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How green innovation shapes the low-carbon transition of the energy structure

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Abstract

Guided by the national “dual carbon” goals, green innovation has become a critical driver of the low-carbon transformation of energy systems. This study employs provincial panel data from China covering the period 2011–2022 and adopts a two-way fixed effects model for regression analysis. It further incorporates mediation effects, moderation effects, and quantile regression methods to examine how green innovation influences the low-carbon transformation of the energy structure. The results show that green innovation significantly promotes the optimization of the energy structure, and its effects vary notably across different levels of decarbonization, industrial structures, policy environments, and regional development conditions.

Keywords: low-carbon transformation of the energy structure; green innovation; industrial upgrading; governmental environmental attention

JEL Classification: O33, Q48, Q55, Q58

1. Introduction

Amidst the accelerating shift toward green and low-carbon energy governance globally, green innovation has become central to facilitating the transition from high-carbon to low- or zero-carbon energy systems (Liu *et al.*, 2024). Unlike traditional aggregate emission reduction approaches, green technologies enable systemic innovation across the entire energy production, conversion, and consumption chain, effectively enhancing the efficiency

and substitution share of clean energy. For example, Denmark has significantly increased the proportion of renewable energy in its consumption mix through its wind technology cluster, while Germany has achieved strong synergy between policy and innovation via its *Energiewende* strategy. However, the journey from green technology innovation to actual energy transition remains constrained by multiple factors, including industrial structure, institutional environment, and regional foundational conditions. Therefore, clarifying the mechanisms and contextual conditions through which green innovation drives the low-carbon transformation of energy structure has become a critical issue in green development economics research.

Green innovation's impact on the low-carbon energy transition has attracted significant attention in academia and policy. Existing research has focused mainly on its effects on overall environmental performance (Opazo-Basáez *et al.*, 2024), eco-efficiency (Liu *et al.*, 2020), and sustainable development (J. M. Li *et al.*, 2022), laying a preliminary theoretical and empirical foundation. From a technological pathway perspective, green technologies effectively reduce the reliance on high-carbon energy sources per unit of output by enhancing energy efficiency and promoting the development and application of alternative energy (Ahmed *et al.*, 2022; Z. Y. Zhao *et al.*, 2024). From a technological substitution perspective, promoting clean energy, energy-saving equipment, and digital efficiency systems reduces reliance on fossil fuels like coal and oil, thereby increasing the share of renewables and ultimately enabling a profound transformation of the energy system (Ramzan *et al.*, 2023; Wu and Kung, 2020). However, significant gaps remain in the current literature regarding the specific mechanisms and contextual conditions through which green innovation drives energy transition. While it is increasingly recognized that the practical implementation of green technologies is heavily constrained by institutional frameworks and industrial structures, research on the underlying mechanisms remains underdeveloped. For instance, Xu *et al.* (2023) emphasize the critical role of synergy between green innovation and environmental policies in achieving net-zero emissions, yet such studies predominantly operate at national levels, lacking in-depth analysis of local governments' environmental attention and their heterogeneous governance effects. Although Y. Zhang *et al.* (2025) highlight the potential of green technologies to optimize industrial structure and generate dual economic and environmental benefits, they fall short of systematically elucidating how this upgrading of industrial structure serves as a mediating pathway influencing energy consumption patterns. Furthermore, despite empirical evidence from countries such as Denmark and Germany underscoring the importance of institution-technology synergy in decarbonizing energy systems, existing research offers limited insight into the effects of contextual factors such as regional development foundations, openness, and digital infrastructure. This gap hinders the expla-

nation of significant regional heterogeneities in the diffusion outcomes of green technologies (J. Li *et al.*, 2022). To bridge this gap, this study employs Chinese provincial panel data to investigate the pathways through which green innovation facilitates the low-carbon transformation of the energy structure: industrial upgrading and governmental environmental attention. This approach aims to uncover the multidimensional mechanisms and contextual heterogeneity underlying this relationship, thereby providing theoretical insights and empirical evidence to inform relevant policy formulation.

