Data Science in Finance and Economics

DSFE, 2 (4): 371–390.
DOI:10.3934/DSFE. 2022019
Received: 02 October 2022
Revised:23 October 2022
Accepted:25 October 2022
Published: 31 October 2022

http://www.aimspress.com/journal/dsfe

Research article

How does the digital economy affect industrial eco-efficiency? Empirical evidence from China

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Abstract: Industry is a sector with large energy consumption and pollutant emissions. Improving industrial eco-efficiency is crucial to energy conservation and pollution reduction. The digital economy has developed rapidly in recent years. However, there is a lack of research on the specific relationship between the digital economy and industrial eco-efficiency. This study measured the industrial eco-efficiency of 30 provinces in China from 2010 to 2020, through a super-efficiency slack-based measure (SBM) considering desirable outputs. By constructing a two-way fixed effect model and a panel quantile model, this study explored the effects of the digital economy on industrial eco-efficiency on a national scale. Furthermore, this study conducted grouping regression and investigated the heterogeneous impacts of the digital economy on industrial eco-efficiency. Finally, this study built a spatial Durbin model to explore the spatial effects of digital economy on industrial eco-efficiency. According to the empirical results, this study yielded the following conclusions. First, the digital economy has a significantly positive effect on industrial eco-efficiency at the national scale, with diminishing marginal returns. Second, the effects of the digital economy on industrial eco-efficiency are significantly heterogeneous on a regional scale. For eastern regions, the effects of the digital economy on industrial eco-efficiency are significantly positive, while they are negative for western regions. Third, the spillover effect of the digital economy on industrial eco-efficiency is not significant in China, indicating that there is digital isolation.

Keywords: industrial eco-efficiency; digital economy; super-SBM; heterogeneity; spatial Durbin model

JEL Codes: O11, Q57

1. Introduction

The issues of energy shortages and environmental pollution have received considerable critical attention. BP's Statistical Review of World Energy 2022 indicates that the challenges and uncertainties facing the global energy system are at their greatest in almost 50 years, and carbon emissions have risen every year. Thus, improving resource utilization efficiency and reducing environmental pollution emissions to pursue sustainable development have become pursuits of all countries in the world. The data from BP's Statistical Review of World Energy 2022 reveals that China remains the world's largest energy consumption market and largest carbon emitter in 2021. In recent decades, the economy of China has grown rapidly, especially in the industrial field, with various ecological problems following. According to data from the National Bureau of Statistics, value added from industry accounted for 30.8% of GDP. Meanwhile, industrial energy consumption accounts for 66.75% of the national total, and SO_2 emissions account for 80% of the national total. Industry is the largest sector for energy consumption and pollution emissions in China. There is an urgent need to better coordinate the relationship of industrial development, resource utilization and environmental protection.

In recent years, the digital economy has experienced rapid and aggressive development. Relying on the development of information technology, such as 5th generation mobile networks, cloud computing and artificial intelligence, the digital economy has become the engine of economic growth. The combination of digital technology and industry promotes the digital transformation of traditional industries. At the same time, it also provides a new perspective for environmental governance, energy conservation and emission reduction (Chen 2022; Shahnazi and Dehghan Shabani 2019; Yi et al. 2022). First of all, data is the core production factor of the digital economy, which exists in virtual, non-physical form. In the process of its acquisition and circulation, data has the characteristics of low natural resource consumption and low pollution discharge, which are environmentally friendly. Second, data resources are reproducible and sharable. These make data a production factor with characteristics of low cost and high return. Therefore, the marginal benefits of the digital economy increase obviously, but the marginal costs of it are almost zero. In addition, with the support of digital technology, the input and output efficiency of industry has been significantly improved, and energy consumption and carbon emissions have been effectively reduced. On these grounds, developing the digital economy may be an effective measure to promote industrial economic growth, relieve pressure on resources and the environment and improve ecological efficiency. However, from another perspective, the digital economy will expand desirable outputs while it may also be accompanied by more undesirable outputs, which will worsen the green development of the country. Park et al. (2018) and Raheem et al. (2020) indicated that the development of information and communications technology promotes carbon emissions. Zhang et al. (2022b) pointed out that the development of the digital economy is not conducive to improving energy efficiency and raises carbon emissions in China. Existing studies have discussed the relationship of the digital economy and sustainable development from different perspectives, but most scholars have ignored the relationship of the digital economy and sustainable development of the industrial sector. The research on industrial eco-efficiency has mainly focused on its evaluation and spatio-temporal characteristics (Liu et al. 2022b;

Shao et al. 2019; Zhang and Liu 2021). For these reasons, it is worth exploring the effects of the digital economy on industrial eco-efficiency.

