CORE INDUSTRY AGGLOMERATION OF DIGITAL ECONOMY AND GREEN TOTAL FACTOR PRODUCTIVITY: EVIDENCE FROM CHINA

Ping Li[1], Huiying Fu[2], Yueyao Li[3]

[1] Hubei University of Technology, School of Economics and Management, Department of International Economics, China, ORCID: 0000-0002-5378-6188, dixiaheliping@163.com;
[2] Hubei University of Technology, School of Economics and Management, Department of International Economics, China, ORCID: 0000-0002-5154-6164, 102001378@hbut.edu.cn;
[3] Hubei University of Technology, School of Economics and Management, Department of Accounting, China, ORCID: 0000-0002-1313-5612, 201911303@hbut.edu.cn.

Abstract: *With the advent of the information age and the development of network technology, the digital economy with digital knowledge and information as crucial production factors has become the core driving force for high-quality green economic and social development. This paper took the exploration of the role of the digital economy as an engine for regional green and high-quality development as the purpose of the study, incorporates the core industry agglomeration of the digital economy into the analysis framework of green total factor productivity (GTFP), depicted the characteristics of GTFP change from the dual dimensions of direct and indirect effects, and analyzed the spatial effects of specialized and diversified digital economy's core industry agglomeration on the impact of GTFP using data and spatial measurement models of 25 provincial-level regions in China from 2003 to 2019. Results show that both the specialized digital economy's core industry agglomeration and the diversified digital economy's core industry agglomeration can significantly improve GTFP, and both have significant spatial spillover effects. At the same time, the impact of the digital economy's core industry agglomeration on GTFP is spatial heterogeneity. GTFP in the eastern region can be significantly enhanced by the digital economy's core industry agglomeration, and the specialized digital economy's core industry agglomeration has a significant negative spillover effect on GTFP in the eastern region. In the contrast, GTFP in the mid-western region can be significantly enhanced only by the specialized digital economy's core industry agglomeration, and the digital economy's core industry agglomeration has no significant spatial spillover effect on GTFP in the mid-western region. The obtained conclusions reveal that each region should reasonably establish a cluster model of core industries in the digital economy to facilitate the green development of the regional economy.*

Keywords: *Digital economy, core industry agglomeration, green total factor productivity, high-quality green development, spatial Durbin model.*

JEL Classification: *L16, Q01.*

APA Style Citation: Li, P., Fu, H., & Li, Y. (2022). Core Industry Agglomeration of Digital Economy and Green Total Factor Productivity: Evidence from China. *E&M Economics and Management, 25*(4), 40–57. https://doi.org/10.15240/tul/001/2022-4-003

Introduction

In recent years, the wave of digitalization has swept the world, and the digital economy, a new economic form, has emerged and become an important driving force for transformation and upgrading, as well as the high point of a new round of industrial competition among countries around the world. In particular, the COVID-19 outbreak in 2020, while giving the traditional manufacturing industry a considerable impact and posed severe challenges to economic development around the world. It has further highlighted the role of the engine of the digital economy and made it a key driving force for the global economic recovery and the development of the world economy (Steiner, 2019). For China, on the one hand, after years of rapid development, the traditional kinetic energy of the national economy continues to weaken and can no longer forcefully pull the economy to soar, so it is urgent to find new economic growth kinetic energy; on the other hand, the extensive traditional pattern of economic growth emphasizes quantity, ignores quality and low efficiency, which causes waste of resources and also brings severe environmental problems. The imbalance between economic development and ecological environmental protection needs to be solved urgently. The concept of green development to lead to high-quality economic development has become the key to solving the problem.

It is worth mentioning that digital technologies such as Information and Communication Technologies (ICTs), which can improve energy efficiency (Rodriguez-Lluesma et al., 2021; Usman et al., 2021), were described by the Sustainable Development Goals (SDGs) as enablers of sustainable development (Lu et al., 2020; Zhang et al., 2021). Moreover, as a new driving force for economic development, the digital economy took ICTs as the core to providing new impetus for environmental improvement. Scholars found that the popularity of the digital economy in the field of energy consumption and environmental protection was conducive to solving problems such as declining environmental carrying capacity and scarcity (Junior et al., 2018; Rehman et al., 2021). The digital economy has great potential to improve the ecological environment (Alam & Murad, 2020) by continuously reducing emissions of pollutants such as carbon dioxide (Nizam et al., 2020), sulfur dioxide (Yang et al., 2021), and industrial wastewater (Sun et al., 2022) through innovation of green technologies, upgrading of industrial structure and improvement of the efficiency of environmental management. Therefore, the development of the digital economy was in line with the concept of green development. The digital economy had a positive impact on high-quality economic development, innovative development, and green development (Yang et al., 2022). In this context, the mechanism of the digital economy driving high-quality economic development had undoubtedly become the focus of academic attention. Li et al. (2022) pointed out that technological innovation was an important way for the digital economy to improve the efficiency level of the green economy. Wang et al. (2022) further improved the impact path of the digital economy on high-quality economic development based on the former, believing that industrial restructuring was also one of the essential intermediary mechanisms for the digital economy to promote high-quality green development directly. Ma and Zhu (2022) shared the same view and argued that the digital economy could influence high-quality green development in the surrounding area through spatial spillover effects. While Ren et al. (2022) argued from urban clusters with different levels of digital economy development that digital economy industry agglomeration affected green inclusive growth through energy consumption, environmental pollution, economic growth, human capital, industrial structure, and technological progress.

In the context of China’s adherence to the concept of green development and promotion of high-quality economic development, the digital economy had become a significant development trend in the new era of its green benefits. At the same time, to further measure the level of high-quality green development, scholars proposed the indicator of the green total factor productivity by comprehensively considering economic growth, energy consumption, and environmental pollution, and used it as an essential basis for evaluating organic coordination between the level of green development and quality of economic development. Through the study of green total factor productivity, it was found that internet growth (Li et al., 2020) and digital technologies represented by ICTs (Hao et al., 2022) could contribute to green total factor productivity. In addition, the development of the digital economy might be accompanied by agglomerations of industries related to the digital economy, which could contribute to the intensification and scale development of the agglomeration area. This agglomeration process might also be accompanied by economic phenomena such as the entire flow of labor and capital, technological innovation, and enterprise competition, which in turn would bring about changes in the intensity of social resource consumption, input-output efficiency, and environmental quality. Then it led to changes in regional green total factor productivity. Therefore, this paper aims to explore the role of digital economy as an engine for regional green and high quality development. By studying the relationship between the digital economy's core industry agglomeration and green total factor productivity, the engine driving role of core industries in the digital economy for high-quality economic development is further explored. This is of great practical significance for further promoting the development of economic digital transformation and high-quality green socio-economic in the new era.

The novelties and contributions of this study are as follows. (1) Based on the perspective of industrial agglomeration, this study clearly defines the connotation and extension of core industries in the digital economy, and the impact mechanisms of different core industries in the digital economy on green total factor productivity were analyzed, which provides a new perspective for promoting high-quality green development of the regional economy through the development of the digital economy. (2) This study fully considers coordinated development between economic growth, energy utilization, and environmental protection. The EBM (Epsilon Based Measure) model was used to construct multi-dimensional and multi-level provincial green total factor productivity including non-desired output, to comprehensively and systematically measure the level of high-quality green development of each region's economy. (3) The spatial Durbin model was used to empirically examine the impact of different digital economy's core industry agglomeration models on green total factor productivity. It further explores the spatial effects of the digital economy's core industry agglomeration on green total factor productivity while studying direct effects. It gives vast differences in geographic location across China's provinces.

