RESEARCH ARTICLE

Nonlinear impact of digital economy on carbon intensity: the moderating role of low-carbon regulation

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Abstract
The development of the digital economy is an effective way to mitigate the carbon emission problem in the broader setting of the significant data era and green development. Based on the panel data of 271 cities in China from 2011 to 2019, this paper constructs a bidirectional fixed model to analyze the nonlinear effect of the digital economy (DE) on carbon intensity (CI) and the moderating role of low-carbon regulation from theoretical and empirical perspectives. The results show that (1) DE has an enormous inverted U-shaped impact on CI. The findings remain after introducing instrumental variables to mitigate endogeneity and robustness tests. (2) Low-carbon regulation (CP) can strengthen the inverted U-shaped impact between the two and shift the inflection point to the left. (3) Heterogeneity analysis shows that the inverted U-shaped effect of DE on CI is more significant in the central and western regions, high human capital (HC) regions, and high urbanization regions. (4) The mediating effect of energy mix (EM) and green technology innovation (GTI) still hold after introducing instrumental variables to alleviate the endogenous effect of the intermediary effect. This study suggests that the adoption of carbon emission reduction strategies, which will more effectively lower carbon intensity CI, should go hand in hand with the development of DE.

Keywords Low-carbon regulation · Digital economy · Carbon intensity · Energy mix · Green technology innovation

Introduction

Continuing increases in carbon emissions have many negative impacts on human life. The severity of severe weather and global warming are two examples of such factors (Xu and Lin 2016). Global warming and severe weather endanger global biodiversity (Demirhan 2020). As per the World Energy Statistics Yearbook, the nation with the most significant CO_2 emissions worldwide is China. In addition, energy demand continues to grow, putting China under long-term pressure to lower carbon emissions. Based on this, China proposed the dual carbon target in 2020 to assume responsibility for global climate change. Strengthening

environmental protection is necessary for development, but realizing the positive interaction between economic development and environmental protection is even more critical. Carbon intensity (CI), measured by the ratio of carbon emissions to GDP, is an effective indicator for countries around the world to measure the balanced development of economic and ecological environmental protection (Zhao et al. 2022b), as well as to measure the efficiency of energy utilization (Cheng et al. 2014). This makes studying methods to lower CI crucial.

The rise in CI is mainly attributable to economic growth (Li et al. 2021b). Moreover, DE has the characteristics of green development, and the current economic growth is closely integrated with the digital Internet (Kim et al. 2021). It offers new options for reducing CI, and this new economy is valuable in encouraging increased productivity. With the advancement of China's Internet technology, it has assumed a greater role in China's economic expansion. China has strategically seized the opportunity of the digital revolution and continues to absorb the digital dividend. Digital industrialization is undergoing a transformation from quantitative expansion to qualitative improvement. In view of this,

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understanding how DE works to lower CI has substantial practical implications.

To our knowledge, active measures to reduce CI have been theoretically and empirically explored by scholars, including reducing the use of unsustainable energy (Tong et al. 2018; Ma and Yu 2017), active application of renewable energy and recycling (Zheng and Suh 2019), upgrading industrial structure (Cheng et al. 2018; Shi et al. 2022a), promoting technological progress (Erdogan 2021; He et al. 2021), implementing low-carbon pilot policies (Li et al. 2022), and optimizing the structure of factor endowments (Ma et al. 2022). These are effective measures to promote carbon emission reduction. The academic community was closely mindful of reducing CI and the quick expansion of DE, and research on those has been conducted from various angles. In addition to focusing on emission reduction strategies (Zhang et al. 2020a; Zheng and Suh 2019), the researchers also focus on the measurement (Guo et al. 2018; Mi et al. 2016; Wiedmann 2009) and influencing factors (Shen et al. 2018; Zhou et al. 2017). Other than that, the study on DE focuses on the measurement (Corrocher and Ordanini 2002; Qiao and Williams 2022) and development's impact (De et al. 2020; Ding et al. 2022).

So, does DE offer new possibilities for reducing CI? Moreover, what are the mechanisms of its impact? This research employs econometric models to experimentally evaluate the influence of DE on CI to address these issues. The results demonstrate that DE significantly impacts CI in an upside-down U-shape, with CP playing a moderating role and EM and GTI playing a mediating role. The findings remain valid after considering tests such as the endogeneity issue of selecting historical data as an instrumental variable.

This study has three major contributions. First, this paper innovatively investigates the important moderating role of CP in DE's impact on CI. It comprehensively examines the vertex shift and slope change on the inverted U-shaped relationship between the two. Second, this paper uses a mediation model to examine the mechanism of EM and GTI, and the use of historical data as an instrumental variable alleviates the endogeneity problem of the model. Most of the literature ignores the error caused by the endogeneity problem when using the mediation model. Third, this paper examines whether the inverted U-shaped effect between the two is achieved through emissions reductions or increased production.

The remainder of the text is divided into several parts. The "Literature review" section reviews related literature. The "Theoretical analysis" section clarifies the theoretical assumptions and impact mechanisms. The "Materials and methods" section presents the econometric model and data treatment. The "Empirical analysis" section discusses the benchmark regressions and tests for moderating effects. The "Further analysis of the mechanism" section discusses the

further analysis of impact mechanisms. Conclusions and policy implications are offered at the end.

Literature review

Factors affecting CI

Many scholars have explored the factors affecting carbon emissions. CI indicators can reflect the close relationship between environmental protection and economic development. More and more scholars focus their research on the factors affecting CI. The main research directions are economic development, different economic activities, government policies, and ICT (information and communication technologies). First, the major aspect determining carbon emissions and environmental issues is the amount of economic growth. Grossman and Krueger (1995) assert that income growth and climate harm are inverted U-shaped. Zaman and Moemen (2017) use stratified random sampling to distinguish between different income groups worldwide, demonstrating that the EKC exists in all countries. Salahuddin et al. (2015) show that income expansion and carbon emissions are positively related throughout time. Carbon emissions also have a non-linear inverse effect on economic development under certain conditions (Li and Wei 2021). Zhao et al. (2022b) focus on the economy's negative effect on CI.

