Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

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To cite this article: Qiang Ma, Qiu Li & Chang Ma (2023) How the digital economy drives energy efficiency in China: a re-examination based on the Environmental Kuznets Curve, Economic Research-Ekonomska Istraživanja, 36:2, 2170903, DOI: 10.1080/1331677X.2023.2170903

To link to this article: https://doi.org/10.1080/1331677X.2023.2170903

Published online: 02 May 2023.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 2, 2170903
https://doi.org/10.1080/1331677X.2023.2170903

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How the digital economy drives energy efficiency in China: a re-examination based on the Environmental Kuznets Curve

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ABSTRACT
The digital economy has become important in the world's major economies. Improving energy efficiency is the key to achieving stable and sustainable economic growth and carbon emissions reduction. However, the impact of the digital economy on energy efficiency remains unclear. Accordingly, this study examines the relationship between the digital economy and energy efficiency from the Environmental Kuznets Curve (EKC) perspective. In doing so, this study confirms that the digital economy follows the EKC in energy utilization efficiency, and there is a U-shaped relationship between the digital economy and energy efficiency, although this relationship differs from one region to another. This study also discusses the moderating effects of environmental regulation and innovation capability in this U-shaped relationship, confirming that they have a moderating effect on this relationship, reducing the inflection point of the U-shaped relationship, and reducing the negative influence of the digital economy on the energy efficiency and enhancing the positive impact. This study can serve as a reference for policymakers and professionals in emerging economies, helping them achieve a win-win situation for economic development and reducing carbon emissions.

ARTICLE HISTORY
Received 18 October 2022
Accepted 15 January 2023

KEYWORDS
Environmental Kuznets Curve; digital economy; energy efficiency; environmental regulation; innovation; U-shaped

JEL CODES
Q01; Q42; Q54; Q55; Q57

1. Introduction

The Environmental Kuznets Curve (EKC) holds that an economy's environmental quality or pollution level tends to deteriorate first and then improve with economic growth. According to the EKC, there is a low level of energy efficiency in the early stage of economic development. When the level of economic development reaches a certain level, energy efficiency will increase with the continuous improvement of the technical level (Grossman & Krueger, 1995; Umar et al., 2020). The EKC has been verified in several fields (Bibi et al., 2021; He et al., 2021; Yilanci et al., 2022). Meanwhile, the issue of carbon emission reduction is gradually gaining attention in various countries, with

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improving energy efficiency a key step in reducing carbon emissions. Indeed, according to the International Energy Agency (2020), some 40% of carbon emissions reductions over the next twenty years should be achieved through improvements in energy efficiency. Amid these emerging concerns, the digital economy is becoming an important driver of economic development and social transformation (Dorfleitner & Grebler, 2022; K. Li et al., 2020; Sidorov & Senchenko, 2020). This raises the question of whether the EKC can be verified in the digital economy and whether there is a U-shaped relationship between the digital economy and energy efficiency.

In contrast to developing countries, most developed countries have achieved the carbon peak goal and are currently in the carbon-neutral stage. For example, the European Union achieved the carbon peak goal in 1990, while the United States reached it in 2007. However, most emerging economies have yet to reach the carbon peak target and remain at the carbon peak stage. China is the largest emerging economy and an important engine of world economic growth. However, China is also the country with the largest carbon emissions in the world, emitting more than 6 billion tons of carbon dioxide a year. Therefore, China makes for a particularly interesting case study.

In recent years, with the help of the technologies like the Internet, big data, cloud computing, artificial intelligence, and blockchains, the digital economy has accelerated innovation and become deeply embedded in all areas of socio-economic development. The booming digital economy has become the new driving force of global economic development (K. Li et al., 2020). According to the Global Digital Economy White Paper (2022) published by the China Academy of Information and Communications Technology (CAICT), the scale of the added value of the digital economy in major countries reached USD 38.1 trillion, making up some 45% of GDP and holding a nominal year-on-year growth of 15.6%. In this respect, developed countries rely on technological advantages to determine the global leadership of the digital economy. Developed countries have large-scale digital economies comprising a significant proportion of their GDP. Indeed, in 2021, the scale of the digital economy in developed countries reached USD 27.6 trillion, accounting for nearly 60% of GDP. The digital economy has grown rapidly in developing countries, accounting for some 22.3% of GDP in 2021. As the largest developing country in the world, China has elevated the development of the digital economy to a national strategy, paying attention to building a digital economy infrastructure and improving the overall layout, supervision, and healthy development of the digital economy. In 2021, the scale of China's digital economy reached USD 7.1 trillion, accounting for 40.05% of the country's GDP. Indeed, the growth rate of China's digital economy is more than three times that of the GDP, indicating that it has become an important driver of the country's economic growth.

Climate change affects the sustainable development of human society (Ielasi et al., 2018; Liang et al., 2022; Martínez, 2018). Attaching great importance to climate issues, in 2020, the advanced Chinese targets of achieving a carbon peak by 2030 and carbon neutrality by 2060. Realizing China's carbon neutrality goal is paramount to mitigating global climate change. The main source of carbon dioxide emissions is burning fossil fuels like coal, oil, and natural gas in industrial production. To reduce carbon emissions, it is necessary to optimize the energy structure, reduce the use of traditional energy, and increase the use of clean energy such as solar, wind, and water energy. However, with energy endowments characterized as ’rich coal, poor oil, and less gas’, China’s economic development still depends on traditional energy in the short term, with a rapid reduction in the use of traditional energy sources not conducive to economic growth.

Improving energy efficiency is key to balancing economic growth and carbon emissions (Z. Chen et al., 2022; Umar et al., 2022). Energy efficiency refers to the output from an input unit of conventional energy, usually expressed as the ratio of GDP to conventional energy consumption. Improved energy efficiency enables the balancing of carbon reduction and economic growth. However, China’s energy efficiency is lower than that of developed countries such as the United States and Japan and that of BRICS countries like India and Brazil. In short, China needs to improve its energy efficiency. In this regard, China’s ’Action Plan for Carbon Peak by 2030’, ’"Fourteenth Five Year" Industrial Green Development Plan’, and ’“Fourteenth Five Year” Circular Economy Development Plan’ all stipulate improving energy efficiency as an important goal during the Fourteenth Five Year period. (Figures 1, 2 and 3)

The rapidly developing digital economy offers new opportunities for improving energy efficiency through new technologies and business models. Using data as a key driver, the digital economy has spawned new economic forms and facilitated profound changes in production and governance patterns (Cong et al., 2021). The digital economy directly improves energy efficiency by empowering traditional industries, helping them save energy, reducing costs, and increasing efficiency. The digital economy also fosters new industries providing digital products and services, thus indirectly improving

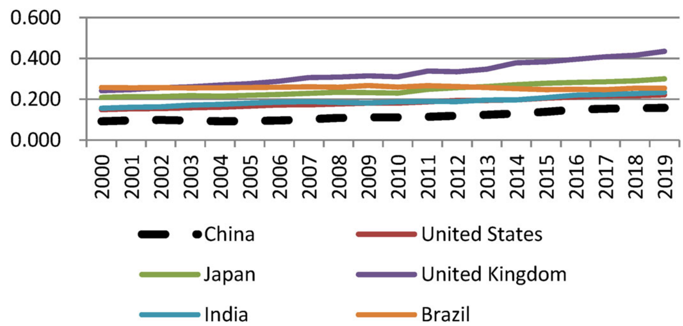

Figure 1. The comparison of energy efficiency in different countries.
Data source: World Bank website.

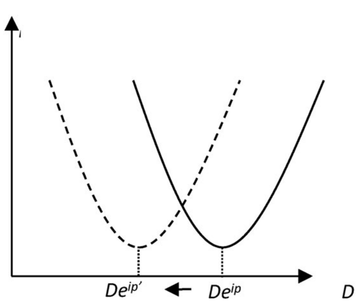

Figure 2. The influence of the larger moderating on the inflection point.
Source: Author own derivations.

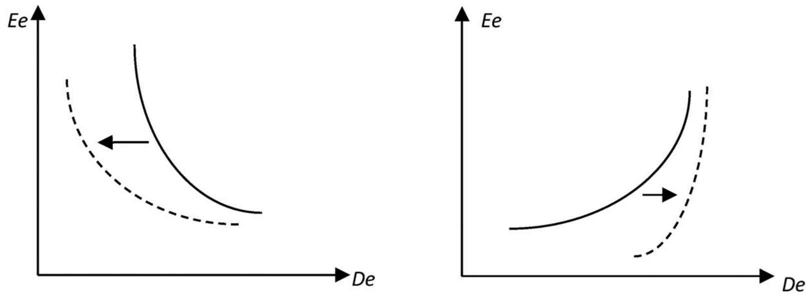

Figure 3. On each side of the inflection point, the influence of the change of the moderating variable on the curve shape.
Source: Author own derivations.

energy efficiency by optimizing the industrial structure and promoting innovation. However, the development of digital technology also has an energy rebound effect (Guo et al., 2022; Lange et al., 2020). For instance, the construction of digital infrastructure and the production and use of digital devices consume a significant amount of energy and emit large amounts of CO2. Therefore, the influence of the digital economy on energy efficiency is complex.

