frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 30 November 2023
DOI 10.3389/fenvs.2023.1287811

OPEN ACCESS

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RECEIVED 02 September 2023
ACCEPTED 13 November 2023
PUBLISHED 30 November 2023

CITATION
Liu C, Wang W, Ding C, Teng X, Ye Y and Zhang Z (2023), The bilateral effects of digital economy on regional carbon emissions in China.
Front. Environ. Sci. 11:1287811.
doi: 10.3389/fenvs.2023.1287811

The bilateral effects of digital economy on regional carbon emissions in China

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The impacts of the digital economy on regional carbon emissions have attracted much concerns from all regions of China. Using panel data for 30 Chinese provinces and cities from 2011 to 2020, the study empirically examined the bilateral effects of the digital economy on regional carbon emissions (RCBs) and the heterogeneous characteristics under different conditions by various econometric models. The results indicate that, the inhibition effect of digital economy development on regional carbon emissions is stronger than the promotion effect, which is 13.38% lower and 12.11% higher than the frontier level respectively. When both effects are combined, it makes regional carbon emissions 1.27% below the frontier boundary. In addition, the inhibition effect of the digital economy on carbon emissions (DECEs) predominant and presents a declining trend during the study period. And the inhibition effect of the digital economy on carbon emissions in the eastern region is highest among all the regions. Moreover, the level of different factors such as digital economy, human capital and economic development, can effectively strengthen the inhibition effect of digital economy on regional carbon emissions. This work will be conducive to fully leveraging the important role of the digital economy in regional environmental governance in China, and promote the achievement of China's carbon peaking and carbon neutrality goals.

KEYWORDS

digital economy, carbon emissions, promotion effect, inhibition effect, heterogeneous characteristics

1 Introduction

There exists a key factor, global warming which affects sustainable development of regions (Xu et al., 2022). Recently, extreme phenomena such as glacier melting all over the world, sea level rising, alongside drought and flood polarization due to the continuous increase of CO_2-based greenhouse gases have occurred frequently (Miao et al., 2022), which have caused serious influences upon agricultural production, human life, and social and economic activities, additionally, hamper the sustainable development all over the world. Under such circumstances, the ways to promote low-carbon development have been an important issue around the world (Zhang and Feng, 2021). And Chinese government has already taken the lead in undertaking the responsibility of carbon emission reduction (CER) and made its emission reduction commitment at the United Nations General Assembly, putting forward strategic targets of striving for carbon peak by 2030 as well as carbon neutrality by 2060, which has intensified the stress of carbon emission reduction to an unprecedented level in China. However, the extensive development mode of China for the long-term is characterized by factor-driven pattern, as well as industrialization and urbanization, which has caused severe problems with environment pollution and energy consumption these years (Shi et al., 2018). In the light of the World Energy Statistics Yearbook 2021 statistics, carbon emissions in China varied between 8.83 billion tons and 9.90 billion tons from 2011 to 2020, denoting that China will confront the long-run stress for CER (Miao et al., 2019). Reducing regional carbon emissions (RCBs) has already been a vital problem with widespread concern within various regions of China. Several researches have conducted to promote the low-carbon development of regions. The determinants such as low-carbon technology (Wen et al., 2022), local government environment (Li and Wen, 2023), energy efficiency (Li et al., 2022), and economic development (Sadik-Zada and Ferrari, 2020; Zhang and Liang, 2022), are usually considered as effective ways to reduce carbon emissions. Nowadays, the digital economy, showing its unique features of high penetration, high added value and relatively lower cost, has been regarded as an effective way to cope with the dramatic changes in this new era of China (Zhang et al., 2021). For another, that economy is capable of bringing profound changes in the way of management and production, thus giving birth to new business models and industries. And with the environment-friendly features of digital economy itself, it is able to impede the progress space of elevated-energy and elevated-emission domains by crowding out effect, and improve the urban industry development (Yang et al., 2020), providing new opportunities and impetus for CER (Xu et al., 2022). On the flip side, the digital economy has gradually unleashed its important role in environmental governance. The informal environmental regulation effect generated by it can promote urban air quality improvement, and instruct the public to establish a green concept, a favorable atmosphere for the whole society to collaborate in environmental management would be thus created. According to the data released in the White Paper on the Development of China's Digital Economy (2022), input of China`s digital economy continued to rise, from 9.5 trillion RMB in 2011 to 45.5 trillion RMBB in 2021. Besides, its proportion to GDP had also increased, with a ratio of 39.8% in 2021 and a growth rate of 16.2%, which significantly exceeds the nominal growth rate of GDP during the identical period. Furthermore, the rapid development attracted continuous attention from all sectors of society. Since carbon peaking and carbon neutrality were proposed, CER has captivated extensive concerns in various regions of China. So, is the digital economy capable of efficiently lessening carbon emissions in regions?

Presently, researchers have implemented numerous useful discussions on the relation between the digital economy and carbon emissions. In general, it contains three types of views as follows. To begin with, the digital economy or digital elements are capable of increasing carbon emissions. The speedy progression of ICTs (the information and communication technology) and industries have triggered the elevated demand for intermediate production inputs such as electricity and carbon-intensive materials, leading to rapid growth in power consumption (Salahuddin and Alam, 2015) and generating painfully much carbon emissions (Erdmann and Hilty, 2010; Wissner, 2011; Hamdi et al., 2014; Yi et al., 2022). A few researchers have claimed that the digital economy is able to reinforce carbon emissions (Park et al., 2018; Raheem et al., 2020). What`s more, apart from digital upgrading and application, establishment of data centers will accelerate to extract resources and consume energies, therefore carbon emissions could be triggered (Miao et al., 2022). Ultimately, it has also been proposed that digital development does not conduce to energy effectiveness enhancements, carbon emissions will thus be exacerbated (Zhang et al., 2022a).

Also, the digital economy or digital elements could implement CER. Several researches have uncovered that the technology of information, as a nuclear part of the above-described economy, is capable of enhancing the environment quality through lessening greenhouse gas emissions through communication technology penetration (Ulucak et al., 2020; Bhujabal et al., 2021). Some researchers have also confirmed that the use and the spread of Internet (Haseeb et al., 2019) is able to prominently implement CER in the long term (Shobande, 2021). Meanwhile, it has also been found that the above-described economy is able to lessen carbonous emissions (Wang et al., 2022a; Dong et al., 2022; Hao et al., 2022), which can be achieved via technological advancement (Wang and Guo, 2022; Xie, 2022), energy consumption structure (Yang et al., 2020), energy utilization efficiency (Cai et al., 2019; Nibedita and Irfan 2021), upgrading of industrial structure (Ge et al., 2022), resource allocation efficiency (Zhang et al., 2021), industry progress, alongside energy depletion (Hao et al., 2022).

Next, the impacts of that economy or digital elements on carbon emissions are non-linear. A few researchers contend that there exists an inverted U-shaped correlation between RCEs and ICT, as well as the correlation between RCEs and digital economy (Salahuddin et al., 2016; Li and Wang, 2022). Similarly, the study by Miao et al. (2022) verifies that there exists nonlinear relationship of inverted U-shaped between RCEs and digital economy, while Ge et al. (2022) further claimed that industrial construct transformation and upgrading are capable of boosting the early formation of the inverted U-shaped correlation between RCEs and digital economy.

