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Nonlinear effects of ICT on carbon emission intensity in China: Evidence from spatial panel smooth transition threshold model

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Abstract:	Information and communication technology (ICT) advancement is essential for China's economic transformation and achieving its carbon peak and neutrality targets. While ICT holds great potential for promoting carbon reduction, further exploration is needed to understand its effectiveness clearly. This paper establishes a framework to analyze the nonlinear effects of ICT on carbon emission intensity (CEI), considering nonlinearity and spatial spillover. By analyzing panel data from 271 Chinese cities from 2003 to 2017, the study utilizes a spatial panel smooth transition threshold model and a moderating effect model to explore the nonlinear and spatial spillover effects of ICT development on urban CEI and its policy implications. The findings reveal that: (1) local ICT development exhibits a significant inverted "U" shaped nonlinear threshold characteristic, indicating that it initially increases and then decreases its direct impact on CEI; (2) ICT development has spatial spillovers on CEI. ICT development in surrounding cities will reduce local CEI, but this effect will only be significant when its level exceeds the threshold value and is in a high regime; (3) the results of heterogeneity analysis indicate that developing ICT within urban agglomerations and non-resource-based cities can reduce CEI, while it can increase CEI in resource-based cities; (4) the government economic competition, environmental regulation, and urban innovation capabilities have moderating effects in the impact of ICT on CEI, which can further strengthen the emission reduction effects of ICT. It is suggested that the construction of the ICT industry be accelerated, collaborative governance in emissions and carbon reduction among multiple departments be promoted, and differentiated ICT development strategies based on urban connections and resource endowments be implemented.

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ABSTRACT

Information and communication technology (ICT) advancement is essential for China's economic transformation and achieving its carbon peak and neutrality targets. While ICT holds great potential for promoting carbon reduction, further exploration is needed to understand its effectiveness clearly. This paper establishes a framework to analyze the nonlinear effects of ICT on carbon emission intensity (CEI), considering nonlinearity and spatial spillover. By analyzing panel data from 271 Chinese cities from 2003 to 2017, the study utilizes a spatial panel smooth transition threshold model and a moderating effect model to explore the nonlinear and spatial spillover effects of ICT development on urban CEI and its policy implications. The findings reveal that: (1) local ICT development exhibits a significant inverted "U" shaped nonlinear threshold characteristic, indicating that it initially increases and then decreases its direct impact on CEI; (2) ICT development has spatial spillovers on CEI. ICT development in surrounding cities will reduce local CEI, but this effect will only be significant when its level exceeds the threshold value and is in a high regime; (3) the results of heterogeneity analysis indicate that developing ICT within urban agglomerations and non-resource-based cities can reduce CEI, while it can increase CEI in resource-based cities; (4) the government economic competition, environmental regulation, and urban innovation capabilities have moderating effects in the impact of ICT on CEI, which can further strengthen the emission reduction effects of ICT. It is suggested that the construction of the ICT industry be accelerated, collaborative governance in emissions and carbon reduction among multiple departments be promoted, and differentiated ICT development strategies based on urban connections and resource endowments be implemented.

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1 Introduction

As the world's largest carbon emitter, China faces significant international pressure to lower its emissions. World Bank data indicates that China's carbon emissions constituted about 32% of the global total in 2020, and its CEI significantly exceeded the world average[①]. In response, China introduced the "dual carbon" goals in 2020, aiming to reach peak carbon emissions by 2030 and strive for carbon neutrality by 2060. However, the strategies that China can use to meet these targets and transition to a green economy are pressing concerns.

While the development of high-tech industries, particularly Information Communication Technology (ICT), is seen as a key approach to reducing CEI, the actual impact of ICT on carbon emissions is still debated. While certain studies posit that ICT effectively reduces CEI (Yahyaoui, 2024), others argue that it has led to increased carbon emissions (Haini, 2021). Additionally, some researchers suggest that the causal relationship between ICT and CEI may not be straightforward, suggesting a more complex interaction (Lahouel et al., 2021). These conflicting conclusions arise from various factors influencing the studies.

Firstly, the inconsistent conclusions on the impact of ICT on CEI stem from the unclear causal relationship between the two. As a high-tech industry, the ICT sector differs significantly from traditional industries in its characteristics and development patterns. Therefore, traditional theories and frameworks are inadequate for analyzing the impact of ICT on CEI. Existing empirical models, such as the GMM model, the IPAT model, the extended STIRPAT model, and the DID model, have been employed to uncover the linear correlation between ICT and CEI (Yahyaoui, 2024; Charfeddine

① https://data.worldbank.org.cn/indicator/

and Kahia, 2021; Shobande and Asongu, 2023; Wei and Yin, 2024). However, the assumption of linearity may not be theoretically valid. Depending on the stage of development, the impact of ICT on CEI may also change accordingly, a subtlety often disregarded in current research.

Secondly, due to the competition and demonstration effects between regions (Awad and Albaity, 2022), it is crucial to consider how empirical models account for the spatial effects of ICT to estimate unbiased parameters. While some researchers have examined the spatial correlation between ICT and CEI, it's important to note that these studies have regarded this effect as entirely linear. Due to the nature of ICT, its spatial spillovers on local CEI in surrounding areas may exhibit a nonlinear threshold effect (Wang and Guo, 2023). Therefore, it is necessary to combine spatial economics and econometrics and establish an empirical model that includes both spatial and temporal effects from a staged and nonlinear perspective in studying the impact of ICT on CEI.

Moreover, current research has placed excessive emphasis on potential transmission methods and overlooked external factors that impact the efficiency of ICT in reducing carbon emissions. As a foundational industry driving economic growth and striving to achieve the "dual carbon goals," the ICT sector has raised greater demands for government oversight and urban innovation. To maximize the emissions and carbon reduction benefits of ICT, it is necessary to have supporting policies, regulations, and corresponding technological innovation foundations. Its impact on CEI will inevitably be shaped by policy factors, including government competition, environmental goal constraints, and innovative environments. Therefore, the regulating effect of relevant policies cannot be ignored when analyzing the impact of ICT on CEI. However, existing research has paid little attention.

The existing research has some limitations that require further investigation. Firstly, what is the theoretical foundation for the impact of ICT on CEI? Secondly, do ICT-related activities exhibit nonlinear and spatial spillovers on carbon emissions? What are the main policy implications of ICT’s impact on CEI? To address these questions, this paper establishes a theoretical analysis framework to clarify the nonlinear and spatial spillovers of the ICT-CEI relationship and the regulatory impact of relevant policies. To achieve this, we utilize panel data from 271 cities from 2003 to 2017 and employ a spatial panel smooth transition threshold model to empirically examine ICT's nonlinear and spatial spillover on CEI. Finally, the research explores the effects of policy interventions on the relationship between ICT and CEI through a moderating effect model.

This paper makes several significant contributions. Firstly, leveraging the technology adoption lifecycle theory and Metcalfe's law, it presents a framework for analyzing the impact of ICT on CEI from the perspectives of nonlinearity and spatial spillover. This framework enriches the theoretical understanding and application scenarios of carbon emission effects in high-tech industries with digitization and informatization. Secondly, the spatial panel and smooth transition threshold models were integrated into empirical research, and ICT's nonlinear and spatial spillovers on CEI are also considered, opening a new perspective for applying spatial nonlinear econometric models. Thirdly, it highlights the often overlooked policy moderating effect in the relationship between ICT and CEI, revealing that government competition, environmental regulation, and urban innovation environment play a significant role in regulating the impact of ICT on CEI, thereby expanding the scope of current research.