In the pages that follow, these specific issues will be discussed: Does the digital economy have a positive impact on industrial ecological efficiency in total? Is there regional heterogeneity? Does the digital economy have spatial effects on industrial ecological efficiency? To clarify these questions, this study uses panel data of 30 provinces in mainland China during 2010-2020. First, this study constructed a two-way fixed effects model and a panel quantile model to examine the total effects of the digital economy on industrial eco-efficiency for the full sample. Second, this study divided the sample into three groups by region to discuss regional heterogeneity. Finally, this study examined the spatial effects by constructing a spatial Durbin model. This paper tries to make the following contributions. (1) This study first integrated the digital economy and industrial eco-efficiency into one theoretical framework to investigate how the digital economy affects industrial eco-efficiency. (2) This paper establishes econometric models to examine the effects of the digital economy on industrial efficiency. The rest of this paper is arranged as follows: Section 2 presents a literature review and research hypotheses. Research design is described in Section 3. Section 4 summarizes the empirical results and discussion. Section 5 presents the conclusions.

2. Literature review and research hypotheses

2.1. Literature review

The concept of ecological efficiency was proposed first in 1990, to measure the environmental performance of economic activities (Schaltegger and Sturm 1990). In 1992, The World Business Council for Sustainable Development (WBCSD) defined eco-efficiency specifically and popularized it as “the delivery of competitively priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth’s estimated carrying capacity.” It emphasized the coordination of resources, environment and economic development. Therefore, it is an effective instrument to evaluate sustainable development and has been applied to various industries and fields, such as agriculture, energy, etc. (Li 2019; Reith and Guidry 2003; Viet-Ngu and Alauddin 2012; Zhang et al. 2015). Historically, much of the research on eco-efficiency has focused on its evaluation, spatial and temporal features and analysis of associated factors (Han et al. 2021; Hickel 2020; Sun et al. 2020; Xu et al. 2020). For measuring eco-efficiency, the methods have been maturing, and they are mainly based on data envelopment analysis (DEA) (Mardani et al. 2017). These methods are also applied to the industrial field. Fujii and Managi (2013) discussed the external impact on industrial eco-efficiency by constructing the weighted Russell directional distance model. Shao et al. (2019) evaluated industrial eco-efficiency from the perspective of overall industry and industry sub-sectors, based on the methodology of two-stage DEA. Liu et al. (2022a) applied the DEA-Malmquist model to analyze the dynamics of industrial eco-efficiency. Zhang and Liu (2021) suggested that the super DEA-SBM considering undesirable outputs is more effective to evaluate the eco-efficiency of industrial enterprises.

Over the past decades, the digital economy has developed rapidly, and researchers have shown an increased interest in it. So far, there has been little agreement about the definition of the digital economy. Moulton (2000) proposed that information technology is the foundation of the digital economy. Kim et al. (2002) pointed out that the digital economy is a fresh economic formation of trading digital goods and digital services. Carlsson (2004) proposed that the digital economy is a dynamic economy that transmits individual behavior and information in digital form. The China Academy of Information and Communications Technology (CAICT) proposed that the digital economy is the economic form which takes digital knowledge and information as key production factors, digital technology as the driving force and digital information networks as the carriers. The research on evaluating the digital economy has also been developing. The American Bureau of Economic Analysis (BEA) established a framework including infrastructure, e-commerce and priced digital services. The China Academy of Information and Communications Technology (CAICT) compiled the Digital Economy Index, to reflect the digital economy development of China with respect to digital industry, digital infrastructure, etc. Xu and Li (2022) compiled a comprehensive index to measure the digital economy on a provincial scale and found out there is a widening gap between regions. In this paper, the digital economy index calculated by Xu and Li (2022) is cited for conducting the empirical analysis.

In recent years, there has been increased emphasis on the relationship of the digital economy and sustainable development. Dabbous and Tarhini (2021) pointed out that with the development of information technology, an innovative business model, the sharing economy, has emerged. This research suggested that the sharing economy contributes to resource saving and cost reduction. Xue et al. (2022) concluded that the digital economy can increase energy consumption but also can optimize the energy consumption structure. Zhang et al. (2022a) reported that the digital economy can reduce carbon emissions by upgrading industrial structures and promoting technological innovation. Tang et al. (2022) showed that telecommunication infrastructure has spillover benefits for knowledge and technology, which are conducive to improving eco-efficiency. Luo et al. (2022) investigated the effect of the digital economy on green development efficiency based on the sample of the Yangtze River Economic Belt. They showed that the digital economy can promote green development, but the effects are regionally heterogeneous.

Industry is a sector with large energy consumption and pollutant emissions. Although some research has suggested that the digital economy may promote sustainable development, the effect of the digital economy on industrial eco-efficiency is still debated. However, there are a few studies discussing how the digital economy affects industrial eco-efficiency. This study established a theoretical framework of industrial eco-efficiency and the digital economy and discussed the possible effects of the digital economy on industrial eco-efficiency based on the empirical results.

