



Impact and mechanism of digital economy on China's carbon emissions: from the perspective of spatial heterogeneity

Haijing Yu¹ · Qin Zhu²

Received: 10 May 2022 / Accepted: 11 August 2022 / Published online: 3 September 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract

Using panel data from 30 provinces and cities in China over the period 2013–2019, we intend to explore the mechanism and regional heterogeneity of the influence of digital economy development on carbon emissions. Specifically, this relationship is analyzed by including the geographical variable coefficient model into the chain mediation effect model, taking spatial correlation and heterogeneity into account. The results indicate that the digital economy decreases carbon emissions by enhancing energy intensity, but raises carbon emissions by fostering economic expansion, making digital economy a net contribution to carbon emissions. Moreover, the effect of the digital economy on carbon emissions varies by geographic location. For instance, the total impact is the greatest in northern China, followed by the southwest and southeast, and relatively minor in the northwest and south. Our findings contribute to the existing research and offer policymakers with a theoretical reference, allowing them to customize carbon reduction plans to local conditions.

Keywords Digital economy · CO₂ · Spatial heterogeneity · MGWPR-SDM model · Chain mediation effect

Introduction

Recent years have seen a rise in the frequency of natural disasters caused by climate change, which has increased the environment's susceptibility. Carbon dioxide (CO₂) emitted by the combustion of fossil fuels is one of the primary causes of climate change (Udara Wilhelm Abeydeera et al. 2019). Therefore, lowering CO₂ emissions, constructing a low-carbon society, creating a green economy, and promoting sustainable development has become the agreement among all governments globally (Wu et al. 2020). Energy consumption in China, a significant carbon emitter, has historically been dominated by coal, and the associated carbon emissions are far more than the sum of those created by oil and natural gas. China's total carbon emissions climbed from 32.232 million tons in 2001, when joined the World Trade Organization,

to 10,881.69 million tons in 2019 (Fig. 1), a 6.49% annual growth rate, accounting for 30.3% of the world's total carbon emissions. In this instance, the Chinese government has successfully implemented a number of emission reduction measures (e.g., shifting gradually to renewable energy on the supply side and promoting new energy vehicles on the demand side) and set the goal of reaching carbon peak by 2030 and carbon neutrality by 2060. Multiple strategies, such as renewable energy, reforestation, and technical innovation, are required to attain this difficult objective. The growth of the digital economy through the Internet and information and communication technology (ICT) is regarded as an effective strategy for reducing carbon emissions (Sahoo et al. 2021; Zhao et al. 2021). China's digital economy has grown significantly in recent years. However, there are significant disparities in the natural environment and social and economic situations between northern and southern China, making the relationship between the digital economy and carbon emissions questionable. Does the digital economy of China effectively reduce carbon emissions? In addition, what are the mechanisms of its influence, and is there spatial heterogeneity? For the creation of targeted emission reduction programs and the successful attainment of "carbon neutrality" and "carbon peak," the research on these issues is of great practical value.

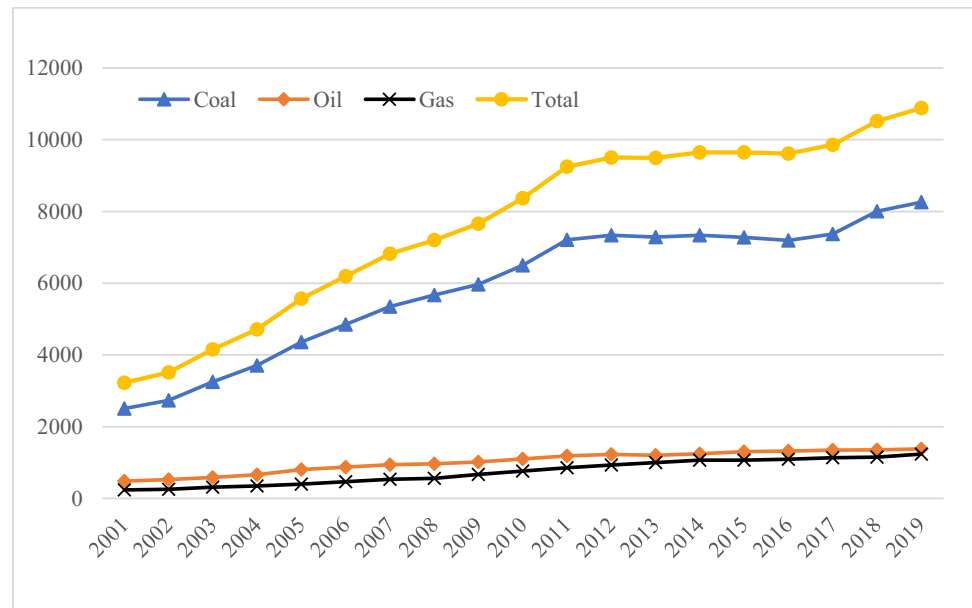
Communicated by Arshian Sharif.

✉ Qin Zhu
zhuqin1220@sina.com

¹ Research Institute of Quantitative Economics, Zhejiang Gongshang University, Hangzhou, China

² School of Economics, Zhejiang Gongshang University, Hangzhou, China

Fig. 1 Carbon dioxide emissions and structural changes in China, 2001–2019



A growing number of research on digital technology have demonstrated that it can successfully enhance the efficiency of carbon emissions (Wu et al. 2021), but it may not lower total carbon emissions (Shahbaz and Sinha 2019). In other words, a digital economy might either increase (Usman et al. 2021) or decrease (Lu 2018) the total quantity CO₂ emissions. Even research in the same place can have inconsistent results (Chen et al. 2020; Zhang et al. 2021). First, there is a dearth of research on the mechanism of the influence of the digital economy on carbon emissions; second, the geographical variability of the impact of the digital economy on carbon emissions is almost completely disregarded (Zhong et al. 2021). Thirdly, the conventional regression analysis approach often assumes that study subjects are independent and uniformly distributed; nevertheless, both the digital economy and carbon emissions exhibit spatial autocorrelation. There is, to the best of our knowledge, a gap in the existing study regarding the investigation of the effect of a digital economy on carbon emissions in relation to the three aforementioned factors.

In order to fill this void, this study contributes as follows. First, in contrast to previous research (e.g., Shahnazi and Dehghan Shabani 2019; Song et al. 2020; Zhang et al. 2021; Xu et al. 2022), we use a new spatially varying coefficient model, the mixed geographically weighted panel regression spatial Durbin model (MGWPR-SDM), which relaxes the implicit assumption that all regions are independent of each other and have equal coefficients in the traditional model setting. In addition, the model has the ability to simultaneously address spatial autocorrelation and spatial heterogeneity (Yu et al. 2021). Therefore, it can more accurately reflect the actual impact of the digital economy on carbon emissions. Second, prior research (e.g., Lin and Zhou 2021;

Wu et al. 2021) has disregarded the link between mediating variables and their geographical heterogeneity (Lu 2018; Avom et al. 2020; Liu et al. 2021). This study investigates the mechanism of the impact of the digital economy on carbon emissions and its spatial heterogeneity by including the MGWPR-SDM model into the chain mediating effect model. Thirdly, in response to the present contentious concerns in academia, our research demonstrates that the digital economy affects carbon emissions through four spatially diverse paths. While the digital economy reduces carbon emissions by decreasing energy intensity, it increases carbon emissions by fostering economic expansion. The overall impact is positive in most areas as the positive and negative effects of the various paths eventually cancel one another out. This work contributes to the research on the impact of the digital economy on carbon emissions and offers governments with theoretical references for formulating strategies to reduce emissions based on local conditions.

The remainder of this study is organized as follows. The “Literature review” section presents a literature review of the controversies in related studies and a summary of the improvement areas. The “Variable selection and data description” section describes the variable selection and data description; by developing a digital economy development index system, we measure the level of digital economy development in each region. The “Model construction” section covers the model building by introducing the method of including the MGWPR-SDM model into the chain-mediated effect model, while the “Analysis of empirical results” section describes the empirical findings analysis by displaying the spatial heterogeneity results via maps. The “Conclusion and policy implication” section concludes the analysis with its conclusion and suggestions.

Literature review

The impact of digital economy on carbon emissions

Specific studies on the impact of digital economy on carbon emissions are scarce, but there is a growing body of research related to this subject, such as the impact of ICT or using the Internet on carbon emissions. Many scholars believe that ICTs effectively curb carbon emissions. The studies by Ulucak and Danish (2020) on Brazil, Russia, India, China, and South Africa (BRICS) from 1990 to 2015 and by Godil et al. (2020) on Pakistan from 1995 to 2018 concluded that ICTs significantly inhibited CO₂ emissions. However, numerous scholars have reached the opposite conclusion. For example, Raheem et al. (2020) studied G7 countries from 1994 to 2014 and showed that ICT significantly contributed to carbon emissions. Chen et al. (2020) analyzed the data of 30 provinces and cities in China from 2001 to 2017 and argued that informatization played a relatively stable role in promoting carbon emissions, mainly because it fostered online shopping and takeout industries in China and led to a sharp increase in transportation demand. Similar studies include Khan et al. (2019), Liu et al. (2021) and Magazzino et al. (2021).