In the view of existing studies, researchers have implemented much beneficial detection on influences of the above-mentioned economy upon RCEs, but the conclusions have not reached an agreement yet. Moreover, most literature only focus on the unilateral impact system of DECEs, ignoring composite features of the influences of that economy upon society and economy (Chen, 2020; Zhao et al., 2020), and fails in completely discussing the distinctions of the impacts of DECEs in disparate conditions. Accordingly, a bilateral theoretical analysis framework of digital economy concerning Chinese RCEs was established in this article, and used various econometric models to assess and analyze the impacts and evolution characteristics of the above-described economy on RCEs. The main functions of the article are listed below. Firstly, proposition about the bilateral influences of DECEs is presented based upon dual attributes of the digital economy, which theoretically expands the research perspective of carbonous emissions. Secondly, on the grounds of the two-tier random frontier pattern, composite outcomes contributed by the digital economy are gauged specifically, and the space and time distribution features of bilateral effects of DECEs are also fully analyzed, which provides empirical evidence for understanding the internal correlation between carbonous emissions and digital economy. Subsequently, apart from the heterogeneous impacts of the above-described economy upon the net effect of carbonous emissions under different conditions of human resources capital, economic advancement levels are explored in depth, which could help to enhance the practical significance of this research.

The other parts of this paper is organized listed: theoretical models and mechanism of the relationship between digital economy and RCEs are illustrated in "Theoretical models and mechanism analysis" section; the variables, approaches, alongside data sources adopted in this article are introduced in "Materials and methods" section; the empirical consequences are depicted in "Empirical Analysis" section, as well as the relevant analysis; the conclusions are summed up and the policy recommendations of this research are brought forward in "Conclusions and policy implications" section.

2 Theoretical models and mechanism analysis

2.1 Theoretical models

With a view to detecting the influences of the DECEs at the level of the theory, the research attempts to set up one theoretical model with the objective to analyzing it. Drawing on the study of Li and Wang (2022), the primary model is built as follows, which contains one production function.

$$Q = A(L)N^{\alpha}E^{\beta}K^{1-\alpha-\beta} \tag{1}$$

In Eq. 1, Q represents economic output, E, N, and K represent energy, labor, and capital inputs. A represents the level of technology, and L represents economic growth driven by the digital economy. α ($0 < \alpha < 1$) and β ($0 < \beta < 1$) represent the contribution of labor and energy inputs to output, respectively.

$$L = \theta_L F \tag{2}$$

In Eq. 2, F is the digital economy and θ_L denotes the marginal economic effects of the digital economy. In addition, assuming that the energy use, technological progress and carbon emissions are mainly affected by the digital economy, thus A(L) can be further expressed by the following formula.

$$A(L) = A_0 + \theta_A L \tag{3}$$

In Eq. 3, A_0 is the initial technology level and θ_A indicates the trend of technological progress caused by the development of digital economy. On this basis, Eq. 1 can be adjusted as follows.

$$Q = (A_0 + \theta_A L)N^{\alpha}E^{\beta}K^{1-\alpha-\beta} \tag{4}$$

Drawing on the study of Sheng (2017), the expression of the carbon emission function can be presented.

$$W = ZQ = (Z_0 + \theta_Z L)Q \tag{5}$$

In Eq. 5, W is the total carbon emission, Z denotes the carbon emission of the marginal output affected by the digital economy; Z_0 is the initial carbon emission, θ_Z represents the change of marginal carbon emission caused by the digital economy.

What's more, in an ideal competitive market circumstance, p is considered to be the product price, b refers to the variable cost. The fixed cost and carbon abatement cost are represented by C_0 and $C_{W0} - \theta_W W$, respectively, where C_{W0} means the initial abatement cost, θ_W refers to the marginal cost trend on account of the digital economy. Thereby, the profit function is capable of being expressed by the following equation.

$$\pi = (p - b)Q - C_0 - C_{W0} - \theta_W W \tag{6}$$

On the basis of the above equation, as for the parameter L, its first-order derivative is found, and the optimal output level as well as carbon emissions are obtained under the condition of profit maximization, which is calculated by the following equation.

$$W_{Q_{max}} = ZQ_{max} = \frac{Z\left[(p - b - \theta_W Z)(A_0 + \theta_A L)\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}\right]}{\theta_W \theta_Z} \tag{7}$$

In Eq. 7, Q_{max} is the optimal output level, and $W_{Q_{max}}$ denotes the carbonous emission at the optimal level of output. Additionally, that carbon emission W refers to the relation function concerning the parameter L reflecting the relation between digital economy and carbonous emission, while L refers to accurately the relation function of digital economy F. Then the marginal DECEs outcome can be obtained via further calculation of first-order derivative and second-order derivatives of the digital economy F. And it can be expressed as Eq. 8 and Eq. 9.

$$\frac{dW_{Q_{max}}}{dF} = \frac{(p - b - 2\theta_W Z)(A_0 + \theta_A L)\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}}{\theta_W \theta_Z} \tag{8}$$

$$\frac{d^2W_{Q_{max}}}{d^2F} = -2\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}\theta_L(A_0 + \theta_A L) \tag{9}$$

According to the Eq. 8 and Eq. 9, we can further obtain the best level F_0 of digital economy restricted by carbon emission targets as below.

$$F_0 = \frac{\frac{(p-b)}{2\theta_W} - Z_0}{\theta_L \theta_Z} \tag{10}$$

The total carbon emissions can reach the maximum value F_0 when $d^2W_{Q_{max}}/d^2F < 0$. And the digital economy is going to facilitate carbon emissions while $F < F_0$. Nevertheless, the digital economy will inhibit carbonous emissions while $F > F_0$. In addition, Eq. 9 is capable of being converted to another different form as follows.

$$dW = (A_0 + \theta_A L) \times \left[\frac{(p - b)\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}}{\theta_W \theta_Z} dF - \frac{2\theta_W Z\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}}{\theta_W \theta_Z} dF\right] \tag{11}$$

In Eq. 11, $\theta_A dF$ can be expressed as the technological progress due to the digital economy. $(p - b)\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}$ indicates that technological progress leads to an increase in fiscal revenue, so as to further increase the carbon emissions. $2\theta_W Z\theta_A N^{\alpha}E^{\beta}K^{1-\alpha-\beta}$ represents the cost of carbon emission reduction (CER) resulting from the growth of output, which will also contribute to the CER. In summary, whether the effect of the DECEs is promotion or inhibition one, rely upon the integration of elevated benefit incentive effect and elevated-cost constraint effect.

