Exploring the nonlinear relationship between digital economy development and industrial carbon unlocking: Threshold effect, tunnel model and "techno-institutional" framework analysis

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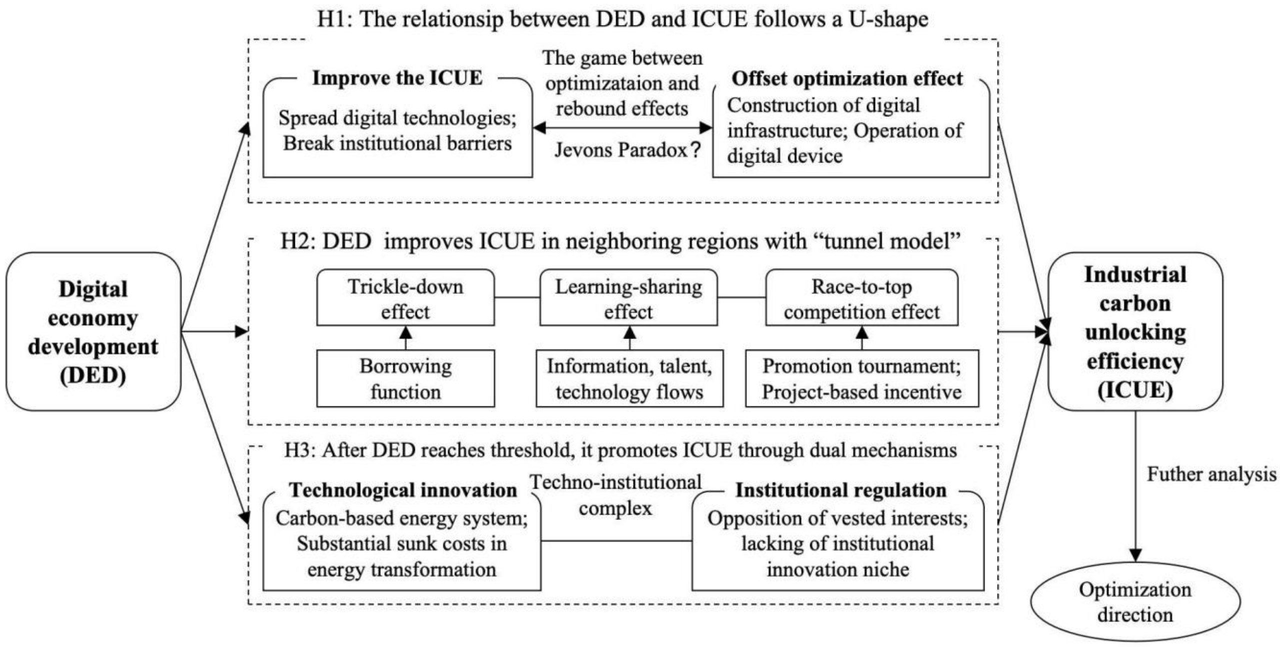
Graphical abstract:



Abstract: The digital economy development (DED) contributes to breaking the path dependency dilemma of industrial carbon lock-in and achieving high-quality development that balances economic and ecological benefits. This study, based on the panel data from 274 cities in China from 2013 to 2022, aims to identify the phased relationship between the digital economy development and industrial carbon unlocking efficiency (ICUE). The main findings are as follows: (1) The impact of digital economy development on industrial carbon unlocking efficiency exhibits a double-threshold effect. After verification through grouped instrumental variable (IV) regression, the conclusion remains valid. It shows a "U-shaped" relationship of first decreasing then increasing, and finally reaching equilibrium. (2) Digital economy development could significantly promote industrial carbon unlocking efficiency in multi-dimensional adjacent regions based on the "tunnel model"; (3) Once digital economy development enters maturity stage, industrial carbon unlocking efficiency is mainly improved through two key pathways: technological innovation and institutional regulation; (4) Based on training and simulations of existing samples, cities most likely to achieve optimal industrial carbon unlocking performance in digital industry development are mainly concentrated around China's "Hu Huanyong Line" and the southeast coastal areas, which can fully leverage their resource endowments, location advantages, and leading roles.

Keywords: digital economy; industrial carbon unlocking; panel threshold model; techno-institutional complex; tunnel model; machine learning model

1. Introduction

The report of the 20th National Congress of the Communist Party of China (CPC) emphasized the key strategy of “promoting green development and fostering harmony between humanity and nature”. In addition, a coordinated approach for industrial restructuring while simultaneously advancing carbon reduction, pollution control, green expansion and economic growth has been proposed to manifest the determination of Chinese government to achieve carbon peaking by 2030 and carbon neutrality by 2060 (Cai et al., 2024). In practice, since the 12th Five-Year Plan has firstly incorporated the reduction of CO_2 emission per unit of GDP as a binding target in China’s national economic and social development planning, subsequent several Five-Year Plans continued to include similar mandatory carbon reduction targets.

However, at the end of 2021, China's total annual CO_2 emissions were 10.523 billion tons, accounting for 45% of global emissions and still the world's largest emitter[1]. The persistent challenge stems from the entrenched reliance on fuels in certain regions, which locks industrial development into carbon-intensive energy systems, creating the dilemma of "industrial carbon lock-in" (Unruh, 2000). Carbon lock-in results from the path dependency of traditional industry development, leading to a self-reinforcing and stable operational model (Niu &Liu, 2021). It inhibits the adoption and diffusion of low-carbon technologies, thereby weakening the effectiveness of carbon reduction policies.

The digital economic development (DED) characterized by the fusion of financial and technological elements (Tian et al., 2024), provides a promising pathway for carbon unlocking due to its features of "low-carbon emission, high output, and high returns." The digital transformation is usually linked with carbon sink and negative carbon technologies, and DED embodies both technological and institutional transformation, providing a dual-pronged approach for industrial carbon unlocking. On one hand, as digital technologies increasingly permeate various sectors, their integration with traditional industries has become a crucial driving force for economic transformation and stable growth. On the other hand, the institutional reforms of DED, such as piloting the establishment of "National Big Data Comprehensive Pilot Zones" and the "Broadband China" initiative, have emerged as key mechanisms for cities to realize their "dual carbon" goals. However, some scholars have also proposed the concept of "digitization paradox", which is adopted to describe the economic growth paradox (Li and Wu, 2023) or carbon reduction paradox (Bai et al., 2023) with the development of digital economy and technology. The study aims to explore the relationship

[1] Referring to: Analysis of global carbon dioxide emissions in 2021: more than half of carbon emissions in the Asia-Pacific region, https://www.163.com/dy/article/HF7K0OPQ055360RU.html

between DED and industrial carbon unlocking in China, with a focus on the puzzle of the "digitization paradox" in carbon unlocking. The findings hold significantly theoretical and practical value for promoting China's low-carbon transformation.

2. Literature review

In recent years, the relationship between DED and urban carbon emissions has gradually gained significant academic attention. DED is not only seen as a new driver of economic growth, but also a key enabler of sustainable development (Nara et al., 2021). Some studies suggest that DED facilitates the transition to a green economy by accelerating industrial upgrading through the widespread dissemination and integration of knowledge, ultimately promoting low-carbon development (Paschou et al., 2020). However, some other studies indicate that the relationship between DED and carbon emissions is nonlinear. The carbon reduction effect of DED will only become apparent when it reaches a certain scale (Kwilinski, 2024; Xin et al., 2023a). Due to the "carbon-intensive" characteristic of digital industry expansion and infrastructure construction in its early stage, which leads to increasing energy consumption (Bai et al., 2023). At the same time, various digital technology types could cause differential impacts on carbon reduction. At the early stage of the integration of digital innovation such as information, calculation, communication and connection technologies, it could be identified that carbon emission will rapidly grow with the construction of digital infrastructure without other policy intervention (Jiang et al., 2021). But the commercial application of digital technology, such as the visualization reform, digital transformation, could gradually result in carbon reduction significantly, since these digital technologies development are linking to industrial process emission reduction and carbon sink, negative carbon technologies (Zhang et al., 2022).

In the field of the industrial carbon lock-in, existing literature has explored its formation mechanism, measurement methods and possible mitigation pathways. Unruh (2000) first proposed the concept of "carbon lock-in", arguing that economic development has gradually locked into a fossil fuel-based energy system during the evolution of modern industry. Furthermore, the interaction between outdated technologies and rigid institutional frameworks reinforces the carbon dependency (Unruh &Carrillo-Hermosilla, 2006). Various methods have been developed to measure the degree of carbon lock-in. The traditional approach of calculating carbon overload rate is defined as the ratio between carbon sequestration capacity and carbon emissions (Zhao et al., 2024). Another method is to construct an indicator system that evaluates carbon lock-in from multiple dimensions, including industrial structure, institutional framework, technological progress, and social norms (Niu &Liu, 2021). Regarding carbon unlocking strategies, existing research has explored the key pathways, including local government interventions (Dong et al., 2020), reducing income inequality (Jin et al., 2020), and implementing energy and environmental policies.