Secondly, different forms of economic activity can also affect CI. Urbanization can lower CI, but this mitigation effect diminishes as urbanization deepens (Wang and Wang 2021; Yao et al. 2018; Zhao et al. 2022b). In addition, other scholars take the opposite view. The advancement of urbanization brings long-term economic development, and the increasing energy demand inevitably increases carbon emissions (Liu et al. 2016; Wang et al. 2016). Trade openness is an essential manifestation of economic activity. The effects of trade openness on CI can be categorized into three groups: (1) facilitating effects, (2) inhibiting effects, (3) bidirectional causality (Dou et al. 2021; Qi et al. 2020; Wang and Zhang 2021; Kivyiro and Arminen 2014). Balsalobre-Lorente et al. (2018) found that trade liberalization in the five EU countries positively impacted carbon emissions. Some scholars take the opposite view of this, arguing that trade openness reduces CI (Wang and Zhang 2021; Wang and Wang 2021). Other scholars have found that trade openness and carbon emissions can influence each other (Rahman et al. 2020).

Thirdly, the broader literature has analyzed the relationship between government low-carbon policies and CI. Zhang et al. (2020b) show that improved environmental regulations can effectively reduce CI. Yang et al. (2020) took the opposite view, finding that environmental regulations

ultimately lead to increased CI. In addition, some studies have considered the influential role of policies other than environmental regulations. Carbon pricing policies have an unstable, non-linear effect on carbon emissions reduction (Zakeri et al. 2015). During urbanization, the reduction of carbon emissions can be achieved through competitive decision-making in local government (Li 2022).

Finally, CI has been significantly impacted by the ICT development that has occurred so quickly in recent years. Some scholars believe that the progress of ICT can improve the environment and provide new opportunities to reduce CI. Not only that, ICT has adverse spatial spillover effects on CI in neighboring cities (Bhujabal et al. 2021; Sun 2022). Other scholars have found that the rapid progress of ICT hurts environmental sustainability and will increase carbon emissions. Throughout the first phases of ICT development, increased equipment production resulted in a rise in energy demand (Dehghan and Shahnazi 2019). As ICT matures, the demand for high-tech goods increases, which causes a rise in carbon emissions as well (Danish et al. 2018).

The impact of the digital economy

It is worth mentioning that DE is not only tied to CI. Many academics view it as a means of fostering economic growth. Kapoor (2014) finds that DE can contribute to economic growth. Using a mediating effects model, Ding et al. (2022) find that it may help countries reach high levels of economic growth. Although most scholars agree that DE can effectively promote economic progress, there are different views on the mechanism of action. The crucial mechanisms at play include industrial structure upgrading, energy structure optimization, technological innovation, and employment structure optimization. For example, Liu et al. (2022) believe that upgrading industrial structures is essential for DE to promote the development of a green economy. DE can also drive economic development by optimizing EM and improving energy utilization (Hwang 2023). Hao et al. (2023) claim that GTI plays a pivotal role in DE's promotion of the green economy. In addition, DE can contribute to economic growth by regulating the employment structure (Zhang et al. 2022a).

Additionally, some academics have begun examining the environmental impacts of DE's rapid rise (Li et al. 2021c; Xu et al. 2022). Ma et al. (2023) found a U-shaped impact of DE on the ecological environment by utilizing the threshold model. The level of development of China's DE at this stage exceeds the threshold, significantly contributing to China's ecological environment. A few academics also examine the affiliation in relation to DE and CI from other angles (Li et al. 2021a) and have yet to reach a consistent result. There are three different views on the impact of DE on CI: (1) positive correlation, (2) negative correlation, (3) non-linear relationship. Zhang et al. (2022b) argue that DE will exacerbate carbon emissions. The development and application of DE will bring about the expansion of infrastructure, and the output value in the early stage of development cannot keep up with the energy consumption, which will inevitably bring about the increase of CI. However, some scholars believe that DE can reduce CI by optimizing the EM, industrial structure, and GTI (Dong et al. 2022; Li et al. 2021b; Zhang et al. 2022a; Zhu et al. 2022; Yan et al. 2022; Yu and Zhu 2023; Yi et al. 2022). Sun et al. (2022) found that EM optimization is an effective way for digital finance to reduce CI. Yan et al. (2022) found that DE can reduce CI by promoting GTI. Another view is that there is an unstable and non-linear relationship between DE and CI. According to Cheng et al. (2023), the link in relation to DE and CI is inverted U-shaped, but the mechanism of action between the two is not fully understood, and the study does not alleviate the endogenous problem, nor does it address the differences in impact in different regions. All in all, no clear conclusion has been reached regarding the overall connection between the two.

Although there is preliminary literature on how DE affects CI, there are still two research gaps. First, scholars have yet to consider the role of CP as a critical moderating role between DE and CI. The impact of DE on CI is regulated by CP, and under different CP, the impact of DE on CI will also change. This paper explores the moderating role played by CP in this non-linear relationship based on considering the non-linear impact of DE on CI. The impact of CP on the shift of the vertex of the inverted U-shaped relationship and the slope change is comprehensively examined. A part of the literature does not consider the non-linear relationship between DE and CI at all (Yan et al. 2022). Although a non-linear relationship between the two has been explored in a few literature (Cheng et al. 2023; Wang et al. 2023; Zhang et al. 2022c), they omit the vital mechanism of CP implementation. Second, this paper uses a mediated effects model to explore the mechanism of action of EM and GTI, and the use of historical data as instrumental variables alleviates the endogeneity problem of the model. It enhances the robustness and persuasiveness of the results of the mechanism of action in this paper. In contrast, most of the literature does not consider the endogeneity problem when using the mediation model to explore the mechanism of action (Cheng et al. 2023; Wang et al. 2023; Yan et al. 2022; Zhang et al. 2022c).

The research objectives and issues to be addressed in this paper are as follows: (1) to theoretically analyze the transmission mechanism of DE on CI and the moderating role of CP in this transmission mechanism, (2) to empirically test the nonlinear impact of DE on CI and the moderating role of CP using the panel data of 271 cities in China as a

macro-sample for the period 2011–2019. Empirical evidence is provided to promote low-carbon development in China.

Theoretical analysis

The expansion of DE has the capability to cut carbon emissions significantly, but at various phases of development, the environment may be affected differently. During the early stages, DE allows for continued expansion of production capacity through increased productivity and economic efficiency, which will increase energy demand (Sadorsky 2012). According to Avom et al. (2020), DE growth in Africa might increase carbon emissions. Ren et al. (2021) found that DE increased consumption via economic development. Additionally, developing DE brought about technological advances that required companies to produce more products, thus releasing more CO_2 (Li et al. 2021a). By deploying more digital machinery and infrastructure in traditional businesses, DE raises energy consumption but does not increase output in time, thereby increasing CI (Zhao et al. 2022a).

