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RESEARCH ARTICLE

Impact of digital economy development on carbon emission intensity in the Beijing-Tianjin-Hebei region: a mechanism analysis based on industrial structure optimization and green innovation

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Abstract
Under the "Digital China" strategy and "Carbon Peaking and Carbon Neutrality" goal, it is significant to explore the carbon reduction effect from the digital economy development in a multi-dimensional way. Based on the panel data of 13 cities in the Beijing-Tianjin-Hebei (BTH) region from 2011 to 2019, this study uses mechanism test model, threshold effect model, and spatial Durbin model which empirically test the influence mechanism and spatial spillover effect of digital economy development on regional CEI. The research found that (1) the digital economy development in the BTH region can reduce regional CEI, and it passes the endogenous test; (2) the digital economy indexes of 13 cities in the BTH region have significantly increased with time evolution, but there is obvious spatial unevenness; the CEI of each city except Tianjin decreases significantly with time evolution, and Tianjin shows a trend of decreasing and then increasing; (3) digital economy has a positive spatial correlation, showing the characteristics of "H–H" and "L-L" clustering. Furthermore, the digital economy has a spatial spillover effect on the CEI of neighboring cities; (4) the digital economy development can promote the industrial structure rationalization and upgrade, improves the urban green innovation quantity and quality, then reduces the regional CEI through them; and (5) the impact strength of digital economy on CEI varies at different threshold intervals of the mechanism variable.

Keywords The Beijing-Tianjin-Hebei region · Digital economy · Industrial structure optimization · Green innovation · Carbon emission intensity · Spatial spillover effect

Introduction

Global greenhouse gas emissions have caused climate change issues and hindered the sustainable development of human society. For this reason, more than 130 countries and regions, including China, have proposed carbon neutrality targets to resolve the contradiction between economic growth and environmental protection (Dong et al. 2022a). In China, the extensive development model and the unreasonable energy and industrial structure have sharply increased carbon emissions. Data from the *Carbon Emission & Accounts Datasets* shows that China's carbon emissions reached 1 billion metric tons in 2018. Compared with other countries, China's carbon emission reduction is under high pressure and will significantly impact the global economy and environment (Wang et al. 2019b). The Beijing-Tianjin-Hebei (BTH) region accounts for about 10% of China's total economic output. It is the core growth pole of the national economy and an essential region for achieving the "carbon peaking

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and carbon neutrality" goal (Bai et al. 2021). The total energy consumption of the BTH region in 2019 is 481 million tons of standard coal, accounting for 9.84% of the national energy consumption. A large amount of CO_2 emissions from fossil energy consumption has caused serious ecological problems. In the context of China's "double carbon" target and the coordinated development of the BTH region, strengthening regional carbon emission management and reducing carbon emission have become critical measures to break the contradiction between the ecological environment and economic development (Wang et al. 2019a; Siqin et al. 2022). This study researches the BTH region's carbon emission intensity (CEI), which is essential to guarantee the quality of low-carbon economic development and reduce regional and even global carbon emissions.

Along with the new round of technological revolution and industrial change, China's economy is facing digital transformation represented by digital economy. According to the *White Paper on China's Digital Economy Development*, the scale of China's digital economy has risen from 9.5 trillion yuan in 2011 to 39.2 trillion yuan in 2020 (CAICT 2020). Along with the iterative upgrading of digital technology, China's digital economy has deeply integrated with the real economy. The *White Paper on Digital Carbon Neutrality (2021)* suggests that digital technologies, through deep integration with major carbon emissions areas such as electricity, industry, and transportation, can promote the optimization of the energy structure of traditional industries and help achieve the goal of "double carbon." However, we cannot ignore the fact that digital technology, on which the development of digital economy depends, will bring more power and energy consumption. The development and operation of infrastructures such as cloud, blockchain, and data centers require more energy-intensive infrastructure, which to a certain extent will result in more carbon emissions. Shvakov et al. (2019) conducted an empirical analysis of the top 10 countries in the world in terms of digital technology competitiveness. They found that the digital economy imposes a heavier burden on environmental protection. Therefore, more evidence is urgently needed on whether digital economy development can serve as a new path to help reduce carbon emissions.

Since the Digital China Strategy and the "Double Carbon" target were proposed, leveraging the digital economy to promote low-carbon development has become a focus of government and academia. There are three main views in existing studies. First, the positive view. Zhang and Liu (2022) found that digital finance contributes to carbon emission reduction. Yi et al. (2022) pointed out that the digital economy has significant spatial spillover effects on carbon emission reduction, and it can indirectly affect carbon emission reduction through the transformation of energy mix. Ma et al. (2022) verified that R&D investment and technological innovation could suppress carbon emissions and mediate between digitalization and carbon emissions. Wang et al. (2022) proposed that the digital economy achieves carbon emission reduction by expanding the economic scale of the tertiary sector, reducing the share of coal consumption, and enhancing green technological innovation. Zhang et al. (2022b) found that the digital economy influences carbon emission performance through the intensity and scale of energy consumption. Second, the negative view. Zhang et al. (2022c) found that the digital economy is not conducive to improving energy efficiency, thus indirectly increasing total carbon emissions. Yu and Zhu (2022) indicated that the digital economy increases carbon emissions by increasing energy intensity and promoting economic expansion. Dong et al. (2022b) suggest that the digital economy can indirectly increase per capita carbon emissions by promoting economic growth, financial development, and industrial structure upgrading. Third, non-linear relationship. Li and Wang (2022) found that the impact of the digital economy on carbon emissions is an inverted U-shaped relationship. In summary, the existing studies on the relationship between digital economy and carbon emissions are inconclusive, and the following aspects need to be expanded: (1) Existing studies focused on the national level, but there are no studies investigating the differences, spatial correlation and spatial spillover effects of digital economy and CEI among cities in the primary regions of carbon emission reduction from the spatial perspective. (2) There are various performance characteristics of industrial structure optimization and green innovation, and previous studies only measure the industrial structure advancement and the quantity of green innovation, lacking a systematic examination of detailed dimensions. (3) There is an urgent need to investigate the linear or non-linear relationship between the digital economy and CEI, under the level change of industrial structure rationalization and upgrade, green innovation quantity and quality.

As mentioned above, this study aims to investigate the mechanism and spatial effects of digital economy on CEI through panel data of 13 cities in the BTH region from 2011 to 2019. The research is as follows: (1) By constructing a digital economy development index system, this study scientifically and objectively measures the development of digital economy in the BTH region. (2) This study uses fixed-effects model regression to test the effect of urban digital economy development on CEI. (3) This study uses ArcGIS analyze the spatial distribution characteristics of the digital economy and CEI in the BTH region, then uses the spatial Durbin model to regress and analyze the spatial spillover effect of digital economy on CEI. (4) This study explores the mechanisms of industrial structure rationalization and upgrading, green innovation quality and quantity in the digital economy affecting carbon emission intensity. (5) The potential relationship between digital economy and CEI is further discussed using the threshold panel model from different levels of technological innovation and industrial structure upgrading. Moreover, this study sets instrumental variables and uses two-stage least squares (2SLS) to test the endogeneity. Meanwhile, this study uses the methods of replacing dependent variables and spatial weight matrix for robustness test.

Distinguishing from previous studies, the marginal contributions of this study are as follows. (1) With the perspective of digital empowerment for low-carbon development as the research perspective, this study takes the BTH priority region of carbon emission reduction as the research unit. This study identifies the spatial spillover effects of digital economy affecting CEI based on the spatial autocorrelation test of the BTH digital economy. Then, this study further analyzes the spatial differences and correlation effects among regional cities through effect decomposition. The study results can provide evidence and management insights for governments to control evolutionary trends and formulate digital synergy development policies. (2) This study further refines and deepens the mechanical effects of industrial structure and green innovation. Specifically, this paper subdivides their dimensions into industrial structure upgrading and rationalization, and innovation "quality" and "quantity," respectively, to study their specific effects on the impact path. This extends and complements the digital economy's analysis of carbon reduction mechanisms. (3) Considering the level of heterogeneity in the industrial structure rationalization and upgrading green innovation quantity and quality, this study uses a threshold panel model to systematically reveal the stage-specific CEI reduction characteristics of the digital economy. This rationalizes the non-linear relationship between the digital economy and CEI, and clarifies the policy focus of the digital economy to promote low-carbon development.

The remaining sections of this study are described below. "Theoretical analysis and research hypothesis" section discusses the theoretical basis and puts forward six hypotheses. "Variable definition and data sources" section defines the relevant variables, introduces the data sources, and performs the descriptive statistics of the data. "Empirical analysis" section mainly including the benchmark regression analysis. "Extended research: spatial spillover effect" section mainly analyzes the spatial distribution characteristics, spatial correlation, and spillover effects. "Further analysis: mechanism effect and threshold effect test" section conducts a test of mechanism effects and analyzes the threshold effects of the four mechanism variables. "Discussion" section provides a discussion of the mechanism. "Robustness test" section tests the robustness of the findings through three methods, including the IV-2SLS test for endogeneity. "Conclusions and policy implications" section summarizes the conclusions and corresponding recommendations.

Theoretical analysis and research hypothesis

Direct effect of digital economy on CEI

The environmental Kuznets theory points out that there is an inverted U-shaped relationship between economic development and the environment. The digital economy can create a carbon reduction effect in many ways, accelerating the Kuznets curve into the right half. First, in terms of social production and life, the digital economy can provide networked and intelligent technologies that empower process development and production operations. It can improve the resource recycling rate and achieve optimal resource allocation, thus reducing the CEI of cities (Zhang et al. 2022a). Moreover, digital technology has given rise to internet shopping platforms, government affairs platforms, and conference platforms. The online shopping and paperless office lifestyle significantly reduce transportation and production energy consumption, thereby reducing carbon intensity (Li et al. 2021). Second, in terms of urban governance. Relying on big data, artificial intelligence and other digital technologies, the digital economy can improve urban informatization and intelligent operation. Then, it can use resources and energy efficiently and reduce carbon emissions. Hanpton et al. (2013) proposed that the application of big data and cloud computing can support the government in formulating carbon emission policies. They help regulators and the public to monitor and predict future trends in corporate carbon emissions reductions to minimize carbon emissions (Yang et al. 2020; Deng and Zhang 2022). Third, in terms of enterprise development. Digital technology will help optimize the end-of-pipe governance technology of enterprise carbon emissions, accurately monitor and analyze energy use data and carbon footprint, and further improve the allocation efficiency of energy elements. Xu et al. (2019) show that resource allocation is the main factor affecting carbon productivity. Therefore, the digital economy can promote enterprises' green transformation, thus empowering carbon reduction (Chen and Hao 2022). In summary, we propose hypothesis H1.

