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How does industry-university-research collaborative green innovation affect regional carbon emissions? —nonlinear effects and multi-mechanism analysis

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Abstract
Amid the deepening implementation of the "dual carbon" strategy, elucidating the multidimensional dynamics of industry-university-research (IUR) collaborative green innovation on regional carbon emissions holds critical significance for reconciling environmental governance with economic development. Leveraging panel data from 30 Chinese provinces (2010–2022), this study employs parametric and non-parametric approaches to decode the nonlinear impact of IUR collaborative green innovation on carbon emissions. Through moderated mediation models and spatial lag analysis, it systematically reveals operational mechanisms. Key findings include: (1) An inverted U-shaped relationship emerges-initial collaboration phases may elevate emissions, but sustained efforts progressively manifest emission reduction effects. (2) Technological substitution drives low-carbon transitions in polluting industries. While restructuring triggers transient carbon pulse peaks from cost surges, long-term trajectories follow inverted U-shaped patterns moderated by industrial composition and structural upgrading. (3) Initial U-shaped suppression effects stem from resource misallocation and adaptation costs, yet enhanced technological absorptive capacity elevates green total factor productivity (GTFP), enabling a 9.57% emission reduction through industrial transformation. (4) Spatiotemporal interactions evolve from short-term U-shaped spatial spillovers to long-term inverted U-shaped synergies, necessitating optimized policy coordination for dynamic emission reduction dividends. (5) Regional heterogeneity persists-eastern China demonstrates stable impacts through industrial maturity, contrasting with volatile central/western regions constrained by fragmented innovation ecosystems. This research advances understanding of collaborative innovation's nonlinear carbon governance effects, offering actionable insights for regionalized decarbonization strategies and cross-regional innovation alliances.

Keywords IUR collaborative green innovation, Carbon emissions, Nonlinear relationship, Multi-effect mechanism

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Introduction

As global climate change becomes a serious challenge, cutting carbon has become a key part of sustainable development plans around the world. China's rapid economic growth during its industrial and urban development has led to high energy use and rising carbon emissions. This has made it harder to reduce carbon [1]. In this situation, green technology innovation plays an important role. It helps improve energy use and resource efficiency. It also helps lower carbon emissions [2, 3]. Cooperation between industry, universities, and research (IUR) has become a key way to support this kind of innovation. It brings together knowledge, helps turn ideas into technology, and supports policy efforts to speed up green technology development [4, 5].

But there are still big questions about how IUR-based green innovation affects carbon emissions in different regions. Many studies still use simple models that assume straight-line effects [6]. These models miss more complex patterns that come from how technology spreads over time. Other studies look at single parts of the process, like replacing old technology [7] or changing the structure of industries [8]. But they do not connect these parts into a full picture. Also, many spatial studies are based on fixed models. These models do not show how innovation spreads over time. Because of this, it is hard to explain why some areas with strong IUR efforts see early increases in carbon emissions, or why areas with similar levels of cooperation have different results.

Using China's provincial panel data (2010–2022), we construct an integrated multi-method analytical framework. First, parametric modeling (quadratic functional specification) synergizes with nonparametric local regression to chart nonlinear emission trajectories. Then, it uses a mediation model to study how green total factor productivity (GTFP) works in this process.It also uses amoderation model toexplore the role of technological substitution (such as the decline in the share of highly polluting industries and the upgrading of industrial structure) in this process.

Last, it uses static and dynamic spatial Durbin models to compare how innovation spreads across areas and over time.

The study's pioneering insights manifest in three dimensions:

- It shows an inverted U-shaped curve for carbon emissions using nonlinear models. This goes beyond the limits of traditional straight-line models.
- It puts together the ideas of technology replacement, resource use changes, and spatial spillovers into one model that looks at process, path, and space.
- It uses spatial analysis to show that policy effects take time to appear. This helps explain when and how different areas should manage carbon reduction in steps.

Literature review

Green technology innovation (GTI) is widely regarded as a core driver of the economy's transition toward low-carbon development. Research on the Environmental Kuznets Curve (EKC) highlights the nonlinear relationship between economic growth and environmental degradation, emphasizing the roles of technological progress, industrial restructuring, and institutional factors in shifting from "more pollution" to "less pollution" [9–15]. Cross-country studies further show that the diffusion of green technologies can help generate an EKC "turning point" and improve environmental performance [16, 17].

Regarding abatement mechanisms, GTI promotes a synergy of three key levers: efficiency leap, pollution control, and structural reconfiguration. At the micro level, the energy-efficiency revolution reduces carbon intensity by improving conversion efficiency [18]. At the meso level, carbon capture and renewable energy technologies provide end-of-pipe abatement solutions [19]. At the macro level, GTI accelerates industrial upgrading and low-carbon restructuring, helping decouple economic growth from carbon emissions [20].

On measurement, the literature has evolved from "quantity tagging—quality measurement—systemic analytics." Early studies relied on visible indicators such as counts of green patents, while later studies shifted to composite measures such as R&D intensity and market share of green products [21]. Recent contributions focus on lifecycle models to trace how technology diffusion and abatement effects propagate along value chains [22]. International evidence shows that the diffusion of green technologies depends not only on local innovation capacity but also on knowledge spillovers, trade networks, and policy incentives [17, 23, 24]. However, research often overlooks geographic and institutional heterogeneity, making it hard to explain why regions with similar technology inputs exhibit different abatement outcomes [25].

At the level of technology diffusion and adoption, industry-university-research (IUR) collaboration plays a central role. The Triple Helix model, which integrates university knowledge spillovers, firm technology absorption, and government policy incentives, forms a dynamic engine for accelerating green innovation. This collaborative framework drives both horizontal industrial agglomeration and vertical technology transfer, contributing to emission reductions through cross-regional cooperation [17, 23, 26, 27].

GTI's regional effects display significant spatial heterogeneity and spillovers, requiring spatial econometric tools for analysis. Advances in spatial econometrics offer a toolkit-from spatial autocorrelation tests to spatial lag/Durbin models and spatial panels [28–31]-to identify the spatial transmission of technology networks, factor flows, and policy externalities. Unlike static metrics such as Moran's I, these approaches reveal diffusion lags and their long-term policy implications [32, 33].

Despite notable progress, three limitations remain. First, the literature often relies on linear assumptions (e.g., OLS), making it difficult to capture nonlinear and threshold effects between collaborative innovation and carbon outcomes [12, 14, 34]. Early collaboration phases may induce carbon lock-in, masking short-term abatement while stronger effects emerge only with technological maturity and scale [26, 35]. Second, mechanism analysis is fragmented, with many studies focusing on technological iteration [36], factor allocation [37], or spatial radiation [38] in isolation. Third, policy analysis tends to be static, relying on single-period spatial correlation measures and rarely quantifying how diffusion lags and network structure shape medium- to long-term policy performance [29, 30].

In response, this study develops a three-dimensional framework of nonlinear identification, mechanism coupling, and dynamic simulation, focusing on three questions: (1) Does IUR-driven innovation exhibit a U-shaped EKC turning point? (2) How do technological iteration, factor allocation, and spatial radiation interact through nonlinear coupling? (3) Do spatial spillovers follow a "diffusion-convergence" cyclical pattern? These findings are expected to overcome the limitations of traditional linear research paradigms, providing theoretical support and empirical evidence for the development of spatiotemporally differentiated policy systems.

Theoretical analysis and research hypotheses

Nonlinear impact of IUR collaborative green innovation on carbon emissions

IUR collaborative green innovation is crucial for advancing regional low-carbon transformation. It involves technological breakthroughs, knowledge diffusion, and industrial evolution, and its impact on carbon emissions varies across different stages, demonstrating nonlinear dynamics.

In the early stage, collaboration may initially lead to a rise in carbon emissions. As companies, universities, and research centers focus on creating and testing new technologies, high research costs and adjustments in production may temporarily increase emissions. This aligns with innovation diffusion theory, where green technologies go through research, testing, scaling, and diffusion phases [39]. Companies continue using older, high-carbon technologies to remain profitable, and new technologies may initially increase energy consumption. This is known as the "technology diffusion lag effect" [40, 41].

Later, as technologies mature and cooperation strengthens, emissions begin to decrease. Green technologies like clean energy and smart systems gradually replace carbon-heavy methods, driven by policies such as green finance and carbon market incentives [42, 43]. This combined effect accelerates emission reductions.

In China, energy system transformation faces challenges due to existing habits and slow regulatory changes [40, 41]. Early-stage collaboration often focuses on basic research and small efficiency improvements, but high costs and weak demand slow full green system adoption. In these phases, emissions may rise due to production growth, but as cooperation reaches a key point, large-scale changes, such as clean energy and smart manufacturing, emerge, reducing emissions. This suggests an inverted U-shaped curve for emissions.

Hypothesis 1: IUR collaborative green innovation exhibits an inverted U-shaped relationship with carbon emissions.