The existing literature emphasizes the urgent need to explore effective carbon unlocking pathways for industrial development under the constrains of the carbon peaking and carbon neutrality goals. As a key driver for achieving dual-carbon goals, the digital economy fosters both economic growth and ecological sustainability. Meanwhile, it cannot be ignored that the construction of digital infrastructure might rely on carbon-intensive industries and greatly promote carbon lock-in. However, current research lacks a rigorous identification of the non-linear relationship between DED and industrial carbon unlocking efficiency. Additionally, few studies assess carbon unlocking performance from the perspective of input-output efficiency. To address these gaps, this study is grounded in the "digitization paradox" hypothesis of industrial carbon unlocking. It aims to identify the phased relationship between DED and industrial carbon unlocking efficiency (ICUE) based on

China’s city samples. Specifically, it examines the impact mechanisms of DED on ICUE within the “techno-institutional” framework. Furthermore, leveraging policy learning models from machine learning, the study proposed optimization strategies for enhancing ICUE through DED.

3. Theoretical framework

The study explores the relationship between DED and ICUE in China, grounded in the digitization paradox, externality theory, and the “techno-institutional” analytical framework. Furthermore, it aims to identify the impact effects, potential mechanisms, and optimization strategies. The specific analytical framework is shown in **Figure 1**.

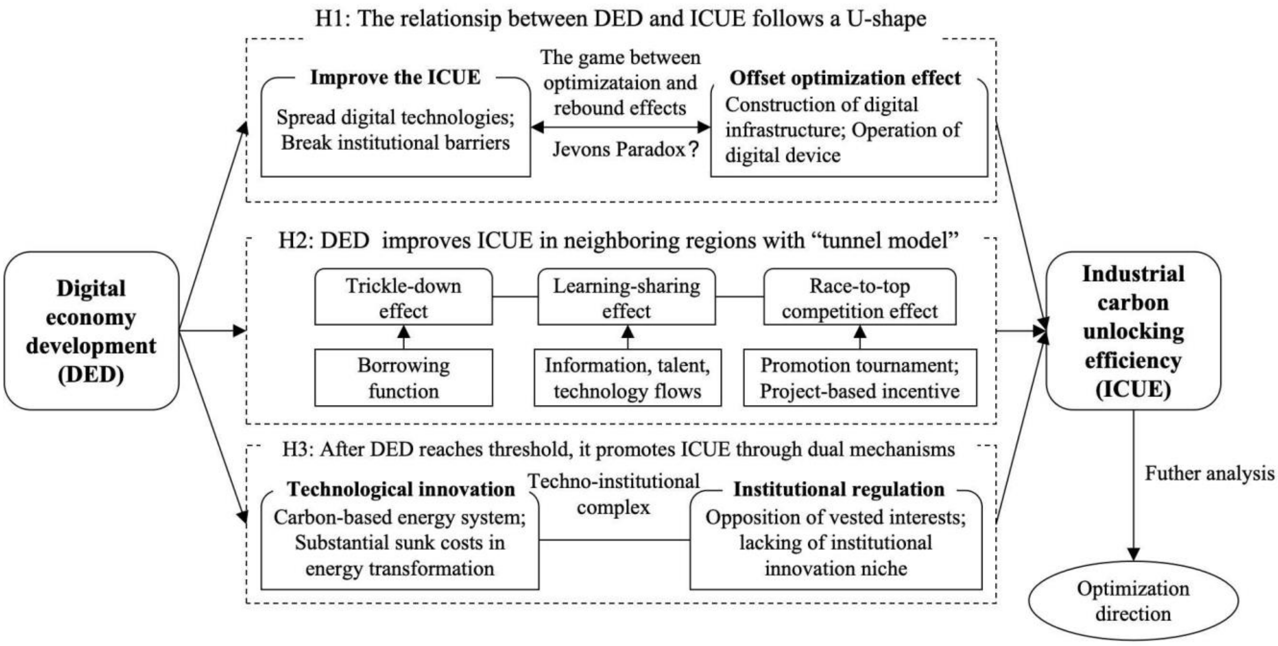


Figure 1. Logical framework

3.1 The digitization paradox of industrial carbon unlocking

The DED promotes industrial carbon unlocking through both technological innovation and institutional regulation mechanisms: **(1) Technological innovation perspective**. The DED is closely related to big data technologies and holds significant potential to achieve both economic growth and ecological sustainability (Wu et al., 2025). Firstly, digital technologies facilitate knowledge diffusion, accelerate industrial upgrading and transformation, thereby paving the way for low-carbon economy. Secondly, digitization enhances energy monitoring and management capabilities, it partially replaces the public supervision which could reduce the cost of clean energy utilization, and supports the transition to renewable energy (Cai, et al., 2025). **(2) Institutional regulation perspective.** Industrial carbon lock-in is reinforced by self-perpetuating institutional frameworks. Bergek et al (2013) emphasized the necessity to empower participants within new technological innovation system to overcome the institutional barriers of carbon lock-in. The widespread adoption of digital technologies requires strong government policy support to mobilize resources and create market demand. For example, increasing subsidies for local digital infrastructure can foster technological innovation, improve energy efficiency, and ultimately break the vicious cycle of carbon lock-in (Healy &Barry, 2017).

However, the DED heavily relies on industrial infrastructure construction, electronic component manufacturing, digital machinery production, and other high energy-intensive industries. Therefore, the early stage of DED may drive up energy consumption, and hinder industrial carbon unlocking. In the initial phase of digitization, the marginal benefits derived from investments in digital infrastructure are lower than the marginal costs. It results in a U-shaped relationship between digital investment and total factor productivity (TFP) (Jin &Yu, 2022). The increase in TFP driven by digitization on the early stage often triggers a series of rebound effects, leading to an unexpected rise in overall energy consumption. This rebound effect could possibly offset the positive effects of technological innovation and industrial restructuring, aligning with the Jevons Paradox (Blake, 2005). Given this reassessment of the digitization paradox, this study proposes the following hypothesis:

H1: The relationship between DED and ICUE in China follows a U-shaped pattern at city-level, initially decreasing and then increasing.

3.2 Spatial spillover effect and "tunnel model" of digital economy

According to the externality theory and regional interdependence theory (Ertur &Koch, 2007), the DED could significantly promote ICUE in cities with multi-dimensional proximity (Chaudhuri, 1996). The concept of muti-dimensional proximity city networks suggests that, as the digital economy evolves, spatial spillover effects have transcended the traditional geographical clusters, forming interconnected networks across geographical, technological, relational, cognitive, and cultural dimensions through the "tunnel model" of digital technologies. The potential mechanisms include: (1) **Trickle-down effect:** when the regional central city's DED exceeds a certain threshold, industrial relocation, investment diffusion and technological spillovers will expand to surrounding areas. That is, cities with highly developed digital industries enable their multi-dimensional adjacent cities to utilize digital infrastructure, improve local energy and industrial structure, while mitigating the negative effects associated with the early stage of DED (Liu et al., 2024). (2) **Learning-Sharing effect:** Innovations in digital technologies, such as big data, block-chain, and artificial intelligence, have improved the efficiency of cross-border information, talent, and technology flows. This process promotes the cross-regional transmission of advanced technologies, facilitates spatial interactions and shared utilization of new digital infrastructure (Fichman et al., 2014). **(3) Race-to-the-top Competition effect:** Driven by the local government promotion tournament mechanism and the project-based nature of digital industry development, local governments increasingly prioritize leveraging the digital economy to promote industrial carbon unlocking. This focus might trigger a race-to-top competition among cities in the field of digital technology development. Through demonstration and spillover effects with inter-city competition (Fluck &Mayer, 2005), it could realize the improvement of ICUE in surrounding cities. Accordingly, we propose the following hypothesis:

H2: The DED exhibits a significant spatial spillover effect, improving the ICUE of cities with multi-dimensional proximity.