The rest of this study is arranged as follows. Section 1 reviews the literature on the core industry agglomeration of the digital economy affecting total green factor productivity and proposes hypotheses. Section 2 introduces data indicators and measurement models used in this study. Section 3 is empirical analysis, which obtains the results of empirical research. Section 4 is the conclusions of this study, which puts forward managerial implications.

1. Literature Review and Hypothesis Development

Green total factor productivity is a green development indicator that considers economic growth, resource conservation, and environmental protection and comprehensively evaluates the quality of economic growth. The agglomeration of strategic emerging industries represented by the digital economy's core industry has an obvious spatial spillover effect on green economic efficiency (Zeng et al., 2020). At the same time, the impact of different industrial agglomeration methods on green development might differ. In this regard, this study focuses on the two industrial agglomeration modes of specialization and diversification. It illustrates the impact path of the digital economy's core industry agglomeration on green total factor productivity based on direct and spillover effects brought by industrial agglomeration from the perspective of spatial association.

1.1 The Direct Effect of the Core Industry Agglomeration of Digital Economy on Interprovincial Green Total Factor Productivity

According to MAR (Marshall-Arrow-Romer) externality theory, and Jacobs's externality theory, the digital economy's core industry agglomeration mainly acted on total green factor productivity through economies of scale, technology, and industrial structure effects. It affected green total factor productivity to some extent.

From the perspective of scale effect, the specialized digital economy's core industry agglomeration could realize common utilization of public infrastructure, intermediate commodities, and labor resources in the agglomeration area by the core enterprises of the same digital economy. Significantly it reduced transaction costs, search costs, and production costs while improving the efficiency of public resource utilization. At the same time, given the wide application of digital products and technologies in other industries, the specialized digital economy's core industry agglomeration would promote specialized agglomeration of other industries with industrial connections, and further, it exerted scale economy through the sharing mechanism.

From the perspective of technical effect, the digital economy's core industry agglomeration would cause a significant accumulation and flow of digital talents and information in the agglomeration area. Specialized industrial agglomeration could promote dissemination and mutual learning of knowledge and technology between enterprises in the industry so that enterprises could learn from each other's strengths and constantly improve their technologies and products. Diversified industrial agglomeration could bring about knowledge collisions between different fields, and promote the cross-border integration and complementarity of knowledge and technology between industries. The digestion and absorption of integrated innovation further promoted wide application and spatial diffusion of technological innovation (Duranton et al., 1999). From the perspective of clean technology, industrial agglomeration could promote the interaction, sharing, and dissemination of energy-saving information and clean technologies among enterprises (Wang et al., 2021; Xie et al., 2019). Spillover effects of clean technologies and knowledge could contribute to environmental technology innovation, thereby improving green total factor productivity. In addition, the specialized digital economy's core industry agglomeration promoted the formation of competitive relations between enterprises in the agglomeration area, which made enterprises in the industry continue to carry out technological innovation and consciously fulfill social responsibilities such as environmental protection to enhance their market competitiveness. Finally, innovative digital technologies and digital products brought by specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration would be further applied to other industries associated with them. Green total factor productivity would be comprehensively improved by improving resource utilization efficiency and energy utilization efficiency of other industries.

From the perspective of the industrial structure effect, on the one hand, the digital economy's core industry agglomeration would promote the development of the digital economy itself. Meanwhile, in the process of integrating the digital economy and the real economy, it would promote the upgrading of the industrial structure by directly influencing the use and allocation of resource elements such as human capital and scientific and technological innovation (Liu & Chen, 2021). On the other hand, technological innovation brought by the digital economy's core industry agglomeration would further promote digital industrialization and industrial digitalization and then promote the upgrading of industrial structure.

Since economic structure affected economic growth, energy demand, and environmental footprints (Ahmed et al., 2022), upgrading the industrial structure brought by core industries in the digital economy would promote green and low-carbon development. Based on the above analysis, this study proposes the following hypothesis:

H1: Specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration can improve green total factor productivity in the region.

1.2 The Spillover Effect of the Core Industry Agglomeration of Digital Economy on the Provincial Green Total Factor Productivity

While the digital economy's core industry agglomeration affected local green total factor productivity, it might also have an impact on green total factor productivity in neighboring regions due to its spatial relevance. That is, there was a spatial spillover effect.

From the perspective of spatial relevance of the digital economy, there was a significant spatial correlation of digital economy development between regions (Li & Liu, 2021; Wang et al., 2022). The development of the local digital economy would affect the development of the digital economy in neighboring regions. The core industry agglomeration of the digital economy would promote the development of the local digital economy because of its economies of scale and technical effects, and it would also affect the development level of the digital economy in neighboring areas through the spatial relevance of the digital economy and ultimately affect the green total factor productivity of neighboring areas.

From the perspective of technological spillover, the digital economy has a significant positive spatial spillover effect on innovation efficiency and was a vital driving force for improving innovation efficiency in China (Wang & Cen, 2022). At the same time, the digital economy's core industry had the advantage of overcoming spatial restrictions for information technology dissemination. When the digital economy's core industry reached a particular agglomeration scale in the local area, the knowledge and technology interaction network within and between the industries would be expanded accordingly. Technological innovation generated by the collision of local knowledge could achieve inter-regional technology spillover by expanding the knowledge interaction network and the barrierless dissemination of digital information and affecting neighboring regions' green total factor productivity.

From the perspective of the demonstration effect between regions, the promotion of green total factor productivity in one region would put neighboring regional governments under pressure from public opinion to adopt similar behaviors in energy conservation and emission reduction work (Zhang et al., 2019). Residents would supervise local governments to make policy improvements by comparing the policy behaviors of local governments. Good policies would attract neighboring regions to adopt similar policies to increase green total factor productivity. Therefore, the core industry agglomeration of the digital economy could urge neighboring regions to increase their green total factor productivity by promoting the improvement of local green total factor productivity. Based on the above analysis, this study proposes the following hypothesis:

H2: Specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration can improve green total factor productivity in neighboring areas.

2. Methodology

2.1 Model Design

The Spatial Lag Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) are three models commonly used for spatial metrology. Compared with SAR and SEM, SDM considers the effect of spatial hysteresis terms of the independent variable and the dependent variable on the dependent variable, which can better estimate the spillover effect driven by different observation individuals. Since green total factor productivity (*GTFP*) in the region will not only be affected by the digital economy industry agglomeration level (*MJ*) in the region, but also by the digital economy industry agglomeration level and green total factor productivity in the surrounding areas. Therefore, SDM is used as a basic empirical model in this study, and other control variables are introduced for the problem of variable omission. The general form of the spatial Durbin model is shown as equation (1):

$$\begin{aligned} \ln GTFP_t = \omega_0 + \rho W \ln GTFP_{it} + \\ + \alpha \ln MJ_{it} + \gamma \ln P_{it} + \beta W \ln MJ_{it} + \\ + \theta W \ln P_{it} + \mu_i + v_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where: P_{it} is the control variable; W is the spatial weight matrix; ρ, β and θ are spatial interaction term coefficients of the dependent, independent, and control variables; α and γ represent the elastic coefficients of the independent and control variables; μ_i and v_t represent spatial and temporal effects, respectively.