In the late stages, DE is based on internet technology, maximizing the integration of various resources to achieve the optimum allocation of production factors, thus significantly reducing costs and waste of resources (Dong et al. 2020; Su et al. 2021). Firstly, from the macro level, the market for carbon emissions trading may benefit greatly from the expansion of DE (Dong et al. 2019). Digital environmental governance systems are prevalent, and governments can identify pollution problems more effectively and quickly (Jia et al. 2022). From the micro level, it breaks the traditional way of using resources, avoids the waste of resources, and reduces the pollution emissions of enterprises (Chen 2022). Hypothesis 1 is put out in light of the study above:

Hypothesis 1: There is an inverted U-shaped relationship between the digital economy and carbon intensity.

Different cities have different manifestations when implementing CP measures, which can generally be divided into imperative and incentive (Li et al. 2022; Liu et al. 2020; Zhang 2020). The directive type is when the government sets strict standards and imposes mandatory constraints on cities or enterprises. In contrast, the incentive type incentivizes enterprises to carry out energy conservation through subsidies or taxes independently. Theoretically, the role of DE on CI could also be affected by CP measures.

The moderating effect of CP has "follow cost effects" and "technological innovation compensation effect." From the level of "follow cost effect," CP measures increase the cost of pollution emissions for enterprises (Guo et al. 2021; Zhang et al. 2019), and the profits brought to enterprises by the hoist of DE are not enough to cover the increased costs.

Enterprises have to shift more costs to pollution control, and expensive production costs crowd out technological innovation funds, reduce enterprise production efficiency, and are not conducive to pollution emission reduction. Furthermore, the government proposes CP measures, such as increasing the price of high-emitting products such as fossil fuels. Companies recognize that fossil energy prices will rise in the future, the exploitation of fossil energy will increase, and the progress of DE can promote extraction efficiency, thereby increasing carbon emissions, which is consistent with the "green paradox" hypothesis (Okullo et al. 2021). It also accelerates the early emergence of CI vertices. Based on this, CP will increase the promotion of CI in the early stage. From the perspective of the "technological innovation compensation effect," CP will affect enterprises' environmental decision-making, forcing enterprises to strengthen technological innovation in emission reduction and improve the energy efficiency of heavily polluting enterprises and green transformation of production methods (Rubashkina et al. 2015; Ghisetti and Quatraro 2017). The progress of DE has made information dissemination simpler and more efficient, and enterprises will be forced to increase expenditures in innovation due to the consideration of reputational damage and increased risk of exposure to pollution incidents. In addition, implementing CP policies will prevent high-emitting enterprises from entering the region, reducing carbon emissions at the source. Based on the above considerations, CP will strengthen the reduction effect on CI in the later stage. Hypothesis 2 is put out in light of the study above:

Hypothesis 2: Low-carbon regulation strengthens the inverted U-shaped impact of the digital economy on carbon intensity and shifts the vertex to the left.

Numerous academics have studied the influence of DE on EM theoretically and practically (Shahzad et al. 2022). Firstly, the growth of DE can accelerate the energy transition to promote capital flows to clean energy technologies (Shahbaz et al. 2022; Murshed et al. 2020). Secondly, resources may be integrated to increase energy efficiency as it expands (Fu et al. 2022; Usman et al. 2021). Digitalization can also modify the population's consumption pattern and reduce the demand for conventional energy sources (Wang et al. 2022b). Some scholars conclude that the growth of the IT sector is contrarily correlated with energy usage (Ishida 2015; Schulte et al. 2016). As DE expands, it aids in the optimization of EM.

Besides increasing energy efficiency, the escalation of EM contributes to reducing carbon emissions. Shafiei and Salim (2014) empirically demonstrate that carbon emissions rise with non-renewable energy. Furthermore, using renewable energy to reduce carbon emissions has been found by Özbuğday and Erbas (2015). Substantial evidence is that improving energy

efficiency and optimizing EM can significantly reduce carbon emissions. Hypothesis 3 is put out in light of the study above:

Hypothesis 3: The energy mix plays a mediating role in the relationship between the digital economy and carbon intensity.

Product production processes are designed to be environmentally friendly through GTI (Razzaq et al. 2021). DE optimizes enterprise structure and management, saves costs, and improves profitability (Dai et al. 2022). Lin et al. (2020) find that advances in web technology can give enterprises a tremendous advantage in accessing resources and significantly improve their innovation performance. Li et al. (2020) claim that the Internet has enhanced the efficiency of green economies by integrating resources and reducing waste. In addition, advances in DE provide financial services, which can indirectly promote GTI by reducing financing constraints (Lin and Ma 2022a).

From many different perspectives, scholars study how GTI reduces carbon emissions. It can reduce carbon emissions by fostering the upgrading of industrial structures (Lin and Ma 2022b). Using GTI, Gao et al. (2022) demonstrate how it can be used to improve production efficiency by optimizing energy-intensive production patterns as well as improving production processes, resulting in a reduction of CO_2. Other scholars have also found that optimizing energy structure is an important mechanism (Cai et al. 2021; Du et al. 2022). When income levels exceeded a certain threshold, GTI contributed significantly to reducing carbon emissions (Du et al. 2019). Hypothesis 4 is put out in light of the study above:

Hypothesis 4: Green technology innovation plays a mediating role in the relationship between the digital economy and carbon intensity.

Materials and methods

Model design

Following Yao et al. (2018), this work selects the relevant control variables and designs the econometric model:

$$lnCI_{i,t} = \beta_0 + \beta_1 DE_{i,t} + \beta_2 DE^2_{i,t} + \beta_3 Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

where $lnCI_{i,t}$ represents the logarithm of the carbon intensity, and $DE_{i,t}$ represents the digital economy. i and t set the city and year. $DE^2_{i,t}$ represents the quadratic term of the digital economy. $Z_{i,t}$ represents control variables. μ_i and δ_t are the city and year fixed effects. $\varepsilon_{i,t}$ represents the error term.

In order to test the moderating effect of low-carbon regulation, we built the following econometric model:

$$lnCI_{i,t} = \varphi_0 + \varphi_1 DE_{i,t} + \varphi_2 DE^2_{i,t} + \varphi_3 DE_{i,t} * CP_{i,t} + \varphi_4 DE^2_{i,t} * CP_{i,t} + \varphi_5 CP_{i,t} + \varphi_6 Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

where $CP_{i,t}$ is the moderating variable, representing low-carbon regulation. The primary and quadratic terms of DE are multiplied by the moderating variables to generate the interaction terms, and the moderating effect is tested by the coefficients and significance of the interaction terms.