2.2 The inhibition effect of digital economy on carbon emissions

Showing unique characteristics, the digital economy is capable of playing its inhibitory part in carbon emissions through the following ways. Firstly, the above-mentioned economy is capable of boosting the upgrading of conventional industries through technology penetration and industrial convergence (Wang et al., 2022b; Li and Wang, 2022; Xue et al., 2022). For another, digital technology is able to assist in enhancing the carbon trading marketplace and boosting the carbon emission rights transferring among enterprises with different levels of energy use efficiency, and facilitate energy saving and emission decrease of corporations (Liu et al., 2015; He and Song, 2022). In addition, platforms of digital network could boost interdisciplinary resource sharing via scale and competition, achieve deep integration of industries, and upgrade conventional industrial production, value chains, alongside supply chains. Accordingly, aside from energy structure, the operational efficiency of industry organizations is capable of being enhanced during this process, which will also issue in CER (Moyer and Hughes, 2012; Zhou et al., 2020; Zhang et al., 2022b). Secondly, digital economy is capable of bringing various changes in technological innovation, which can affect carbon emission efficiency. For example, the above-mentioned economy has helped regions to overcome the inherent deficiency of uneven distribution of traditional innovation resource endowments, and improve overall innovation level and energy utilization efficiency (Kloppenburg and Boekelo, 2019; Chen et al., 2021). Meanwhile, that economy breaks the administration obstacles of geography and promotes the spillover of technological renovation, bring the enhancement of innovation levels and the CER in different regions (Pan et al., 2022). What's more, the digital economy could be conduce to flows of talent and technology as well, thus accelerating the spillover effects of green technologies and regional low-carbon transition (Markandya et al., 2016; Schultes et al., 2018; van den Buuse and Kolk, 2019). Thirdly, the digital economy increases effective information based on the network effect, which can improve the price mechanism, realize supply matching, change the transaction and circulation activities, and thereby enhance resource allocation efficiency (Carlsson, 2004; Pan et al., 2022). Meanwhile, enterprise producers can optimize their production processes based on digital technologies, optimize the resource allocation, alongside energy construct, and enhance resource use efficiency. Thereby carbon emissions can be reduced (Wang et al., 2022c). What`s more, digital finance is also capable of lessening the corporate financing constraints and alleviate resource mismatch, thus regional total factor productivity and energy use efficiency can be promoted (Wang et al., 2022d; Wang and Guo, 2022). Based on these theoretical mechanisms, this hypothesis is capable of being put forward as below.

Hypothesis 1. The digital economy can significantly inhibit the RCE.

2.3 The promotion effect of digital economy on carbon emissions

The above-mentioned economy also has a certain "green blindness," which brings negative externalization on the circumstance and consequences in carbon emission increasing (CEI). Firstly, digital technological advancement is going to induce corporations with the intention of reseting production equipment capacity, expand production scale, and increase production by expanding the resource exploitation and energy consumption, conducing to the CEI (Li et al., 2021; Zhang et al., 2022a; Li and Wang, 2022). In particular, that technology has been widely used in mining industries which can lead to an increasing scale of rare metals and minerals, bringing about resource overconsumption as well as negative environmental problems (Miao et al., 2022). Secondly, advancement and usage of green technologies, alongside the environmental protection effects are usually in need of a time lag or a relatively long cycle. Therefore, non-green technology progression showing far more economic growth effects is frequently more appropriate, which will intensify carbonous emissions at last. Thirdly, the above-described economy is facilitated with software and information technology services, alongside telecommunications, and is a high power-intensive form of economy. In addition, there is an elevated percentage of coal-based electricity in our country. As a result, as to the related industries, their electricity consumption will bring more coal consumption and carbonous emissions (Wang et al., 2022a). Based upon the theoretical mechanisms, the hypothesis is capable of being presented as below.

Hypothesis 2. The digital economy can significantly promote the regional carbon emission.

According to the above-mentioned analysis, the analysis on system for the impacts of DECEs is depicted in Figure 1.

3 Methodology and data

3.1 Model settings

With a view to addressing composite impacts of DECEs and accurately analyzing the system of interaction between digital economy and RCEs, a two-tier stochastic frontier model is constructed referring to researches of Kumbhakar and Parmeter. (2009), Papadopoulos (2021) and Hu and Pei (2020).

$$\ln Co2_{it} = i(x_{it}) + \omega_{it} - u_{it} + \varepsilon_{it} = i(x_{it}) + \xi_{it} = x_{it}\delta + \xi_{it} \qquad (12)$$

where $\ln Co2_{it}$ is carbon emissions; x_{it} is control variables which contributes to the carbon emissions, such as population density, government fiscal expenditure, industrialization, environmental regulation, etc.; δ is a vector of parameters to be evaluated; $i(x_{it})$ denotes the frontier level of carbon emissions, ξ_{it} is the composite residual disturbance term. And $\xi_{it} = \omega_{it} - u_{it} + \varepsilon_{it}$,where, ε_{it} stands for the stochastic error, showing the deviation according to the optimal level due to uncontrolled elements. Since the conditional expectation of the composite residual term ε_{it} is not always equal to 0, the OLS estimation results may be biased. When it happens, we

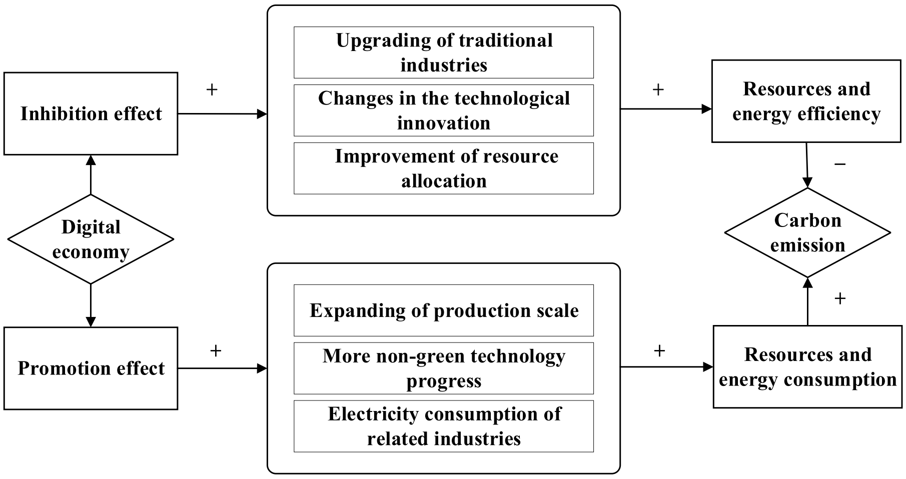

FIGURE 1
The mechanism analysis for the impacts of digital economy on carbon emissions.

can use the MLE method to bring valid results. Therefore, based on the estimation of the Maximum Likelihood Estimation (MLE), ω_{it} and u_{it} can be decomposed by Eq. 12 respectively, to reflect bias effects in the best case. The related effects of the DECEs are depicted in Eq. 12. In that equation, it indicates the promotion effect exists when $\omega_{it} \geqslant 0$; while the inhibition effect exists when $u_{it} \leqslant 0$. When $u_{it} \leqslant 0$, $\omega_{it} = 0$ or $\omega_{it} \geqslant 0$, $u_{it} = 0$, it indicates that it is a one-sided random frontier model, and there is only a one-sided effect. In addition, when $\omega_{it} = u_{it} = 0$, it indicates that it is an OLS model. If neither of u_{it} and ω_{it} is 0, it indicates the bilateral effects occur. Since ξ_{it} may not be zero, the biased OLS model estimation will be taken then.

According to Eq. 12, the actual carbon emissions are affected by positive and negative effects upon account of the digital economy. Specifically, the promotion effect makes carbon emissions exceed the frontier level, whereas the inhibition effect enables carbon emissions to be under the frontier level. And the deviation of actual carbon emissions is measured by calculating the net effect of their combined effects. Furthermore, considering the biased results obtained from OLS estimation, the use of MLE can be used to obtain valid estimation results. Therefore, the assumptions about the residual distribution can be set as follows. ε_{it} should follow the normal distribution, and the its mean value the variance is zero and σ_ε^2. Besides, u_{it} should follow the exponential distributions, which is, $\omega_{it} \sim iddEXP(\sigma_\omega, \sigma_\omega^2)$, $u_{it} \sim iddNEXP(\sigma_u, \sigma_u^2)$.

