hypothesis that the random effect model is superior to the fixed effect model is rejected in three models. So, the fixed effect models are more appropriate. Finally, this paper examines whether the SDM can be simplified to SLM or SEM through LR and Wald tests. Table 8 shows that all the statistics pass the significance test, signifying that the null hypothesis that SDM can be simplified to SLM or SEM is rejected.

Table 7. Results of robust LM tests.

Test	Statistic	P value
Robust LM spatial lag	15.827	0.000
Robust LM spatial error	217.221	0.000

In summary, the fixed effect SDM is used for the empirical analysis.

Then, this paper selects the appropriate spatial model according to the log-likelihood and R^2. From the results shown in Table 9, the two-way fixed effect model is superior to the other models. The empirical analysis, therefore, is according to the SDM with spatial and time fixed effects.

SDM can reveal the relationship between the digital economy and TFCP; unfortunately, the estimated coefficients of explanatory variables may not reflect the marginal effects on TFCP [62]. Referring to Lesage and Pace [62], this study, therefore, further decomposes the marginal effects of SDM. The results in Table 10 show that the direct and spillover effects of the digital economy on TFCP are all significantly positive. Specifically, the direct effect of lnDE is 0.129, signifying

Table 8. Results of Hausman test, LR tests and Wald tests.

Test	Statistic		
	Spatial fixed effects	Time period fixed effects	Spatial and time fixed effects
Hausman test	36.09***	27.80***	160.86***
LR test (spatial lag)	17.68***	42.85***	10.72*
LR test (spatial error)	18.09***	47.24***	5.65***
Wald test (spatial lag)	18.02***	47.98***	10.68*
Wald test (spatial error)	16.41***	50.39***	16.31***

Notes: *, **, and *** signify significance at 10%, 5%, and 1% level.

Table 9. Spatial effect results.

	(1)	(2)	(3)
Variable	Spatial fixed effects	Time fixed effects	Spatial and time fixed effects
lnDE	0.0787	0.154***	0.117*
	(0.0780)	(0.0495)	(0.0671)
W*lnDE	-0.0919	0.155**	0.210**
	(0.0936)	(0.0754)	(0.0980)
Control variables	Yes	Yes	Yes
W*Control variables	Yes	Yes	Yes
rho	0.555***	0.0103	0.150**
	(0.0519)	(0.0952)	(0.0731)
sigma2_e	0.00474***	0.0163***	0.00335***
	(0.000445)	(0.00149)	(0.000307)
N	240	240	240
Log-L	289.485	153.280	342.699
R^2	0.259	0.563	0.511

Notes: Figures in () are the standard errors. *, **, and *** signify significance at 10%, 5%, and 1% level.

Table 10. Marginal effects of digital economy on TFCP.

Variable	Composite matrix			Inverse matrix		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
lnDE	0.129*	0.241**	0.370***	0.152**	0.500**	0.652***
	(0.0671)	(0.0963)	(0.0913)	(0.0609)	(0.196)	(0.188)

Notes: *, **, and *** signify significance at 10%, 5%, and 1% level.

that a 1% increase in the digital economy directly leads to a 0.129% improvement in a local province's TFCP. The finding confirms the H1 again. Moreover, the indirect effect of lnDE is 0.241, suggesting that every 1% increase in the digital economy in adjacent provinces results in a 0.241% enhancement in a local province's TFCP. Interestingly, the spillover impact is much higher than the direct one, signifying that the digital economy has substantial positive spillovers on TFCP; therefore, H2 is proved. The possible reason behind this spatial effect is that the digital economy is conductive to shortening the space-time distance and accelerating

Table 11. Mediating effect results.

	(1)	(2)
	lnEI	lnCO2
lnDE	-0.225***	0.171**
	(0.0270)	(0.0523)
lnEI		-0.262**
		(0.0781)
Control variables	Yes	Yes
Constant	-4.849***	-8.503**
	(1.105)	(2.652)
Regional fixed	Yes	Yes
Time fixed	Yes	Yes
N	240	240
R^2	0.492	0.607
Bootstrap test (500 samples)	0.0664***	

Notes: Figures in () are the Driscoll and Kraay standard errors. *, **, and *** signify significance at 10%, 5%, and 1% level.

the technological innovation, therefore boosting the spillover effect of TFCP. It is argued that the spatial weight matrix can influence the estimated results of spatial models. Consequently, this paper employs an inverse distance matrix to conduct robustness checks. As reported in Table 10, the spatial effect of the digital economy on TFCP is significantly positive, proving the robustness of H2.