In order to analyze the possible indirect influence mechanisms, it tests whether EM and GTI were mediating variables between the two. The following are the precise test procedures: the coefficients of the non-linear regression model (1) in β_1 and β_2 passed the significance test. We also built the following econometric model:

$$M_{i,t} = \delta_0 + \delta_1 DE_{i,t} + \delta_2 DE^2_{i,t} + \delta_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{3}$$

$$lnCI_{i,t} = \vartheta_0 + \vartheta_1 DE_{i,t} + \vartheta_2 DE^2_{i,t} + \vartheta_3 M_{i,t} + \vartheta_c Z_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{4}$$

where $M_{i,t}$ are mediating variables and represent energy mix (EM) and green technology innovation (GTI), respectively.

Variable measurement

The dependent variable is CI in cities. CI is a better index of its economic condition than total emissions and per capita emissions of carbon (Dong et al. 2018). Urban carbon emissions include CO_2 from the consumption of natural gas (NG), liquefied petroleum gas (LPG), electricity, and heat (Cheng et al. 2023). First, the calculation of carbon emissions from NG and LPG: Guidelines for National Greenhouse Gas Inventories issued by the Intergovernmental Panel on Climate Change (IPCC) in 2006 provide conversion factors for calculating CO_2 emissions from NG and LPG use. The CO_2 produced by both can be calculated directly from the conversion factors. Second, the calculation of carbon emissions generated by electricity: This paper refers to Glaeser and Kahn (2010) to calculate the carbon dioxide produced by electrical energy based on the benchmark emission coefficient of China's power grid. Third, the calculation of carbon emissions generated by heat: There are two main ways to supply heat to the city: boiler houses and cogeneration plants, and the raw material is based on raw coal. The thermal efficiency value of the boiler used in this paper is 70%. Raw coal's average low-level heat generation is 20,908 kJ/kg. The quantity of raw coal used can be calculated based on the thermal efficiency value, raw coal heat coefficient, and heat supply. Raw coal has a carbon content per unit calorific value of 26.37 tons of carbon/TJ. The carbon oxidation rate is 0.94. The CO_2 emission factor of raw coal can be calculated from the heat, carbon content per unit calorific value, and carbon oxidation rate. Using the amount of raw coal produced by heat consumption, it is possible to calculate the carbon emissions produced by heat supply. We add

the carbon emissions calculated for the four main components to arrive at the total. CI in this paper is measured as the logarithm of the ratio of carbon emissions to GDP.

DE is the independent variable. Considering that DE is centered on Internet development and digital finance, this paper measures DE in a dual dimension (Li and Wang 2022). Referring to Cheng et al. (2023), digital finance is measured using the Peking University Digital Financial Inclusion Index, which has comprehensive coverage. Internet development is measured using four sub-indicators: Internet output, Internet users, Internet penetration, and Internet workers (Huang et al. 2019). They are measured by total telecommunications per capita, Internet users per 100 people, mobile phone subscribers per 100 people, and proportion of computer employees, respectively. These four indicators can broadly cover a wide range of aspects, such as Internet output, employment, and penetration rate, and can comprehensively describe the development of the Internet. A composite index is obtained by the entropy method.

CP is the moderating variable. This paper uses carbon concern to measure the degree of CP by extracting the carbon dioxide field as a proportion of the total words from each city government report. Because low-carbon regulatory policies generally take several months to have an effect, the variables are lagged by one period.

Five control variables were also selected for this paper. Considering the plethora of factors affecting CO_2 emissions, this manuscript uses the current research findings of (Yao et al. 2018). The influence of economic development has been controlled using the GDP growth rate (RGDP) and the logarithm of GDP per capita (lnPGDP). Energy consumption as a share of GDP (ES) is a control variable (Huang and Wen 2022). The environmental regulation (ER) is determined by the frequency of words containing the phrase "environmental protection" as a percentage of all the words in each city's government work report (Jiang and Ma 2021). Human capital (HC) is measured using the general education enrollment ratio of the population (Sadia et al. 2018).

Two mediating variables were chosen. The logarithm of coal use as a percentage of total use represents EM (Wang et al. 2022a). Patent applications for green utility models are used to measure GTI (Wang et al. 2019).

Data sources

This paper conducts research on 271 cities in China from 2011 to 2019. City yearbooks and construction yearbooks provide information on CI. The statistics yearbooks of each city and the Financial Data Research Center of Peking University provide data on the state of DE. The China National Intellectual Property Administration is where one obtains patent applications. Other data were obtained from the China Statistical

Table 1 Descriptive statistics

Variables	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
lnCI	2439	1.199	0.740	− 1.650	4.497
DE	2439	0.113	0.0693	0.0149	0.674
DE²	2439	0.0175	0.0335	0.000223	0.455
CP	2439	0.00184	0.00647	0	0.0598
EM	2439	0.802	0.0450	0.436	1
GTI	2439	3.897	9.816	0.0100	124.9
RGDP	2439	1.086	0.0844	0.540	1.640
ES	2439	8.601	9.462	0.242	167.3
ER	2439	5.861	2.304	0	18.15
HC	2439	1.755	2.039	0.00516	12.76
lnPGDP	2439	10.77	0.587	8.773	13.10
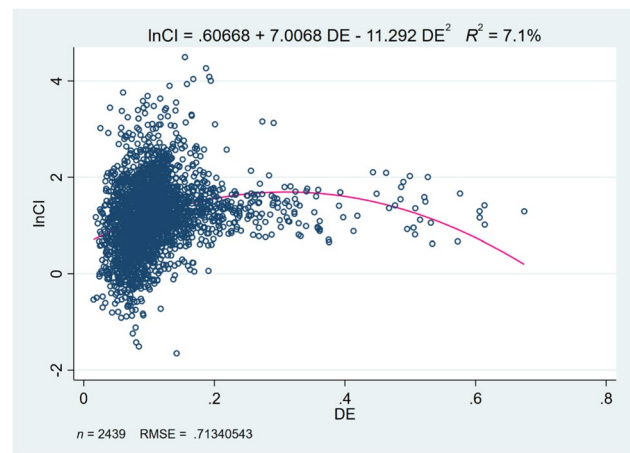
Fig. 1 Scatterplot and fitted curve of DE on CI

Yearbook, the China Environmental Statistics Yearbook, and the Wind Database.