2.2. Research hypotheses

2.2.1. Impact of the digital economy on industrial eco-efficiency

According to previous research, the positive effects of the digital economy on industrial eco-efficiency chiefly embody the following aspects. For one thing, the development of the digital economy can improve industrial products' quality and reduce production costs, thus improving industrial production efficiency. With the development of Internet technology, the emergence of new business models has narrowed the distance between enterprises and consumers. Unlike a traditional business model, the new business model focuses on consumers. The application of big data can mine a large amount of information from massive data sets, so producers can accurately grasp the needs and preferences of consumers and quickly adjust products to satisfy the needs of consumers (Ng 2014). That promotes the product upgrading of industrial enterprises. In addition, the development of the digital economy is conducive to enhancing the innovative technological capability of industrial enterprises (Zhang et al. 2022a). The shareability of the digital economy reduces barriers to the flows of information, data, knowledge and talents among enterprises, making innovation knowledge spillover and interactions faster and cheaper. Thus, industrial enterprises can acquire and accumulate knowledge and information more easily and master new knowledge and skills more quickly. This helps enterprises to improve their innovative knowledge reserve, promote technological upgrading and upgrade their existing products and services. Furthermore, the production cost structure of the digital economy has the characteristics of high fixed cost and low marginal cost (Yi et al. 2022), which is conducive to the formation of economics of scale and scope, thus improving production efficiency (Carlsson 2004). In addition, the application of digital technology can enlarge market reach and reduce operational costs (Swamy 2020). For example, the adoption of ICT can solve the problem of information asymmetry, reduce the search and match costs between enterprise and user and improve the communication efficiency of enterprises on a global scale. Also, the traditional way of payment has been transformed gradually. The widespread use of electronic payment, like Alipay and WeChat Pay, can bypass time and regional restrictions and reduce remote transaction costs.

For another thing, the digital economy can help industrial enterprises save energy and reduce pollution emissions to achieve green transformation. The development of traditional industrial enterprises relies heavily on energy and the environment, and this mode of economic growth is characterized by high energy consumption, high input and high pollution. The digital economy can help industrial enterprises effectively improve the efficiency of resource collection and use through optimizing the production process and technology (Mawson and Hughes 2019; Yi et al. 2022). With the digital transformation of industrial enterprises, the excessive dependence of industry on energy is gradually reduced, and energy waste and loss decrease greatly. Meanwhile, the development of the digital economy can effectively solve the misallocation problem of labor, capital, technology and data factors in the market. It is conducive to efficient circulation of production factors, thus improving the utilization efficiency of resources (Chen et al. 2019). Furthermore, the openness and real-time nature of the digital economy can alleviate the information asymmetry of the traditional way of environmental regulation. Relying on digital technology, the environmental information platform can collect real-time pollutant emission information on the whole industrial process (ElMassah and Mohieldin 2020). Through precise environmental monitoring and transparency of pollution information, the channel of environmental supervision can be broadened. The traditional government-led vertical form of supervision will transform into the form of multi-directional supervision by the government and the public, strengthening the intensity of environmental regulation. In addition, digital finance is an important part of the digital economy. Financial institutions can obtain the real information of enterprises' operating conditions through big data technology and provide financial support for the green transformation of industrial enterprises. This will effectively alleviate the financing constraints of industrial enterprises in the green transformation (Cui et al. 2022). At the same time, digital finance can accurately locate green projects, limit the flow of resources to high-polluting industries and expand the scale of support for industrial enterprises to upgrade energy-saving technologies and for research and development of green products. On these grounds, this study hypothesized the following:

Hypothesis 1(H1): The digital economy can improve industrial eco-efficiency.

2.2.2. Regional heterogeneity

Due to the influences of policy, history, geographical location and other factors, there are some differences between regions in China. The eastern region developed rapidly, while the central and western regions developed relatively slowly, forming a stepwise pattern of development. The industrial development in the eastern coastal area is more concentrated, while the inland area is relatively scattered. From the perspective of industrial distribution characteristics, the industries in the eastern region are mainly high-tech industries, while the labor-intensive and resource-intensive industries are mainly in the central and western regions. Due to differences in innovation capacity, infrastructure, human capital and foreign direct investment, it is difficult for the central and western regions to attract high-tech industries. Although the reserves of natural resources in the western region are more abundant than those in the eastern region, industrial development in the western region started later. Industrial development in the western region is too dependent on natural resources, and there are problems such as relatively isolated industrial structure, overcapacity, etc. In addition, there is an obvious Matthew effect in the development of the digital economy among regions in China, which has formed a serious phenomenon of digital divide. In underdeveloped regions, the infrastructure is backward, and relevant laws, regulations and encouraging policies lag behind. Information resources and knowledge resources are unevenly distributed in the eastern, central and western regions. For these reasons, the development level of the digital economy in the eastern region is significantly ahead of that in the central and western regions. In addition, the effect of the digital economy on industrial eco-efficiency may be affected by industrial structure, independent innovation ability, natural resources, information resources, etc. Therefore, different regions may have different impacts of the digital economy on industrial eco-efficiency. Based on this, this study suggested the second hypothesis:

Hypothesis 2(H2): The digital economy has a heterogeneous effect on industrial eco-efficiency in China.