3.3 Identification of carbon unlocking pathways with DED under the "Techno-Institutional" framework

The techno-institutional complex formed by the inertia of high-carbon energy consumption reinforces the industrial carbon lock-in effect in certain cities, making industrial production and social consumption dependent on carbon-based energy systems. It not only hinders the adoption of low-carbon technologies, but also weakens the effectiveness of relevant carbon reduction policies (Seto et al., 2016). **(1) Technological pathways**: Firstly, the existing fossil fuel-based energy system has been highly mature, with strong complementarity among mainstream technologies, which reduces the uncertainty of sustained investment. In contract, low-carbon and renewable energy technologies lack integration with dominant energy system, contributing to higher short-term opportunity costs for their adoption (Janipour et al., 2020). Secondly, there are still substantial sunk costs in transforming fossil fuel infrastructure, including industrial production lines, logistics support, and equipment, which lock the energy system into a high-carbon trajectory (Arbuthnott &Brett, 2013). To achieve scale economy and maintain competitive advantages, related carbon-intensive enterprises tend to adhere to current energy utilization and production models. **(2) Institutional pathways:** Firstly, the vested interests in high-carbon energy sector have institutional advantages in power distribution, allowing them to formulate policy rules that obstruct the transition to low-carbon energy. For example, in Norway, high emission private enterprises leveraged exclusive social networks to resist tax incentives policies for renewable energy vehicles, thereby maintaining fossil fuel dependence in the transportation sector (Normann, 2017). Secondly, existing policies, technical standards, and energy production contracts predominantly encourage firms to focus on technological innovation and production related to fossil fuels, leaving little institutional improvement space for disruptive green innovation niche (Sanden &Hilman, 2011). Therefore, breaking carbon lock-in requires strategies that address both technological and institutional barriers.

The relationship between DED and industrial carbon lock-in exhibits a strong correspondence within the “techno-institutional” framework. The digital economy can similarly break industrial carbon lock-in through both technological innovation and institutional regulation. However, the initial construction of digital infrastructure might partially offset the optimization effects driven by digital innovation and industrial structural improvements. Thus, this study put forward **Hypothesis 3:**

H3: In the early stage of DED, digital infrastructure investment weakens ICUE. However, once the construction of digital infrastructure reaches a certain level of maturity, the DED mainly enhances ICUE through a dual mechanism of technological innovation and institutional regulation.

According to the empirical results, the improvement effects of carbon unlocking efficiency before and after the maturity threshold are -29.17% and 38.39%, respectively, showing a "U-shaped" relationship of first decreasing then increasing, and finally reaching equilibrium. At the same time, the key carbon unlocking pathways of “techno-institutional” complex are identified through intermediary mechanism analysis while “tunnel model” of DED is also proved with spatial econometric regression. These theoretical hypotheses above have been quantitatively validated.

4. Data, Variables and Models

4.1 Data source

The study selects a sample of 274 Chinese cities from 2013 to 2022. Data of carbon emissions and most socio-economic variables come from the *China City Statistical Yearbook, China Regional Statistical Yearbook, China Energy Statistical Yearbook*, and various municipal-level statistical yearbooks. The indicator *Digital Inclusive Finance Index* is calculated based on the *Digital Inclusive Finance Indicator System and Index Compilation* (Guo et al., 2020). The *Green Patent Authorization* data comes from the *National Intellectual Property Patent Database*, while *Industrial Land Transfer* data is obtained from the transaction records on the China Land Market website.

4.2 Variables measurement

4.2.1 Dependent variable: Industrial Carbon Unlocking Efficiency (ICUE)

The measurement of ICUE should consider the balance between socio-economic benefits and ecological sustainability, and systematically evaluate the efficiency of industrial carbon unlocking at the city level from an input-output perspective. Following the Super-efficiency SBM model proposed by Tone &Tsutsuim (2009), the study constructs an input indicator system from institutional, technological and social dimensions, and the output indicator system consists of desirable economic output and undesirable carbon emissions output (**Table 1**), aiming to evaluate the multi-objective performance of economic growth and carbon reduction.

Table 1. The input-output indicator system for the measurement of ICUE

Dimension	Indicator type	Specific indicator	Measurement method
Input indicators	Institutional input	Environmental regulation level	Ratio of energy conservation &environmental protection expenditure to local fiscal expenditure

		Institutional quality level	Marketization index
	Technological input	R&D investment	Ratio of R&D expenditure to local GDP
		R&D human resources	Number of R&D personnel per 10000 people
	Social input	Public environmental awareness	Environmental attention index (Baidu search index)
		Urban greening investment	Built-up area greening rate
Output indictors	Desirable output	Economic development level	GDP per capita
	Undesirable output	Carbon emission intensity	Ratio of local CO_2 emissions to GDP

4.2.2 Independent variable and threshold variable: Digital economy development (DED) level and Digital infrastructure level

This study comprehensively evaluates the DED level across multiple domains, including digital infrastructure, digital industries and digital finance (Xin et al., 2023b). Several sub-dimension indicators are selected to construct the assessment framework for the DED level (*dig_econ*), namely: long-distance optical cable density, per capita broadband internet access ports, mobile phone penetration rate, internet penetration rate, employment ratio in information transmission, computer services and software industries, per capita telecommunications business revenue, and the digital inclusive finance index (**Table 2**). Entropy method is adopted to determine the indicator weights, with a standardized scoring process involving normalization, weight assignment, weighted aggregation and logarithmic transformation to generate a panel dataset reflecting the DED level.

According to **hypothesis 1**, in the early stage of DED, the high-carbon energy requirement for digital infrastructure construction might result in its marginal costs exceeding marginal benefits, however, it could promote low-carbon transition when digital infrastructure emerging from the integration of digitalization and low-carbon development (Lei et al., 2025). Therefore, the study employs the digital infrastructure level (*dig_infra*) as the threshold variable.

Table 2. The measurement index system of DED level

Dimension	Indicator
Digital infrastructure	Long-distance optical cable density
	Per capita broadband internet access ports
	Mobile phone penetration rate
	Internet penetration rate
Digital industry	Employment ratio in information transmission, computer services and software industries
	Per capita telecommunications business revenue
Digital finance	Digital inclusive finance index

4.2.3 Mechanism variables: Corporate green innovation and Governmental industrial regulation

Based on **hypothesis 3**, the study explores the mechanism pathways of DED promoting ICUE within the "techno-institutional" framework. The technological pathway could be measured by **Corporate green innovation** at city level, with the number of granted green patents (*patent*) as an indicator, aiming to capture the scale of corporate green innovation output from a technological perspective. The calculation is based on the total number of granted green invention patents and green utility model patents each year.

The institutional pathway could be evaluated by the **intensity of local government industry regulation**, measured by the deviation of industrial land transfer prices at city level. Local governments regulate the industrial sectors through differential land supply strategies, utilizing selective industrial land pricing mechanisms (Wang et al., 2021). Specially, when local governments exhibit a weak preference for selective land supply, they tend to adopt unified pricing policy, leading to low deviations in industrial land prices. Conversely, they adopt a "one plot, one price" method to screen industrial projects, resulting in significant deviations in industrial land prices. The formula for calculating industrial land price deviation is shown as follow:

$$Land\_SD_{it} = \frac{\sqrt{\sum_{j=1}^{n}(P_{ijt}-\overline{P_{jt}})^2}}{n} \tag{1}$$

Where $\mathrm{Land\_SD_{it}}$ represents the industrial land price deviation index, used to measure the intensity of local government industry regulation. $\mathrm{P_{ijt}}$ denotes the average land transfer price for industry *j* in city *i* in year *t*, while $\overline{\mathrm{P_{ijt}}}$ is the overall average land transfer price for all industries in city *i* in year *t*. And *n* represents the number of industrial sectors.

4.2.4 Instrumental variable:

Given the potential endogeneity caused by reverse causality or omitted variables in the relationship between DED and ICUE, the study adopts an instrumental variable (IV) approach, following the methodology proposed by Chen &Chen (2018). Local governments' preferences for DED are quantified by counting the frequency of digital economy-related terms[2] (*IV_word*) in the annual work reports of municipal governments. Since these reports are typically released at the beginning of the year, setting the policy agendas in advance, the carbon reduction performance within the same year cannot retrospectively affect their intentions. Meanwhile, to address the omitted

[2] Using Python for text processing, a digital economy-specific corpus was employed to segment and extract 39 relevant terms, including "smart economy", "information economy", "intelligent economy", "information and communication technology", "ICT", and "telecommunication infrastructure."

variable bias caused by geographical and natural factors, the study incorporates the average slop of the city (*IV_pd*) as another instrumental variable. All in all, the study constructs an interaction term between the frequency of digital economy-related terms in local government reports and the reciprocal of the city's average slope as the final instrumental variable (*IV*) for DED.

4.2.5 Control variables

To mitigate potential confounding effects, the study incorporates a series of control variables, including: (1) **The degree of openness (fore_gdp)**: It could be measured by the ratio of foreign direct investment (FDI) to local GDP; (2) **Population density (pop_den)**: It could be measured by the number of population per unit of administrative area; **(3) Industrial structure (second)**: It could be represented by the ratio of the added value of the secondary industrial to GDP; **(4) Local government fiscal capacity (fis_income)**: It could be measured by the proportion of local fiscal revenue to GDP; **(5) Innovation potential (uni_stu)**: It could be measured by the ratio of the number of registered higher education students to the total local population. **(6) Road transport capacity (traffic):** It can serve as an indicator of the level of local transportation infrastructure.