Mediating Effect

The above analysis confirms the direct and spatial spillover effect of the digital economy, but the intermediary effect is also worth studying. Table 11 lists the results of the three-step method. Specifically, the results of formula (9) are shown in column (1) of Table 6. The results of formula (10) and (11) are presented in Table 11. The coefficient of lnDE is significantly positive in Table 6 while significantly negative in column (1) of Table 11. And the coefficient of lnEI is significantly negative in column (2) of Table 11. The results illustrate that the development of the digital economy is conductive to boosting TFCP through reducing the energy intensity, which confirms H3 of this paper. Generally, the digital economy plays a crucial role in the economic mode transformation and energy conservation. The wide application of digital economy in life and production contributes to the decoupling between the economic development and energy consumption, thus lowering the energy intensity, which is consistent with the conclusion drawn by Zhang et al. [22]. At the same time, low energy density is conductive to TFCP improvement. Furthermore, to check the robustness of the mediating effect, this paper

Table 12. Heterogeneity effect results.

Variable	(1) Eastern	(2) Central	(3) Western	(4) Northeastern
lnDE×D1	0.0688*			
	(0.0320)			
lnDE×D2		0.163*		
		(0.0800)		
lnDE×D3			-0.0488	
			(0.0307)	
lnDE×D4				-0.119
				(0.126)
Control variables	Yes	Yes	Yes	Yes
Constant	-8.393**	-8.748**	-9.160**	-8.026***
	(2.972)	(2.689)	(2.949)	(2.214)
Regional fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
N	240	240	240	240
R^2	0.565	0.576	0.562	0.561

Notes: Figures in () are the Driscoll and Kraay standard errors. *, **, and *** signify significance at 10%, 5%, and 1% level.

adopts the Bootstrap test, and the results are shown in Table 11. The significant of the mediating effect is at the 1% level, which confirms the robustness of H3.

Heterogeneous Effect

To further investigate the heterogeneous impact of the digital economy on TFCP, this paper divides the sample into four regions: eastern region, central region, western region, and northeastern region, respectively. Then, four dummy variables are introduced to examine the heterogenous effect. Specifically, if $i \in$ eastern region, D1 = 1; if $i \in$ central region, D2 = 1; $i \in$ western region, D3 = 1; and $i \in$ northeastern region, D4 = 1. As shown in Table 12, the impact of the digital economy on TFCP is significantly positive in Mid-Eastern China; however, this impact is not significant in other areas. The Mid-Eastern China has a sound economic foundation and close regional cooperation strategies, accounting for its green and low-carbon development. Comparatively, in western and northeastern areas, the impact is not significant, possibly because of their backward digital infrastructure, underdeveloped digitalization level, and poor digital innovation.

Robustness Test

(1) Substitution of the explained variable. This paper introduces the carbon intensity (CI), represented by ratio of carbon emissions to the real GDP, to replace TFCP. Column (1) of Table 13 illustrates that the digital economy can significantly decrease CI, which is the same as the favorable impact of the digital economy on enhancing TFCP. In addition, the estimated coefficients of the control variables have not changed significantly, which demonstrates the robustness of H1.

(2) Replacement of the core explanatory variable. Instead of the improved entropy method, this paper applies the factor analysis to measure the digital economy and conduct robustness test. Specifically, the factor score (lnDE_F) is applied to substitute the explanatory variable (lnDE). Again, Column (2) of Table 13 confirms the positive nexus between the digital economy and TFCP, proving the robustness of H1.

Table 13. Robustness test results.

Variable	(1)	(2)	(3)	(4)
	lnCI	lnTFCP	SYS-GMM	2SLS
lnDE	-0.0147***		0.0853**	
	(0.00320)		(0.0400)	
lnDE_F		0.151***		
		(0.0371)		
L.lnTFCP			0.784***	
			(0.0688)	
lnIV				0.210**
				(0.0982)
Control variables	Yes	Yes	Yes	Yes
Constant	-0.000937	-8.564**	0.800***	
	(0.0741)	(2.699)	(0.295)	
Regional fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
N	240	240	210	210
R^2	0.279	0.567		0.546
AR (1)			0.005	
AR (2)			0.395	
P-value of Hansen			0.999	
Under-identification test				19.082***
Weak identification test				46.467***

