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Digital economy, environmental regulation and green eco-efficiency—Empirical evidence from 285 cities in China

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Strengthening green eco-efficiency has emerged as one of China's key objectives for its present economic green development. All walks of life have progressively begun to pay attention to how to leverage the rapidly developing digital economy to promote regional green eco-efficiency upgrading. This work first develops a mathematical model to investigate the inherent mechanism of digital economy development on green eco-efficiency enhancement and presents a research hypothesis, which is then followed by a fixed-effects model and a spatial econometric model to evaluate the geographic spillover effect of digital economy development on green eco-efficiency enhancement and the moderating influence of environmental regulation. According to the test results, the growth of the digital economy can greatly increase green eco-efficiency, with environmental legislation acting as a helpful moderator. Additional empirical research revealed that environmental regulation and the development of the digital economy both favourably promote and adjust green eco-efficiency. However, there are various effects of different regions and different time periods, it shows that there are "strong in the East and weak in the west," "weak in the East and weak in the west" and "weak first and then strong." Therefore, each region in China should promote the development of digital economy, accelerate the digitization of industry, and promote the green ecological efficiency of China's industry with the digital economy a grip. At the same time, the regulating role of government environmental regulations should be given full play to narrow the differences between regions and promote the green, coordinated, and sustainable development of each regional economy.

KEYWORDS

digital economy, green development, environmental regulation, eco-efficiency, moderating effects

1 Introduction

As China's economy has gradually shifted to high-quality development after a period of rapid development, the issue of coordination of economy, environment, and resources has become particularly important. The rough and loose development model of the early reform and opening-up period promoted rapid economic growth while destroying the natural environment and disturbing the ecological balance, making natural disasters and environmental pollution problems increasingly prominent. In September 2020, President Xi Jinping, at the 75th session of the United Nations General Assembly, proposed for the first time a "double carbon goal" and announced the "carbon peak" and "carbon neutral" targets. This shows that adopting green development and enhancing the ecological environment have grown to be critical issues that China must deal with. Enhancing green eco-efficiency is the key to resolving the ecological environment and implementing green development because it is a crucial indicator of the harmonious relationship between the economy, resources, and environment as well as one of the indicators to measure the green development of industry.

Technological progress and innovation can reduce pollution emissions and environmental pollution by enhancing resource utilization efficiency, reducing resource waste in production processes, and promoting resource recycling (Bosseboeuf and Richard, 1997; Liu et al., 2021). At the level of environmental governance, technological progress and innovation have improved ecology and alleviated environmental pressure by enhancing environmental monitoring and governance (Ding, 2019). With significant advancements in big data, cloud computing, blockchain, the Internet of Things, and artificial intelligence, the expansion of the digital economy has recently emerged as the primary factor driving scientific and technical advancement. The implementation of environmental monitoring is effectively supported by big data and artificial intelligence technologies, and resource utilization efficiency is increased through the use of the Internet of Things and cloud computing technologies. The development of these technologies has produced favorable environmental externalities in a variety of fields. The interaction between the economy, environment, and resources in production life has gradually changed as a result of digital technology, a major current factor of production. Additionally, since the beginning of the new crown epidemic at the end of 2019, when the movement of labor factors was restricted and travel and business activities were impacted, digital technologies started to replace traditional technologies widely. During this time, the digital economy developed quickly, the scale of the digital economy increased, and the impact it had gradually grew. Has the growth of the digital economy improved green eco-efficiency from an ecological perspective? This has become the focus of analysis in this paper.

The government's implementation of environmental regulations has an effect on the ecological environment and manufacturers' emissions on the one hand, and on economic activity due to the increased costs of emissions, and the digital economy as a significant component of economic activity may also be affected. This paper will also examine the crucial role played by government environmental regulation in the regulation of the green eco-efficiency of the digital economy in order to determine whether the actions of government environmental regulation have an effect on the scope and direction of the role of the digital economy. In order to assess the mechanism by which the digital economy impacts green eco-efficiency and how environmental regulation affects that influence, this study will first conduct a review of the relevant literature. We then employ a variety of econometric techniques to empirically test the impact of the digital economy on green eco-efficiency. We also concentrate on the regulatory function of environmental regulation in order to provide China with theoretical points of reference for achieving its "double carbon" and green development goals.

2 Literature review

At present, issues related to digital economy, environmental regulation and green eco-efficiency have become hot spots in academic circles. In-depth research has been done on the connections between the green eco-efficiency movement, environmental regulation, and the digital economy, with the following topics receiving the majority of attention.

First, studies on the connotation, measurement and key influencing factors of green eco-efficiency. According toSchaltegger and Sturm (1990), green eco-efficiency can be used to gauge the extent of regional green growth by comparing value rise to environmental effect. Some other scholars consider green eco-efficiency as the ability to achieve maximum economic value with minimum environmental cost (Schmidheiny and Timberlake, 1992; Peng et al., 2017; Su et al., 2021). The previous years, the methods of green eco-efficiency measurement have been improved and improved, and the early measures of green eco-efficiency mainly used the single ratio method, which uses the ratio of economic and environmental indicators to measure eco-efficiency, but it has the disadvantage of not being able to estimate the environmental impact in detail and accurately (Yin et al., 2012). Later, some scholars constructed indicator systems to estimate green eco-efficiency more accurately, for example, Jiansu Mao et al. (2010) used industrial output value, pollution emission and energy consumption to construct an indicator system to measure industrial eco-efficiency, and Michelsen (Michelsen et al., 2006) selected nine environmental indicators to assess the eco-friendliness of furniture products. To quantify green eco-efficiency, some academics have recently used the data envelopment analysis (DEA) method (Yin et al., 2012). Some academics have also performed more thorough research in recent years on the critical elements influencing green eco-efficiency. Some researchers have examined the impact of low-carbon city pilot on green eco-efficiency using a quasi-natural experiment and found that low-carbon city pilot policies can significantly improve urban eco-efficiency (Yang and Deng, 2019), while other researchers have found that both resource inputs and social inputs have a positive effect on eco-efficiency, but there is an uneven growth trend of green eco-efficiency among different regions (Feng and Zhang, 2021). Sneideriene et al. (2020) evaluated green growth based on a mixed method of data analysis, generalization and index assessment and measured green growth indices for developing and developed countries, and found that green growth was uneven in European countries and the indices varied greatly in lagging countries. Rybalkin et al. (2021) constructed EEPSE green economy indicators using a five-fold helix model, which combines five dimensions—educational, economic, social, political and environmental—to assess the green economy trends in EU countries. Furthermore, Andryeyeva et al. (2021) constructed a new system of indicators using economic and environmental indicators to assess the process of green growth and provide recommendations for the management of the natural environment.