4.3 Model designing

4.3.1 Panel threshold model

Some related studies chose to adopt the quadratic regression method of independent variable to identify the non-linear relationship (Li et al., 2025), but it might cause multi-collinearity issues of regression coefficients. The study adopts a panel threshold regression model based on Hansen's panel threshold framework (Hansen, 1999), with the digital infrastructure level as the threshold variable. As the threshold value changes, the relationship between DED and ICUE exhibits nonlinear characteristics. therefore, the baseline regression model for this study is formulated as Equation (2):

$$ICUE_{it} = \alpha + \beta_1 fore\_gdp_{it} + \beta_2 pop\_den_{it} + \beta_3 second_{it} + \beta_4 fis\_income_{it} + \beta_5 uni\_stu_{it} + \beta_6 traffic_{it} + \theta_1 dig\_econ_{it} * I(dig\_infra \leq \gamma_1) + \theta_2 dig\_econ * I(\gamma_1 \leq dig\_infra \leq \gamma_2) + \theta_3 dig\_econ_{it} * I(dig\_infra > \gamma_2) \ + \varepsilon_{it} \quad (2)$$

Equation (2) represents a double-threshold panel regression model, where *dig_econ* denotes the digital economy development level, and *dig_infra* serves as the threshold variable in the study, with the threshold number determined through estimation. In the equation, *i* represents the city number, *t* denotes the year, and α is the constant term. β_n represent the coefficients of the control variables, while θ_n denote the regression coefficients of the core dependent variable *dig_econ*. Finally, ε is the error term.

4.3.2 Spatial econometric model

Given that DED exceeds the geographical constraints, its impacts on ICUE might exhibit spatial spillover effects. To account for this, a spatial econometric model is constructed based on the baseline regression model. Previous studies have compared the estimation results of the Spatial Durbin model (SDM), Spatial Auto-regressive model (SAR), and Spatial Error model (SLM), concluding that only the SDM could provide unbiased estimates and represent the most general form of spatial econometric modeling (LeSgae &Pace, 2009). Therefore, the study adopts the following SDM model:

$$ICUE_{it} = \alpha + \beta \sum_{i=1}^{n} X_{it} + \rho \sum_{j=1}^{n} W_{ij}\, ICUE_{jt} + \sigma \sum_{j=1}^{n} W_{ij}\, X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (3)$$

In Equation (3), the DED level is selected as the core independent variable, while $ICUE_{it}$ represents the ICUE of city *i* in year *t*. The term X_{it} denotes the set of covariates, including both the core independent variable and control variables. The spatial weigh matrix W_{ij} captures the spatial dependency between city *i* and city *j*. In this study, a nested matrix combining economic distance and geographical distance is used to identify the spatial spillover effects of DED on multi-dimensional adjacent cities. The term μ_i represents city-fixed effects, τ_t denotes year-fixed effects, ε_{it} is the error term, and ρ is the spatial auto-regressive coefficient.

4.4 Descriptive statistics

The descriptive statistics for the dependent variable, independent variables, threshold variable, mechanism variables, instrumental variables and control variables used in the study are listed in **Table 3**. In order to reduce the heteroscedasticity of the results, natural logarithm transformation is applied to continuous variables where appropriate.

Table 3. The descriptive statistics

Type	Variable	Symbol	Sample	Mean	Std. Dev.	Min	Max
Dependent variable	Industrial carbon unlocking efficiency	*ICUE*	2694	1.014	0.114	0.381	2.899
Independent variable	Digital economic development level	*dig_econ*	2740	0.006	0.005	0.001	0.056
Threshold variable	Digital infrastructure level	*dig_infra*	2720	0.036	0.035	0.003	0.703
Mechanism variables	Green patent grants	*patent*	2740	841.341	2356.129	0	34670
	Deviation of industrial land price	*lnland_SD*	2740	4.393	0.778	1.882	9.963
Instrumental variables	Frequency of digital economy-related terms	*IV_word*	2660	39.501	24.685	0	188
	Slope	*IV_pd*	2740	10.626	5.567	1.592	27.139
	Interaction term	*IV*	2660	5.505	5.837	0	45.618
	Degree of openness	*fore_gdp*	2740	0.002	0.003	0	0.029

	Population density	*lnpop_den*	2740	5.771	0.901	1.609	7.882
	Industrial structure	*lnsecond*	2740	3.778	0.263	2.368	4.477
Control variables		*lnfis_income*	2740	6.599	0.331	5.457	7.729
	Innovation potential	*lnuni_stu*	2740	10.669	1.285	5.793	14.161
	Highway transport capacity	*lntraffic*	2740	8.126	1.111	2.303	12.016

Before conducting the baseline regression, the study first conducts a preliminary analysis of the sample data. Through plotting a scatter diagram of DED level and ICUE, we compare the goodness of fit between linear and nonlinear regression models. As shown in **Figure 2**, the quadratic fit demonstrates a significantly higher goodness of fit than the linear model, indicating that the relationship between DED and ICUE can be better captured using a quadratic function. The preliminary result supports the nonlinear hypothesis mentioned above.

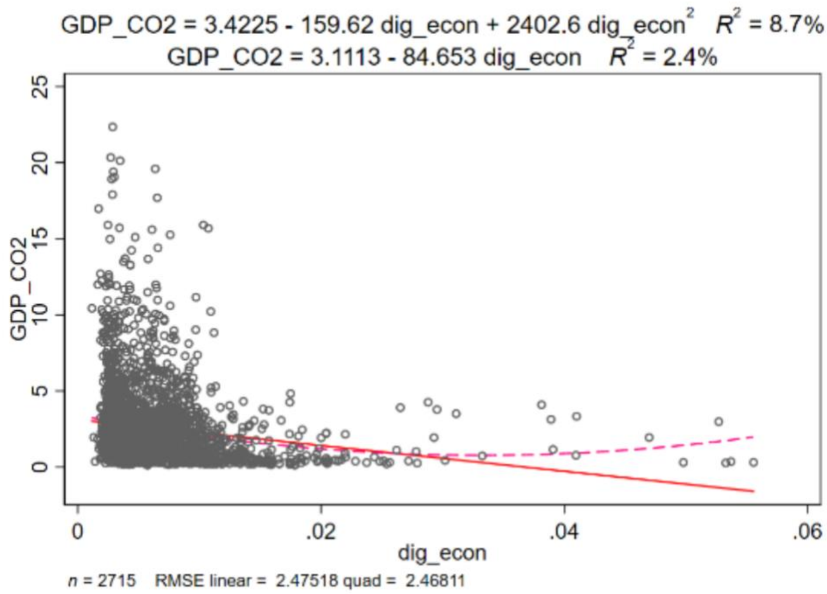


Figure 2. Sample scatter plot of the relationship between the DED level and ICUE

Additionally, most sample points are concentrated on the left side of the threshold value, indicating that most sample cities are still in the early stage of DED, where their improvement on ICUE remains relatively limited.

5. Empirical results

5.1 Panel threshold regression results

The study adopts a panel threshold regression model, which can accurately estimate the number of thresholds and perform statistical significance tests on the threshold variables. The econometric methods help avoid subjective bias caused by qualitative judgments when determining the quantity and value of thresholds. According to **Equation (2)**, digital infrastructure level is selected as the threshold variable. By conducting hypothesis tests for single-threshold, double-threshold and triple-threshold models, the study identifies the optimal number of thresholds for the baseline model.

The test results of threshold effect are shown in **Table 4**. After 500 bootstrap iterations, it could be observed that the single-threshold and double-threshold effects are significant at the 5% and 1% confidence levels, respectively. Therefore, double-threshold model is adopted for more precise estimation results based on the existing samples.