Notes: Figures in () are the Driscoll and Kraay standard errors in Model (1) and (2). Figures in () are the robust standard errors in Model (3) and (4). *, **, and *** signify significance at 10%, 5%, and 1% level

(3) Replacement of the estimated method. To check the validity of the two-way fixed effects model, this paper employs the System Generalized Method of Moment (SYS-GMM) method to estimate the benchmark model. As presented in column (3) of Table 13, the AR (1) and AR (2) tests illustrate that the first-order serial correlation is not rejected, and the second-order serial correlation is rejected. Also, the results of Hansen test reject the null hypothesis, signifying that the instrument variables are effective. Therefore, the SYS-GMM method is applicable to the baseline model. Column (3) of Table 13 indicates that the digital economy can significantly boost TFCP, proving the robustness of H1 again.

(4) Solving the endogeneity problem. To cope with the potential endogeneity issue between the digital economy and TFCP, this paper applies the instrumental variable regression. Using the research by Bartik as a guide [63], this study introduces the "Bartik instrument" variable. Specifically, the product of the digital economy level lagging by one period and the first order difference of national digital economy level ($lnDE_{i,t-1} \times \Delta lnDE_{i,t-1}$) to is used to construct the instrumental variable. Obtained from an average level of 30 provinces, the national digital economy level is not easily impacted by a province. Moreover, the difference item is exogenous to a single province. Consequently, this paper adopts the two-stage least square (2SLS) method based on the "Bartik instrument" variable to solve the endogeneity problem. Column (4) of Table 13 lists the relevant tests and regression results. Specifically, the statistics of the under-identification test and weak identification test are all significant at 1% level, signifying that the model can be identified, and no weak instrumental variable exists. The construction of this instrumental variable, therefore, is appropriate for empirical analysis. Moreover, the estimated coefficient of lnIV is significantly positive, thus proving the robustness of H1.

Conclusions

The digital economy has become an essential pillar of energy conservation and carbon reduction. Applying the panel data of China's provinces from 2012 to 2019, this paper innovatively investigates the impact of the digital economy on total factor carbon productivity (TFCP) from multiple perspectives. The main conclusions are as follows: (1) The digital economy development is beneficial to boost TFCP. Moreover, this impact is significantly positive in Mid-Eastern China; however, the impact is not significant in other areas. (2) The effect of the digital economy on TFCP has a significant positive spillover effect. (3) Energy intensity plays a significant intermediary role in the impact of the digital economy on TFCP. Based on the above conclusions, this paper provides some practical policy implications.

(1) Chinese government should vigorously encourage the wide application of digital technologies in enterprises and promote the digital infrastructure construction. The application of digital technologies, such as cloud computing, artificial intelligence, and Internet of Things, can help the whole society to achieve green and low-carbon development. Therefore, the government should build a digital economy level evaluation system for different types of enterprises, thus providing appropriate financial and technical support for them. More importantly, the government should pay a closer attention to digital infrastructure construction, especially for the underdeveloped regions. The construction and upgrading of the digital infrastructure can build a solid foundation for the high-speed development of digital economy in a region, further stimulating its potential to achieve green transition.

(2) Chinese government should effectively utilize the spatial effects of the digital economy to formulate regional collaboration policies for boosting TFCP. Specifically, local governments should formulate the strategies for developing the digital economy based on economic conditions and environmental recourses, entirely playing the positive externality of the digital economy. In the Mid-Eastern China, the government should not only promote the green technology innovation and economic model transition, but also focus on cultivate the green and low-carbon awareness and behaviors of residents through the "soft governance", thus promoting TFCP comprehensively. In contrast, other regions should clearly realize the "Digital Gap" and properly reduce carbon emission reduction targets. Moreover, local government should strongly promote interregional cooperation with their neighboring regions and upgrade the digital infrastructure, boosting the TFCP step by step.

(3) Chinese government should pay attention to the energy conservation and reduce the energy intensity. The traditional economic activities are closely related to high energy consumption; however, the attributes of the digital economy are associated with green and sustainable development. Specifically, the government should promote the digitalization in traditional high-polluting industries, further helping them to transform to a low energy consumption stage. Moreover, the government should also accelerate the application of digital technologies in the carbon emission monitoring of enterprises. With the help of such technologies, relevant regulations should be formulated to strictly limit carbon emissions in energy-intensive industries, thus reducing the energy intensity.