2.2.3. Spatial effects of the digital economy on industrial eco-efficiency

Everything is related to everything else, but near things are more related to each other (Tobler 1970). Krugman (1991) and other economists believed that the degree of correlation between things would be affected by the spatial distance and various connections between them. In the process of the flow of production factors, the economic development of a region will not only depend on its own factor input and technological advances, but it will also be affected by the economic development level of neighboring regions to a certain extent, that is, the spatial spillover effect in new economic geography. The digital economy takes modern information networks as carriers and data as key production factors. It can break the limitations of geographical space, realize cross-regional division of labor and cooperation and increase the economic interaction between regions. With the continuous increase of economic activities between regions, interaction effects between different regions have gradually emerged. The industrial eco-efficiency of one region may be affected by the industrial eco-efficiency of other regions, resulting in spatial autocorrelation. For example, the industrial economic benefits and environmental profits brought by the improvement of industrial eco-efficiency in one region will motivate industrial enterprises in other regions to constantly imitate and learn advanced innovative technologies. At the same time, compared with the traditional way of knowledge dissemination, the development of the digital economy can broaden the channel of knowledge circulation among regions, promote the sharing of knowledge and technology and give full play to the knowledge spillover effect. For instance, relying on digital technology such as cloud computing, big data and industrial internet, the information resources in the industrial field can be digitized to better achieve the cross-regional flow of knowledge and accelerate the communication between areas. Then, industrial enterprises can master and apply advanced technologies and cutting-edge concepts more quickly, to improve industrial eco-efficiency and reduce industrial pollution. In addition, as the government attaches great importance to the development of the digital economy and industrial green transformation, it may cause competition among regions. In other words, the development of the digital economy may not only promote the improvement of local industrial eco-efficiency but also stimulate the development of the digital economy in neighboring areas, thereby improving the industrial eco-efficiency of the surrounding areas. Therefore, this study developed the following hypothesis:

Hypothesis 3(H3): There may be a spatial effect of the digital economy on industrial eco-efficiency.

3. Research design

3.1. Model construction

3.1.1. Benchmark regression model

Based on the previous discussion, a benchmark regression model was constructed to verify the effects of the digital economy on industrial eco-efficiency. The formula of the baseline regression model in this paper is as follows:

$$IEE_{it} = \beta_0 + \beta_1 Dig_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

In equation (1), i denotes the province, and t represents time. IEE_{it} is the dependent variable in this study, representing the industrial ecological efficiency of province i in year t. Dig_{it} is the core independent variable representing the digital economy development level of province i in year t. X is the vector of control variables, μ_i represents the individual fixed effects, δ_t represents the time fixed effects, ε_{it} is the stochastic error term, and β_0 is a constant term. β_1 and γ denote the regression coefficients of the explanatory variables.

Considering that least squares estimation results are easily affected by extreme values, this study further built a quantile regression model (Koenker and Bassett Jr 1978). Quantile regression is a method of fitting a linear function of explanatory variables based on the conditional distribution of the explained variable. In contrast, the least squares estimation is to examine the influence of the explanatory variables on the conditional expectations of the explained variables. Compared with least squares estimation, the result of quantile regression is less sensitive to outliers and more robust. In addition, by constructing a panel quantile model, we can observe the regression coefficients under different quantiles and further explore the trend of the marginal impact of the digital economy on industrial eco-efficiency. The formula of the panel quantile model is specified as follows:

$$IEE_{it\tau} = \beta_{0\tau} + \beta_{1\tau} Dig_{it} + \gamma_\tau X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

where τ denotes the quantile. In this study, the values of τ are set to 10%, 25%, 50%, 75% and 90%.

3.1.2. Spatial panel model

Considering the possible spatial effects of the digital economy on industrial eco-efficiency, it is necessary to build a spatial econometric model for further investigation. There are three basic forms of spatial econometric models: spatial auto-regressive model (SAR), spatial error model (SEM) and spatial Durbin model (SDM). The spatial conduction mechanisms of these three models are different. The SAR model assumes that the explained variables have spatial influences on other regions (Anselin et al. 2008). The SEM describes the spatial effect of the disturbance terms. The spatial Durbin model takes into account the spatial correlation of both the explained variable and the explanatory variable (LeSage and Pace 2009; Lee and Yu 2016). In other words, explained variables in this region are not only affected by the explanatory variables in the region but also affected by the explanatory variables and explained variables in the neighboring regions. This study established the models of the SAR, SEM and SDM, as shown in equations (3) to (6), respectively.

- Spatial auto-regressive model (SAR)

$$IEE_{it} = \rho WIEE_{it} + \beta_0 + \beta_1 Dig_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

- Spatial error model (SEM)

$$IEE_{it} = \beta_0 + \beta_1 Dig_{it} + \gamma X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \omega_{it} \tag{5}$$

- Spatial Durbin model (SDM)

$$IEE_{it} = \rho WIEE_{it} + \beta_0 + \beta_1 Dig_{it} + \gamma X_{it} + \alpha_1 + \varphi WX_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{6}$$

In formulas (3) to (6), W is an $n \times n$ weight matrix which represents the spatial relationship of provinces. ρ, λ, α_1 and φ are the spatial correlation coefficients. Other symbols are set as above.

Before applying the spatial econometric models, it is necessary to test the spatial auto-correlation of variables. In the existing research, the Global Moran's I is often used to measure the global spatial auto-correlation. The formula for calculating Moran's I is specified as follows:

$$Moran's\ \mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{7}$$

where w_{ij} denotes the elements in weight matrix W, S^2 is the sample variance, and y_i is the observation of region i. The value interval of Moran's I is [−1, 1]. If Moran's I > 0, then there is a positive spatial correlation among regions. Similarly, if Moran's I < 0, then there is a negative spatial correlation. The closer the absolute value of Moran's I is to 1, the stronger the spatial correlation is.