Technological substitution effect of IUR collaborative green innovation

IUR collaborative green innovation accelerates the transformation of high-pollution industries to low-carbon industries, primarily by reducing the share of high-pollution industries and promoting industrial restructuring.

In early collaboration, limited capacity to absorb low-carbon technologies andhigh market transformation costs hinder the substitution effect. Equipment upgrades and capacity expansion may initially increase emissions, creating an "emission transfer effect." However, as technology matures and market demand for low-carbon products rises, the substitution effect becomes more evident. The green technology market grows, and traditional high-carbon industries are gradually replaced by cleaner alternatives.

The substitution effect operates through two key pathways:

- Decreased share of high-pollution industries: IUR collaboration promotes clean energy, reducing high-pollution industries' market share and lowering emissions, especially in regions with low-pollution industries.
- Industrial upgrading: The transformation toward green sectors like smart manufacturing and clean energy speeds up in regions with strong absorptive capacities, leading to lower emissions.

However, the substitution process is constrained by path dependence and market barriers in high-pollution regions. This can cause short-term emission reductions, followed by long-term rebounds, sometimes leading to a U-shaped pattern.

Hypothesis 2: IUR collaborative green innovation affects regional carbon emissions through the technological substitution effect.

Resource optimization allocation effect of IUR collaborative green innovation

The resource optimization effect improves carbon emissions by optimizing the allocation of capital, technology, and human resources. IUR collaborative green innovation fosters knowledge flow and technology diffusion, enhancing the efficiency of green technology R&D and application.

In early collaboration, companies' limited capacity and high adjustment costs hinder resource optimization, leading to possible emission increases. However, as cooperation deepens, companies gradually master green technologies, and resource integration begins to reduce carbon emissions. This process is influenced by regional economic development, policy support, and market conditions, with developed regions showing quicker emission reductions.

This effect may also present an inverted U-shape. Initially, the adaptation phase may lead to emission increases, but as the benefits of resource optimization outweigh the negatives, emissions decrease.

Hypothesis 3: IUR collaborative green innovation affects regional carbon emissions through the resource optimization allocation effect.

Spatial spillover effect of IUR collaborative green innovation

IUR collaborative green innovation not only impacts local carbon emissions but also influences neighboring areas through technology diffusion, knowledge sharing, and industrial linkages, known as the spatial spillover effect. As regions become more interconnected, green technology spreads across regions, affecting their carbon emission patterns.

The spatial spillover effect accelerates emissions reduction in adjacent regions as advanced technologies and knowledge spread. Strong IUR cooperation leads to more skilled labor mobility, patent sharing, and industry linkages, helping neighboring regions adopt low-carbon technologies faster.

However, spatial spillovers manifest nonlinearly. In early stages, regional disparities in absorptive capacity and industrial foundations slow technology adoption. Initially, some areas may even increase emissions by relocating polluting industries. As cooperation grows, stronger spillovers emerge, and regions become better at adopting and applying green technologies, leading to greater emission reductions.

Hypothesis 4:

IUR collaborative green innovation governs regional carbon emissions through spatial spillover dynamics.

Research methodology and data sources

Model construction

In order to explore the impact of Industry-University-Research collaborative green innovation (IUR-GI) on carbon emissions (CE), the following regression model is established:

$$\begin{aligned} lnCE_{it} =& \alpha_0 + \alpha_1 lnIUR - GI_{it} + \alpha_2 (lnIUR - GI_{it})^2 \\ &+ \sum_{j=1}^{p} \alpha_j Control_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where:

- $lnCE_{it}$ represents the carbon emission level of region *i* in year *t*;
- $lnIUR - GI_{it}$ represents the level of Industry-University-Research collaborative green innovation (IUR-GI);
- $(lnIUR - GI_{it})^2$ represents the squared term of IUR-GI, used to test its nonlinear impact on carbon emissions;

- $Control_{it}$ represents control variables, including economic development level, total energy consumption, environmental regulation, technological innovation capability, government investment, and green finance index;
- μ_i represents individual fixed effects, controlling for unobservable regional characteristics;
- ϑ_t represents time fixed effects, controlling for time trends;
- ε_{it} represents the error term.

Considering that the relationships between variables and the specification of the regression function involve a certain degree of subjectivity, a non-parametric additive model is introduced to further test the nonlinear relationship between Industry-University-Research collaborative green innovation and carbon emissions, as shown in Eq. (2):

$$\begin{aligned} lnCE_{it} =& \beta_0 + \beta_1 lnIUR - GI_{it} + \sum_{j=1}^{p} \beta_j Control_{it} \\ &+ f(lnIUR - GI_{it}) + \sum_{j=1}^{p} f_i(Control_{it}) + \varepsilon_{it} \end{aligned} \tag{2}$$

where:

- $f(lnIUR - GI_{it})$ and $f_i(Control_{it})$ represent the non-parametric functional forms of IUR collaborative green innovation and control variables, aiming to capture the nonlinear relationship.
- Other parameters are the same as in Eq. (1).

This study establishes mediation, moderation, and spatial effect models to delve into the intricate mechanisms through which IUR collaborative green innovation influences regional carbon emissions. Recognizing the multifaceted nature of carbon emissions—shaped by economic dynamics, policy interventions, and technological evolution—the intricate interplay between mediating variables and carbon outputs may engender reverse causality, while heterogeneous moderating factors could introduce nuanced estimation biases. To address these complexities, the research first validates the causal relationship through robust parametric and non-parametric frameworks (Eqs. 1, 2), adroitly addressing potential endogeneity concerns. Subsequently, the moderation effect model (Eq. 3) illuminates how industrial structure upgrading and high-pollution industry ratios shape the carbon emission effects through technological substitution. The mediation effect model (Eqs. 4; 5) then rigorously probes whether resource optimization allocation serves as a hidden conduit for IUR collaborative innovation's environmental impact. Finally, through meticulously crafted static and dynamic spatial lag models (Eqs. 6; 7), the investigation unravels the spatial spillover effects across regions, revealing both the radiating influence of green innovation practices and the profound interconnectedness of carbon emission patterns across geographical boundaries.

$$\begin{aligned} lnCE_{it} =& \sigma_0 + \sigma_1 lnIUR - GI_{it} + \sigma_2 (lnIUR - GI_{it})^2 \\ &+ \sigma_3 \mathrm{D}_{it} + \sigma_4 \mathrm{D}_{it} \times lnIUR - GI_{it} \\ &+ \sigma_5 \mathrm{D}_{it} \times (lnIUR - CI_{it})^2 \\ &+ \sum_{j=1}^{p} \sigma_j Control_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where:

- D_{it} represents the moderating variable, indicating the technological substitution pathway, which can be measured by the industrial structure upgrading index (ISA) or the proportion of high-pollution industries (PHI);
- $\mathrm{D}_{it} \times lnGIUR_{it}$ represents the interaction term between IUR collaborative green innovation and the industrial structure moderating variable;
- $\mathrm{D}_{it} \times (lnGIUR_{it})^2$ represents the interaction term between the squared term of IUR collaborative green innovation and the industrial structure moderating variable;
- Other parameters are the same as in Eq. (1)

$$\begin{aligned} \mathrm{M_{it}} =& \gamma_0 + \gamma_1 lnIUR - GI_{it} + \gamma_2 (lnIUR - GI_{it})^2 \\ &+ \sum_{j=1}^{p} \gamma_j Control_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} lnCE_{it} =& \rho_0 + \rho_1 lnIUR - GI_{it} + \rho_2 (lnIUR - GI_{it})^2 + \delta M_{it} \\ &+ \sum_{j=1}^{p} \rho_j Control_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where:

- M_{it} represents the mediating variable, which can be measured by green total factor productivity (GTFP);
- Other parameters are the same as in Eq. (1);
- If δ is significant and the coefficient of α_1 decreases or becomes insignificant after adding M_{it}, it indicates that the mediation effect is significant.

$$\begin{aligned} lnCE_{it} =& \varphi_0 + \eta W \cdot lnCE_{it} + \varphi_1 lnIUR - GI_{it} \\ &+ \varphi_2 (lnIUR - GI_{it})^2 + \sum_{j=1}^{p} \varphi_j Control_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{6}$$

$$\begin{aligned} lnCE_{it} =& \theta_0 + \eta W \cdot lnCE_{it} + \theta_1 lnCE_{it-1} \\ &+ \theta_2 lnIUR - GI_{it} + \theta_3 (lnIUR - GI_{it})^2 \\ &+ \sum_{j=1}^{p} \theta_j Control_{it} + \mu_i + \vartheta_t + \varepsilon_{it} \end{aligned} \tag{7}$$

where:

- $W \cdot lnCE_{it}$ represents the spatial lag term of carbon emissions, used to measure the impact of carbon emissions in neighboring regions on local carbon emissions;
- $lnCE_{it-1}$ represents the time lag term of carbon emissions, used in the dynamic model to measure the path dependence of carbon emissions;
- W represents the spatial weight matrix, where this study adopts the inverse distance geographical matrix as the spatial weight matrix;
- η represents the spatial autoregressive coefficient, reflecting the spatial dependence of carbon emissions.