Secondly, the study of the meaning of the digital economy and how it affects environmentally friendly efficiency. Data has recently risen to the top of the list of production elements, having a significant impact on life, production, and ecology (Wang et al., 2021). Numerous literatures have been published to define the connotation of digital economy. Some scholars define it in terms of the scope of the digital economy, which encompasses the hardware facilities of e-commerce, the processes of e-commerce and e-business (Mesenbourg, 2001), the digital economy is that part of output that is increased by producing products and providing services based on digital technologies (Bukht and Heeks, 2017), and there are definitions that view the digital economy as an economic activity. According to the G20 Digital

Economy Development and Cooperation Initiative, the digital economy is, for instance, "a set of economic activities that use digital knowledge and information as key factors of production, modern information networks as important carriers, and the effective use of information and communication technologies as an important driving force for efficiency improvement and economic structure optimization." Knickrehm et al. (2016) considers the digital economy as the output brought by the input of digital skills and digital facilities. The digital economy is characterized by "economies of scope, decreasing transaction costs and creative destruction" (Pei et al., 2018). The majority of studies on the relationship between the digital economy and green eco-efficiency primarily employ econometric techniques to test this relationship. For instance, He et al. (2022) used provincial panel data and a two-way fixed effects model to test the influence of digital economy development on eco-efficiency enhancement. Liu et al. (2022) also used empirical methods to verify the effect of digital economy on green eco-efficiency enhancement, in addition, it was found that digital industrialization promotes green eco-efficiency more than digitalization of industry, and at the same time, digital economy development needs to reach a threshold value to promote green eco-efficiency.

Third, study on how environmental regulation affects sustainable development. For example, Lei and Yu (2013) discovered that environmental regulation measures, primarily pollution control investment and emission permits, would impede the improvement of the green total factor productivity of industry. Li and Bi (2012) demonstrated that environmental regulation would increase the cost of enterprises' development and thus indirectly result in a decrease in the level of green development. According to Luo and Wang (2017), different environmental regulations have different relationships with green eco-efficiency, with governance-input-based regulations and green eco-efficiency having a U-shaped relationship. However, the impact of economic incentive-based regulations on green eco-efficiency is minimal. Other researchers think that environmental regulation will boost local green total factor productivity or green eco-efficiency. For instance, Li et al. (2013) used industry-level data to conduct an empirical test and discovered that environmental regulation can successfully boost green total factor productivity once its level of intensity reaches a specific value. Higher levels of government environmental governance can promote green total factor productivity in regional industries, but there is regional heterogeneity in the green eco-efficiency of environmental governance or environmental regulation (Wang and Sheng, 2015), while other scholars have examined the effect of environmental regulation on economic growth under environmental constraints. Klimas, E. (2020) analyzed the impact of spatial planning regulations on climate change management using the latest sustainable development principles in Lithuania and found that spatial planning regulations should provide for specific measures to effectively enhance climate management.An empirical study of the pilot policy's impact on civilized cities discovered that environmental regulation by the government can lower pollution levels and encourage the growth of green urban areas.

Our analysis of the existing literature shows that few researchers have examined the digital economy, environmental regulation, and green eco-efficiency within a single theoretical analytical framework. Instead, the majority of the literature primarily focuses on the connections between the digital economy and green eco-efficiency as well as the relationship between the two. This study will fill a research gap, analyze the relationship between the digital economy, environmental regulation, and green eco-efficiency, and focus on the regulatory role of environmental regulation in that relationship. The goal is to unleash the development potential of the digital economy, improve green eco-efficiency, support green development, and advance the construct. The structure of this essay is as follows. This paper's precise structure is as follows: Part IV will use data from 285 Chinese cities to empirically test the internal logical relationship between the digital economy and green eco-efficiency and test the heterogeneity by period and region. Part V will draw a conclusion. Part III will build a mathematical model to investigate the internal logical relationship between the digital economy and green eco-efficiency and put forward the corresponding research hypotheses.

3 Theoretical model

In order to build a theoretical model about the relationship between the digital economy and green eco-efficiency, this paper primarily draws on Acemoglu et al. (2012) and Jing and Zhang (2014) mathematical modeling ideas. It focuses on exploring the internal logical relationship between the digital economy and green eco-efficiency.

Assume that two production sectors a and b exist in a country or region for the digital technology sector and the traditional technology sector, respectively, and that the production function for the total capacity Y_t of the two sectors is as follows:

$$\boldsymbol{Y_t = \left(Y_{at}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{bt}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}} \tag{1}$$

where Y_{at} is the input produced using digital technology, Y_{bt} is the input produced using traditional technology, and ε represents the elasticity of substitution between the two production inputs. When $\varepsilon > 1$, there is a substitution effect between the two inputs; when $\varepsilon < 1$, there is a complementary effect between the two inputs. In addition, both sectors require the use of labor and related equipment for production, and their production functions are:

$$\boldsymbol{Y_{jt} = L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}X_{jit}^{\alpha}\,di} \tag{2}$$

$$\boldsymbol{G(A_{jt}, Y_{jt}) = \tau(A_{jt})Y_{jt} = \tau(A_{jt})L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}\,di} \tag{3}$$

where A_{jit} represents the mass of type i machines used in sector $j \in \{a, b\}$ at time t, and L_{jt} represents the amount of labor input in sector j at time t. $G(A_{jt}, Y_{jt})$ is the total pollution reduction in sector j due to technological progress, and $\tau(A_{jt})$ is the abatement capacity of technological progress while satisfying $\frac{\partial\tau(A_{jt})}{\partial A_{jt}} > 0$. This indicates that the abatement capacity increases with technological progress. Set the green eco-efficiency $g(A_{jt}) = \frac{\partial G(A_{jt}, Y_{jt})}{\partial A_{jt}}$, meaning the rate of change of marginal emission reduction triggered by the improvement of machine quality in sector j, i, technological progress.

The market clearing condition demands that the total labor supply be normalized to 1, with the total labor demand being smaller than the entire labor supply, resulting in:

$$\boldsymbol{L_{at} + L_{bt} \leqslant 1} \tag{4}$$

Also set the average productivity A_{jt} for period t of the equipment in sector j as:

$$A_{jt} = \int_0^1 A_{jit}\, di \tag{5}$$

The difference equation between A_{jt} and A_{jt-1} as time progresses is:

$$A_{jt} = (1 + \gamma\delta_j e_{jt}) A_{jt-1} \tag{6}$$

γ is the coefficient of the increase in machine quality due to innovation, δ_j is the probability of successful innovation in sector $j \in \{a, b\}$, and e_{jt} is the number of vendors involved in R&D of digital or traditional technologies in sector j at time t.