2 Theoretical Analysis and Research Hypotheses

The research emphasizes the causal link between ICT and CEI. Therefore, it considers theories such as the technology diffusion lifecycle theory, Metcalfe's law, and the ICT's industrial characteristics and development laws. This forms a theoretical framework for analyzing the impact of ICT on CEI, considering the aspects of stage, nonlinearity, and spatial spillover, as depicted in Figure 1:

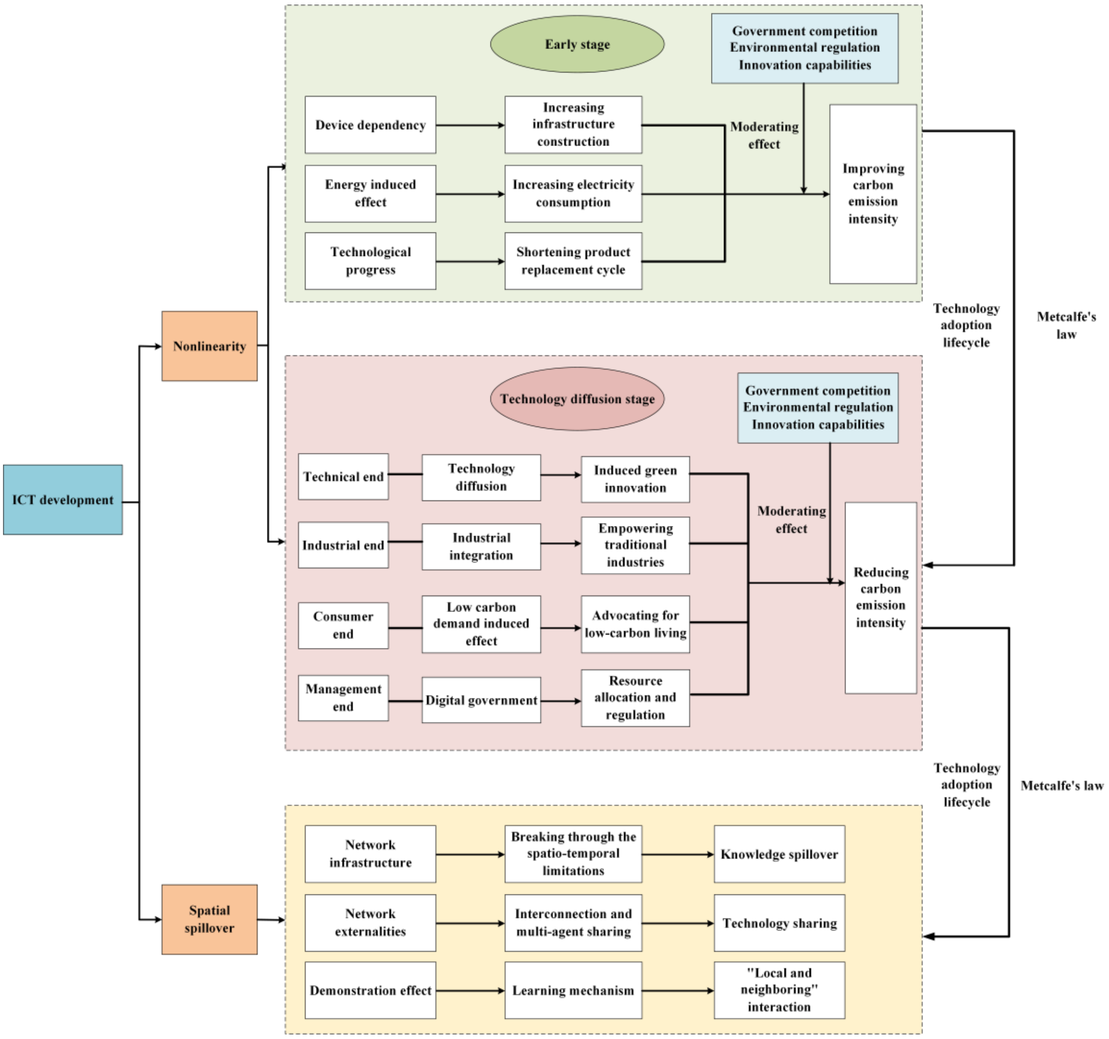

Figure 1 Theoretical framework

2.1 Nonlinear effects of ICT on CEI

As a high-tech industry, the progress and implementation of ICT align with the stages of technology diffusion and adoption (Geroski, 2000). This progression encompasses innovators, early adopters, early majority, late majority, and laggards. Meanwhile, ICT development adheres to Metcalfe's law, which postulates that the value of a network is directly proportional to the square of its nodes. Once ICT development surpasses a critical threshold, its externalities experience explosive growth. The economies of scale and technology spillover of ICT development contribute to reducing carbon emissions (Sun, 2022). Therefore, the impact of ICT on CEI is significantly contingent upon the adoption rate of ICT technology and its contribution to enhancing energy efficiency.

Firstly, the ICT industry itself is not inherently environmentally friendly. During the early adoption stage, ICT development consumes significant electricity. Studies have shown that manufacturing electronic components and computer hardware is energy-intensive (Masanet et al., 2020). As digital infrastructure expands, the share of electricity consumed by ICT and related industries will also rise, resulting in massive energy consumption and carbon emissions. (Zhuo et al., 2023). Thus, the initial growth of ICT and related industries stimulates high energy consumption and increases CEI. Without leveraging ICT to empower and transform traditional industries, its emissions and carbon reduction potential will be hard to achieve.

In the second stage of ICT development, ICT technology has significantly expanded into traditional industries. Incorporating ICT technology across a broader spectrum of industrial sectors has the potential to upgrade, thereby improving resource efficiency and reducing waste (Thompson et al., 2013). Due to its openness, efficiency, and collaborative nature, ICT has become a vital tool in production applications (Mishra and Sharma, 2023). ICT facilitates industrial upgrading by enhancing the integration of production processes and reducing carbon emissions. Compared to other industries, ICT exhibits high integration and technology spillover (Sergio et al., 2023). According to the theory of technology adoption lifecycle, as the adoption rate of ICT in major carbon-emitting industries (transportation and construction) increases, ICT reduces energy consumption throughout their entire lifecycle, promoting technological upgrades and carbon reduction (Pearson and Foxon, 2012). From the consumer's perspective, ICT development promotes a greener lifestyle, following Metcalfe's law. The widespread implementation of ICT technology will bolster the demand for low-carbon development in cities, reshaping consumer preferences and demand concepts (Li et al., 2024) **Error! Reference source not found.**. Finally, from a management perspective, ICT technology has also driven innovation in the whole process of government governance. Digital government leverages digital technology to improve the management and prediction of carbon emissions, enhancing the efficiency of environmental protection efforts (Liu et al., 2024). As ICT reaches a critical threshold, its impact on CEI is expected to shift from promotion to reduction. Therefore, we proposed hypothesis 1.

H1: ***The relationship between ICT and CEI is nonlinear, exhibiting an inverted U-shaped pattern where CEI initially rises and then falls, with a threshold value for transformation.***

2.2 The spatial spillover of ICT on CEI

The academic community widely acknowledges that interregional economic behaviour is spatially correlated (Wheeler, 2001). Hence, facilitating cross-regional collaborative emission reduction is crucial for China to accomplish its "dual carbon" objectives within the framework of global climate change. However, the division of administrative boundaries remains an important factor restricting knowledge spillovers and cross-regional cooperation in reducing emissions (Singh and Marx, 2013). An important feature of ICT is its spatial diffusion over time due to the adoption of technology. Regional exchanges facilitate ICT's spatial diffusion via expansion and migration diffusion, thus affecting the CEI of neighboring areas through spatial spillovers (Bai et al., 2023).