Table 4. Test results for the threshold effect of digital infrastructure level

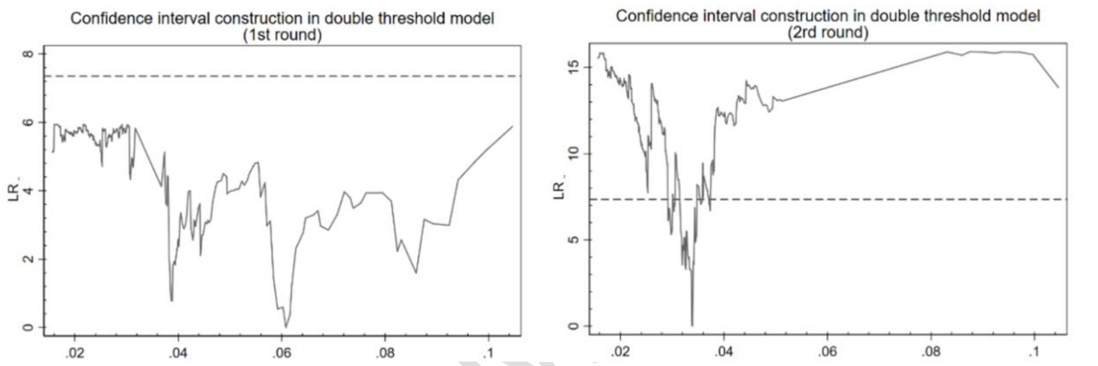
Threshold number	F-value	P-value	Bootstrap iterations	1% critical value	5% critical value	10% critical value
Single threshold	6.724**	0.010	500	6.236	2.820	2.196
Double threshold	5.940***	0.000	500	3.646	2.252	1.946
Triple threshold	0.000	0.513	500	0.000	0.000	0.000

(Notes: *p<0.10, **p<0.05, ***p<0.01.)

Table 5 presents the estimated threshold values and their corresponding 95% confidence intervals. **Figure 3** illustrates the likelihood ratio (LR) function curve of the estimated double-threshold model. The threshold estimates could be obtained at the points (γ) where the likelihood ratio statistic (LR) intersects the 5% significance level line. From the LR plot (**Figure 3**), it can be observed that the single-threshold value at 0.034 could reject the null hypothesis, although the F-value for the double-threshold effect is also statistically significant, and the 0.034 threshold value matches the single-threshold estimate (Table 5). Given these findings, the study adopts the double-threshold model for exploratory analysis, identifying two threshold values, 0.034 and 0.061, for digital infrastructure level.

Table 5. Threshold value estimation results

Threshold	Threshold estimator	95% confidence interval
Single threshold (γ_1)	0.034	(0.016, 0.092)
Double threshold (γ_1)	0.061	(0.016, 0.105)
Double threshold (γ_2)	0.034	(0.029, 0.037)
Triple threshold (γ_3)	0.039	(0.037, 0.051)



(a) First threshold estimator. (b) Second threshold estimator

Figure 3. Likelihood ratio function diagram of the threshold estimators

Table 6. Panel threshold model estimation results

Variables	Coefficient	T-value	Prob.	Sample quantity
dig_econ×I(dig_infra≤0.034)	-2.427**	-2.21	0.027	1782（66.1%）
dig_econ×I(0.034＜dig_infra≤0.061)	3.167**	2.01	0.045	870（32.3%）
dig_econ×I(dig_infra＞0.061)	0.339	0.50	0.616	42（1.6%）
fore_gdp	0.128	0.10	0.917	
lnpop_den	0.001	0.27	0.789	
lnsecond	0.005	0.39	0.697	
lnfis_income	-0.019*	-1.79	0.073	
lnuni_stu	0.0002*	1.75	0.080	
lntraffic	0.0038	1.19	0.233	
_cons	1.084***	13.15	0.000	
F-statistics	2.21**		0.019	
Adjusted-R^2	0.0249			

(Notes: *p<0.10, **p<0.05, ***p<0.01.)

Table 6 presents the panel regression results of the double-threshold model. The regression coefficients of the core independent variable (*dig_econ*) vary across different threshold intervals, exhibiting a nonlinear relationship with the ICUE. Based on the estimated thresholds, the study classifies the digital infrastructure level into three different stages: **(1) Expansion phase** (Early stage: *dig_infra* ≤ 0.034). The relationship between DED and ICUE is significantly negative (θ=-2.427，p=0.027), indicating that in the expansion stage of DED, the expansion of energy-intensive digital infrastructure offsets the carbon reduction of technological innovation and industrial restructuring. This phenomenon confirms the Jevons Paradox, which assumes that efficiency improvement leads to increased overall energy consumption. **(2) Maturity phase** (Mid-stage: $0.034 \leq$ *dig_infra* ≤ 0.061). The relationship becomes significantly positive (θ=3.167，p=0.045). At this stage, the optimization effect of DED dominates, since digital innovation and institutional improvements play a key role in promoting ICUE. **(3) Equilibrium phase** (Final stage: *dig_infra* ＞0.061). The relationship remains positive but statistically insignificant (θ=0.339， p=0.616). It demonstrates that with the deep integration of new generation information technology and the real economy, a dynamic equilibrium between DED and ICUE has been realized. These empirical findings are consistent with the theoretical predictions of Xu et al. (2024).

Furthermore, the comparative analysis of regression coefficients for different stages and sample distributions reveals important findings. During the maturity stage, a 10% increase in DED level promotes the ICUE by 31.67%, significantly exceeding the rebound effect of -24.27% observed in the expansion stage. This indicates that as digital infrastructure reaches a certain scale, its role in promoting ICUE through agglomeration effects becomes increasingly prominent. Overall, the positive impact of DED om improving ICUE outweighs the initial carbon lock-in effect observed in the early stages. Additionally, the examination of sample distribution at different stages shows that 66.1% of the samples remain in the expansion stage, while 32.3% have entered the maturity stage, achieving the efficiency improvement of carbon unlocking driven by digital transformation. Only 1.6% of the samples belong to the equilibrium stage, with DED and industrial carbon unlocking reaching a dynamic balance.

Given this distribution, the study mainly focuses on the initial two stages of DED, with a particular emphasis on analyzing the U-shaped relationship between DED and ICUE at city level.

5.2 Instrumental variable regression

The study adopts a composite instrumental variable (IV) for the variable DED level, which is constructed as the interaction term between the frequency of digital economy-related words in government work reports and the reciprocal of local average slope. Within the 2SLS estimation framework, this method allows for a more robust evaluation of the relationship between DED and ICUE, addressing potential endogeneity issues caused by reverse causality and omitted variable bias.

Table 7. The relationship between DED and ICUE: IV estimation

	Expansion phase (*dig_infra≤0.034*)		Maturity phase (*dig_infra* >*0.034*)	
	First stage: *dig_econ*	Second stage: *ICUE*	First stage: *dig_econ*	Second stage: *ICUE*
Variable	(1)	(2)	(3)	(4)
IV	0.0001***		0.0001***	
	(7.35)		(4.77)	
dig_econ		-2.917***		3.839*
		(-2.61)		(1.68)
fore_gdp	0.099***	1.342	0.309***	-4.079
	(4.60)	(1.19)	(4.01)	(-1.50)
lnpop_den	-0.0004***	-0.0063	-0.0009***	-0.0013
	(-4.88)	(-1.34)	(-3.34)	(-0.16)
lnsecond	0.0025***	0.301	0.0011	-0.0089
	(11.80)	(1.47)	(1.39)	(-0.40)
lnfis_income	0.0006***	-0.0084	0.0044***	-0.0395
	(3.52)	(-0.95)	(6.72)	(-1.29)
lnuni_stu	-0.000018	0.0019	0.0006***	-0.0092
	(-0.32)	(0.69)	(3.09)	(-1.60)
lntraffic	0.0004***	0.0033	0.0009***	-0.0079
	(6.21)	(0.76)	(5.17)	(-1.04)

_cons	-0.0094***	0.954***	-0.044***	1.440***
	(-6.47)	(10.38)	(-8.77)	(5.08)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1782	1782	870	870
R^2		0.3468		0.7380
Kleibergen-Paap rk Wald F statistic	53.984		22.734	

(Notes: *p<0.10, **p<0.05, ***p<0.01. values in parentheses are T-statistics)

It can be observed that columns (1) and (2) of **Table 7** present the IV estimation results for the expansion phase, while columns (3) and (4) report the results for the maturity phase. Firstly, the first-stage regression analysis of IV estimation shows that, regardless of whether the *dig_infra* is on the left or right side of the threshold, the IV is significantly and positively correlated with DED level at a 1% confidence level. The Kleibergen-Paap rk Wald F-values of the first stage regression are 53.984 and 22.734, both far above the critical threshold of 10, indicating that the IV is strongly relevant and alleviating weak instrument concerns. Secondly, the second-stage regression results of the IV estimation reveal that the impact of DED on ICUE is consistent with the baseline regression results reported in **Table 6** in terms of both coefficient direction and significance level, further verifying the U-shaped relationship between DED and ICUE. However, in terms of absolute coefficient values, the IV estimation results exhibit a certain degree of inflation, indicating that potential endogeneity issues lead to partial underestimation of estimated effects in the baseline regression.

In summary, **Hypothesis 1** has been quantitatively validated through panel threshold regression and causal inference analysis using segmented IV approach.

5.3 Spatial spillover effect and tunnel model analysis

Spatial Durbin Model (SDM) is adopted to explore the spatial spillover effect of DED on ICUE.