To analyze the spatial spillover effect of green total factor productivity more comprehensively and objectively, this study refers to the existing literature. It selects a contiguity-based spatial weights matrix based on geographical characteristics and an economic distance special weights matrix based on economic and social characteristics.

W_1 is the contiguity-based spatial weights matrix. It reflects the spatial connection between two adjacent units (Morton et al., 2018), where the elements on the diagonal are 0. The other element expressions are based on the adjacency matrix, shown as equation (2):

$$W_{ij} = \begin{cases} 1, Zone_i \text{ and } Zone_j \text{ are adjacent} \\ 0, Zone_i \text{ and } Zone_j \text{ are adjacent} \end{cases} \quad (\boldsymbol{i} \neq \boldsymbol{j}) \tag{2}$$

where: $i = j = 1, 2, 3, ..., n$.

W_2 is the economic distance the special weights matrix. Considering the impact of differences in economic development levels in different regions on the spatial spillover effect of *GTFP*, this study borrows the method of Han et al. (2018) to construct an economic distance special weights matrix through per capita GDP, shown as equation (3):

$$W^e_{ij} = \begin{cases} \frac{1}{|\bar{Y}_i - \bar{Y}_j|} & (i \neq j) \\ 0 \end{cases} \quad (3)$$

where: $\bar{Y}_i$ and $\bar{Y}_j$ are GDP per capita in the sample period for region i and region j, respectively. The main diagonal elements in the matrix are 0.

2.2 Variable Selection and Data Source

The interpreted variable is green total factor productivity (*GTFP*) by province. The EBM model proposed by Tone and Tsutsutsui (2010) compensates for the shortcomings of the DEA model and SDM model to a certain extent by effectively combining radial and non-radial models. At the same time, compared with the Malmquist-Luenberger index, the GML index overcomes the problem of no solution in the linear programming of ML exponent, and the calculation results are transitive and cyclically accumulative. Therefore, this study refers to the method of Li and Wang (2022), using the EBM-GML model to measure *GTFP*.

In this study, labour, capital, and energy inputs are chosen as input indicators, and GDP and pollution emissions are chosen as expected and unintended output indicators respectively. Among them, the total energy consumption of energy input is expressed after the provinces are converted into standard coal. The labor input is measured by the sum of the employment of the three industries in each province. The capital input is based on the physical capital stock of each province as the agent variable. Concerning the findings of Shan (2008), physical capital stock is estimated using the perpetual inventory method. The expected output is expressed by the total GDP value of each province. The GDP index is used to calculate the actual GDP of each province based on 2000. Undesirable outputs are represented by sulfur dioxide emissions, general industrial solid waste emissions, and industrial wastewater emissions.

Explanatory variables include specialized digital economy's core industry agglomeration (*Mar*) and diversified digital economy's core industry agglomeration (*Jacobs*). According to the Statistical Classification of Digital Economy Industries and Core Industries (2021) issued by China, the digital economy industry can be divided into digital product manufacturing (01), digital product service industry (02), digital technology application industry (03), digital elements driving industry (04) and digital efficiency improvement industry (05). Among them, the 01–04 categories are the core industry of the digital economy. However, due to the initial collation of the digital economy industry division in 2021, its targeted industrial data statistics have not yet been formed. Based on consideration of data availability and statistical caliber consistency, this study refers to the "information transmission, software, and information technology service industry" classification standard in the High-tech Industry (Manufacturing) Classification (2017) and the National Economic Industry Classification of China (GB/T 4754–2017), by comparing various sub-categories of the digital economy industry with it. Finally, core industries in the digital economy are selected for research and divided into the following three categories, namely information transmission, computer services, and software industries, electronic and communication equipment manufacturing industries, and computer and office equipment manufacturing industries. Based on the practice of Duranton and Puga (1999), this study constructs indicators of the specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration, respectively, shown as equations (4) and (5):

$$Mar_i = \max_j \left(\frac{Q_{ij}}{Q_i} \right) \quad (4)$$

$$Jacobs_i = \frac{1}{\sum_j |Q_{ij} - Q_i|} \quad (5)$$

Among them, Q_{ij} represents the proportion of the digital economy's core industry j in region i to the total number of employment of all core industries in the digital economy in region i. Q_i is the ratio of the number of employees in the digital economy's core industry j nationwide and the total number of employees in the core industries in the national digital economy.

To better interpret the impact of the digital economy's core industry agglomeration on *GTFP*, this study selects infrastructure construction (*Infra*), foreign direct investment (*FDI*), environmental regulation (*Env)*, human capital (*Edu*), urbanization level, degree of government intervention (*Expend*), energy consumption structure (*Energy*), and regional technological innovation (*Patent*) as control variables. Among them, *Infra* is measured by the sum of railway mileage, road

Tab. 1: Descriptive statistics of the variables

Variable	Variable-definition	Mean	Standard error	Least value	Crest value	Sample value
ln*GTFP*	Green total factor productivity in all provinces	−0.1443	0.2840	−1.1128	0.5644	400
ln*Mar*	Specialized industry agglomeration	0.7020	0.4666	0.0174	1.6402	
ln*Jacobs*	Diversified industry agglomeration	0.8292	0.8593	−0.4147	5.0238	
ln*Infra*	Infrastructure construction	11.8379	0.8134	9.4389	13.0491	
ln*FDI*	Direct investment in trauma	0.6527	0.7833	−2.2878	2.1032	
ln*Env*	Environmental regulation	−1.3210	0.7172	−4.0610	0.3926	
ln*Edu*	Human capital	0.5467	0.3627	−0.7889	1.2750	
ln*Urban*	Urbanization level	3.9720	0.2640	3.2696	4.4954	
ln*Expend*	Government intervention	2.8928	0.3368	2.0691	3.6943	
ln*Energy*	Structure of energy consumption	3.7064	0.5308	−1.0991	4.3537	
ln*Patent*	Regional technological innovation	7.7009	1.4483	4.5850	10.9978	

Source: own

mileage and long-distance cable length in each province. *FDI* is expressed by the actual use of foreign direct investment as a proportion of GDP. *Env* is measured by the proportion of investment in industrial pollution control to total industrial output. *Edu* is measured by the proportion of students enrolled in ordinary colleges and universities as a proportion of the total population at the end of the year. The level of urbanization is expressed as the urbanization rate of each province. *Expend* is expressed as a proportion of government fiscal expenditure to GDP. *Energy* is measured by the proportion of coal consumption converted into standard coal in total energy consumption. *Patent* is expressed in the number of patented inventions authorized.

Due to a large amount of missing data in Hainan, Gansu, Qinghai, Xinjiang, Ningxia, Tibet, Hong Kong, Macau, and Taiwan, this study uses relevant data from 2003 to 2019 from 25 provinces for research except the above 9 provinces.

The data are mainly derived from the China Statistical Yearbook, China Energy Statistics Yearbook, China Environmental Statistics Yearbook, China High Technology Statistical Yearbook, Wind Database, Provincial Statistical Yearbook, Provincial Statistical Bureau official website, and local statistical bulletin. At the same time, the missing values are supplemented by the interpolation method and linear extension prediction method. To reduce the heteroscedasticity, this study performs logarithmic treatment on all variables, and the descriptive statistics of the variables can be seen in Tab. 1.