In addition, the error terms need to be independent with one another, and are also uncorrelated with inter-provincial variables. On the grounds of the above-described hypotheses, the probability density calculation of ξ_{it} is further derived.

$$f(\xi_{it}) = \frac{\exp(\alpha_{it})}{\sigma_u + \sigma_\omega}\Phi(\gamma_{it}) + \frac{\exp(\beta_{it})}{\sigma_u + \sigma_\omega}\int_{-\eta_{it}}^{\infty}\varphi(x)dx = \frac{\exp(\alpha_{it})}{\sigma_u + \sigma_\omega}\Phi(\gamma_{it}) + \frac{\exp(\beta_{it})}{\sigma_u + \sigma_\omega}\varphi(\eta_{it}) \tag{13}$$

In this equation, $\Phi(\cdot)$ is the standard normal distribution based on the cumulative distribution function (CDF);, while $\varphi(\cdot)$ is the standard normal distribution based on the Probability Density Function (PDF). And the other parameters are set as follows.

$$\alpha_{it} = \frac{\sigma_v^2}{2\sigma_\omega^2} + \frac{\xi_i}{\sigma_\omega};\quad \beta_{it} = \frac{\sigma_v^2}{2\sigma_u^2} - \frac{\xi_i}{\sigma_u}$$
$$\gamma_{it} = -\frac{\xi_{it}}{\sigma_v} - \frac{\sigma_v}{\sigma_u};\quad \eta_{it} = \frac{\xi_{it}}{\sigma_v} - \frac{\sigma_v}{\sigma_\omega} \tag{14}$$

On the basis of the parameter estimation of Eq. 14, the expression of MLE is constructed below.

$$\ln L(X;\pi) = -n\ln(\sigma_\omega + \sigma_u) + \sum_{i=1}^{n}\ln\left[e^{\alpha_{it}}\Phi(\gamma_{it}) + e^{\beta_{it}}\Phi(\eta_{it})\right] \tag{15}$$

wherein, $\pi = [\beta, \sigma_v, \sigma_\omega, \sigma_u]$, and all parameter values are obtained through further maximizing the likelihood function (Eq. 15). Besides, to estimate ωit and u_{it}, the conditional density function for the both can be further derived.

$$f(\omega_{it} \mid \xi_{it}) = \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\exp\left[-\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\omega_{it}\right]\Phi\left(\frac{\omega_{it}}{\sigma v} + \eta_{it}\right)}{\exp(\beta_{it} - \alpha_i)\left[\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})\right]} \tag{16}$$

$$f(u_{it} \mid \xi_{it}) = \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\exp\left[-\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)u_{it}\right]\Phi\left(\frac{u_{it}}{\sigma v} + \eta_{it}\right)}{\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})} \tag{17}$$

Then the conditional expectations of ω_{it} and u_{it} can be estimated.

$$E(\omega_{it} \mid \xi_{it}) = \frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)} + \frac{\sigma_v\left[\Phi(-\eta_{it}) + \eta_{it}\Phi(\eta_{ii})\right]}{exp(\beta_{it} - \alpha_{it})\left[\Phi(\eta_{it}) + exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})\right]} \tag{18}$$

$$E(u_{it} \mid \xi_{it}) = \frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)} + \frac{\exp(\alpha_{it} - \beta_{it})\sigma_v\left[\Phi(-\gamma_{it}) + \eta_{it}\Phi(\gamma_{ii})\right]}{\Phi(\eta_{it}) + \exp(\alpha_{it} - \beta_{it})\Phi(\gamma_{it})} \tag{19}$$

With the Eq. 18 and Eq. 19, it is possible to estimate the absolute level of carbon emissions deviation from the frontier level attributed to combination of the bias effects. For our further comparison, it is necessary to convert the absolute deviation value into a ratio of the deviation from the optimal level based on the Eq. 20 and Eq. 21.

$$E(1-e^{-\omega_{it}} \mid \xi_{it}) = 1-\frac{\left(\frac{1}{\sigma_u}+\frac{1}{\sigma_\omega}\right)\left[\Phi(\gamma_{it})+\exp(\beta_{it}-\alpha_{it})\exp\left(\frac{\sigma_v^2}{2}-\sigma_v\eta_{it}\right)\Phi(\eta_{it}-\sigma_v)\right]}{\left[1+\left(\frac{1}{\sigma_u}+\frac{1}{\sigma_\omega}\right)\right]\exp(\beta_{it}-\alpha_{it})\left[\Phi(\eta_{it})+\exp(\alpha_{it}-\beta_{it})\Phi(\gamma_{it})\right]} \tag{20}$$

$$E(1-e^{-u_{it}} \mid \xi_{it}) = 1-\frac{\left(\frac{1}{\sigma_u}+\frac{1}{\sigma_\omega}\right)\left[\Phi(\eta_{it})+\exp(\alpha_{it}-\beta_{it})\exp\left(\frac{\sigma_v^2}{2}-\sigma_v\gamma_{it}\right)\Phi(\gamma_{it}-\sigma_v)\right]}{\left[1+\left(\frac{1}{\sigma_u}+\frac{1}{\sigma_\omega}\right)\right]\left[\Phi(\eta_{it})+\exp(\alpha_{it}-\beta_{it})\Phi(\gamma_{it})\right]} \tag{21}$$

Accordingly, the net effects on carbon emissions can be obtained and calculated as follows.

$$NE = E(1-e^{-\omega_{it}} \mid \xi_{it}) - E(1-e^{-u_{it}} \mid \xi_{it}) = E(e^{-u_{it}}-e^{-\omega_{it}} \mid \xi_{it}) \tag{22}$$

Wherein NE refers to the distinction between promotion and inhibition effects. When NE > 0, it suggests that the promotion effect dominates, compared to the inhibition effect; while NE < 0, it indicates the inhibition effect dominates, compared to the promotion effect.

3.2 Description of the data

3.2.1 Variable selection

(1) Carbon emissions

In view of the fact that no official carbon emission data is published, the formula provided by Intergovernmental Panel on Climate Change (IPCC) is select for the purpose of figuring out greenhouse gas (GHG) emissions. Besides, based on the approach of Kuang et al. (2022), GHG emissions at the production side are considered, and eight energy sources, containing coke, gasoline, natural gas, raw coal, fuel oil, crude oil, kerosene, alongside diesel are selected for the end consumption. Then the carbon emissions are figured out in the light of the listed formula.

$$CE = \sum_{i=1}^{8} CO_{i_{i,jjt}} = \sum_{i=1}^{\varepsilon} M_{ijt} \times K_j \tag{23}$$

In this equation, t is the year; i is the region; j is the energy resource; M is the energy consumption; CE is the co_2 emission; and K_j is the carbon emission factor. The logarithm of the obtained carbon emissions is stated as $\ln CO_2$.

(2) Level of digital economy development

According to Zhao et al. (2020), the integrated advancement degree of the above-described economy is evaluated on the part of digital financial inclusion and Internet progress. Concerning methods of Liu et al. (2020) and Huang et al. (2019), the level of Internet progress is capable of being evaluated via Internet penetration rate, employees in related industries, and telecommunication services. Moreover, the quantity of Internet broadband users in 100 individuals is chosen to characterize the Internet penetration rate; the percentage of workers in computer and software service to the quantity of workers in urban units is used to represent the employees in related industries; the overall quantity of telecommunication services per caput, alongside the quantity of cell phone users among 100 individuals are used to measure telecommunication services. Meanwhile, digital inclusive finance becomes the important reflection of the above-described economy progression. Compiled by Guo et al. (2020), we select digital financial inclusion indices for different provinces to measure regional digital financial inclusion in China, which includes depth and breadth of utilization, alongside digitization. The entropy weight method is then adopted finally with the objective to attaining the level of regional digital economy advancement, which is meant as Sdig.