In addition, the market in which the two sectors compete is assumed to be perfectly competitive. Thus, the final product is produced under perfectly competitive conditions and the relative prices of the two intermediate input products satisfy.

$$\frac{p_{at}}{p_{bt}} = \left(\frac{Y_{at}}{Y_{bt}}\right)^{-\frac{1}{\varepsilon}} \tag{7}$$

where p_{at} and p_{bt} represent the prices of intermediate input products in the digital technology sector and the traditional technology sector, respectively. Then the profit maximization problem for intermediate input production in sector j is:

$$\max_{x_{jit}, L_{jt}} \left\{ p_{jt} L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha}\, di - w_t L_{jt} - \int_0^1 p_{jit} x_{jit}\, di \right\} \tag{8}$$

w_t is the price of hired labor in period t and p_{jit} is the price of machine i in period t. This leads to the following isoelastic inverse demand function:

$$x_{jit} = \left(\frac{\alpha p_{jt}}{p_{jit}}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jit} \tag{9}$$

Substituting Eq. 9 into the first-order condition of labor $(1-\alpha) p_{jt} L_{jt}^{-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di = w_t$, and then associating Eq. 5 yields the relative prices of digital technology products and traditional technology products as:

$$\frac{p_{at}}{p_{bt}} = \left(\frac{A_{at}}{A_{bt}}\right)^{-(1-\alpha)} \tag{10}$$

Assuming that the unit cost of machine production is a constant ψ, the problem of profit maximization for a monopoly producer of machine type i in sector j is:

$$\max_{p_{jit}} \left\{ (p_{jit} - \psi) x_{jit} \right\} \tag{11}$$

Due to this elasticity of demand, the price of the machine when profit is maximized is an equal proportional markup of marginal cost, thus:

$$p_{jit} = \frac{\psi}{\alpha} \tag{12}$$

Substituting Eq. 10 into Eq. 8 yields the demand for machine i in sector j at equilibrium as:

$$x_{jit} = \left(\frac{\alpha^2 p_{jt}}{\psi}\right)^{\frac{1}{1-\alpha}} A_{jit} L_{jt} \tag{13}$$

This leads to the equilibrium profit of the machine manufacturer under monopoly conditions as:

$$\pi_{jit} = (1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \tag{14}$$

Using the definitions in Eqs 5, 6, the expected profit of a manufacturer in sector j at time t is derived as:

$$\pi_{jt} = (1 + \gamma\delta_j e_{jt})(1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jt-1} \tag{15}$$

Thus the relative returns of the two sectors are obtained as:

$$\frac{\pi_{at}}{\pi_{bt}} = \frac{(1 + \gamma\delta_a e_{at})}{(1 + \gamma\delta_b e_{bt})} \left(\frac{p_{at}}{p_{bt}}\right)^{\frac{1}{1-\alpha}} \frac{L_{at}}{L_{bt}} \frac{A_{at-1}}{A_{bt-1}} \tag{16}$$

When the relative returns $\frac{\pi_{at}}{\pi_{bt}}$ are higher, the stronger is the willingness of R&D in the digital technology sector. Where $(\frac{p_{at}}{p_{bt}})^{\frac{1}{1-\alpha}}$ represents the price effect, which promotes innovation in sectors with higher input prices. $\frac{L_{at}}{L_{bt}}$ represents the labor market size effect, which promotes innovation in sectors with high employment. $\frac{A_{at-1}}{A_{bt-1}}$ is the direct productivity effect, which promotes innovation in sectors with higher productivity. Substituting the demand function (13) at equilibrium into Eq. 2 yields the equilibrium production level:

$$Y_{jt} = \left(\frac{\alpha^2 p_{jt}}{\psi}\right)^{\frac{\alpha}{1-\alpha}} A_{jt} L_{jt} \tag{17}$$

Then, by associating Eqs 5, 7, the relationship between relative productivity and relative employment is:

$$\frac{L_{at}}{L_{bt}} = \left(\frac{A_{at}}{A_{bt}}\right)^{-1-(1-\alpha)\varepsilon} \left(\frac{p_{at}}{p_{bt}}\right)^{\frac{-\alpha}{1-\alpha}} = \left(\frac{A_{at}}{A_{bt}}\right)^{-(1-\varepsilon)(1-\alpha)} \tag{18}$$

According to Eq. 18 and then linking Eqs 10, 16, it follows that:

$$\frac{\pi_{at}}{\pi_{bt}} = \frac{\delta_a}{\delta_b} \left(\frac{1 + \gamma\delta_a e_{at}}{1 + \gamma\delta_b e_{bt}}\right)^{-1-(1-\varepsilon)(1-\alpha)} \left(\frac{A_{at-1}}{A_{bt-1}}\right)^{-(1-\varepsilon)(1-\alpha)} \tag{19}$$

The following conclusions can be drawn from Eq. 19:

When $\varepsilon > \frac{\alpha-2}{\alpha-1}$, $\frac{\pi_{at}}{\pi_{bt}}$ is accompanied by increasing e_{at}, if innovation in a country or region occurs in the digital technology sector, technological progress is biased toward digital technology, and at this time it is the technological progress in the digital technology sector that drives green eco-efficiency growth.

When $\varepsilon < \frac{\alpha-2}{\alpha-1}$, $\frac{\pi_{at}}{\pi_{bt}}$ decreases along with e_{at}. Technology progress favors traditional technology if innovation in a nation or region happens in the traditional technology sector, and the rise of green eco-efficiency is fueled by technological advancement in the traditional technology sector.

When $\varepsilon = \frac{\alpha-2}{\alpha-1}$, $\frac{\pi_{at}}{\pi_{bt}}$ is accompanied by increasing e_{at}. If innovation in a country or region occurs in both sectors, technological progress is biased by uncertainty, and technical progress in both sectors jointly propels green eco-efficiency growth at this time.

On the basis of the results mentioned above, the following research hypothesis can be developed: Green eco-efficiency will be encouraged as a nation or region's digital economy grows.

4 Data sources and study design

4.1 Data sources and sample selection

Data from 285 cities between 2011 and 2019 will be used in this study. The reason for choosing this time period is that, although digital technology was invented in the late 20th century, it was not widely adopted until the early 21st century, and it was not until 2010 that provinces and cities all over the country started to fully explore digital practices, making this period a time of rapid development for the digital economy. City-level data were selected because provincial samples cannot more accurately observe inter-city spillover effects and regional heterogeneity. Municipalities that fall under the direct control of the national government are included as city-level samples in this paper's sample selection process. In this study, the sample of cities with administrative areas that merged after 2019 is kept, while the sample of cities with missing data is excluded. The sample data sources in this paper are mainly statistical yearbooks and government work reports.

4.2 Variable description and descriptive statistics

4.2.1 Explained variable: Green eco-efficiency (gee)

By studying the existing literature on measuring green eco-efficiency, we found that there are several methods to measure it: first, by constructing an indicator system and using the Super-SBM model or Super-EBM model (Pan and Xie, 2019; Feng and Zhang, 2021); second, using the factor decomposition method to measure green energy efficiency and green environmental efficiency from (He et al., 2022); third, the super-efficient EBM model is used to quantitatively evaluate green efficiency by adding non-expected output factors and considering non-oriented, constant payoffs of scale (Zhao et al., 2021); fourth, the DEA model is used to address the input-output inconsistency problem, while environmental pollution is treated as a non-consensual factor (Grosskopf et al., 1989). Among the above methods, the super-efficient SBM model is the most widely used and has a more comprehensive assessment of green eco-efficiency.