The descriptive statistics of the variables are shown in Table 1. The maximum value of the logarithm of CI is 4.497, the minimum value is − 1.65, and the standard deviation is 0.74. This indicates a large gap between the CI of different cities. DE, EM, and GTI are similarly characterized by small means and large standard deviations. Observing the data situation of the control variables, the level of economic development, HC, and ES are all significantly different in different regions. The scatter plot in Fig. 1 demonstrates an inverse U-shaped link between DE and CI.

Empirical analysis

Baseline regression results

Table 2 shows the baseline regression results. Column (1) shows that the primary coefficients for the explanatory variables are positive, and the quadratic coefficients are negative. Columns (2–4) add control variables and prescribed effects sequentially, and the conclusion still holds. Our conclusions are consistent with Cheng et al. (2023). When DE was taking shape, the development of digitalization boosted electricity consumption and energy usage (Ren et al. 2021; Sadorsky 2012). It promotes carbon emissions by expanding investment in digital equipment and infrastructure (Zhao et al. 2022a). Additionally, as DE matures, it can speed up industrial modernization by promoting the upgrading of industries to promote carbon emissions reduction (Dong et al. 2020; Su et al. 2021). The late stage breaks the traditional way of using resources, improving enterprises' efficiency in using resources (Chen 2022). As a result, DE and CI have an inverse U-shaped connection. This result supports hypothesis 1.

In column (4), the estimating equation can be used to determine the turning point. DE index coefficients are −5.872 for the quadratic term and 2.250 for the primary

term. The turning point is 0.192, meaning CI reaches its maximum when DE rises to 0.192. From this point onwards, DE will decrease as DE continues to dilate. Additionally, CI is significantly negatively correlated with GDP growth rate (Cai et al. 2021).

Moderating effects of low-carbon regulation

Table 3 shows the results of the moderating effect of CP. The inverted U-shaped curve moderating effect is reflected in two aspects (Haans et al. 2016). First, this paper explores whether the curve shape becomes flatter or steeper. As shown in column (2), the coefficient of the quadratic interaction term is significantly negative, the moderating variable strengthens the inverted U-shaped curve, and the curves on either side of the inflection point are steeper than before. This is because governments propose low-carbon regulations such as raising the price of fossil fuels. Companies will recognize that fossil fuel prices will rise in the future, accelerating energy extraction in the short term (Okullo et al. 2021). Therefore, the promotion effect on CI is enhanced, manifested as an increase in the slope on the left side. The implementation of CP will affect enterprises' environmental decisions, forcing enterprises to strengthen technological innovation in emission reduction and realize the green transformation of production methods (Rubashkina et al. 2015). The progress of DE has made information dissemination simpler and more efficient, and enterprises will be forced to increase investment in technological innovation, considering the increased risk of exposure to pollution incidents. Therefore, the emission reduction effect on CI will

Table 2 Baseline regression results

Variables	(1) lnCI	(2) lnCI	(3) lnCI	(4) lnCI
DE	7.550***	2.063**	2.293***	2.250**
	(8.73)	(2.41)	(2.64)	(2.28)
DE^2	−12.587***	−4.610***	−5.247***	−5.872***
	(−6.14)	(−2.92)	(−2.85)	(−2.88)
lnPGDP		0.168***	0.142***	0.154**
		(3.26)	(2.77)	(2.17)
RGDP		−0.340**	−0.679***	−0.583***
		(−2.40)	(−3.70)	(−3.20)
HC		−0.002	0.007	0.017
		(−0.19)	(0.61)	(0.62)
ES		0.056***	0.049***	0.047***
		(4.42)	(4.27)	(3.98)
ER		−0.007*	−0.001	0.001
		(−1.78)	(−0.29)	(0.29)
Constant	0.568***	−0.831*	−0.131	−0.354
	(6.75)	(−1.69)	(−0.25)	(−0.49)
Year FE	No	No	Yes	Yes
City FE	No	No	No	Yes
N	2439	2439	2439	2439
R-squared				0.594

"()" show t-values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 3 Moderating effect regression results

Variables	(1) lnCI	(2) lnCI
DE	3.867***	2.879***
	(3.78)	(3.57)
DE^2	−9.275***	−6.534***
	(−5.40)	(−4.83)
CP	−10.359*	−8.189*
	(−1.66)	(−1.68)
DE*CP	132.668*	110.896**
	(1.90)	(2.04)
DE^2*CP	−332.315**	−261.776**
	(−2.28)	(−2.30)
Control variables	No	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
N	2144	2144
R-squared	0.358	0.611

"()" show t-values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

be strengthened in the later stage of CP, manifested in an increase in the slope on the right side of the inflection point. Zhang et al. (2021) can support this conclusion. Second, this paper discusses whether the curve inflection point moves to the left or right. If $\varphi_1\varphi_4 - \varphi_2\varphi_3 < 0$, the curve inflection point shifts to the left. Table 3's regression results demonstrate that $\varphi_1\varphi_4 - \varphi_2\varphi_3 = -29.06$. The implementation of CP has brought the highest point of CI ahead of schedule.

In order to gain further insight into the moderating effects of CP, this paper follows Sinacore (1993) and Zhong (2020) to decompose the interaction terms in Fig. 2. The high group (the group above the CP average) has a greater slope, and
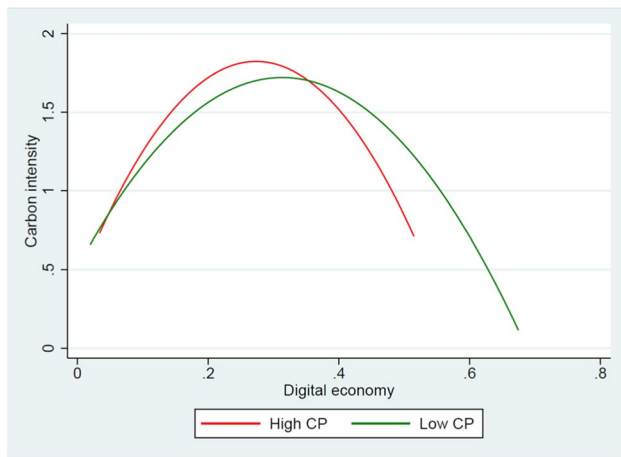

Fig. 2 Decomposing the interaction effects

the vertices shift left compared to the low group (the group below the CP average). This result supports hypothesis 2.

Endogeneity analysis

The mitigation of endogeneity is a vital topic in economics research. First, DE can reduce CI through the optimization of EM and GTI. Conversely, CI can also affect DE by influencing government policies and industrial restructuring. Therefore, there is an inverse causal relationship. On the other hand, there may be a problem of missing variables. This paper proposes to mitigate the problem of endogenous by using instrumental variables.