There are three possible reasons why this topic is controversial. First, there is spatial heterogeneity in the impact of ICT on CO₂ emissions. The model settings of existing studies are primarily mean regressions, which assume that the impact coefficients are the same for all regions. Zhong et al. (2021) conducted a study on 30 provinces in China from 2007 to 2017 and showed that the impact of Internet development on carbon emission reduction in China was mainly concentrated in the eastern and central regions, while the Internet development in northeast and western regions increased carbon emissions. Xu et al. (2022) analyzed the panel data of 286 cities in China from 2011 to 2017 and found that the development of digital economy in eastern China had a significant negative impact on carbon emissions. In contrast, the development of digital economy in central China significantly promoted carbon emissions; however, the development of digital economy in western China did not. Second, traditional econometric models assume that study objects are independently and identically distributed, but carbon emissions, as an environmental variable that can flow with geographical space, do not necessarily agree with this assumption. Many studies have demonstrated the spatial autocorrelation of CO₂ (Shahnazi and Dehghan Shabani 2019; Wu et al. 2021; Xu et al. 2022); thus, it is necessary to use spatial econometric models rather than traditional regression models. Third, most studies only consider the direct effects of digital technologies on carbon emissions without considering their

indirect effects, let alone the spatial heterogeneity of these indirect effects. If the direct and indirect impacts are in opposite directions, combined with spatial heterogeneity, the direction of the total effect after summing is uncertain. In other words, only by simultaneously considering spatial correlation, spatial heterogeneity, and direct and indirect effects can we gain a more systematic and comprehensive understanding of the impact of digital economy on carbon emissions. However, to our knowledge, no such investigation has been performed in the existing research. Therefore, the hypothesis 1 proposed in this paper is.

H1: The impact of digital economy on carbon emissions is spatially heterogeneous, and the relationship between the two is uncertain.

The impact mechanism of digital economy on carbon emissions

Digital economy, energy consumption, and carbon emissions

Energy consumption such as coal, oil, and natural gas is the core driver of CO₂ emissions (Liu et al. 2015; Zhou et al. 2021). In the context of the development of digital economy, the role of Internet development or ICT in correcting improper resource allocation, promoting technological development, and improving energy utilization efficiency has been confirmed by an increasing number of empirical studies (Wu et al. 2021; Lin and Zhou 2021; Li and Du 2021). However, the relationship between the development of digital technology and energy consumption is complex. Ishida (2015) and Khayyat et al. (2016) analyzed the historical data of Japan and South Korea. These authors showed that ICT investment can be used to substitute labor and energy input and can effectively reduce energy consumption. Khuntia et al. (2018) study on Indian data supports this conclusion.

In contrast, numerous studies suggest that improving energy efficiency will increase energy consumption, thus partially or wholly offsetting the potential energy savings. This phenomenon is known as the rebound effect or the “Jevons paradox.” Siami and Winter (2021) demonstrated the existence of the Jevons paradox using a mathematical derivation. The aforementioned authors argued that unless there was a breakthrough in carbon capture and storage technology, energy efficiency improvements would continuously increase total carbon emissions. Many empirical studies support this paradox. For example, Salahuddin and Alam (2015) using panel data from the Organisation for Economic Co-operation and Development from 1985 to

2012, examined the long-term and short-term impact of ICT on electricity consumption. Their results showed that the use of ICT led to an increase in electricity consumption. Using panel data from 1990 to 2010, Longo and York (2015) found that ICT penetration was positively correlated with energy consumption. ICT does not significantly improve the environment and may even add to environmental problems. Sadorsky (2012) argued that there was a significant positive correlation between ICT use and electricity consumption in developing economies, while ICT did not reduce energy consumption. Takase and Murota (2004) studied the impact of informatization investment on energy consumption in Japan and the USA. The results showed that informatization investment in Japan significantly reduced energy consumption, whereas informatization investment in the USA increased energy consumption through the income effect. This is likely due to the different natural conditions and socioeconomic environments of the two countries. Ren et al. (2021) analyzed the panel data of 30 Chinese provinces and cities from 2006 to 2017 and showed that although the overall Internet development promoted energy consumption, there was spatial heterogeneity: the impact of Internet development on energy consumption was significantly positive in Beijing, Shanxi, Zhejiang, Fujian, Qinghai, and Xinjiang, whereas it was significantly negative in Tianjin, Shaanxi, Jiangxi, Guangxi, Gansu, and Ningxia. For the other regions, it was not significant. In conclusion, although there is debate, the Internet and other digital technologies are undoubtedly essential factors that affect energy consumption. Energy consumption is a key factor that directly influences carbon emissions (Godil et al. 2021; Bekun 2022). Therefore, we have sufficient evidence that digital economy affects carbon emissions by affecting energy consumption. Therefore, our proposed mediating effect hypothesis is.

H2: Energy consumption is a mediating variable for the digital economy to affect carbon emissions, i.e., the digital economy can affect carbon emissions through energy consumption, and the impact has spatial heterogeneity.

Digital economy, economic growth, and carbon emissions

The impact of digital technologies such as ICT on economic growth is evident. Over the past 50 years, numerous studies have proved that ICT can reduce search costs, narrow spatial distance, increase transaction opportunities, and promote enterprise output and economic growth (Lu 2018; Ren et al. 2021). The relationship between economic growth and carbon emissions, particularly the discussion on the effectiveness of environmental Kuznets curve (EKC),

has been a research hotspot in academic circles for a long time. However, no unanimous research conclusions have been reached. For example, York's (2007) study on 14 EU countries from 1960 to 2000 showed that the relationship between economic growth and CO₂ emissions was inverted U-shaped; this result was supported by the findings of Kasman and Duman (2015), Ahmed et al. (2016), and Saqib and Benhmad (2021). Suki et al. (2020) and Sharif et al. (2020b) research on Malaysia, Sharif et al. (2019) research on 74 countries, Sharif et al. (2020a) research on Turkey, and Bekun et al. (2021b) research on 27 EU countries also support the existence of Environmental Kuznets Curve. However, Destek et al. (2018) study on EU15 countries from 1980 to 2013 concluded that the relationship between economic growth and CO₂ emissions was U-shaped. Madaleno and Moutinho (2021) verified this conclusion. Sterpu et al. (2018) investigated 28 EU countries from 1990 to 2016 and concluded that the relationship is unstable. Frodyma et al. (2022) categorically tested the existence of EKC in 28 EU countries from 1970 to 2017, showing that both production and consumption emissions rejected the EKC hypothesis. In addition, some empirical studies have confirmed the existence of N-type EKC, such as Bekun et al. (2021a), Shahbaz et al. (2019), Balsalobre et al. (2018), etc. In response to this divergent phenomenon, Shahbaz and Sinha (2019) argued that the lack of consensus among scholars was mainly due to differences in research methods, model settings, and variable selection. Furthermore, we argue that the main reason for the controversy is that few scholars have considered both spatial correlation and spatial heterogeneity in their model settings. In any case, it is recognized that digital economy can influence carbon emissions by affecting economic growth. Therefore, we propose another mediating effect hypothesis.

H3: Economic growth is also a mediating variable for the digital economy to affect carbon emissions. However, the impact of digital economy on carbon emissions through economic growth is spatially uncertain.

Variable selection and data description

Variable selection

Explained variable

The CO₂ emissions of 30 provinces and cities in China from 2013 to 2019, excluding Hong Kong, Macao, Taiwan, and Tibet. Data are available on the website for carbon emission accounts and datasets: <https://www.ceads.net/data/province/> obtain, and mainly includes all anthropogenic emissions from energy consumption (i.e., the energy-related emissions of 17 fossil fuel types) and industrial production (i.e., the

process-related emissions of cement production). The methodology used is the sectoral approach of the Intergovernmental Panel on Climate Change. The calculation process refers to Shan et al. (2020).

Core explanatory variable

Digital economy development level (*Digi*). Following previous studies, such as Xu et al. (2022), Yang and Jiang (2021), and Li and Liu (2021), combined with the availability of data, this study constructs a provincial digital economy development level index for China with three levels: digital infrastructure, digital industry, and digital finance. The index consists of three primary indicators, seven secondary indicators, and 51 tertiary indicators (Table 1). Finally, it is reduced to a comprehensive index using a generalized principal component analysis to represent the development level of digital economy.

Digital infrastructure (A1) is the foundation of digital economy development, digital industry (A2) is the core of digital economy development, and digital finance (A3) provides a guarantee for digital economy development. Digital infrastructure (A1) includes two secondary indicators: hardware infrastructure (B1) and software infrastructure (B2).

Moreover, digital industry (A2) contains two secondary hands: digital industrialization (B3) and industrial digitization (B4). Among them, digital industrialization indicates that digital technology is no longer merely a technology or service tool but develops itself into an industry composed of seven representative three-level indicators. Industrial digitization refers to the digital transformation of existing industries and the integration of digital technology, which can optimize the structure and improve the production efficiency. It is composed of four representative three-level indicators. Digital finance (A3) refers to the digital inclusive finance index of Peking University (2011–2020) (see <https://idf.pku.edu.cn/yjcg/zsbjg/513800.htm>), which was compiled by Guo et al. (2020); the index mainly reflects the development level of digital finance in various regions from three aspects: the coverage of digital finance (B5), application depth of digital finance (B6), and level of financial digitization (B7).