3. Results Analysis

3.1 Spatial Autocorrelation Test

The presence or absence of the spatial autocorrelation of primary variables in the model is a prerequisite for the ability to model a spatial panel. Referring to Geniaux and Martinetti (2018), the Moran index is selected as an index for spatial autocorrelation test in this study, to comprehensively detect spatial distribution characteristics of the green total factor productivity from perspectives of both the whole and the local. This study uses MaxDEA professional software to measure and process each province's *GTFP* from 2004 to 2019. Then, the Moran's I index of the green total factor productivity based on

Tab. 2: Moran's I values of the green total factor productivity from 2004 to 2019

Spatial weights matrix	Contiguity-based		Economic distance	
Year	Moran's I	*P*-value	Moran's I	*P*-value
2004	0.111	0.142	0.053	0.286
2005	0.102	0.215	0.081	0.216
2006	0.137	0.139	0.037	0.445
2007	0.148	0.129	0.068	0.304
2008	0.177	0.082	0.135	0.100
2009	0.183	0.061	0.131	0.092
2010	0.174	0.068	0.210	0.013
2011	0.180	0.064	0.251	0.004
2012	0.225	0.033	0.335	0.000
2013	0.238	0.025	0.381	0.000
2014	0.271	0.011	0.416	0.000
2015	0.283	0.008	0.465	0.000
2016	0.306	0.005	0.384	0.000
2017	0.355	0.002	0.385	0.000
2018	0.319	0.004	0.438	0.000
2019	0.294	0.006	0.476	0.000

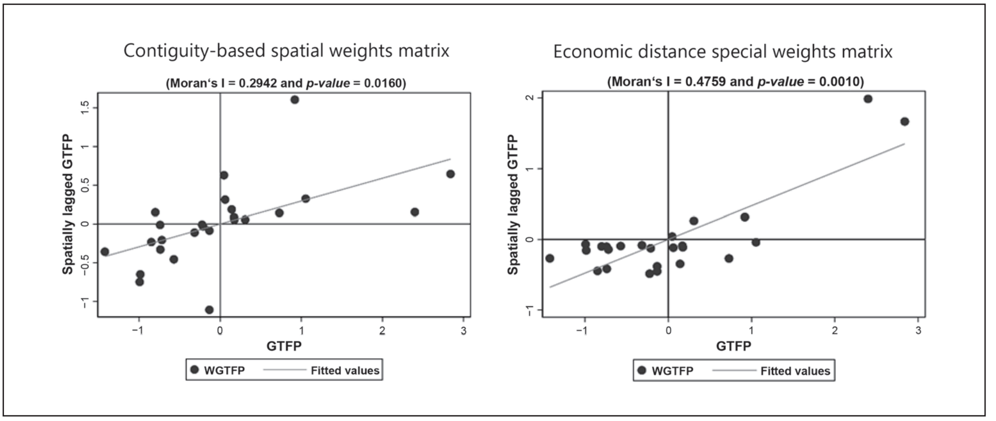
Source: own

a contiguity-based spatial weights matrix and an economic distance special weights matrix is calculated by Stata 15.1 software to test spatial correlation of the green total factor productivity under different spatial matrices. Spatial autocorrelation test results are shown in Tab. 2. It is not difficult to see that when using the contiguity-based spatial matrix and economic distance special weights matrix, except for Moran's I index between 2004 and 2007, which is not significant and *GTFP* does not have apparent spatial autocorrelation. The *p*-value of Moran's I index in the remaining years is less than 10%, rejecting the null hypothesis of random spatial distribution, and *GTFP* shows significant spatial autocorrelation in the sample. At the same time, Moran's I of the green total factor productivity is greater than 0, indicating a positive spatial correlation between *GTFP* in various provinces. That is, *GTFP* has solid spatial agglomeration.

To more intuitively display the local correlation relationship of the green total factor productivity and reveal the spatial correlation between the green total factor productivity and neighboring provinces in various provinces, this study takes 2019 data as an example. It draws Moran's I scatter plots based on contiguity-based spatial weightsmatrix and economic distance special weights matrix, as shown in Fig. 1.

It can be seen that when the contiguity-based spatial weights matrix is adopted, most provinces in China are mainly located in the first quadrant (*HH*) and the third quadrant (*LL*). The provinces with higher green total factor productivity have higher *GTFP* than neighboring provinces. *GTFP* in neighboring provinces with lower green total factor productivity is also lower, indicating local spatial agglomeration *GTFP* in various provinces under the spatial proximity weight. When using the economic distance special weights matrix, most provinces in China are located in the third quadrant (*LL*). A few provinces are in the first quadrant (*HH*) and fourth quadrant (*HL*), indicating that, *GTFP* in various provinces has local spatial dependence and local spatial heterogeneity under the economic distance special weights weight.

Fig. 1: Moran's I scatter plot of green total factor productivity in 2019



Source: own

To determine the most suitable spatial econometric model, this study uses Stata 15.1 software to test the spatial econometric model from assumptions of the contiguity-based spatial weights matrix (W_1) and the economic distance special weights matrix (W_2) respectively. Test results are shown in Tab. 3.

From the LM test results based on the ordinary linear OLS regression model, it can be seen that LM-lag, LM-error, Robust LM-lag, and Robust LM-error in the contiguity-based spatial weights matrix all pass at least 10% of the significance test, and LM-lag and Robust LM-lag in the economic distance special weights

Tab. 3: Test results of spatial Durbin model under different spatial weight matrices

Inspection	W_1		W_2	
	Statistical value	*P*-value	Statistical value	*P*-value
LM-lag	25.028***	0.0000	7.042**	0.0080
Robust LM-lag	16.662***	0.0000	15.470***	0.0000
LM-error	11.173**	0.0010	0.878	0.3490
Robust LM-error	2.808*	0.0940	9.306**	0.0020
Spatial effects LR	34.21***	0.0002	44.970***	0.0000
Time effect LR	650.640***	0.0000	728.290***	0.0000
Hausman test	22.270*	0.0138	50.140***	0.0000
Wald spatial lag	48.440**	0.0000	118.810***	0.0000
Wald spatial error	50.640***	0.0000	105.330***	0.0000
LR spatial lag	46.630***	0.0000	104.210***	0.0000
LR spatial error	48.470***	0.0000	125.780***	0.0000

Source: own

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

matrix both pass at least a 5% significance test, indicating that under the assumption of both matrices, SAR and SEM have at least one valid. Based on Elhorst's (2010) criterion, concerning the findings of Wu and Zhou (2018), if the LM test supports at least one of SAR and SEM, SDM needs to be further established. Wald statistic and LR statistic need to be constructed to test whether SDM will degenerate into SAR or SEM. Under the hypothesis of the contiguity-based spatial weights matrix and the economic distance special weights matrix, both the Wald test and the LR test pass the 1% significance test and reject SDM degenerates into the null hypothesis of SAR (SEM). At the same time, both the spatial effect LR and the time effect LR in the contiguity-based spatial weights matrix and the economic distance special weights matrix reject the null hypothesis at a significance level of 1%, indicating that the model may be a spatial-time double fixed model. Under both matrix assumptions, the Hausman test passes at least a 10% significance test, indicating that SDM is the optimal model under the double fixed effect.

3.2 Spatial Metering Estimates

In this study, the effect of the digital economy's core industry agglomeration on the green total factor productivity is verified using two different spatial weight matrices. The regression results are shown in Tab. 4.