In this study, we make extensive use of the existing literature to calculate the green eco-efficiency using the methodology of Hu and Yang (2011), which is based on the global reference DEA analysis framework. We then calculate the green eco-efficiency by taking the Super-SBM model of undesired output and the Malmquist productivity index into account. The China Statistical Yearbook, China Statistical Yearbook of Industrial Economy, China Statistical Yearbook of Environment, and China Statistical Yearbook of Regional Economy were the primary sources of the data used. The regional GDP at constant prices was chosen as the expected output indicator, while the set input indicators were the amount of electricity consumed, the number of people employed, and the capital stock. The unanticipated output indicators were wastewater emissions, industrial soot emissions, sulfur dioxide emissions, and PM2.5.

4.2.2 Explanatory variables: Development stage of the digital economy (dig)

The majority of studies currently in existence on the measurement of digital economy development level indicators are centered on the provincial level, for example, the digital economy is divided into three dimensions for measurement: information development, Internet development, and digital transaction development (Liu et al., 2020). As a result, some indicators for the prefecture-level cities' digital economy measurement have to be reduced. In order to improve the measurement of the digital economy at the municipal level, this article refers to Zhao et al. (2020) and assesses the level of development of the digital economy from two perspectives: digital finance and Internet development. The Digital Finance Research Center of Peking University's Digital Inclusive Finance Index is used to measure one of them, the digital finance dimension. Four variables were utilized to measure the growth of the internet: mobile phone penetration, related practitioners, related output, and Internet penetration rate. The data were primarily taken from the China Urban Statistical Yearbook. The digital economy index was then calculated using the coefficient of variation approach. The basic idea behind the coefficient of variation method, an objective assignment based on the size of the difference between indicators, is that in the indicator system for evaluating the digital economy, the bigger the difference between the indicator values, the more it reflects the variation of the evaluated target. This is the precise computation process.

By removing the impact of the magnitude difference, the coefficient of variation is computed. Each index's coefficient of variation is determined as follows:

$$\boldsymbol{Z_i = \delta_i \Big/ \overline{x_i} (i = 1, 2, \ldots, n)} \tag{20}$$

where, Z_i refers to the coefficient of variation of the ith indicator, i.e., the standard deviation coefficient; δ_i is the standard deviation of the ith indicator; and $\overline{x_i}$ the mean value of the ith indicator. After that, the weights of each indicator are calculated as follows:

$$\boldsymbol{w_i = z_i \Big/ \sum\nolimits_{i=1}^{n} z_i} \tag{21}$$

Finally, the individual values of the system can be evaluated according to the calculated weights.

4.2.3 Moderating variable: Intensity of environmental regulation (err)

The approach used by Chen et al. (2018) to calculate the environmental regulatory intensity indicator is used in this work. These are the precise steps: Collect all the terms that are related to the environment in the government work report, count how often they occur, and then determine what percentage of the total number of words in the report are related to the environment. The phrases connected to the environment are: pollution, energy use, emission reduction, emissions, ecology, low carbon, air, chemical oxygen demand, sulphur dioxide, carbon dioxide, PM10, and PM2.5 (Chen and Chen, 2018).

4.2.4 Control variables

The degree of economic development (eco), the volume of foreign investment (fdi), the level of industrial structure (ind), the level of financial development (fin), and the level of government intervention (gov) were chosen as control variables in this paper by drawing on studies on factors affecting green eco-efficiency (Chen and Tang, 2018; Liu et al., 2018; Ji et al., 2022). The gross domestic product (GDP) *per capita* for the area is used to gauge its level of economic development. The ratio of actual foreign investment used to GDP serves as a gauge for the extent of foreign investment. The ratio of tertiary sector output to overall output indicates the level of industrial structure. The ratio of the total deposits and loans to the regional GDP is used to gauge the region's level of financial development. The proportion of public finance spending to regional GDP indicates the degree of government intervention. Table 1 provides explanations for each variable.

TABLE 1 Definition and interpretation of variables.

Variable category	Variable symbols	Variable name	Explanation of variables
Explained variables	Gee	Green	Using the Super-SBM model and the Malmquist productivity index, and based on the DEA framework
		Eco-efficiency	
Explanatory variables	Dig	Level of development of the digital economy	The system of indicators was constructed from two perspectives: digital finance and Internet development, and was measured using the coefficient of variation method
Adjustment variables	Err	Environmental regulation intensity	Statistics on the frequency of words related to the environment as a percentage of all words according to the government work report
Control variables	Eco	Level of economic development	GDP *per capita* in the region (in million)
	Fdi	Scale of foreign investment	Real use of foreign investment in the region as a percentage of GDP
	Ind	Level of industrial structure	Tertiary sector output as a proportion of total output
	Fin	Level of financial development	Total deposits and loans as a percentage of GDP at the end of the year
	Gov	Level of government intervention	Public finance expenditure as a proportion of regional GDP

TABLE 2 Variables' descriptive statistics.

Variable name	Sample size	Mean	Sd	Mid	Min	Max	1/4 quartile	3/4 quartile
Gee	2,565	1.01	0.24	1.01	0.96	4.63	0.98	1.03
ln_dig	2,565	10.55	2.15	10.79	7.81	14.94	10.25	11.39
Err	2,565	0.01	0.00	0.01	0.00	0.02	0.00	0.01
Ind	2,565	0.38	0.15	0.39	0.1	0.83	0.32	0.46
Gov	2,565	0.2	0.11	0.17	0.04	1.59	0.13	0.24
Fin	2,565	2.41	1.2	2.09	0.5	21.3	1.65	2.81
Fdi	2,565	0.02	0.02	0.01	0.00	0.13	0.00	0.02
Eco	2,565	3.63	3.53	3.07	0.69	21.55	1.67	5.33

The level of economic development is chosen as a control variable because the process of economic development, especially the rapid expansion of industry, brings pollution, which leads to a decline in green eco-efficiency, while the pursuit of sustainable development at a higher level of economic development is likely to focus on green eco-efficiency. The indicator of industrial structure level is chosen because most of the development of cities is the continuous transformation from primary industry to tertiary industry, and the higher the proportion of tertiary industry in a city, the higher the environmental efficiency and green eco-efficiency are likely to be. The indicator of the level of financial development is chosen because financial institutions can provide financial support for the development of enterprises, which is conducive to upgrading machinery and equipment, strengthening technological investment, eliminating backward production capacity and improving energy utilization efficiency, as well as financing for the service industry, supporting the rapid development of the tertiary industry, and continuously promoting the upgrading of industrial structure, which in turn has an indirect impact on green total factor productivity. The variable of the degree of government intervention is chosen because the government, through scientific and reasonable planning, guides the adjustment and transformation of the industrial structure in each region, gradually eliminates backward production capacity and reduces the existence of environmentally polluting industries, which also affects green eco-efficiency. FDI is selected as a control variable because according to the "pollution paradise" hypothesis, the level of environmental regulations in China as a developing country is often lower than that in developed countries, which makes developed countries' high pollution and high energy consumption industries move to developing countries, especially those developing countries that are desperate for development and lower environmental regulations, which will become the gathering place of high pollution industries, so the increase of FDI may affect the green eco-efficiency.