The results indicate a positive association between green innovation and the low-carbon transition of the energy consumption structure, which is contingent on the regional low-carbon development level, revealing a pattern of low-carbon foundation dependency. Further mechanistic tests reveal that green technologies indirectly optimize the energy structure by driving industrial upgrading—specifically, the shift toward low-carbon, high-value-added industries. Government environmental attention plays a positive moderating role, enhancing the transformation efficiency of green technologies through strengthened policy support and resource allocation. Moreover, the low-carbon effects of green technologies are more pronounced in regions with higher levels of openness and digital economic development, suggesting that favorable institutional and technological environments can amplify their structural impact.

This study makes three primary contributions: First, it proposes and validates the mediating pathway of “green innovation – structural upgrading – energy transition,” enriching the theoretical mechanisms of green innovation. Second, it reveals the moderating effect of policy environments on green technology transformation, expanding the research perspective on institutional empowerment. Third, by employing quantile regression and heterogeneity analysis, it deeply identifies regional disparities and distributional characteristics of green technology effects, advancing empirical methodologies in energy economics.

2. Theoretical Framework and Hypothesis Development

Green innovation serves as a core driver for the decarbonization of energy systems by reshaping the technological boundaries of energy production and consumption. Traditional endogenous growth theory (Aghion and Howitt, 1992) emphasizes that knowledge accumulation and technological progress are endogenous sources of sustained economic growth. Building on this, Yang *et al.* (2023) further argue that green technology RandD can effectively break the lock-in effects of conventional high-carbon energy technologies through knowledge spillovers, thereby reducing the marginal cost of clean energy adoption. Specifically, breakthroughs in renewable energy technologies, carbon capture and storage, and

similar innovations directly enhance the supply efficiency of low-carbon energy. Meanwhile, advancements in smart grids and energy storage technologies improve the flexibility and stability of energy systems, which in turn reduces the market share of high-carbon energy via substitution effects (Pilatin *et al.*, 2025). However, endogenous growth theory has certain limitations in explaining the diffusion of green technologies, as it often underestimates the influence of institutional, behavioral, and social factors on technological pathways. To address these limitations, this paper introduces a perspective from evolutionary economics, emphasizing that green innovation constitutes an evolutionary process shaped by cumulative dynamics, path dependency, and selective environments. Its diffusion outcomes are co-determined by existing technological regimes, market structures, and institutional conditions (Wen *et al.*, 2023).

Through its reshaping of factor allocation, green innovation not only directly drives the energy structure's low-carbon transition but also spurs the industrial system's advancement toward higher-end, cleaner production. According to industrial structure theory, technological revolutions guide the transfer of capital and labor from energy-intensive industries to low-carbon sectors by altering factor allocation and comparative advantages (Ma *et al.*, 2009). Green technologies have given rise to emerging industries such as new energy equipment manufacturing and energy conservation and environmental protection, while also enhancing the energy efficiency of traditional industries through digital and intelligent upgrades – thereby advancing the transition to a lighter and higher value-added industrial structure. Furthermore, industrial structure upgrading enhances the market compatibility of clean energy through a demand-pull mechanism (Xia *et al.*, 2024). For instance, the high requirements for power quality and reliability in high-end manufacturing drive investment in smart grids, creating a synergistic evolution among technological advancement, industrial upgrading, and energy transition.

The institutional environment plays a pivotal role in shaping the realization of effects from green innovation. According to institutional theory, the stringency and consistency of government environmental policies directly influence the direction and pace of corporate technological innovation (Yuan *et al.*, 2025). When the intensity of environmental regulations aligns with heightened governmental attention, a stronger compensatory effect for innovation emerges, incentivizing firms to increase green RandD investment to mitigate policy risks and capture first-mover advantages. Through stable policy expectations, public procurement, and infrastructure support, governments can effectively reduce uncertainties in the industrialization of green technologies, thereby accelerating the transformation and application of technological achievements (Wang and Wei, 2020; Q. Y. Zhao *et al.*, 2024).

Moreover, the interaction between governmental environmental targets and public discourse can enhance the legitimacy of green innovation, forming a dynamic mechanism between policy guidance and market response.

In summary, this study constructs an integrated theoretical framework incorporating technological innovation, industrial structure, and institutional environment. It emphasizes that green innovation drives the low-carbon energy transition through dual pathways – direct technological substitution and indirect industrial structure upgrading – with government environmental attention serving as a key moderating factor. Based on the above theoretical analysis, the following hypotheses are proposed:

H₁: Green innovation exerts a positive influence on the transformation of the energy structure toward lower carbon intensity.