The setting of the spatial weight matrix is a key step in constructing a spatial econometric model. The common spatial weight matrices include the geographic adjacency weight matrix, geographic distance weight matrix, economic distance weight matrix, etc. In consideration of the influence of inter-province economic intercourse, this research constructed the economic distance weight matrix. The elements of the economic distance weight are set as follows:

$$w_{ij} = \begin{cases} \dfrac{1}{\left|\overline{pGDP_i} - \overline{pGDP_j}\right|} & i \neq j \\ 0 & i = j \end{cases} \tag{8}$$

where $\overline{pGDP_i}$ represents the mean of per capita GDP of province i.

3.2. Variable description

3.2.1. Dependent variable

In this study, industrial eco-efficiency (IEE) is the dependent variable. In existing studies, eco-efficiency is measured by data envelopment analysis (DEA) generally. Based on DEA-related theories, methods such as super-efficiency DEA, three-stage DEA and Slack-based Measure (SBM) have been gradually developed. According to the WBCSD definition of eco-efficiency, its main purpose is to obtain maximum economic output while minimizing resource consumption and environmental damage. In addition to the desired output, industrial production activities are also accompanied by undesired outputs that are harmful to the ecological environment. Hence, this study applied super SBM-DEA with undesirable output to evaluate industrial eco-efficiency (Du et al. 2010). Next, referring to previous research, this study constructed the measurement index system of industrial eco-efficiency, as shown in Table 1. The input indicator includes labor, capital and resources. According to data availability, labor input was represented by number of employed persons in industrial urban units. Fixed capital stock was estimated by the perpetual inventory method, setting 9.6% as the capital depreciation rate. Resource inputs were represented by industrial water consumption and industrial energy consumption. Meanwhile, industrial added value was taken as desirable input describing industrial economic performance, and industrial SO_2 emissions, industrial Nitrogen Oxide emissions and industrial COD discharge were taken as undesirable output, describing environmental pollution caused by industry.

Table 1. The measurement index system of industrial eco-efficiency.

Primary Indicator	Secondary Indicator	Tertiary Indicator	Units
Input index	Labor	Number of employed persons in industrial urban units	10,000 people
	Capital	Fixed capital stock	100 million yuan
	Resources	Industrial water consumption	100 million cubic meters
		Industrial energy consumption	10,000 tons of standard coal
Output index	Desirable output	Industrial added value	100 million yuan
	Undesirable output	Industrial SO_2 emissions	10,000 tons
		Industrial Nitrogen Oxide emissions	10,000 tons
		Industrial COD discharge	10,000 tons

3.2.2. Independent variables

The core independent variable is the digital economy (Dig). This study referred to the research results from Xu and Li (2022) and took the digital economy index to indicate the development level of the digital economy, evaluating digital economy from four dimensions: digital users, digital platforms, digital industries and digital innovation. Considering that the digital economy is not the only factor affecting ecological efficiency, this study took economic development level (PGDP), environmental regulation (ER), foreign direct investment (FDI) and the structure of energy consumption (SEC) into the model to control the possible effects of other factors on industrial eco-efficiency. (1) According to the Environmental Kuznets Curve (EKC), economic growth is closely connected with environmental quality (Panayotou 1993). The economic development level was indicated by the logarithm of real GDP per capita in this study. (2) Weaker environmental regulation may increase pollutant emissions and lower eco-efficiency, while stronger environmental regulation may lead to a significant reduction of pollutant emissions and promote the improvement of eco-efficiency (Yuan et al. 2017). We used the logarithm of completed investment in industrial pollution control to indicate environmental regulation. (3) Foreign direct investment may aggravate local environmental pollution through the construction of “pollution havens” (Ren and Yang 2013). Considering price changes, this study used ratio of actually utilized FDI to GDP as the indicator of foreign direct investment. (4) The coal-dominated energy structure has a driving effect on carbon emissions (Li et al. 2021). The structure of consumption was represented by the proportion of industrial coal consumption in industrial energy consumption.

3.3. Data sources and descriptive statistics

Considering data availability, this paper selected the panel data of 30 provincial administrative regions in China from 2010 to 2020 (Tibet, Hong Kong, Macau and Taiwan are excluded). The original data were obtained from the official website of the National Bureau of Statistics of China.

The descriptive statistics of variables are reported in Table 2. As shown in Table 2, the minimum of industrial eco-efficiency is 0.363, while the maximum is 1.908, indicating that there is a certain gap in industrial eco-efficiency among regions. Thus, considering the harmful effects of outliers, it is necessary to apply quantile regression to verify the effects of the digital economy on industrial eco-efficiency. Also, it can be observed that the standard deviation of the digital economy is 23.265, the minimum of the digital economy is 101.228, and the maximum of the digital economy is 267.606. This further proves that there is an obvious digital divide in China.