- Hypothesis H1: The development of digital economy can reduce CEI in the BTH region.

Mechanism of digital economy on carbon emission intensity

As Zhu and Wang (2020) proposed that the digital economy promotes industrial structure optimization through efficiency improvement, cost savings, economies of scale, precise allocation, and innovation empowerment. In terms of industrial structure rationalization. Based on the Enterprise Value Creation theory, the digital economy can effectively reduce operating costs and improve the operational efficiency of enterprises. First, the digital economy can utilize its technological effects to help companies improve information search efficiency and matching, it helps reduce ineffective production links and avoid wasting resources (Ren et al. 2021). Furthermore, the digital economy relies on digital trading and industrial internet platforms to attract upstream and downstream industries to form virtual clusters (Halbert 2012; Tang et al. 2021). Based on the industrial agglomeration theory, this can improve the reasonable allocation of resources among industries, thus reducing the energy consumption of enterprises, and then reducing CEI (Chen et al. 2019). In terms of industrial structure upgrade. According to the economic development theory of new structural economics, the industrial structure will migrate to the tertiary industry with the improvement of the economic development level. Along with digital industrialization, the tertiary industries such as e-commerce, information communication, and digital services in the BTH region have developed rapidly, and the industrial structure upgrading level has been continuously improved. Furthermore, the application of digital technology promotes the transformation of industries from labor-intensive to technology-intensive, then enhances the industrial structure upgrading level. Zhu and Shan (2020) suggest that the tertiary sector and other industries after digital transformation are mostly clean industries with high efficiency and low energy consumption, which can significantly reduce urban CEI. In summary, we propose hypothesis H2a and H2b.

- Hypothesis H2a: The development of digital economy reduces regional CEI by promoting the rationalization of industrial structure in the BTH region.
- Hypothesis H2b: The development of digital economy reduces regional CEI by promoting the upgrading of industrial structure in the BTH region.

According to the innovation economics theory, the new combination of production factors for enterprises can realize innovation and promote development. The digital economy can promote knowledge and technology spillovers, innovate production technologies through resource restructuring, etc., so as to improve the level of urban green innovation (Halbert 2012; Tang et al. 2021). The improvement of urban digital economy development level will increase the demand for high-tech and academic talents, and then optimize the human capital structure, which lays the foundation for green innovation. Relying on the digital economy, banks can ease the debt financing constraints of enterprises by improving the credit rationing structure. This can provide financial support for the green innovation of enterprises and promote the growth of green innovation output (Zhang and Liu 2022; Zhang et al. 2022a). Third, digital transformation can combine digital technology with enterprise R&D innovation, leading to the effective allocation of green R&D resources, improving the efficiency of green innovation and avoiding wasting resources (Mikalef et al. 2018; Paunov and Rollo 2016). Green innovation is an effective way to reduce carbon emission levels (Xu et al. 2021). In the energy field, green innovation can promote green energy consumption, accelerate the development of photovoltaic, wind power, and renewable energy. It facilitates a low-carbon transformation of energy consumption structure and directly reduces urban carbon emissions. Furthermore, Dong et al. (2022c) found that green innovation can indirectly improve carbon emission efficiency by promoting urbanization. In summary, we propose hypothesis H3a and H3b.

- Hypothesis H3a: The development of digital economy reduces CEI by increasing the quantity of green innovations in the BTH region.
- Hypothesis H3b: The development of digital economy reduces CEI by improving the quality of green innovation in the BTH region.

Spatial spillover effects of digital economy on CEI

The new economic geography theory posits that geographical proximity can facilitate the flow of production factors by increasing the exchange of knowledge and technology, which can have a spatial spillover effect on adjacent areas. As digital technology has high mobility and reproducibility, it can promote the realization of cross regional industrial economic activities, thus showing spatial spillover effects (Yang et al. 2022; Zhang et al. 2022b). The specific analysis is as follows. First, the digital economy achieves iterative development through technological innovation. In innovation activities, enterprises, universities, and research institutes in adjacent regions have more opportunities for exchanges and cooperation. The cross-regional flow of talents realizes knowledge overflow, and the cross-regional flow of data realizes information overflow (Keller 2002). Second, the digital economy can optimize the industrial structure, strengthen the relationship between supply and demand within the industrial chain, and realize the rational allocation of resources. It enhances the utilization rate of urban resources and generates resource spillover effects. Third, using digital technologies for carbon emission monitoring and governance can realize data sharing and joint prevention and control among cities. It helps exert the effect of collaborative governance, reduce the intensity of regional carbon emissions, and promote the coordinated development of low carbon in the BTH region (Li and Wang 2022). In terms of the spatial spillover of CO_2, Yue et al. (2022), Lv et al. (2022), Liu and Liu (2019) showed that urban carbon emissions have an impact on the local ecological environment, in addition to ripple effects on neighboring cities. In summary, we propose hypothesis H4.

- Hypothesis H4: The development of digital economy reduces CEI through spatial spillover effects in the BTH region.

Comprehensive three-part analysis, this study draws the impact mechanism of digital economy development on CEI in the BTH region, as shown in Fig. 1.

Variable definition and data sources

Variable definition

Explained variable

Carbon emission intensity (CEI). Since there are significant disparity in economic development between cities in the BTH region, so this study uses CEI to measure the carbon emission level of cities (Cary 2020). CEI is expressed as CO_2 produced per unit of GDP. According to Ren's (2020) research, it uses the consumption of liquefied petroleum gas, natural gas, coal gas, electricity, and thermal energy to calculate energy consumption. Coal-based heat demand is the leading cause of CO_2. So, this study converts all heat into raw coal, then multiplies the carbon emission coefficient of raw coal to measure the carbon emissions (Liu et al. 2015; Lu et al. 2018), thus calculates the CEI. The formula is as follows:

$$CO_{2i}^{t} = \sum_{j} CO_{2ij}^{t} kE_1 + vE_2 + rE_3 + uE_4 + \theta E_5 \tag{1}$$

$$\mathrm{CEI} = \frac{\mathrm{CO_2}}{\mathrm{GDP_{real}}} \tag{2}$$

In Formula (1), CO_{2i}^{t} is the total energy-related carbon emission of city i in year t. CO_{2ij}^{t} is the carbon emission of city i using fuel type j in year t. E_1, E_2, E_3, E_4, and E_5 are natural gas, liquefied petroleum gas, gas, electricity consumption and heat energy, respectively. k, v, r, u, and θ are energy correlation coefficients from the IPCC guidelines for *National GHG Emission Inventories 2006*. In Formula (2), CEI is the carbon emission intensity of a city, and GDP is the actual gross regional product.

Explanatory variable

Digital economy development index. The quantification of indicators is necessary to objectively gauge the trends and impact of the digital economy. This study reference Zhao's (2020) and Li's (2021) digital economy development index measurement method and takes into account the availability of relevant data at the city level. This study focuses on the longitudinal development of the digital economy and considers the impact of three aspects on the digital economy: the current state of development of digital industries, digital infrastructure development, and digital financial services. As shown in Table 1, we use six indicators to construct the digital economy index system. Then we use the entropy weight method to calculate the city's digital economy comprehensive index.

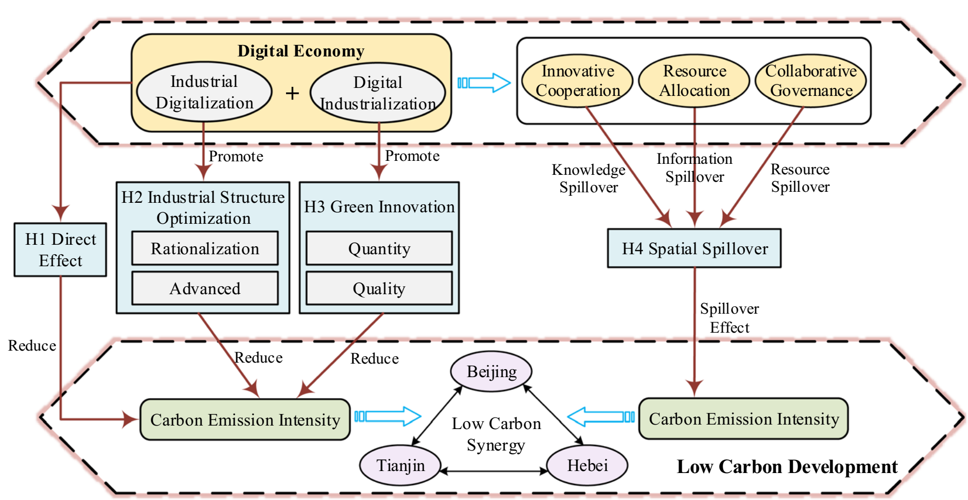

Fig. 1 Impact mechanism

Table 1 Digital economy development index

Target layer	Criterion layer	Index layer	Interpretation	Weight
Digital economy development	Digital industry development	Industrial base	Percentage of computer services and software employees	0.315
		Telecommunications output	Total telecom service per capita	0.1484
		E-commerce and online shopping development	Total postal service per capita	0.2624
	Digital infrastructure	Fundamentals of broadband network technology	Internet users per 100 people	0.1237
		Fundamentals of mobile Internet	Mobile phone users per 100 people	0.0803
	Digital finance	Digital financial inclusion	Digital financial inclusion index	0.0700

Mechanism variables

1) Industrial structure optimization, including two sub-mediating variables of industrial structure rationalization and industrial structure upgrade. Based on Gan's (2011) research, this study uses the tertiary industry added value divided by the secondary industry added value to calculate the industrial structure upgrade index (Isu), and uses the Theil index to calculate the industrial structure rationalization index (Isr) (Gan et al. 2011; Zhang and Cui 2018). The formula is as follows.

$$H = \sum_{i=1}^{n} \left(\frac{Y_i}{Y} \right) \ln \left(\frac{Y_i}{L_i} / \frac{Y}{L} \right) \tag{3}$$

In formula (3), i is the industrial sector. n is the quantity of industrial sectors. Y is the urban GDP. L is the quantity of employees. Y_i/Y is the output structure. Y_i/Li is the productivity of the industrial sector i. Y/L is the total output of the industry.