The number of post offices per city in 1984 was used as an instrumental variable to determine DE (Ren et al. 2022). Generally, locations with many post offices are the first to adopt Internet technology. This meets the relevance criteria. In addition, as the frequency of post office use declines, the impact on carbon emissions is disappearing. Meet the requirements of exclusivity. The instrumental variables of DE and its squared term are represented by IV and IV^2, respectively.

We first test whether instrumental variables directly affect CI. This is indicated in column (1) of Table 4. The instrumental variable's coefficient is insignificant, indicating that the number of post offices does not affect CI after controlling for the relevant variables. This satisfies the condition of exogenous. The outcomes of the first stage regression are presented in columns (2–3). The LM statistic for the original hypothesis, "Test for Under-identification of Instrumental

Table 4 Endogeneity analysis

Variables	(1)	(2)	(3)	(4)
	lnCI	DE	DE^2	lnCI
IV	−0.020	0.015**		
	(−0.22)	(2.23)		
IV^2			0.004***	
			(2.65)	
DE	2.191**			17.099***
	(2.20)			(3.33)
DE^2	−5.698***			−30.741***
	(−2.84)			(−4.47)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F		7.552	7.552	
		{7.03}	{7.03}	
Kleibergen-Paap rk LM		16.93	16.93	
		[0.000]	[0.000]	
R-squared	0.597			0.813
N	2412	2412	2412	2412

"()" show *t*-values, "[]" show *p*-values, "{}" show critical values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Variables" significantly rejected the hypothesis at the 1% level. In the weak instrumental variable identification test, the *F* value is 7.552, greater than the critical value of 7.03 at the 10% level of the weak identification test. Therefore, the instrumental variables selected in this paper are not weak instrumental variables. The outcomes of the second stage regression are provided in Column (4). After accounting for endogeneity, the conclusion still holds.

Robustness tests

Substitution of the dependent variable

This work uses the logarithm of carbon emissions per capita as the dependent variable for robustness testing (Zhu et al. 2022). The outcomes of the regressions are shown in Table 5. Examining the coefficients and importance of the factors concur with benchmark findings.

Substitution of the key independent variable

The growth of DE is correlated with the amount of digital finance. The Digital Inclusive Finance Index was used as the independent variable in robustness testing since it covers various topics. The outcomes of the regressions are shown

in columns (3–4) of Table 5. The results demonstrate the robustness of the paper's findings.

Excluding systematic changes in macro factors

By setting the interaction effect of provinces and years, we can exclude systemic changes in macro factors. The outcomes, which are shown in Table 5's columns (5–6), match those of the benchmark regression.

Heterogeneity analysis

Regional heterogeneity

Both DE and CI are characterized by significant regional heterogeneity in their distribution. The 271 cities were divided into East, Central, and West.

Table 6 reports the regression analysis of regional heterogeneity. The findings demonstrate that the quadratic term's coefficients are significant in all three regions. The coefficients of the East are the smallest. In the East, DE was developed earlier than the West. Furthermore, the industrial structure was transformed earlier. CI is low, resulting in a smaller coefficient of influence on CI. CI is high in the Central and West due to the construction of infrastructure

Table 5 Robustness tests

Variables	Substitution of the dependent variable		Substitution of the key independent variable		Excluding systematic changes in macro factors	
	(1)	(2)	(3)	(4)	(5)	(6)
DE	4.834***	2.962***	1.753***	1.088***	3.155**	2.112*
	(3.57)	(3.09)	(5.29)	(4.27)	(2.03)	(1.71)
DE^2	−10.346***	−6.739***	−0.413***	−0.252***	−8.777***	−5.829**
	(−3.59)	(−3.29)	(−7.97)	(−5.53)	(−2.71)	(−2.34)
lnPGDP		0.811***		0.137*		0.360**
		(9.69)		(1.96)		(2.48)
RGDP		−0.253		−0.529***		−0.745***
		(−1.31)		(−2.95)		(−2.97)
HC		0.036		0.027		0.004
		(1.23)		(1.16)		(0.13)
ES		0.045***		0.045***		0.045***
		(3.85)		(3.90)		(3.62)
ER		0.002		−0.001		0.005
		(0.40)		(−0.25)		(1.16)
Constant	5.224***	−3.919***	−0.227	−1.126	1.268***	−2.191*
	(35.15)	(−4.49)	(−0.37)	(−1.29)	(7.74)	(−1.71)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year province FE	No	No	No	No	Yes	Yes
N	2439	2439	2439	2439	2439	2439
R-squared	0.579	0.735	0.372	0.608	0.477	0.668

"()" show *t*-values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6 Regional heterogeneity

Variables	(1) East	(2) Central	(3) West
DE	1.944	4.732**	7.104***
	(1.63)	(2.37)	(2.83)
DE^2	−3.995*	−19.741**	−17.858***
	(−1.90)	(−2.38)	(−3.20)
lnPGDP	0.202**	0.130	0.169
	(2.62)	(0.88)	(0.59)
RGDP	−0.656***	−0.193	−0.606*
	(−3.77)	(−0.91)	(−1.91)
HC	0.040	0.004	−0.010
	(1.17)	(0.11)	(−0.24)
ES	0.062***	0.074***	0.027***
	(3.70)	(4.62)	(2.92)
ER	−0.001	0.001	−0.006
	(−0.16)	(0.15)	(−0.52)
Constant	−0.899	−0.800	−0.529
	(−0.99)	(−0.51)	(−0.18)
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
N	999	927	513
R-squared	0.643	0.742	0.533

"()" show t-values; ***$p<0.01$, **$p<0.05$, *$p<0.1$

as well as the use of conventional resources. As a result, there is a more excellent marginal utility to CI in the Central and West. Developing countries with a low level of DE have great potential to improve their production structure and technological level, thereby making a more outstanding marginal contribution to carbon reduction (Shi et al. 2022b).

Heterogeneity in the level of human capital

Cities must have access to human resources in order to implement technological innovation. Therefore, DE may have varying effects on CI according to human capital. By means of human capital, cities were classified into high and low human capital.

The results for high human capital are presented in column (1) of Table 7. The coefficient for the quadratic term of the independent variable is negative. When the human capital is high, it provides the basic elements for GTI, which helps DE to achieve carbon reduction eventually. Column (2) reports the regression results for low human capital, and the coefficient is insignificant. When the human capital is low, it does not provide the talent to support green technology innovation GTI to lower carbon emissions, resulting in a non-significant coefficient for DE.