Judging from the results of the general regression coefficient of the core explanatory variables, the elastic coefficients of the specialized digital economy's core industry agglomeration to the local *GTFP* are 0.1402 and 0.1554 in the contiguity-based spatial weights matrix and 0.1554, respectively, which are significantly positive at the level of 1%, indicating that the increase in the concentration of specialized digital economy's core industry agglomeration will promote the improvement of *GTFP* in the region. The estimated parameters of the diversified digital economy's core industry agglomeration in the contiguity-based spatial weights matrix and the economic distance special weights matrix are 0.0253 and 0.0423, respectively. The significance level test of 10% and 1% is passed, indicating that the increase in the specialized digital economy's core industry agglomeration can also improve *GTFP*. Therefore, *H1* is verified.

Judging from the spatial regression coefficient results of the core explanatory variables, although the spatial regression coefficient of the specialized digital economy's core industry agglomeration is greater than 0 in the two matrices, it has not passed the significance test. It is preliminarily judged that the concentration of specialized digital economy's core industry agglomeration has no noticeable positive spillover effect on *GTFP*. The spatial

Tab. 4: Regression results of spatial Durbin models under different spatial weights matrices

Variable	Spatial weights matrix	
	W_1	W_2
ln*Mar*	0.1402***	0.1554***
ln*Jacobs*	0.0253*	0.0423***
*W**ln*Mar*	0.0749	–0.0879
*W**ln*Jacobs*	0.0569*	0.0628*
Control variables	Yes	Yes
*W**Control variables	Yes	Yes
Spatial rho	0.2632***	0.2182**
Variance sigma2_e	0.0052***	0.0043***
R-sq	0.1126	0.0106
Log-likelihood	481.5795	519.9274

Source: own

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. Control variables are not shown due to limited space.

regression coefficient of the diversified digital economy's core industry agglomeration is significantly positive at the level of 10% in both matrices, indicating a significant positive spillover effect on *GTFP* caused by the diversified digital economy's core industry agglomeration. It can be seen that only the diversified digital economy's core industry agglomeration satisfies *H2*, and the concentration of the specialized digital economy's core industry agglomeration is contrary to *H2*.

Since the general regression coefficient and spatial lag coefficient of the explanatory variables do not consider the spatial feedback effect, this study uses the partial differential matrix to decompose the spatial effect of the explanatory variable concerning Sun et al. (2019) to obtain direct effects, indirect effects, and total effects. The decomposition results are shown in Tab. 5.

The regression results of Tab. 5 show that in the contiguity-based spatial weights matrix,

Tab. 5: Decomposition results of spatial Durbin model effects under different spatial weight matrices

Variable	Direct effects		Indirect effects		Total effect	
	W_1	W_2	W_1	W_2	W_1	W_2
ln*Mar*	0.1490***	0.1863***	0.1436*	0.1239	0.2926**	0.3102**
ln*Jacobs*	0.0298*	0.0510***	0.0843*	0.1336**	0.1141**	0.1846**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Source: own

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. Control variables are not shown due to limited space.

the direct effect coefficients of the specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration are significantly positive at the levels of 1% and 10%, respectively. Meanwhile, the indirect effect coefficients pass the significance level test of 10%, indicating that the increase of the digital economy's core industry agglomeration will increase the *GTFP* of the region and the *GTFP* of other provinces at the same time, thus verifying *H1* and *H2*. The direct effect coefficients of specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration are positive and pass the significance level test of 1%, proving that *H1* is verified. In contrast, for the indirect effect coefficient, only the diversified digital economy's core industry agglomeration passed the significance test, and *H2* is only partially verified.

3.3 Endogenous Testing

According to the analysis and comparison of the coefficients of the core explanatory variables under the contiguity-based spatial weights matrix and the economic distance special weights matrix in Tab. 4–5, it can be found that the symbols and signs of the coefficients of the specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration are the same in the two different spatial weight matrices. It indicates that the influence of the specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration on *GTFP* is stable.

However, to avoid endogenous and multicollinearity, this study refers to the spatial econometric model construction method adopted by Xue et al. (2021). It selects the lag term of the specialized digital economy's core industry agglomeration, the lag term of the diversified digital economy's core industry agglomeration, and the lag term of each control variable as explanatory variables and control variables, respectively. Then, this study constructs the spatial Durbin model (SDM1 & SDM2) under different weight matrices. By comparing the regression results, the signs and significance of the coefficients in SDM1 and SDM2 are found to be broadly consistent with the previous study, indicating that the findings on the impact of the digital economy's core industry agglomeration on *GTFP* are relatively reliable.

3.4 Further Analysis Based on Spatial Heterogeneity

From the perspective of urban location, there are apparent differences in resource endowments and industrial bases between eastern and mid-western China. In contrast, differences in location conditions may lead to differences in the impact of the digital economy's core industry agglomeration on GTFP. Based on this, this study divides 25 provinces in China into the eastern region and the mid-western region to further explore the spatial heterogeneity impact of the digital economy's core industry agglomeration on green total factor productivity, including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong.

Starting from the assumptions of the contiguity-based spatial weights matrix and the economic distance special weights matrix, this study finds that *GTFP* in the eastern region only has a spatial correlation with the economic distance special weights matrix, and *GTFP* in the mid-western region is only spatially concentrated in the contiguity-based spatial weight matrix, through testing the spatial correlation between green total factor productivity in the eastern and central and western regions. This is due to the small differences in resource endowments caused by the different geographical locations of the eastern provinces, but there are still specific differences in the level of economic development. For different levels of economic development, the realistic path for regions to achieve green economic transformation and to achieve high-quality economic development goals is also different. In addition, compared with learning to imitate geographically adjacent areas, relevant policy measures in neighboring economic areas are more valuable. At the same time, the mid-western region has uneven terrain and is generally lagging in terms of economic development. Therefore, for the mid-western region, compared with the differences in the level of economic development between provinces, the differences in resource endowments brought about by geographical differences are more prominent. The geographical differences between neighboring regions are more minor, so the resource endowments are more similar, and the policy measures to enhance *GTFP* are more of reference significance.

Based on the above analysis, this study assumes that the contiguity-based spatial weights matrix applies to the eastern region and the economic distance special weights matrix applies to the mid-western region, respectively. SDM model under the double fixed effect is determined as the most suitable spatial econometric model after completing the spatial econometric model test, and the spatial spillover effect is decomposed. The decomposition result is shown in Tab. 6.

From Tab. 6, it can be seen that the autocorrelation coefficient of *GTFP* in the eastern region is significantly negative, and the autocorrelation coefficient of *GTFP* in the mid-western region is significantly positive. The possible reason for the discrepancy is that the green economy in the eastern region has strong momentum, but the number of resources to match it is limited. Although *GTFP* in the eastern region is clustered in spatial distribution, there is still competition for resources between provinces. This competitive relationship is particularly significant in neighboring regions. Provinces with higher *GTFP* will attract the superior resources of neighboring provinces, which will hurt the *GTFP* of neighboring provinces. This siphoning effect is far greater than the demonstration effect between provinces. The development of the mid-western region is lagging compared with the eastern region. Its potential available resource stock is more extensive, and the interregional resource competition is not apparent, so the demonstration effect of inter-provincial *GTFP* development is more significant.

Considering the spatial feedback effect, the direct effect results of the two industrial agglomeration modes of the digital economy's core industries in the eastern region are significantly positive, indicating that the digital economy's core industry agglomeration can significantly enhance *GTFP* in the eastern region. In the mid-western region, only the direct effect of the specialized digital economy's core industry agglomeration passes the significance test, indicating that the improvement of *GTFP* in the mid-western region stems from the positive impact of the specialized digital economy's core industry agglomeration in the region.