2) Green innovation. It includes two sub-mediator variables, the quantity of innovation achievements and the quality of innovation achievements. According to Deng's (2022) and Tao's (2021) research, the quantity of green innovation achievements is expressed by the quantity of green patent applications (Gpa), and the quality of green innovation achievements is expressed by the quantity of green invention patents granted (Gpg).

Control variables

This study sets environmental regulation (Er), science and technology support (Tec), employment number (Emp), economic development level (Eco), and energy consumption (Ene) as control variables to control the accuracy of the impact of industrial digitalization on carbon emissions (Ye et al. 2018). Referring to the studies of Song et al. (2022) and Zheng et al. (2023), this study selected industrial SO_2 emissions, industrial smoke (dust) emissions, and industrial wastewater emissions to form the ER index system. Then, this study uses the entropy value method to calculate the comprehensive ER index. Local financial expenditures on science and technology indicates science and technology support. Economic development level is expressed region real GDP per capita. Industrial electricity consumption indicates energy consumption.

Samples and data sources

The sample of this study is the panel data of 13 cities in the BTH region from 2006 to 2019. The financial technology expenditure, the quantity of employees, the quantity of green patents, and the per capita electricity consumption of each city are derived from the "China Urban Statistical Yearbook," "China Energy Statistical Yearbook," and statistical bulletins (Wei et al. 2017). The digital financial inclusion index is derived from the "Digital Financial Inclusion Index System and Index Compilation" (Guo et al. 2020). Missing values are supplemented by linear interpolation and the mean value method. This study takes logarithms for all variables when conducting regression analysis to eliminate heteroskedasticity. The variables' explanatory and descriptive statistics are shown in Table 2.

Empirical analysis

Model construction

In order to accurately evaluate the effect of digital economy on CEI of the BTH region, this study uses the White test, and the result shows that the p value is 0.0007, which indicates that there is a heteroskedasticity problem in the short panel data. So, this study uses the clustering robust standard

Table 2 Variables' explanatory and descriptive statistics

Category	Variable	Interpretation	Mean	Std. dev	Max	Min
Explained variable	CEI	Carbon emission intensity (t/yuan)	0.000214	0.0000843	0.000378	0.0000185
Explanatory variable	DE	Digital economy development index	0.103	0.0601	0.376	0.0328
Mechanism variables	Isr	Industrial structure rationalization index	0.309	0.189	0.656	0.000146
	Isu	Industrial structure upgrade index	1.205	0.883	5.169	0.516
	Gpa	Quantity of green patent applications	2594	6538	36,576	23
	Gpg	Quantity of green invention patent granted	453.9	1375	6820	0
Control variables	Tec	Local financial technology expenditure (million)	3425	8486	43,342	67.06
	Emp	Quantity of employees (million)	1.273	1.967	8.193	0.228
	Eco	GDP per capita (million)	0.0526	0.0316	0.164	0.0200
	Ene	Industrial electricity consumption (million kWh)	17,940	17,640	71,610	1789.68
	Er	Environmental regulation index	0.109	0.127	0.815	0.000065

error method to overcome it. Then, this study uses the robust Hausman test to select the model, and the result of the p value is 0.0000, which rejects the original hypothesis and indicates that the fixed-effects model should be used. Thus, this study constructs the fixed-effects model as follows to verify the role of digital economy on urban CEI (Li et al. 2019; Zhang et al. 2022b).

$$\ln\mathrm{CEI}_{it} = \alpha_0 + \alpha_1 \ln\mathrm{DE}_{it} + \alpha_2 \ln\mathrm{Tec}_{it} + \alpha_3 \ln\mathrm{Emp}_{it} + \alpha_4 \ln\mathrm{Er}_{it} + \alpha_5 \ln\mathrm{Ene}_{it} + \alpha_6 \ln\mathrm{Eco}_{it} + u_i + v_t + \sigma_{it} \tag{4}$$

In model (4), i is city. t is year. CEI is carbon emission intensity. DE is digital economy index. Tec is local financial technology expenditure. Emp is employment. Er is environmental regulation index. Ene is energy consumption. u is individual fixed effect, v is time fixed effect, and σ is random error.

Benchmark regression analysis

The correlation analysis and multicollinearity test results are shown in Appendix Table 12. Most of the correlation coefficients between the variables were less than 0.5. The maximum variance inflation factor was 5.18, which was less than the critical value of 10. The above indicates that there is no serious multicollinearity problem among the variables (Chen 2022a, b; Zhang et al. 2022c). The benchmark regression results for model (4) are shown in Table 3, with the difference between the two columns being whether or not control variables are added. The results show that the coefficients of lnDE in columns (1) and (2) are significantly negative at the 1% level. It indicates that the digital economy development in the BTH region significantly impacts reducing CEI. Specifically, every 1% increase in lnDE reduces CEI by 0.224%, which confirms the hypothesis H1. The reason may be that the digital economy development in the BTH region has apparent advantages, such as digital industry development in Beijing and digital transformation of manufacturing in Tianjin and Hebei. It realizes the deep integration and coordinated development of digital technology and required carbon emissions fields such as power, industry, and transportation. Then, it promotes the technological upgrading of traditional industries, reduces energy and resource consumption, and thus reduces CEI. Moreover, the BTH region improves the efficiency of urban operation and environmental management by constructing "smart cities." It promotes a low-carbon transformation of residents' lifestyles and reduces CEI.

Table 3 Benchmark regression results

Variable	(1) lnCEI	(2) lnCEI
lnDE	−0.415*** (−8.97)	−0.224*** (−5.24)
lnTec		−0.011* (0.47)
lnEmp		−0.044 (−0.68)
lnEne		0.040* (1.47)
lnEco		−0.702*** (−6.44)
lnEr		0.022*** (3.08)
Constant	−9.584*** (−86.31)	−11.672*** (−27.82)
Year	Yes	Yes
City	Yes	Yes
R^2	0.728	0.856

The t values adjusted for clustering robust standard errors are in parentheses. ***$p<0.01$, *$p<0.1$

The analysis of the control variables is as follows. Eco and Tec negatively affect CEI at 1% and 10% levels, respectively.

The possible explanation is that the industrial pollution problem caused by economic development makes citizens more aware of environmental protection and strengthens government regulatory actions, which reverse the effect on carbon emissions. Urban economic growth causes technological innovation, institutional change, and economic restructuring, which help reduce the intensity of urban carbon emissions. Increasing government spending on S&T can encourage companies and research institutions to accelerate R&D in green and digital technologies. It promotes the application of advanced green technology in practical production. Furthermore, digital technology can help enterprises and governments to identify and track carbon emission issues accurately, then improve regulatory efficiency. Er and Ene positively affect CEI by 1% and 10%, respectively. The reason is that the increase in Er indicates that the government reduces its efforts to manage various actions that pollute the environment, which increases carbon emissions. In terms of Ene, coal is the primary source of thermal power generation. The rise in industrial electricity consumption increases coal consumption, then increases carbon emissions.

Extended research: spatial spillover effect

Spatial distribution characteristics

Spatial distribution of digital economy

This part uses ArcGIS 10.7 software to visualize the spatial distribution of digital economy in the BTH region, as shown in Fig. 2 (Xue et al. 2022). In general, the digital economy index of each city has increased significantly over time. Furthermore, the development of the urban digital economy in the BTH region is uneven, with an overall spatial pattern of central > northern > southern. Specifically, Beijing has always been in a leading position throughout the digital economy development. The neighboring cities such as Langfang and Baoding are rapidly rising in the digital economy index. On the one hand, the reason may be affected by the spillover effect of Beijing's digital technology. On the other hand, Beijing's digital resources have spread outward, realizing the optimal allocation of digital elements. However, southern cities such as Handan and Xingtai are always in a backward state due to low spillover impact and their development constraints.

Spatial distribution of CEI

Similarly, the spatial distribution of CEI is shown in Fig. 3. In general, the CEI of most cities has decreased significantly over time. During the study period, Beijing's CEI was always at a low level, while Xingtai's CEI was always at a high level. Langfang has the most significant reduction in CEI. It reflects that Langfang has taken into account the control of carbon emissions while developing the economy and has promoted the development of a low-carbon economy. However, Tianjin's CEI shows a trend of decreasing and then increasing. This may be because on 11 January 2018, Tianjin Binhai New Area announced that it had adjusted its GDP from RMB 1002 billion to RMB 665.4 billion for 2016, and the sudden reduction in GDP value led to an increase in the calculation of its CEI. However, from a regional perspective as a whole, Tianjin's CEI has been at a low level, which shows that it has balanced its strong development of manufacturing with carbon emission management.