H₂: Green innovation indirectly promotes the low-carbon transformation of the energy structure by driving industrial upgrading.

H₃: Governmental environmental attention enhances the positive effect of green innovation on the low-carbon transformation of the energy structure.

3. Research Methodology

3.1 Variable measurement

Dependent variables. The low-carbon transformation of the energy structure (*Gec*) describes the gradual shift in the energy mix, characterized by a rising share of clean energy and a corresponding decline in reliance on traditional high-carbon sources. It reflects the overall trend of the energy system evolving toward a greener and more low-carbon trajectory. Following the methodology of Tao *et al.* (2024), the construction of the *Gec* index proceeds as follows: To begin with, energy consumption is classified into three distinct categories: coal, oil and gas, and other clean energy sources. For each province *i* and year *t*, the consumption share of each category is calculated, forming a three-dimensional vector: $E_t = (e_t^1, e_t^2, e_t^3)$. The second stage involves calculating the angle between each observation's energy composition vector and a standard vector arranged in order from carbon-intensive to clean energy types: $E_0^1 = (1,0,0)$, $E_0^2 = (0,1,0)$, $E_0^3 = (0,0,1)$. The angle is calculated using the following formula:

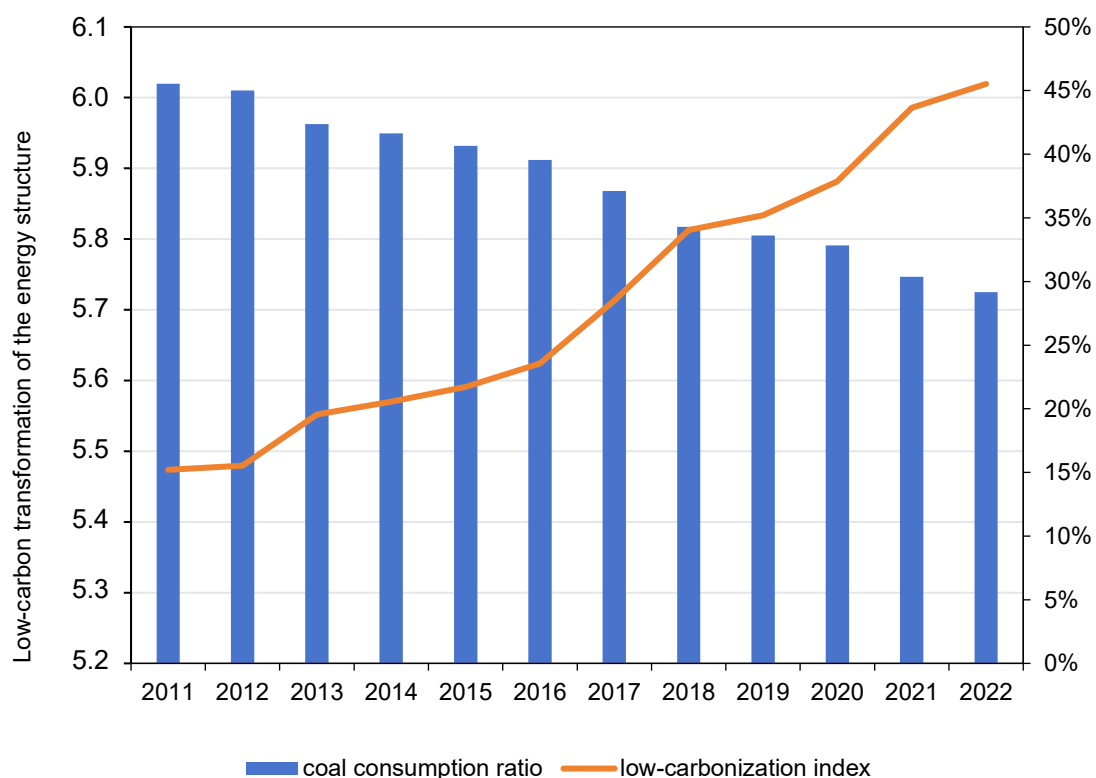
$$\theta_t^j = \arccos \left(\frac{\sum_{k=1}^3 (e_t^k \times e_0^k)}{(\sum_{k=1}^3 (e_t^k)^2 \times \sum_{k=1}^3 (e_0^k)^2)^{1/2}} \right), j = 1, 2, 3 \quad (1)$$