Table 2. Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
IEE	330	0.777	0.186	0.363	1.098
Dig	330	127.518	23.265	101.228	267.606
PGDP	330	10.731	0.465	9.482	11.795
ER	330	11.839	1.073	6.165	14.164
FDI	330	14.633	1.691	7.99	16.932
SEC	330	0.33	0.132	0.026	0.643

Table 3 reports the Pearson correlation coefficients of variables. According to Table 3, the correlation coefficients of industrial eco-efficiency and other variables are all significant, and it can be seen that there is a certain internal relationship among the variables. Especially, the correlation coefficient of industrial eco-efficiency and digital economy is 0.519, which is positive at a significance level of 1%. Thus, it is likely that the digital economy has a positive effect on industrial eco-efficiency.

Table 3. Pearson correlation coefficients.

Variables	IEE	Dig	PGDP	ER	FDI	SEC
IEE	1					
Dig	0.519***	1				
PGDP	0.526***	0.619***	1			
ER	0.308***	0.208***	0.165***	1		
FDI	0.617***	0.560***	0.497***	0.419***	1	
SEC	−0.220***	−0.412***	−0.628***	0.114**	−0.0880	1

Note: *, **, ***denote significance levels of 10%, 5% and 1%, respectively.

4. Empirical results and discussion

4.1. Benchmark regression results

In order to analyze the average effects of the digital economy on industrial eco-efficiency, the results of the benchmark regression model (1) by least squares estimation are reported in Table 4. According to the Hausman test and F test, the two-way fixed effect model is more suitable than the random effect model and pooled OLS. In Table 4, it can be seen that the coefficient of digital economy is 0.0023, which is significantly positive at a confidence level of 5%. It indicates that the digital economy has a significantly positive effect on industrial eco-efficiency. Furthermore, the coefficients of PGDP and ER are 1.118 and 0.022, respectively, and are both positive at a significance level of 5%. It can be explained that economic development level and environmental regulation can also be helpful to improve industrial eco-efficiency.

Table 4. The results of the two-way fixed effect model.

Dig	PGDP	ER	FDI	SEC	Cons_	Hausman test (p-value)	F test (p-value)
0.00230**	1.118**	0.0220**	0.0166	0.125	−11.54**	37.65	11.34
(3.45)	(8.19)	(2.21)	(1.51)	(1.07)	(−8.23)	（0.0000）	（0.0000）

Note: The values in parentheses are t statistics. *, **, ***denote significance levels of 10%, 5% and 1%, respectively.

Table 5. The results of quantile regression.

Variable	10%	25%	50%	75%	90%
Dig	0.00272*	0.00256**	0.00229***	0.00205**	0.00188
	(2.14)	(2.69)	(3.70)	(2.64)	(1.75)
PGDP	0.774*	0.906***	1.125***	1.318***	1.457***
	(2.13)	(3.33)	(6.25)	(5.91)	(4.72)
ER	0.0239	0.0232	0.0219*	0.0208	0.0200
	(1.06)	(1.37)	(2.00)	(1.51)	(1.05)
FDI	0.0310	0.0255	0.0163	0.00814	0.00231
	(1.23)	(1.35)	(1.32)	(0.53)	(0.11)
SEC	0.111	0.117	0.126	0.134	0.139
	(0.42)	(0.59)	(0.97)	(0.82)	(0.62)
Cons_	0.00272*	0.00256**	0.00229***	0.00205**	0.00188
	(2.14)	(2.69)	(3.70)	(2.64)	(1.75)
Time fixed	Yes	Yes	Yes	Yes	Yes
individual fixed	Yes	Yes	Yes	Yes	Yes
Obs	330	330	330	330	330

Note: The values in parentheses are t statistics. *, **, ***denote significance levels of 10%, 5% and 1%, respectively.

To further investigate the effects of the digital economy on industrial eco-efficiency at different quantiles, this paper conducted panel quantile regression. Table 5 reports the results of the quantile regression. Obviously, the coefficients of the digital economy are all positive, indicating that the digital economy plays a positive role in improving industrial eco-efficiency indeed. Although the difference between the coefficients is small, this study noted that there is a slight downward trend of the coefficient of the digital economy with the improvement of industrial eco-efficiency. The results indicate that the marginal effect of the digital economy on industrial eco-efficiency is diminishing. It also can be observed that the coefficient of digital economy at 90% is not significant. A possible reason is that for high quantiles of industrial eco-efficiency, there is less potential for improvement. Meanwhile, the results of quantile regression also prove that the benchmark model is robust. To sum up, the digital economy has a positive effect on industrial eco-efficiency for the full sample.

4.2. Analysis of regional heterogeneity

Table 6. The regression results of sub-samples.

Variable	Eastern	Central	Western
Dig	0.00139**	0.00432	−0.00630*
	(2.19)	(0.81)	(−1.71)
PGDP	0.971**	0.623	2.423**
	(4.46)	(1.20)	(9.13)
ER	0.00353	0.0140	0.0657**
	(0.30)	(0.55)	(3.67)
FDI	0.0444**	−0.0212	0.0406**
	(2.71)	(−0.60)	(2.62)
SEC	0.272	−0.159	0.0498
	(1.43)	(−0.66)	(0.25)
Cons_	−10.51**	−5.787	−24.21**
	(−4.60)	(−1.18)	(−9.53)
Time fixed	Yes	Yes	Yes
individual fixed	Yes	Yes	Yes
Obs	121	88	121

Note: The values in parentheses are t statistics. *, **, ***denote significance levels of 10%, 5% and 1%, respectively.