Variable selection and data sources

This study uses provincial panel data from China from 2010 to 2022, sourced from the National Bureau of Statistics, the China Economic and Social Big Data Research

Platform, the China Science and Technology Statistical Yearbook, and the China Statistical Yearbook. Due to severe data gaps in Hong Kong, Macau, Taiwan, and Tibet, 30 provincial-level regions (including provinces, autonomous regions, and municipalities) were selected to ensure robustness. To improve data comparability and accuracy in regression analysis, the following adjustments were made: (1) economic indicators affected by price changes were converted to constant 2010 prices to eliminate inflation effects; (2) moderating variables were centered to reduce multicollinearity; (3) non-percentage variables were log-transformed to address heteroskedasticity and improve model fit; (4) missing values were interpolated using linear methods; and (5) descriptive statistics, correlation analysis, and unit root tests were conducted to verify data validity.

(1) Dependent Variable: Carbon Emissions.

Carbon emissions serve as the dependent variable, drawn from the CEDAs Database to quantify regional carbon output. This metric captures the cumulative environmental impact of industrial and economic activities across provinces.

(2) Independent Variable: IUR Collaborative Green Innovation.

The regional level of IUR collaborative green innovation is measured by the number of jointly applied green patents filed by enterprises (Industry), universities (University), and research institutions (Research Institution). Green patents are identified using the WIPO IPC Green Inventory, ensuring coverage of fields such as energy conservation, pollution control, clean production, and renewable energy. A patent is considered an IUR collaborative innovation if its applicants include at least two different types of innovation actors (e.g., enterprise + university, enterprise + research institution, or full three-party collaboration). The annual count of such patents is aggregated by region, log-transformed as lnIUR-GI, with its squared term $(\ln\text{IUR-GI})^2$ introduced to capture potential nonlinear effects [44].

(3) Moderating Variables: Industrial Structure and High-Pollution Industry Ratio.

To investigate technological substitution dynamics, the study incorporates dual moderators: industrial structure advancement and the economic footprint of high-pollution sectors.

High-carbon industries—including steel production, chemical manufacturing, power generation, and construction materials—constitute primary emission sources. Their contribution to regional industrial output quantifies economic reliance on carbon-intensive practices. Following the First National Pollution Source Census Plan (2007), eleven high-pollution sectors were analyzed, with their industrial output share calculated as a critical moderating factor.

Industrial restructuring, propelled by digital transformation and service sector growth, embodies modern economic evolution [45]. This transition is measured through the tertiary-to-secondary industry output ratio, reflecting structural shifts in production paradigms.

(4) Mediating Variable: Green Total Factor Productivity.

GTFP quantifies how IUR collaborative innovation optimizes resource flows and enhances energy efficiency. Employing the SBM-DEA model with undesirable outputs [46], this metric integrates energy inputs, capital, labor, and carbon emissions to evaluate sustainable productivity. The analysis further dissects GTFP's mediating role in channeling green innovation effects toward emission reduction.

(5) Control Variables.

To mitigate omitted variable bias and strengthen empirical reliability, sixcontrol dimensions were incorporated:

- Economic Development: Provincial GDP per capita.
- Energy Demand: Aggregate electricity consumption.
- Regulatory Intensity: Industrial pollution control investment as percentage of secondary sector output.
- Innovation Capacity: R&D expenditure relative to GDP.
- Fiscal Prioritization: Science/technology spending as share of local government budgets.
- Green Finance: Composite index blending green credit, securities, insurance, and investment metrics [47, 48].

Descriptive statistics from Table 1 reveal a 30-province panel dataset spanning 2011–2022 (n = 390). Carbon emissions (CE) average 383.963 Mt with substantial standard deviation, underscoring stark interprovincial disparities. IUR-GI collaboration averages 529.98 projects but exhibits pronounced volatility, highlighting uneven regional innovation ecosystems. While TIC, GFI, and GI display modest variability, EC and EDL metrics demonstrate extreme dispersion, mirroring China's imbalanced regional development. These patterns align with observed economic realities, where variance in green innovation capacity, industrial composition, and

Table 1 Descriptive statistics

Variable	Symbol	Unit	Mean	Std. dev	Min	Max	Obs
Carbon emissions	CE	Mt	383.963	326.250	37.140	2099.792	390
Industry-university-Research collaboration Green innovation	IUR-GI	Pieces	529.980	898.711	2	6429	390
Technological innovation capability	TIC	%	1.758	1.149	0.340	6.845	390
Green finance index	GFI	%	0.158	0.068	0.073	0.474	390
Government investment	GI	%	0.261	0.237	0.057	1.216	390
Environmental regulation	ER	%	0.003	0.003	0.000	0.025	390
Energy consumption	EC	Mtec	1,408,815	992,390.7	152,649.4	4,227,082	390
Economic development level	EDL	Billion CNY	26,782.18	22,502.950	1350.430	129,118.6	390
Proportion of high-pollution industries	PHI	%	0.466	0.129	0.078	0.826	390
Industrial structure upgrading	ISU	%	1.236	0.714	0.500	5.297	390
Green total factor productivity	GTFP	%	1.748	0.989	0.443	5.396	390

Table 2 Benchmark regression results

Variable	(1)	(2)	(3)	(4)	(5)
lnIUR-GI	0.143***	0.066*	0.916***	0.243***	0.131***
	(0.034)	(0.035)	(0.147)	(0.062)	(0.040)
(lnIUR-GI)^2			−0.073***	−0.015**	
			(0.015)	(0.006)	
lnTIC		−0.016		−0.262***	−0.046
		(0.089)		(0.093)	(0.100)
lnGFI		−0.151***		0.141***	0.097
		(0.058)		(0.043)	(0.09)
lnGI		−0.121***		−0.050	−0.002
		(0.046)		(0.046)	(0.05)
lnER		57.742***		−2.334	78.969***
		(8.696)		(4.322)	(10.833)
lnEC		0.868***		0.114**	0.844***
		(0.052)		(0.053)	(0.059)
lnEDL		0.119*		0.155*	−0.201***
		(0.066)		(0.083)	(0.072)
Constant	4.856***	−7.906***	2.972***	0.886	
	(0.184)	(0.373)	(0.364)	(0.943)	
Region FE	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
Obs	390	390	390	390	390
Adj R^2	0.069	0.783	0.144	0.977	0.927
F	17.28***	194.06***	36.24***	689.28***	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses in columns (1)–(5) represent cluster-robust standard errors

emission trajectories provides empirical traction for analyzing technology-driven decarbonization pathways.

Empirical analysis

Baseline regression analysis

This study employs panel data regression (Columns 1–4) and a non-parametric additive model (Column 5) to examine the impact of IUR collaborative green innovation (*lnIUR-GI*) on carbon emissions (*lnCE*) and further analyzes the roles of technological innovation, green finance, government investment, environmental regulation, energyconsumption, and economic development.

From the panel regression results (see Table 2), the coefficient of the linear term of IUR collaborative green innovation is significantly positive, while that of the squared term is significantly negative, clearly revealing an inverted U-shaped relationship with carbon emissions. This indicates that in the initial stage of green innovation, rapid growth in R&D investment, firms' limited adaptability to green technologies, and the high costs associated with industrial restructuring contribute to a temporary rise in carbon emissions. However, as industry-university-research collaboration deepens, the effects of technology diffusion and optimized resource allocation gradually emerge, and the emission reduction effects of green innovation progressively strengthen, ultimately driving carbon emissions into a downward trajectory. This dynamic pattern aligns closely with the technology innovation diffusion theory [49] and strongly supports Hypothesis H1. Notably, even after incorporating multiple control variables in Column (4), this nonlinear characteristic remains robust, indicating that green innovation promotes the transition of carbon emissions from a phase of “innovation-driven temporary increase” to a phase of “steady decline during technological maturity,” through the mechanisms of technology diffusion, knowledge spillovers, and industrial chain optimization.

The estimation results of the non-parametric additive model (Column 5) further reinforce the above conclusions. Without the need to predefine a functional form, this model still captures a significant inverted U-shaped relationship between green innovation and carbon emissions (as shown in Fig. 1), indicating that as the level of IUR collaborative green innovation rises, carbon emissions first increase and then decline. This finding not only avoids potential biases caused by functional form misspecification in parametric models but also demonstrates that the nonlinear emission-reduction effect of green innovation is both robust and generalizable. Meanwhile, the non-parametric kernel regression results show that the average marginal effect of IUR collaborative green innovation is significantly positive (0.131, $p < 0.01$), suggesting that, on average, higher levels of green innovation are associated with increased carbon emissions. This positive effect primarily reflects the characteristics of the early stage of green innovation, where rapid increases in R&D investment, limited technological adaptability among firms, and frictions and cost pressures during industrial transformation lead to a short-term rise in carbon emissions.