To fully examine the relationship between the digital economy and energy efficiency, this study selected China, the largest emerging economy, as the research object and attempts to answer the following questions. First, the literature has yet to reach a consensus regarding the relationship between the digital economy and energy efficiency. More specifically, it is unclear whether the relationship between them is nonlinear. In accordance with the KEC, is the relationship U-shaped such that it first inhibits and then improves? If there is a U-shaped relation between the digital economy and energy efficiency, then the development of the digital economy will first reduce energy efficiency and then improve it once it develops to a certain extent. As a decline in energy efficiency means an increase in carbon emissions, the stage in which the digital economy reduces energy efficiency can be regarded as the carbon peaking stage of the digital economy. As the improvement of energy efficiency should result in a reduction in carbon emissions, the stage in which the digital economy improves energy efficiency can be regarded as the carbon-neutral stage of the digital economy. Second, if the relationship between the digital economy and energy efficiency is U-shaped, is it possible that the inflection point of the U-shaped curve can be achieved earlier due to external effects? If this is possible, the carbon reduction stage can be reached sooner. Third, if there is a U-shaped relation between the digital economy and energy efficiency, can the inhibitory effect of the digital economy on energy efficiency be alleviated by the moderating effect on the left side of the inflection point (i.e., when the digital economy value is below the inflection point) and can the improvement effect be amplified on the right side (i.e., when above the inflection point value)? Answering these questions is of great significance for China, particularly in ensuring the digital economy's green value and balancing carbon emissions and economic development. Moreover, by focusing on China, the largest developing country, this study provides a reference for other emerging economies to promote green development through the development of the digital economy.

To answer the foregoing questions, this study selected panel data from 275 cities in China as the research sample. First, this study calculates single-factor energy efficiency and total-factor energy efficiency as energy efficiency indicators and digital economy development level indicators based on the entropy method. Second, this study empirically tests the relationship between the digital economy and energy efficiency, confirming a U-shaped relationship between the digital economy and single and total factor energy efficiency. When the development level of the digital economy is low, energy efficiency will be reduced; when it exceeds the inflection point, energy efficiency will be improved. Third, this study uses regional innovation capability and environmental regulation as moderating variables to test the moderating effects of the U-shaped relation, finding that they all have a positive regulatory effect. In addition to making the inflection point value of the U-shaped relation smaller, these moderating variables reduce the negative impact of the digital economy on energy efficiency on the left side of the U-shaped relation inflection point and improve the positive impact on the right side of the inflection point.

This study makes several contributions. First, this study verifies the U-shaped relationship between the digital economy and energy efficiency, validates the EKC in more areas, and contributes to the academic debate on the relations between the digital economy and energy efficiency. Second, this study confirms that higher innovation capacity and environmental regulation contribute to the positive effects of the digital economy on energy efficiency. On the left side of the inflection point, the higher level of innovation and higher intensity of environmental regulation weaken the digital economy's negative impact on energy efficiency. On the right side of the inflection point, the higher level of innovation and higher intensity of environmental regulation improve the role of the digital economy in promoting energy efficiency. These findings have clear policy implications. Certainly, policies intended to improve innovation ability and strengthen environmental regulation are conducive to both economic development and exerting the carbon reduction effects of the digital economy. Third, this study's findings are consistent with China's 'peak carbon, carbon neutral' strategy. When the digital economy development level is below the inflection point, it can reduce energy efficiency and potentially increase carbon emissions. However, China's 'double carbon' strategy is also a process of first achieving carbon peaking and then carbon neutrality. Therefore, the digital economy should be developed continuously in different regions, especially those with a low level of digital economy development.

The rest of this study is organized as follows. The second section provides a structured literature review, the third introduces the data, variables, and methods used in this study, and the fourth presents the empirical results. The fifth section summarises the research conclusions and puts forward policy recommendations to leverage the positive effects of the digital economy.

2. Literature review

2.1. The digital economy

The concept of the digital economy was first proposed by Tapscott (1995), who described it as an economic system heavily reliant on information and communication technology, including corresponding digital technology, the digital infrastructure, and a series of related business models and economic activities. According to the Fourteenth Five-Year Plan for China's Digital Economy, the digital economy is the main economic form after the agricultural and industrial economies. More specifically, the digital economy is a new economic form that relies on data resources as its key element, modern information networks as its main carrier, considers the integration and application of information and communications technology (ICT) and the digital transformation of total factor as the primary driving force for efficiency improvement and economic structure optimization, and promotes fairness and efficiency.

As a result of its rapid development, the digital economy has become a hot topic of research in academia. Indeed, despite the concept of the digital economy appearing some time ago, it has only become the focus of academic research in recent years. Early studies were based on one dimension of the digital economy, such as ICT, Internet development, digitization, and digital technology. Tapscott was the first to define the digital economy. Focusing on China, this study combines Tapscott's definition of the digital economy with that of the Fourteenth Five-Year Plan of China's Digital Economy. Accordingly, this study includes all the foregoing concepts in defining the digital economy. Essentially, the digital economy is a data-based, technology-driven economy carried by the Internet that alleviates the 'digital divide' between different regions, enhances the inclusiveness of economic development (Rumana & Richard, 2019), reduces transaction costs, improves business competitiveness (Teece, 2018), and facilitates government governance (Sama et al., 2022).

Early research on the digital economy was largely qualitative. With the deepening of related research, measuring the digital economy has become a popular topic. The earliest quantitative studies employed the direct (Chihiro, 2018) and comparative (Sidorov & Senchenko, 2020) methods, typically limited to provincial and national levels (Pan et al., 2022). However, these methods lack both statistical data and a corresponding indicator system. Consequently, the entropy method (H. Wu et al., 2021) and principal component analysis (D. Gao et al., 2022), which are based on statistical data and indicator systems, gradually became more popular for calculating the digital economy. Both methods calculate the development level of the digital economy by selecting appropriate indicator systems based on the definition of the digital economy, such as dimensions of the Internet, industry digitization, digital industrialization, digital infrastructure, development environment, and digital transactions.

Based on the measurement of the digital economy, researchers have examined the economic effects of the digital economy, generally agreeing that it has positive economic impacts (Usman et al., 2021). At the macro level, the digital economy has advanced industrial structure upgrading (B. Wu & Yang, 2022), improved productivity (J. Chen et al., 2022), and promoted regional innovation (Lin & Ma, 2022), thus contributing to high-quality economic development (Pan et al., 2022). At the micro level, the digital economy has alleviated corporate financing constraints (Y. Wu & Huang, 2022), increased corporate innovation capacity (Gaglio et al., 2022), enhanced corporate efficiency (Peng & Tao, 2022), and stimulated the entrepreneurial enthusiasm of the workforce (Atasoy, 2013).

Regarding the ecological effects of the digital economy, although some scholars have used specific samples to demonstrate that the digital economy may be detrimental to improving the environment (Belkhir & Elmeligi, 2018), most studies indicate that the digital economy has positive ecological effects. For example, (Amin & Rahman, 2019) argued that the Internet improved the level of waste management and reduced pollutant emissions in both developed and developing countries. In the Chinese context, (H. Wu et al., 2021) found that the Internet promoted the upgrading of industrial structure and improved regional green total factor energy efficiency, while (Q. Ma et al., 2022) concluded that the digital economy improved China's green total factor productivity.

How the digital economy affects carbon emissions remains controversial. One view holds that the digital economy increases carbon emissions ((Park et al., 2018; Salahuddin & Alam, 2016). However, a greater number of studies suggest that the digital economy reduces carbon emissions (Q. Ma et al., 2022; Ozcan & Apergis, 2018; Q. Xu et al., 2022). For example, using provincial panel data in China, (Lin & Zhou, 2021) found that the development of the Internet improved the country's carbon performance by promoting industrial structure upgrading and technology diffusion. Similarly, based on panel data from 277 cities in China, (W. Zhang et al., 2022) concluded that the development of the digital economy had improved carbon performance by reducing energy intensity (expressed by dividing energy input by output, revealing the amount of energy required to be input per unit of output; it is reciprocal to single factor energy efficiency), reducing the scale of energy consumption, and promoting urban greening improved carbon emission performance.