In Table 1, we use Internet Broadband Access Port Density (C1), long-distance fiber optic cable line density (C2), and local telephone exchange capacity (C3) to represent digital hardware infrastructure (B1). Digital software infrastructure (B2) is expressed in terms of number of websites (C4), number of web pages (C5), number of Ipv4 addresses (C6), and number of domain names (C7), etc. Digital industrialization (B3) is represented by the telecommunications

Table 1 Digital economy development level index system

Total index	Primary indicator	Secondary indicator	Tertiary indicator		
Digital Economy Index	Digital infrastructure (A1)	Hardware infrastructure (B1)	Internet Broadband Access Port Density (C1) Long-distance fiber optic cable line density (C2) Local telephone exchange capacity (C3)		
		Software infrastructure (B2)	Number of websites (C4) Number of web pages (C5) Number of Ipv4 addresses (C6) Number of domain names (C7)		
	Digital industry (A2)	Digital industrialization (B3)	Telecommunications Service Volume (C8) Mobile Phone Production (C9) Production of Integrated Circuits (C10) Microcomputer Equipment Production (C11) Software business revenue (C12) Revenue from Information Technology Services (C13) Information transmission, computer services and software industry employees (C14)		
			Industry digitization (B4)	Express delivery volume (C15) E-commerce transaction volume (C16) Number of websites per 100 enterprises (C17) Percentage of enterprises with e-commerce transaction activities (C18)	
			Digital finance (A3)	Breadth of coverage (B5)	Refer to Guo et al. (2020)
				Depth of application (B6)	Refer to Guo et al. (2020)
	Digitization level (B7)	Refer to Guo et al. (2020)			

Service Volume (C8), mobile phone production (C9), production of integrated circuits (C10), microcomputer equipment production (C11), software business revenue (C12), revenue from information technology services (C13), and information transmission, computer services, and software industry employees (C14). Industry digitization (B4) indicates the express delivery volume (C15), e-commerce transaction volume (C16), number of websites per 100 enterprises (C17), and percentage of enterprises with e-commerce transaction activities (C18).

Mediator variables

Energy intensity (*Ener*) and economic development level (gross domestic product [GDP]). The former (*Ener*) is expressed by the ratio of energy consumption to GDP (Lu 2018; Chen et al. 2020), and the latter (*GDP*) is defined by per capita GDP (Zhao et al. 2021). Moreover, there is evidence that energy consumption has a significant effect on economic growth, i.e., there is a possibility of a chain mediating effect (Sharif et al. 2017a, b; Solarin et al. 2021a).

Control variables

In the IPAT framework proposed by Dietz and Rosa (1997), population (*P*), economic development level (*A*), and technological progress (*T*) are the core influencing factors affecting environmental variables, such as carbon emissions in this paper. Therefore, this paper takes all these three factors into account in the model. Where the level of economic development is the GDP mentioned above, population (*P*) is defined by the number of permanent residents in each region (Usman et al. 2021), technological progress (*T*) is expressed in the number of authorized invention patents (Chen et al. 2020). In addition, according to the existing literature, urbanization will lead to the growth of industries, including construction, which will significantly increase carbon emissions. Foreign direct investment in many pollution-intensive industries, especially in countries or regions with relatively low environmental standards, will also significantly increase carbon emissions to a certain extent. We also consider urbanization and foreign direct investment as important influencing factors of carbon emissions (Solarin et al. 2021b). The urbanization (*Urban*) level is represented by the proportion of permanent urban residents in the total population (Lin and Zhou 2021). Foreign direct investment (*FDI*) is expressed by the logarithm of the utilized foreign direct investment.

Data description

Given the availability of data, the data in this study include 30 provinces, cities, and autonomous regions in

China except for Hong Kong, Macao, Taiwan, and Tibet. The data from 2013 to 2019 are chosen for this study because the energy structure in China has changed significantly since 2013; the carbon emissions from coal consumption began to decline continuously and rebounded in 2017. In addition, COVID-19 broke out at the end of 2019, and the lives and production of the residents began to break down or stop, resulting in a structural change in carbon emissions. All the data in this study, excluding the explanatory variables, are from the website of the National Bureau of Statistics of China or the China Statistical Yearbook from 2014 to 2020.

The level of digital economy development and CO₂ emissions are the two main variables in this study; consequently, it is necessary to briefly analyze their spatial and temporal change status. Figure 2 compares the spatial distribution of China's digital economy development level in 2013 and 2019. From this figure, it can be seen that China's digital economy development level shows a significant spatial heterogeneity in which the provinces with a higher digital economy development level are all located in coastal areas, followed by individual provinces in central and southwest regions. The northern and northwestern areas have a relatively lower digital economy development level. Figure 3 compares the spatial and temporal distribution of carbon emissions between 2013 and 2019. It also shows the significant regional differences and obvious spatial correlation of carbon emissions in China. The provinces with higher carbon emissions are concentrated in North China, while the regions with lower carbon emissions are concentrated in Southwest China. How digital economy affects carbon emissions is the main research issue of this study. In the next section, we conduct an in-depth investigation of this issue through an empirical analysis.

Model construction

This study uses the MGWPR-SDM model proposed by Yu et al. (2021). It is a combination of MGWPR and SDM and has the advantages of both. On the one hand, the model is generalized and can be degraded to several spatially varying coefficient panel models, such as the spatially varying coefficient auto-regressive model (SAR) and the spatially varying coefficient error model (SEM), which can suit different research needs. On the other hand, the model considers spatial correlation and spatial heterogeneity simultaneously, which is an improvement of the traditional regression model and spatial econometric model respectively and suitable for the topic of this study. According to a series of test results in part 5, both the benchmark model and the mediation effect model herein use the MGWPR-SDM model.

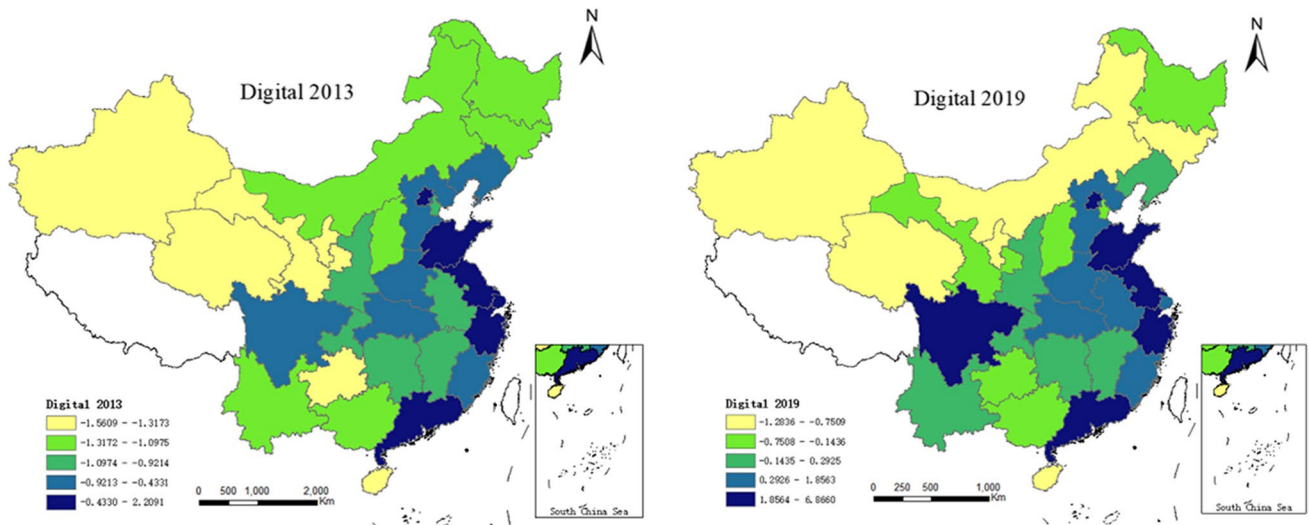


Fig. 2 Spatial and temporal distribution of China’s digital economy development level (2013, 2019)

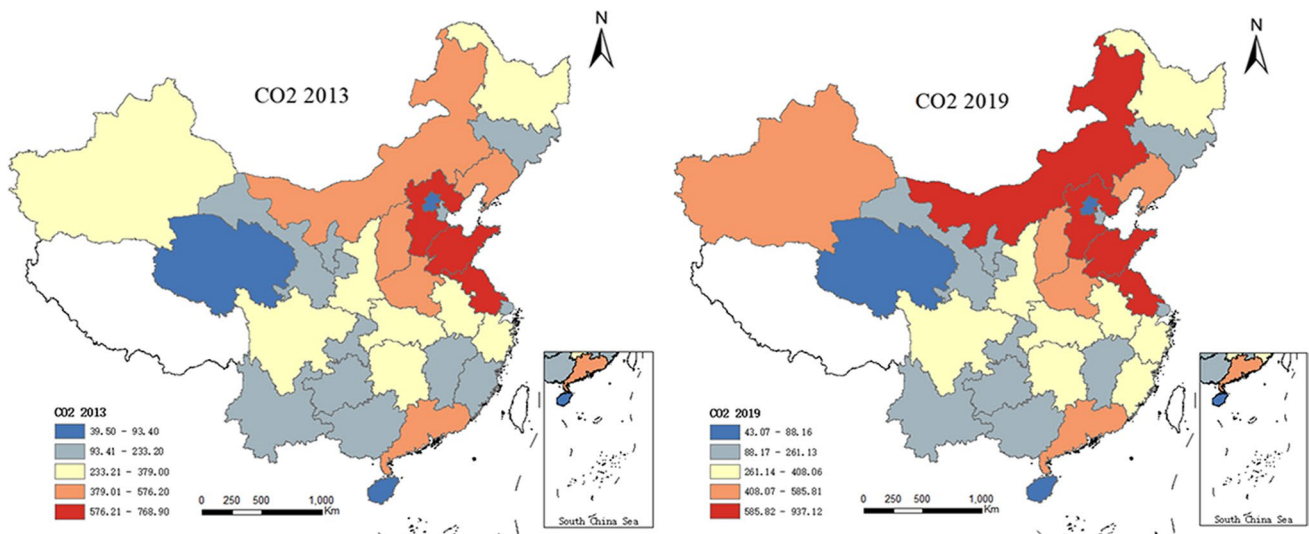


Fig. 3 Spatial and temporal distribution of carbon emissions in China (2013, 2019)

Direct effects model

We are embedding the digital economy (*Digi*) into the STRIPAT framework.