Regarding control variables, technological innovation (*lnTIC*) has an insignificant effect in some models but shows a significant negative impact on carbon emissions in Column (4) (−0.262, $p < 0.01$), suggesting that technological innovation can reduce carbon emissions under certain conditions. However, regional differences in technology conversion rates may weaken this effect. The green finance index (*lnGFI*) significantly reduces carbon emissions in Column (2) (−0.151, $p < 0.01$), indicating that green finance directs capital toward low-carbon industries, but its effect is inconsistent across models, possibly due to structural adjustments in financing.

Government investment (*lnGI*) significantly reduces carbon emissions in Column (2) (−0.121, $p < 0.01$), suggesting that fiscal support facilitates green transformation. However, its effect is insignificant in other models, likely due to differences in industry allocation and policy efficiency. Environmental regulation intensity (*lnER*) has a significant positive effect in Columns (2) and (5) (57.742, $p < 0.01$; 78.969, $p < 0.01$), indicating that in the short term, strict environmental regulations increase compliance costs, leading to higher emissions, which is consistent with the "inverted U-shaped hypothesis of environmental regulation" [50].

Additionally, energy consumption (*lnEC*) consistently shows a significant positive effect on carbon emissions in all models, emphasizing the importance of energy structure adjustments. The impact of economic development (*lnEDL*) varies; in some models (Columns 2 and 4), economic growth increases carbon emissions, whereas in the non-parametric additive model (Column 5), it has a negative impact (−0.201, $p < 0.01$). This suggests that some regions may have entered the declining phase of the Environmental Kuznets Curve (EKC) [10, 15], where higher economic development leads to industrial upgrading and energy transition, reducing carbon emissions.

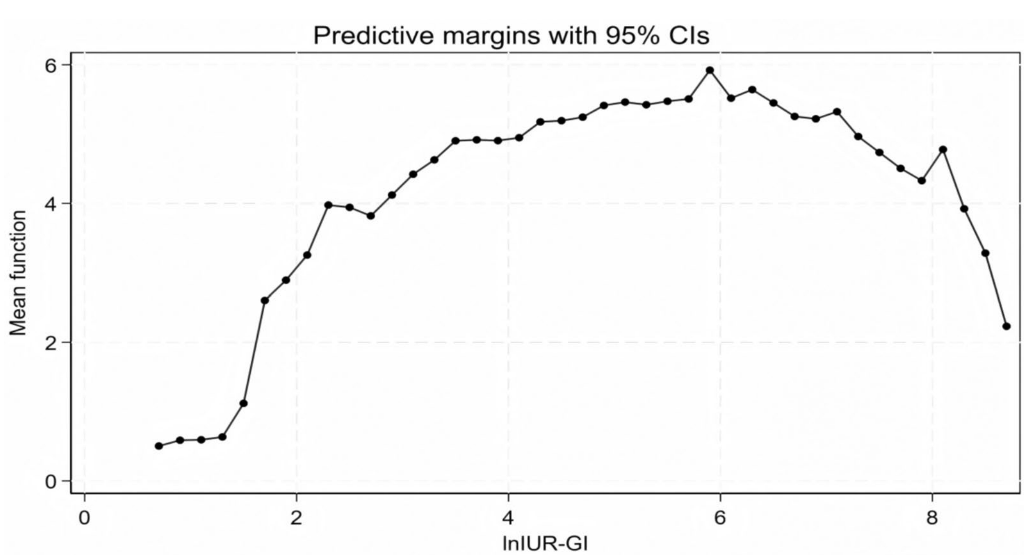

Fig. 1. Non-parametric Curve

Endogeneity issues

This study employs the instrumental variable method (2SLS) and system generalized method of moments (SYS-GMM) to address potential endogeneity and omitted variable bias in IUR collaborative green innovation (see Table 3). In the 2SLS estimation (Columns 1–3), we use the first-order lag of IUR collaborative green innovation and its squared term (lnIUR_GI_lag, lnIUR_GI_lag_sq), the first-order lag of the annual average number of green patents per province (lnGP_lag), as well as the first-order lags of the number of higher education institutions and research institutes (lnHEI_lag, lnRI_lag) as instrumental variables. This instrument set demonstrates strong explanatory power for the endogenous variables in the first stage, with the Cragg–Donald Wald F-statistic (86.682) far exceeding the critical threshold of 10. The rk-LM and Anderson–Rubin Wald tests are significant, confirming the strength and relevance of the instruments.

In the SYS-GMM estimation (Column 4), the first-order lag of carbon emissions (L.lny) is introduced to capture the dynamic inertia of carbon emissions and control for unobservable fixed effects, enhancing the robustness of the estimates. The regression results show that IUR collaborative green innovation (lnIUR-GI) significantly influences carbon emissions across all models and exhibits an inverted U-shaped relationship, consistent with the baseline regression results. This finding suggests that in the early stages, IUR collaborative green innovation may lead to increased resource consumption and higher carbon emissions, but as innovation activity reaches a certain threshold, the accumulation and transformation of green technologies can effectively contribute to carbon reduction.

Table 3 Regression results of 2SLS and GMM

Variable	2SLS			SYS-GMM
	(1) lnIUR-GI	(2) (lnIUR-GI)^2	(3) lny	(4) lny
lnIUR_GI_lag	0.2855*** (0.0061)	−3.1949*** (1.0449)		
lnIUR_GI_lag_sq	0.0303*** (0.0093)	1.0090*** (0.0869)		
lnGP_lag	0.2775*** (0.777)	2.1780*** (0.4929)		
lnHEI_lag	−0.0069** (0.0224)	−0.41235* (0.0557)		
lnRI_lag	0.0347*** (0.0069)	0.25606* (0.0201)		
L.lny				1.007*** (0.047)
lnIUR-GI			0.9618*** (0.2546)	0552* (0.032)
(lnIUR-GI)^2			−0.0730*** (0.0248)	−0.004* (0.003)
Control variable	Yes	Yes	Yes	Yes
Constant	0.4543* (0.2586)	4.1730** (2.0354)	2.8413*** (0.9479)	−0.133 (0.403)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2			0.6837	
F	269.61***	266.53***	121.46***	
CD wald F	86.682	86.682	86.682	
rk LM	8.290*	8.290*	8.290*	
Anderson-rubin wald	18.20***	18.20***	18.20***	
Stock-wright LM S statistic	15.13***	15.13***	15.13***	
AR(1)				*−2.34***
AR(2)				*1.36*
Sargan test	20.251***	20.251***	20.251***	*38.22****
Hansen test	3.546	3.546	3.546	*18.97*
Obs	360	360	360	*360*

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses in columns (1)–(4) represent cluster-robust standard errors

The diagnostic tests further validate the reliability of the estimates. In the 2SLS estimations, all Wald F-tests are highly significant ($p < 0.01$), indicating strong overall model fit. In the SYS-GMM estimation, the AR(1) test is significant ($p < 0.05$), while the AR(2) test is not significant ($p > 0.1$), indicating the absence of second-order autocorrelation and satisfying the requirements for SYS-GMM estimation. Although the Sargan test is significant, suggesting potential redundancy in some instruments, the Hansen test ($p > 0.1$) fails to reject the null hypothesis of instrument exogeneity, overall supporting the validity of the selected instruments and the robustness of the estimation results.

Robustness tests

To verify the robustness of the research conclusions, multiple robustness checks were conducted (see Table 4). First, the model was extended to include a cubic term regression (Column 1). The results indicate that the linear term is significantly positive, the quadratic term is significantly negative, and the cubic term is also significantly negative. This finding reveals a more complex nonlinear relationship between green innovation and carbon emissions, while confirming the stability of the inverted U-shaped pattern. Second, to control for the potential effects of policy changes, the sample period was truncated to 2018 (Column 2). The coefficients for industry–university–research (IUR) collaborative green innovation remain significant, indicating that policy adjustments do not substantially alter the core conclusions. Third, to account for the lagged effects of green patents, all variables were lagged by one period (Column 3). The results show that while the emission reduction effects of green innovation exhibit some time lag, the long-term impacts remain significant and stable. Lastly, to eliminate the influence of outliers, a 1% two-sided winsorization was applied to all variables (Column 4), and the regression results remained significant with the nonlinear relationship intact.

All robustness checks passed the F-test, and the adjusted R^2 values remained high, demonstrating the strong explanatory power of the model. Overall, regardless of the functional form expansion, sample truncation, time lag adjustments, or winsorization of extreme values, the nonlinearemission reduction effect of IUR collaborative green innovation on carbon emissions remains consistently robust, further reinforcing the study's core findings.

Extended analysis

Heterogeneity analysis

Using a Generalized Additive Model (GAM), this study further investigates the nonlinear effects of Industry–University–Research (IUR) collaborative green innovation on carbon emissions across four spatial dimensions: Nationwide, Eastern, Central, and Western regions. The results confirm pronounced nonlinearities in all subsamples, with estimated effective degrees of freedom (EDF) consistently above unity (Nationwide: 1.24; Eastern: 1.24; Central: 1.19; Western: 1.22) and highly significant p-values (all $p < 0.01$; see Fig. 2). These findings indicate that the impact of collaborative green innovation on carbon emissions deviates markedly from a simple monotonic pattern and instead follows complex, region-specific trajectories.