2.2. Energy efficiency

Typically referring to the utilization efficiency of traditional energy, energy efficiency comprehensively reflects the impact of efficiency and technology on economic development. Therefore, improving energy efficiency is the key to balancing economic development and carbon emissions. The two most frequently used methods for measuring energy efficiency are single-factor energy efficiency and total-factor energy efficiency. Single-factor energy efficiency is expressed as the ratio of economic output to energy input (Elı́asson & Turnovsky, 2004), revealing the output produced by a unit of traditional energy input. Single-factor energy efficiency considers energy as the only input factor; it ignores other inputs, such as labor and capital, and simply considers the relation between energy and output. Therefore, it has considerable limitations. To overcome the shortcomings of single-factor energy efficiency, (Hu & Wang, 2006) proposed total-factor energy efficiency based on the DEA measurement method. Total factor energy efficiency fully considers the substitution effect among each input factor.

Scholars have continuously improved the DEA method and measured total factor energy efficiency using various methods, including SBM-DEA (Choi et al., 2012; Gomez-Calvetdeng et al. 2014; Iftikhar et al., 2016; Zhou et al., 2019), three-stage DEA (Choi et al., 2012; Gómez-Calvet et al., 2014; Iftikhar et al., 2016; Zhou et al., 2019), and DEA-Malmquist (Kortelainen, 2008; Z. Wang et al., 2014). Based on the measurement of energy efficiency, scholars have explored the factors influencing total factor energy efficiency. Resultant research shows that economic size (Z.-H. Wang et al., 2012), technological innovation (Su et al., 2022; Y. Xu et al., 2022; Z. Zhang & Ye, 2015), energy structure (Muhammad et al., 2022; Xie et al., 2014), openness to the outside world (Imbruno & Ketterer, 2018; Khan et al., 2020), industrial structure (Q.-S. Wang et al., 2021; Xue et al., 2022) and environmental regulation (C. Li et al., 2020; X.-P. Zhang et al., 2011) can influence total factor energy efficiency.

However, few studies have directly examined the impact of the digital economy on energy efficiency, with those that have typically done so from a single dimension (e.g., the Internet, ICT) failing to reach a consensus. In this respect, one view holds that the digital economy has an energy rebound effect. For example, (Khayyat et al., 2016) found that continued price reductions allowed ICT to replace some traditional inputs and produce more products along with energy, thereby reducing energy efficiency. (Saidi et al., 2017) study demonstrated that the higher the ICT level, the higher the power consumption level. (Lange et al., 2020) found that instead of saving energy, digitization increased energy consumption. (Lan & Wen, 2021) showed a significant positive relationship between energy intensity and ICT adoption in Chinese manufacturing, with ICT directly increasing energy intensity. Meanwhile, in the context of OECD countries, (Salahuddin & Alam, 2016) found that using mobiles and the internet increased electricity consumption and that ICT failed to improve energy efficiency.

Others believe that the digital economy has an energy-saving effect, thus reducing energy consumption and increasing energy efficiency. For example, (Lin & Zhou, 2021) proposed that the Internet significantly improves energy efficiency through the mechanisms of industrial structure upgrading and technology diffusion. (Ishida, 2015) found that higher energy prices and technological advances resulting from increased ICT investments effectively reduced energy intensity in most sectors. In the Chinese context, (Berger, 2022; Ferrat et al., 2021; J. Gao et al., 2021; Karim et al., 2022; H. Wu et al., 2021) argued that the Internet's development improved energy efficiency locally and in neighbouring regions. (Usman et al., 2021) reached similar conclusions in the Indian context, contending that the development of the Internet improved energy efficiency.

As such, scholars have conducted a significant amount of research on the digital economy and energy efficiency, recognizing the positive role of the former. Such research provides an important foundation for this study. However, there are notable research gaps requiring in-depth investigation and discussion. First, the existing literature has primarily examined the impact of the digtal economy on energy efficiency from a single dimension, such as Internet development or ICT. However, a single indicator necessarily faces the problems of limitations and one-sidedness. Second, there is no consensus on the impact of such dimensions on energy efficiency, with the literature largely split into two opposing views: enhancing energy efficiency and reducing energy efficiency. Third, few studies have discussed how to harness and control the positive role of the digital economy, curb the rebound effect, and enhance the energy-saving effect.

Accordingly, this study makes the following improvements. First, comprehensively considering the availability of the data, this study selects indicators from the dimensions of Internet development, digital technology, and digital transactions to construct the digital economy index. Second, in light of the two opposing views, this study verifies that there is not a simple linear relation between the two but a possible U-shaped or inverted U relationship. Third, this study discusses how we might harness the positive role of the digital economy by building a model of the moderating effect of the U-shaped relationship.

3. Research methods

3.1. Empirical strategy

This study established the benchmark regression model (1) to verify the U-shaped relation between the digital economy and energy efficiency, where Eeit denotes the energy efficiency of the city i in year t, Deit denotes the level of digital economy development of city i in year t, CV denotes a series of control variables, μi and νt denote city fixed effects and time fixed effects, respectively, and εit is a random error term.

$$Ee_{it} = \alpha_0 + \alpha_1 De_{it} + \alpha_2 De_{it}^2 + \alpha_k CV_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

If there is a U-shaped relation between the digital economy and energy efficiency, according to the characteristics of the U-shaped curve, the value of the digital economy at its inflection point is $De^{ip} = -\frac{\alpha_1}{2\alpha_2}$.

This study also discusses the moderating effects of regional innovation capacity and environmental regulation on the relationship between the digital economy and energy efficiency. Compared with the linear relationship, the moderating effect of the U-shaped relation is more complex. This study refers to (Haans & Pieters, 2016) to analyse the moderating effect of the U-shaped curve by introducing the interaction term of the moderating variable with the digital economy as the core explanatory variable and the interaction term of the moderating variable with the squared term of the digital economy. Accordingly, the model was set as follows:

$$Ee_{it} = \beta_0 + \beta_1 De_{it} + \beta_2 De_{it}^2 + \beta_3 MV_{it} \times De_{it} + \beta_4 MV_{it} \times De_{it}^2 + \beta_k CV_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

where MV is the moderating variable in this study, with regional innovation capacity, Ina, and environmental regulation, Er, respectively.

This study verifies the moderating effect of the U-curve in two ways. First, it examines how moderating variables affect the location of inflection points. In model (2), the derivative of Ee to De is identified, and the position of the inflection point is obtained via the following:

$$De^* = -\frac{\beta_1 + \beta_3 MV}{2(\beta_2 + \beta_4 MV)} \tag{3}$$

Where De* is the digital economy value of the inflection point of the U-shaped relation. To analyse the influence of changes in the moderating variable on inflection points, the partial derivative of the inflection point to the moderating variable can be obtained using the following Equation:

$$\frac{\partial De^*}{\partial MV} = \frac{\beta_1\beta_4 - \beta_2\beta_3}{2(\beta_2 + \beta_4 MV)^2} \tag{4}$$

In Equation (4), the denominator is the squared term, which must be greater than 0. Therefore, the effect of a change in the moderating variable on the inflection point is determined by examining the positive or negative of the numerator (β1β4-β2β3).

As the moderating variable increases, if $\beta1\beta4\text{-}\beta2\beta3 > 0$, the inflection point shifts to the right; if $\beta1\beta4\text{-}\beta2\beta3 < 0$, the inflection point shifts to the left.

Second, this study examined how the change in moderating variable influences the shape of the curve, that is, what effect the moderating variable has on each side of the inflection point. On both sides of the inflection point of the U-shaped curve, the relation between the digital economy and energy efficiency is approximately linear. Therefore, the moderating effect is examined using the linear relation moderating effect model, which is set as follows.

$$Ee_{it} = \gamma_0 + \gamma_1 De_{it} + \gamma_k CV_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{5}$$

$$Ee_{it} = \gamma_0 + \gamma_1 De_{it} + \gamma_2 De_{it} \times MV_{it} + \gamma_k CV_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{6}$$

3.2. Energy efficiency

This study uses both single-factor energy efficiency and total-factor energy efficiency as energy efficiency indicators.

3.2.1 Single factor energy efficiency (See)

Single factor energy efficiency is expressed using the ratio of GDP (in CNY 10,000) to energy input (in 10,000 tonnes of standard coal) as follows: $See_{it} = GDP_{it}/Energy_{it}$, where Energy is the standard coal of input, and GDP is fixed at the constant prices of 2010. Data are primarily drawn from the statistical yearbook of each province and the statistical bulletin of the national socio-economic development of each city. (Table 1)

3.2.2. Total factor energy efficiency (Mee)

Based on (Oh, 2010) and (Yu et al., 2021), this study constructed the SBM directional distance function by adding 'unexpected output' and measured total factor energy

Table 1. The conversion factor of different energy sources.