$$CO2_{it} = aDigi_{it}^b P_{it}^c A_{it}^d T_{it}^e \epsilon_{it} \tag{1}$$

where P_{it} represents the population size of region i at time t , A_{it} represents the economic development level of an area expressed by the per capita gross domestic product (*GDP*) of that year, T_{it} represents the technical level of the region, edefined by the number of authorized invention patents in

each area, and ϵ_{it} represents the random disturbance item. Take logarithm on both sides of Eq. (1), then

$$\ln CO2_{it} = \ln a + b \ln Digi_{it} + c \ln P_{it} + d \ln GDP_{it} + e \ln T_{it} + \ln \epsilon_{it} \tag{2}$$

Add other control variables C in the above equation, including energy intensity (*Ener*), foreign direct investment (*FDI*), urbanization development level (*Urban*), etc., then:

$$\ln CO2_{it} = \ln a + b \ln Digi_{it} + c \ln P_{it} + d \ln GDP_{it} + e \ln T_{it} + FC + \ln \epsilon_{it} \tag{3}$$

where $FC = fEner_{it} + gFDI_{it} + hUrban_{it}$. Equation (3) is a standard panel regression model with the underlying

assumption that all individuals are iid, meaning that there is no correlation between individuals, which is largely unrealistic. CO₂ emissions in one region are likely correlated with CO₂ emissions in neighboring regions, because greenhouse gases are mobile. Therefore, the spatial econometric model should be used to add the influence of adjacent areas, the spatial lag term of explained variables and explanatory variables into the model. Then, Eq. (3) is rewritten as

$$\ln CO_{2it} = \ln a + \rho \sum_{j \neq i} w_{ij} \ln CO_{2jt} + \beta \ln Digi_{it} + \gamma \ln P_{it} + \delta \ln GDP_{it} + \epsilon \ln T_{it} + FC + WX + \ln \epsilon_{it} \tag{4}$$

where $\sum_{j \neq i} w_{ij} \ln CO_{2jt}$ is the logarithm of the average carbon dioxide emission in the neighboring regions of region i , which is also the spatial lag term of the explained variable $\ln CO_{2it}$. The coefficient ρ characterizes the degree of spatial autocorrelation. $WX = \sum_r \theta_r (\sum_{j \neq i} w_{ij} x_{rjt})$ is the spatial lag term of r explanatory variables. Note that the coefficients of all variables in Eq. (4) are fixed constants. Actually, the coefficients of some explanatory variables may vary with spatial and geographical location. If this is true, the above formula can be simplified into a partially varying coefficient model:

$$Y = X_c \lambda_c + X_v \lambda_{v(u_i, v_i)} + \epsilon$$

where X_c and X_v represent the fixed coefficient variable matrix and varying coefficient variable matrix respectively. λ_c and $\lambda_{v(u_i, v_i)}$ correspond to the coefficient matrix of X_c and X_v respectively. (u_i, v_i) is the latitude and longitude of region i . ϵ is the random disturbance term.

Mediating effect model

To further analyze the mechanism of the impact of the digital economy (*Digi*) on carbon dioxide emissions ($\ln CO_2$), we refer to VanderWeele and Vansteelandt (2014) to construct a chain mediating effect model.

$$Ener_{it} = \alpha_0 + \alpha_1 \ln Digi_{it} + \alpha_2 \ln P_{it} + \alpha_3 \ln T_{it} + \alpha_4 FDI_{it} + \vartheta WX + \ln v_{it} \tag{5}$$

$$GDP_{it} = \beta_0 + \beta_1 \ln Digi_{it} + \beta_2 Ener_{it} + \beta_3 \ln P_{it} + \beta_4 \ln T_{it} + \beta_5 FDI_{it} + \delta WX + \ln u_{it} \tag{6}$$

where WX in Eqs. (5) and (6) denotes the spatial lag term matrices of the respective explanatory variables, and ϑ and δ are their corresponding coefficient matrices. As in (4), the coefficients of some of the explanatory variables in Eq. (5) and (6) may also vary with spatial location, so they are also applicable to the MGWPR-SDM model.

From Fig. 4 above, there are three pathways for the digital economy (*Digi*) to affect carbon dioxide emissions ($\ln CO_2$): (1) the digital economy (*Digi*) affects carbon dioxide emissions ($\ln CO_2$) by affecting energy intensity (*Ener*), with an effect size of $\alpha_1 * f$; (2) the digital economy

(*Digi*) affects carbon dioxide emissions ($\ln CO_2$) by affecting economic growth (*GDP*), with an effect size of $\beta_1 * d$; and (3) the digital economy (*Digi*) affects economic growth (*GDP*) by affecting energy intensity (*Ener*), which in turn affects carbon dioxide emissions ($\ln CO_2$), with an effect size of $\alpha_1 * \beta_2 * d$.

Analysis of empirical results

Model selection

First, it is crucial to answering whether a spatial econometric model needs to be used. A common approach is to test whether the sample individuals are spatially independent of each other using Moran's I statistic. The results of the Moran's I test when using carbon emission ($\ln CO_2$), economic development level (*GDP*), or energy intensity (*Ener*) as the explanatory variables are given in Table 2. The Moran's I statistics significantly reject the original assumption that the variables do not have a spatial correlation at the level of 5%. The three variables have a significant spatial autocorrelation, which is consistent with Figs. 2 and 3. Therefore, in the modeling process, the spatial lag term should be added to the model as an explanatory variable, that is, a spatial econometric model should be used.

Second, according to whether individual effects are related to explanatory variables, a panel regression model is divided into a fixed-effect model and a random-effect model. The results of a spatial Hausman test (Table 3) show that the chi-square statistics of model (4), model (5), and model (6) are 79.857, 34.093, and 79.938, respectively. The corresponding p -values are all 0.000; that is, the original assumption that the individual effect is not related to the explanatory variable (i.e., the random-effect model) is rejected, so the fixed-effect model should be selected. This study also controls for the

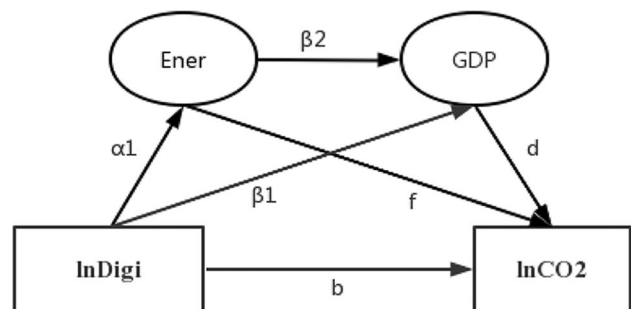


Fig. 4 Diagram of the chain mediating effect model

Table 2 Moran’s I test results

	<i>lnCO₂</i>	<i>GDP</i>	<i>Ener</i>
2013	0.040 (0.016)	0.153 (0.000)	0.140 (0.000)
2014	0.039 (0.018)	0.148 (0.000)	0.125 (0.000)
2015	0.035 (0.023)	0.140 (0.000)	0.113 (0.000)
2016	0.034 (0.023)	0.133 (0.000)	0.109 (0.000)
2017	0.032 (0.029)	0.127 (0.000)	0.117 (0.000)
2018	0.038 (0.018)	0.129 (0.000)	0.118 (0.000)
2019	0.035 (0.022)	0.128 (0.000)	0.117 (0.000)

The *p*-values corresponding to Moran’s *I* statistic are in parentheses

Table 3 Spatial Hausman test results

Model (4)	Model (5)	Model (6)
79.857	34.093	79.938
0.000	0.000	0.000

unobservable individual effect and time effect; thus, the endogeneity problem caused by omitted variables can be mitigated to some extent.

Third, spatial econometric models have various forms, such as the spatial panel lag model (SAR), spatial error model (SEM), and SDM, and the specific choice of model should be properly tested. In this study, we test whether the SDM degenerates into a SAR and SEM using a likelihood ratio (LR) test. The results in Table 4 show that the *p*-values corresponding to the chi-square statistics of model (4), model (5), and model (6) are all 0.000, which indicates that all three models reject the original hypothesis that the SAR and SEM models are true. Thus, the SDM with two-way fixed effects should be selected in the end.

Variable selection: spatial varying or fixed coefficient variable

Because some of the varying coefficient variables may exist in models (4)–(6), examining which variables have coefficients that vary with spatial location is necessary. To solve the problem of variable selection in the mixed geographically weighted regression model, Mei et al. (2016) proposed a bootstrap method for variable selection, which is more robust compared to the F test proposed by

Table 4 LR test results

	Model (4)	Model (5)	Model (6)
SDM or SAR	25.990 (0.000)	22.881 (0.000)	62.224 (0.000)
SDM or SEM	27.264 (0.000)	22.340 (0.000)	69.983 (0.000)

Brunsdon et al. (1999). Therefore, we use this method for testing, and the results are given in Table 5.

As Table 5 shows, the bootstrap tests for some of the explanatory variables in both model (4) and model (6) are insignificant, indicating that they are fixed coefficients, while the other explanatory variables are varying coefficients. Thus, these two models are applied to the mixed geographically weighted panel regression model. The *p*-values corresponding to all explanatory variables in the model (5) are greater than 0.05, which indicates that they are not applicable to the spatially varying coefficient models.

Combining the results of the variable selection in Table 5 and making a comparison with the model arrangement of Eq. (11) in the study by Yu et al. (2021), it can be seen that model (4) in this study is applicable to the MGWPR-SDM(0,kv,kc) model, and model (6) is applicable to the MGWPR-SDM(1,kv,kc) model. For model (5), a general spatial panel regression model can be used because all the explanatory variables are fixed coefficients.