Considering that there are differences in industry structure, resource endowment, etc. among regions, it is necessary to investigate the heterogeneity of effects of the digital economy on industrial eco-efficiency. In this study, samples were divided into three groups, namely, the eastern regions, the central regions and the western regions. The eastern regions include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The central regions include Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. The western regions include Inner Mongolia, Sichuan, Chongqing, Guizhou, Yunnan, Shanxi, Gansu, Guangxi, Qinghai, Ningxia and Xinjiang. The regression results of sub-samples are reported in Table 6, and some interesting conclusions were noted. For the eastern regions, the coefficient of the digital economy is significantly positive. For the central regions, the coefficient of the digital economy is positive but not significant. However, the coefficient of the digital economy is significantly negative for the western regions. Plenty of evidence has shown that there is an obvious digital divide in China, and the development level of the digital economy in the east is clearly ahead of the central and western regions (Xu and Li 2022). Currently, the digital economy in the central and western regions has not yet formed economies of scale. The positive function of the digital economy is not fully played out. Especially, for western regions, the development of the digital economy is still in its infancy, and the digital infrastructure lags behind. However, the initial input costs of the digital economy are high. In addition, the industrial structure in the western region is relatively simple, and the degree of digital transformation of traditional industries is low. The development of industry in the western regions relies more on natural resources. In consequence, for the western regions, the digital economy has a negative effect on industrial eco-efficiency instead. From this, it can be concluded that the effects of the digital economy on industrial eco-efficiency present pronounced regional heterogeneity.

4.3. Analysis of spatial effects

In this section, we will discuss the spatial effects of the digital economy on industrial eco-efficiency. First, this paper calculated the global Moran's I of industrial eco-efficiency, which is shown in Table 7. It can be seen that the global Moran's I ranges from 0.114 to 0.276, and it is significantly positive in most years. It shows that industrial eco-efficiency has a positive spatial auto-correlation. Furthermore, this study confirmed if there is any spatial correlation by Lagrange Multipliers (LM) and Moran's I on the residuals of OLS. The results suggest that it is necessary to take into account spatial error effects and spatial lag effects both. Thus, it is more suitable to construct a model with parameters rho (ρ) and lambda (λ), like the spatial Durbin model (SDM). Next, this study tried to model the SDM. According to the results of the LR test, the constructed SDM in this paper will not reduce to the SAR or SEM. The Hausman test result suggests that SDM with fixed effects is better than with random effects. The fixed effects include time fixed effect, individual fixed effect and two-way fixed effect. The LR test results show that the two-way fixed effect is best. Hence, this paper finally selected the SDM with two-way fixed effect. All diagnostic test results are reported in Table 8.

Table 7. Global Moran's I of industrial eco-efficiency.

Year	I	z statistic	p-value*
2010	0.276	3.039	0.002
2011	0.197	2.271	0.023
2012	0.194	2.237	0.025
2013	0.218	2.466	0.014
2014	0.235	2.631	0.009
2015	0.242	2.702	0.007
2016	0.223	2.517	0.012
2017	0.242	2.708	0.007
2018	0.184	2.121	0.034
2019	0.180	2.080	0.037
2020	0.114	1.435	0.151

Note: * denotes 2-tail test.

Table 8. The results of model diagnostic tests.

Diagnostic test	Statistic	p-value
Moran's I(error)	7.368	0.000
LM-error	49.633	0.000
Robust-LM-error	66.779	0.000
LM-lag	20.680	0.000
Robust-LM-lag	37.797	0.000
Hausman test	34.97	0.000
LR test (SDM&SAR)	110.25	0.007
LR test (SDM&SEM)	104.54	0.012
LR test(two-way&time)	0.242	0.007
LR test(two-way&ind)	0.184	0.034

Table 9. The regression results of the Spatial Durbin model.

Variable	(1) Two-way	(2) Time	(3) Ind
Dig	0.00170**	0.00325***	0.00151*
	(2.58)	(6.74)	(2.26)
PGDP	1.329***	0.412***	1.347***
	(10.17)	(7.90)	(10.18)
ER	0.0243**	0.00183	0.0249**
	(2.71)	(0.26)	(2.85)
FDI	0.0129	0.0121*	0.00907
	(1.32)	(2.11)	(0.92)
SEC	0.129	0.293***	0.0217
	(1.21)	(4.34)	(0.21)
W*Dig	0.000874	0.00145	−0.000499
	(0.54)	(1.41)	(−0.40)
W*PGDP	−1.186***	−0.177	−1.420***
	(−3.61)	(−1.75)	(−10.15)
W*ER	−0.0377	−0.0491**	−0.0412**
	(−1.93)	(−2.92)	(−3.25)
W*FDI	0.0303	−0.0827***	0.00652
	(1.20)	(−5.50)	(0.28)
W*SEC	0.470	0.103	−0.0259
	(1.68)	(0.53)	(−0.11)
rho(ρ)	0.218*	−0.0414	0.419***
	(2.26)	(−0.43)	(5.39)
sigma2_e	0.00582***	0.0115***	0.00605***
	(12.77)	(12.85)	(12.63)
Obs	330	330	330

Note: The values in parentheses are t statistics. *, **, ***denote significance levels of 10%, 5% and 1%, respectively.