Energy	Unit	Conversion factor
Raw coal	(10,000 tons)	0.7143
Washed coal	(10,000 tons)	0.9000
Other coal washing	(10,000 tons)	0.2857
Briquette	(10,000 tons)	0.6
Coke	(10,000 tons)	0.9714
Coke oven gas	(100 million cubic meters)	6.143
Other gas	(100 million cubic meters)	3.5701
Other coking products	(10,000 tons)	1.3
Crude oil	(10,000 tons)	1.4286
Gasoline	(10,000 tons)	1.4714
Kerosene	(10,000 tons)	1.4714
Diesel oil	(10,000 tons)	1.4571
Fuel oil	(10,000 tons)	1.4286
Liquefied petroleum gas	(10,000 tons)	1.7143
Refinery gas	(10,000 tons)	1.5714
Other petroleum products	(10,000 tons)	1.2
Natural gas	(100 million cubic meters)	13.30
Thermal	(Kilojoule)	0.0341
electric power	(hour)	1.229
Other energy sources	(10,000 tons of standard coal)	1

Data source: China Energy Statistical Yearbook.

efficiency using the GML index; Appendix A provides the calculation steps in greater detail. The GML index requires the determination of inputs, expected outputs, and unexpected outputs. The inputs include labor (per 10,000 people), capital (per CNY10,000), and energy (per 10,000 tonnes of standard coal), and the expected output is GDP (CNY 100 million), with GDP and capital stock fixed at constant prices in 2010. The unexpected output is CO2 (per 10,000 tons).

3.3. Digital economy

The core explanatory variable in this study is the digital economy index. The existing literature on measuring China's digital economy mainly includes two levels, namely, the provincial and city levels. As more indicators can obtain data at the provincial level, such as infrastructure, digital industrialization, and industrial digitalization, the digital economy index at the provincial level is more detailed. Compared with provinces, there are few indicators through which to obtain city-level data, making the construction of a digital economic index at the city level relatively simple. For example, (J. Li et al., 2022) and (Pan et al., 2022) selected indicators to measure the urban digital economy from the two aspects of Internet development and digital finance. Based on the literature and availability of data, this study is based on city-level data and selects indicators from the three dimensions of digital infrastructure, industrial digitalization, and digital industrialization. Appendix Table C1 presents the indicator for building the digital economy and uses the entropy method to calculate the development level of China's digital economy.

The steps for calculating the digital economic index using the entropy method are as follows:

1. Build the original matrix by creating a matrix containing n rows and m columns, as shown below:

$$A = X_{ij}$$

Where Xij represents the value of index j in year i.

1. Normalize the sample data and calculate the proportion of index j in the year i as follows:

$$Y_{ij} = X_{ij} / \sum_{j=1}^{m} X_{ij}$$

2. Calculate the entropy value Ej of index j as follows:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{n} Y_{ij} \ln Y_{ij}$$

3. Calculate the weight of index j:

$$w_j = \frac{d_j}{\sum_{i=1}^{n} d_j}$$

Where $d_j = 1 - E_j$.

1. The digital economy index Deit of the city i in year t is obtained according to the weight as follows:

$$De_{it} = \sum_{j=1}^{n} w_j Y_{ij}$$

3.4. Moderating variables

The moderating variables in this study include regional innovation capacity and environmental regulation. On the one hand, to improve energy efficiency and optimize the industrial structure with the help of the digital economy, enterprises' digital transformation and other activities are inseparable from innovation. The stronger the innovation capacity, the easier it will be to play a positive role in the digital economy and improve energy efficiency. On the other hand, strengthening environmental regulation is conducive to restraining highly polluting production activities and reducing CO2 emissions. With the help of digital technology, the accuracy of carbon emission identification can be improved, and the efficiency of regulation enhanced.

This study selected specific indicators for each of the moderating variables. First, for regional innovation capacity, this study used the regional innovation and entrepreneurship index of Peking University divided by 100 (Z. Li & Wang, 2022). Second, concerning environmental regulation, the data on the investment amount of environmental pollution control at the city level was no longer published after 2011, while data related to industrial soot removal rate, industrial sulphur dioxide removal rate, and industrial wastewater compliance were no longer published after 2010. Based on data accessibility, this study selected the comprehensive utilization rate of industrial solid waste, centralized treatment rate of sewage treatment plants, harmless treatment rate of domestic waste, and greening coverage rate of built-up areas as the basic indicators of environmental regulation. The index of environmental regulation was then calculated using the entropy value method.

3.5. Control variable

To reduce the interference of other factors, this study included the following control variables: (1) government intervention (Gov), expressed by the proportion of government fiscal spending to GDP; (2) population density (Popd), taken as the logarithm in the empirical process; (3) openness (Open), expressed by the proportion of total import and export trade to GDP; (4) industrial structure (Ins), calculated using $Ins_{it} = \sum_{i=1}^{3} o_i \times i = o_1 + o_2 \times 2 + o_3 \times 3,$ where oi refers to the proportion of the output of each industry in GDP; (5) financial development (Fin), expressed by the proportion of deposit and loan balance to GDP; and (6) green innovation capabilities (Gpat), expressed by the ratio of the number of authorized green patents to total green patent applications.

3.6. Data sources

Data are mainly drawn from the China City Statistical Yearbook and WIND database, energy consumption data are taken from resources like the China Energy Yearbook and China Environment Yearbook, Internet-related data are extracted from China

High-Tech Industry Statistical Yearbook, while digital finance data are from the China Digital Inclusive Finance Development Index (Phase II). Table 2 presents the descriptive statistics of 2,750 samples from 275 cities in China from 2010–2019.

4. Results

4.1. Baseline estimation results

Table 3 presents the benchmark regression results. As results show, the significance of the digital economy coefficient is weak when using the digital economy to explain the two types of energy efficiency. After the square term of the digital economy is added to the model, the digital economy coefficient is significantly negative, while the square term coefficient of the digital economy is significantly positive. After other control variables were added to the model, the digital economy coefficient remained significantly negative, and so was the digital economy's square term coefficient. Results thus confirmed the U-shaped relation between the digital economy and energy efficiency. When the level of digital economy development is low, it reduces the economic output per unit of energy and decreases energy efficiency. After the level of the digital economy development exceeds the inflection point, the digital economy increases the economic output per unit of energy input and improves energy efficiency. The findings of this study thus align with those of (J. Li et al., 2022). The rapid development of the digital economy is inseparable from the massive investment in digital equipment and the construction of digital infrastructure in the early stage. During this stage, the production and operation of many digital devices increase energy consumption and reduce energy efficiency. When the digital economy develops to a certain extent, its marginal cost will gradually converge to zero, thus revealing the characteristics of increasing marginal benefits, exerting positive external economic effects and 'green attributes' (Abukhader, 2008), and improving energy efficiency.

According to the results presented in Columns (5) and (6) of Table 3, when the explained variable is single-factor energy efficiency, the inflection point value of the U-shaped relation is 0.119. In other words, when the development level of the digital economy exceeds 0.119, the impact of the digital economy on single factor energy efficiency will change from inhibiting to promoting. When the explained variable is total energy efficiency, the inflection point value of the U-shaped relation is 0.125. That is to say when the development level of the digital economy exceeds 0.125, the impact of the digital economy on total factor energy efficiency changes from inhibiting to promoting.

Table 2. Descriptive statistics of variables.

Variable	Obs	Mean	Std.Dev	Min	Max
See	2750	22.730	17.430	1.297	122.000
Mee	2750	0.479	0.206	0.119	1.183
De	2750	0.095	0.053	0.017	0.552
Ina	2750	0.502	0.287	0.004	1.000
Er	2750	0.067	0.042	0.013	0.517
Gov	2750	2.791	1.782	0.649	15.002
Popd	2750	442.504	347.813	51.342	1016.730
Open	2750	0.304	0.608	0.000	25.668
Ins	2750	2.314	0.226	1.924	2.763
Fin	2750	2.749	2.230	0.588	39.417
Gpat	2750	0.493	0.265	0.007	0.999

Source: Author own derivations.

Table 3. Baseline regression results.

Variables	(1)lnSee	(2)Mee	(3)lnSee	(4)Mee	(5)lnSee	(6)Mee
De	−0.108	−0.036*	−0.344**	−0.158***	−0.382**	−0.188***
	(0.162)	(0.020)	(0.169)	(0.039)	(0.179)	(0.046)
De-squared			2.239**	0.465***	1.604**	0.752**
			(0.864)	(0.232)	(0.751)	(0.347)
Gov					0.102*	0.237***
					(0.056)	(0.058)
lnPopd					0.316*	0.540***
					(0.016)	(0.042)
Open					0.146	0.617***
					(0.076)	(0.195)
Ins					0.003***	0.015*
					(0.001)	(0.001)
Fin					0.002	0.014***
					(0.001)	(0.002)
Gpat					0.004**	0.013*
					(0.002)	(0.007)
Cons	2.884***	1.021***	2.927***	1.939***	2.946***	1.121***
	(0.016)	(0.007)	(0.023)	(0.062)	(0.039)	(0.101)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	2750	2750	2750	2750	2750	2750
R-squared	0.302	0.271	0.343	0.319	0.472	0.438

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

4.2. Robustness checks

To ensure the reliability of the results, this study conducted robustness tests from three aspects. First, this study winsorized the continuous variables by 1% and 99% to remove the impact of extreme values; the results are listed in Columns (1) and (2) of Table 4. Second, this study recalculated the digital economy indicators using principal component analysis and included the explained variables; the results are presented in Columns (3) and (4) of Table 4. Third, this study used the generalized system method of moments (SYS-GMM) to conduct regression analysis. The possible bi-directional causality and the

Table 4. The results of robustness checks.