Judging from the results of indirect effects, the indirect effect results of the diversified

Tab. 6: Influences of nature of property right, industrial characteristic, and market concentration

Variable	Eastern region	Mid-western region
LR_Direct_ ln*Mar*	0.1103*	0.2134***
LR_Direct_ ln*Jacobs*	0.0407**	0.0243
LR_Indirect_ ln*Mar*	−0.2575**	0.0458
LR_Indirect_ ln*Jacobs*	0.0007	0.0499
Spatial rho	−0.3409**	0.2439**
Variance sigma2_e	0.0029***	0.0026***
R-sq	0.0495	0.0281
Log-likelihood	212.3536	395.1887
Observations	144	256

Source: own

Note: *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively. For space limitations, only core explanatory variables are reported for reference.

digital economy's core industry agglomeration in both the eastern and the mid-western region failed the significance test, indicating that the diversified digital economy's core industry agglomeration has no significant spillover effect on *GTFP*. The impact coefficient of the specialized digital economy's core industry agglomeration on *GTFP* in the mid-western region does not pass the significance test. However, the impact on *GTFP* in the eastern region is significantly negative, indicating that there is a significant negative spillover of the specialized digital economy's core industry agglomeration on *GTFP* in eastern China.

3.5 Discussion

Both specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration have a direct role in promoting the improvement of green total factor productivity in the region. From the results of Tab. 4–5, it can be seen that with the deepening of the concentration of specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration, the local *GTFP* will also increase, indicating that *GTFP* in China is closely related to the concentration of digital economy's core industries in the region. At the same time, the choice of the specialized agglomeration mode for technology-intensive industries is more conducive to environmental protection, and the adoption of a diversified agglomeration mode by the capital-intensive industry will result in lower levels of environmental pollution (Pei et al., 2021). The digital economy's core industry is both technology-intensive and capital-intensive, so both of its agglomeration models are effective in contributing to *GTFP*.

With the differences in regional geographical locations, the impact of the digital economy's core industry agglomeration on the local *GTFP* is also different. *GTFP* in the eastern region is more susceptible to diversified digital economy's core industry agglomeration. The improvement of *GTFP* in the mid-western region is only related to the specialized digital economy's core industry agglomeration. This is due to the differences in the development stages of the digital economy's core industries in the eastern region and the mid-western region. Different industrial agglomeration models and different development stages of the same industrial agglomeration model both have different effects on the eco-innovation efficiency and thus on *GTFP*. The digital economy's core industry agglomeration in the eastern region is moving from the growth period to the maturity period, where the role of diversified industrial agglomeration in promoting eco-innovation efficiency has been further strengthened (Zhang et al., 2021), so the impact of diversified industrial agglomeration on *GTFP* is more significant. Due to the backward resource conditions, fewer large cities and lower level of digital economy development in the mid-western region, the digital economy's core industry agglomeration is mainly manifested as specialized industrial agglomeration. *GTFP* is only significantly influenced by the specialized digital economy's core industry agglomeration.

At the same time, the concentration of specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration will also affect the green total factor productivity in other regions. From Tab. 4–5, it can be found that there are significant differences in the spatial effects of the two digital economy's core industry agglomeration models on *GTFP*. A diversified digital economy's core industry agglomeration has a more significant impact on *GTFP* in other regions than specialized digital economy's core industry agglomeration. The reason for this is that the specialized industrial agglomeration can lead to monopolization and technology locking in the region, which is not conducive to the technology distribution between regions. In contrast, diversified industrial agglomeration is conducive to regional technological innovation, promoting the improvement of *GTFP* in surrounding areas.

Similar to the direct effect, there is also a regional heterogeneity in the spatial effect of the digital economy's core industry agglomeration on *GTFP*. In eastern China, only the specialized digital economy's core industry agglomeration has a significant negative impact on *GTFP* in other regions, while the digital economy's core industry agglomeration has no significant spillover effect on *GTFP* in mid-western China. This is because of the deepening of the scale of the specialized digital economy's core industry agglomeration in the eastern region. It not only exacerbates the technology lock-in effect but also leads to the 'siphon effect' due to the huge labor demand, which makes relevant talents in the surrounding areas continue to pour into the local area (Zhao et al., 2020), while their regional decisions also tend to transfer unrelated industries with high pollution, high emissions and low efficiency to the surrounding areas (Wei & Hou, 2021), which in turn has a negative impact on the *GTFP* of the surrounding areas. In addition, because of the digital divide between Chinese regions and the imbalance in the construction of regional digital infrastructure (Yang, 2021), the more backward construction of digital economy facilities in the mid-western region makes barriers exist to the flow of digital factors between regions, which eventually leads to a significant reduction in the spillover effect of industrial agglomeration. At the same time, differences in user capabilities can lead to differences in the use of digital technologies. Residents of the relatively backward mid-west region have less ability to learn to use digital technologies due to a lack of educational resources (Bonfadelli, 2002; Hawash & Langm, 2020), thus weakening the inter-regional learning effect brought about by industrial agglomeration and making the digital economy's core industry agglomeration fails to influence *GTFP* in other regions.

Conclusions and Implications

This study selects a panel data research sample of 25 Chinese provinces from 2003 to 2019 and selects the contiguity-based spatial weights matrix and economic distance special weights matrix as the spatial weight matrix. Based on the green total factor productivity of provinces measured using EBM-GML, from perspectives of specialized industrial agglomeration and diversified industrial agglomeration, it analyzes the spatial heterogeneity of the impact of the digital economy's core industry agglomeration on the green total factor productivity by constructing a spatial Durbin model. The following conclusions are obtained:

(1) From the national level, the Chinese provincial *GTFP* has a significant positive spatial correlation in both spatial weight matrices. Moreover, both specialized digital economy's core industry agglomeration and diversified digital economy's core industry agglomeration also significantly promote *GTFP* in both weight matrices.

(2) From the perspective of spatial spillover effect, under the assumption of spatial proximity matrix, both specialized and diversified digital economy's core industry agglomeration can significantly promote *GTFP* in this province and neighboring provinces. Under the assumption of the economic distance special weights matrix, the specialized digital economy's core industry agglomeration only has a significant direct promotion effect on *GTFP*, but not a positive spillover effect.

(3) From the perspective of different regions, spatial heterogeneity in the impact of the digital economy's core industry agglomeration on *GTFP*. In the eastern region, the digital economy's core industry agglomeration can

significantly enhance local *GTFP*, while the specialized digital economy's core industry agglomeration has a significant negative spillover effect on *GTFP* in neighboring areas due to the technological monopoly brought about by the deepening degree of industrial agglomeration. In the mid-western region, the specialized digital economy's core industry agglomeration has a significant positive impact on *GTFP* in the province. In contrast, the spatial spillover effect of both industrial concentration patterns on *GTFP* is not significant.