The main results of the Spatial Durbin model are reported in Table 9, in which columns (1) to (3) show, respectively, the regression results based on two-way fixed effect, time fixed effect and individual fixed effect. In terms of independent variables, the significance and signs of regression coefficients are almost consistent with the benchmark regression result. This is more evidence of the positive effect of the digital economy on industrial eco-efficiency. From column (1), the coefficient of spatial lag term (ρ) is significantly positive. LeSage and Pace (2009) proposed that while the coefficient of ρ is significantly not zero, there will be systematic bias in the spatial interaction coefficients of the SDM. That may cause wrong conclusions on the spatial spillover effect. By the method of partial differentials, the total spatial effect is decomposed into direct effect and indirect effect. This method can be more effective to estimate the spatial interaction coefficients. The direct effect reflects the average impact of the independent variable on the local dependent variable. The indirect effect reflects the average impact of the independent variable on the dependent variable for other regions, namely, spatial spillover effect. The total effect reflects the average impact of the independent variable on the dependent variable for all regions. Hence, this study decomposed the spatial effect based on the SDM with two-way fixed effect, as shown in Table 10.

As can be seen from Table 10, the coefficients of the digital economy are all positive, which again proves the positive impact of the digital economy on industrial eco-efficiency. However, the indirect effect coefficient of the digital economy is not significant. In other words, on a national scale, there is a certain degree of digital isolation. Digital technology and the digital economy have not played their role in infiltrating and driving the sustainable development of neighboring regions. Possible reasons include the lack of awareness and standards of big data opening and sharing, the lack of big data legislation and the lack of big data talents in China. These lead to data a monopoly, which is not conducive to information flow and knowledge transfer. In addition, the different regions of China are at different stages of economic development,which is also confirmed by the results of the heterogeneity analysis above. However, the threshold for digital economy development is high. For underdeveloped regions, backward infrastructure and lack of independent innovation capacity may hinder the spillover of the digital economy to a certain extent.

Table 10. Decomposition of spatial effects.

	Dig	PGDP	ER	FDI	SEC
Direct	0.00178^{**}	1.288^{**}	0.0238^{**}	0.0142	0.153
	(2.68)	(10.33)	(2.78)	(1.45)	(1.41)
Indirect	0.00160	-1.093^{**}	-0.0409^{*}	0.0433	0.644^{*}
	(0.86)	(−2.73)	(−1.75)	(1.39)	(1.81)
Total	0.00338^{*}	0.195	−0.0171	0.0576^{*}	0.798^{**}
	(1.82)	(0.47)	(−0.67)	(1.65)	(1.96)

Note: The values in parentheses are t statistics. *, **, ***denote significance levels of 10%, 5% and 1%, respectively.

5. Conclusions

Studying the relationship between the digital economy and industrial eco-efficiency is of great significance for environmental governance, energy conservation and pollutant emission reduction. This study evaluated the industrial eco-efficiency of 30 provinces in mainland China during the period from 2010 to 2020. Then, this paper discussed the possible effects of the digital economy on industrial eco-efficiency theoretically, with the construction of the two-way fixed effect model and the spatial Durbin model to empirically analyze how the digital economy affects industrial eco-efficiency. Finally, we can draw some conclusions as follows.

First, the digital economy has a significantly positive effect on industrial eco-efficiency at the national scale. Both the results of benchmark regression and quantile regression proved that. With the increase of industrial eco-efficiency, the positive effect from the digital economy may decrease slightly.

Second, there is significant regional heterogeneity in the effects of the digital economy on industrial eco-efficiency in China. For eastern regions, the digital economy can improve industrial eco-efficiency effectively. For western regions, however, the digital economy has a negative effect on industrial eco-efficiency. The western region is still in the initial stage of the digital economy, and the early development of the digital economy needs the input of a lot of resources. This may put great pressure on the western region to improve ecological efficiency.

Finally, there may be digital isolation in China. At present, China lacks relevant standards and legal systems for data opening and sharing. The spillover effects of the digital economy have not been fully exploited. The industrial developments of different regions are at different stages, and the development threshold of the digital economy may hinder its spillover in underdeveloped areas.

Therefore, the regions should accelerate the development of the digital economy, especially for western regions. The government should increase financial support for western regions and accelerate the construction of digital infrastructure. Industrial enterprises should speed up the digital transformation of industries, to form a digital economy of scale, which has increasing returns with scale.

Acknowledgments

This work was supported by the National Social Science Foundation of China (Grant No.21BTJ006).

Conflict of interest

All authors declare no conflicts of interest in this paper.

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