Table 5 Bootstrap test results (*P*-value)

Variables	Model (4)	Model (5)	Model (6)
<i>Intercept</i>	0.458	0.342	0.00
<i>WY</i>	0.753	0.696	0.00
<i>Digi</i>	0.011	0.407	0.00
<i>GDP</i>	0.001	-	-
<i>lnP</i>	0.00	0.198	0.00
<i>lnT</i>	0.008	0.120	0.028
<i>Ener</i>	0.00	-	0.022
<i>FDI</i>	0.251	0.068	0.003
<i>Urban</i>	0.483	0.211	0.00
<i>w_Digi</i>	0.036	0.681	0.006
<i>w_GDP</i>	0.568	-	-
<i>w_lnP</i>	0.562	0.153	0.00
<i>w_lnT</i>	0.501	0.490	0.171
<i>w_Ener</i>	0.80	-	0.113
<i>w_FDI</i>	0.280	0.308	0.001
<i>w_Urban</i>	0.355	0.108	0.00

WY is the spatial lag term of the explained variables of each model, the variable starting with “w_” represents the spatial lag term of the variable, and “-” represents the missing value. Same as the following tables

Fixed coefficient regression results

Because the focus of this study is on the core explanatory variable digital and the mediator variables *Ener* and *GDP*, we will not interpret the remaining control variables. As shown in Table 6, the coefficient of the digital economy development level (*Digi*) in the model (5) is negative and statistically significant at the 1% level, which indicates that the development of digital economy is conducive to reducing energy intensity and that the difference of influence degree in each region is small. The impact of the development level of digital economy (*w_Digi*) in adjacent areas on the energy intensity of the region is negative but not significant. The results of model (4) show that the development level of digital economy (*w_Digi*) in adjacent areas will have a positive spillover on the local CO₂ emission level, which is also not significant.

Varying coefficient regression results

Table 7 shows the varying coefficient results of model (4). The coefficients of the variable *Digi* are all negative, with a maximum value of −0.004 and a minimum value of −0.115, which implies that the direct impact of digital economy development level on carbon emissions is negative in different regions, but the spatial difference is large. The coefficient of variable *GDP* has positive and negative values, indicating that economic development is conducive to directly promoting carbon emissions for some regions but not for others. The coefficients for energy intensity (*Ener*) are also positive and negative but mostly positive, which demonstrates that more CO₂ emissions are produced for most regions as the energy intensity increases.

Table 8 shows the results of the varying coefficients of the mediation model (6). The coefficients of the digital economy development level (*Digi*) are positive and negative but mostly positive. Overall, its impact on economic development is positive but with significant spatial heterogeneity. Energy intensity (*Ener*) has a positive contribution to the economic development level of all regions. The variable *w_Digi* is similar, indicating that the digital economy development in the surrounding areas has a positive spillover effect on the region's economic development.

Mediating effect analysis

To demonstrate the spatial heterogeneity of the digital economy (*Digi*) impact mechanism on carbon emissions (*lnCO₂*) more clearly, we present the mediating and direct effects in maps. The left side of Fig. 5 to Fig. 7 shows the effect values, and the right side shows the *p*-values corresponding to the Sobel (1982) test. The results in Fig. 5 show that the digital

Table 6 Fixed coefficient results

Variables	Model (4)	Model (5)	Model (6)
<i>WY</i>	1.903*** (0.634)	−0.060*** (0.015)	†
<i>Digi</i>	†	−1.409*** (0.456)	†
<i>GDP</i>	†	-	-
<i>lnP</i>	†	0.860*** (0.326)	†
<i>lnT</i>	†	0.021* (0.011)	†
<i>Ener</i>	†	-	†
<i>FDI</i>	0.003 (0.011)	0.041 (0.037)	†
<i>Urban</i>	1.094** (0.468)	−0.280** (0.123)	†
<i>w_Digi</i>	0.166 (0.135)	−0.987 (1.833)	†
<i>w_GDP</i>	0.600 (0.673)	-	-
<i>w_lnP</i>	−3.748 (2.808)	0.252 (0.304)	†
<i>w_lnT</i>	0.346 (0.310)	0.055 (0.076)	0.368 (0.231)
<i>w_Ener</i>	0.688 (0.688)	-	−0.765 (0.508)
<i>w_FDI</i>	0.044 (0.074)	−13.639*** (3.663)	†
<i>w_Urban</i>	8.431* (4.317)	−1.465** (0.634)	†
R ²	0.102	0.170	0.026

“†” indicates varying coefficient variables. “-” represents the missing value. *, **, and *** indicate statistically significant at the 0.1, 0.05, and 0.01 levels, respectively, with standard deviations in parentheses

Table 7 Varying coefficient results of model (4)

Variables	Min	1st Qu	Median	3rd Qu	Max
<i>Digi</i>	−0.115	−0.065	−0.052	−0.043	−0.004
<i>GDP</i>	−1.014	−0.010	0.232	0.714	1.601
<i>lnP</i>	−0.626	−0.506	−0.483	−0.394	−0.008
<i>lnT</i>	−0.062	0.175	0.188	0.205	0.562
<i>Ener</i>	−0.060	0.123	0.145	0.191	0.326

economy (*Digi*) effect on carbon emissions (*lnCO₂*) through pathway 1 is significantly spatially heterogeneous. At the 10% significance level, the pathway is negatively significant in only two provinces, Guangdong and Yunnan, which indicates that the development of digital economy in these two regions effectively suppresses carbon emissions by reducing

Table 8 Varying coefficient results of mediation model (6)

Variables	Min	1st Qu	Median	3rd Qu	Max
<i>WY</i>	0.049	0.093	0.103	0.110	0.134
<i>Digi</i>	-0.116	0.464	0.566	0.732	1.446
<i>lnP</i>	-0.842	-0.532	-0.477	-0.218	0.626
<i>lnT</i>	-0.031	0.001	0.003	0.011	0.034
<i>Ener</i>	0.023	0.125	0.147	0.161	0.192
<i>FDI</i>	0.035	0.183	0.204	0.223	0.278
<i>Urban</i>	-0.152	0.155	0.213	0.269	0.332
<i>w_Digi</i>	4.417	7.406	8.623	10.679	18.156
<i>w_lnP</i>	-0.439	-0.095	-0.011	0.044	0.068
<i>w_FDI</i>	-1.335	5.010	5.676	6.755	8.739
<i>w_Urban</i>	-2.212	-1.494	-1.143	-0.893	-0.550

energy intensity. The positive coefficients for North China and southeast coastal regions suggest that digital economy increases carbon emissions in these regions through pathway 1, but it is not significant at the 10% statistical level. Overall, the effect of China’s digital economy development in curbing carbon emissions by affecting energy intensity, i.e. technical effect, is insignificant.

Figure 6 shows that the effect of digital economy on CO₂ emissions by promoting economic development also has significant spatial heterogeneity. The Liaoning, Shanxi, Fujian, and Inner Mongolia provinces have the largest effect, while the Qinghai, Guangxi, and Jilin provinces have the smallest effect. This effect is significantly positive in most provinces, indicating that digital economy significantly increases carbon emissions by improving economic development. The mediating effect of pathway 2, i.e., income effect, is significantly positive on the whole.

Figure 7 shows the value and significance of the chain mediating effect. The digital economy (*Digi*) affects the level of economic development and thus carbon emissions by improving energy intensity. This mediating effect is negative in most regions and significant at the 10% level. The province of Fujian has the largest effect, followed by North China and Central China.

Analysis of direct and aggregate effects

In addition to the impact of digital economy (*Digi*) on carbon emissions by mediating variables such as energy intensity and economic development level, its own development also has a direct effect on carbon emissions. Figure 8 presents the direct effects and their significance. The results show that the direct inhibitory effect of digital economy development on carbon emissions is larger in the northwest, southwest, and southeast regions, with the largest effects in provinces such as Gansu, Guizhou, and Hunan, while the effects in North and Northeast China are smaller and insignificant. The direct effect values in the Qinghai, Guangxi, and Jiangsu provinces are positive; namely, digital economy development has a positive contribution to carbon emissions. However, the right panel in Fig. 8 shows that it is not significant at the 10% level.

From this analysis, it is clear that all three pathways of the impact of digital economy on CO₂ emissions are spatially heterogeneous and have both positive and negative effects, thereby canceling each other out. Thus, it is necessary to sum up the three mediating effects to examine their total indirect effect sizes. Figure 9 presents the total indirect effect and the total effect size. From the left panel of Fig. 9, it is evident that the total mediating effect