Because of the above conclusions, the following managerial implications are proposed: (1) Different regions have different resource endowments. The industrial agglomeration model of core industries in the digital economy should be reasonably established according to their comparative advantages to maximize the positive promotion effect and positive spatial spillover effect of different industrial agglomeration models on green total factor productivity. It will contribute to the green and high-quality development of the regional economy. (2) All localities should speed up the construction of perfect policies for the development of core industries in the digital economy to promote efficient industrial development and high-quality industrial agglomeration, alleviate the adverse problems such as technology monopoly caused by excessive digital economy's core industry agglomeration, and promote high-quality green development of the regional economy by realizing green technology innovation and industrial structure optimization. (3) All regions, especially the mid-western region, should actively promote the construction of digital and other infrastructure, eliminate barriers to factor flow between regions through the improvement of infrastructure, and promote the efficient dissemination of knowledge and technology. Then it should give full play to the positive spatial spillover effect of the digital economy's core industry agglomeration on the green total factor productivity to achieve synergy of the high-quality green economy between regions. (4) Through the introduction of a complete industrial transfer policy, a reasonable spatial overall layout of core industries in the digital economy can be achieved. While solving the problem of technological monopoly caused by excessive industrial agglomeration in the eastern region, the level of digital economy's core industry agglomeration in the mid-western region can be improved, thereby deepening the promotion effect of the digital economy's core industry agglomeration on the green total factor productivity and accelerating the process of green digital transformation of the regional economy.

This study sorts out the influence mechanism of the digital economy's core industry agglomeration on the green total factor productivity, but there are still certain limitations: (1) Definition of core industries in the digital economy can be more accurate and specific and even expand from core industries in the digital economy to the entire digital economy industries. However, at present, the statistics of the digital industry are not perfect. Limited by the availability of data, only available data from 25 provinces in 16 years can be collected for empirical research at this stage. The research will be more universal if the sample capacity can be expanded based on a clear and accurate definition of core industries in the digital economy. (2) This study is based only on static analysis, ignoring the dynamic evolution of different industrial agglomeration patterns and the nonlinear effect of industrial agglomeration on *GTFP*. Furthermore, this study fails to use the tool variable method when dealing with endogenous problems and creatively finds the appropriate tool variable. (3) In the empirical analysis part, this study uses provincial sample data, which fails to consider the enterprise level and ignores the heterogeneity between individuals.

In summary, future research can improve on the following three points. Firstly, the time factor is included in the scope of research, and an appropriate dynamic model is selected based on refining the theoretical mechanisms to make the model more scientific and practical. Secondly, with continuous improvement of the database, core industries in the digital economy are more accurately and clearly defined. On this basis, selecting more consistent and long-term data for empirical study can enrich quantitative findings and make research results more representative, to achieve the purpose of providing empirical support for the rational formulation of relevant policies. Finally, fully considering individual differences between research subjects from the enterprise level, the green total factor productivity of different enterprises within core industries in the digital economy is studied separately, to formulate a more targeted development strategy.

Acknowledgments: *Supported by China Postdoctoral Science Foundation Project (2021M700985), Key Projects of Philosophy and Social Sciences Research, Ministry of Education (21JZD030) and Hubei Provincial Social Science Foundation (21ZD056).*

References

Ahmed, Z., Adebayo, T. S., Udemba, E. N., Murshed, M., & Kirikkaleli, D. (2022). Effects of economic complexity, economic growth, and renewable energy technology budgets on ecological footprint: The role of democratic accountability. *Environmental Science and Pollution Research, 29*(17), 24925–24940. https://doi.org/10.1007/s11356-021-17673-2

Alam, M. M., & Murad, M. W. (2020). The impacts of economic growth, trade openness and technological progress on renewable energy use in organization for economic co-operation and development countries. *Renewable Energy, 145*(28), 382–390. https://doi.org/10.1016/j.renene.2019.06.054

Bonfadelli, H. (2002). The Internet and Knowledge Gaps: A Theoretical and Empirical Investigation. *European Journal of Communication, 17*(1), 65–84. https://doi.org/10.1177/0267323102017001607

Duranton, G., & Puga, D. (2000). Diversity and Specialisation in Cities: Why, Where and When Does it Matter? *Urban Studies, 37*(3), 533–555. https://doi.org/10.1080/0042098002104

Elhorst, J. P. (2010). Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis, 5*(1), 9–28. https://doi.org/10.1080/17421770903541772

Geniaux, G., & Martinetti, D. (2018). A new method for dealing simultaneously with spatial autocorrelation and spatial heterogeneity in regression models. *Regional Science and Urban Economics, 72*(44), 74–85. https://doi.org/10.1016/j.regsciurbeco.2017.04.001

Han, F., Xie, R., Fang, J., & Liu, Y. (2018). The effects of urban agglomeration economies on carbon emissions: Evidence from Chinese cities. *Journal of Cleaner Production, 172*(4), 1096–1110. https://doi.org/10.1016/j.jclepro.2017.09.273

Hao, Y., Guo, Y., & Wu, H. (2022). The role of information and communication technology on green total factor energy efficiency: Does environmental regulation work? *Business Strategy and the Environment, 31*(1), 403–424. https://doi.org/10.1002/bse.2901

Hawash, R., & Lang, G. (2020). Does the digital gap matter? Estimating the impact of ICT on productivity in developing countries. *Eurasian Economic Review, 10*(2), 189–209. https://doi.org/10.1007/s40822-019-00133-1

Junior, J. A. G., Busso, C. M., Gobbo, S. C. O., & Carreão, H. (2018). Making the links among environmental protection, process safety, and industry 4.0. *Process Safety and Environmental Protection, 117*(23), 372–382. https://doi.org/10.1016/j.psep.2018.05.017

Li, J., Chen, L., Chen, Y., & He, J. (2022). Digital economy, technological innovation, and green economic efficiency – Empirical evidence from 277 cities in China. *Managerial and Decision Economics, 43*(3), 616–629. https://doi.org/10.1002/mde.3406

Li, M., & Wang, J. (2022). Spatial-temporal evolution and influencing factors of total factor productivity in China's logistics industry under low-carbon constraints. *Environmental Science and Pollution Research, 29*(1), 883–900. https://doi.org/10.1007/s11356-021-15614-7

Li, T., Han, D., Ding, Y., & Shi, Z. (2020). How Does the Development of the Internet Affect Green Total Factor Productivity? Evidence From China. *IEEE Access, 8,* 216477–216490. https://doi.org/10.1109/ACCESS.2020.3041511

Li, Z., & Liu, Y. (2021). Research on the Spatial Distribution Pattern and Influencing Factors of Digital Economy Development in China. *IEEE Access, 9,* 63094–63106. https://doi.org/10.1109/ACCESS.2021.3075249

Liu, Y., & Chen, X. D. (2021). The impact of China's digital economy development on industrial structure upgrading. *Economics and Management Research, 42*(8), 15–29 (in Chinese). https://doi.org/10.13502/j.cnki.issn1000-7636.2021.08.002

Lu, J., Ren, L., Yao, S., Rong, D., Skare, M., & Streimikis, J. (2020). Renewable energy barriers and coping strategies: Evidence from the Baltic States. *Sustainable Development, 28*(1), 352–367. https://doi.org/10.1002/sd.2030

Ma, D., & Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *Journal of Business Research, 145*(53), 801–813. https://doi.org/10.1016/j.jbusres.2022.03.041

Morton, C., Anable, J., Yeboah, G., & Cottrill, C. (2018). The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom. *Journal of Transport Geography, 72,* 119–130. https://doi.org/10.1016/j.jtrangeo.2018.08.020