Finally, the three angles are aggregated through a weighted sum to derive the low-carbon energy consumption index for year t , denoted as Gec_t :

$$Gec_t = \sum_{s=1}^3 \sum_{t=1}^s \theta_t^j \quad (2)$$

A higher value of the Gec index indicates that the energy structure is closer to a clean-energy-dominated, low-carbon state. This study also employs an alternative proxy – $Gec1$, measured as the proportion of coal consumption in total energy use. A lower value of $Gec1$ reflects reduced dependence on high-carbon energy and thus a more effective low-carbon transition. Figure 1 illustrates the temporal evolution of the national average coal consumption share and the Gec index from 2011 to 2022. The significant negative correlation between the two indicates that the Gec index effectively captures the progression of low-carbon transition in the energy consumption structure, providing intuitive evidence for its validity as the explained variable.

Figure 1: Level of low-carbon transition in energy consumption structure



Source: Authors' own elaboration

Independent variables. Green innovation (*GT*) is measured by the ratio of the number of green patent applications to the total population in each province and year, capturing the intensity and diffusion potential of *GT* activities (Xie *et al.*, 2025; J. X. Zhang *et al.*, 2025). For robustness checks, green total factor productivity (*GT1*) is adopted as a supplementary indicator. This metric is estimated by applying the super-efficiency SBM directional distance function combined with the Malmquist-Luenberger (ML) index. The model incorporates three inputs—capital stock, labor force, and energy consumption. The desirable output is regional gross domestic product (GDP), with undesirable outputs comprising emissions of industrial wastewater, sulfur dioxide, and industrial solid waste.

Mediating variable. Following the approach of Shen and Ren (2023) and Xia *et al.* (2024), industrial upgrading (*Ris*) is defined as the reciprocal of the industrial structural deviation index (*SR*), *i.e.*, $Ris = 1/SR$, which reflects the degree of balance in factor allocation and the coordination of industrial development. The structural deviation index is calculated as follows:

$$SR = \sum_{l=1}^n \left(\frac{Y_l}{Y} \right) \left| \frac{Y_l/Y}{L_l/L} - 1 \right| \quad (3)$$

Where Y_l denotes the output value of industry l , Y is the total output of the three main industries, L_l represents the employment in industry l , and L is the total employment across the three industries. A higher value of *Ris* indicates a more rational industrial structure and a resource allocation closer to the Pareto optimal state.

Moderating variable. Following the study by Leiter *et al.* (2011), governmental environmental attention (*ER*) is measured by the ratio of environmental protection expenditure to total local government expenditure. This indicator reflects the degree of policy prioritization and resource allocation intensity dedicated to ecological and environmental governance. A higher value of *ER* indicates a stronger governmental commitment to environmental regulation through fiscal instruments.

To control for other potential factors that may influence *Gec*, this study incorporates the following control variables, drawing on Radulescu *et al.* (2024): human capital (*Edu*), social consumption level (*Consum*), artificial intelligence development (*AI*), urban–rural income gap (*Gap*), degree of government intervention (*Gov*), urbanization level (*Urb*), government fiscal self-sufficiency (*Govself*), and informatization level (*IT*). The specific definitions and explanations of the variables are outlined in Appendix, Table A1.

3.2 Empirical model

To systematically examine the impact of green innovation on the low-carbon transition of energy consumption structure and its underlying mechanisms, this study establishes a benchmark regression model, a mediation effect model, a moderation effect model, and a quantile regression model. These models are designed to comprehensively investigate the direct effects, transmission mechanisms, boundary conditions, and heterogeneous characteristics of this relationship. The benchmark regression model is employed to test the direct impact of green innovation on the low-carbon transition of energy consumption structure, with its basic form specified as follows:

$$Gec_{it} = \alpha_0 + \alpha_1 GT_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (4)$$

where i and t denote province and year. Gec_{it} is the dependent variable representing the low-carbon transformation of the energy structure, and GT_{it} is the independent variable representing green innovation. Z_{it} denotes a vector of control variables at the provincial level. ε_i and μ_t represent province and year fixed effects, respectively, and ϵ_{it} is the error term.