(3) Other inter-provincial characteristic variables

Following the research of Kuang et al. (2022), population density is chosen to measure the population scale, which is coped with logarithmic treatment then and denoted as lnPM; Referring to the study of Kang and Ru (2020), government financial expenditure is characteristic of the percentage of general financial budget cost to GDP. That is coped with logarithmic then and denoted as lnGOF; the degree of industrialization is represented by added value of the secondary sector as a share of GDP, and which is coped with logarithmic then and denoted as lnInd; the economic advancement level is shown via GDP per caput (Han et al., 2019), which is coped with logarithmic then and denoted as lnPGdp; urbanization is expressed by the share of non-farm population (Xu et al., 2022), which is coped with logarithmic then and denoted as lnCity; environment regulation is characteristic of the quantity of investing in environment pollution to GDP, which is denoted as EG; energy structure is gauged by coal depletion to overall energy depletion (Shao et al., 2016), which is denoted as EnS; the intensity of energy is gauged by energy consumption each GDP unit (Ren et al., 2021), which is illustrated as EQ. Overall, the depicted statistics consequences of variables are exhibited in Table 1.

3.2.2 Data sources

The figures applied to the research is chosen from China Statistical Yearbook (2012–2021), ESP Global Database, alongside China Science and Technology Statistical Yearbook (2012–2021). On account of the data availability, four zones of Tibet, Taiwan, Macao and Hong Kong, Macao, are not contained in this research. Besides, variables involving price factors are deflated according to the base year of 2011. And all provinces are split into three sections based upon the geographical position, which is the eastern, the central and the western regions. The eastern parts are comprised of 11 provinces or cities, and they are Fujian, Jiangsu, Hebei, Zhejiang, Liaoning, Hainan, Beijing, Guangdong, Shandong, Tianjin, and Shanghai. The central parts are comprised of 8 provinces or cities, which is Heilongjiang, Shanxi, Hubei, Jilin, Hunan, Anhui, Jiangxi, and Henan. And the western parts are comprised of 11 provinces or cities, which is Sichuan, Yunnan, Inner

TABLE 1 Descriptive statistics of variables.

Variables	Symbols	Obs	Mean	Std	Min	Max
Carbon emissions	$lnCO_2$	300	10.430	0.741	8.494	12.180
Digital economy	Sdig	300	0.327	0.142	0.125	0.937
Population density	lnPM	300	7.892	0.410	6.639	8.710
Government financial expenditures	lnGOF	300	3.147	0.376	2.400	4.160
Industrialization degree	lnInd	300	3.064	0.409	1.678	4.019
GDP *per capita*	lnPGdp	300	10.840	0.436	9.706	12.010
Urbanization	lnCity	300	4.046	0.199	3.555	4.495
Environmental regulation	EG	300	0.049	0.090	0.016	0.767
Energy structure	EnS	300	0.387	0.148	0.008	0.687
Energy intensity	EQ	300	0.825	0.485	0.207	2.327

Mongolia, Ningxia, Guangxi, Xinjiang, Gansu, Guizhou, Chongqing, Shaanxi, and Qinghai.

4 Empirical analysis

4.1 The estimation based on two-tier stochastic frontier model

4.1.1 Basic regression models

Related composite effects are decomposed according to Eq. 12, based upon the MLE estimation. And these consequences are depicted in Table 2. Among them, these consequences based on OLS model is presented in the second column. The results based on model (2) is used to obtain the estimation without considering area and time fixed effects; model (3) is established taking the area fixed effects into account only; and model (4) is adopted when considering both time and area fixed effects. Besides, Model (5) is a one-sided estimation concerning merely the passive impact of regional digital economy; model (6) is a one-sided estimation considering only the opposite impact; Furthermore, model (7) is estimation taking both positive and passive outcomes of the above-mentioned economy into account. Based upon the likelihood ratio experiment (LR) as well as the deviation effect, it is found that comparing to the OLS estimation and the residual model, the model (7) is more appropriate to be chosen to analyze the digital economy's bilateral effect decomposition.

4.1.2 Variance decomposition of bilateral effects of digital economy

The promotion and inhibition effects are further decomposed based upon model (7). Moreover, the decomposition consequences are depicted in Table 3. The effects of DECEs are researched within this chapter. Promotion and inhibition effects reach 0.2050 and 0.3024, separately. And the net effect is $E(\omega - u) = \sigma_\omega\text{-}\sigma_u = -0.0974$, the function of the digital economy net effect serves to impede the carbon emission growth. Overall, impacts of above-mentioned economy upon regional carbonous emissions have promotion and inhibition effects. However, the inhibition effect is larger, which ultimately leads to the practical regional carbon emissions less than the optimal level, i.e., RCEs are inhibited by the digital economy.

Furthermore, the dual effects is also estimated based upon the decomposition model. As shown in Table 3, the inhibition effect reaches 68.52%, while the promotion effect accounts for 31.48%. Additionally, the inhibition effect significantly exceeds the promotion effect, showing that the inhibition effect dominates, thus verifying once again the accuracy of the above estimation.

4.1.3 The bilateral effects of the digital economy on carbon emissions

After examining how the DECEs, Eqs 19–21 are used to further determine the RCEs' divergence from the optimal carbon emission level. Through the above formula, we can get the actual ratio of deviation from the optimal level and the above-mentioned net effect. These consequences are put forward in Table 4. And on this basis, by comparing the percentages of promotion effect and inhibition effect, we can determine the practical influences. According to the consequences in Table 4, the promotion effect makes carbon emissions exceeding the frontier level by 12.11%, whereas the inhibition effect enables carbon emissions to be less than that level by 13.38%. Thereby, the combined effect of those two effects enables carbonous emissions to be less than that level by 1.27%, which indicates that the bilateral effects impede the carbon emissions. Specifically, under p25 and p50 quartiles, the above-mentioned economy lessens carbonous emissions by 5.16% and 0.23%, respectively. It indicates that the inhibition effect offsets the promotion effect, thus keeping the conclusion that the digital economy impedes the carbon emissions. However, under the p75 percentile, the effect of the DECEs is reversed, with the promotion effect obviously exceeding the inhibition effect. It indicates that energy depletion is often excessive at places with the elevated degree of digital economy. The possible cause maybe that the energy consumption of related digital industries in China is still dominated by thermal power, which will bring an energy rebound effect on electricity, and thus contribute to the increase of RCEs.

Furthermore, frequency distribution of different kinds of effects contributed by digital economy is given in Figure 2. The inhibition effect shows a right trailing feature, indicating that carbon emissions

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TABLE 2 Basic regeression results of the outcomes contributed by digital economy.