Firstly, a key feature of ICT is its significant knowledge spillover effect. Efficient network infrastructure construction provides a convenient channel for knowledge and technology spillovers. By facilitating efficient information transmission, ICT transcends spatio-temporal constraints and administrative barriers. It is vital in promoting the transfer and sharing of knowledge, technology, and other essential elements across different regions, thereby enhancing the scope and depth of economic activities between these areas (Hong et al., 2023). Secondly, data and information, as the main carriers of ICT, are a new type of production factor. Compared with traditional production factors such as land, capital, and labor, they have unique advantages such as high mobility, strong replicability, and a wide dissemination range, which helps to achieve interconnectivity and multi-agent sharing (Kedron et al., 2021). According to

Metcalfe's law, when the adoption rate of ICT technology continues to increase until it exceeds the critical point, its network externalities will show explosive growth, promoting knowledge spillover and technology sharing for energy intensification and carbon reduction between regions. demonstration effects emerge during technology diffusion in the context of digital and information transformation and high-quality development. When a city vigorously promotes digital and information transformation, enhances its development, reduces CEI, and becomes a leading region, its development experience, introduced policies, and innovative path serve as a demonstration and learning opportunity for surrounding and related cities, helping these areas adapt their local policies based on these proven strategies (Meseguer, 2005). This spatial effect on the diffusion of surrounding areas varies in speed and is influenced by various factors, such as geographical distance, infrastructure construction, learning ability in different regions, cooperation intensity between regions, and implementation of environmental policies in different regions. The different spatial diffusion rates of ICT technology can lead to different adoption rates and coverage rates in different regions. Metcalfe's law and the technology adoption curve suggest that, in the initial phases of ICT development, it is evident that in the early stages of ICT development, its impact on CEI is not substantial enough to influence surrounding areas through spatial spillovers. Only when ICT development breaks through a certain critical point will ICT not be limited to affecting local emissions and carbon reduction but will also have important impacts on neighboring areas through spatial spillovers. Based on the analysis provided, we propose the following hypothesis:

H2: ***ICT reduces CEI through spatial spillover effects, meaning that improvements in ICT in nearby regions can lead to a decline in local CEI. However, this reduction is evident only when the neighboring regions have achieved a significant level of ICT development.***

2.3 Policy moderating effects of government competition, environmental regulation, and innovation capabilities for the impact of ICT on CEI

It is worth noting that the exact timing at which ICT affects the transformation of CEI and the magnitude of its impact on CEI depend on several factors. Firstly, the coverage of ICT technology in society plays a crucial role. Generally speaking, the faster the adoption of ICT technology and the wider its application in industrial development, the sooner the turning point for CEI reduction will appear. Due to the pressure of promotion tournaments and economic development performance (Pang et al., 2023), local governments will use the invested financial funds to vigorously develop digital new infrastructure, develop the ICT industry, and introduce relevant talents. Consequently, government economic competition accelerates ICT development, leading to an earlier turning point for CEI reduction and amplifying the impact of ICT on CEI. Secondly, the formulation and implementation of carbon reduction policies. Constrained by environmental goals, local governments will introduce corresponding policies and regulations to reduce emissions and carbon emissions. Appropriate environmental regulations can motivate enterprises to innovate, upgrade production technologies, and improve previously inefficient and heavily polluting methods, enhancing technological capabilities and greater production efficiency (Li et al., 2023).

It can be seen that enterprises will accelerate their digital transformation in response to environmental regulations, thereby reducing their CEI. In addition, enterprises have closer interactions and stronger mechanisms for learning, imitation, and competition under the urban innovation and competition system of survival of the fittest. This will greatly improve the efficiency of adopting and transforming new technologies. As a high-tech industry represented by digitization and informatization, urban innovation will greatly affect ICT (Agboola et al., 2023). Therefore, the policy regulation of urban innovation should also be considered when analyzing the impact of ICT on CEI. The inflection point of ICT's impact on CEI will appear earlier, and the magnitude of the impact will also change under the moderation of various factors such as government competition, environmental regulation, and innovation capabilities. Based on the above analysis, the following hypothesis is proposed:

H3: ***The impact of ICT on CEI is moderated by policies such as government competition, environmental regulation, and urban innovation.***

3 Data and Methods

3.1 Study area and data sources

This study uses panel data from 271 cities in China, spanning 2003 to 2017. Given that different cities have different resource endowments, economic levels, and close relationships with other cities, the impact of ICT on CEI may differ across cities. Therefore, the cities are categorized into 105 resource-based cities and 166 non-resource-based cities[②]. The sample is divided into 128 cities within mature urban

[②] https://www.gov.cn/gongbao/content/2013/content_2547140.htm agglomerations and 143 cities outside these agglomerations, focusing on the nine major urban agglomerations (Figure 2)[3]. In variable selection, ICT-related data mainly originate from the China Urban Statistical Yearbook, while carbon emission data are sourced from the China Emission Accounts and Datasets (CEADs) (https://www.ceads.net.cn/data/). Other control variables are derived from *China Urban Statistical Yearbook*, government work reports and national economic and social development statistical bulletins. Missing data are filled in using interpolation and mean algorithms.

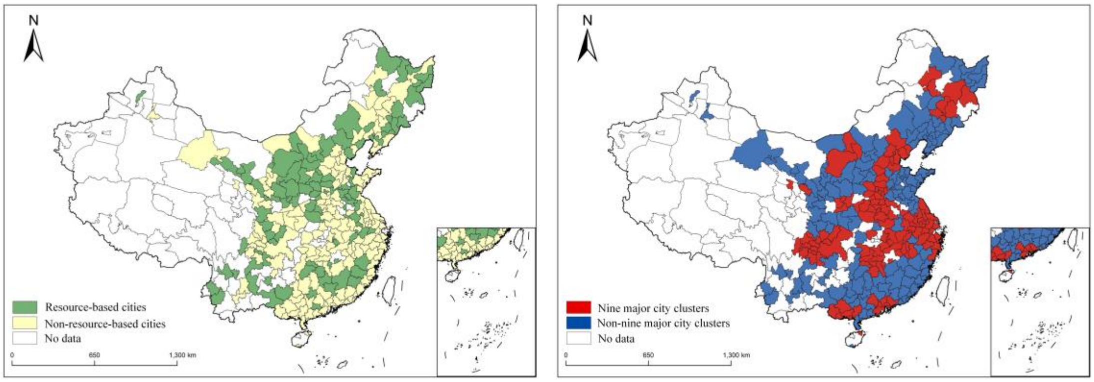

Figure2 Schematic diagram of the division of the two types of cities

3.2Variable description and data processing

3.2.1 Explained variable

The explained variable is carbon emission intensity (CEI), defined as the ratio of carbon emissions to GDP. Due to potential issues with estimating carbon dioxide emissions using energy statistics data, it uses nighttime lighting data to invert carbon dioxide emissions for research. Chen et al. demonstrated the high correlation between nighttime lighting and carbon emissions from human activities and established a fitting

[3] https://www.gov.cn/gongbao/content/2013/content_2547140.htm

relationship between the two. They also estimated the carbon dioxide emissions of 2,735 countries in China from 2003 to 2017(Chen et al., 2020). The carbon emission data of 271 cities in China is summarized and calculated based on their research. The conversion of GDP is based on the year 2003.