Nizam, H. A., Zaman, K., Khan, K. B., Batool, R., Khurshid, M. A., Shoukry, A. M., Sharkawy, M. A., Aldeek, F., Khader, J., & Gani, S. (2020). Achieving environmental sustainability through information technology: "Digital Pakistan" initiative for green development. *Environmental Science and Pollution Research, 27*(9), 10011–10026. https://doi.org/10.1007/s11356-020-07683-x

Pei, Y., Zhu, Y., Liu, S., & Xie, M. (2021). Industrial agglomeration and environmental pollution: Based on the specialized and diversified agglomeration in the Yangtze River Delta. *Environment, Development and Sustainability, 23*(3), 4061–4085. https://doi.org/10.1007/s10668-020-00756-4

Rehman, A., Ma, H., Ahmad, M., Ozturk, I., & Işık, C. (2021). Estimating the connection of information technology, foreign direct investment, trade, renewable energy and economic progress in Pakistan: Evidence from ARDL approach and cointegrating regression analysis. *Environmental Science and Pollution Research, 28*(36), 50623–50635. https://doi.org/10.1007/s11356-021-14303-9

Ren, S., Li, L., Han, Y., Hao, Y., & Wu, H. (2022). The emerging driving force of inclusive green growth: Does digital economy agglomeration work? *Business Strategy and the Environment, 31*(4), 1656–1678. https://doi.org/10.1002/bse.2975

Rodriguez-Lluesma, C., García-Ruiz, P., & Pinto-Garay, J. (2021). The digital transformation of work: A relational view. *Business Ethics, the Environment & Responsibility, 30*(1), 157–167. https://doi.org/10.1111/beer.12323

Shan, H. J. (2008). Re-estimation of China's capital stock K: 1952–2006. *Journal of Quantitative and Technical Economics, 25*(10), 17–31 (in Chinese).

Steiner, F. (2019). Industry 4.0 and business process management. *Tehnički Glasnik, 13*(4), 349–355. https://doi.org/10.31803/tg-20181008155243

Sun, J., Wang, J., Wang, T., & Zhang, T. (2019). Urbanization, economic growth, and environmental pollution: Partial differential analysis based on the spatial Durbin model. *Management of Environmental Quality: An International Journal, 30*(2), 483–494. https://doi.org/10.1108/MEQ-05-2018-0101

Sun, X., Chen, Z., Shi, T., Yang, G., & Yang, X. (2022). Influence of digital economy on industrial wastewater discharge: Evidence from 281 Chinese prefecture-level cities. *Journal of Water and Climate Change, 13*(2), 593–606. https://doi.org/10.2166/wcc.2021.447

Tone, K., & Tsutsui, M. (2010). An epsilon-based measure of efficiency in DEA – A third pole of technical efficiency. *European Journal of Operational Research, 207*(3), 1554–1563. https://doi.org/10.1016/j.ejor.2010.07.014

Usman, A., Ozturk, I., Hassan, A., Zafar, S. M., & Ullah, S. (2021). The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis. *Telematics and Informatics, 58,* 471–471. https://doi.org/10.1016/j.tele.2020.101537

Wang, H., Hu, X., & Ali, N. (2022). Spatial Characteristics and Driving Factors Toward the Digital Economy: Evidence from Prefecture-Level Cities in China. *The Journal of Asian Finance, Economics and Business, 9*(2), 419–426. https://doi.org/10.13106/jafeb.2022.vol9.no2.0419

Wang, J., Wang, W., Ran, Q., Irfan, M., Ren, S., Yang, X., Wu, H., & Ahmand, M. (2022). Analysis of the mechanism of the impact of internet development on green economic growth: Evidence from 269 prefecture cities in China. *Environmental Science and Pollution Research, 29*(7), 9990–10004. https://doi.org/10.1007/s11356-021-16381-1

Wang, P., & Cen, C. (2022). Does digital economy development promote innovation efficiency? A spatial econometric approach for Chinese regions. *Technology Analysis & Strategic Management,* 1–15. https://doi.org/10.1080/09537325.2022.2065980

Wang, Z., Jebli, M. B., Madaleno, M., Doğan, B., & Shahzad, U. (2021). Does export product quality and renewable energy induce carbon dioxide emissions: Evidence from leading complex and renewable energy economies. *Renewable Energy, 171*(31), 360–370. https://doi.org/10.1016/j.renene.2021.02.066

Wei, L. L., & Hou, Y. Q. (2021). Research on the impact effect of specialization and diversified industrial agglomeration on regional green development. *Management Review, 33*(10), 22–33 (in Chinese). https://doi.org/10.14120/j.cnki.cn11-5057/f.2021.10.003

Wu, W. L., & Zhou, X. L. (2018). Evaluation and influencing factors of inclusive green growth in China. *Social Science Research, 40*(1), 27–37 (in Chinese).

Xie, R., Yao, S., Han, F., & Fang, J. (2019). Land Finance, Producer Services Agglomeration, and Green Total Factor Productivity. *International Regional Science Review, 42*(5–6), 550–579. https://doi.org/10.1177/0160017619836270

Xue, G., Liu, Y., & Yan, B. (2020). Industrial agglomeration, spatial spillover and local government tax competition: An empirical study based on the spatial Dubin model. *Exploration of Economic Issues, 41*(8), 22–32 (in Chinese).

Yang, Q., Ma, H., Wang, Y., & Lin, L. (2022). Research on the influence mechanism of the digital economy on regional sustainable development. *Procedia Computer Science, 202*(11), 178–183. https://doi.org/10.1016/j.procs.2022.04.025

Yang, W. P. (2021). Digital economy and regional economic growth: Late-comer advantage or late-comer disadvantage? *Journal of Shanghai University of Finance and Economics, 23*(3), 19–31 (in Chinese). https://doi.org/10.16538/j.cnki.jsufe.2021.03.002

Yang, X., Wu, H., Ren, S., Ran, Q., & Zhang, J. (2021). Does the development of the internet contribute to air pollution control in China? Mechanism discussion and empirical test. *Structural Change and Economic Dynamics, 56*(32), 207–224. https://doi.org/10.1016/j.strueco.2020.12.001

Zeng, G., Geng, C., & Guo, H. (2020). Spatial Spillover Effect of Strategic Emerging Industry Agglomeration and Green Economic Efficiency in China. *Polish Journal of Environmental Studies, 29*(5), 3901–3914. https://doi.org/10.15244/pjoes/116443

Zhang, D., Wang, L., Xu, J., & Chen, K. (2021). Simulation analysis of the evolutionary mechanism of low-carbon rural logistics. *Dyna, 96*(5), 484–491. https://doi.org/10.6036/10236

Zhang, L., Mu, R., Hu, S., Zhang, Q., & Wang, S. (2021). Impacts of Manufacturing Specialized and Diversified Agglomeration on the Eco-Innovation Efficiency – A Nonlinear Test from Dynamic Perspective. *Sustainability, 13*(7), 3809. https://doi.org/10.3390/su13073809

Zhang, S. Y., Wang, C. X., & Ren, Y. J. (2019). Spatial spillover effect of productive service agglomeration on green total factor productivity. *Soft Science, 33*(11), 11–15 (in Chinese). https://doi.org/10.13956/j.ss.1001-8409.2019.11.03

Zhao, H., Cao, X., & Ma, T. (2020). A spatial econometric empirical research on the impact of industrial agglomeration on haze pollution in China. *Air Quality, Atmosphere & Health, 13*(11), 1305–1312. https://doi.org/10.1007/s11869-020-00884-w