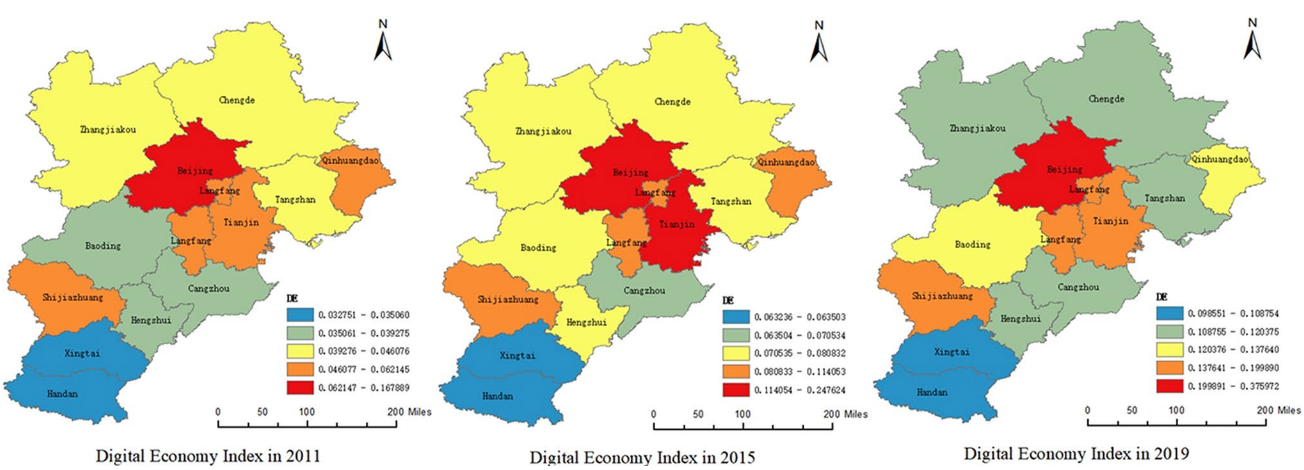

Fig. 2 Spatial distribution of digital economy

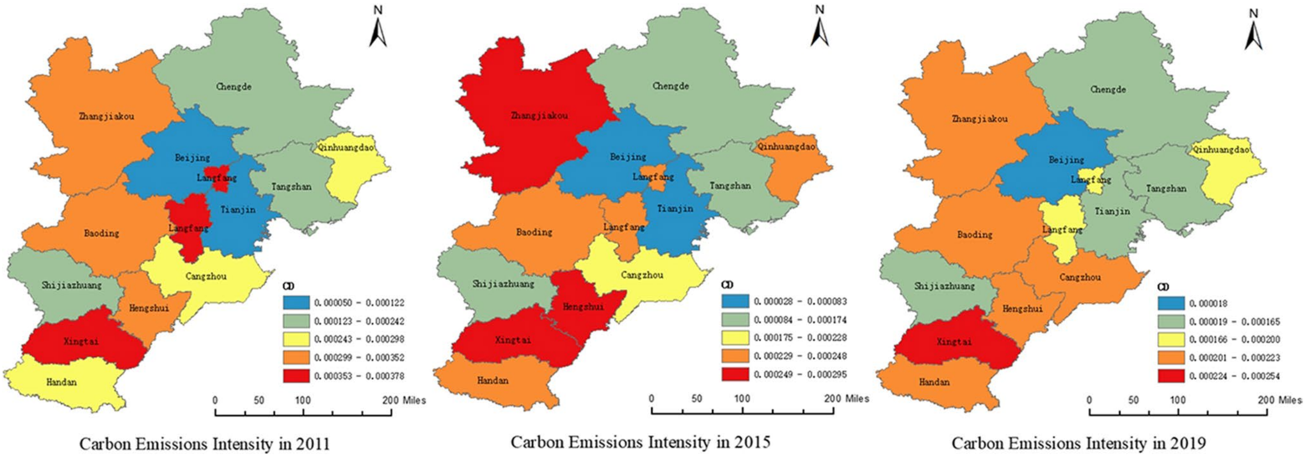

Fig. 3 Spatial distribution of CEI

Spatial correlation analysis

This part uses the global Moran index to measure the global spatial correlation of the digital economy, which can reflect the overall characteristics of the spatial correlation of the digital economy (Zhao and Sun 2022; Zeng et al. 2022). The formula is as follows.

$$\text{MoranI} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{5}$$

In formula (5), S^2 is the variance of the sample, and ω_{ij} is the i and j elements of the spatial weight matrix. When Moran's I > 0 indicates a positive spatial correlation between regions. Moran's I < 0 indicates a negative spatial correlation between regions. Moran's I = 0 indicates no correlation. The spatial unit in the spatial weight matrix is described by the inverse of the geographic distance. The distance is inversely proportional to the spatial weight coefficient and spatial correlation (Lv et al. 2022; Zeng et al. 2022).

The results show that the global Moran value of digital economy is 0.469 and passes the significance test of 1%. It indicates that there is a positive spatial correlation in the digital economy. Global Moran's I reflect the overall distribution of variables in the space. This part draws the Moran scatter plot shown in Fig. 4 to reveal the spatial correlation of digital economy, where (a) is the global Moran scatter plot from 2011 to 2019, (b), (c), and (d) are the local Moran scatter plots for 2011, 2015, and 2019 respectively (Chen 2022b; Zeng et al. 2022). The figure shows that the distribution of the digital economy Moran index is more concentrated and mostly concentrated in the first and third quadrants, showing obvious "H–H" and "L-L" agglomeration states. It indicates that cities with high/low levels of digital economic development are surrounded by other cities with equally high/low levels of digital economic development. Furthermore, the digital economy development of 13 cities in the BTH region has significantly transitioned. Beijing shifted from the fourth quadrant to the first quadrant, and other cities shifted from the second and third quadrant to the first, showing a positive correlation. It indicates that cities in the BTH region have experienced joint development from 2011 to 2019, and the digital economy has transitioned from a generally lower level to a higher level. This study plots the local indicator of spatial association (LISA) map as shown in Fig. 5 (Chen 2022a). The map shows that "H–H" cities are concentrated in the central part of the BTH region, mainly in digitally developed cities such as Langfang and Tianjin, while "L-L" cities are mainly located in the southern part of the BTH region, where digitization is slow.

Spatial impact effect analysis

Model construction

This study uses LR test to verify the SLM model and SEM model. The results all passed the significance test, thus rejecting the original hypothesis of using the SLM model and SEM model. It indicates that there are spatial error terms and lagged terms and that the spatial Durbin model should be used. The Hausman test results indicate that using a fixed-effects model is better than a random-effects model, and the LR test results indicate that the time-point fixed-effects spatial Durbin model is more appropriate for this study (Xie et al. 2022; Feng et al. 2022). Therefore, this study adds the spatial interaction term into the model (4) and constructs