3.2.2 Core explanatory variable

The main explanatory variable is the level of ICT development. To comprehensively and objectively reflect ICT development at the urban level in China, the entropy weight method is employed (See Appendix A for details). This method integrates six indicators across three dimensions: ICT human resource base, ICT facility access, and ICT industry development (Table 1).

Table 1

ICT Indicator System and Weight

First-level indicator	Second-level indicator	Indicator description	Unit	Weight
ICT development	ICT human resource base	Number of employees in the information transmission, computer services, and software industries	10,000 persons	0.3077
		Number of university and college students enrollment per 10,000	person	0.1610
	ICT facility access	Number of local telephone users	10,0000 households	0.0961
		Number of mobile phone users	10,0000 households	0.1070
		Number of Internet users	10,0000 households	0.1631

ICT industry development	Telecommunication services	RMB 10,000	0.1650

3.2.3 Control variable

Reviewing existing literature, it employs a series of economic, social, and demographic factors as control variables that may affect CEI (Guo and Fang, 2023; Lee and Zhao, 2023; Jiang and Sun, 2023; Yahyaoui, 2024; Yang and Liu, 2023). Specifically, ①Industrial Structure (STRU): Gauged by the ratio of tertiary industry to secondary industry. Changes in industrial composition significantly impact carbon emissions. ②Government intervention (GOV): Evaluated by the proportion of fiscal expenditure to GDP, reflecting how government fiscal policies aimed at environmental protection or economic growth influence carbon emissions. ③Population density (POP-D) : Determined by the number of individuals per square kilometer of administrative area, where higher population density is positively associated with local economic activity and human capital, which in turn raises higher environmental protection requirements. ④Economic development (GDPPC): Represented by per capita GDP, recognizing that a fast-growing economy also requires more energy, while sustainable growth encourages energy conservation and emission reduction. ⑤Foreign direct investment (FDI): Measured as the ratio of foreign direct investment to GDP, with its environmental impact varying. FDI can either create "pollution havens" that worsen local environmental pressures or "pollution halos" that help alleviate them.

3.2.4 Regulating variable

Theoretical analysis indicates that the impact of ICT on CEI is moderated by government economic competition (GEC), environmental regulation (ER), and urban innovation (INN). Government economic competition (GEC) is characterized by prefecture-level cities' annual GDP growth rate (Zhang et al., 2021). The relevant data on urban innovation (INN) originate from the *2017 China Urban and Industrial Innovation Report* by Kou Zonglai's team at Fudan University[④].

Environmental regulation (ER) is evaluated using the methodology outlined by Bai et al. (2023). Selected indicators for measurement, due to data availability, include industrial wastewater, sulfur dioxide emissions, smoke and dust emissions, and secondary industry GDP. The procedure are as follows: First, defining the standardized environmental performance of pollutant j in region i for year t as $n_j ep_{it}$:

$$n_j ep_{it} = ep_{ijt} / \frac{1}{271} \sum_{i=1}^{271} ep_{ijt} \tag{1}$$

Where ep_{ijt} is the ratio of the actually added value of the secondary industry at time t in city i to the emission of pollutant j. Then the differences in different variables and dimensions are eliminated, and environmental regulations can be characterized as: $ER = \frac{1}{3} \sum_{j=1}^{3} n_j ep_{it}$.

All variables are described in Table 2.

[④] https://econ.fudan.edu.cn/info/1652/17207.htm

Table 2

Variables and descriptive statistics

Variables	Implications	Obs	Mean	Std. dev.	Min	Max
CEI	CEI	4065	2.480	1.688	0.156	18.402
ICT	ICT Development Level	4065	0.091	0.573	0.0170	0.668
STRU	Industry Structure	4065	0.857	0.607	0.0943	28.065
GOV	Government Intervention	4065	16.007	9.517	3.1284	148.516
POP_D	Population Density	4065	426.251	329.771	4.6995	2648.256
GDPPC	Economic Growth	4065	34608.420	29827.472	1892	290477
FDI	Openness to the outside world	4065	2.099	2.257	0.001	32.689
GEC	Government Economic Competition	4065	11.769	4.854	0.1	39.974
ER	Environmental regulation	4065	0.794	1.038	0.008	19.133
INN	Level of urban innovation	4065	8.581	47.324	0.001	1336.490

3.3 Model setting and test

3.3.1 Model setting

The theoretical analysis indicates that ICT exerts a staged nonlinear impact and spatial spillovers on CEI, with the latter also exhibiting nonlinear staged characteristics. Consequently, traditional econometric models may yield inaccurate results. To accurately identify the causal relationship between ICT and CEI, this study draws on the research of Pede et al. (2014) and employs a novel approach that accounts for both nonlinearity and spatial effects: the Spatial Panel Smooth Transition Autoregressive Threshold Model (STAR). Pede et al. (2014) used the quasi-maximum likelihood method and Monte Carlo method to theoretically study the setting of spatial nonlinear models and the estimation of parameters. Thus, the impact of ICT on CEI is further explored between local and neighboring areas. The model settings are as follows:

$$LnCEI_{it} = \rho \sum_{j=1}^{n} W_{ij} \cdot LnCEI_{jt} + \beta_1 LnICT_{it} + \beta_2 WLnICT_{jt} \tag{2}$$

$$+\beta LnControls + X_{it}\delta \circ G(s, \gamma, c) + v_i + \mu_i$$

$$u_{it} = \lambda \sum_{j=1}^{n} W_{ij} \cdot u_{it} + \varepsilon_{it}$$

$$G(s, \gamma, c) = [1 + \exp(-\gamma(s - c)/\sigma)]^{-1} \tag{3}$$

In the model, i denotes the region, t the year, and CEI the carbon emission intensity. To explore the impact of ICT on CEI between "local and neighboring" areas, we followed the approach of Shen et al. (2017), selecting $ICT_{i,t}$ and $WICT_{i,t}$ as core explanatory variables, representing the local and neighboring ICT development levels, respectively. $W_{i,t}$ is the spatial weight matrix, based on the reciprocal of geographical distance. This implies that closer geographical proximity enhances local effects from technology adoption and diffusion, resulting in higher weights in the spatial weight matrix. $Controls_{i,t}$ represents a series of control variables, including STRU, GOV, POP-D, GDPPC, and FDI. $X_{i,t}$ represents all variables, $X_{i,t}$ = [$ICT_{i,t}$, $WICT_{i,t}$, $Controls_{i,t}$]. δ represents the coefficients of the nonlinear part in the model, $\circ$ represents the Hamilton product, G(s， γ， c) is a logistic function, a continuous, smooth, and bounded function concerning the transformation variable s, ranging from 0 to 1. The slope parameter γ determines the transformation speed. c is a positional parameter that sets the transformation's threshold. the transformation variable is typically chosen as the spatial error of the dependent variable or an explanatory variable. Concerning existing research (Pede et al., 2014), WICT was selected as the transformation variable, i.e., s=Wx. The coefficients of $X_{i,t}$ monotonically change between $\beta(\beta_1/\beta_2/\beta)$and $\beta(\beta_1/\beta_2/\beta)$

$+\delta$ as the transformation variable s increases. Here, v_i represents individual fixed effect, and $\varepsilon_{i,t}$ denotes the random perturbation term. The parameters ρ and λ represent the spatial lag and error effects, respectively. If $\lambda = 0$, the model is referred to as the spatial autoregressive smooth transition model (SAR-STAR model)., If $\rho = 0$, it is termed the spatial error smooth transition model (SEM-STAR model).