To examine the mediating role of industrial structure upgrading, the following mediation effect models are established:

$$Ris_{it} = \theta_0 + \theta_1 GT_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (5)$$

$$Gec_{it} = \theta_0 + \theta_1 GT_{it} + \theta_2 Ris_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (6)$$

Where Ris_{it} is the mediating variable capturing industrial upgrading. Models (5) and (6) employ a regression-based approach to effectively identify the transmission mechanism through which green innovation affects the low-carbon transition of energy consumption structure via industrial structure upgrading.

To further investigate the moderating effect of government environmental attention, an interaction term is introduced into the baseline model:

$$Gec_{it} = \beta_0 + \beta_1 GT_{it} + \beta_2 ER_{it} + \beta_3 GT_{it} \times ER_{it} + \sum_{i=1}^n \omega_i Z_{it} + \varepsilon_i + \mu_t + \epsilon_{it} \quad (7)$$

Where ER_{it} is the moderating variable reflecting governmental environmental attention. $GT_{it} \times ER_{it}$ represents the interaction term between green innovation and governmental environmental attention. Model (7) tests the moderating role of government environmental attention by including an interaction term with green innovation, assessing its influence on the energy consumption structure's low-carbon transition.

Finally, to explore the heterogeneous effects of green innovation, a quantile regression model is constructed:

$$Q_{\tau}(Gec_{it}) = \gamma_0(\tau) + \gamma_1(\tau)GT_{it} + \sum_{i=1}^n \omega_i(\tau)Z_{it} + \varepsilon_i + \mu_t \quad (8)$$

where $Q_{\tau}(Gec_{it})$ denotes the conditional quantile of the low-carbon transition level of energy consumption structure at the τ quantile. Model (8) addresses the limitation of traditional OLS estimation, which is driven by mean values and may obscure heterogeneity within the sample, thereby revealing heterogeneous characteristics at different points of the conditional distribution.

3.3 Data sources

The analysis draws on a balanced panel of 30 Chinese provincial-level administrations (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2011 to 2022. Primary data sources include the *China Statistical Yearbook*, the *China Energy Statistical Yearbook*, and the National Intellectual Property Administration, supplemented by the EPS database, and provincial statistical yearbooks. For partially missing data, linear interpolation combined with historical trends was applied to ensure completeness, resulting in a final sample of 360 observations to guarantee the representativeness and robustness of the analysis.

4. Empirical Analysis

4.1 Descriptive statistics

According to Table 1, the dependent variable *Gec* exhibits a mean and median in close proximity, which implies an approximately normal distribution in the degree of provincial low-carbon transformation. However, the large spread between the extreme values, along with a relatively high standard deviation, points to pronounced disparities in low-carbon transformation among provinces: while some provinces exhibit significantly higher levels of decarbonization than the national average, others are lagging behind in their transition efforts. The distribution of the core independent variable *GT* is notably right-skewed, with a mean far below the maximum value and a relatively high standard deviation. This pattern reflects the spatial concentration of green technological RandD, where a small number of innovation-intensive provinces dominate the national supply of green technologies, while the majority of regions remain at a relatively low level of innovation activity. In summary, the spatial polarization of *GT* coexists with regional heterogeneity in *Gec*.

Table 1: Descriptive statistics of variables

Variable name	Obs	Mean	SD	Min	Median	Max
<i>Gec</i>	360	5.7114	0.4093	5.0412	5.6456	7.1455
<i>Gec1</i>	360	0.3769	0.1502	0.0042	0.3895	0.6921
<i>GT</i>	360	1.5345	2.0820	0.0475	0.8552	14.6021
<i>GT1</i>	360	0.9391	1.2472	0.0335	0.5125	8.8502
<i>Ris</i>	360	1.1994	0.1414	1.0075	1.1690	1.5990
<i>ER</i>	360	0.0291	0.0095	0.0106	0.0275	0.0681
<i>Edu</i>	360	0.0210	0.0058	0.0080	0.0205	0.0436
<i>Consum</i>	360	0.3917	0.0655	0.1796	0.3958	0.6101
<i>AI</i>	360	6.3970	1.8243	1.0986	6.6066	10.3094
<i>Gap</i>	360	2.5468	0.3789	1.8266	2.4884	3.6716
<i>Gov</i>	360	0.2590	0.1115	0.1050	0.2313	0.7583
<i>Urb</i>	360	0.6012	0.1206	0.3503	0.5875	0.8960
<i>Govself</i>	360	0.4913	0.1879	0.1514	0.4492	0.9314
<i>IT</i>	360	0.2412	0.1132	0.0524	0.2263	0.5228