Table 2 provides more information on the outcomes of the descriptive statistics. Although there are significant variances between cities, the median and mean values indicate that the level of digital economy development is generally high. This is mainly because different regions are at different phases of this growth. The highest value is significantly bigger than the mean, showing the existence of a limited number of cities with high green eco-efficiency. The values of most cities' green eco-efficiency are focused around the mean. The low mean and variance of environmental regulation intensity show that the values are more concentrated and that total environmental regulation intensity varies relatively little.

TABLE 3 Baseline regression results.

Variables	(1)	(2)	(3)	(4)
	Gee	Gee	Gee	Gee
ln_dig	0.0800***	0.0436***	0.0801***	0.0789***
	(33.4632)	(20.2817)	(33.5520)	(32.8407)
Eco		0.0131***	0.0034	0.0117***
		(9.8196)	(1.5271)	(4.4706)
Ind		0.1572***	−0.0821*	0.1126*
		(4.4597)	(−1.8375)	(1.9065)
Fin		−0.0099**	−0.0034	0.0021
		(−2.1930)	(−0.6133)	(0.3732)
Fdi		0.4761*	−0.1443	−0.4333
		(1.8746)	(−0.4155)	(−1.2268)
Gov		0.3927***	−0.0194	0.0357
		(8.5836)	(−0.2754)	(0.5045)
constant	0.3002***	0.4250***	0.3248***	0.2348***
	(5.4935)	(14.7434)	(5.4364)	(3.7910)
City Effect	YES	NO	YES	YES
Year Effect	YES	YES	NO	YES
Number of samples	2,565	2,565	2,565	2,565
adj. R-sq	0.6257	0.2028	0.6219	0.6283

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively.

4.3 Model setting

The baseline regressions were first conducted using controls for city fixed effects, year fixed effects and two-way fixed effects, and the model was set up as follows:

$$gee_{it} = \beta_0 + \beta_1 ln\_dig_{it} + \sum\nolimits_{i=1}^{n} X_{it} + v_i + v_t + \varepsilon_{it} \tag{22}$$

where $\sum_j X_{it}$ is the control variable, v_i represents the city fixed effect, v_t represents the year fixed effect, and ε_{it} represents the random error term. If the digital economy has an enhancing effect on green eco-efficiency, the sign of β_1 should be significantly positive. To demonstrate that environmental regulation has a moderating effect on the digital economy and green eco-efficiency, the econometric model is set as follows:

$$gee_{it} = \beta_0 + \beta_1 ln\_dig_{it} + \beta_2 err_{it} + \beta_3 ln\_dig_{it} \times err_{it} + \sum\nolimits_{i=1}^{n} X_{it} + v_i + v_t + \varepsilon_{it} \tag{23}$$

If environmental legislation has a major moderating effect but the digital economy still has a significant capacity to boost green eco-efficiency, then β_3 will be significantly positive and β_1 will also continue to be significantly positive. To further examine the spatial spillover effect among cities, we will also put up a spatial econometric model in this work.

5 Empirical results

5.1 Baseline regression

The outcomes of the benchmark regressions are presented in Table 3. Without adjusting for the control variables but for the city impact and the year effect, the regression findings in Column (1) reveal that the level of development of the digital economy greatly increases green eco-efficiency. Columns (2) and (3) show the regression findings after adjusting for the city effect and the year effect, respectively. Even with the addition of control factors, the digital economy still significantly improves green eco-efficiency. The results of column (4), where the year effect, city impact, and control factors are all taken into account, reveal that the degree of development of the digital economy is considerably and favorably associated to green eco-efficiency.

5.2 Moderating effect analysis

This paper includes the intensity of environmental regulation (err) and its cross-product term with the level of digital economy development (ln dig) into the econometric model for regression to analyze the moderating effect of environmental regulation on the digital economy and green eco-efficiency. Table 4 displays the results of the regression. The digital economy significantly enhances green

TABLE 4 Regression results of moderation effects.

Variables	(1)	(2)	(3)
	Gee	Gee	Gee
ln_dig	0.0208***	0.0598***	0.0591***
	(5.0387)	(11.3129)	(11.2209)
ln_dig_err	3.5558***	2.7508***	2.6901***
	(6.4392)	(4.3008)	(4.2293)
Err	−34.0871***	−28.4229***	−27.3366***
	(−6.0041)	(−4.1792)	(−4.0327)
Eco	0.0124***	0.0030	0.0112***
	(9.2876)	(1.3413)	(4.2796)
Ind	0.1506***	−0.0727	0.1177**
	(4.2883)	(−1.5910)	(1.9962)
Fin	−0.0084*	−0.0038	0.0018
	(−1.8507)	(−0.6702)	(0.3108)
Fdi	0.5072**	−0.1452	−0.4375
	(2.0118)	(−0.4195)	(−1.2411)
Gov	0.3911***	−0.0208	0.0333
	(8.6064)	(−0.2968)	(0.4728)
constant	0.6473***	0.5212***	0.4257***
	(14.0794)	(6.9473)	(5.5484)
City Effect	NO	YES	YES
Year Effect	YES	NO	YES
Number of samples	2,565	2,565	2,565
adj. R-sq	0.2150	0.6246	0.6309

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

eco-efficiency, i.e., the higher the level of the digital economy, the higher the green eco-efficiency, even when controlling for the year impact, urban effect, and two-way fixed effect. Additionally, environmental legislation has a substantial positive moderating effect, meaning that the more environmental control there is, the more the digital economy will boost green eco-efficiency.

6 Spatial spillover effect test

6.1 Spatial measurement model setting

There may be regional movements of pertinent components and an impact on surrounding cities in the process of the development of the digital economy in cities, which means that the growth of the digital economy is not occurring in isolation in each city. Therefore, this article employs a spatial econometric model to estimate the spatial spillover effect in order to more precisely assess the relationship between digital economy, environmental regulation, and green eco-efficiency and to take into account the effects of spatial correlation. The spatial econometric model can be used for estimate once more because the Moran indices are all integers, all significant at the 10% level, and all show a clear positive spatial correlation.