Since the DED relies on internet, block-chain, big data and other technological industries, it possesses a "tunnel model" advantage that transcends geographical distance. Therefore, the study adopts a composite nested matrix of economic distance and geographical distance as the spatial weight matrix. The detailed analysis results are shown in **Table 8**.

Table 8. The relationship between DED and ICUE: SDM analysis

Variable	*Main*	*W*X*	*LR_Direct*	*LR_Indirect*
dig_econ	-0.620	0.980*	-0.614	0.721*
	(-0.63)	(1.64)	(-0.63)	(1.67)
fore_gdp	-0.109	4.022	-0.269	4.713
	(-0.07)	(0.36)	(-0.20)	(0.39)
lnpop_den	-0.065	0.171	-0.059	0.140
	(-0.78)	(0.29)	(-0.64)	(0.20)
lnsecond	0.027	0.018	0.029	0.032
	(1.06)	(0.17)	(1.06)	(0.25)
lnfis_income	-0.009	-0.098	-0.013	-0.103
	(-0.60)	(-1.52)	(-0.67)	(-1.35)
lnuni_stu	-0.015	0.062	-0.015	0.074
	(-1.38)	(0.67)	(-1.39)	(0.66)
lntraffic	0.011*	-0.007	0.011*	-0.006
	(1.88)	(-0.41)	(1.93)	(-0.31)
ρ (W×ICUE)	0.115***		*Variance*	0.012***
	(3.79)		*sigma2_e*	(37.01)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	2740	2740	2740	2740

(Notes: *p<0.10, **p<0.05, ***p<0.01. values in parentheses are T-statistics)

Several key findings can be concluded from the estimation results in **Table 8**. Firstly, the spatial autoregressive coefficient ρ (*W×ICUE*) is significantly positive at the 1% level, indicating that ICUE has a strong positive spillover effect at city level. It validates the appropriateness of adopting spatial econometric model to estimate the spillover effects of DED. Secondly, the two indicators reflecting the local impact of DED on ICUE (*Main* and *LR_Direct*) are both statistically insignificant. It indicates that without considering spatial spillover effects, the direct impact of DED on ICUE is not significant, which is consistent with the nonlinear relationship assumed in the study above. Finally, to accurately estimate the spatial spillover effect of DED, in addition to checking the spillover effect coefficient *W*X* in the SDM, it is also necessary to decompose the influence of the independent variables. The indirect effect coefficient (*LR_Indirect*) further quantifies the spatial effect of DED. The results indicate that both mutually verified spatial spillover effect coefficients are significantly positive at the 10% level. Specially, a 10% increase of local DED level contributes to 7.2% improvement of ICUE in surrounding areas. The effect is mainly caused by the functional borrowing of digital infrastructure from neighboring regions. Through trickle-down effect and learning-sharing mechanism, the DED generates positive externalities while mitigating the negative externalities of digital infrastructure construction. At the same time, inter-governmental competition tends to be rational, with no obvious "race-to-top" effect observed.

From the magnitude of the coefficients, the spatial spillover effect is noticeably lower than the optimization effect of DED on ICUE in the maturity phase, indicating that the spatial spillover effect has a certain temporal lag. This finding is consistent with the remaining literature (Li &Wang, 2022), thus quantitatively verifying **Hypothesis 2**.

In practice, China has initiated the construction of eight national computing center nodes and planned ten national data center clusters, forming the foundation of a nationwide integrated big data center system. The initiative, known as the "Eastern data, Western computing" project, promotes a "tunnel-type" development model that bridges spatial non-adjacent regions, thereby facilitating regional coordination (Bell &Oliver, 2022). On one hand, the project systematically shifts the high-intensity computing demand from the eastern region to the western region, promoting cross-regional data flow and alleviating energy constraints in the east, while simultaneously opening up new development pathway for the west. On the other hand, by leveraging the functional borrowing of digital infrastructure in computing center cities, the project promotes the diffusion of positive externalities in multi-dimensional adjacent areas, preventing the occurrence of the "Jevons Paradox" in the early stage of DED. A typical case is the establishment of the National Big Data Science and Technology Innovation City in Guiyang, which has significantly contributed to the high-quality economic development with digital technology.

5.4 The mechanism analysis of carbon unlocking

According to **Hypothesis 3**, the study adopts mediation effect analysis to quantitatively verify the mechanism of digital economy driving industrial carbon unlocking. The mechanisms can be measured from three perspectives: digital infrastructure construction, governmental industrial regulation and corporate green innovation. **Table 9** shows the mechanism analysis of how DED weakens ICUE during the expansion phase, while **Table 10** shows the mechanism of how DED promotes ICUE during the maturity phase. Specially, columns (1) and (2) demonstrate the role of governmental industrial regulation, columns (3) and (4) examine the role of corporate green innovation, and columns (5) and (6) explore the impact of digital infrastructure construction.

Table 9. The mechanism analysis in the stage of expansion phase

	lnland_SD	*ICUE*	*patent*	*ICUE*	*dig_infra*	*ICUE*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
dig_econ	0.026		138.801***		0.116***	
	(0.53)		(4.88)		(2.61)	
lnland_SD		0.0029				
		(0.62)				
patent				-1.16×10^{-6}		
				(-0.16)		
dig_infra						-0.847***
						(-2.87)
fore_gdp	-2.137	1.054	-1072.297	1.028	0.112**	1.106
	(-0.31)	(0.84)	(-0.26)	(0.81)	(2.11)	(0.73)
lnpop_den	0.054	-0.0024	89.317***	-0.0022	-0.0003	0.0009
	(1.40)	(-0.52)	(3.56)	(-0.48)	(-1.18)	(0.17)
lnsecond	-0.081	0.188	-103.721**	0.019	-0.003***	0.025
	(-1.04)	(1.45)	(-2.24)	(1.43)	(-4.89)	(1.54)

lnfis_income	-0.115**	-0.0136	-51.592	-0.0139	-0.0008*	-0.016
	(-2.00)	(-1.32)	(-1.50)	(-1.34)	(-1.86)	(-1.34)
lnuni_stu	0.105***	0.0011	133.637***	0.0017	0.0021***	0.0012
	(3.97)	(0.31)	(8.03)	(0.43)	(12.00)	(0.30)
lntraffic	-0.049***	0.0015	-16.205	0.0014	-0.0028***	-0.0016
	(-2.69)	(0.45)	(-1.46)	(0.42)	(-19.26)	(-0.39)
_cons	4.301***	0.999***	-753.036**	1.008***	0.042***	1.044***
	(7.66)	(11.05)	(-2.18)	(11.21)	(10.30)	(9.95)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	1842	1817	1842	1817	1842	1799
R^2	0.0719	0.0042	0.2557	0.0074	0.3645	0.0543

(Notes: *p<0.10, **p<0.05, ***p<0.01. values in parentheses are T-statistics)

Table 9 shows that when DED is in the expansion phase, the mechanism variables, *industrial land price deviation (lnland_SD)* and *the number of corporate green patent grants (patent)*, cannot form a complete causal chain. It indicates that in the early stage of DED, the "techno-institutional" framework does not effectively promote industrial carbon unlocking. Instead, a rebound effect emerges due to large-scale digital infrastructure construction. Specially, DED significantly enhances digital infrastructure construction (β=0.116，T=2.61), which in turn significantly weakens local ICUE (β=-0.847，T=-2.87).

Table 10. The mechanism analysis in the stage of maturity phase

	lnland_SD	*ICUE*	*patent*	*ICUE*	*dig_infra*	*ICUE*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
dig_econ	0.349***		2009.955***		1.666***	
	(5.40)		(7.92)		(6.02)	
lnland_SD		0.014**				
		(2.16)				
patent				6.26×10^{-6}*		
				(1.86)		
dig_infra						0.069
						(0.70)
fore_gdp	-8.871	-0.716	-44689.32	0.237	-1.489***	-1.177
	(-0.96)	(-0.37)	(-1.22)	(0.07)	(-2.25)	(-0.60)
lnpop_den	0.310***	-0.0002	691.536***	-0.223	0.0104***	0.0049
	(5.80)	(-0.02)	(4.34)	(-1.32)	(4.83)	(0.74)
lnsecond	-0.364***	0.008	-2327.959***	0.0012	-0.022***	0.0026
	(-3.08)	(0.41)	(-5.75)	(0.02)	(-3.36)	(0.12)

lnfis_income	0.210**	-0.0067	2174.783***	-0.057	0.0252***	0.0006
	(2.10)	(-0.41)	(6.25)	(-1.14)	(4.51)	(0.04)
lnuni_stu	0.191***	-0.0059	378.801***	-0.061	0.0017	-0.0056
	(5.13)	(-1.27)	(3.31)	(-1.35)	(1.08)	(-1.18)
lntraffic	-0.069***	0.0012	363.097***	0.016	-0.0075***	0.0026
	(-3.15)	(0.27)	(4.33)	(1.13)	(-5.15)	(0.52)
_cons	1.160	1.039***	-15565.51***	3.305***	-0.055	1.054***
	(1.39)	(8.20)	(-5.60)	(2.87)	(-1.16)	(6.71)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	898	877	898	877	878	857
R^2	0.3569	0.0608	0.4117	0.0293	0.1926	0.0191