Source: Authors' own calculations

4.2 Regression results

Table 2 displays the primary regression findings that evaluate how *GT* influences *Gec*. Specifically, column (1) presents a significantly positive coefficient for *GT* in the absence of control variables, offering initial evidence that *GT* directly promotes energy decarbonization. Column (2) introduces socioeconomic background factors such as human capital and social consumption level as control variables. Although the coefficient of *GT* slightly decreases in magnitude, its significance remains robust, indicating that the effect of *GT* on energy structure decarbonization is not confounded by these socioeconomic conditions. In column (3), after further controlling for province and year fixed effects, the coefficient of *GT* remains significantly positive and stable, suggesting that the impact of *GT* is independent of regional heterogeneity and macroeconomic cycle characteristics. Taken together, the baseline re-

gression results provide robust empirical support for H_1 , confirming that GT significantly promotes Gec .

Table 2: Baseline regression results

	(1) Gec	(2) Gec	(3) Gec
GT	0.1282*** (14.5841)	0.0738*** (9.2058)	0.0394*** (4.4259)
Edu		−14.1625*** (−6.3649)	17.3917** (2.5491)
Consum		−0.6249*** (−10.0919)	−0.3028*** (−3.9133)
AI		0.0080 (0.3974)	−0.0687*** (−4.2480)
Gap		−0.2052*** (−9.4599)	0.2749*** (2.8335)
Gov		1.5920*** (6.4381)	0.2769 (1.3601)
Urb		−0.2356 (−0.9335)	1.2971*** (5.6256)
Govself		0.9107*** (8.9124)	0.3471** (2.2649)
IT		1.7363*** (14.2253)	−0.7522*** (−2.9426)
_cons	5.5147*** (133.6422)	5.4743*** (70.9785)	4.3033*** (10.6959)
Id FE	No	No	Yes
Year FE	No	No	Yes
N	360	360	360
adj. R^2	0.4235	0.6614	0.9373

Note: ***, ** and * note significance at less than 1%, 5% and 10% levels, respectively. Values in () are t -values.

Source: Authors' own calculations

4.3 Mechanism tests

Table 3 presents the results of the mediation effect analysis concerning industrial upgrading. The findings indicate that *GT* indirectly promotes *Gec* by facilitating *Ris*. Specifically, *GT* is shown to significantly enhance *Ris*, confirming its critical role in optimizing industrial structure. When *Ris* is included in the regression model, the direct effect of *GT* on *Gec* decreases but remains statistically significant. This implies that industrial upgrading plays an intermediary role, partially channeling the influence of *GT* on *Gec*, thereby validating H_2 . The results of the Sobel test further confirm the statistical significance of this mediating pathway.

Table 3: Mediation effect results

	(1) <i>Ris</i>	(2) <i>Gec</i>
<i>GT</i>	0.0107*** (3.9983)	0.0315*** (3.4040)
<i>Ris</i>		0.7337*** (4.1257)
_cons	0.5935*** (3.8824)	3.8678*** (8.2983)
Controls	Yes	Yes
Id FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	360	360
adj. R^2	0.9223	0.9421
Sobel test statistic	2.8712***	