Variables	lnSee (1)	Mee (2)	lnSee (3)	Mee (4)	lnSee (5)	Mee (6)
L.lnSee					0.687***	
					(0.103)	
L.Mee						0.748***
						(0.047)
De	−0.203***	−0.214***	−0.493***	−0.139***	−1.036***	−0.121***
	(0.049)	(0.069)	(0.106)	(0.031)	(0.237)	(0.029)
De-squared	0.937***	0.881*	0.528***	0.140***	3.769***	0.446***
	(0.202)	(0.482)	(0.143)	(0.032)	(0.813)	(0.121)
CV	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES		
Year FE	YES	YES	YES	YES		
Observations	2750	2750	2750	2750	2475	2475
R-squared	0.446	0.423	0.384	0.347		

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$; In the two results of SYS-GMM, the P values of AR(1) are 0.000 and 0.001 respectively, and the P values of AR(2) are 0.264 and 0.598 respectively, which indicating that there is no autocorrelation in the random errorterm. The Sargan test results are 0.207 and 0.243, respectively, which indicating that there is no over-identification of instrumental variables, and the selection of instrumental variables is effective.
Source: Author own derivations.

difficulty of considering all the factors affecting energy efficiency may cause endogeneity problems in the model. As the endogeneity problem of the U-shaped relationship is relatively complex, this study followed the method of (N. Chen et al., 2022) and used the SYS-GMM to deal with the endogeneity of the model. SYS-GMM can effectively alleviate the endogeneity problem by taking the lag period's explanatory variables as instrumental variables. Table 4 shows that the relation between them is still U-shaped after the robustness test using different methods. Therefore, the conclusions of this study can be considered fairly robust.

4.3. Heterogeneity analysis

Significant differences exist in the economic development stage, resource endowments, and industrial structures in different regions of China. Therefore, this study further examined the heterogeneity of the impact of the digital economy on energy efficiency from three aspects. First, according to the standard of the China Statistical Yearbook, this study divided its sample into the eastern and mid-western regions. Second, based on (D. Ma & Zhu, 2022), this study classified first-, new first-, second-, and third-tier cities as high-level cities and the remaining cities divisions as low-level cities. Third, this study categorized the cities situated in the more economically developed Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, Central Yangtze River, Central Plains City Cluster, and Chengdu-Chongqing urban agglomeration as key urban agglomerations, and other cities as non-key urban agglomeration.

According to the results presented in Tables 5, 6, and 7, the impact of the digital economy on energy efficiency varied greatly from one region to another. The relation remained significantly U-shaped in the results of the sample of eastern regions, high-level

Table 5. Regional heterogeneity analysis.

Variables	See (1)Eastern	Mee (2)Eastern	See (3) Mid-western	Mee (4) Mid-western
De	−1.122*(0.613)	−0.447**(0.209)	−0.979*(0.556)	−0.547***(0.146)
De-squared	4.378***(1.085)	1.591**(0.781)	2.033(2.265)	2.865(2.597)
CV	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1180	1180	1570	1570
R-squared	0.364	0.370	0.285	0.253

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

Table 6. Heterogeneity of urban development level.

Variables	See (5)High-level	Mee (6)High-level	See (7)Low-level	Mee (8)Low-level
De	−0.542**(0.297)	−1.157***(0.265)	−0.401**(0.197)	−1.249***(0.370)
De-squared	2.041***(0.725)	3.659***(0.840)	2.252(2.253)	3.329(3.263)
CV	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1160	1160	1590	1590
R-squared	0.293	0.274	0.286	0.253

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

Table 7. Heterogeneity of urban agglomeration.

Variables	See (1)Key	Mee (2)Key	See (5)Non-key	Mee (6)Non-key
De	−1.011*(0.558)	−1.406**(0.703)	−1.432**(0.586)	−7.750***(1.338)
De-squared	4.234*(2.281)	5.008**(2.344)	0.777(1.981)	16.653(15.524)
CV	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	880	880	1870	1870
R-squared	0.354	0.347	0.326	0.302

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

cities, and key urban agglomerations. According to the results for the mid-west, low-level cities, and non-key urban agglomerations, although the coefficient of the digital economy was significantly negative, none of the coefficients of the squared term of the digital economy were significant. This indicates that, in these regions, the relation is no longer U-shaped but linear, and the digital economy reduces energy efficiency. In contrast, eastern cities, high-level cities, and key urban agglomerations have better information infrastructures, more advanced digital technology, and higher levels of digital economic development. The higher level of digital development has enabled these cities to release the digital dividend fully. With the advantage of the digital economy, many cities have surpassed the inflection point of the U-shaped relationship, with the digital economy had begun to exert energy-saving effects and improve energy efficiency. In contrast, the level of the digital economy in mid-western regions, low-level cities, and non-key urban agglomeration is lower and is still in the stage of the energy rebound effect, which cannot improve energy efficiency.

4.4. Moderating effects

First, this study examined how the change of moderating variables impacts the inflection point. Table 8 presents the regression results of model 3, which show that the significance of β1, β2, β3, and β4 is high, while (β1 × β4-β2 × β3) is less than 0. Therefore, using regional innovation capacity and environmental regulation as moderating variables can make the inflection point of the U-shaped relation shift left. In other words, by improving innovation ability and strengthening environmental regulation, the impact of the

Table 8. The influence of moderating variables on inflection point.

Variables	See (1)Ina	Mee (2)Ina	See (3)Er	Mee (4)Er
De	−0.508*(0.279)	−0.381**(0.198)	−0.716(0.743)	−0.296(0.197)
De-squared	0.154**(0.076)	1.138***(0.396)	0.921**(0.429)	0.818**(0.368)
MV × De	−0.482**(0.229)	0.251**(0.106)	−0.193*(0.106)	0.227*(0.123)
MV × De-squared	1.363*(0.702)	−0.235**(0.113)	0.801**(0.370)	−0.094**(0.044)
CV	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	2750	2750	2750	2750
R-squared	0.413	0.424	0.456	0.517
$\beta_1\beta_4$-$\beta_2\beta_3$	−0.618	−0.196	−0.396	−0.158

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

digital economy on energy efficiency can be transformed from inhibiting to promoting at a lower level of digital economic development. In other words, innovation and environmental regulation will help the digital economy reach its carbon peak earlier.

Second, this study examined how the change of moderating variables affects the shape of the curve on both sides of the inflection point. In other words, this study analysed the influence of regional innovation capacity and environmental regulation on the curve shape on both sides of the inflection point. First, this study obtained the inflection point based on the regression results of model (1). The inflection point is 0.119 when the explained variable is single factor energy efficiency and 0.125 when it is total factor energy efficiency. This study then substituted the data on both sides of the two energy efficiency inflection points into models (5) and (6), the results of which are presented in Tables 9 and 10, respectively.

Table 9. The influence of moderating variables on curve shape on both sides of the inflection point (single factor energy efficiency).

Variables	(1)lnSee Left side	(2)lnSee Left side	(3)lnSee Left side	(4)lnSee Right side	(5)lnSee Right side	(6)lnSee Right side
De	−0.870***	−1.013***	−0.415**	0.701***	0.613**	0.044*
	(0.239)	(0.294)	(0.204)	(0.209)	(0.287)	(0.024)
Ina		0.141***			1.047***	
		(0.043)			(0.283)	
Er			0.002*			0.116**
			(0.001)			(0.051)
Ina × De		2.390***			0.070**	
		(0.450)			(0.033)	
Er × De			0.005*			0.094**
			(0.003)			(0.044)
CV	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	2008	2008	2008	742	742	742
R-squared	0.351	0.394	0.372	0.328	0.346	0.367

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

Table 10. The influence of moderating variables on curve shape on both sides of the inflection point (total factor energy efficiency).

Variables	(1)Mee Left side	(2)Mee Left side	(3)Mee Left side	(4)Mee Right side	(5)Mee Right side	(6)Mee Right side
De	−0.552***	−0.536**	−0.518	0.217*	0.261	0.902***
	(0.074)	(0.490)	(0.391)	(0.119)	(0.211)	(0.298)
Ina		0.081*			0.130*	
		(0.047)			(0.065)	
Er			0.017***			0.154**
			(0.006)			(0.076)
Ina × De		0.078**			0.288***	
		(0.043)			(0.097)	
Er × De			0.026*			0.353***
			(0.014)			(0.081)
CV	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	1994	1994	1994	756	756	756
R-squared	0.367	0.426	0.453	0.324	0.351	0.360

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.
Source: Author own derivations.