At the national level, the partial-effect curve displays distinct oscillations with multiple inflection points. Carbon emissions initially rise at lower levels of green innovation (around sub lnIUR - $\mathrm{GI} \approx 9.3$) sequently decline to a local trough near $\ln IUR - GI \approx 10.1$ and rebound

Table 4 Results of robustness test

Variable	(1)	(2)	(3)	(4)
	Cubic regression	Patent reform	Lagged processing	Winsorization
lnIUR-GI	0.1043***	0.597***	0.577***	0.508***
	(0.040)	(0.208)	(0.190)	(0.182)
(lnIUR-GI)^2	−0.0111**	−0.076***	−0.061***	−0.053***
	(0.012)	(−0.018)	(0.016)	(0.017)
(lnIUR-GI)^3	−0.004**			
	(0.079)			
Control variable	Yes	Yes	Yes	Yes
Constant	4.666**	1.64	1.857***	−1.749
	(2.068)	(1.562)	(1.752)	(1.785)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adj.R^2	0.741	0.730	0.694	0.677
F	46.73***	38.82***	51.55***	40.37***
Obs	390	270	360	390

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses in columns (1)–(4) represent cluster-robust standard errors

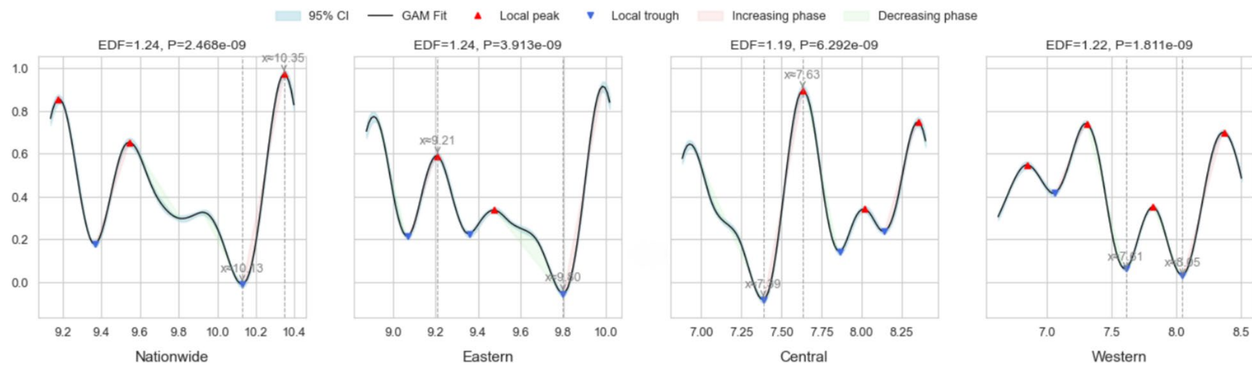

Fig. 2. Nonlinear effect of IUR collaborative green innovation on carbon emissions

toward a secondary peak around $\ln IUR - GI \approx 10.35$ This dynamic trajectory suggests that the nationwide diffusion of green innovation is not immediately emission-reducing; rather, it undergoes a "short-term escalation–adjustment–stabilization" pathway as technological diffusion, industrial upgrading, and resource optimization progressively take effect.

The Eastern region exhibits a trajectory similar to the national pattern but with attenuated fluctuations. A modest peak occurs near lnIUR - $\mathrm{GI} \approx 9.21$ followed by a decline toward a trough around lnIUR - $\mathrm{GI} \approx 9.8$. This smoother curve reflects the region's advanced innovation base, robust absorptive capacity, and strong policy execution, which collectively accelerate the transition from innovation-driven emission increases to mature emission-reduction effects, yielding a more stable and predictable pattern.

By contrast, the Central region demonstrates pronounced volatility in the marginal effect curve. A local minimum is evident near lnIUR - $\mathrm{GI} \approx .4$ followed by a rapid surge to a prominent peak around lnIUR - $\mathrm{GI} \approx .63$ with continued fluctuations at higher levels. These oscillations highlight the instability of green innovation's decarbonization effect in the region, where evolving industrial restructuring, limited market absorption, and incomplete policy incentives jointly contribute to a more complex and less consistent emission trajectory. These resultssuggest that the Central region requires more time, deeper integration mechanisms, and stronger institutional support to achieve stable and sustained emission reductions.

In the Western region, the curve is steep and highly erratic, reflecting the region's structural vulnerabilities. Carbon emissions initially drop to a local minimum at approximately $\ln IUR - GI \approx 7.5$, surge sharply to a peak near lnIUR - $\mathrm{GI} \approx 8.05$ and oscillate thereafter. This instability underscores the region's weaker technological absorption capacity, underdeveloped industrial foundation, and relatively lower economic level, which together hinder the immediate effectiveness of green innovation in reducing emissions. Only as technological capabilities accumulate and collaborative networks deepen does the potential for sustained decarbonization begin to materialize.

Overall, these results reveal distinct regional heterogeneity in the nonlinear effects of IUR collaborative green innovation on carbon emissions. The Eastern region demonstrates an early and stable decarbonization response, the Central region shows a volatile and transitional dynamic, and the Western region exhibits the greatest uncertainty and sensitivity. These findings underscore the necessity of region-specific policy frameworks: strengthening diffusion and scaling mechanisms in the East, fostering innovation-market integration and policy efficiency in the Central region, and enhancing technological absorption, investment, and institutional support in the West to ensure that green innovation translates into tangible and sustained reductions in carbon emissions.

Technological substitution effect: the role and pathway of green technology replacing traditional high-carbon technology

The technological substitution effect refers to how IUR collaborative green innovation facilitates the transition from high-pollution industries to low-carbon industries by reducing the share of high-pollution industries and promoting industrial upgrading, ultimately achieving carbon emission reduction. This study selects the proportion of high-pollution industries (*lnPHI*) and the industrial structure upgrading index (*lnISU*) as key moderating variables to explore the technological substitution pathways and their nonlinear characteristics under different industrial structures.

The regression results show that IUR collaborative green innovation (lnIUR-GI) is significant in all models (1)-(7), indicating its consistent impact on regional carbon emissions (see Table 5). However, its mechanisms and nonlinear characteristics vary across different industry structures. In the pooled samples (Columns 1,

Table 5 Technology substitution effect

Variable	Proportion of high-pollution industries			Industrial upgrading Index			Comprehensive model
	(1) Full sample	(2) Low high-pollution industry group	(3) High high-pollution industry group	(4) Full sample	(5) Low industrial upgrading group	(6) High industrial upgrading group	(7) Full sample
lnIUR-GI	0.082* (0.049)	1.56*** (0.544)	−0.448*** (0.150)	0.147*** (0.041)	−0.090* (0.051)	0.127* (0.069)	0.313*** (0.114)
(lnIUR-GI)^2	−0.002** (0.001)	−0.112** (0.043)	0.063*** (0.019)	−0.010** (0.004)	0.011** (0.005)	−0.010** (0.004)	−0.020* (0.011)
lnPHI	−0.154 (0.181)	−5.747*** (1.623)	1.908*** (0.640)				−1.030** (0.468)
*lnIUR-GI*lnPHI*	−0.047** (0.018)	1.682*** (0.526)	−0.973*** (0.282)				0.256* (0.151)
*(lnIUR-GI)^2*lnPHI*	0.007*** (0.002)	−0.121*** (0.041)	0.119*** (0.033)				−0.017** (0.008)
lnISU				0.143** (0.059)	4.46*** (0.965)	0.021** (0.009)	−0.389* (0.229)
*lnIUR-GI*lnISU*				−0.078*** (0.029)	−1.580*** (0.350)	−0.033*** (0.011)	−0.173** (0.084)
*(lnIUR-GI)^2*lnISU*				0.009* (0.004)	0.134*** (0.031)	0.006*** (0.001)	0.017** (0.008)
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.45*** (0.716)	−2.185 (2.142)	1.816* (0.951)	2.43*** (0.694)	3.38*** (1.194)	2.27** (0.938)	1.934*** (0.741)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj.R^2	0.972	0.980	0.983	0.971	0.973	0.977	0.976
F	335.38***	249.58***	308.27***	330.02***	182.64***	164.66***	312.44***
Obs	390	195	195	390	195	195	390

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses in columns (1)–(7) represent cluster-robust standard errors

4, and 7), the quadratic term of IUR collaborative green innovation is significantly negative (−0.002, $p<0.05$; −0.010, $p<0.05$; −0.020, $p<0.1$), confirming an inverted U-shaped relationship with carbon emissions. This suggests that in the early stages, increased R&D investment, higher equipment replacement costs, and longer industrial adaptation periods may lead to a temporary increase in carbon emissions. However, as collaboration reaches a certain scale, the technological substitution effect strengthens, driving carbon emissions downward.