This paper empirically investigates the impact of the digital economy on China's TFCP, but scholars can make some improvements in future research. First, this paper employs the provincial-level panel data to conduct empirical analysis; however, there are tremendous internal disparities in China's provinces. If data is available, scholars can apply China's prefecture-level panel data to conduct empirical research. Secondly, this paper takes the China's provinces as the sample from a macro perspective. But limited by the data from a micro perspective, how the digital economy influences the TFCP of enterprises is worth studying in the future.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. BELKHIR L., ELMELIGI A. Assessing ICT global emissions footprint: Trends to 2040 recommendations. Journal of Cleaner Production, **177**, 448, **2018**.
2. BEKUN F.V., ALOLA A.A., SARKODIE S.A. Toward a sustainable environment: Nexus between CO_2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries. Science of The Total Environment, **657**, 1023, **2019**.
3. COHEN A.J., BRAUER M., BURNETT R., ANDERSON H.R., FROSTAD J., ESTEP K., BALAKRISHNAN K., BRUNEKREEF B., DANDONA L., DANDONA R., FEIGIN V., FREEDMAN G., HUBBELL B., JOBLING A., KAN H., KNIBBS L., LIU Y., MARTIN R., MORAWSKA L., POPE C.A., SHIN H., STRAIF K., SHADDICK G., THOMAS M., VAN DINGENEN R., VAN DONKELAAR A., VOS T., MURRAY C.J.L., FOROUZANFAR M.H. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. The Lancet, **389** (10082), 1907, **2017**.
4. MUKUL S.A., ALAMGIR M., SOHEL MD.S.I., PERT P.L., HERBOHN J., TURTON S.M., KHAN MD. S.I. MUNIM S.A. REZA A.H.M.A. LAURANCE W.F. Combined effects of climate change and sea-level rise project dramatic habitat loss of the globally endangered Bengal tiger in the Bangladesh Sundarbans. Science of The Total Environment, **663**, 830, **2019**.
5. SHI X., ZHENG Y., LEI Y., XUE W., YAN G., LIU X., CAI B., TONG D., WANG J. Air quality benefits of achieving carbon neutrality in China. Science of The Total Environment, **795**, 148784, **2021**.
6. ZHOU C., ZHANG R., LOGINOVA J., SHARMA V., ZHANG Z., QIAN Z. Institutional Logic of Carbon Neutrality Policies in China: What Can We Learn? Energies, **15** (12), 4391, **2022**.
7. ZHANG M., LIU Y. Influence of digital finance and green technology innovation on China's carbon emission efficiency: Empirical analysis based on spatial metrology. Science of The Total Environment, **838**, 156463, **2022**.
8. LI S., WANG S. Examining the effects of socioeconomic development on China's carbon productivity: A panel data analysis. Science of The Total Environment, **659**, 681, **2019**.
9. XU Q., ZHONG M., CAO M. Does digital investment affect carbon efficiency? Spatial effect and mechanism discussion. Science of The Total Environment, **827**, 154321, **2022**.
10. ANSER M.K., AHMAD M., KHAN M.A., ZAMAN K., NASSANI A.A., ASKAR S.E., ABRO M.M.Q., KABBANI A. The role of information and communication technologies in mitigating carbon emissions: evidence from panel quantile regression. Environmental Science and Pollution Research, **28** (17), 21065, **2021**.
11. MIAO Z. Digital economy value chain: concept, model structure, and mechanism. Applied Economics, **53** (37), 4342, **2021**.
12. LI Z., LIU Y. Research on the Spatial Distribution Pattern and Influencing Factors of Digital Economy Development in China. IEEE Access, **9**, 63094, **2021**.
13. DONG F., HU M., GAO Y., LIU Y., ZHU J., PAN Y. How does digital economy affect carbon emissions? Evidence from global 60 countries. Science of The Total Environment, **852**, 158401, **2022**.
14. KJAER L.L., PIGOSSO D.C.A., MCALOONE T.C., BIRKVED M. Guidelines for evaluating the environmental performance of Product/Service-Systems through life cycle assessment. Journal of Cleaner Production, **190**, 666, **2018**.
15. USMAN A., OZTURK I., HASSAN A., MARIA ZAFAR S., ULLAH S. The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis. Telematics and Informatics, **58**, 101537, **2021**.
16. ZHOU P., ANG B.W., HAN J.Y. Total factor carbon emission performance: A Malmquist index analysis. Energy Economics, **32** (1), 194, **2010**.
17. TENG X., LIU F., CHIU Y. The change in energy and carbon emissions efficiency after afforestation in China by applying a modified dynamic SBM model. Energy, **216**, 119301, **2021**.
18. SUN W., HUANG C. How does urbanization affect carbon emission efficiency? Evidence from China. Journal of Cleaner Production, **272**, 122828, **2020**.
19. ZHANG C., CHEN P. Industrialization, urbanization, and carbon emission efficiency of Yangtze River Economic Belt-empirical analysis based on stochastic frontier model. Environmental Science and Pollution Research, **28** (47), 66914, **2021**.
20. CHOI Y., ZHANG N., Zhou P. Efficiency and abatement costs of energy-related CO_2 emissions in China: A slacks-based efficiency measure. Applied Energy, **98**, 198, **2012**.
21. ZHAO P., ZENG L., LI P., LU H., HU H., LI C., ZHENG M., LI H., YU Z., YUAN D., XIE J., HUANG Q., QI Y. China's transportation sector carbon dioxide emissions efficiency and its influencing factors based on the EBM DEA model with undesirable outputs and spatial Durbin model. Energy, **238**, 121934, **2022**.
22. ZHANG W., LIU X., WANG D., ZHOU J. Digital economy and carbon emission performance: Evidence at China's city level. Energy Policy, **165**, 112927, **2022**.
23. DU K., LU H., YU K. Sources of the potential CO_2 emission reduction in China: A nonparametric meta frontier approach. Applied Energy, **115**, 491, **2014**.
24. ZHOU P., ANG B. W., WANG, H. Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research, **221** (3), 625, **2012**.
25. HE A., XUE Q., ZHAO R., WANG D. Renewable energy technological innovation, market forces, and carbon