	OLS	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$	$lnCO_2$
LnPM	−0.392**	−0.039***	0.024***	−0.079***	−0.118***	0.008***	−0.111***
	(−2.33)	(−4.94)	(24.56)	(−2.60)	(−232.74)	(60.02)	(−238.58)
lnGOF	−0.112	0.409***	0.029***	−0.003***	0.076***	0.025***	0.017***
	(−0.82)	(47.33)	(41.68)	(−12.26)	(743.92)	(148.15)	(131.62)
lnInd	0.670**	0.753***	0.041***	0.330***	0.346***	0.226***	0.320***
	(2.59)	(302.72)	(18.09)	(7.81)	(937.37)	(293.64)	(333.07)
lnPGdp	−0.072	0.077***	0.017***	−0.001	0.028***	0.015***	−0.004***
	(−0.74)	(7.13)	(48.95)	(-0.37)	(397.63)	(215.44)	(-73.89)
lnCity	1.592*	0.993***	1.094***	0.962***	0.546***	0.469***	0.315***
	(1.84)	(160.45)	(516.33)	(37.80)	(444.37)	(320.05)	(138.29)
EG	−0.395	−1.386***	−0.117***	−0.427***	−0.351***	−0.281***	−0.336***
	(−0.82)	(−91.44)	(−59.02)	(−5.57)	(−1933.87)	(−1104.69)	(−775.20)
EnS	1.835**	1.758***	0.500***	0.767***	0.135***	0.594***	0.498***
	(2.34)	(71.11)	(54.28)	(61.37)	(259.98)	(773.56)	(726.20)
EQ	−0.358	0.028***	0.153***	0.300***	0.556***	0.525***	0.407***
	(−1.08)	(3.90)	(90.60)	(7.11)	(3551.95)	(1175.77)	(1154.67)
Constant item	5.172	1.625***	4.425***	4.948***	7.754***	4.329***	7.236***
	(1.09)	(9.86)	(583.63)	(94.34)	(1114.33)	(1106.38)	(689.01)
Constant item		−32.807	−17.179	−20.220	−18.855	−18.373	
		(−0.00)	(−0.03)	(−0.01)	(−0.05)	(−0.05)	
Inhibition effect					−13.269***		−6.608***
					(−19.40)		(−14.57)
Constant item			−1.713***	−1.661***	−6.977***	−3.246***	−4.349***
			(−23.92)	(−23.78)	(−24.85)	(−36.64)	(−27.78)
Promotional effects						10.771***	9.410***
						(20.10)	(16.19)
Constant item			−1.641***	−1.736***	−2.549***	−5.529***	−5.639***
			(−23.48)	(−24.24)	(−35.42)	(−27.80)	(−26.00)
Pro fixed	No	No	Yes	Yes	Yes	Yes	Yes
Year fixed	No	No	No	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300	300

Note: ***, **, and * are tabulated as passing the test at 1%, 5%, and 10% significance levels, respectively; the corresponding Z statistics are given in parentheses. Similarly, hereinafter.

in some provinces are very sensitive to variations of digital economy. And the promotion effect ends at roughly 90%, which is prominently less than the inhibition effect. Besides, consequences of the net effect distribution demonstrates that inhibition effect contributed by digital economy dominates in most of provinces, showing that the above-described economy exerts an active function upon lessening carbonous emissions and tend achieve the "carbon peaking and carbon neutrality" target.

4.2 Characteristics of the digital economy's impacts on regional CO_2 emissions

These features of the net effect distribution in different regions are further examined. Additionally, the consequences are illustrated in Table 5, and the net effects are negative in the overall three regions, which is −7.03%, −5.90%, and −2.83%, respectively. It indicates that regional digital economy

TABLE 3 Variance decomposition of the effects contributed by digital economy.

	Variable meaning	Symbols	Measurements coefficients
Digital economy impacts	Random error term	sigma_v	0.0000
	Promotion effect	sigma_w	0.2050
	Inhibition effect	sigma_u	0.3024
Variance decomposition	Random total error term	Total sigma_sqs	0.1334
	The weight of the two effects	(sigu2 + sigw2)/Total	1.0000
	Promotion effect weight	sigw2/(sigu2 + sigw2)	0.3148
	Inhibition effect weight	sigu2/(sigu2 + sigw2)	0.6852

TABLE 4 Estimation of the effects of digital economy on carbon emissions (%).

Variable	Mean	Variance	P25	P50	P75
Promotion effect	12.11	18.79	2.06	4.09	12.16
Inhibition effect	13.38	18.84	3.01	6.52	12.57
Net effect	−1.27	19.23	−5.16	−0.23	1.15

prominently limits carbon emissions within these regions. Specifically, the inhibition effect in the eastern region is highest in the overall regions. The possible cause is that, there are obvious advantages in digital infrastructure and industry in the east of the region, and the dividend of digital economy has been released during these years. Moreover, aside from innovation capital, vast quantities of digital innovation talents have gathered to support the technological progress and green development, resulting in the stronger inhibition effect within this region. However, the above-described economy between central and western regions is still at an initial stage of advancement, and the carbon emissions from infrastructure construction and resource depletion are partially offset by the inhibition effect of the above-described economy, bringing about one weaker inhibition function by the regional digital economy. Overall, the spatial pattern of digital economy's effects upon carbon emissions in disparate regions exhibits these features of a decreasing spatial distribution within the eastern, central and western regions.

4.3 Temporal characterization of the impacts of digital economy on carbon emissions

The time variation trend of above-mentioned impacts is further identified. Additionally, these consequences are illustrated in Figure 3. The net effect contributed by digital economy takes the lead during these years is ranging from −0.2% to −4.0%. It indicates that the inhibiting impact predominates and presents a decreasing tendency in the study period. The main cause of this consequence might be that, the progression of the above-described economy is often together with by a prominent growth in the need of energy, which will bring more energy consumption and resource investment. However, with the progression of the above-described economy, the digital technology utilization has accelerated the process of energy construct transformation, and enhanced the

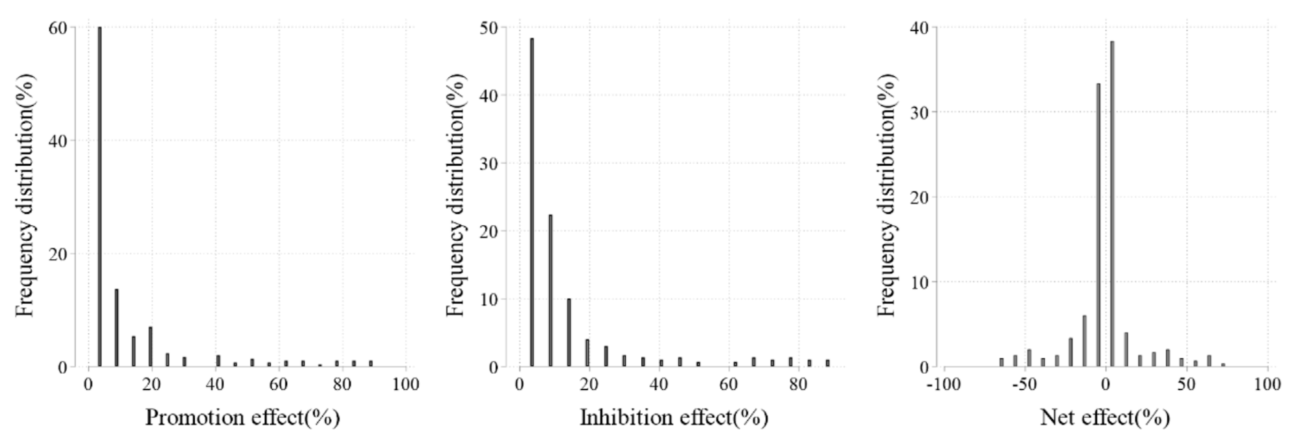

FIGURE 2
Frequency distribution of the effects contributed by digital economy.