Table 7 Heterogeneity of human capital and urbanization level

Variables	(1) High human capital	(2) Low human capital	(3) High urbanization	(4) Low urbanization
DE	2.701**	2.078	2.312*	3.357
	(2.60)	(1.65)	(1.89)	(1.28)
DE^2	−5.482***	−1.826	−4.405**	−10.559
	(−3.79)	(−0.56)	(−2.18)	(−0.80)
lnPGDP	−0.000	0.151*	0.080	0.130
	(−0.00)	(1.66)	(0.98)	(1.03)
RGDP	−0.804***	−0.573**	−0.559***	−0.579**
	(−3.81)	(−2.59)	(−3.20)	(−2.38)
HC			0.014	0.027
			(0.60)	(0.41)
ES	0.046***	0.044***	0.036***	0.051***
	(3.98)	(3.15)	(2.65)	(5.06)
ER	0.000	−0.003	−0.000	0.003
	(0.05)	(−0.57)	(−0.02)	(0.49)
Constant	1.496	−0.243	0.480	−0.139
	(1.31)	(−0.25)	(0.53)	(−0.11)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	718	1721	1222	1217
R-squared	0.614	0.616	0.480	0.696

"()" show t-values; ***$p<0.01$, **$p<0.05$, *$p<0.1$

Heterogeneity of urbanization levels

By developing DE, rural economies can be transformed, and urbanization can be achieved (Zhang and Zhou 2022). When the level of urbanization is at different stages, CI may be affected differently. The median level of urbanization is divided into two cases: high and low urbanization.

At higher urbanization levels, the coefficient for the dependent variable is significant in column (3) of Table 7. Urbanization has contributed to enhanced energy efficiency due to the increased use of concentrated energy (Yao et al. 2018). At lower urbanization levels, the coefficient is not significant in column (4). This is because DE may be at an early stage when urbanization is low. Digital industrialization and digitization of industries are not well-built.

Further analysis of the mechanism

Emission reduction or production increase

This section examines the causes of benchmark results. Separate regressions were conducted using the logarithm of total carbon emissions and total output as the dependent variable.

Columns (1–2) of Table 8 represent the results for total carbon emissions. Its primary term has a positive coefficient, whereas its quadratic term has a negative coefficient.

During the beginning stage, the increase in economic efficiency brings about an expansion of production capacity, which increases energy usage (Avom et al. 2020). During the later stage, the development of infrastructure, technological advances, and industrial structure upgrades driven by DE reduce the use of traditional energy sources (Zhang et al. 2022a; Zhu et al. 2022).

Columns (3–4) represent the regression results for total output. This shows that the total output is impacted in a U-shaped manner. During the early stage, digital infrastructure is being built with a long construction period and high cost, inhibiting the economy's growth. The network scale level during the initial use period of the Internet is not high, the spread of the network is small, and the intensity is not large (Han et al. 2019), and the cost of information acquisition is relatively high so that it will inhibit economic growth to a certain extent. During the later stage, it increases resource allocation effectiveness to support economic growth (Ding et al. 2022; Kapoor 2014). Both total carbon emissions and total output are significantly affected, as evidenced by the above findings.

Energy mix

The section examines the impact of EM. Column (2) of Table 9 displays that DE has a positive coefficient for its primary term, whereas its quadratic term has a negative

Table 8 Total carbon emissions and total output as the dependent variable

Variables	(1) Total carbon emissions	(2) Total carbon emissions	(3) Total output	(4) Total output
DE	4.192***	2.400***	− 13.699*	− 14.744*
	(3.20)	(2.61)	(− 1.75)	(− 1.85)
DE^2	− 8.912***	− 5.480***	49.208**	48.703**
	(− 3.48)	(− 3.10)	(2.13)	(2.07)
lnPGDP		0.814***		1.006***
		(8.99)		(2.91)
RGDP		− 0.227		1.407***
		(− 1.16)		(2.70)
HC		0.004		− 0.005
		(0.16)		(− 0.04)
ES		0.045***		− 0.031**
		(3.90)		(− 2.46)
ER		0.000		− 0.022
		(0.04)		(− 1.00)
Constant	6.592***	− 2.553***	4.701***	− 7.281**
	(45.04)	(− 2.73)	(6.27)	(− 2.01)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	2439	2439	2439	2439
R-squared	0.593	0.743	0.350	0.390

"()" show t-values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 9 Analysis of mediating effect results

Variables	(1) lnCI	(2) EM	(3) CI	(4) GTI	(5) lnCI
DE	2.250**	0.154*	1.735*	−58.899*	1.709*
	(2.28)	(1.67)	(1.93)	(−1.80)	(1.87)
DE^2	−5.872***	−0.256*	−5.021***	196.339*	−4.068**
	(−2.88)	(−1.82)	(−2.72)	(1.81)	(−2.56)
EM			3.331***		
			(4.27)		
GTI					−0.009***
					(−4.64)
lnPGDP	0.154**	−0.007*	0.177**	−0.854	0.146**
	(2.17)	(−1.79)	(2.55)	(−0.58)	(2.07)
RGDP	−0.583***	0.001	−0.586***	2.011	−0.565***
	(−3.20)	(0.07)	(−3.26)	(0.90)	(−3.14)
HC	0.017	0.001	0.014	0.107	0.018
	(0.62)	(0.39)	(0.52)	(0.18)	(0.70)
ES	0.047***	−0.000	0.048***	−0.119**	0.046***
	(3.98)	(−0.65)	(4.04)	(−2.23)	(3.94)
ER	0.001	0.000	0.000	−0.154	−0.000
	(0.29)	(0.84)	(0.01)	(−1.52)	(−0.03)
Constant	−0.350	−0.188***	0.276	21.013	−0.157
	(−0.46)	(−4.22)	(0.38)	(1.30)	(−0.20)
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
N	2439	2439	2439	2439	2439
R-squared	0.594	0.376	0.623	0.269	0.603

"()" show t-values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

coefficient. This is because, during the beginning stage, an increase in traditional energy usage has been caused by DE (Avom et al. 2020). During the later stage, its growth can endorse capital flows to clean energy technologies (Murshed et al. 2020; Shahbaz et al. 2022). The above arguments support the view that DE influences EM by first promoting and then inhibiting it.

Finally, column (3) puts EM back into the benchmark equation and finds a significantly positive coefficient for EM. According to particular research, using renewable energy sources may help cut carbon emissions (Dogan and Seker 2016; Shafiei and Salim 2014; Özbuğday and Erbas 2015). The empirical results support hypothesis 3.