(Notes: *p<0.10, **p<0.05, ***p<0.01. values in parentheses are T-statistics)

Table 10 shows that when DED reaches the maturity stage, the industrial carbon unlocking pathway under the “techno-institutional” framework holds a dominant position. From an institutional perspective, DED significantly prompts local governments to strengthen industrial regulation (β=0.349，T=5.40), which in turn significantly increases ICUE (β=0.014，T=2.16). And the regulation instruments such as resource input, punitive measures for non-compliance and reward incentives could all influence the green performance (Lei et al., 2024). From a technological perspective, DED significantly enhances the green technological innovation capability of local enterprises (β=2009.955，T=7.92), which also significantly improves local ICUE (β=6.26×10^{-6}， T=1.86). Related literature has concluded the micro-mechanisms of technological pathway as knowledge spillover, reputation incentive and supervisory innovation (Lei and Xu, 2025). However, the mediating effect of digital infrastructure construction is not significant. It indicates that as DED enters the maturity stage, new infrastructure construction sheds its traditional “carbon-intensive” characteristics and breaks the “Jevons paradox”. Thus, the mechanism of industrial carbon unlocking driven by the DED, as proposed in **Hypothesis 3**, is quantitatively validated.

6. Further analysis: Exploration of optimization directions based on machine learning

Policy learning model is adopted to estimate the marginal benefits of top-down promotion of DED (such as the National big data comprehensive pilot zone policy) on industrial carbon unlocking under resource constraints (Athey &Wager, 2021). Additionally, it ranks cities based on their potential for ICUE improvement and provides decision-making references for optimizing pilot policy implementation. Specially, following the principle of maximizing ICUE, the policy learning model combines both existing observational data and policy shocks. By training city-specific response functions under budget constraints, the model ranks cities based on their potential for improving ICUE. The heterogeneous impacts of DED driving industrial carbon unlocking in different regions provide a rich dataset for training the policy learning model.

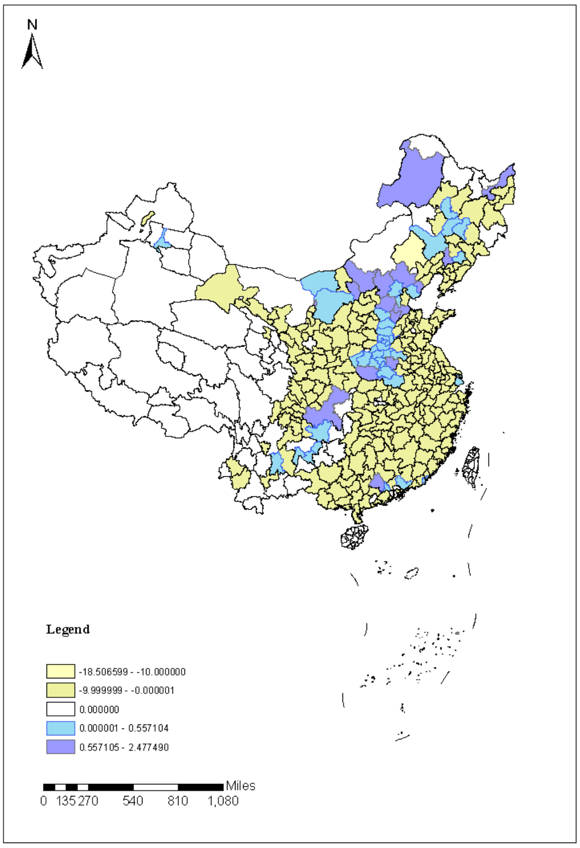


Figure 4. The ICUE improvement potential distribution driven by DED in Chinese cities

Figure 4 illustrates the distribution of ICUE improvement potential under the central government's top-down policy support for DED, using the generalized random forest algorithm. The results indicate that the cities with the greatest improvement potential for industrial carbon unlocking performance are mainly concentrated along the "Hu Huanyong Line" and in the southeastern coastal regions of China.

7. Conclusion and policy implications

7.1 Conclusions

The study utilizes panel data of 274 Chinese cities from 2013 to 2022 to explore the nonlinear relationship between DED and ICUE at the city level. In addition, it identifies the mechanisms driving this process and proposes optimization strategies. The key findings are shown as follows:

(1) The study firstly adopts a panel threshold regression model to identify the nonlinear "U-shaped" relationship between DED and ICUE. The conclusion remains robust after phased instrumental variable (IV) analysis. The findings indicate that, during the expansion phase of DED, the construction of digital infrastructure and growth of carbon-intensive industries hinder the improvements in ICUE, and even leading to a rebound effect for carbon lock-in. However, once it exceeds the maturity threshold, the positive effects of technological innovation and institutional regulation gradually become apparent.

(2) Secondly, spatial econometric analysis reveals that DED has a significantly positive spillover effect on ICUE in multi-dimensional adjacent areas. Unlike its direct impact on local ICUE, DED exerts positive externalities through the diffusion and sharing of information technology, thereby enhancing ICUE in adjacent area by trickle-down and knowledge-sharing effects. Meanwhile, the functional borrowing of cross-regional digital infrastructure can help alleviate the "Jevons paradox" observed in the early stage of DED, providing empirical support for China's implementation of the

"Eastern data, Western computing" strategy. And it can be summarized as the "tunnel model".

(3) Thirdly, the study finds that after the DED exceeding the maturity threshold, it plays a crucial role in improving ICUE through both technological and institutional pathways. Specially, the technological pathway is reflected in the promotion of digital tools, information-based methods and green technologies, which improve the efficiency of energy utilization and resource allocation. The institutional pathway can be manifested as regulatory innovation and governance optimization driven by digital technologies, creating a more favorable institutional environment for industrial carbon unlocking.

(4) Finally, based on training and simulation using the existing datasets, the study adopts machine learning technique to identify potential directions for optimizing top-down support for DED. The empirical results indicate that cities with the highest potential for performance improvement are mainly located along the "Hu Huanyong Line" and in China's southeastern coastal regions. Firstly, cities along the "Hu Huanyong Line" are mostly located in the core regions with energy and resource-intensive industries layouts due to their unique geographical locations and resource endowments, they own high potential for improving ICUE. Secondly, these cities mostly play the role of crucial strategic hub of China, and have the potential to maximize positive externalities of DED through large-scale digital infrastructure construction. Finally, other southeastern coastal cities exhibit high-intensity economic activity, integral industrial chains and mostly exceeding the maturity stage threshold of DED. Improving ICUE in these areas could serve as an exemplary role for carbon reduction across the whole country.

7.2 Policy implications

Based on the empirical findings of this study, the following policy implications are proposed:

(1) Accelerating digital economy development and seizing the opportunity window for industrial carbon unlocking. The central government should strengthen support for cities developing the digital economy, especially by providing policy incentives for the digital transformation of small and medium-sized enterprises, digital infrastructure construction and digital talent cultivation. Policymakers should seize the opportunity window for industrial carbon unlocking in high-potential cities, especially cities along the "Hu Huanyong line" and southeastern coastal cities, by coordinating the city demands, technological capabilities and policy support, these cities could maximize the performance of industrial carbon unlocking driven by the digital economy, while amplifying its positive spillover effects, such as their resource endowment, geographical connectivity and demonstration role,

(2) Promoting regional coordination for digital economy development to maximize spillover effects. A coordinated development strategy for the digital economy should be formulated to strengthen inter-regional information sharing, technological exchange and policy alignment. In practice, priority should be given to strengthening the inter-connectivity of digital infrastructure to facilitate functional borrowing across regions. Additionally, cross-regional industrial policies and subsidies support should be implemented to promote effective linkages among digitization transformation enterprises, ultimately establishing a well-balanced, market-oriented digital economy ecosystem on a national scale.

(3) Strengthening technological innovation and institutional reform to promote industrial carbon unlocking. Policymakers should prioritize incentives for digital technology innovation, particularly in the development and application of green and low-carbon technologies. Digital technology identification and hedging policies should be promoted in the early stage to reduce the adverse environmental effects caused by digital technology exploration (Xin et al., 2023a). At the same time, institutional framework supporting digital economic growth should be refined, incorporating both command-and-control policies (e.g., differentiated industrial land allocation policies) and market-based mechanisms (e.g., carbon emission trading systems). Establishing a comprehensive and conducive regulatory environment will ensure the effective industrial carbon unlocking.