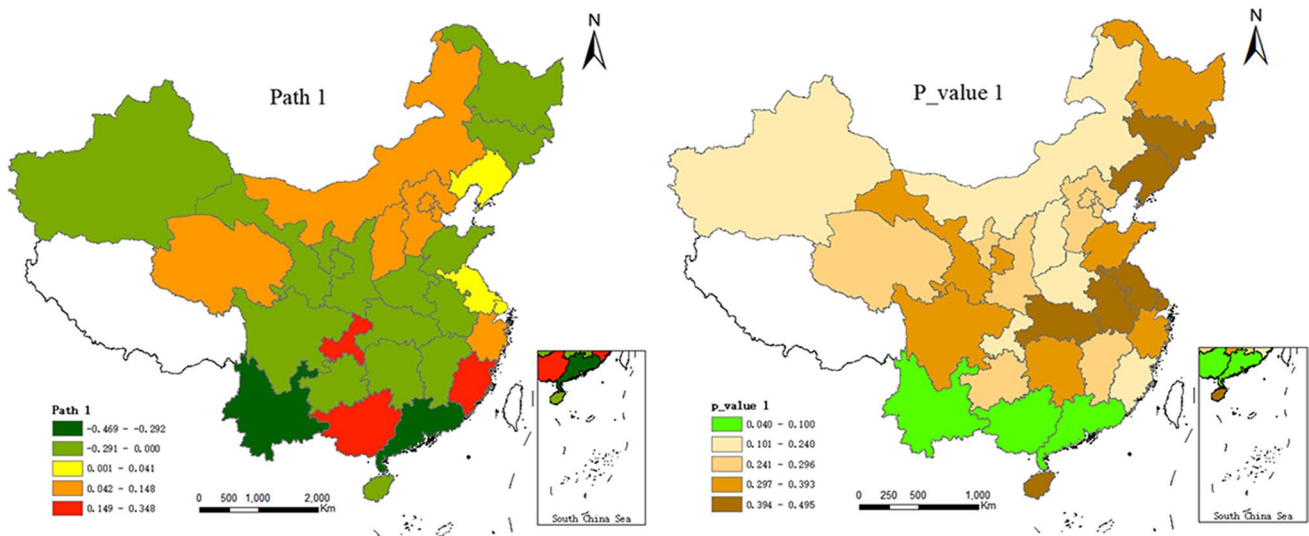


Fig. 5 Mediating effect and statistical significance of path 1

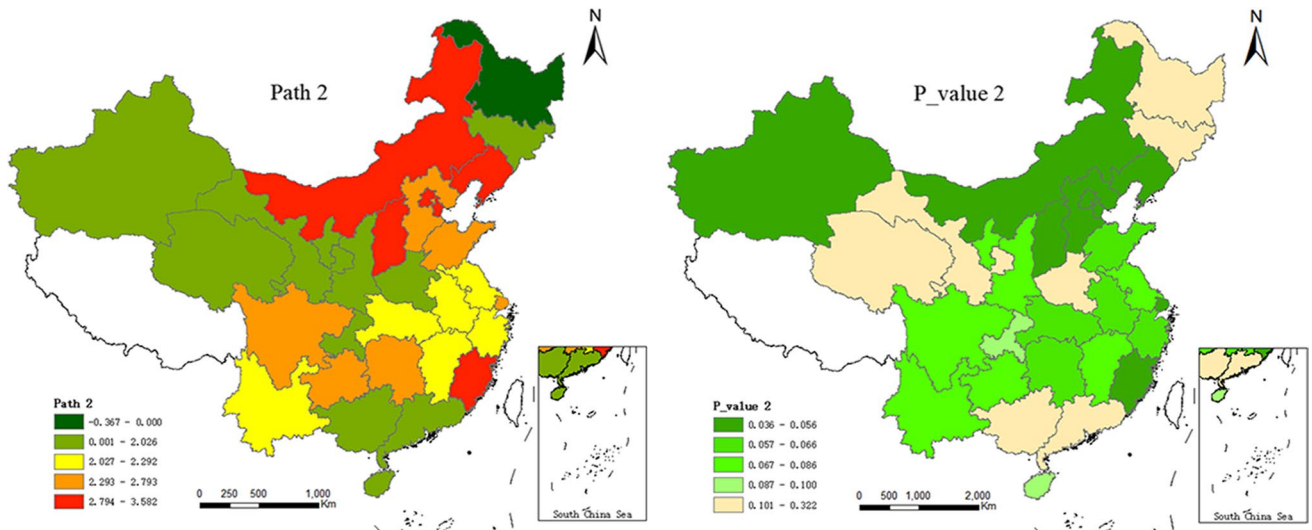


Fig. 6 Mediating effect and statistical significance of path 2

Fig. 7 Chain mediating effect and statistical significance of path 3

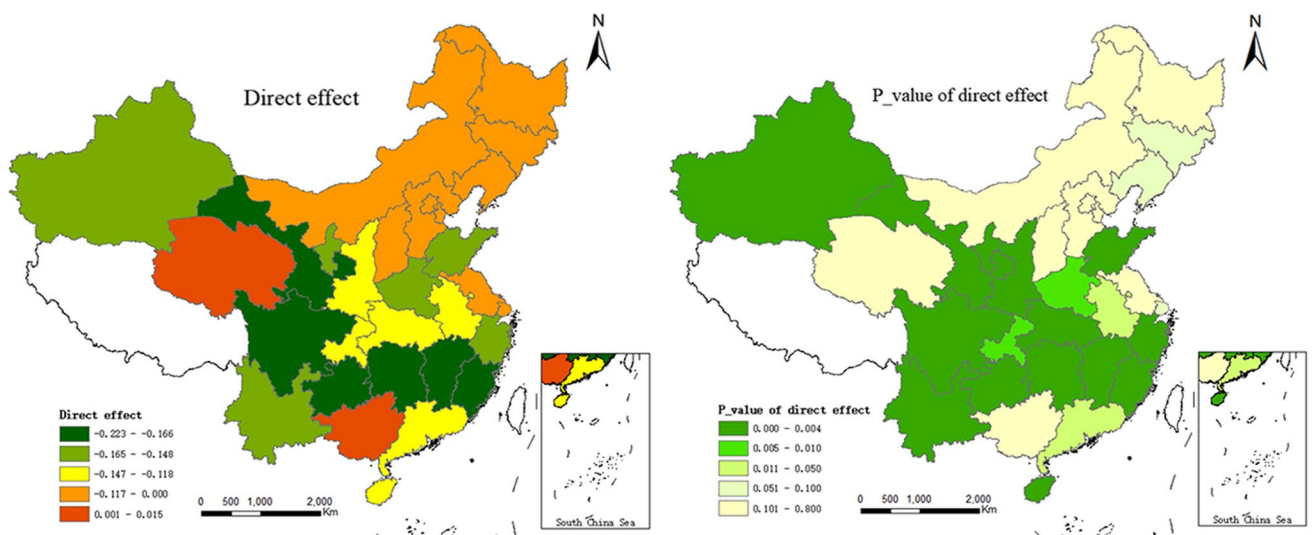
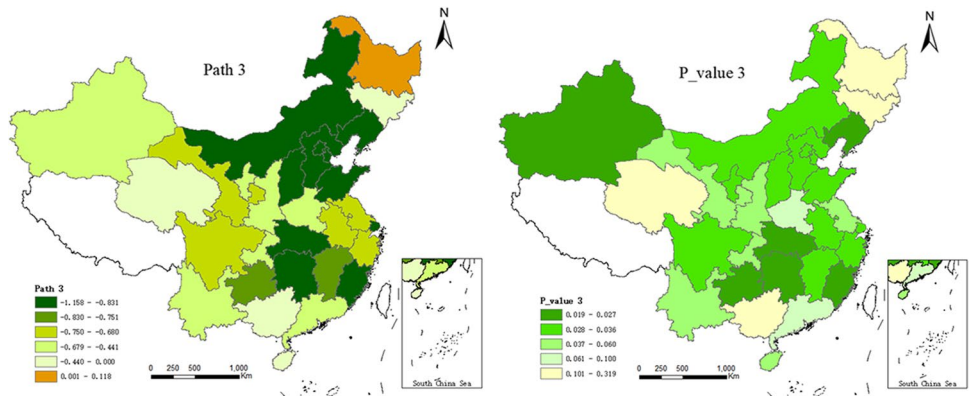


Fig. 8 Direct effect and statistical significance of digital economy on CO₂

of digital economy on CO₂ emissions is positive in most regions. This is because the positive promotion effect of pathway 2 is far larger than the negative inhibition effect of pathway 1 and pathway 3. The total mediating effect is the largest in Liaoning in Northeast China, Fujian in Southeast China, and the entirety of North China, followed by the Yangtze River Delta and Sichuan and Guizhou in Southwest China, while Central and South China are relatively small. The right panel of Fig. 9 shows the spatial distribution of the total mediating effect and the total effect size after adding up the direct effect, and it can be seen that the effect of digital economy development on carbon emissions is positive in most regions of the country, that is, digital economy promotes carbon emissions. In addition, the spatial distribution of the total effect is extremely similar to that of the total indirect effect in the left panel because the total indirect effect is positive and far greater than the direct effect.

Comparison and discussions

Our findings validate the spatial heterogeneity of the impact of digital economy on carbon emissions, which is not only in line with our expectations (H₁) but also consistent with the findings of Zhong et al. (2021) and Xu et al. (2022). The direct impact of digital economy on carbon emissions is significantly negative in the vast majority of regions, which means that digital economy development effectively reduces regional carbon emissions. Digital economy in Northwest, Southwest, and Southeast China has a greater direct inhibitory effect on carbon emissions, while North China and Northeast China have a smaller effect. This is not consistent with the conclusion of Zhong et al. (2021) and Xu

et al. (2022), who found only negative values in the eastern coastal areas. This discrepancy may be because Zhong et al. (2021) did not consider spatial autocorrelation and Xu et al. (2022) only roughly divided 30 provinces into the east, central, and western regions.

Regarding the indirect effect, although digital economy can effectively reduce energy intensity (Table 6), digital economy is not effective in curbing carbon emissions by reducing energy intensity in most regions. The results of Fig. 5 verify hypothesis 2 (H₂). The mediating effect in North China and southeast coastal areas is positive, which indicates that digital economy increases carbon emissions in these areas through pathway 1, but it is not significant at the 10% statistical level. The effect of pathway 1 in most provinces in Central and Northwest China is negative, and it is also not significant at the 10% statistical level. This is probably due to the “rebound effect” generated by improving energy efficiency, which increases the total energy consumption. The solution is to accelerate the development of low-carbon technologies and considerably improve energy consumption efficiency (Siami and Winter 2021), or increase the share of renewable energy use (Godil et al. 2021; Bekun 2022).