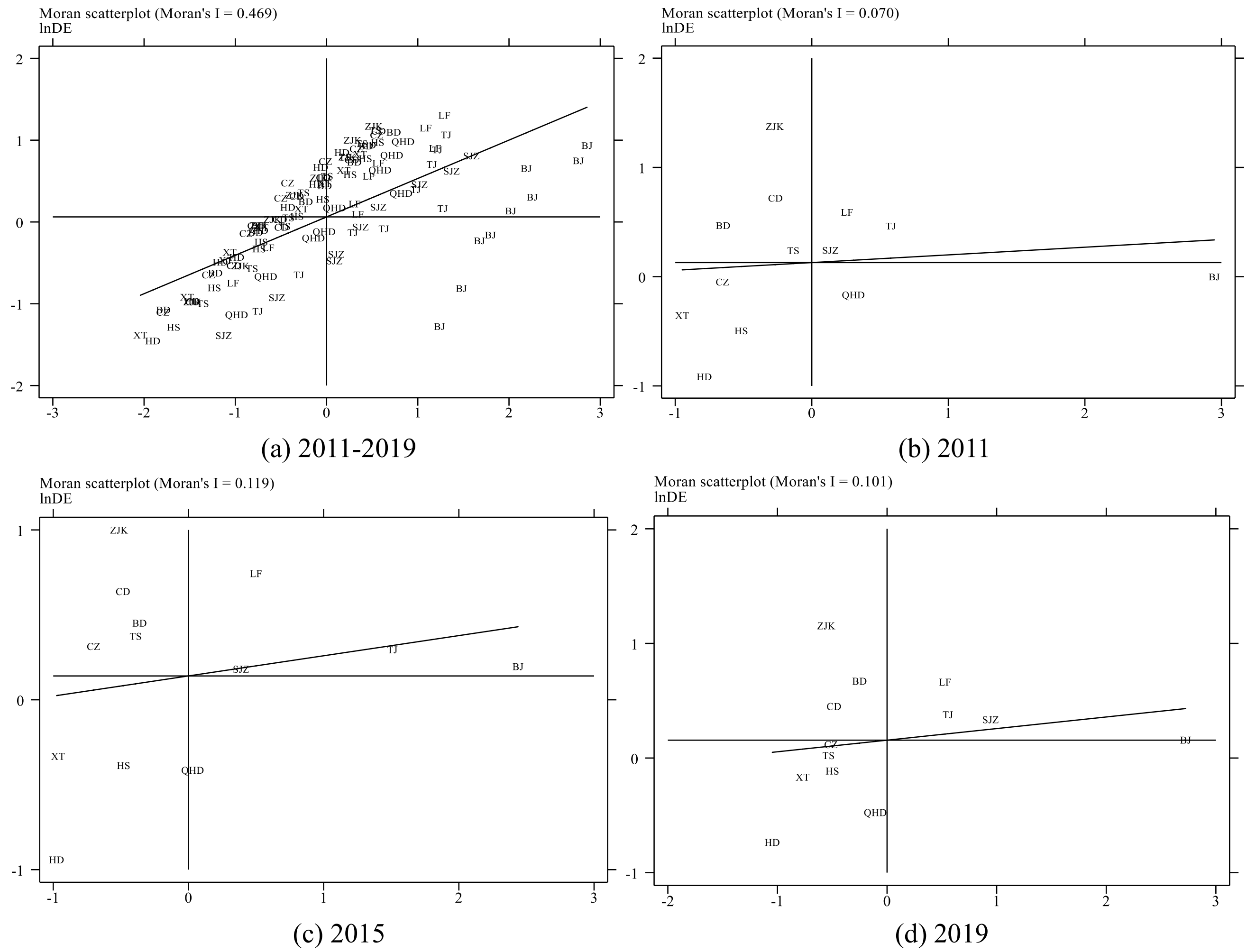

Fig. 4 Moran's I scatter chart of digital economy

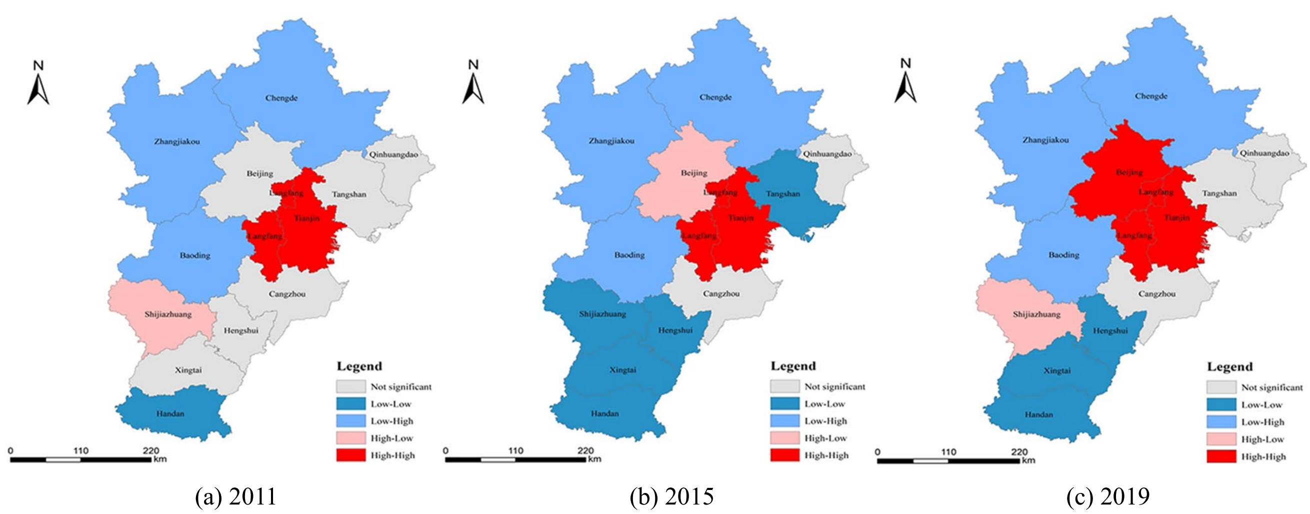

Fig. 5 LISA map

Table 4 SDM regression results

Variable	(1) Carbon intensity lnCEI	(2) Spatial lag term lnCEI	(3) Direct effect lnCEI	(4) Indirect effect lnCEI	(5) Total effect lnCEI
lnDE	-0.583^{***} (−6.03)	-3.298^{***} (−5.02)	-0.435^{***} (−3.84)	-2.022^{***} (−3.04)	-2.457^{***} (−3.39)
lnTec	−0.078 (−1.43)	−0.011 (−0.03)	-0.082^{*} (−1.84)	−0.025 (−0.14)	−0.107 (−0.56)
lnEmp	−0.105 (−1.57)	0.963^{*} (2.24)	-0.151^{**} (−2.39)	0.766^{**} (2.51)	0.616^{*} (1.80)
lnEne	0.200^{***} (4.92)	0.345 (1.94)	0.194^{***} (4.56)	0.167 (1.14)	0.361^{**} (2.22)
lnEco	-0.403^{***} (−4.98)	−0.748 (−1.92)	-0.393^{***} (−4.14)	−0.288 (−1.02)	-0.681^{***} (−2.84)
lnEr	0.0101 (0.60)	-0.481^{***} (−4.21)	0.035^{*} (1.85)	-0.341^{***} (−3.00)	-0.306^{**} (−2.48)
Spatial rho	-0.631^{*} (−1.98)				
Variance sigma2 e	0.0182^{***} (7.68)				
R^2	0.593				

The t values adjusted for clustering robust standard errors are in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

the time-point fixed-effects spatial Durbin model to discuss the spatial spillover effect of digital economy on CEI (Chen 2022b; Lv et al. 2022). The model is as follows.

$$\begin{aligned} \ln\mathrm{CEI}_{it} &= \alpha_0 + \rho W\ln\mathrm{CEI}_{it} + \alpha_1 \ln\mathrm{DE}_{it} \\ &\quad + \varphi_1 W\ln\mathrm{DE}_{it} + \alpha_2 \mathrm{C}_{it} + \varphi_2 \mathrm{WC}_{it} + v_i + \sigma_{it} \end{aligned} \tag{6}$$

In model (6), ρ is the spatial autocorrelation coefficient. W is the spatial weight matrix. C_{it} is each control variable. φ_1 is independent variables' spatial interaction term coefficient. φ_2 is control variables' spatial interaction term coefficient. The remaining variables are consistent with model (4).

Regression analysis

The regression results are presented in Table 4. The coefficient of lnDE in column (1) is significantly negative at the 1% level. It indicates that digital economy development significantly inhibits the CEI in the BTH region, which is coherent with the above findings. The spatial lag coefficient of lnDE in column (2) is significantly negative at the 1% level. It indicates that the digital economy development in a given city has an interactive effect on the CEI of the surrounding cities. The coefficients of lnDE in columns (3) and (4) are all significantly negative at the 1% level. Where the absolute value of the coefficient of lnDE in column (4) is greater than that in column (3). It indicates that the indirect suppression effect of the digital economy on CEI is greater than the direct suppression effect. That is, the inhibitory effect of digital economy development in neighboring cities on the CEI of the sample city is better than the inhibitory effect of digital economy development in a local city on the local CEI (Feng et al. 2022; Qin and Zhang 2022). The coefficient of lnDE in column (5) total effect is significantly negative. It indicates that digital economy development can suppress the total CEI in the BTH region. The above research confirms that the digital economy has a negative spatial spillover effect on urban CEI.

The coefficients of all control variables in column (3) are significant, indicating that the local financial and technological expenditure, the quantity of employees, per capita GDP, industrial power consumption, and environmental regulation index of the sample cities significantly impact the local CEI. In column (4), the coefficient of lnEmp is significantly positive. It indicates that Emp has a significant positive spillover effect. This may be because cities with high levels of digital economy development (such as Beijing) will have a certain siphoning effect on neighboring cities. It manifests itself as the plundering of talents from neighboring cities, thus respectively reducing this city and increasing the neighboring cities' CEI. The coefficient of lnEr is significantly negative. It indicates that Er has a significantly negative spillover effect. This may be due to the sample cities receive manufacturing transfer from neighboring cities with higher degree of digital economy development (such as Beijing), thereby respectively increasing this city and reducing the neighboring cities' CEI. In column (5), the coefficient sign of the total effect of lnEmp and lnEr are consistent with the indirect effect, which indicate that the indirect effect is stronger than the direct effect. And the coefficient of lnEco is significantly negative, indicating that an increase in economic development level can reduce CEI. In addition, the coefficient of lnEne is significantly positive, indicating that Ene increases the CEI. This is because the increase in industrial electricity consumption exacerbates fossil energy consumption, and increase carbon emissions.

Further analysis: mechanism effect and threshold effect test

Mechanism effect analysis

Mechanism test

To test the existence of the mechanism paths, the selection of the test methods is crucial to the reliability of the conclusions. Since the traditional three-step test may have endogeneity problems, it will lead to lower reliability in the results (Jiang 2022). For the sake of rigorous research process, the current recommended practice is adopted here. First, through the construction of a mathematical model (7) to verify whether the independent variable has an effect on the mediating variables. Then, the literature review was used for theoretical derivation to verify the effect of DE on CEI under the role of mediating variables. It is important to note that the regression results of model (8) are only used as an aid to support the above mechanism effect test.

$$\begin{aligned}\ln\mathrm{INT}_{it} &= \beta_0 + \beta_1 \ln\mathrm{DE}_{it} + \beta_2 \ln\mathrm{Tec}_{it} + \beta_3 \ln\mathrm{Emp}_{it} \\ &+ \beta_4 \ln\mathrm{Er}_{it} + \beta_5 \ln\mathrm{Ene}_{it} + \beta_6 \ln\mathrm{Eco}_{it} + u_i + v_t + \sigma_{it}\end{aligned} \tag{7}$$

Table 5 Digital economy and mechanism variables

Variable	(1) lnIsr	(2) lnIsu	(3) lnGpa	(4) L.lnGpg
lnDE	−0.098	0.578***	1.580***	1.487***
	(−0.48)	(10.76)	(6.97)	(8.41)
lnTec	0.243**	−0.023	−0.121	0.212**
	(2.77)	(−0.46)	(−0.73)	(2.24)
lnEmp	−0.591	−0.185***	−0.609*	−0.244
	(−1.37)	(−3.32)	(−2.13)	(-1.19)
lnEne	−0.011	0.085**	0.130**	0.040
	(−0.11)	(2.50)	(1.73)	(0.47)
lnEco	−0.305	−0.077	0.225	0.059
	(−0.53)	(−0.43)	(1.23)	(0.21)
lnEr	0.135**	−0.033*	−0.061**	0.037
	(2.94)	(−1.79)	(−2.15)	(0.86)
Constant	−1.442	0.825	11.997***	8.335***
	(−0.34)	(1.03)	(4.20)	(5.03)
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
R^2	0.044	0.826	0.838	0.821

The t values adjusted for clustering robust standard errors are in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

$$\begin{aligned}\ln\mathrm{CEI}_{it} &= \varphi_0 + \varphi_1 \ln\mathrm{DE}_{it} + \varphi_2 \ln\mathrm{INT}_{it} + \varphi_3 \ln\mathrm{Tec}_{it} \\ &+ \varphi_4 \ln\mathrm{Emp}_{it} + \varphi_5 \ln\mathrm{Er}_{it} + \varphi_6 \ln\mathrm{Ene}_{it} \\ &+ \varphi_7 \ln\mathrm{Eco}_{it} + u_i + v_t + \sigma_{it}\end{aligned} \tag{8}$$

where, INT refers to Isr, Isu, Gpa, Gpg. Since patents are granted with a lag, this study measures the quality of innovation by the number of green invention patents granted with a one-period lag (L.Gpg). $\beta_1\varphi_2$ is the mechanism effect, indicating that industrial digitization has an impact on carbon emissions through industrial structure optimization or green innovation. The remaining variables are consistent with model (4).