The binary spatial adjacency matrix is chosen as the spatial weight matrix in this study. When cities I and j share a boundary in the spatial cross section, the matrix is set to have a value of 1; otherwise, it has a value of 0, and all diagonal values are set to 0. The spatial weight matrix is normalized in the estimation process. The specific form of the matrix is:

$$W_{ij} = \begin{cases} \mathbf{1}; & \textbf{\textit{City i shares a common border with city j}} \\ \mathbf{0}; & \textbf{\textit{Other}} \end{cases} \tag{24}$$

In recent years, spatial econometric techniques have been widely used in research in the field of economics. The more frequently used models are the spatial autoregressive model (SAR), which contains lagged terms of explanatory variables, and the spatial error model (SEM), which contains only spatial error terms, and the spatial Durbin model (SDM), which combines the two models (Li et al., 2010). The spatial transmission mechanisms used in the different models selected are not the same, and there are differences in the practical implications of their inclusion (Bai et al., 2017). In order to select a more appropriate econometric model, LM test and robust LM test were

TABLE 5 Results of selected tests of the model.

Test	SAR model	SEM model
LM Test	23.891***	142.789***
Robust LM Test	0.787	119.685***
WALD Test	101.89***	199.29***
LR Test	101.65***	204.48***
Joint city and time fixed effects test Statistical quantities *p*-value	Time fixed effects 2197.85 0	City fixed effects 28.89 0.0013

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively.

TABLE 6 Spatial econometric regression results.

Variables	SAR		SEM		SDM	
	(1)	(2)	(3)	(4)	(5)	(6)
ln_dig	0.0622***	0.0474***	0.0694***	0.0544***	0.0478***	0.0350***
	(25.2639)	(9.8634)	(25.2589)	(11.1050)	(16.5523)	(7.1094)
Err		−21.1858***		−22.2633***		−18.6187***
		(−3.4674)		(−3.5625)		(−3.0509)
ln_dig*err		2.0514***		2.1411***		1.7361***
		(3.5760)		(3.6596)		(3.0355)
Eco	0.0100***	0.0096***	0.0127***	0.0122***	0.0117***	0.0115***
	(4.2283)	(4.0795)	(4.7743)	(4.6311)	(4.2331)	(4.1729)
Ind	0.1070**	0.1114**	0.1290**	0.1361**	0.1173*	0.1219*
	(2.0180)	(2.1026)	(2.1217)	(2.2510)	(1.6756)	(1.7432)
Fin	0.0002	0.0000	−0.0007	−0.0008	0.0001	−0.0002
	(0.0455)	(0.0023)	(−0.1367)	(−0.1504)	(0.0213)	(-0.0406)
Fdi	−0.5425*	−0.5399*	−0.5796*	−0.5696	−0.8014**	−0.8321**
	(−1.7105)	(−1.7033)	(−1.6624)	(−1.6401)	(−2.2312)	(−2.3214)
Gov	0.0416	0.0396	0.0361	0.0296	0.0505	0.0549
	(0.6554)	(0.6254)	(0.5454)	(0.4490)	(0.7866)	(0.8568)
W*ln_dig					0.0458***	0.0240**
					(9.4695)	(2.5602)
W*err						−22.6917**
						(−2.0231)
W*ln_dig*err						2.7631***
						(2.6090)
ρor λ	0.3179***	0.3118***	0.2561***	0.2448***	0.2028***	0.1976***
	(13.9972)	(13.6755)	(8.9288)	(8.4797)	(7.6281)	(7.4271)
Log-L	1,509.647	1,516.039	1,457.914	1,464.624	1,557.692	1,566.863
Number of samples	2,565	2,565	2,565	2,565	2,565	2,565
R-sq	0.1754	0.1876	0.1694	0.1769	0.1511	0.1915

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

TABLE 7 Direct, indirect and total effects.

Variables	Direct effects		Indirect effects		Total effects	
	(1)	(2)	(3)	(4)	(5)	(6)
ln_dig	0.0504***	0.0366***	0.0654***	0.0373***	0.1158***	0.0739***
	(17.6695)	(7.2070)	(14.4027)	(3.5512)	(29.0940)	(6.0678)
Err		−19.7267***		−29.8516**		−49.5784***
		(−3.2277)		(−2.3105)		(−3.2756)
ln_dig_err		1.8803***		3.5359***		5.4161***
		(3.2464)		(2.8529)		(3.6856)
Eco	0.0114***	0.0113***	−0.0048	−0.0051	0.0066*	0.0062
	(4.3793)	(4.3159)	(−1.2174)	(−1.1801)	(1.7723)	(1.4804)
Ind	0.1201*	0.1176*	−0.0871	−0.1167	0.0329	0.0010
	(1.8548)	(1.7889)	(−0.7997)	(−1.0463)	(0.3546)	(0.0097)
Fin	0.0009	0.0009	0.0229*	0.0217*	0.0238*	0.0226*
	(0.1786)	(0.1716)	(1.9429)	(1.7771)	(1.8764)	(1.7313)
Fdi	−0.7582**	−0.7904**	1.0273*	1.0393*	0.2690	0.2489
	(−2.2104)	(−2.1628)	(1.6778)	(1.6920)	(0.4401)	(0.4058)
Gov	0.0535	0.0529	0.0030	0.0337	0.0565	0.0866
	(0.8348)	(0.8992)	(0.0205)	(0.2280)	(0.3437)	(0.5562)

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

conducted in this paper. The results of LM test showed that both LM-error and LM-lag statistics were significant, indicating that both spatial autoregressive model and spatial error model were supported, so the spatial Durbin model (SDM), which combined the two, could be chosen. The results of the robust LM test, on the other hand, significantly support the use of the spatial error model (SEM). In this paper, the WALD test and the LR test were conducted again, and the test results significantly rejected the degeneration to SEM model or SAR model. The results of the tests are shown in Table 5.

Under comprehensive consideration, the spatial Durbin model is used for estimation in this paper. Subsequently, the Hausman test concludes that a fixed-effects model is appropriate over a random effect. In order to select the appropriate fixed effects, this paper also conducts a joint significance test for urban and temporal fixed effects, and the results are shown in Table 5 strongly support the dual fixed effects model. The spatial Durbin model was set as follows:

$$\boldsymbol{gee_{it}} = \boldsymbol{\alpha} + \boldsymbol{\beta W gee_{jt}} + \boldsymbol{\gamma}\sum\nolimits_{i=1}^{n} \boldsymbol{X_{it}} + \boldsymbol{\delta}\sum\nolimits_{i=1}^{n} \boldsymbol{W X_{it}} + \boldsymbol{v_t} + \boldsymbol{z_i} + \boldsymbol{\varepsilon_{it}} \quad (25)$$

Where W is the spatial weight matrix, gee_{jt} is the lag term, δ is the spatial regression coefficient, v_t denotes the time fixed effect, z_i denotes the city fixed effect, and ε_{it} is the random disturbance term.