The regional heterogeneity results of pathway 2 verify hypothesis 3 (H₃) and show that digital economy increases CO₂ emissions in most regions by promoting economic development (Godil et al. 2021), with larger effects in the provinces in North China, such as Shanxi, Hebei, Beijing, Tianjin, Inner Mongolia, and Liaoning, and smaller effects in the Guangdong, Guangxi, and Hainan provinces in South China (Fig. 6). This is more consistent with the findings of Li and Wei (2021). It may be that North China has a high proportion of industry, relatively high carbon emissions

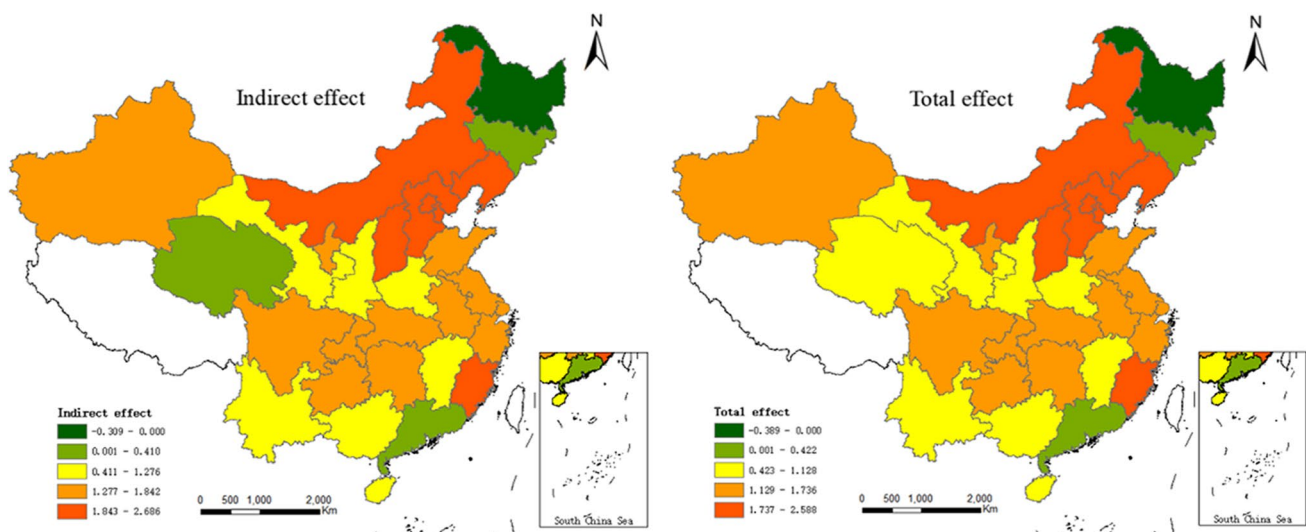


Fig. 9 Total indirect effect and total effect of the digital economy on CO₂

itself, and a comparatively poor ecological environment. Although the Guangxi and Hainan provinces in South China have relatively backward economies, these provinces have a comparatively small proportion of industry with an adequate ecological environment.

The spatial divergence of pathway 3, that is, the chain mediating effect, is also significant (Fig. 7). Unlike pathway 2, the contribution of digital economy to economic development through improved energy intensity in most regions can significantly curb carbon emissions and is significant at the 10% statistical level. This indicates that regional economic development must use low-carbon energy or alternative energy sources to reduce CO₂ emissions (Lu 2017).

The total indirect effect of digital economy on carbon emissions is highly consistent with the total effect (Fig. 9). The positive effect of pathway 2 counteracts the negative effect of the other pathways. Therefore, in general, digital economy boosts CO₂ emissions in most provinces, which is consistent with the findings of Chen et al. (2020), Magazzino et al. (2021), and Liu et al. (2021) but not entirely consistent with Zhong et al. (2021) and Xu et al. (2022).

Conclusion and policy implication

This study intends to investigate the carbon emission impact mechanism and regional heterogeneity of the digital economy. We have constructed a digital economy development indicator system and measured the digital economy development indices of 30 Chinese provinces and cities between 2013 and 2019. The results indicate that the digital economy can influence carbon emissions via three paths, all of which are spatially heterogeneous to a significant degree. Although the expansion of the digital economy in most locations can directly and efficiently reduce carbon emissions, the effects of many indirect channels cancel each other out, resulting in a net positive indirect effect and total effect. By fostering economic expansion, the digital economy has dramatically boosted CO₂ emissions in the majority of regions. This path's impact was significant in five provinces in northern China, but a negligible impact on four provinces in the northwest and three provinces in the south. The digital economy influences economic development by increasing energy intensity, and its effect on carbon emissions is notably negative in the majority of provinces, especially in North China.

In light of the research's empirical findings, we propose the following: (1) given the spatial autocorrelation of carbon emissions, local governments should not formulate carbon policies independently, but instead collaborate

to address the externality problem of carbon emissions. (2) The technical effect is negligible in the majority of provinces (Fig. 5), so the government should encourage the research and development of high-efficiency and low-energy emission reduction technologies, such as hydro-power and solar energy, in order to reduce the nation's reliance on coal consumption over time. (3) Based on Figs. 6 and 8, provinces in the North, Northeast China, and Yangtze River Economic Belt should intensify the construction of digital economy infrastructure, digital industrialization, and industrial digitization; adjust the industrial structure; build a resource-saving and environmentally friendly society; and achieve high-quality economic growth. (4) Local governments should pick FDI in a particular manner, stimulate foreign investment with energy-saving and emission-reducing technologies, and discourage FDI that transfers pollution.

We make a contribution by being the first to directly examine the regional heterogeneity of the mechanism and impact of the digital economy on CO₂ while taking into account both spatial correlation and heterogeneity. In addition, we provide policymakers with a theoretical reference for reducing emissions in accordance with local conditions and reply to disputes in the literature.

This study's shortcoming is that it focuses solely on the heterogeneity of the impact of digital economy development on carbon emissions at the macro-regional level and does not examine specific subsectors. It is vital to perform independent sub-sectoral research on agriculture, service industry, international trade, and other industries because there may actually be sectoral heterogeneity in the influence of the digital economy on carbon emissions. In addition, there is heterogeneity in the production and consumption of carbon emissions (Frodyma et al. 2022), and there is a need to further disaggregate the potential heterogeneous outcomes from various emission types. These are all potential areas for future in-depth research.

Acknowledgements The authors are very grateful to anonymous reviewers for their valuable comments that improved the quality of this paper. This work is supported by the National Social Science Foundation of China (grant number 21BJY054) "Research on the mechanism and policy of digital trade promoting the position of China's global industrial chain."

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, analysis, and first draft of the manuscript were performed by Haijing Yu. Review and editing and supervision were performed by Qin Zhu. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The datasets and materials used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