Furthermore, the inverted U-shaped pattern varies across different industrial structures. In regions with a lower share of high-pollution industries (Column 2) and regions with higher industrial upgrading levels (Column 6), the quadratic term is significantly negative (−0.112, $p<0.05$; −0.010, $p<0.05$), indicating a stronger inverted U-shaped relationship—higher short-term emission growth but greater long-term reduction. In contrast, in regions with a higher share of high-pollution industries (Column 3) and regions with lower industrial upgrading levels (Column 5), the quadratic term is significantly positive (0.063, $p<0.01$; 0.011, $p<0.05$), suggesting a weaker inverted U-shaped effect or even a U-shaped pattern, where short-term emissions decrease, but long-term emissions may rebound. These findings indicate that the effectiveness of the technological substitution process is highly influenced by industrial structure. In regions with a high share of high-pollution industries, path dependence and high transition costs may prevent IUR collaborative green innovation from achieving significant long-term carbon reduction.

Further analysis of the interaction between IUR collaborative green innovation and the proportion of high-pollution industries reveals that in Columns (1) and (3), the interaction term is significantly negative (−0.047, $p<0.05$; −0.973, $p<0.01$), while the interaction term for the quadratic term is significantly positive (0.007, $p<0.01$; 0.119, $p<0.01$). This indicates that in regions with a high share of high-pollution industries, the inverted U-shaped effect of IUR collaborative green innovation is weaker and may even turn into a U-shaped relationship, where carbon emissions decrease in the short term but rebound in the long run. This could be due to strong path dependence in traditional high-carbon industries, making low-carbon technology substitution more challenging. Additionally, insufficient policy incentives and weak market orientation may suppress the low-carbon transformation effects of IUR collaborative green innovation. Furthermore, the high cost of industrial transformation could lead to short-term emission reductions in some industries, but rising market demand or policy adjustments may eventually cause emissions to rebound.

In contrast, in regions with a lower share of high-pollution industries (Column 2), the interaction term is significantly positive (1.682, $p < 0.01$), while the interaction term for the quadratic term is significantly negative (−0.121, $p < 0.01$). This suggests that in these regions, the inverted U-shaped relationship is more pronounced, meaning that short-term emissions rise more quickly, but long-term emission reductions are greater. This could be attributed to greater acceptance of IUR collaborative green innovation, stronger policy support, and higher marketization, which facilitate faster adoption of low-carbon technologies and more effective emission reduction outcomes.

Similarly, the industrial structure upgrading index also plays a significant moderating role in the technological substitution effect. The results from Columns (4), (5), and (6) show that the interaction term between industrial structure upgrading and IUR collaborative green innovation is significantly positive (0.143, $p < 0.05$; 4.46, $p < 0.01$; 0.021, $p < 0.05$), while the interaction term for the quadratic term is significantly negative (−0.078, $p < 0.01$; −1.580, $p < 0.01$; −0.033, $p < 0.01$). This suggests that industrial structure upgrading enhances the technological substitution effect, making the inverted U-shaped relationship steeper. As industrial upgrading advances, short-term emission increases are more pronounced, but once a critical level of collaboration is reached, carbon emissions decline more rapidly. This result aligns with findings in existing literature. For instance, Zhang et al. [51] highlighted that during industrial upgrading, the expansion of high-end industries increases energy demand, leading to greater short-term carbon emission pressures. Similarly, Cheng et al. [52] demonstrated that as industrial structures evolve, the penetration and efficiency of green technologies significantly improve, enhancing emission reduction effects in the later stages. However, compared to these studies, this research uncovers the interaction mechanism between industrial upgrading and IUR collaborative innovation. It not only captures the nonlinear trajectory of green innovation alone but also emphasizes how industrial upgrading, as a structural moderator, accelerates the process of green technology substitution. This integrated analytical framework —“collaborative innovation—structural upgrading—dynamic evolution of carbon emissions”— enriches the theoretical understanding of how green technological innovation drives low-carbon transformation.

In summary, the technology substitution effect of industry-university-research collaborative green innovation is moderated by the proportion of high-pollution industries and the advancement of industrial structure, exhibiting distinct nonlinear characteristics, thereby validating hypothesis H_2. In regions with concentrated high-pollution industries, the technological substitution process may be strongly influenced by path dependence, while insufficient policy incentives and market orientation could further hinder low-carbon transition. Therefore, governments should enhance green financial support and implement mandatory environmental policies to lower barriers for corporate low-carbon transformation and improve the penetration rate of low-carbon technologies. Concurrently, in areas experiencing rapid industrial structure upgrading, the industry-university-research collaborative green innovation model shouldbe optimized to ensure sustained strong emission reduction effects during mature phases, preventing diminishing marginal returns from collaborations.

Resource optimization allocation effect: how collaboration enhances resource efficiency

The resource optimization allocation effect refers to the process of optimizing capital, technology, and human resource allocation to improve resource utilization efficiency, ultimately reducing carbon emissions. In the context of green and low-carbon transformation, effective resource allocation promotes industrial upgrading, enhances technology absorption capacity, and reduces energy waste. This study introduces green total factor productivity (GTFP) as a mediating variable to measure resource utilization efficiency and examine how IUR collaborative green innovation facilitates knowledge flow, technology diffusion, and resource integration, thereby improving regional GTFP and achieving carbon reduction goals. In this study, the non-radial, non-angular SBM (Slack-Based Measure) model is used to measure GTFP. During the measurement process of GTFP, relevant input and output variables need to be introduced, as detailed in Table 6.

The regression results indicate that the impact of IUR collaborative green innovation on GTFP follows a U-shaped pattern (see Table 7). In the early stages, IUR collaborative green innovation negatively affects GTFP (−0.213, $p < 0.01$), suggesting that resource misallocation, limited enterprise absorption capacity, and high industrial adjustment costs may initially lead to a decline in GTFP. This phenomenon could stem from the adaptation period required for the introduction and application of green technologies, during which enterprises face factor adjustment costs and technical adaptation challenges, preventing an immediate improvement in resource utilization efficiency. However, as collaboration deepens, the coefficient of the quadratic term becomes significantly positive (0.031, $p < 0.01$), indicating that enhanced

Table 6 GTFP indicator system

Primary indicator	Secondary indicator	Description	Data source
Input	Labor	Number of employees at the end of each year for each province	Provincial Statistical Yearbook
	Capital	Capital input measured using the perpetual inventory method, with 2000 as the base year	China Statistical Yearbook
	Energy	Energy consumption (in 10,000 tons of standard coal) for each province	China Energy Statistical Yearbook
Expected output	GDP	Actual GDP for each province, adjusted for 2010 as the base year	Provincial Statistical Yearbook
Non-expected output	Industrial wastewater COD Emissions	COD emissions from industrial wastewater in each province	China Environmental Statistical Yearbook
	industrial SO^2 emissions	SO^2 emissions from industry in each province	China Environmental Statistical Yearbook

Table 7 Resource optimization allocation effect

Variable	lny	lnGTFP	lny
lnIUR-GI	0.253*** (0.088)	−0.213*** (0.067)	0.204** (0.088)
(lnIUR-GI)²	−0.025*** (−0.008)	0.031*** (0.006)	−0.018** (0.008)
lnGTFP			−0.231*** (0.066)
Control Variable	Yes	Yes	Yes
Constant	−8.049*** (0.417)	0.370 (0.319)	−7.963*** (0.411)
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
adj.R²	0.751	0.603	0.759
F	143.70***	74.70***	132.89***
Obs	390	390	390

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses represent cluster-robust standard errors

technology absorption capacity and resource integration effects gradually emerge, leading to a recovery in GTFP. This further confirms the positive role of IUR collaborative green innovation in optimizing resource allocation and improving production efficiency.

Further regression analysis shows that GTFP has a significant negative impact on carbon emissions (−0.231, $p<0.01$), demonstrating that improving resource utilization efficiency effectively reduces carbon emissions. This is likely because higher GTFP encourages the transformation of traditional high-carbon industries into low-carbon industries, enhances energy efficiency, and promotes industrial structure optimization, thereby lowering carbon emission levels. Additionally, the direct impact of IUR collaborative green innovation on carbon emissions is positive (0.204, $p<0.05$), while its quadratic term is significantly negative (−0.018, $p<0.05$). This further supports the inverted U-shaped relationship, where collaboration initially increases emissions, but as cooperation deepens, the emission reduction effect gradually appears and strengthens. Overall, IUR collaborative green innovation enhances GTFP, facilitating resource optimization allocation, which becomes a crucial mechanism affecting carbon emissions.