Green technology innovation

This section explores GTI as a mechanism variable. Table 9 presents the results of the mediating model used in this paper for empirical testing. In column (4), the primary terms in DE are negative coefficients, whereas the quadratic terms are positive coefficients. Significant at the 10% level. Thus, GTI is significantly impacted by DE in a positive U-shaped manner. The initial stage of digital development prompted

companies to change their business models. However, it was difficult for companies to successfully modify their business models in a brief amount of time (Gebauer et al. 2020). During the later stage, the digital economy optimizes enterprise structure and management, thereby promoting the advancement of the level of GTI (Dai et al. 2022).

Column (5) illustrates the results of the intermediate variable of GTI put back into the benchmark regression equation. GTI have a negative coefficient. A significant reduction in CI can be achieved through an increase in GTI. Carbon emissions can be reduced by promoting the upgrade of industrial structures through green innovation (Gao et al. 2022; Lin and Ma 2022b). In the process of making judgments, the coefficient values are observed, as well as any significant changes in them. The coefficient in column (5) decreased compared to the benchmark regression result. This suggests that advances in GTI are its mechanism. The empirical results support hypothesis 4.

Endogenous testing of mediation models

This article considers endogenous issues that can arise when using the mediation model. This paper uses the instrumental

variables in the "Moderating effects of low-carbon regulation" section to mitigate the endogenous between the digital economy and mediation variables. The lag term of the mediation variable is used as the instrumental variable of the mediation variable to reduce the endogeneity between the mediation variable and CI.

Column (1) of Table 10 represents the results obtained using the instrumental variable approach to alleviate endogenous problems between DE and EM. The results reveal that the DE still affects the EM in an inverted U-shape. The columns (2–3) show the results obtained using instrumental variable methods to mitigate endogenous problems between EM and CI. In column (2), the coefficient is significant in the first-stage regression findings, with an F-value of 91.89, indicating that it is not a weak instrumental variable. In column (3), the regression results of the second phase indicate that the conclusions still hold after considering endogeneity.

Column (4) represents the results of mitigating the endogenous problems between DE and GTI. The columns (5–6) show the results obtained to mitigate the endogenous between GTI and CI. The coefficient is significant in column (5), with an F-value of 714.9, indicating that it is not a weak instrumental variable. In column (6), the results of the second phase indicate that the conclusions still hold after considering endogeneity.

Conclusions and policy implication

China has the opportunity to lessen its carbon footprint through the expansion of its DE. Although preliminary studies have been analyzed, there are still research gaps. For example, the existing literature lacks systematic studies focusing on the city level. At present, no scholars have studied the mechanism of low-carbon regulation. This paper proposes the impact mechanism of DE on CI under the background of the 2011–2019 dual carbon goals. Primary conclusions:

(1) CI is significantly impacted by DE in an inverted U-shaped manner. In the event that DE reaches 0.192, CI reaches its maximum. This conclusion remains valid after introducing instrumental variables to mitigate endogeneity and a number of robustness tests.

(2) CP strengthens the inverted U-shaped relationship between the two and shifts the inflection point to the left. This finding suggests that the implementation of CP will eventually strengthen the effect on CI and can lead to the peak of CI appearing earlier and entering the emission reduction stage earlier.

(3) In the central and western areas, the marginal utility of DE on CI is greater. This finding suggests that there is

Table 10 Endogenous analysis of mediating effects

Variables	(1) EM	(2) EM	(3) lnCI	(4) GTI	(5) GTI	(6) lnCI
EM			3.103***			
			(4.39)			
L. EM		0.551***				
		(9.59)				
GTI						−0.011***
						(−7.91)
L. GTI					1.181***	
					(26.74)	
DE	2.988***	0.172***	2.261***	−197.6	9.150	2.293***
	(4.81)	(2.96)	(2.94)	(−1.31)	(1.13)	(3.19)
DE^2	−4.156***	−0.237***	−5.662***	993.6***	−12.31	−4.894***
	(−5.28)	(−2.92)	(−4.11)	(4.07)	(−0.66)	(−4.45)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F		91.89			714.9	
		{16.38}			{16.38}	
Kleibergen-Paap rk LM		68.70			34.19	
		[0.000]			[0.000]	
R-squared	0.684		0.876	0.28		0.849
N	2412	2168	2168	2412	2168	2168

"()" show t-values, "[]" show p-values, "{}" show critical values; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

a stronger dependence on conventional resources and, thus, a higher degree of CI in the central and western areas. DE may boost the efficiency of energy usage, leading to a higher marginal utility. The inverted U-shaped conclusion holds in cities with higher human capital and urbanization. This result suggests that cities with high urbanization and human capital have greater potential to eventually reduce CI.

(4) Mechanism analysis shows that optimizing EM and promoting GTI are two essential ways to reduce CI. Specifically, EM is significantly impacted by DE in an inverted U-shaped manner. CO_2 is finally reduced via EM optimization. GTI is significantly impacted by DE in a U-shaped manner. Advances in GTI ultimately reduce CI.

Following are the policy implications.

(1) Further promote the vital role of CP and DE in reducing CI. The findings suggest that CP plays a positive regulatory role in reducing CI. The government can support DE to play a deeper role in the process of carbon emission reduction through low-carbon regulatory means such as laws and regulations, administrative control, and financial and tax support. For example, the government should encourage enterprises to implement digital technologies and provide tax breaks for enterprises utilizing new technologies. At the same time, the government should set appropriate low-carbon targets for digital enterprises through policy guidance to strengthen their ability to reduce emissions.

(2) Dynamic management should be carried out when increasing Internet investment, and enterprises in the central and western regions should invest more to increase the effect of emission reduction. Before exerting the effect of DE to reduce CI, the government should increase local investment in education to attract high-tech talents. In addition, the government should scientifically plan urban land, complete infrastructure, and create urban employment opportunities to break through the urban–rural divide and accelerate the urbanization process.

(3) The government should strengthen the role of optimizing EM and promoting GTI in reducing CI. Specifically, governments should develop policies to encourage investment in renewable energy, support enterprises to use green energy, and encourage green innovation activities by enterprises. In addition, for high-emitting enterprises, the government can support the transformation of enterprises through taxes or subsidies.

There are still some limitations in this study. Firstly, further analysis at the firm level is necessary to reflect some new features at the micro level. Secondly, subsequent studies can continue to focus on updating the data for further analysis.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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