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References:

Arbuthnott, K.D., Dolter, B. (2013). Escalation of commitment to fossil fuels. Ecological Economics, 89, 7-13.

Athey, S., & Wager, S. (2021). Policy learning with observational data. Econometrica, 89(1), 133-161

Bai, L., Guo, T., Xu, W. (2023). Effects of digital economy on carbon emission intensity in Chinese cities: A life-cycle theory and the application of non-linear spatial panel smooth transition threshold model. Energy Policy, 183, 113792.

Bell, E.V., Olivier, T. (2022). Following the paper trail: systematically analyzing outputs to understand collaborative governance evolution. Journal of Public Administration Research and Theory, 32(4), 671-684.

Bergek, A., Jacobsson, S., Sandén, B.A. (2013). “Legitimation” and “development of positive externalities”: two key processes in the formation phase of technological innovation systems. The Dynamics of Sustainable Innovation Journeys. Routledge, 55-72.

Blake, A. Jevon’s Paradox. (2005). Ecological Economics, 54(1), 9-21.

Cai, Q., Chen, W., Wang, M., Di, K. (2024). Optimizing resource allocation for regional employment governance: A dynamic fuzzy-set QCA analysis of low-carbon pilot cities in China. Global Nest Journal, 26(8), 006336.

Cai, Q., Chen, W., Wang, M., Di, K. (2025). Drivers of green finance development: a nonlinear fsQCA-ANN analysis. International Journal of Global Warming. 36(1), 86-105.

Chaudhuri, B.B. (1996). A new definition of neighborhood of a point in multi-dimensional space. Pattern Recognition Letters, 17(1), 11-17.

Chen, S., Chen, D. (2018). Air pollution, government regulation and high-quality economic development. Economic

Research Journal, 53(02), 20-34. (in Chinese)

Dong, Y., Jin, G., Deng, X. (2020). Dynamic interactive effects of urban land-use efficiency, industrial transformation, and carbon emissions. Journal of Cleaner Production, 270, 122547.

Ertur, C., Koch, W. (2007). Growth, technological interdependence and spatial externalities: theory and evidence. Journal of Applied Econometrics, 22(6), 1033-1062.

Fichman, R.G., Dos Santos, B.L., Zheng, Z. (2014) Digital innovation as a fundamental and powerful concept in the information systems curriculum. MIS quarterly, 38(2), 329-354.

Fluck, Z., Mayer, C. (2005). Race to the top or bottom? Corporate governance, freedom of reincorporation and competition in law. Annals of Finance, 1, 349-378.

Guo, F., Wang, J., Wang, F., Cheng, Z., Kong, T., Zheng, X. (2020). Measuring China's digital financial inclusive: Index compilation and spatial characteristics. China Economic Quarterly. 19(4), 1401-1418. (in Chinese).

Hansen, B.E. (1999). Threshold effects in non-dynamic panels: Estimation, testing and inference. Journal of Econometrics. 93(2), 345-368.

Healy, N., & Barry, J. (2017). Politicizing energy justice and energy system transitions: Fossil fuel divestment and a "just transition". Energy policy, 108, 451–459.

Janipour, Z., de Nooij, R., Scholten, P. (2020). What are Sources of Carbon Lock-in in Energy-intensive Industry? A Case Study into Dutch Chemicals Production. Energy Research &Social Science, 60, 101320.

Jiang, S., Li, Y., Lu, Q. (2021). Policy assessments for the carbon emission flows and sustainability of Bitcoin block chain operation in China. Nature Communications, 12, 1-10.

Jin, G., Guo, B., Deng, X. (2020). Is there a decoupling relationship between CO2 emission reduction and poverty alleviation in China? Technological Forecasting and Social Change, 151, 119856.

Jin, X., Yu, W. (2022). Information and communication technology and carbon emissions in China: The rebound effect of energy intensive industry. Sustainable Production and Consumption, 32, 731-742.

Kwilinski, A. (2024). Understanding the nonlinear effect of digital technology development on CO2 reduction. Sustainable Development, 32, 5797-5811.

Lei, X., Lin, O., Lin, J. (2024). Evolutionary game analysis of enterprises' green production behavior in the context of China's economic green transformation. Global Nest Journal. 26(3), 05781.

Lei, X., Xu, J., Chen, Y., Liu, C., Zhao, K. (2025). Digital Oasis: How Green Infrastructure Is Reshaping China's Energy Resilience Landscape. Systems. 13(5), 306.

Lei, X., Xu, X. (2025). The "spider web" of venture capital: An invisible force driving corporate green technology innovation. Technology in Society. 82, 102882.

LeSage, J.P., Pace, R.K. (2009). Spatial econometric models[M]. Handbook of applied spatial analysis: Software tools, methods and applications. Berlin, Heidelberg: Springer Berlin Heidelberg, 355-376.

Li, X., Wu, Q. (2023). The impact of digital economy on high-quality economic development: Research based on the consumption expansion. PLos ONE, 18, e0292925.

Li, Z., & Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China. Journal of Cleaner Production, 351, 131570.

Li, X., Zhang, H., Peng, Z. (2025). The nonlinear dynamic effects of fintech on carbon emissions: Evidence from Chinese cities. International Review of Financial Analysis. 104, 104335.

Liu, X., Liu, C., Piao, J. (2024). Unpacking technology flows based on patent transactions: does trickle-down, proximity, and siphon help regional specialization? The Annals of Regional Science, 1-26.

Nara, E.O.B., da Costa, M.B., Baierle, I.C. (2021). Expected impact of industry 4.0 technologies on sustainable development: A study in the context of Brazil's plastic industry. Sustainable Production and Consumption, 25, 102-122.

Niu, H., Liu, Z. (2021). Measurement on carbon lock-in of China based on RAGA-PP model. Carbon Management, 12(5), 451-463.

Normann, H.E. (2017). Policy Networks in Energy Transitions: The Cases of Carbon Capture and Storage and Offshore Wind in Norway. Technological Forecasting and Social Change, 118, 80-93.

Paschou,T., Rapaccini, M., Adrodegari, F, et al. (2020). Digital servitization in manufacturing: A systematic literature review and research agenda. Industrial Marketing Management, 89, 278-292.

Sanden, B.A., Hillman, K.M. (2011). A Framework for Analysis of Multi-Mode Interaction Among Technologies with Examples from the History of Alternative Transport Fuels in Sweden. Research Policy, 40(3), 403 -414.

Seto, K.C., Davis, S.J., Mitchell, R.B., et al. (2016). Carbon lock-in: types, causes, and policy implications. Annual Review of Environment and Resources, 41(1), 425-452.

Tian, L., Zhang, C., Lei, X. (2024). Digital Economy's Role in Environmental Sustainability: Air Quality Enhancement through the "Broadband China" Initiative. Polish Journal of Environmental Studies, 193135.

Tone, K., Tsutsuim, J. (2009). Network DEA: a slacks-based measure approach. European Journal of Operational Research, 197(1), 243-252.

Unruh, G.C., Carrillo, H.J. (2006). Globalizing carbon lock-in. Energy Policy, 34(10), 1185-1197.

Unruh, G.C. (2000) Understanding carbon lock-in. Energy Policy, 28, 817-830.

Wang, C., Huang, J., Zou, W. (2021). Selective land supply, industrial structure adjustment and urban innovation. China Land Science. 35(09), 24-32. (in Chinese)

Wu, H., Chang, M., Su, Y., Xu, X., & Jiang, C. (2025). Digital Economy, Government Innovation Preferences, and Regional Innovation Capacity: Analysis Using PVAR Model. Systems, 13(5), 382.

Xin, J., Lei, X., Wu, W. (2023a). Can digital investment improve corporate environmental performance? – Empirical evidence from China. Journal of Cleaner Production. 414, 137669.

Xin, Y., Song, H., Shen Z, &Wang, J. (2023b). Measurement of the integration level between the digital economy and industry and its impact on energy consumption. Energy Economics, 126, 106988.

Xu, R., Yao, H., & Li, J. (2024). Digital Economy's Impact on High-Quality Economic Growth: A Comprehensive Analysis in the Context of China. Journal of the Knowledge Economy, 1-19.

Zhang, X., Huang X., Zhang, D. (2022). Research on the pathway and policies for China’s energy and economy transformation toward carbon neutrality. Management World, 38(1):35-66. (in Chinese).

Zhao, C., Dong, K, Lee, C.C. (2024). Carbon lock-in endgame: Can energy trilemma eradication contribute to decarbonization? Energy, 293, 130662