Regression results of model (7) are shown in Table 5, the coefficient of lnDE on lnIsr in column (1) is insignificant and the R^2 is too small, which means that digital economy in the BTH region does not significantly promote the rationalization of the industrial structure. The finding is contrary to hypothesis H2a. The coefficient of lnDE on lnIsu in column (2) is significantly positive at the 1% level. It indicates that the development of digital economy in the BTH region has extensively promoted the upgrading of industrial structure. The finding is consistent with hypothesis H2b. Furthermore, the coefficients of lnDE on lnGpa and L.lnGpg in columns (3) and (4) are significantly positive at the 1% level. It indicates that the digital economy in the BTH region has significantly increased the quantity and quality of green innovation. The finding is consistent with hypotheses H3a and H3b.

The regression results of the model (8) are shown in Appendix Table 13 It can be found that when lnIsr, lnIsu, lnGpa, and L.lnGpg are added sequentially, the coefficients of lnDE on lnCEI are all significantly negative at the 5% or 1% level. Meanwhile, lnIsr is significantly positive at the 1% level, and lnIsu, lnGpa, and L.lnGpg are all significantly negative at the 5% level. Since lnIsr is a negative indicator, this means that the rationalization and upgrading of industrial structure, as well as the quantity and quality of green innovation can significantly inhibit the city's CEI. Next, this study further verifies the influence of intermediary variables on CEI through literature theoretical derivation. In terms of industrial structure optimization, Gu et al. (2022) verify that both the industrial structure rationalization and the industrial structure upgrade significantly reduce CEI in the BTH region. Chen et al. (2019) verify that industrial structure optimization can reduce carbon emissions in the BTH region. In addition, Mi et al. (2015), Zhu and Shan (2020) verified that industrial structure optimization can significantly reduce CEI in Beijing. In the aspect of green innovation, Liu et al. (2022) verify that green innovation can reduce CEI, and has a spatial spillover effect. Xu et al. (2021) found that green innovation had a positive impact on China's carbon performance. Furthermore, Li et al. (2022) suggest that green innovation

Table 6 Bootstrap test

	Indirect effect	Direct effect	Indirect effect	Direct effect
	(1) lnIsr		(2) lnIsu	
Observed cofe	−0.5716942	−0.4192974	−0.4490558	−0.5419357
Bootstrap std. err	0.0904325	0.0517208	0.1568378	0.1364297
95% conf. interval	[−0.7489386 ~ −0.3944498]	[−0.5206682 ~ −0.3179266]	[−0.7564522 ~ −0.1416595]	[−0.809333 ~ −0.2745384]
z	−6.32	−8.11	−2.86	−3.97
p > |z|	0.000	0.000	0.004	0.000
	(3) lnGpa		(4) lnGpg	
Observed cofe	−0.6236241	−0.3673674	−0.6099488	−0.3810428
Bootstrap std. err	0.1137858	0.1015801	0.10866	0.1062389
95% conf. interval	[−0.8466402 ~ −0.4006081]	[−0.5664608 ~ −0.1682741]	[−0.8229186 ~ −0.396979]	[−0.5892672 ~ −0.1728183]
z	−5.48	−3.62	−5.61	−3.59
p > |z|	0.000	0.000	0.000	0.000

can help reduce China's carbon emissions. In summary, both industrial structure optimization and green innovation have a restraining effect on CEI.

Bootstrap method to strengthen the test

To strengthen the verification of hypothesis H2a, and improve the test validity of mechanism effects in H2b, H3a, and H3b, the bootstrap method is further used to test the coefficient multiplication term. The null hypothesis for the bootstrap sampling method is that the regression coefficient $\beta_1\varphi_2 = 0$. If the 95% confidence interval does not include 0, the null hypothesis is rejected, indicating that it has a mechanism effect. The bootstrap test results after setting 500 samplings are shown in Table 6. Columns (1) to (4) show the results of the mechanism tests for H2a, H2b, H3a, and H3b, respectively. The multiplication items of the regression coefficients of the four mechanism variables do not contain the number 0 within the 95% confidence interval, and they are all significant at the 1% level. This confirms that Isr, Isu, Gpa, and Gpg significantly repress the urban CEI. Therefore, the bootstrap test strengthens the verification of hypotheses H2a, H2b, H3a and H3b.

Threshold effect test

Threshold effect significance test

To explore the differences of digital economy impact on CEI under different levels of industrial structure rationalization and upgrading as well as the quantity and quality of green innovation, this study selects lnIsr, lnIsu, lnGpa, and lnGpg as threshold variables and uses Hansen's threshold model to test the linear or nonlinear relationship between digital economy and CEI (Hansen 2000; Dong et al. 2022a). The threshold model is constructed as follows.

$$\begin{aligned}\mathrm{lnCEI}_{it} = {} & \omega_0 + \omega_1 \mathrm{lnDE}_{it} \times I\left(\mathrm{lnIN}_{it} \le \gamma_1\right) + \omega_2 \mathrm{lnDE}_{it} \\ & \times I\left(\gamma_1 < \mathrm{lnIN}_{it} \le \gamma_2\right) + \omega_3 \mathrm{lnDE}_{it} \times I\left(\gamma_2 < \mathrm{lnIN}_{it}\right) \\ & + \sum_{j=4}^{T} \omega_j CV_{it}^{j} + u_i + v_t + \sigma_{it}\end{aligned} \tag{9}$$

In model (9), $\mathrm{lnIN}_{\mathrm{it}}$ is the threshold variable that represents lnIsr, lnIsu, lnGpa, and lnGpg, respectively. γ_1 and γ_2 are the two threshold values. ω_1, ω_2, and ω_3 are the coefficients of the impact of the digital economy on CEI when the threshold variables are in different intervals. $I()$

Table 7 Threshold effect test results

Variable	Threshold type	F value	p value	10%	5%	1%	Threshold value	95% confidence interval
lnIsr	Single-threshold	47.28	0.020	37.101	40.384	49.420	−5.6098	[−6.0097 ~ −5.0033]
	Double-threshold	18.85	0.080	21.606	32.039	64.090	−3.8767	[−4.0336 ~ −3.7438]
lnIsu	Single-threshold	88.47	0.007	60.895	66.316	80.556	1.4268	[1.3951 ~ 1.4438]
	Double-threshold	25.32	0.072	21.928	28.262	68.865	1.2142	[0.6077 ~ 1.2364]
lnGpa	Single-threshold	53.36	0.003	55.917	64.253	74.959	10.1227	[9.9636 ~ 10.2707]
	Double-threshold	33.98	0.050	37.280	41.742	70.650	9.3272	[9.2756 ~ 9.6848]
lnGpq	Single-threshold	61.69	0.033	44.965	56.397	66.305	8.7124	[8.6188 ~ 9.0609]

is the indicative function, which takes the value of 1 in () and 0 otherwise. The other variables are the same as the model (4).

This study uses the bootstrap method to repeat the test 300 times, and the results are shown in Table 7. lnIsr, lnIsu, and lnGpa pass the significance test at 1% and 5% levels for the single threshold and the double threshold, respectively. lnGpg does not pass the significance test for the double-threshold. Based on Hansen's threshold theory, it is determined that lnIsr, lnIsu, and lnGpa have significant double threshold characteristics and are suitable for constructing double threshold regression models (Hansen 2000). lnGpg only has a single threshold. The threshold values of each variable are in the 95% confidence interval. Furthermore, this study uses the likelihood ratio (LR) statistic to test the veracity of the threshold estimates. As seen in Appendix Fig. 6, the threshold estimates are consistent with the true values.

Panel threshold regression analysis

The results of the threshold effect regressions are shown in Table 8, in terms of structural effects. In column (1), when $\ln Isr \leq -5.6098$, the marginal effect of lnDE is 0.597. When $-5.6098 \leq \ln Isr \leq -3.8767$, the marginal effect of lnDE decreases to 0.296. When $\ln Isr > -3.8767$, the marginal effect of lnDE is 0.409. With the improvement of industrial structure rationalization, the suppression intensity of digital economy on CEI decreases first and then increases. In column (2), the coefficient of lnDE is significantly negative in the threshold interval of $\ln Isu \leq 1.2142$ and $1.2142 \leq \ln Isu \leq 1.4268$, with marginal effects of 0.156 and 0.399, respectively. This indicates that within this interval, upgrading the industrial structure can enhance the suppression of the digital economy on CEI. When $\ln Isu > 1.4268$, the coefficient of lnDE is 0.068 but insignificant. This reflects the trend that digital economy will promote CEI. In summary, with the upgrading level of industrial structure, the impact of digital economy on CEI may show a non-linear U-shaped trend. However, this conclusion still needs to be supplemented by subsequent data validation.