In order to explore the possible regulating mechanisms by which ICT affects CEI, we identified the effects of government economic competition, environmental regulation, and innovation capacity by constructing the following model:

$$\begin{aligned} LnCEI_{it} = {} & \rho \textstyle\sum_{j=1}^{n} W_{ij} \cdot LnCEI_{jt} + \beta_1 LnICT_{it} + \beta_2 WLnICT_{jt} \\ & + \beta_3 LnADJUST_{it} + \beta_4 LnICT_{it} \cdot LnADJUST_{it} \\ & + \beta LnControls + X_{it}\delta \circ G(s,\gamma,c) + v_i + \mu_i \end{aligned} \tag{4}$$

Where ADJUST is the regulating variable, including government economic competition GEC, environmental regulation ER, and urban innovation INN. The coefficients β_4 and δ_4 are the focus of this section, reflecting the intensity and direction of the regulatory variables influencing the impact of ICT on CEI. When the main effects (β_1 and δ_1) are positive, coefficients β_4 and δ_4 are negative, indicating that the regulating variable weakens the promoting effect of ICT on CEI. Conversely, the regulating variable strengthens the promoting effect of ICT on CEI. When the main effects (β_1 and δ_1) are negative, coefficients β_4 and δ_4 are negative, indicating that the regulating variable will strengthen the inhibitory effect of the ICT on CEI. Conversely, the regulating variable will weaken the inhibitory effect of the ICT on CEI.

3.3.2 Model test

When conducting empirical research, the primary challenges involve selecting and configuring models. Is there a spatial dependency between samples? Is there a nonlinear relationship? If there are both spatial dependencies and nonlinear relationships, which one should be chosen among the ARAR-STAR model, SAR-STAR model, and SEM-STAR model? The LM test was used to examine nonlinearity and spatial dependence in the data (Pede et al., 2014).

Firstly, a unilateral LM test is conducted, which is an univariate test for spatial error (ERR), spatial dependence (LAG), and nonlinearity (NLIN). The second step is a conditional test, including the spatial error ($LM_{\lambda|\delta}$), spatial lag ($LM_{\rho|\delta}$) tests under nonlinear conditions, as well as the nonlinear tests under spatial error ($LM_{\delta|\lambda}$) and spatial dependence ($LM_{\delta|\rho}$) conditions. Next is the bilateral LM test, which involves three joint tests: joint spatial error and spatial nonlinearity (ERR+NLIN), joint spatial lag and spatial nonlinearity (LAG+NLIN), and joint spatial error and spatial lag (ERR+LAG). Finally, a multilateral LM test is conducted to examine whether there are simultaneous spatial lags, spatial errors, and nonlinearity (See Appendix B for details).

4 Result Analysis

4.1 Model selection

The LM test shows that they are statistically not 0 at the 1% significance level whether it is the univariate test LM_{λ}, LM_{r}, and LM_{δ}, the conditional test $LM_{\lambda|\delta}$, $LM_{\rho|\delta}$, $LM_{\delta|\lambda}$ and $LM_{\delta|\rho}$, or the multivariate test $LM_{\lambda\delta}$, $LM_{r\delta}$, $LM_{r\lambda}$, and $LM_{r\lambda\delta}$. There is spatial dependence, spatial error, and nonlinearity in the CEI between cities. Ignoring any of these situations will result in biased estimation. Therefore, the model can be best described as the ARAR-STAR model (Due to the length of the article, we did not report the results of the LM test in the main text; see Appendix B for details.).

4.2 Benchmark regression results

Using the ARAR-STAR model, the smoothing parameter γ and positional parameter c were estimated using the quasi-maximum likelihood method (Di Caro, 2017). The benchmark results of the estimation can be found in Table 3. These findings highlight the segmented impact of ICT on CEI in two distinct regions (low and high) in the presence of transfer variables. The positional parameter c determines the threshold for shifting between the first (low) and second (high) spatial regimes and is linked to the spatially weighted average of ICT (W·LnICT). The spatial autoregressive coefficient ρ measures the spatial spillovers of CEI. At a coefficient of 0.877, it indicates significant positive spatial spillovers, suggesting that the CEI of local areas is significantly influenced by the CEI of neighboring regions.

The results in Table 3 reveal that ICT's impact on CEI differs markedly between two distinct regimes, as indicated by the coefficients β and δ. The values of β_1 (0.012) and δ_1 (-0.166), along with a threshold value of c at -0.736, point to a significant inverted U-shaped relationship between ICT and CEI. Initially, ICT increases CEI, but beyond a certain point, it leads to a reduction, confirming hypothesis 1. Specifically, when W•LnICT is below the threshold of -0.736, the model operates in a low regime where ICT development results in a 0.012% increase in CEI for every 1% increase in ICT. Conversely, when W·LnICT surpasses the threshold of -0.736, the model enters a high regime where ICT leads to a 0.155% decrease in CEI for every 1% increase. Figure 3 illustrates the distribution of most subsample observations across both regimes, on either side of the positional parameter c. The effect of ICT on CEI starts with an increase in the low regime, weakens during the transition, and ultimately leads to a decrease in the high regime.

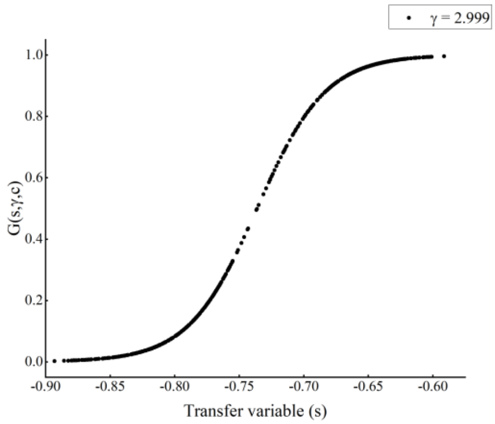

Figure3 Plot of transfer function

The regression results further reveal that the impact of ICT development in neighboring areas on local CEI is nonlinear, with marked differences between the low and high regimes. β_2 and δ_2 are -0.002 and -0.045, respectively, showing that ICT development in neighboring areas significantly inhibits local CEI. This inhibitory effect is significant only when ICT development exceeds a certain threshold, supporting hypothesis 2. Specifically, when W·LnICT is below the threshold value of -0.736, the model is in a low regime. Although the coefficient of W·LnICT is negative, it is not statistically significant, suggesting that low levels of ICT development do not significantly impact emissions and carbon reduction. When W·LnICT exceeds the threshold value, the model shifts to a high regime, where higher ICT development and significant technology diffusion effects lead to spatial spillovers that reduce local CEI.

Results for the control variables show that the adjustment of industrial structure (LnSTRU) increases CEI under the low regime but suppresses it under the high regime. High ICT development drives related industries towards digital and information transformation, improving energy utilization efficiency and reducing CEI. Government intervention (LnGOV) significantly promotes CEI by distorting resource allocation and inhibiting market efficiency. The coefficient of population density (LnPOP_D) on CEI is significantly negative when the transfer variable is below the threshold value. However, when the transfer variable exceeds the threshold value, the result is insignificant, indicating that population concentration reduces CEI without nonlinear characteristics. Economic growth (LnGDPPC) significantly reduces CEI, with a more pronounced inhibitory effect under the high regime. This suggests that high-quality economic growth, driven by technological progress and green development, promotes energy conservation and emission reduction in conjunction with ICT development. FDI (LnFDI) has a negative effect on CEI under the low regime and a positive effect under the high regime, resulting in an overall positive impact. This indicates the presence of "pollution havens" at the urban level in China.