TABLE 5 Characteristics of the net effect of the digital economy on regional carbon emissions (%).

Province	Mean value	Province	Mean value	Province	Mean value
Hebei	−7.18	Heilongjiang	−0.33	Sichuan	−7.04
Liaoning	−15.68	Jilin	6.14	Yunnan	−7.95
Fujian	7.99	Shanxi	−4.09	Neimenggu	−5.59
Shandong	−6.13	Hubei	−1.10	Ningxia	1.92
Jiangsu	−8.47	Hunan	−1.02	Guangxi	2.66
Zhejiang	−9.6	Anhui	−8.54	Xinjiang	3.25
Guangdong	−7.15	Jiangxi	5.47	Gansu	12.64
Hainan	7.66	Henan	3.80	Guizhou	5.96
Beijing	−4.68			Chongqing	−12.29
Tianjin	10.04			Shaanxi	−14.08
Shanghai	4.59			Qinghai	10.72
Eastern region	−7.03	Central region	−5.90	Western region	−2.83

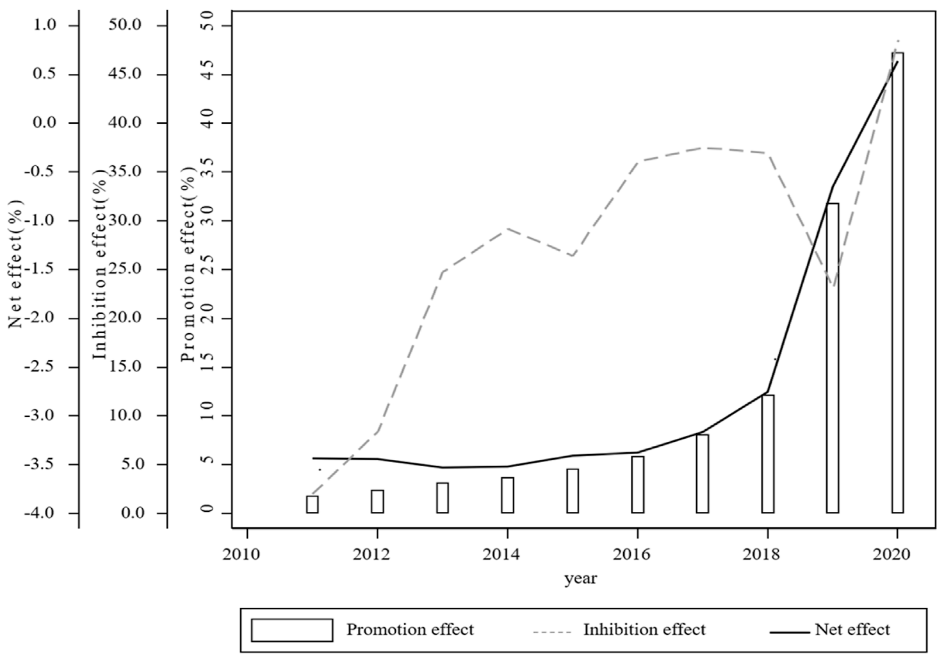

FIGURE 3
Temporal characterization of the impacts contributed by digital economy (%).

energy efficiency, thus greatly facilitating the fulfillment of energy saving and emission reduction targets.

4.4 Analysis on the impacts at different levels of digital economy

Bilateral effects at disparate digital economy levels are presented inside Table 6. And the results under 25%, 50%, and 75% quartiles are also demonstrated simultaneously. With the increase of the digital economic advancement level, the mean value of promotion effect on carbon emissions increases from 1.75% for Sdig ≤ 0.223 to 34.09% for Sdig > 0.408, respectively. And the average value of the inhibition effect increases from 5.33% for Sdig ≤ 0.223 to 35.56% for Sdig > 0.408, respectively. Besides, the net effect is always negative. These consequences means that, as the digital economic level raises, the inhibition effect always dominates.

TABLE 6 Differences of the bilateral effects at various digital economy levels (%).

Distribution intervals	Effects decomposition	Mean	SD	P25	P50	P75
Sdig ≤ 0.223	Promotion effect	1.75	1.19	1.12	1.49	1.74
	Inhibition effect	5.33	5.42	1.38	2.98	7.63
	Net effect	−3.58	5.82	−6.12	−1.80	0.00
0.223 < Sdig ≤ 0.408	Promotion effect	6.30	8.06	2.46	3.81	6.93
	Inhibition effect	6.31	5.23	3.03	5.21	7.50
	Net effect	−0.01	9.48	−3.54	−0.07	0.77
Sdig > 0.408	Promotion effect	34.09	25.07	14.19	21.45	52.21
	Inhibition effect	35.56	26.15	13.33	26.12	59.81
	Net effect	−1.48	35.65	−28.92	−0.08	20.85

TABLE 7 Differences of the bilateral effects under various human capital levels (%).

Distribution intervals	Effects decomposition	Mean	SD	P25	P50	P75
EDU ≤ 8.725	Promotion effect	9.57	19.17	1.36	2.16	6.91
	Inhibition effect	8.82	9.83	2.01	6.03	10.25
	Net effect	0.76	17.31	−7.08	−1.29	1.67
8.725 < EDU ≤ 9.485	Promotion effect	9.41	15.31	2.07	3.19	8.81
	Inhibition effect	11.03	16.54	2.81	5.52	10.88
	Net effect	−1.62	16.63	−3.95	−0.63	0.64
EDU > 9.485	Promotion effect	20.05	22.42	4.41	10.91	22.34
	Inhibition effect	22.64	25.83	5.57	11.39	31.65
	Net effect	−2.59	25.12	−6.62	0.00	3.45

4.5 Analysis on the impacts at different levels of human capital

The regional human capital is just one of the macro-social environmental elements for the above-described economy operation. It is capable of offering favorable conditions for regional knowledge dissemination and technological innovation, and have a great impact of the function of digital economy upon the carbon emission. Herein, the average years of education (EDU) is selected to represent human capital, and the formula for calculating the indicator of EDU is: average years of education *per capita* = proportion of primary school educated population * 6 + proportion of junior high school educated population * 9 + proportion of senior high school educated population * 12 + proportion of college and above educated population * 16. Then we divide the human capital into three groups according to the 25%, 50%, and 75% quartile, and the consequences are depicted in Table 7. When EDU ≤ 8.725, the net effect of digital economy is 0.76%; when 8.725 < EDU ≤ 9.485, the net effect reaches −1.62%; when EDU > 9.485, the net effect reaches −2.59%. According to the above analysis, with the continuous increase of human capital, the net effect varies from positive to negative, which means the inhibition utility of the DECEs takes the dominant position step by step. These consequences indicate that the inhibition effect can be strengthened by the element of human capital, and it primarily consists these conclusions of Guo et al. (2022).

4.6 Analysis on the impacts at different levels of economic development

The regional economic development is one of the macro-economic environmental elements for the digital economy operation. It is highly correlated with local markets and industrial structure, and subsequently lead to a huge influence of digital economy upon carbon emission. As a result, GDP *per capita* (PGdp) are selected with the intention of representing the regional economic advancement. What`s more, it is also divided into three groups according to the 25%, 50%, and 75% quartile as the above. The consequences are illustrated in Table 8. The net effect is −1.07% when PGdp ≤ 3.717, and −1.13% when 3.717 < PGdp ≤ 6.686. According to the above analysis, the inhibition effect gradually increases as the economic development rises,

TABLE 8 Differences of the bilateral effects under various economic development levels (%).