6.2 Analysis of spatial Durbin model results

Table 6 displays the geographic regression findings, where columns (5) and (6) represent the spatial Durbin model regression results. There is a strong regional spillover effect, as evidenced by the spatial autocorrelation coefficients of green eco-efficiency (gee), which are all significantly greater than zero in the regression results. ln_dig regression coefficients are all positive and pass the 1% significance level test, indicating that the development level of digital economy has a strong positive effect on green eco-efficiency. After adding the moderating variable environmental regulation (err), its cross product term with the digital economy (ln_dig) is significantly positive, indicating that environmental regulation plays a significant positive moderating role in the relationship between the digital economy and green eco-efficiency. At the same time, the spatial regression coefficients of the cross-products of digital economy, environmental regulation and digital economy are also significantly positive, which indicates that the digital economy has positive spatial spillover effects and environmental regulation in neighboring cities also has spatial transmission effects on the local area. To specifically explain the degree of impact of the digital economy on green eco-efficiency and the moderating effect of environmental regulation, the effect decomposition of the Durbin model is performed below.

6.3 Spatial Durbin model effect decomposition

After the effect decomposition of the spatial Durbin model, the results of the direct effect, indirect effect and total effect are shown in Table 7. The results show that the coefficients of the cross product terms of explanatory and moderating variables in the direct effect are significantly positive, which indicates that the digital economy in the region can significantly improve the green eco-efficiency, and the

TABLE 8 Robustness test results.

Explanatory variables	Replacement weight matrix		Supplementary variable method	
	Gee	Gee	Gee	Gee
ln_dig	0.0483***	0.0361***	0.0485***	0.0374***
	(16.8052)	(7.3552)	(17.0039)	(7.6753)
Err		−17.5645***		−16.1190***
		(−2.8850)		(−2.6679)
ln_dig*err		1.6943***		1.5329***
		(2.9666)		(2.7031)
W*ln_dig	0.0418***	0.0275***	0.0432***	0.0311***
	(8.6611)	(3.6302)	(9.0011)	(4.1266)
W*err		−15.6955**		−14.4295*
		(−1.9682)		(−1.8233)
W*ln_dig*err		1.7635**		1.4621*
		(2.2455)		(1.8726)

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

environmental regulation effectively improves the effect of the digital economy on the green eco-efficiency. The results of the indirect effects show that the development of digital economy also has a significant effect on the green eco-efficiency of neighboring cities, and environmental regulation also plays a positive moderating role in it. The spatial spillover effects of the cross-products of the digital economy and the regulating variables account for more than half of the total effects, indicating that the spatial spillover effects of the regulating effects of the digital economy and environmental regulations play an important role in the improvement of green eco-efficiency. At the same time, the estimated coefficients of the cross-products of digital economy and regulatory variables in the spatial Durbin model are smaller than the estimated coefficients of OLS in the previous section, indicating that the spatial effects are underestimated without considering the spatial effects on the enhancement of green eco-efficiency and the regulatory effects of environmental regulation.

6.4 Robustness tests

6.4.1 Replacement of the weight matrix

The adjacency matrix used in the spatial effects test can estimate the spatial spillover effects among neighboring cities, and to test the robustness of the results, the adjacency matrix is replaced with the inverse distance matrix for estimation again. The results are shown in columns (1)(2) in Table 8. The level of digital economy development significantly enhances green eco-efficiency, and environmental regulation has a positive moderating effect, so the regression results are still robust.

6.4.2 Supplementary variable method

According to Liu et al. (2022), the density of population may also have an impact on green eco-efficiency. The denser the population, the greater the environmental impact from economic activities will be, and the greater the ecological pressure faced by that city will be, so this paper takes population density into account to test the robustness of the results. As the results in columns (3)(4) in Table 8 show, the digital economy can still significantly improve green eco-efficiency after adding control variables, while environmental regulation also has a significant positive moderating effect.

7 Further analysis

7.1 Spatial Durbin model estimation by period

At the Second World Internet Conference held in December 2015, General Secretary Xi Jinping formally proposed to build "Digital China." Since then, the construction of digital economy has risen to the level of national strategy and has been developed rapidly. There may be differences in the development of digital economy before and after this point in time, so there may be different impacts of digital economy on green eco-efficiency in different periods. In this paper, we take 2015 as the time point and estimate the sample in groups, and the results are shown in Table 9.

The results in Table 9 show that the digital economy did not have an enhancing effect on green eco-efficiency between 2011 and 2015, and the regulating effect of environmental regulation was not significant. This is because in that period, the digital economy was in its infancy, digital technology was not widely applied, and the digital economy was being explored in various places, which made the digital economy did not reach the scale effect. However, from the spatial autoregressive coefficients, the digital economy is negatively significant, which may be because the digital economy first produces scale effects in larger cities or more economically developed regions, and has a siphoning effect on the surrounding areas. For a deeper analysis, it will be re-estimated by region below.

Between 2016 and 2019, the digital economy played a significant role in enhancing green eco-efficiency. This may be due to the rapid

TABLE 9 Estimation results by period.

Variable Name	2011–2015		2016–2019	
	(1)	(2)	(3)	(4)
ln_dig	−0.0015	−0.0022	0.0386***	0.0339***
	(−0.8554)	(−1.0960)	(7.5443)	(2.9024)
Err		−0.0373		−6.6402
		(−0.0179)		(−0.4265)
ln_dig_err		0.1101		0.4646
		(0.5632)		(0.3241)
W*ln_dig	−0.0071**	−0.0084**	0.0756***	0.0264
	(−2.1351)	(−2.2594)	(8.9412)	(0.9244)
W*err		−1.8017		−58.6609
		(−0.5659)		(−1.5634)
W*ln_dig_err		0.2178		6.1789*
		(0.7153)		(1.8040)
P	−0.0278	−0.0300	0.1609***	0.1667***
	(−0.7097)	(−0.7647)	(3.9419)	(4.0819)
Log-L	3059.127	3061.563	353.0389	355.2259
Control variables	YES	YES	YES	YES
Double fixed effect	YES	YES	YES	YES
R-sq	0.002	0.0019	0.2262	0.2844
N	1,425	1,425	1,140	1,140

Note: "*," "**" and "***" indicate significant at the "10%," "5%" and "1%" levels, respectively. The t-values are in parentheses.

development of the digital economy after 2015, when "Digital China" was formally elevated to the level of national strategy(Huang and Pan, 2021). It may be because the level of development of the digital economy reached a certain threshold and had a growth effect on green eco-efficiency. At the same time, the spatial autoregressive coefficient ρ for this period is significantly positive, which indicates that the growth of green eco-efficiency in this region also has a "radiative effect" on the surrounding regions, i.e., a positive spatial spillover effect.

7.2 Spatial Durbin model estimation by region

Due to the "insufficient and uneven" development, the relationship between digital economy, environmental regulation and green eco-efficiency may also differ among regions. Most of the eastern regions are coastal regions with strong economic power and are at the forefront of development in all aspects. The digital economy started earlier and has already formed a scale, but the developed manufacturing industries in the early stage are more polluting. The central region has accepted the transfer of manufacturing industries from some developed regions in recent years, which also brings pollution problems, and green development has become particularly important. Most cities in the western region originally have good ecological environment and relatively single industry, less serious pollution problems, while the development of digital economy lags behind, may have less marginal effect on green eco-efficiency. To analyze the inter-regional differences in depth, this paper divides 285 cities into three regions, East, West and Central, according to the division of regions by the Development and Reform Commission, and the estimation results are shown in Table 10.