Table 3

Estimation results of nonlinear impact of ICT on CEI

Transfer Variable	Variables	Coefficients	Parameter Estimates	t-values
W·LnICT	LnICT	β_1	0.012***	2.995
		δ_1	-0.167***	-2.985
	W·LnICT	β_2	-0.002	-1.608
		δ_2	-0.045***	-3.695
	LnSTRU	β_3	0.082***	7.860
		δ_3	-0.302***	-3.967
	LnGOV	β_4	0.329***	25.371
		δ_4	0.289	1.228
	LnPOP_D	β_5	-0.229***	-5.467
		δ_5	0.690	1.314
	LnGDPPC	β_6	-0.113***	-11.445
		δ_6	-0.5038***	-3.355
	LnFDI	β_7	-0.054**	-2.155
		δ_7	0.469***	3.043
Position parameter c			-0.736***	-541.198
Smoothing parameter γ			2.999***	3.833
Spatial autocorrelation coefficient ρ			0.877***	29.706
Spatial error coefficient λ			0.902***	37.327
Covariance σ^2			0.010***	44.201

Note: ***, **, and * represent significant at the 1%, 5%, and 10% levels, respectively;

4.3 Robustness test

4.3.1 Change of econometric model

Following the methodology of Chernozhukov and Hong (2003), we utilized the MCMC method to evaluate the model's robustness. Table 4 presents the results of repeatedly sampling (1×10^5 times) and averaging the final samples (the last 8×10^4) for parameter estimation. A 95% confidence interval was applied to the MCMC method, with Table 4 displaying the upper and lower bounds represented by "para95_high" and "para95_low." Parameters falling within this interval have successfully cleared the 5% significance test. The findings in Table 4 demonstrate that the majority of the estimated values meet the 5% significance test criteria. Furthermore, the consistency of coefficients in both high and low regimes between the MCMC and quasi-maximum likelihood methods highlights the robustness and precision of the ARAR-STAR model.

Table 4

MCMC estimate

Transfer Variable	Variables	Coefficients	Parameter Estimates	para95_low	para95_high
W·LnICT	LnICT	β_1	0.013	0.006	0.019
		δ_1	-0.111	-0.144	-0.067
	W·LnICT	β_2	-0.003	-0.005	0.000
		δ_2	-0.031	-0.050	-0.008
	LnSTRU	β_3	0.095	0.073	0.114
		δ_3	-0.221	-0.296	-0.160
	LnGOV	β_4	0.327	0.305	0.350
		δ_4	0.275	0.236	0.352
	LnPOP_D	β_5	-0.245	-0.337	-0.156
		δ_5	0.845	0.764	0.936
	LnGDPPC	β_6	-0.108	-0.128	-0.090
		δ_6	-0.532	-0.600	-0.493
	LnFDI	β_7	-0.017	-0.057	0.014
		δ_7	0.426	0.382	0.527
Position parameter c			-0.738	-0.743	-0.736
Smoothing parameter γ			2.902	2.808	2.982
Spatial autocorrelation coefficient ρ			0.890	0.856	0.932
Spatial error coefficient λ			0.909	0.868	0.946
Covariance σ^2			0.010	0.009	0.010

4.3.2 Consideration of policy shocks

The study considered the potential disruption of empirical results by low-carbon policies. Pilot low-carbon city policies might affect CEI and interfere with the impact of ICT on CEI. It was suggested that experimental low-carbon city policies could influence CEI and disrupt the influence of ICT on CEI. To verify the robustness of the benchmark results, we excluded data from pilot low-carbon cities and re-estimated the model. Model 1 in Table 5 illustrates that the relationship between ICT and CEI continues to follow a significant inverted U-shaped pattern, further validating the reliability of the original findings.

4.3.3 Endogeneity

It is essential to address the model's potential endogeneity. To mitigate this issue, we utilized the instrumental variable (IV) method with exogenous variables. Certain natural conditions, like landforms, are external to social and economic activities and do not directly affect CEI. For example, flatter terrain can facilitate infrastructure development, which may support local ICT growth. In line with Bai et al. (2023), we selected the interaction between regional terrain undulations and the previous year's internet user count as the IV to assess the empirical model. Model 2 in Table 5 shows that the coefficient remained consistent, reinforcing the robustness of the initial findings.

In addition, we utilized the interaction between the distance to Hangzhou and the internet user count from the previous year as an alternative IV. Results revealed that the F-statistic exceeded 10, indicating the validity of IV (Model 3 in Table 5). The second source of endogeneity is the omission of variables. Previous regressions controlled for fixed effects on years and individuals, but omitted provincial fixed effects, potentially missing important variables. Model 4 in Table 5 incorporated provincial fixed effects along with year and individual fixed effects. The impact coefficient of ICT on CEI remained stable, further verifying robustness.

Table 5

Robust test

Transfer Variable	Variables	Coefficients	Model 1	Model 2	Model 3	Model 4
	LnICT	β_1	0.012***	0.030***	0.018***	0.025***
			(2.753)	(7.621)	(3.282)	(4.726)
		δ_1	-0.064*	-0.128***	-0.076**	-0.123***
			(1.761)	(-4.618)	(-2.075)	(-3.895)
	W·LnICT	β_2	0.005	-0.001	-0.001	0.001
			(1.413)	(-1.130)	(-0.252)	(0.537)
		δ_2	-0.030**	-0.017**	-0.021*	-0.031***
			(-2.328)	(-2.380)	(-1.786)	(-3.155)
	R^2			0.421	0.297	-
	CDW-F			15.08	53.84	-
	K-P LM			14.87	41.79	
	<P-value>			<0.000>	<0.000>	
W·LnICT	Controls		Yes	Yes	Yes	Yes
	Position parameter *c*		-0.772***	-0.736***	-0.736***	-0.736***
			(-91.648)	(-125.221)	(-108.787)	(-87.866)
	Smoothing parameter γ		1.643***	1.054***	1.163***	1.065***
			(3.949)	(8.489)	(4.560)	(4.515)
	Spatial autocorrelation coefficient ρ		0.877***	0.868***	0.851***	0.883***
			(28.854)	(41.098)	(23.703)	(51.047)
	Spatial error coefficient λ		0.862***	0.952***	0.879***	0.887***
			(23.748)	(134.498)	(30.293)	(53.006)
	Covariance σ^2		0.009***	0.010***	0.010***	0.010***
			(41.796)	(71.587)	(43.661)	(72.543)
	Obs		3485	4065	4065	4065

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively; t-values are provided in parentheses. k-Paaprk LM statistics were used for the identification test, where the p-values for the corresponding statistics are in pointed brackets. Critical values for the Stock-Yogo weak IV test at the 10% significance level are shown in square brackets.

4.4 Heterogeneity analysis

Urban agglomerations, due to their strong spatial expansion and synergistic effects in functional division of labor, have emerged as pivotal areas in the new regional economic development paradigm. However, they also pose significant challenges for emissions and carbon reduction. The high-tech industries, the application of information technology, rapid transportation network construction, economic growth, structural optimization, and regional integration are key drivers in urban agglomerations (Martinus and Sigler, 2018). The disparity in ICT between urban and non-urban areas is influenced by several factors. To examine the variation in ICT's impact on CEI between urban agglomeration and non-urban agglomeration, we performed a grouped regression analysis. Results indicate that ICT exerts a more substantial inhibitory effect on CEI in urban clusters, with more significant spatial spillovers than non-urban clusters.