To further validate whetherthe resource optimization allocation effect serves as a key mechanism through which IUR collaborative green innovation impacts carbon emissions, this study conducts a Bootstrap mediation effect test with 1,000 replications. The results reveal that IUR collaborative green innovation indirectly affects carbon emissions through GTFP, with the mediation effect accounting for 9.57%. This indicates that resource optimization allocation plays a partial mediating role between IUR collaborative green innovation and carbon emissions. However, despite its ability to optimize resource allocation, the carbon reduction effect of IUR collaborative green innovation remains constrained by factors such as enterprise technology absorption capacity, market incentive mechanisms, and policy support, thereby validating Hypothesis H_3. Therefore, relying solely on IUR collaborative green innovation may not maximize carbon reduction benefits. It is essential to implement supporting policies that enhance enterprises' capacity for green technology adoption and resource integration, ensuring a more effective low-carbon transformation.

Spatial spillover effect: the diffusion impact of cross-regional collaboration on emission reduction

Selection and testing of spatial econometric model

Before selecting a spatial econometric model, a series of tests are conducted to ensure the rationality of the model specification and the robustness of estimation results. First, this study examines the spatial correlation of provincial carbon emissions (see Table 8). The Moran's I statistic is positive throughout 2010–2022, with significant Z-values ($p<0.01$), indicating a significant spatial clustering effect in carbon emissions. This suggests that carbon emission levels in neighboring regions influence each other, meaning that regional carbon emissions are not independent but exhibit spatial dependence.

Further LM diagnostic evaluations (see Table 9) reveal that both LM-lag and Robust LM-lag statistics

Table 8 Global correlation of carbon emissions in chinese provinces

year	Moran's I	Z	P-value
2010	0.1634	5.2363	0.0000
2011	0.1678	5.3313	0.0000
2012	0.1700	5.3907	0.0000
2013	0.1799	5.6687	0.0000
2014	0.1835	5.7554	0.0000
2015	0.1872	5.8681	0.0000
2016	0.1920	6.0061	0.0000
2017	0.1980	6.2003	0.0000
2018	0.1943	6.0462	0.0000
2019	0.1943	6.0146	0.0000
2020	0.1908	5.8804	0.0000
2021	0.2024	6.2385	0.0000
2022	0.2054	6.3153	0.0000

Table 9 LM, hausman, wald, and LR statistical tests

Test Method	Statistic/chi2	p-value/Prob > chi2
LM-error	0.703	0.402
Robust LM- error	0.393	0.531
LM- lag	9.272	0.002
Robust LM- lag	8.962	0.003
Hausman	31.81	0.000
Wald- error	36.19	0.000
Wald—lag	37.84	0.000
LR- error	35.18	0.000
LR- lag	36.42	0.000

demonstrate pronounced significance ($p < 0.01$), whereas LM-error and Robust LM-error remain statistically negligible. This compellingly indicates that carbon emissions primarily manifest through spatial lag effects rather than spatial error propagation, thereby validating the application of the Spatial Autoregressive Model (SAR) over the Spatial Error Model (SEM). Moreover, the Hausman test yields decisive significance ($p < 0.01$), conclusively establishing the Fixed Effects (FE) model's statistical superiority relative to the Random Effects (RE) framework. Such findings underscore the existence of inherent, unobservable regional heterogeneity factors-including divergent energy structures, environmental governance strategies, and green finance mechanisms-which collectively reinforce the rationale for employing Fixed Effects modeling. Simultaneously, both the Wald test and Likelihood Ratio (LR) test exhibit robust significance ($p < 0.01$), confirming the spatial econometric model's rigorous specification while emphasizing the indispensability of spatial effect integration. These findings show the limits of using traditional OLS estimation, which can lead to biased results. This study uses a step-by-step approach to choose the Fixed Effects Spatial Autoregressive Model (SAR) to better explain the complex spatial links between IUR collaborative green innovation and regional carbon emissions.

Table 10 Regression results of spatial lag model

Variable	(1) lny	(2) lny
Main		
L.lny		0.757***
		(0.030)
lnIUR-GI	0.112***	−0.044*
	(0.035)	(0.025)
(lnIUR-GI)^2	−0.003	0.008**
	(0.004)	(0.003)
Wx		
L.lny		−20.61***
		(6.026)
lnIUR-GI	0.294***	3.339**
	(0.066)	(1.299)
(lnIUR-GI)^2	−0.0224***	−0.222***
	(0.007)	(0.070)
Control variable	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
Spatial rho	0.0739***	3.546***
	(0.009)	(0.869)
Variance sigma2_e	0.0132***	0.00450***
	(0.001)	(0.001)
r2	0.373	0.845
Obs	390	360

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses in columns (1)–(2) represent cluster-robust standard errors

To capture the spatial autocorrelation effect between regions, the inverse distance matrix was chosen as the spatial weight matrix. The inverse distance matrix effectively quantifies the mutual influence between geographically proximate regions, particularly suitable for research areas with spatial spillover effects such as technology diffusion and green innovation. By weighting the geographic distance, the inverse distance matrix reflects the strong interaction between neighboring regions, aligning with the reality of technology spillovers and spatial cooperation [28, 53].

The spatial impact of IUR collaborative green innovation on carbon emissions

This study uses the Spatial Autoregressive Model (SAR) to closely examine how IUR collaborative green innovation affects carbon emissions in different regions over time (see Table 10). Model (1) shows a clear positive link between IUR collaborative green innovation (*lnIUR-GI*) and carbon emissions (0.112, $p < 0.01$). This means that in the early stages, more collaboration can lead to higher emissions. This may happen because of higher R&D costs, the pressure of changing industrial structures, and slow use of green technologies in the market. This short-term increase reflects common problems seen during green transitions, where new sustainable technologies

Table 11 Decomposition of spatial effects

Variable	Short-term effect			Long-term effect		
	Direct	Indirect	Total	Direct	Indirect	Total
lnIUR-GI	−0.0468**	−0.1210	−0.1678*	0.0184***	0.0475	0.0659**
	(0.021)	(0.095)	(0.097)	(0.006)	(0.037)	(0.026)
(lnIUR-GI)²	0.0079***	0.0086	0.0166*	−0.0031***	−0.0034	−0.0065*
	(0.003)	(0.008)	(0.009)	(0.001)	(0.003)	(0.004)

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses represent cluster-robust standard errors

need a lot of energy and adjustments before they start helping the environment.

In the dynamic spatial lag regression (Model 2), adding time lag effects shows a clear change. The coefficient for IUR-GI goes from positive to negative (−0.044, $p<0.1$). At the same time, the squared term (*lnIUR-GI*^{2}) stays strongly positive (0.008, $p<0.05$). This nonlinear dynamic unveils a U-shaped trajectory in how IUR collaborative green innovation influences carbon emissions. During early-stage implementation, such innovation drives substantial low-carbon technology adoption and emission reductions, yet as collaborations intensify, diminishing returns emerge. Potential drivers of this phenomenon include technological marginal utility decline, heterogeneous enterprise absorption capacities, uneven policy implementation, and geographically divergent diffusion rates of green innovation.

Notably, Model (2)'s spatial lag variable (L.ly) exhibits pronounced temporal persistence (0.757, $p<0.01$), demonstrating carbon emissions' self-reinforcing temporal inertia—prior-period emissions exert enduring influence on current levels. This empirical validation of carbon emission path dependence carries critical policy implications. The findings underscore the necessity for dynamic, forward-looking regulatory frameworks that account for intertemporal carbon lock-in effects. Strategic optimization of innovation incentive mechanisms emerges as pivotal for sustaining the decarbonization potential of IUR collaborations across their developmental lifecycle.

The spatial spillover effects of IUR collaborative green innovation stand out prominently, with Wx.lnIUR-GI demonstrating robust positive significance across both models (0.294, $p<0.01$; 3.339, $p<0.05$). This compellingly demonstrates that neighboring regions' IUR-driven green innovation exerts a tangible dampening effect on local carbon emissions, vividly illustrating the vigorous cross-regional diffusion mechanism of green technologies. Crucially, the data reveals that collaborative green innovation achievements transcendgeographical boundaries, amplifying the radiating benefits of emission mitigation. Moreover, Wx.lnIUR-GI^2 manifests a striking negative coefficient (−0.0224, $p<0.01$; −0.222, $p<0.01$), signaling that advancing IUR collaboration intensifies its transregional decarbonization impact—a testament to the snowballing prominence of technology sharing and demonstration effects that propel more extensive decarbonization initiatives. The significantly positive spatial autocorrelation coefficient (rho) further validates carbon emissions' inherent interdependence across territories, rendering isolated regional efforts insufficient to meet overarching emission reduction targets. These compelling findings robustly validate Hypothesis H_4. Such groundbreaking insights cry out for paradigm-shattering policy frameworks: low-carbon strategies must imperatively prioritize cross-jurisdictional symbiosis to combat insidious emission displacement while supercharging the dissemination of IUR innovation. Ultimately, only through forging unshakable regional coalitions and harnessing synergistic knowledge spillovers can collaborative green innovation truly unleash its transformative potential to orchestrate large-scale, sustainable carbon neutrality transitions.

Decomposing spatial effects: short-term dynamics and long-term evolution

The decomposition of spatial effects systematically reveals the spatiotemporal impact mechanisms of industry-university-research (IUR) collaborative green innovation on carbon emissions. By disaggregating the impact into direct effects, indirect effects (spatial spillover effects), and total effects, this study precisely captures the dual-dimensional differences in the spatial transmission pathways and dynamic evolution patterns of IUR collaborative green innovation (see Table 11).