The results in column (1) of Table 9 show that the digital economy has a positive and significant effect on green eco-efficiency in the eastern region, and there is also a positive spatial spillover effect. The positive moderating effect is more significant with the addition of the moderating variable environmental regulation in column (2), but there is no significant positive spatial spillover effect, probably because the digital economy in the eastern region is maturing and its marginal effect on green eco-efficiency decreases to a lower level. In the central region, the digital economy significantly enhances green eco-efficiency and jointly has a positive effect on green eco-efficiency under the regulation of environmental regulations. The digital economy produced a significant positive spatial spillover effect before the inclusion of the moderating variables, but this effect became insignificant after the inclusion of the moderating variables. However, there is no significant effect of both digital economy and environmental regulation in the western region, which may be due to the late start and small scale of digital economy in the western region, which does not produce scale effect, and the environmental problems

TABLE 10 Estimation results by region.

Variable Name	Eastern region		Middle region		Western region	
	(1)	(2)	(3)	(4)	(5)	(6)
ln_dig	0.0248***	0.0023	0.0790***	0.0667***	−0.0058	−0.0106
	(4.7721)	(0.2012)	(47.9507)	(24.2983)	(−0.5080)	(−0.7812)
Err		−36.9308**		−16.7759***		−4.2564
		(−2.1001)		(−5.6467)		(-0.3830)
ln_dig*err		3.2924**		1.5337***		0.6457
		(2.1020)		(5.3724)		(0.5898)
Wx ln_dig	0.0763***	−0.0463*	0.0082*	−0.0053	−0.0171	−0.0175
	(8.8801)	(−1.7972)	(1.8129)	(−0.7945)	(−0.7407)	(−0.6781)
Wx err		−195.8396***		−16.2633**		−3.1377
		(−4.7401)		(−2.2786)		(−0.1882)
Wx ln_dig_err		18.3571***		1.6982**		0.0930
		(5.0530)		(2.4995)		(0.0552)
P	0.2482***	0.2095***	0.0844*	0.0698	−0.0481	−0.0485
	(6.1503)	(5.0779)	(1.8551)	(1.5177)	(−0.8733)	(−0.8805)
Log-L	431.9840	447.3082	1831.4237	1847.7704	262.3563	262.7100
Control variables	YES	YES	YES	YES	YES	YES
Double fixed effect	YES	YES	YES	YES	YES	YES
R-sq	0.0891	0.1990	0.3841	0.4254	0.0451	0.0416
N	1,035	1,035	981	981	549	549

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

are not very serious, so the effect of environmental regulation is not obvious. Therefore, this paper suggests that the eastern region may be in the "green development maturity period," the central region is in the "green development growth period," and the western region may be in the "green development start-up period The western region may be in the initial stage of green development."

8 Conclusion

This study first investigated the inherent mechanisms of the development of the digital economy to improve green eco-efficiency by building a theoretical model and proposing the research hypothesis that the development of the digital economy in a nation or region can foster green eco-efficiency. Next, the research hypothesis was empirically tested using data from 285 cities from 2011 to 2019 and environmental regulation variables were added to test the moderating effect of environment. This paper uses the spatial Durbin model to test the spatial spillover effect, as well as to investigate the heterogeneity of different regions and different periods, and to make the regression results more robust, this paper also conducts a robustness test. These investigations are done in order to further investigate the spatial spillover effect of digital economy development on green eco-efficiency and the moderating effect of environmental regulation.

This study reveals that environmental legislation and the growth of the digital economy both have the potential to dramatically increase green eco-efficiency. This indicates that the rapid development of the digital economy in recent years is conducive to enhancing green eco-efficiency, and that the development of the digital economy is consistent with green sustainability goals. After accounting for the spatial effect, it is still clear that environmental legislation has a regulatory effect and that the digital economy continues to have a facilitative effect. After breaking down the spatial effect, we discover that environmental regulation and the development of the digital economy both have a significant impact on the green eco-efficiency of nearby cities. Additionally, the spatial spillover effect of these two regulating factors also contributes significantly to the improvement of green eco-efficiency. The heterogeneity test also revealed that the digital economy did not contribute to increased green eco-efficiency during its early stages, from 2011 to 2015, and that the regulatory impact of environmental regulation was not statistically significant. But between 2016 and 2019, when the digital economy was at its most developed level, it significantly contributed to the growth of green eco-efficiency. The enhancing effect of the digital economy and the regulating effect of environmental regulation are again most noticeable in the central-eastern region, followed by the central region, and least noticeable in the western region, due to differences in economic development levels and environmental resource endowments of different regions. This result illustrates that there is an uneven impact of the digital economy development process on green eco-efficiency.

For China to explicitly encourage green growth and build its digital economy, the aforementioned findings serve as critical benchmarks.

On the one hand, every region in China needs to work to encourage the growth of the digital economy and fully utilize this sector's contribution to environmental improvement and the improvement of green ecological efficiency, to rationalize the use of digital economy development to achieve green and sustainable goals. The growth of a regional digital economy can help industries digitize, increase their rate of resource utilization and production efficiency, and realize industry management refinement. This will lessen the detrimental effects of economic activity on the environment. Each region should combine market demand and local factor endowment, improve digital infrastructure, and promote the development of digital economy with the implementation and construction of digital infrastructure in order to achieve the goal of green, coordinated a digital economy. Of course, in order to apply digital technology, complete digital infrastructure is a prerequisite. At the same time to promote the balanced development of the digital economy in regions with different levels of development.

On the other hand, each region in China should fully utilize the regulatory function of the government's environmental rules in the process of encouraging the digitalization and greening of the economy. To guide the development of the digital economy and prevent its harmful effects on the environment, all regions of China should therefore constantly improve their environmental regulation policies. For instance, in recent years, "mining" activities have had both a negative impact on the environment due to their high energy consumption and a lack of any actual output. For example, in recent years, "mining" activities not only have no actual output but also have a negative impact on the environment due to high energy consumption. Therefore, through policies and administrative orders, the government should limit the output of high energy consumption and high pollution in the digital economy, promote the development of green technology, and encourage businesses to change their production processes in a green and sustainable way. Additionally, it should integrate market dynamics for investments in pollution prevention and control, enhance and optimize the emission trading system, and fully exploit the regulatory role of environmental regulation in the advancement of the digital economy for the improvement of green eco-efficiency.

There are also some limitations in this study. Due to the limitation of data this study cannot take all the influencing factors of green eco-efficiency into consideration, and there is still room for improvement regarding the evaluation method of green eco-efficiency. In addition, more detailed research is needed on how the digital economy affects green eco-efficiency.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The sample data sources in this paper are mainly statistical yearbooks and government work reports.

Author contributions

YY and QL contributed to conception and design of the study. QL organized the database. QL performed the statistical analysis. QL wrote the first draft of the manuscript. YY wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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