Resource-based cities, constrained by long-term anchoring effects and path dependence, have progressed slowly in their informatization transformation. These cities continue to rely on abundant resource endowments, resulting in a "resource curse" in urban transformation (Chiroleu-Assouline et al., 2020). To examine differences in low-carbon transformation facilitated by ICT among city types, grouped regression analysis was conducted on resource-based and non-resource-based cities. Table 6 illustrates that while ICT development significantly promotes CEI in both types of cities under the low regime, it markedly reduces CEI in non-resource-based cities under the high regime. In contrast, ICT development enhances CEI in resource-based cities even under high regimes.

Table 6

Heterogeneity analysis

Transfer Variable	Variables	Coefficients	City clusters	Non-city clusters	Resource-based cities	Non-resource-based cities
W·LnICT	LnICT	β_1	0.050**	0.010***	0.013**	0.013***
			(1.993)	（7.621）	（2.485）	(7.351)
		δ_1	-0.193***	-0.075***	-0.198	-0.200***
			（-2.671）	(-4.618)	（-0.883）	(-7.683)
	W·LnICT	β_2	0.020	0.002	-0.007***	0.019*
			（1.428）	(-1.130)	（-3.654）	(1.658)
		δ_2	-0.194**	-0.081**	0.003	-0.346***
			（-2.210）	(-2.380)	（-0.151）	(-5.009)
	Controls		*Yes*	*Yes*	*Yes*	*Yes*
	Position parameter *c*		-0.692***	-0.706***	-0.771***	-0.711***
			(-43.130)	(-243.134)	(-1116.62)	(-594.174)
	Smoothing parameter γ		0.460**	4.506***	9.533*	2.500***
			(2.223)	(3.324)	(1.748)	(14.357)
	Spatial autocorrelation coefficient ρ		0.771***	0.623***	0.795***	0.883***
			(14.563)	(22.863)	(11.898)	(51.047)
	Spatial error coefficient λ		0.852***	0.841***	0.894***	0.615***
			(20.620)	(48.757)	(18.049)	(23.737)
	Covariance σ^2		0.0116***	0.0076***	0.0118***	0.0090***
			(31.796)	(82.180)	(26.733)	(94.835)
	Obs		1920	2145	1570	2495

Note: ***, **, and * represent significant at the 1%, 5%, and 10% levels, respectively; t-values are in parentheses.

4.5 Analysis of policy moderating effect

In Table 7, the moderating effect analysis reveals that when β_4 is significantly negative, it suggests that government economic competition, environmental regulation, and urban innovation capabilities under the low regime will cripple the facilitating role of ICT on CEI. In the case of the high regime, the interaction term between ICT and GEC & INN is not significant, indicating that government economic competition and urban innovation will strengthen the emission reduction effect of IC. Still, it does not have a nonlinear regulating effect (the regulating effect under the high regime is β_4). However, the interaction term between ICT and ER is significant, signifying that environmental regulations further amplify the emission reduction effect of ICT in the high regime (the regulating effect under the high regime is $\beta_4 + \delta_4$).

Table 7

The results of policy moderating effect

Transfer Variable	Variables	Coefficients	GEC	ER	INN
W·LnICT	LnICT	β_1	0.043***	0.019***	0.019***
			(5.841)	(13.800)	(3.145)
		δ_1	-0.338***	-0.203***	-0.092**
			(-4.380)	(-4.618)	(-2.264)
	W·LnICT	β_2	-0.002	-0.003	-0.000
			(-1.116)	(-1.503)	(-0.165)
		δ_2	-0.049***	-0.0376***	-0.023*
			(-4.628)	(-6.398)	(-1.764)
	LnADJUST	β_3	-0.031***	-0.004***	-0.001***
			(-4.380)	(-7.193)	(-5.062)

	δ_3	0.022	-0.006*	-0.001
		(0.198)	(-1.912)	(-0.361)
LnICT·LnADJUST	β_4	-0.031***	-0.004***	-0.001***
		(-4.913)	(-7.193)	(-5.062)
	δ_4	-0.021	-0.005*	-0.001
		(0.198)	(-1.911)	(-0.361)
Controls		*Yes*	*Yes*	*Yes*
Position parameter c		-0.736***	-0.736***	-0.736***
		(-757.631)	(-2254.61)	(-70.664)
Smoothing parameter γ		2.999***	3.500***	1.098***
		(3.925)	(21.678)	(3.710)
Spatial autocorrelation coefficient ρ		0.771***	0.848***	0.890***
		(14.563)	(61.092)	(33.762)
Spatial error coefficient λ		0.868***	0.930***	0.892***
		(26.590)	(138.155)	(33.390)
Covariance σ^2		0.010***	0.009***	0.009***
		(44.285)	(119.893)	(43.980)
Obs		4065	4065	4065

Note: ***, **, and * represent significant at the 1%, 5%, and 10% levels, respectively; t-values are in parentheses.

5 Conclusion and policy implications

5.1 Conclusion

We first introduce a theoretical analytical framework to explore the complex causal relationship between ICT and CEI, including possible non-linearities and spatial spillover features. Following this, we analyze panel data from 271 cities in China from 2003 to 2017. We utilize an innovative method, the spatial panel smooth transition threshold model, to empirically validate the influence of ICT on CEI. Additionally, we assess the role of policies in these relationships using a regulatory effect model.

(1) Our study reveals a non-linear, inverted U-shaped impact of ICT on CEI, where ICT initially increases CEI but eventually leads to a decrease, with a noticeable threshold where promotion turns into inhibition. While previous research has suggested a non-linear relationship between ICT and CEI (Wang and Ye, 2017), specific threshold dynamics have been relatively unexplored. Additionally, the study uncovers that ICT development in surrounding areas can inhibit local CEI, supported by both theoretical insights and empirical findings. This spatial effect becomes significant only when ICT development in surrounding areas reaches a certain stage.

(2) The influence of ICT on CEI varies significantly depending on the level of urban connectivity and resource endowments. Prior research has tended to overlook these differences, often focusing solely on geographical distinctions. However, our analysis demonstrates that ICT has a more pronounced inhibitory impact on CEI in urban areas, with stronger spatial spillover effects. Conversely, the influence of ICT has not shown significant effects in resource-based cities.

(3) The analysis of policy moderating effects show that the government's economic competition, environmental regulation, and urban innovation capabilities reinforce the role of ICT in reducing emissions. Moreover, under a high-ICT regime, environmental regulation further amplifies the effectiveness of ICT in this area. Previous studies have mainly focused on ICT's transmission mechanism and impact on CEI. Effective carbon reduction requires a systematic governance approach that integrates efforts across various perspectives, directions, and departments. This study explores the potential

regulatory effects of ICT on CEI, addressing gaps in previous research and providing a scientific basis for targeted measures to develop urban ICT and reduce carbon emissions.

5.2 Policy implications

The research findings hold significant policy implications for local governments and businesses, highlighting the need to accelerate the implementation of ICT to achieve the "dual carbon" objectives.