In terms of technological effects. In column (3), the coefficient of lnDE is significantly negative in the threshold intervals of $\ln Gpa \leq 9.3272$ and $9.3272 \leq \ln Gpa \leq 10.1227$, with marginal effects of 0.159 and 0.389, respectively. When $\ln Gpa > 10.1227$, the coefficient of lnDE is positive but insignificant, with a marginal effect of 0.006. In summary, the increase in the quantity of green innovations can strengthen the suppression effect of the digital economy on CEI. However, the positive effect is minimal when the high threshold of 10.1227 is crossed. Therefore, its non-linear U-shaped trend needs further verified and supplemented by subsequent data. In column (4), when $\ln Gpg \leq 8.7124$, the marginal impact of lnDE is 0.143. When $\ln Isr > 8.7124$, the marginal impact of lnDE increases significantly and jumps

Table 8 Threshold effect regression results

Variable	(1) lnCEI	Variable	(2) lnCEI
lnDE ($\ln Isr \leq -5.6098$)	$-0.597^{***}(-9.86)$	lnDE ($\ln Isu \leq 1.2142$)	$-0.156^{***}(-3.80)$
lnDE ($-5.6098 < \ln Isr \leq -3.8767$)	$-0.296^{***}(-6.00)$	lnDE ($1.2142 < \ln Isu \leq 1.4268$)	$-0.399^{***}(-14.53)$
lnDE ($\ln Isr > -3.8767$)	$-0.409^{***}(-8.72)$	lnDE ($\ln Isu > 1.4268$)	0.068 (1.29)
Control variable	Yes	Control variable	Yes
Constant	$-9.546^{***}(-17.62)$	Constant	$-9.442^{***}(-25.29)$
Year	Yes	Year	Yes
City	Yes	City	Yes
R^2	0.8845	R^2	0.9208
Variable	(3) lnCEI	Variable	(4) lnCEI
lnDE ($\ln Gpa \leq 9.3272$)	$-0.159^{***}(-3.57)$	lnDE($\ln Gpg \leq 8.7124$)	$-0.143^{**}(-2.91)$
lnDE ($9.3272 < \ln Gpa \leq 10.1227$)	$-0.389^{***}(-12.86)$		
lnDE ($\ln Gpa > 10.1227$)	0.006(0.10)	lnDE ($\ln Gpg > 8.7124$)	$-0.414^{***}(-12.55)$
Control variable	Yes	Control variable	Yes
Constant	$-9.343^{***}(-23.00)$	Constant	$-9.470^{***}(-21.08)$
Year	Yes	Year	Yes
City	Yes	City	Yes
R^2	0.9067	R^2	0.8965

The t values adjusted for clustering robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

to 0.414. The above indicates that the improvement in the green innovation quality helps to increase the suppressive effect of the digital economy on CEI.

Discussion

In summary, this study provides the following specific analysis of the heterogeneity of the four mechanism variables and their impact effects across the different intervals, based on the mediating and threshold effects results.

1) With the improvement of industrial structure rationalization level, the suppression intensity of the digital economy on CEI first decreases and then increases. In the early stage of digital economy allocates industrial resources and adjusts industrial structure. Due to the imbalance between supply and demand in the industrial system, the utilization efficiency of resources is low, increasing resource consumption accordingly. Therefore, the digital economy reduces the suppression intensity of CEI. When the level of industrial structure rationalization reaches a certain threshold, it achieves the rational allocation of production factors and improves the utilization rate of resources. The digital economy increases the suppression intensity of CEI.
2) With the increase of industrial structure upgrading level, the impact of digital economy on CEI may present a U-shaped trend of inhibiting and then promoting. The digital economy promotes the BTH region's industrial structure upgrading from secondary to tertiary industries, which reduces energy consumption and thus increases the intensity of the suppression of CEI. When the industrial structure upgrading level reaches a certain threshold, the excessive expansion of the tertiary industry may restrain economic growth. At the same time, increased transportation and electricity consumption in digital industries may increase the use of coal, thus increasing CEI.
3) With the increase of green innovation quantity, the impact of digital economy on CEI may present a U-shaped trend of inhibiting and then promoting. Under the development mode of digital economy, enterprises' innovation and optimization of production processes and products will increase the quantity of green innovations. This can improve the efficiency of enterprise resources and energy utilization, thereby reducing CEI. However, excessive application for green innovation will result in repeated and ineffective innovation. This can crowd out innovation resources, cause energy waste in the innovation process, and increase CEI.
4) Improving the quality of green innovation with the support of digital technology can avoid the waste of innovation resources and improve innovation efficiency. Enterprises can improve their economic output and reduce pollution emissions by applying innovative results to the production process. This can strengthen the suppression of the digital economy on CEI.

Table 9 Robustness test using per capita carbon emissions as the dependent variable

Variable	(1) lnPC	(2) lnPC
lnDE	-0.082^{***}	-0.070^{**}
	(−3.98)	(−2.94)
Controls		Yes
Constant	1.977^{***}	1.187^{**}
	(39.70)	(2.95)
Year	Yes	Yes
City	Yes	Yes
R^2	0.317	0.380

The t values adjusted for clustering robust standard errors are in parentheses. $^{***}p<0.01$, $^{**}p<0.05$

Robustness test

Replace dependent variable

As the population size is one of the factors affecting economic aggregates, therefore, this part adopts the per capita carbon emissions (PC) to replace CEI for the robustness test; the results as shown in Table 9. The coefficient of lnDE is significantly negative regardless of whether control variables are added. It indicates that the digital economy development can significantly reduce PC. The sign and significance of lnDE are the same as the benchmark regression results. It confirms the robustness of this study's findings.

Endogenous test

This part uses the instrumental variables approach which is to test the endogeneity of the possible reverse causality between digital economy development and CEI. Referring to Bartik's research, this part constructs the "Bartik instrument" variable, which is the product of the lnDE with a lag of one period and the first-order difference of the lnDE ($\mathrm{lnDE}_{i,\,t\text{-}1} \times \Delta\mathrm{lnDE}_{t,\,t\text{-}1}$) (Bartik 2009; Deng and Zhang 2022). Selecting the lag period of the digital economic development index as an instrumental variable can make the instrumental variable and the explained variable have a significant correlation. Therefore, there is no weak instrumental variable, which satisfies the correlation constraint. In addition, the disturbance term of the current period cannot affect the results of the lag period of the digital development index, so

Table 10 2SLS estimates of the impact of the digital economy on carbon emissions intensity

Variable	2SLS phase 1 lnDE	2SLS phase 2 lnCEI
$\ln DE_{i,t\text{-}1} * \Delta \ln De_{t,t\text{-}1}$	0.276*** (2.92)	
lnDE		−0.826** (−2.47)
Controls	Yes	Yes
Year	Yes	Yes
City	Yes	Yes
Constant	−2.709** (−3.48)	−11.572*** (−9.32)
R^2		0.855
Gpa	104	104
Kleibergen-Paap rk LM statistic	8.09 [0.0045]	
Kleibergen-Paap Wald rk F statistic	18.18 {16.38}	

() is the standard error value, [] is the p value, {} is the critical value at the 10% level of stock Yogo weak identification test. *** $p < 0.01$, ** $p < 0.05$

it satisfies the exogenous constraint (Feng et al. 2022; Deng and Zhang 2022). Then, the two-stage least squares (2SLS) method was used for estimation test. As shown in Table 10, The Kleibergen-Paap rk LM test is significant at the 1% level, it indicates that the instrumental variable is strongly correlated with the endogenous variable. Meanwhile, the Kleibergen-Paap Wald rk F statistic is higher than the critical value of 10% bias in Stock-Yogo weak ID test critical values, which reject the original hypothesis of "instrumental variables are weak instrumental variables." The above test proves the rationality of the selection of instrumental variables. The coefficient of the instrumental variable in column (1) is significantly positive. In the second-stage regression results, the coefficient of *lnDE* remains negative and passes the 5% level of a significance test. It confirms the robustness of this study's findings.

Replace spatial weight matrix

This part uses a geographic adjacency matrix to further validate the spatial impact of digital economy on CEI (Xu et al. 2022). The regression results of the SDM are shown in Table 11. The coefficient of lnDE in columns (3), (4), and (5) is all significantly negative. The sign and significance of the coefficients for the remaining variables are generally coherent with the above. It confirms the robustness of this study's findings.

Conclusions and policy implications

The development of digital economy is the inevitable path for cities to achieve low-carbon development. This study uses the fixed-effects model, mediated-effects model, and spatial Durbin model to examine the influencing mechanism and spatial spillover effects of digital economy development on carbon emission intensity (CEI), based on 13 cities' panel data in the BTH region from 2011 to 2019. This study found that (1) the fixed-effects regression result confirms that the

Table 11 Robustness test of SDM regression results

Variable	(1) Carbon intensity lnCEI	(2) Spatial lag term lnCEI	(3) Direct effect lnCEI	(4) Indirect effect lnCEI	(5) Total effect lnCEI
lnDE	−0.405*** (−3.61)	−1.336*** (−4.25)	−0.348*** (−2.99)	−1.161*** (−4.30)	−1.509*** (−5.50)
lnTec	−0.143** (−2.42)	−0.190 (−1.23)	−0.141*** (−2.77)	−0.017 (−1.29)	−0.315** (−2.30)
lnEmp	−0.148** (−1.90)	0.419** (2.36)	−0.158** (−2.17)	0.424** (2.76)	0.266 (1.49)
lnEne	0.164*** (3.33)	0.048 (0.48)	0.168*** (3.20)	0.027 (0.29)	0.195* (1.75)
lnEco	−0.268** (−2.55)	0.131 (0.71)	−0.290** (−2.49)	0.191 (1.18)	−0.099 (−0.80)
lnEr	0.045** (2.28)	−0.190*** (−5.05)	0.052*** (2.61)	−0.180*** (−5.46)	−0.128*** (−3.85)
Spatial rho	−0.159 (−1.32)				
Variance sigma2 e	0.029*** (7.79)				
R^2	0.723				

The t values adjusted for clustering robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

development of digital economy significantly reduces CEI in the BTH region; (2) spatial correlation analysis shows that digital economy has significant positive spatial correlation in the BTH region, presenting "H–H" and "L-L" clustering; (3) the regression results of the spatial Durbin model show that the digital economy development has a spatial spillover effect on CEI, which proves that the digital economy development reduces the overall CEI in the BTH region; (4) the mechanism effect test results show that the development of digital economy promotes the rationalization and upgrading of the industrial structure, and improves the urban green innovation quantity and quality. It reduces the CEI of the BTH region through the mechanism effect of industrial structure optimization and green innovation; and (5) the threshold effect test results show that as the level of industrial structure rationalization increases, the suppression intensity of digital economy on CEI first decreases and then increases. As the level of industrial structure upgrading and the quantity of green innovation increases, the impact of digital economy on CEI may show a non-linear U-shaped trend. As the quality of green innovation increases, the suppression effect of digital economy on CEI increases linearly.