On the left side of the inflection point, where the digital economy values below the inflection point, the coefficient on the digital economy in the regression results of model (5) is significantly negative. In other words, the digital economy significantly inhibits energy efficiency when below the inflection point. However, after adding the interaction term of the digital economy and the moderating variable, the coefficient of the interaction term of the model (6) is significantly positive, indicating that two moderating variables—namely, regional innovation capacity and environmental regulation—play a negative moderating role, weakening the negative impact of the digital economy on energy efficiency.

On the right side of the inflection point, where the digital economy value is above the inflection point, the coefficient of the digital economy in the regression result of the model (5) is significantly positive. In other words, the digital economy significantly improves energy efficiency after exceeding the inflection point. After adding the interaction term of the digital economy and moderating variables in the model (6), the coefficient of the interaction term is significantly positive. This implies that regional innovation capacity and environmental regulation play a positive moderating role, enhancing the positive impact of the digital economy on energy efficiency.

5. Discussion and conclusion

5.1. Conclusions and policy implications

This study established a research framework based on the Kuznets Environmental Curve, incorporating both the digital economy and energy efficiency. Using panel data from 275 Chinese cities, this study comprehensively analysed the impact of the digital economy on energy efficiency. The findings of this study confirm the U-shaped relation between the digital economy and energy efficiency, thus narrowing the gap in existing research to some extent. This finding is also consistent with China's ‘carbon peaking and carbon neutrality goals. This study also showed how the relationship between the digital economy and energy efficiency is clearly heterogeneous, varying from city to city. More specifically, there is a U-shaped relation among eastern cities, high-level cities, and key urban agglomerations. Meanwhile, in mid-western cities, low-level cities, and non-key urban agglomerations, the digital economy is still in the stage of the energy rebound effect, reducing energy efficiency. One of the reasons for studying the relationship between the digital economy and energy efficiency is to mitigate the energy rebound effect and exploit the energy-saving effect of the digital economy. Therefore, this study explored the moderating effects of innovation capability and environmental regulation, finding that they can both play a good moderating role able to advance the inflection point of the U-shaped relation, alleviate the energy rebound effect on the left side, and enhance the energy saving effect on the right side.

The results of this study have some policy implications. First, the government should vigorously and strategically develop the digital economy. Although the digital economy has not improved energy efficiency in some areas, this aligns with the objective law. With further development, the digital economy will finally cross the inflection point, improve energy efficiency, and achieve a win-win situation of carbon emission reduction and economic development. Therefore, it remains necessary to strengthen the infrastructure construction of the digital economy, expand the application fields of the digital economy, enhance the breadth and depth of the digital economy, and encourage the digital transformation of enterprises. Second, all parties need to work together to improve energy efficiency continuously. China's endowment of coal resources means that the country cannot simply replace coal with other energy sources in the short term. Therefore, improving energy efficiency remains the only way to achieve the dual carbon target. In this respect, high-emission enterprises' green digital transformation activities should be encouraged, the industrial structure should be optimized, and the development of new energy should be promoted through macro-control. Third, it is necessary to strengthen innovation. More specifically, the state should increase investment in innovation, support the green innovation activities of research institutions and universities, provide tax concessions to enterprises that produce good green innovation results, and actively guide social capital to invest in green enterprises. Fourth, environmental regulation should be strengthened. To better achieve carbon reduction, the government should increase investment in environmental pollution control. Meanwhile, regulators should strengthen law enforcement and resolutely crack down on illegal emissions to ensure that enterprises stick to the bottom line and clarify the boundaries of their production and market activities.

5.2. Limitations and future research

Like most empirical research, this study has some limitations. First, although this study used data from 275 Chinese cities as its research sample, it did not obtain data for all Chinese cities. As a result of the slow updating of data in some cities, this study only collected data from 2010 to 2019 to ensure the integrity and consistency of data. Future research should consider more cities and updated data to study the impact of the digital economy. Second, this study selected indicators and measured the digital economy index based on relevant information and literature. However, the definition and measurement method of the digital economy may change in the future. Therefore, if there are significant changes, future research needs to keep pace with the times and re-calculate the digital economy index. Moreover, less data for the digital economy is available at the city level compared to the provincial level. Consequently, the construction of the city digital economy index is not as comprehensive and detailed as the provincial digital economy index, with the latter comprising more dimensions (e.g., infrastructure, industry digitization, digital industrialization, digital transactions, digital economy services, and governance system). Should more data become available in the future, such as digital governance and digital services, a more detailed digital economy indicator system should be constructed accordingly. Third, this study examined the relationship between the digital economy and energy efficiency using China as an example, thus exposing this research to certain limitations. It is necessary to continue exploring how the digital economy affects energy efficiency in other emerging countries, thus establishing the generalisability of the findings.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Liaoning social science planning fund project "Research on mechanism and path of digital development promoting carbon emission reduction" (grant number L21BJY031).

References

Abukhader, S. M. (2008). Eco-efficiency in the era of electronic commerce–should 'Eco-Effectiveness' approach be adopted? *Journal of Cleaner Production*, *16*(7), 801–808. https://doi.org/10.1016/j.jclepro.2007.04.001

Amin, S. B., & Rahman, S. (2019). The role of ICT in energy sector: Towards a digital Bangladesh by 2021. In *Energy resources in Bangladesh* (pp. 31–35). Springer.

Atasoy, H. (2013). The effects of broadband internet expansion on labor market outcomes. *ILR Review*, *66*(2), 315–345. https://doi.org/10.1177/001979391306600202

Belkhir, L., & Elmeligi, A. (2018). Assessing Ict Global Emissions Footprint: Trends to 2040 & Recommendations. *Journal of Cleaner Production*, *177*(3), 448–463. https://doi.org/10.1016/j.jclepro.2017.12.239

Berger, D. (2022). Investor sentiment: A retail trader activity approach. *Review of Accounting and Finance*, *21*(2), 61–82. https://doi.org/10.1108/RAF-06-2021-0152

Bibi, A., Zhang, X., & Umar, M. (2021). The imperativeness of biomass energy consumption to the environmental sustainability of the United States revisited. *Environmental and Ecological Statistics*, *28*(4), 821–841. https://doi.org/10.1007/s10651-021-00500-9

Chen, J., Guo, X., & Zhong, S. (2022). The financialization of urban development and urban labour productivity: Evidence from China. *Regional Studies*, *56*(8), 1295–1307. https://doi.org/10.1080/00343404.2022.2030055

Chen, N., Sun, D., & Chen, J. (2022). Digital transformation, labour share, and industrial heterogeneity. *Journal of Innovation & Knowledge*, *7*(2), 100173. https://doi.org/10.1016/j.jik.2022.100173

Chen, Z., Mirza, N., Huang, L., & Umar, M. (2022). Green banking—Can financial institutions support green recovery? *Economic Analysis and Policy*, *75*, 389–395. https://doi.org/10.1016/j.eap.2022.05.017

Chihiro, S. (2018). *Accounts and Images of Six Kannon in Japan*. JSTOR.

Choi, Y., Zhang, N., & Zhou, P. (2012). Efficiency and abatement costs of energy-related CO2 emissions in China: A slacks-based efficiency measure. *Applied Energy*, *98*, 198–208. https://doi.org/10.1016/j.apenergy.2012.03.024

Cong, L. W., Xie, D., & Zhang, L. (2021). Knowledge accumulation, privacy, and growth in a data economy. *Management Science*, *67*(10), 6480–6492. https://doi.org/10.1287/mnsc.2021.3986

Dorfleitner, G., & Grebler, J. (2022). Corporate social responsibility and systematic risk: International evidence. *The Journal of Risk Finance*, *23*(1), 85–120. Article 1. https://doi.org/10.1108/JRF-07-2020-0162

Elı́asson, L., & Turnovsky, S. J. (2004). Renewable resources in an endogenously growing economy: Balanced growth and transitional dynamics. *Journal of Environmental Economics and Management*, *48*(3), 1018–1049. https://doi.org/10.1016/j.jeem.2003.12.004

Ferrat, Y., Daty, F., & Burlacu, R. (2021). Short- and long-term effects of responsible investment growth on equity returns. *The Journal of Risk Finance*, *23*(1), 1–13. https://doi.org/10.1108/JRF-07-2021-0107

Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2022). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technological Forecasting and Social Change*, *182*, 121785. https://doi.org/10.1016/j.techfore.2022.121785

Gao, D., Li, G., & Yu, J. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy*, *247*, 123395. https://doi.org/10.1016/j.energy.2022.123395