(1) Strengthen the transformation of traditional industries through ICT. The empirical results of this study indicate that ICT's impact on CEI follows an inverted U-shaped trend, initially increasing and then decreasing, with a tipping point from promotion to inhibition. The timing of this shift is affected by the adoption rate of ICT technology. Therefore, government investment should focus on the ICT industry to drive its development. Simultaneously, active guidance should be provided for integrating and advancing ICT technology within traditional industries, expanding technology coverage to create an early-stage inverted U-shaped inflection point for CEI. Specifically, digital infrastructure serves as a prerequisite and foundation, and the government should consciously implement supportive policies in areas with underdeveloped ICT industries, such as launching initiatives like "Channel Computing Resources from the East to the West" to bridge the "digital divide" and expand ICT technology coverage. Moreover, the government should provide technical support and offer tax incentives to encourage enterprises to achieve digital transformation. This approach will help mitigate the risks associated with the transition of traditional industries and promote the early adoption of ICT technology in key industrial sectors.

(2) Establishing a collaborative mechanism is important to promote energy efficiency to reduce emissions across different regions. Research findings suggest a highly spatial positive correlation with the CEI, while the development of ICT has a negative spillover on urban CEI. Therefore, it is crucial to promote local-neighboring collaborative governance to advance emission and carbon reduction efforts. This involves prioritizing coordination in allocating ICT infrastructure among urban areas to ensure the rational and effective use of resources. Additionally, fostering learning and demonstration effects among cities and implementing policy pilot projects, such as "smart cities," can drive the development of ICT and facilitate technology diffusion to promote digital transformation in surrounding cities.

(3) Develop differentiation strategies based on urban connections and resource endowments. It is necessary to guide school-enterprise cooperation to achieve research and development and promote green technology. At the same time, it is also necessary to encourage and support urban clusters to become a highland for developing and promoting ICT technology. Since ICT technology can enable resource monitoring, accurate measurement, and prediction of carbon emissions, it is important to strengthen cooperation between resource processing enterprises and local ICT enterprises. This will help actively promote their digital transformation and achieve carbon reduction.

(4) Analyzing moderating effects indicates that achieving collaborative governance among multiple departments is necessary to reduce emissions and carbon emissions through ICT effectively. Firstly, leveraging the positive effects of competition among local governments in carbon reduction efforts is crucial. Central

government should reevaluate its performance metrics to move beyond the pursuit of GDP growth, continuously improve the environmental performance evaluation system and supervision system that includes carbon emissions reduction, and promote "healthy competition" among local governments. Secondly, formulate moderate environmental regulations. The carbon reduction effect of environmental regulation needs to be matched with environmental regulation tools. Incentive tools such as emission allowance and environmental subsidies can be adopted to encourage enterprises to upgrade their industries. Finally, it enhances the competitiveness of technological innovation. Underdeveloped regions with relatively backward ICT development can promote efficient resource allocation by imitating and introducing the technological experience of the first mover regions, and then catch up to gradually achieve independent innovation, promoting healthy cooperation and competition between regions.

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Appendix A Entropy weighting method to calculate ICT

$$ICT_{it} = \sum_{j=1}^{m} w_j \, x_{ijt}^{*} \quad \text{(A.1)}$$

Where ICT_{it} is the level of ICT development of city i in year t. x^{*}_{ijt} is the standardized ICT indicator for the city i in year t. j. w_j is the weight of each indicator j. m is the number of ICT indicators.

All variables used to measure ICT indicators are standardized to ensure that the impact of inconsistent indicator units on the calculation of indicator weights is avoided in calculating the comprehensive index. The standardization method is as follows:

$$x_{ijt}^{*} = [x_{it} - \min_{it}(x_{ijt})]/[\ \max_{it}(x_{ijt}) - \max_{it}(x_{ijt})] \quad \text{(A.2)}$$

Where x_{ijt} represents the original value of indicator j for city i in year t, $\max_{it}(x_{ijt})$ and $\min_{it}(x_{ijt})$ denote the maximum and minimum values of x_{ijt} .

The entropy weight method calculates as follows:

Step 1: Calculate the information entropy (e_j) of each ICT indicator j:

$$e_j = -k \sum_{t=1}^{T} \sum_{i=1}^{n} p_{ijt} \ln(p_{ijt}) \quad \text{(A.3)}$$

Where $k = \frac{1}{ln\ (nT)}$; n is the total number of cities, taken as 271; T is the research period. In this paper, T=15, and p_{ijt} represents the proportion of the ICT indicator j of city i to all city indicators j at time t. It can be expressed as follows:

$$p_{ijt} = x_{ijt}^{*} / \sum_{t=1}^{T} \sum_{i=1}^{n} x_{ijt}^{*} \quad \text{(A.4)}$$

Step 2: Calculate the weight w_j of indicator j:

$$w_j = (1 - e_j) / \sum_{j=1}^{m} (1 - e_j) \quad \text{(A.5)}$$

Appendix B LM test

Table B.1 LM test principles

Model	Test	Statistic	Distribution
1	ERR（$\lambda = 0$，given $\rho = \delta = 0$）	LM_{λ}	χ^2_1
2	LAG（$\rho = 0$，given $\lambda = \delta = 0$）	LM_{ρ}	χ^2_1
3	NLIN（$\delta = 0$，given $\rho = \lambda = 0$）	LM_{δ}	χ^2_k
4	$\lambda = 0$，given $\delta \neq 0$	$LM_{\lambda\|\delta}$	χ^2_1
5	$\rho = 0$，given $\delta \neq 0$	$LM_{\rho\|\delta}$	χ^2_1
6	$\delta = 0$，given $\lambda \neq 0$	$LM_{\delta\|\lambda}$	χ^2_k
7	$\delta = 0$，given $\rho \neq 0$	$LM_{\delta\|\rho}$	χ^2_k
8	ERR+NLIN（$\lambda = \delta = 0$）	$LM_{\lambda\delta}$	χ^2_{k+1}
9	LAG+NLIN（$\rho = \delta = 0$）	$LM_{\rho\delta}$	χ^2_{k+1}
10	ERR+LAG（$\rho = \lambda = 0$）	$LM_{\rho\lambda}$	χ^2_2
11	LAG+ERR+NLIN（$\rho=\lambda=\delta=0$）	$LM_{\rho\lambda\delta}$	χ^2_{k+2}

Table B.2 Model selection

Model	Test	Statistic	Distribution	Value
1	ERR($\lambda = 0$，given $\rho = \delta = 0$)	LM_{λ}	χ^2_1	11813.341***
2	LAG($\rho = 0$，given $\lambda = \delta = 0$)	LM_{r}	χ^2_1	4226.793***
3	NLIN($\delta = 0$，given $\rho = \lambda = 0$)	LM_{δ}	χ^2_k	423.583***
4	$\lambda = 0$，given $\delta \neq 0$	$LM_{\lambda\|\delta}$	χ^2_1	7154.597***
5	$\rho = 0$，given $\delta \neq 0$	$LM_{\rho\|\delta}$	χ^2_1	3064.038***
6	$\delta = 0$，given $\lambda \neq 0$	$LM_{\delta\|\lambda}$	χ^2_k	191.088***
7	$\delta = 0$，given $\rho \neq 0$	$LM_{\delta\|\rho}$	χ^2_k	141.851***
8	ERR+NLIN($\lambda = \delta = 0$)	$LM_{\lambda\delta}$	χ^2_{k+1}	12236.972***
9	LAG+NLIN($\rho = \delta = 0$)	$LM_{r\delta}$	χ^2_{k+1}	4479.971***
10	ERR+LAG($\rho = \lambda = 0$)	$LM_{r\lambda}$	χ^2_2	12637.621***
11	LAG+ERR+NLIN($\rho=\lambda=\delta=0$)	$LM_{r\lambda\delta}$	χ^2_{k+2}	12763.893***

Note: *** represents significant at 1% level.