(1) Short-Term Effects: Direct Dominance.

Empirical results demonstrate that the direct effect of IUR-GI (*lnIUR-GI*) is significantly negative (−0.0468, $p<0.05$), confirming its immediate effectiveness in curbing local carbon emissions. Notably, the quadratic term coefficient (*lnIUR-GI*^{2}) exhibits a significant positive value (0.0079, $p<0.01$), revealing a U-shaped dynamic characteristic of short-term emission reduction effects—where emission reduction efficiency displays marginal diminishing returns after innovation levels surpass a critical threshold. In spatial spillover dimensions, the indirect effect of lnIUR-GI shows negative but statistically insignificant values, suggesting pronounced spatial time-lag effects in green technology diffusion. The non-significance of its quadratic term further corroborates insufficient development of cross-regional collaborative emission reduction mechanisms in the short term. The short-term total effect reaches −0.1678 (significant at 10% level), while its quadratic term remains positive (0.0166, $p < 0.1$), reaffirming the U-shaped impact pattern of green innovation characterized by a "rapid effectiveness-efficacy attenuation" trajectory.

(2) Long-Term Effects: Paradoxical Reversals.

Under long-term perspective, the direct effect of IUR-GI undergoes significant reversal (0.0184, $p < 0.01$), reflecting energy rebound effects and technological conversion lags during industrial upgrading. However, the significantly negative moderating effect of the quadratic term (−0.0031, $p < 0.01$) delineates an emission reduction inflection point after cumulative innovation surpasses critical thresholds, forming a typical inverted U-shaped evolutionary trajectory. Spatial spillover analysis shows non-significant positive indirect effects (0.0475) combined with the inverted U-shaped trend of quadratic terms (−0.0034), collectively unveiling the long-term transition from "competition effects" to "synergistic effects" in technology diffusion. The statistical significance of total effect (0.0659, $p < 0.05$) and its quadratic term (−0.0065, $p < 0.1$) systematically constructs a three-phase development model of IUR-GI: "initial adjustment-costs—mid-term equilibrium—long-term optimization".

This study reveals that the carbon reduction effects of IUR-GI exhibit significant spatiotemporal regulation characteristics. In the short term, the mechanism follows a "localized rapid response–spatial spillover hysteresis" pattern, while in the long term, the evolution demonstrates a governance trajectory of "global optimization–spatial synergy." This dynamic shift from a U-shaped to an inverted U-shaped pattern aligns with the Environmental Kuznets Curve framework, highlighting notable "temporal window effects" and "spatial threshold effects." Although existing studies emphasize the spatial spillovers of green innovation and the importance of regional collaboration, they largely analyze spatial and temporal effects in isolation. In contrast, this study integrates the temporal dynamics and spatial heterogeneity of IUR-GI into a unified analytical framework, illustrating that localized, policy-driven mechanisms dominate in the short term, whereas cross-regional technological symbiosis and collaborative innovation ecosystems are essential for achieving sustained long-term carbon neutrality.

Conclusion and recommendations

Conclusion

This study explores how IUR collaborative green innovation affects regional carbon emissions in a non-linear way. The findings show that IUR collaborative green innovation follows a striking inverted U-shaped curve in influencing carbon emissions. In the early stages, higher R&D costs and the need to adjust industries may cause emissions to go up. As cooperation becomes stronger, shared technology and better industry systems help lower emissions.

Furthermore, the effect of IUR collaborative green innovation on cutting emissions is very different across regions. Eastern regions show steady results with strong carbon reduction, while Central regions show more changes over time, reflecting transitional industrial upgrading phases that make emission control unstable. Western regions face the highest level of uncertainty, where IUR collaboration struggles to achieve stable short-term reductions due to weak infrastructure and unstable markets.

The technological substitution effect of IUR collaboration emerges as an important factor, curbing high-pollution industry dominance and accelerating industrial modernization to achieve emission cuts. But in areas with many polluting industries and strong past habits, new technologies are harder to use. This can cause short-term increases in emissions. Simultaneously, IUR collaborative green innovation improves green total factor productivity (GTFP) to optimize resource allocation, thereby reducing carbon emissions to a certain extent, with a mediation effect of 9.57%. However, this emission reduction effect is phased and nonlinear.

The study also finds that carbon emissions' robust spatial interdependence. IUR collaboration not only reshapes local emission profiles but also propagates spillover effects across neighboring regions, underscoring the vital importance of cross-regional coordination in green innovation networks. In addition, IUR collaborative green innovation shows clear spatiotemporal differences in carbon reduction. In the short term, it works through local effects. In the long term, it follows an inverted U-shaped path with emission rebound first, then steady decline, and shifts from competition to cooperation across regions.

Recommendations

1. Establish a Joint Innovation Platform

Rely on leading enterprises, universities, and research institutes to build industrial joint laboratories or collaborative innovation centers, focusing on key areas such as green process optimization, energy-saving equipment upgrades, and carbon capture, utilization, and storage (CCUS). Form a closed-loop mechanism of "enterprise demand–research collaboration–pilot testing–technology transfer." Through resource sharing and dynamic management, accelerate the transformation and demonstration of R&D outcomes, and combine green funds, financial instruments, and policy support to match funding with industrial demand, thereby expediting the diffusion and market application of green technologies.

2. Improve Industry–Academia–Research Collaboration Mechanisms and Implement a "Researchers in Enterprises" Program

Strengthen mechanisms for collaboration among industry, universities, and research institutes while systematically promoting the "Researchers in Enterprises" initiative. Use digital platforms to achieve precise matching between research outcomes and enterprise needs; adopt multiple cooperation models such as secondments, short-term placements, and joint research to integrate researchers into corporate R&D and production processes, thereby aligning technical solutions with industrial practice. At the same time, refine incentive mechanisms, such as revenue sharing, promotion bonuses, and project priority support, to encourage researcher participation. Establish a results transfer service center providing integrated technical evaluation, IP protection, and financing support, and adopt performance indicators like technology transfer rate, economic returns, and carbon reduction outcomes to drive efficient commercialization.

3. Strengthen Green Financial Support

Build a multi-tiered and targeted green financial support system, integrating policy guidance, market incentives, and innovation platforms. In central regions, leverage the experience of the Yangtze River Delta Green Finance Pilot Zone by introducing tools such as green bills and green supply chain financing to support collaborative innovation projects, expediting the transformation of outcomes in energy storage retrofits, waste heat recovery, and green industrial upgrades. In western regions, adopt the "Green Finance + Technology Transfer" model of the Guangdong–Hong Kong–Macao Greater Bay Area, using financial innovations to channel capital and technology from the east to accelerate project implementation. At the financial instrument level, promote green patent pledge financing and sustainability-linked loans (SLL), and issue green or special-purpose bonds to lower the financing costs for enterprises. Leverage regionalgreen technology transfer centers and joint engineering centers to integrate research, industry, and capital resources, accelerating technology diffusion. Establish green project databases and dynamic performance evaluation mechanisms to ensure accurate and efficient capital allocation and promote the wide deployment and sustainable diffusion of innovation outcomes.

4. Accelerate the Transition of High-Pollution Industries

Develop differentiated roadmaps for industrial transformation, setting phased carbon intensity targets and annual reduction goals for high-emission industries such as steel, chemicals, cement, and electricity. Dynamically adjust energy efficiency benchmarks and emission caps based on technological advancements and performance, driving continuous upgrades in processes and equipment. Simultaneously, intensify R&D and promotion of green technologies by establishing "green process improvement demonstration projects," prioritizing areas such as blast furnace gas recycling, low-carbon cement alternatives, CCUS technologies, and intelligent energy management systems. Build industry-wide green technology databases and sharing platforms to publish assessments of technological maturity, applicability, and cost-effectiveness, helping enterprises choose optimal solutions and thereby enhancing transition efficiency and accelerating the shift toward green and low-carbon industrial structures.

Limitations

This study has several limitations. First, despite using provincial panel data from 2010 to 2022, the analysis may not fully capture micro-level heterogeneity at the city or enterprise level, which could provide deeper insights into collaboration dynamics. Second, while the nonlinear models and spatial econometric techniques enhance robustness, potential omitted variables and measurement errors-especially in proxies for collaborative green innovation and carbon emissions-may bias the results. Third, the study focuses on provincial-level interactions, and cross-border innovation linkages or international spillover effects are not examined. Future research could incorporate finer-grained datasets and extended modeling approaches to address these gaps and strengthen the generalizability of the findings.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13021-025-00329-w.

Additional file1

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethical approval and consent to participate
This study did not involve human participants or animals, so ethical approval was not required.

Consent to participate
This study did not involve human participants, so consent was not applicable.

Disclaimer
The views expressed in this article are those of the authors.

Competing interests
The authors declare no competing interests.

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