Gao, J., O'Sullivan, N., & Sherman, M. (2021). Chinese securities investment funds: The role of luck in performance. *Review of Accounting and Finance*, *20*(5), 271–297. https://doi.org/10.1108/RAF-07-2020-0182
Gómez-Calvet, R., Conesa, D., Gómez-Calvet, A. R., & Tortosa-Ausina, E. (2014). Energy efficiency in the European Union: What can be learned from the joint application of directional distance functions and slacks-based measures? *Applied Energy*, *132*, 137–154. https://doi.org/10.1016/j.apenergy.2014.06.053
Grossman, G. M., & Krueger, A. B. (1995). Krueger, 1995. Economic growth and the environment. *The Quarterly Journal of Economics*, *110*(2), 353–377. https://doi.org/10.2307/2118443
Guo, X., Liang, C., Umar, M., & Mirza, N. (2022). The impact of fossil fuel divestments and energy transitions on mutual funds performance. *Technological Forecasting and Social Change*, *176*, 121429. https://doi.org/10.1016/j.techfore.2021.121429
Haans, R., Pieters, C., & He, Z. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, *37*(7), 1177–1195. https://doi.org/10.1002/smj.2399
He, L., Zhang, X., & Yan, Y. (2021). Heterogeneity of the Environmental Kuznets Curve across Chinese cities: How to dance with 'shackles'? *Ecological Indicators*, *130*, 108128. https://doi.org/10.1016/j.ecolind.2021.108128
Hu, J.-L., & Wang, S.-C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy*, *34*(17), 3206–3217. https://doi.org/10.1016/j.enpol.2005.06.015
Ielasi, F., Rossolini, M., & Limberti, S. (2018). Sustainability-themed mutual funds: An empirical examination of risk and performance. *The Journal of Risk Finance*, *19*(3), 247–261. https://doi.org/10.1108/JRF-12-2016-0159
Iftikhar, Y., He, W., & Wang, Z. (2016). Energy and CO2 emissions efficiency of major economies: A non-parametric analysis. *Journal of Cleaner Production*, *139*, 779–787. https://doi.org/10.1016/j.jclepro.2016.08.072
Imbruno, M., & Ketterer, T. D. (2018). Energy efficiency gains from importing intermediate inputs: Firm-level evidence from Indonesia. *Journal of Development Economics*, *135*, 117–141. https://doi.org/10.1016/j.jdeveco.2018.06.014
Ishida, H. (2015). The effect of ICT development on economic growth and energy consumption in Japan. *Telematics and Informatics*, *32*(1), 79–88. https://doi.org/10.1016/j.tele.2014.04.003
Karim, S., Naeem, M. A., Mirza, N., & Paule-Vianez, J. (2022). Quantifying the hedge and safe-haven properties of bond markets for cryptocurrency indices. *The Journal of Risk Finance*, *23*(2), 191–205. Article 2. https://doi.org/10.1108/JRF-09-2021-0158
Khan, Z., Ali, S., Umar, M., Kirikkaleli, D., & Jiao, Z. (2020). Consumption-based carbon emissions and international trade in G7 countries: The role of environmental innovation and renewable energy. *The Science of the Total Environment*, *730*, 138945. https://doi.org/10.1016/j.scitotenv.2020.138945
Khayyat, N. T., Lee, J., & Heo, E. (2016). How ICT investment influences energy demand in South Korea and Japan. *Energy Efficiency*, *9*(2), 563–589. https://doi.org/10.1007/s12053-015-9384-9
Kortelainen, M. (2008). Dynamic environmental performance analysis: A Malmquist index approach. *Ecological Economics*, *64*(4), 701–715. https://doi.org/10.1016/j.ecolecon.2007.08.001
Lan, J., & Wen, H. (2021). Industrial Digitalization and Energy Intensity: Evidence from China's manufacturing sector. *Energy RESEARCH LETTERS*, *2*(2), 25733. https://doi.org/10.46557/001c.25733
Lange, S., Pohl, J., & Santarius, T. (2020). Digitalization and energy consumption. Does ICT Reduce Energy Demand? *Ecological Economics*, *176*, 106760.
Li, C., Liu, X., Bai, X., & Umar, M. (2020). Financial development and environmental regulations: The two pillars of green transformation in China. *International Journal of Environmental Research and Public Health*, *17*(24), 9242. Article 24. https://doi.org/10.3390/ijerph17249242
Li, J., Chen, L., Chen, Y., & He, J. (2022). Digital economy, technological innovation, and green economic efficiency—Empirical evidence from 277 cities in China. *Managerial and Decision Economics*, *43*(3), 616–629. https://doi.org/10.1002/mde.3406

Li, K., Kim, D. J., Lang, K. R., Kauffman, R. J., & Naldi, M. (2020). How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electronic commerce Research and Applications*, *44*, 101004. https://doi.org/10.1016/j.elerap.2020.101004

Li, Z., & Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: Evidence city-level empirical data in China. *Journal of Cleaner Production*, *351*, 131570. https://doi.org/10.1016/j.jclepro.2022.131570

Liang, C., Umar, M., Ma, F., & Huynh, T. L. (2022). Climate policy uncertainty and world renewable energy index volatility forecasting. *Technological Forecasting and Social Change*, *182*, 121810. https://doi.org/10.1016/j.techfore.2022.121810

Lin, B., & Ma, R. (2022). How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective. *Journal of Environmental Management*, *320*, 115833. https://doi.org/10.1016/j.jenvman.2022.115833

Lin, B., & Zhou, Y. (2021). Does the Internet development affect energy and carbon emission performance? *Sustainable Production and Consumption*, *28*, 1–10. https://doi.org/10.1016/j.spc.2021.03.016

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

Ma, Q., Tariq, M., Mahmood, H., & Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development. *Technology in Society*, *68*, 101910. https://doi.org/10.1016/j.techsoc.2022.101910

Martínez, C. I. P. (2018). Climate change in Colombia: A study to evaluate trends and perspectives for achieving sustainable development from society. *International Journal of Climate Change Strategies and Management*, *10*(4), 632–652.

Muhammad, S., Pan, Y., Agha, M. H., Umar, M., & Chen, S. (2022). Industrial structure, energy intensity and environmental efficiency across developed and developing economies: The intermediary role of primary, secondary and tertiary industry. *Energy*, *247*, 123576. https://doi.org/10.1016/j.energy.2022.123576

Oh, D. (2010). A global Malmquist-Luenberger productivity index. *Journal of Productivity Analysis*, *34*(3), 183–197. https://doi.org/10.1007/s11123-010-0178-y

Ozcan, B., & Apergis, N. (2018). The impact of internet use on air pollution: Evidence from emerging countries. *Environmental science and Pollution Research International*, *25*(5), 4174–4189. https://doi.org/10.1007/s11356-017-0825-1

Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research*, *139*, 303–311. https://doi.org/10.1016/j.jbusres.2021.09.061

Park, Y., Meng, F., & Baloch, M. A. (2018). The effect of ICT, financial development, growth, and trade openness on CO2 emissions: An empirical analysis. *Environmental science and Pollution Research International*, *25*(30), 30708–30719. https://doi.org/10.1007/s11356-018-3108-6

Peng, Y., & Tao, C. (2022). Can digital transformation promote enterprise performance?—From the perspective of public policy and innovation. *Journal of Innovation & Knowledge*, *7*(3), 100198. https://doi.org/10.1016/j.jik.2022.100198

Saidi, K., Toumi, H., & Zaidi, S. (2017). Impact of information communication technology and economic growth on the electricity consumption: Empirical evidence from 67 countries. *Journal of the Knowledge Economy*, *8*(3), 789–803. https://doi.org/10.1007/s13132-015-0276-1

Salahuddin, M., & Alam, K. (2016). Information and communication technology, electricity consumption and economic growth in OECD countries: A panel data analysis. *International Journal of Electrical Power & Energy Systems*, *76*, 185–193. https://doi.org/10.1016/j.ijepes.2015.11.005

Sama, L. M., Stefanidis, A., & Casselman, R. M. (2022). Rethinking corporate governance in the digital economy: The role of stewardship. *Business Horizons*, *65*(5), 535–546. https://doi.org/10.1016/j.bushor.2021.08.001

Sidorov, A., & Senchenko, P. (2020). Regional digital economy: Assessment of development levels. *Mathematics*, *8*(12), 2143. https://doi.org/10.3390/math8122143

Su, C.-W., Pang, L.-D., Tao, R., Shao, X., & Umar, M. (2022). Renewable energy and technological innovation: Which one is the winner in promoting net-zero emissions? *Technological Forecasting and Social Change*, *182*, 121798. https://doi.org/10.1016/j.techfore.2022.121798

Teece, D. J. (2018). Profiting from innovation in the digital economy: Standards, complementary assets, and business models in the wireless world. *Research Policy (Forthcoming)*, *47*(8), 1367–1387. https://doi.org/10.1016/j.respol.2017.01.015

Umar, M., Ji, X., Kirikkaleli, D., Shahbaz, M., & Zhou, X. (2020). Environmental cost of natural resources utilization and economic growth: Can China shift some burden through globalization for sustainable development? *Sustainable Development*, *28*(6), 1678–1688. Article 6. https://doi.org/10.1002/sd.2116