Based on the findings, this study proposes the following policy implications:

1) Give full play to the carbon reduction effect of the digital economy. First, the BTH region should construct a digital economy policy system to provide a good institutional environment and development foundation. Second, the BTH region should use digital economy to promote the transformation of smart city governance. It can create convenient and efficient smart low-carbon living application models in transportation, construction, and waste disposal. This can reduce resource consumption and pollution emissions in living and production, thus helping to reduce carbon emissions. Third, the BTH region should accelerate the construction of cloud service platforms and industrial internet to promote the intelligent transformation of enterprises. By using intelligent technology, enterprises can achieve optimal allocation of resources and improve their carbon emission reduction efficiency.
2) In terms of industrial structure optimization. The BTH region should use digital technology to integrate into traditional industries, while vigorously developing low-carbon industries. This will promote the overall industry to be intelligent and low carbonization. Specifically, Beijing should take advantage of its digital resources to develop advanced service industries such as science and technology innovation services and digital technology services. Tianjin should attach importance to the development of advanced manufacturing industry, improve energy utilization efficiency, and eliminate backward production capacity. Hebei should use digital technology to provide effective green solutions to major energy consuming industries. It should also promote low-carbon process innovation and digital transformation of traditional manufacturing industries to reduce coal resource consumption.
3) In terms of green innovation. First, the BTH region should accelerate the development of green innovation system, and vigorously promote the deep application of digital technology in the energy and environment fields. Meanwhile, the BTH region uses digital technology to improve energy efficiency and develop technologies such as carbon capture and sequestration. Second, the BTH region should improve talent introduction policy, cultivate green innovative talents, and promote cross regional exchange and cooperation of talents through digital exchange platform. Third, the government should guide enterprises to carry out green innovation by increasing financial expenditure and developing digital financial services. For enterprises that use digital technology to achieve innovative applications of energy conservation and carbon reduction, the government needs to provide R&D subsidies and tax incentives to help them reduce carbon emissions.
4) The BTH region should balance the difference of urban digital economy development, and give full play to the spatial spillover effect. First, each city should formulate a differential digital development strategy based on the actual resources and industrial development to help reduce carbon emissions. Specifically, the BTH regions can formulate tax incentives and fiscal technology expenditure policies to support the development of digital economy in relatively backward cities. Of course, the government can also narrow the development gap of the digital economy by coordinating intelligent services, training digital professionals, and balancing digital infrastructure construction and other measures. Furthermore, Beijing and Tianjin should spill their advanced technology and experience to other cities to accelerate the overall regional low-carbon technology progress and green technology innovation. Hebei should actively absorb the advanced digital technology and low-carbon technology of Beijing and Tianjin to promote low-carbon technological innovation of local energy intensive industries. In this way, urban digital transformation and low-carbon development can be realized.

This study has some limitations and further research directions to consider. First, this study uses six indicators to measure the digital economy development index, but it still cannot accurately evaluate its status. Future research should continue to improve the evaluation index system under data availability. Second, exogenous effects are not considered in this study. Future studies can use the policy to construct DID models as exogenous shocks to test the effect of digital economy on carbon emissions.

Appendix

Table 12 Correlation analysis and multicollinearity test

	CEI	Isr	Isu	Gpa	Gpg	DE	Tec	Emp	Eco	Ene	Er	VIF
CEI	1.000											—
Isr	0.432***	1.000										3.82
Isu	-0.487***	-0.443***	1.000									4.84
Gpa	-0.504***	-0.350***	0.502***	1.000								3.78
Gpg	-0.455***	-0.497***	0.316***	0.272***	1.000							2.76
DE	-0.474***	-0.520***	0.405***	0.366***	0.524***	1.000						3.97
Tec	-0.437***	-0.493***	0.398***	0.486***	0.462***	0.341***	1.000					5.18
Emp	-0.458***	-0.334***	0.475***	0.327***	0.331***	0.483***	0.465***	1.000				4.27
Eco	-0.362***	-0.440***	0.446***	0.464***	0.489***	0.443***	0.494***	0.484***	1.000			2.76
Ene	-0.484***	-0.433***	0.224**	0.358***	0.262***	0.400***	0.389***	0.422***	0.453***	1.000		4.23
Er	0.343***	0.377***	-0.309***	-0.295***	-0.264***	-0.357***	-0.306***	-0.313***	-0.311***	-0.151	1.000	2.69

***$p<0.01$, **$p<0.05$.

Table 13 Mediating variables and CEI

Variable	(1) lnCEI	(2) lnCEI	(3) lnCEI	(4) lnCEI
lnDE	−0.219***	−0.183***	−0.126***	−0.193**
	(−6.31)	(−3.59)	(−3.13)	(−2.84)
lnIsr	0.048***			
	(5.04)			
lnIsu		−0.071**		
		(−1.49)		
lnGpa			−0.062**	
			(−2.82)	
L.lnGpg				−0.099**
				(−2.98)
lnTec	−0.000	0.010	0.004	0.011
	(−0.01)	(0.42)	(0.15)	(0.39)
lnEmp	−0.015	−0.057	−0.081	−0.113
	(−0.23)	(−0.87)	(−1.05)	(−1.30)
lnEne	0.041	0.046**	0.048**	0.050*
	(1.52)	(1.72)	(1.71)	(2.07)
lnEco	−0.688***	−0.708***	−0.689***	−0.407**
	(−5.56)	(−6.74)	(−6.54)	(−2.90)
lnEr	0.016**	0.020**	0.018**	0.031***
	(2.70)	(2.80)	(2.62)	(5.37)
Constant	−11.603***	−11.614***	−10.929***	−9.971***
	(−20.52)	(−30.37)	(−20.61)	(−16.02)
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
R^2	0.866	0.857	0.865	0.847

The t values adjusted for clustering robust standard errors are in parentheses. ***$p<0.01$, **$p<0.05$.

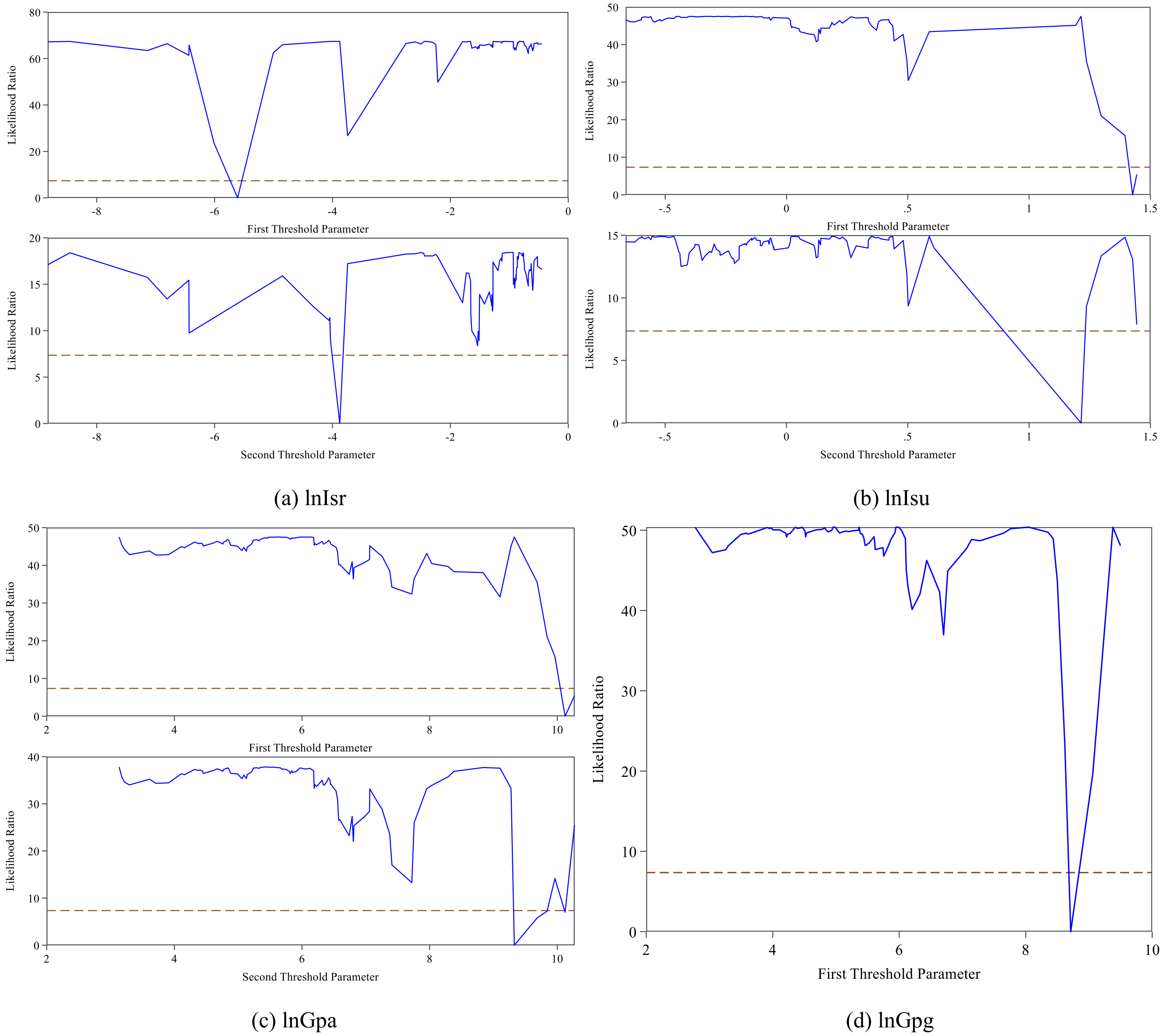

Fig. 6 LR test results. When LR is 0, the parameter values are the threshold estimates for each variable

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Declarations

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