emission efficiency. Science of The Total Environment, **796**, 148908, **2021**.
26. WANG K., WU M., SUN Y., SHI X., SUN A., Zhang P. Resource abundance, industrial structure, and regional carbon emissions efficiency in China. Resources Policy, **60**, 203, **2019**.
27. TAPSCOTT D. The digital economy: promise and peril in the age of networked intelligence. Choice Reviews Online, **33** (09), 33, **1996**.
28. CHIEN F., CHAU K.Y., ADY S.U., ZHANG Y., TRAN Q.H., ALDEEHANI T.M. Does the combining effects of energy and consideration of financial development lead to environmental burden: social perspective of energy finance? Environmental Science and Pollution Research, **28** (30), 40957, **2021**.
29. TEECE D.J. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. Research Policy, **47** (8), 1367, **2018**.
30. LI Y., YANG X., RAN Q., WU H., IRFAN M., AHMAD M. Energy structure, digital economy, and carbon emissions: evidence from China. Environmental Science and Pollution Research, **28** (45), 64606, **2021**.
31. ZHAO S., PENG D., WEN H., WU Y. Nonlinear and spatial spillover effects of the digital economy on green total factor energy efficiency: evidence from 281 cities in China. Environmental Science and Pollution Research, **2022**.
32. ZHOU X., ZHOU D., ZHAO Z., WANG Q. A framework to analyze carbon impacts of digital economy: The case of China. Sustainable Production and Consumption, **31**, 357, **2022**.
33. ZHU Z., LIU B., YU Z., CAO J. Effects of the Digital Economy on Carbon Emissions: Evidence from China. International Journal of Environmental Research and Public Health, **19** (15), 9450, **2022**.
34. YU Z., LIU S., ZHU Z. Has the Digital Economy Reduced Carbon Emissions? Analysis Based on Panel Data of 278 Cities in China. International Journal of Environmental Research and Public Health, **19** (18), 11814, **2022**.
35. ZHANG J., LYU Y., LI Y., GENG Y. Digital economy: An innovation driving factor for low-carbon development. Environmental Impact Assessment Review, **96**, 106821, **2022**.
36. LI Z., WANG, J. The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. Journal of Cleaner Production, **351**, 131570, **2022**.
37. HAN D., DING Y., SHI Z., HE Y. The impact of digital economy on total factor carbon productivity: the threshold effect of technology accumulation. Environmental Science and Pollution Research, **29** (37), 55691, **2022**.
38. LIU L., ZHANG Y., GONG X., LI M., LI X., REN D., JIANG P. Impact of Digital Economy Development on Carbon Emission Efficiency: A Spatial Econometric Analysis Based on Chinese Provinces and Cities. International Journal of Environmental Research and Public Health, **19** (22), 14838, **2022**.
39. GHOBAKHLOO M., CHING N.T. Adoption of digital technologies of smart manufacturing in SMEs. Journal of Industrial Information Integration, **16**, 100107, **2019**.
40. QIN S.-F., CHENG K. Future Digital Design and Manufacturing: Embracing Industry 4.0 and Beyond. Chinese Journal of Mechanical Engineering, **30** (5), 1047, **2017**.
41. WENG Q., XU H. A review of China's carbon trading market. Renewable and Sustainable Energy Reviews, **91**, 613, **2018**.
42. SONG Y., ZHANG X., ZHANG M. The influence of environmental regulation on industrial structure upgrading: Based on the strategic interaction behavior of environmental regulation among local governments. Technological Forecasting and Social Change, **170**, 120930, **2021**.