- Ahmed A, Uddin GS, Sohag K (2016) Biomass energy, technological progress and the environmental Kuznets curve: evidence from selected European countries. *Biomass Bioenerg* 90:202–208
- Avom D, Nkengfack H, Fotio HK, Totouom A (2020) ICT and environmental quality in Sub-Saharan Africa: effects and transmission channels. *Technol Forecast Soc Chang* 155:120028
- Balsalobre D, Shahbaz M, Roubaud D, Farhani S (2018) How economic growth, renewable electricity and natural resources contribute to CO₂ emissions? *Energy Policy* 113:356–367
- Bekun FV, Alola AA, Gyamfi BA, Ampomah AB (2021a) The environmental aspects of conventional and clean energy policy in sub-Saharan Africa: is N-shaped hypothesis valid? *Environ Sci Pollut Res* 28(47):66695–66708
- Bekun FV, Alola AA, Gyamfi BA, Yaw SS (2021b) The relevance of EKC hypothesis in energy intensity real-output trade-off for sustainable environment in EU-27. *Environ Sci Pollut Res* 28(37):51137–51148
- Bekun FV (2022) Mitigating emissions in India: accounting for the role of real income, renewable energy consumption and investment in energy. *Int J Energy Econ Policy* 12(1):188–192
- Brunsdon C, Fotheringham AS, Charlton M (1999) Some notes on parametric significance tests for geographically weighted regression. *J Reg Sci* 39(3):497–524. <https://doi.org/10.1111/0022-4146.00146>
- Chen F, Zhao T, Liao Z (2020) The impact of technology-environmental innovation on CO₂ emissions in China's transportation sector. *Environ Sci Pollut Res* 27:29485–29501
- Destek MA, Ulucak R, Dogan E (2018) Analyzing the environmental Kuznets curve for the EU countries: the role of ecological footprint. *Environ Sci Pollut Res* 25(29):29387–29396
- Dietz T, Rosa EA (1997) Effects of population and affluence on CO₂ emissions. *Proc Natl Acad Sci* 94:175–179. <https://doi.org/10.1073/pnas.94.1.175>
- Frodyma K, Papi ez M,  miech S (2022) Revisiting the Environmental Kuznets Curve in the European Union countries. *Energy* 241:122899
- Godil DI, Sharif A, Agha H, Jermisittiparsert K (2020) The dynamic nonlinear influence of ICT, financial development, and institutional quality on CO₂ emission in Pakistan: new insights from QARDL approach. *Environ Sci Pollut Res* 27:24190–24200. <https://doi.org/10.1007/s11356-020-08619-1>
- Godil DI, Yu Z, Sharif A, Usman R, Khan SAR (2021) Investigate the role of technology innovation and renewable energy in reducing transport sector CO₂ emission in China: A path toward sustainable development. *Sustain Dev* 29(4):694–707
- Guo F, Wang QY, et al (2020) Measuring China's digital financial inclusion: index compilation and spatial characteristics. *China Econ Quarterly* 19(04):1401–1418. <https://doi.org/10.13821/j.cnki.ceq.2020.03.12>
- Ishida H (2015) The effect of ICT development on economic growth and energy consumption in Japan. *Telematics Inform* 32(1):79–88
- Kasman A, Duman YS (2015) CO₂ emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. *Econ Model* 44:97–103
- Khan SAR, Sharif A, Golp ra H, Kumar A (2019) A green ideology in Asian emerging economies: From environmental policy and sustainable development. *Sustain Dev* 27(6):1063–1075
- Khayyat NT, Lee J, Heo E (2016) How ICT investment influences energy demand in South Korea and Japan. *Energy Effi* 9(2):563–589
- Khuntia J, Saldanha TJ, Mithas S, Sambamurthy V (2018) Information technology and sustainability: evidence from an emerging economy. *Prod Oper Manag* 27(4):756–773
- Li M, Du W (2021) Can Internet development improve the energy efficiency of firms: Empirical evidence from China. *Energy* 237:121590
- Li G, Wei W (2021) Financial development, openness, innovation, carbon emissions, and economic growth in China. *Energy Econ* 97:105194
- Li Z, Liu Y (2021) Research on the spatial distribution pattern and influencing factors of digital economy development in China. *IEEE Access* 9:63094–63106
- Lin B, Zhou Y (2021) Does the Internet development affect energy and carbon emission performance? *Sustain Prod Consum* 28:1–10
- Liu X, Latif Z, Latif S, Mahmood N (2021) The corruption-emissions nexus: do information and communication technologies make a difference? *Utilities Policy* 72:101244
- Liu Y, Zhou Y, Wu W (2015) Assessing the impact of population, income and technology on energy consumption and industrial pollutant emissions in China. *Appl Energy* 155:904–917
- Longo SB, York R (2015) How does information communication technology affect energy use? *Hum Ecol Rev* 22(1):55–72
- Lu WC (2017) Greenhouse gas emissions, energy consumption and economic growth: a panel cointegration analysis for 16 Asian countries. *Int J Environ Res Public Health* 14(11):1436
- Lu WC (2018) The impacts of information and communication technology, energy consumption, financial development, and economic growth on carbon dioxide emissions in 12 Asian countries. *Mitig Adapt Strat Glob Change* 23(8):1351–1365
- Madaleno M, Moutinho V (2021) Analysis of the new kuznets relationship: considering emissions of carbon, methanol and nitrous oxide greenhouse gases—evidence from EU countries. *Int J Environ Res Public Health* 18(6):2907
- Magazzino C, Mele M, Morelli G, Schneider N (2021) The nexus between information technology and environmental pollution: application of a new machine learning algorithm to OECD countries. *Utilities Policy* 72:101256
- Mei CL, Xu M, Wang N (2016) A bootstrap test for constant coefficients in geographically weighted regression models. *Int J Geogr Inf Sci* 30(8):1622–1643
- Raheem ID, Tiwari AK, Balsalobre-Lorente D (2020) The role of ICT and financial development in CO₂ emissions and economic growth. *Environ Sci Pollut Res* 27(2):1912–1922
- Ren S, Hao Y, Xu L, Wu H, Ba N (2021) Digitalization and energy: how does internet development affect China's energy consumption? *Energy Econ* 98:105220
- Sadorsky P (2012) Information communication technology and electricity consumption in emerging economies. *Energy Policy* 48:130–136
- Sahoo M, Gupta M, Srivastava P (2021) Does information and communication technology and financial development lead to environmental sustainability in India? *Empirical Insight Telemat Inform* 60:101598

- Salahuddin M, Alam K (2015) Internet usage, electricity consumption and economic growth in Australia: a time series evidence. *Tele-matics Inform* 32(4):862–878
- Saqib M, Benhmad F (2021) Updated meta-analysis of environmental Kuznets curve: Where do we stand? *Environ Impact Assess Rev* 86:106503
- Shahbaz M, Balsalobre-Lorente D, Sinha A (2019) Foreign direct investment–CO₂ emissions nexus in Middle East and North African countries: importance of biomass energy consumption. *J Clean Prod* 217:603–614
- Shahbaz M, Sinha A (2019) Environmental Kuznets curve for CO₂ emissions: a literature survey. *J Econ Stud* 46(1):106–168
- Shahnazi R, DehghanShabani Z (2019) The effects of spatial spillover information and communications technology on carbon dioxide emissions in Iran. *Environ Sci Pollut Res* 26(23):24198–24212
- Shan Y, Huang Q, Guan D, Hubacek K (2020) China CO₂ emission accounts 2016–2017. *Scientific Data* 7(1):1–9
- Sharif A, Jammazi R, Raza SA, Shahzad SJH (2017a) Electricity and growth nexus dynamics in Singapore: Fresh insights based on wavelet approach. *Energy Policy* 110:686–692
- Sharif A, Saha S, Loganathan N (2017b) Does tourism sustain economic growth? Wavelet-based evidence from the United States. *Tour Anal* 22(4):467–482
- Sharif A, Raza SA, Ozturk I, Afshan S (2019) The dynamic relationship of renewable and nonrenewable energy consumption with carbon emission: a global study with the application of heterogeneous panel estimations. *Renew Energy* 133:685–691
- Sharif A, Baris-Tuzemen O, Uzuner G, Ozturk I, Sinha A (2020a) Revisiting the role of renewable and non-renewable energy consumption on Turkey's ecological footprint: Evidence from Quantile ARDL approach. *Sustain Cities Soc* 57:102138
- Sharif A, Afshan S, Chrea S, Amel A, Khan SAR (2020b) The role of tourism, transportation and globalization in testing environmental Kuznets curve in Malaysia: new insights from quantile ARDL approach. *Environ Sci Pollut Res* 27(20):25494–25509
- Siami N, Winter RA (2021) Jevons' paradox revisited: implications for climate change. *Econ Lett* 206:109955
- Sobel ME (1982) Asymptotic confidence intervals for indirect effects in structural equation models. *Sociol Methodol* 13:290–312
- Solarin SA, Bello MO, Bekun FV (2021a) Sustainable electricity generation: the possibility of substituting fossil fuels for hydropower and solar energy in Italy. *Int J Sust Dev World* 28(5):429–439
- Solarin SA, Nathaniel SP, Bekun FV, Okunola AM, Alhassan A (2021b) Towards achieving environmental sustainability: environmental quality versus economic growth in a developing economy on ecological footprint via dynamic simulations of ARDL. *Environ Sci Pollut Res* 28(14):17942–17959
- Song M, Wu J, Song M, Zhang L, Zhu Y (2020) Spatiotemporal regularity and spillover effects of carbon emission intensity in China's Bohai Economic Rim. *Sci Total Environ* 740:140184
- Sterpu M, Soava G, Mehedintu A (2018) Impact of economic growth and energy consumption on greenhouse gas emissions: Testing environmental curves hypotheses on EU countries. *Sustainability* 10(9):3327
- Suki NM, Sharif A, Afshan S, Suki NM (2020) Revisiting the Environmental Kuznets Curve in Malaysia: the role of globalization in sustainable environment. *J Clean Prod* 264:121669
- Takase K, Murota Y (2004) The impact of IT investment on energy: Japan and US comparison in 2010. *Energy Policy* 32(11):1291–1301
- UdaraWillhelmAbeydeera LH, WaduMesthrige J, Samarasinghalage TI (2019) Global research on carbon emissions: a scientometric review. *Sustainability* 11(14):3972
- Ulucak R, Danish KSUD (2020) Does information and communication technology affect CO₂ mitigation under the pathway of sustainable development during the mode of globalization? *Sustain Dev* 28:857–867. <https://doi.org/10.1002/sd.2041>
- Usman A, Ozturk I, Ullah S, Hassan A (2021) Does ICT have symmetric or asymmetric effects on CO₂ emissions? Evidence from selected Asian economies. *Technol Soc* 67:101692
- VanderWeele T, Vansteelandt S (2014) Mediation analysis with multiple mediators. *Epidemiol Methods* 2(1):95–115
- Wu H, Xue Y, Hao Y, Ren S (2021) How does internet development affect energy-saving and emission reduction? Evidence China *Energy Econ* 103:105577
- Wu D, Wang Y, Qian W (2020) Efficiency evaluation and dynamic evolution of China's regional green economy: A method based on the Super-PEBM model and DEA window analysis. *J Clean Prod* 264:121630
- Xu WX, Zhou JP, Liu CJ (2022) The impact of digital economy on urban carbon emissions: based on the analysis of spatial effects. *Geogr Res* 41(01):111–129 ((In Chinese))
- Yang HM, Jiang L (2021) Digital economy, spatial effect and total factor productivity. *Stat Res* 38(04):3–15. <https://doi.org/10.19343/j.cnki.11-1302/c.2021.04.001> ((In Chinese))
- York R (2007) Demographic trends and energy consumption in European Union Nations, 1960–2025. *Soc Sci Res* 36(3):855–872
- Yu H, Devece C, Martinez JMG, Xu B (2021) An analysis of the paradox in R&D Insight from a new spatial heterogeneity model. *Technol Forecast Soc Change* 165:120471
- Zhang W, You J, Lin W (2021) Internet plus and China industrial system's low-carbon development. *Renew Sustain Energy Rev* 151:111499
- Zhao S, Hafeez M, Faisal C M N (2021) Does ICT diffusion lead to energy efficiency and environmental sustainability in emerging Asian economies? *Environ Sci Pollut Res*: 1–10
- Zhong S, Xin C, Shen, H., Chen, X (2021) Effects of land urbanization and internet penetration on environmental sustainability: a cross-regional study of China. *Environ Sci Pollut Res*: 1–21
- Zhou Y, Zhang J, Hu S (2021) Regression analysis and driving force model building of CO₂ emissions in China. *Sci Rep* 11(1):1–14

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.