Distribution intervals	Effects decomposition	Mean	SD	P25	P50	P75
PGdp ≤ 3.717	Promotion effect	18.91	23.82	3.39	8.90	20.27
	Inhibition effect	19.98	24.67	4.76	9.31	24.22
	Net effect	−1.07	27.52	−7.40	−1.39	3.68
3.717 < PGdp ≤ 6.686	Promotion effect	13.01	18.95	2.13	4.40	17.40
	Inhibition effect	14.14	18.52	3.27	7.20	16.36
	Net effect	−1.13	18.89	−5.48	−0.02	2.24
PGdp > 6.686	Promotion effect	3.50	3.60	1.58	2.21	3.48
	Inhibition effect	5.26	4.71	2.12	3.35	7.23
	Net effect	−1.75	4.22	−3.53	0.00	0.10

TABLE 9 Robustness tests for the effects and variance decomposition.

	Variable Meaning	Symbols	Measurements coefficients
Digital economy impacts	Random error term	sigma_v	0.0000
	Promotion effect	sigma_w	0.5590
	Inhibition effect	sigma_u	0.9486
Variance decomposition	Random total error term	Total sigma_sqs	1.2124
	The weight of the two effects	(sigu2 + sigw2)/Total	1.0000
	Promotion effect weight	sigw2/(sigu2 + sigw2)	0.2577
	Inhibition effect weight	sigu2/(sigu2 + sigw2)	0.7423

indicating that the economic development can reinforce the inhibition effect.

4.7 Robustness

With a view to verifying the consequence robustness, according to the research by Guo et al. (2022), the percentage of total RCEs to gross domestic product (GDP) in cities is chosen to represent the carbon emissions. In this respect, the bilateral effects are evaluated again, additionally, these consequences are illustrated in Table 9. The consequences exhibit that the promotion effect reaches 0.5590, furthermore, the inhibition effect is 0.9486. It indicates that there are bilateral effects of digital economy on RCEs, which is still consistent with the discoveries obtained above. In addition, according to influencing weights, the promotion and inhibition impact of the above-mentioned economy account for 25.8% and 74.2% of it, respectively. It shows that the inhibition effect plays a dominant part all the time during these years, thus further verifying the consequence robustness we obtained above.

The deviation of inhibition effect, the net effect and the promotion effect are then estimated again. And these consequences of deviation are illustrated in Table 10. It is discovered that, with the advancement of the digital economy, its promotion effect raises RCEs by 3.04%, whereas the inhibition effect reduces regional carbon emissions by 12.71%. And the net effect makes the practical RCEs less than the frontier level by 9.67%, which is in line with the conclusions obtained above.

TABLE 10 Robustness test for the deviation of digital economy's impacts on regional carbon emissions (%).

Effects decomposition	Mean	SD	P25	P50	P75
Promotion effect	3.04	5.51	0.67	1.06	2.60
Inhibition effect	12.71	11.25	3.72	9.05	19.44
Net effect	−9.67	12.20	−17.86	−6.67	−0.57

5 Conclusion and policy implications

5.1 Conclusion

This study intends to investigate the mechanisms and the actual functions of DECEs in China. Via panel data originating in 30 provinces in China between 2011 and 2020, the two-tier stochastic frontier pattern has been adopted with the intention of gauging the inhibition effect, the promotion effect, alongside the net effect of the digital economy in this research. What`s more, the consequences denote that: the promotion effect of digital economy enables the level of the carbon emission to exceed the optimal level by 12.11%, while the inhibition effect enables the level of the carbon emission level to be less than the optimal level by 13.38%. With the combination of these two effects, the actual effect of the above-mentioned economy enables the carbonous emissions to be lower than the frontier boundary by 1.27%. In addition, on the part of space and time temporal distribution, the inhibition effect of the above-mentioned economy upon carbon emissions predominant and presents a declining trend during the study period. However, the inhibition effect in the east of the region is the highest in all of the other regions. Moreover, the digital economic level, economic advancement and human resource capital can also enhance the inhibition effect of DECEs.

5.2 Policy implications

In accordance with the conclusions above, some of policy recommendations are proposed as follows.

To begin with, it is in great need of accelerating the progression of the digital economy in all regions of China. Therefore, the establishment of a novel generation of information infrastructure needs to be established rapidly, the infrastructure containing big data centers, 5G network base stations, artificial intelligence, block-chain services, and the like, with the intention of sustaining the above-described economy transformation and expanding the digital economy function in reducing carbonous emissions. Besides, the data risk supervision laws and regulations also need to be enhanced as well as upgrading of the top-level design and mechanism construction of regional development.

Secondly, on the grounds of the regional development distinctions, the heterogeneous digital guidance and supporting strategies should be implemented. It is suggested that the government need to regulate the rate of above-described economy advancement in any of the regions, break up the industry barriers and geographical limitations of the novel models and novel commerce models, and improve the synergetic effect of digital economy governance in regions. Specifically, in the center and west of the regions, several strategies can be adopted. For example, the construction of information and communication infrastructure, innovation support and subsidy policies need to be implemented. And the digital industry support from the eastern region can be undertook as well. Meanwhile, in the east region, on the premise of maintaining the stable growth of the quality and scale of the original digital industry, the governments can expand the utilization scenarios of big data, facilitate the extensive usage of information technology and data elements in social and economic activities, and also explore new models of digital management and application.

Thirdly, the talent environment and economic development environment for China's green and low-carbon transition are needed to be improved. On the one hand, the governments should upgrade the talent training model, deepen the discipline construction in the fields related to digital economy, actively cultivate high quality and comprehensive talents, so as to enhance the number and quality of regional talent. What`s more, apart from scientific &technological innovation, the regional industrial structure should be promoted in order to improve the core competitiveness and regional green development. Moreover, the new energy economy and the renewable energy industries are also needed to be accelerated, as well as improving the public's awareness of energy conservation and energy efficiency, so as to gradually replace the traditional fossil resources with new energy and improve the energy conversion rate.

5.3 Research limitation and future work

The research concentrates upon the bilateral effects of the DECEs, providing a theoretical reference to facilitate the regional green and sustainable development. Nevertheless, there still exist certain limitations which demands to be enhanced further. For one thing, on account of data availability, the indicators we choose cannot accurately cover the various aspects of the digital economy in zones, additionally, a more complicated evaluation system is preferred to enhance the practical significance of relative researches. For another, the study focuses upon the above-mentioned bilateral effects from a macro perspective, and fails in thinking about the analysis on effects of micro corporation digital transformation on emission reduction and regional energy conservation, which will be the expanded orientation of the follow-up work.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

CL: Conceptualization, Writing–original draft, Writing–review and editing. WW: Investigation, Writing–review and editing. CD: Methodology, Writing–original draft. XT: Funding acquisition, Writing–review and editing. YY: Investigation, Writing–review and editing. ZZ: Investigation, Writing–review and editing.

Funding

The authors declare financial support was received for the research, authorship, and/or publication of this article. The work was supported by the National Social Science Fund (21BJY254), General Project of Philosophy and Social Sciences Research in colleges and Universities of Jiangsu Province (2023SJYB0042), and Graduate Research and Innovation Projects of Jiangsu Province (KYCX22_0691).

Conflict of interest

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

Publisher's note

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