43. ALAM N., HASHMI N.I., JAMIL S.A., MURSHED M., MAHMOOD H., ALAM S. The marginal effects of economic growth, financial development, and low-carbon energy use on carbon footprints in Oman: fresh evidence from autoregressive distributed lag model analysis. Environmental Science and Pollution Research, **29** (50), 76432, **2022**.
44. GUO Q., WU Z., JAHANGER A., DING C., GUO B., AWAN A. The spatial impact of digital economy on energy intensity in China in the context of double carbon to achieve the sustainable development goals. Environmental Science and Pollution Research, **2022**.
45. ZHOU P., ANG B.W., WANG H. Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research, **221** (3), 625, **2012**.
46. ZHANG N., CHOI Y. Total-factor carbon emission performance of fossil fuel power plants in China: A meta frontier non-radial Malmquist index analysis. Energy Economics, **40**, 549, **2013**.
47. BARROS C.P., MANAGI S., MATOUSEK R. The technical efficiency of the Japanese banks: Non-radial directional performance measurement with undesirable output. Omega, **40** (1), 1, **2012**.
48. ZHANG N., KONG F., CHOI Y., ZHOU P. The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants. Energy Policy, **70**, 193, **2014**.
49. ELHORST J.P. Spatial Econometrics: From Cross-sectional Data to Spatial Panels. Springer, Heidelberg, **2014**.
50. BARON R.M., KENNY D.A. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, **51** (6), 1173, **1986**.
51. LI Q., WU Y. Intangible capital, ICT and sector growth in China. Telecommunications Policy, **44** (1), 101854, **2020**.
52. DING Q., KHATTAK S.I., AHMAD M. Towards sustainable production and consumption: Assessing the impact of energy productivity and eco-innovation on consumption-based carbon dioxide emissions (CCO_2) in G-7 nations. Sustainable Production and Consumption, **27**, 254, **2021**.
53. XU L., FAN M., YAN, L., SHAO S. Heterogeneous green innovations and carbon emission performance: Evidence at China's city level. Energy Economics, **99**, 105269, **2021**.
54. GAO D., LI G., YU J. Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. Energy, **247**, 123395, **2022**.
55. GUO F., WANG J., WANG F., CHENG Z., KONG T., ZHANG X. Measuring China's digital financial inclusion; index compilation and spatial characteristics. China Economic Quarterly, **19** (4), 1401, **2020**.
56. HAUSMAN J.A. Specification Tests in Econometrics. Econometrica, **46** (6), 1251, **1978**.

57. GREENE W.H. Econometric Analysis. Pearson Education India, **2003**.
58. WOOLDRIDGE J.M. Econometric Analysis of Cross Section and Panel Data. The MIT press, **2002**.
59. FREES E.W. Longitudinal and Panel Data: Analysis and Applications in the Social Sciences (1st ed.). Cambridge University Press, **2004**.
60. DRISCOLL J.C., KRAAY A.C. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. Review of Economics and Statistics, **80** (4), 549, **1998**.
61. TANG C., XU Y., HAO Y., WU H., XUE Y. What is the role of telecommunications infrastructure construction in green technology innovation? A firm-level analysis for China. Energy Economics, **103**, 105576, **2021**.
62. LESAGE J.P., PACE P.K. Introduction to spatial econometrics (statistics, textbooks and monographs). CRC Press, **2009**.
63. BARTIK T.J. How Do the Effects of Local Growth on Employment Rates Vary With Initial Labor Market Conditions? W.E. Upjohn Institute, **2006**.