Umar, M., Mirza, N., Hasnaoui, J. A., & Rochoń, M. P. (2022). The nexus of carbon emissions, oil price volatility, and human capital efficiency. *Resources Policy*, *78*, 102876. https://doi.org/10.1016/j.resourpol.2022.102876

Usman, A., Ozturk, I., Hassan, A., Zafar, S. M., & Ullah, S. (2021). The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis. *Telematics and Informatics*, *58*, 101537. https://doi.org/10.1016/j.tele.2020.101537

Wang, Q.-S., Su, C.-W., Hua, Y.-F., & Umar, M. (2021). Can fiscal decentralisation regulate the impact of industrial structure on energy efficiency? *Economic Research-Ekonomska Istraživanja*, *34*(1), 1727–1751. https://doi.org/10.1080/1331677X.2020.1845969

Wang, Z., Feng, C., & Zhang, B. (2014). An empirical analysis of China's energy efficiency from both static and dynamic perspectives. *Energy*, *74*, 322–330. https://doi.org/10.1016/j.energy.2014.06.082

Wang, Z.-H., Zeng, H.-L., Wei, Y.-M., & Zhang, Y.-X. (2012). Regional total factor energy efficiency: An empirical analysis of industrial sector in China. *Applied Energy*, *97*, 115–123. https://doi.org/10.1016/j.apenergy.2011.12.071

Wu, B., & Yang, W. (2022). Empirical test of the impact of the digital economy on China's employment structure. *Finance Research Letters*, *49*(10), 103047. https://doi.org/10.1016/j.frl.2022.103047

Wu, H., Hao, Y., Ren, S., Yang, X., & Xie, G. (2021). Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy*, *153*, 112247. https://doi.org/10.1016/j.enpol.2021.112247

Wu, Y., & Huang, S. (2022). The effects of digital finance and financial constraint on financial performance: Firm-level evidence from China's new energy enterprises. *Energy Economics*, *112*, 106158. https://doi.org/10.1016/j.eneco.2022.106158

Xie, B.-C., Shang, L.-F., Yang, S.-B., & Yi, B.-W. (2014). Dynamic environmental efficiency evaluation of electric power industries: Evidence from OECD (Organization for Economic Cooperation and Development) and BRIC (Brazil, Russia, India and China) countries. *Energy*, *74*, 147–157. https://doi.org/10.1016/j.energy.2014.04.109

Xu, Q., Zhong, M., & Cao, M. (2022). Does digital investment affect carbon efficiency? Spatial effect and mechanism discussion. *The Science of the Total Environment*, *827*, 154321. https://doi.org/10.1016/j.scitotenv.2022.154321

Xu, Y., Umar, M., Kirikkaleli, D., Adebayo, T. S., & Altuntaş, M. (2022). Carbon neutrality target in Turkey: Measuring the impact of technological innovation and structural change. *Gondwana Research*, *109*, 429–441. https://doi.org/10.1016/j.gr.2022.04.015

Xue, L., Li, H., Xu, C., Zhao, X., Zheng, Z., Li, Y., & Liu, W. (2022). Impacts of industrial structure adjustment, upgrade and coordination on energy efficiency: Empirical research based on the extended STIRPAT model. *Energy Strategy Reviews*, *43*, 100911. https://doi.org/10.1016/j.esr.2022.100911

Yilanci, V., Cutcu, I., & Cayir, B. (2022). Is the environmental Kuznets curve related to the fishing footprint? Evidence from China. *Fisheries Research*, *254*, 106392. https://doi.org/10.1016/j.fishres.2022.106392

Yu, D., Li, X., Yu, J., & Li, H. (2021). The impact of the spatial agglomeration of foreign direct investment on green total factor productivity of Chinese cities. *Journal of Environmental Management*, *290*, 112666.

Zhang, W., Liu, X., Wang, D., & Zhou, J. (2022). Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy*, *165*, 112927. https://doi.org/10.1016/j.enpol.2022.112927
Zhang, X.-P., Cheng, X.-M., Yuan, J.-H., & Gao, X.-J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy*, *39*(2), 644–650. https://doi.org/10.1016/j.enpol.2010.10.037
Zhang, Z., & Ye, J. (2015). Decomposition of environmental total factor productivity growth using hyperbolic distance functions: A panel data analysis for China. *Energy Economics*, *47*, 87–97. https://doi.org/10.1016/j.eneco.2014.10.023
Zhou, Y., Liu, W., Lv, X., Chen, X., & Shen, M. (2019). Investigating interior driving factors and cross-industrial linkages of carbon emission efficiency in China's construction industry: Based on Super-SBM DEA and GVAR model. *Journal of Cleaner Production*, *241*, 118322. https://doi.org/10.1016/j.jclepro.2019.118322

Appendix A

Table A1. Nomenclature interpretation.

Nomenclature	Interpretation
Energy efficiency	Including single factor energy efficiency and total factor energy efficiency
Single factor energy efficiency	Proportion of GDP to traditional energy consumption
Total factor energy efficiency	Calculated by SBM-GML method
Energy intensity	Proportion of energy consumption to output
Carbon performance	Proportion of output to carbon emissions or total factor carbon efficiency calculated by the DEA method
ICT	Information and communication technology

Source: Author own derivations.

Appendix B

The calculation steps of the SBM-GML method are as follows:

1. Assuming that each city is a decision-making unit and each decision making unit contains N kinds of input factors, $x_{in} = (x_{i1}, x_{i2}, \ldots, x_{iN}) \in R_N^+$, we can get M kinds of expected outputs, $y_{im} = (y_{i1}, y_{i2}, \ldots, y_{iM}) \in R_M^+$, and K kinds of unexpected outputs, $b_{ik} = (b_{i1}, b_{i2}, \ldots, b_{iK}) \in R_K^+$. Accordingly, the global production possibility set is constructed as the following Equation:

$$P^G(x) = \begin{cases} (y^t, b^t) : \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t y_{im}^t \geq y_{im}^t, \forall m; \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t b_{ik}^t, \forall k \\ \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t x_{in}^t \leq x_{in}^t, \forall n; \sum_{t=1}^{T} \sum_{i=1}^{I} \beta_i^t = 1, \beta_i^t \geq 0, \forall i \end{cases} \tag{1}$$

2. For global SBM directional range function, $(x^{t,i}, y^{t,i}, b^{t,i})$, (g^x, g^y, g^b), and (S_n^x, S_m^y, S_k^b) denote the input-output, direction, and relaxation vectors, respectively, and z_i^t is the weight of each cross section. Therefore, the global SBM directional distance function can be expressed as follows:

$$\begin{aligned} S_v^G(x^{t,i}, y^{t,i}, b^{t,i}, g^x, g^y, g^b) = \max & \frac{\frac{1}{N}\sum_{n=1}^{N} \frac{s_n^x}{g_n^x} + \frac{1}{M+K}\left(\sum_{m=1}^{M} \frac{s_m^y}{g_m^y} + \sum_{k=1}^{K} \frac{s_k^b}{g_{ik}^b}\right)}{2} \\ & s.t. \sum_{t=1}^{T}\sum_{i=1}^{I} z_i^t x_{in}^t + S_n^x = x_{in}^t, \forall n; \\ & \sum_{t=1}^{T}\sum_{i=1}^{I} z_i^t y_{im}^t - S_{nm}^y = y_{in}^t, \forall m; \\ & \sum_{t=1}^{T}\sum_{i=1}^{I} z_i^t b_{ik}^t + S_i^b = b_{ik}^t, \forall i; \\ & \sum_{i=1}^{I} z_i^t = 1, z_k^t \geq 0, \forall i; \\ & S_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i \end{aligned} \tag{2}$$

3. To calculate total factor energy efficiency, the GML index is the total factor energy efficiency expressed in the following Equation:

$$Mee_t^{t+1} = GML_t^{t+1} = \frac{1 + S_v^G(x^t, y^t, b^t, g^x, g^y, g^b)}{1 + S_v^G(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b)} \tag{3}$$

where $S_v^G(\cdot)$ is the global directional distance function. The GML index measures the dynamics of the *Mee* between two periods.

Appendix C

Table C1. Comprehensive index system of the digital economy.

Target level	Standard level	Index level	Indicator attribute
Digital economy	Digital infrastructure	Mobile phone penetration rate	Positive
		Fixed telephone penetration rate	Positive
		Internet broadband penetration rate	Positive
		Digital financial digitization index	Positive
	Digitisation of industry	Proportion of total telecommunications business to GDP	Positive
		Proportion of software business income to GDP	Positive
		Proportion of information practitioners	Positive
	Industrialization of digital	Proportion of enterprises with e-commerce trading activities	Positive
		Proportion of e-commerce transaction volume to GDP	Positive
		Number of websites per 100 enterprises	Positive
		Per capita e-commerce sales	Positive

Source: Author own derivations.