Source: Authors' own calculations

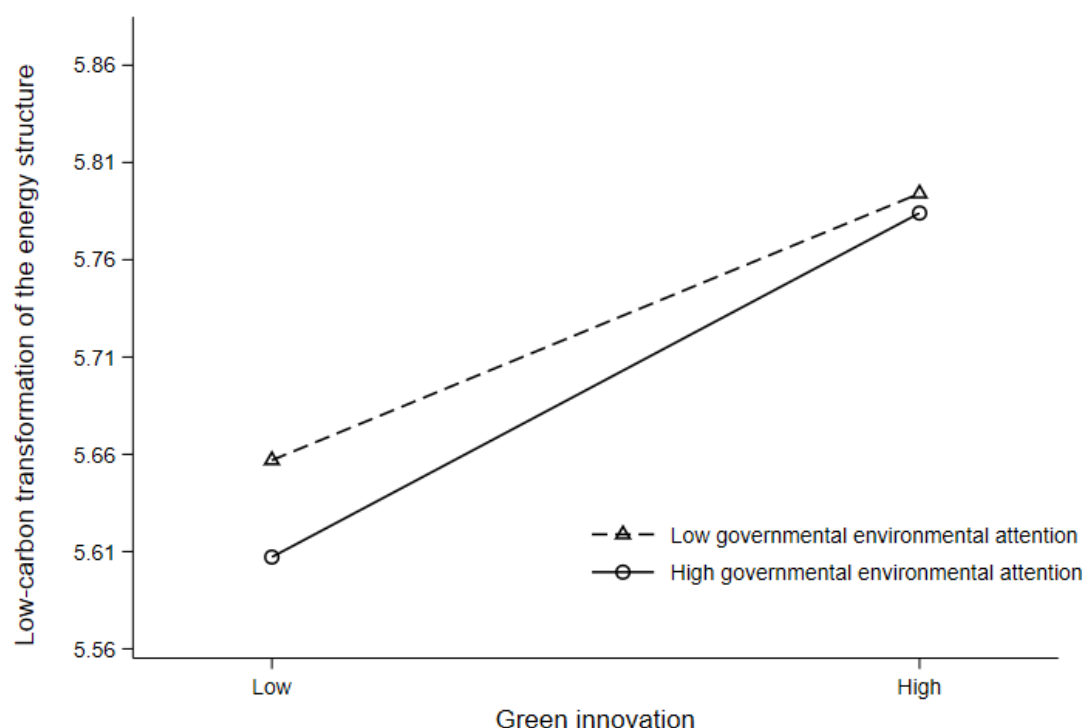
Table 4 explores in greater depth the extent to which governmental attention to environmental issues influences the link between *GT* and *Gec*. The regression results show that the coefficient of the interaction term $GT \times ER$ is significantly positive, indicating that governmental environmental attention significantly enhances the positive effect of *GT* on energy decarbonization. This finding supports H_3 . Governmental environmental attention creates a favorable institutional foundation for green technology RandD and application

by strengthening policy orientation, optimizing resource allocation, and enhancing public oversight. Additionally, Figure 2 verifies the positive moderating effect of *ER* on the relationship between *GT* and *Gec* through an interaction effect plot.

Table 4: Moderating effect results

	(1) <i>Gec</i>	(2) <i>Gec</i>
<i>GT</i>	0.0394*** (4.4259)	0.0230** (2.1154)
<i>ER</i>		−2.3555*** (−2.7752)
<i>GT</i> × <i>ER</i>		0.5044*** (5.0743)
_cons	4.3033*** (10.6959)	4.3257*** (11.1738)
Controls	Yes	Yes
Id FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	360	360
adj. <i>R</i> ²	0.9373	0.9376

Source: Authors' own calculations

Figure 2: Moderating effect of government environmental attention

Source: Authors' own elaboration

4.4 Heterogeneity analysis

The quantile regression results presented in Table 5 reveal a clear upward trend in the marginal influence of *GT* as the advancement of energy structure decarbonization. In the early stages of the low-carbon transition (25th percentile), the coefficient of *GT* is relatively small, indicating that limited absorptive capacity and weak institutional coordination substantially constrain the diffusion efficiency of green technologies in lagging regions. By contrast, in the advanced stages of the transition (75th and 90th percentiles), the coefficient of *GT* becomes significantly larger, suggesting the presence of a technology accumulation effect in regions with higher levels of decarbonization. These regions benefit from well-developed clean energy technology clusters and a sound market-oriented application ecosystem, enabling the large-scale diffusion and collaborative innovation of green technologies, which amplifies their emission reduction effects. This finding implies that for regions that are forerunners in low-carbon transition, policymaking should prioritize building a green technology innovation ecosystem – such as developing technology trading markets and industrial alliances – to fully leverage their accumulated technological advantages. For regions that are lagging behind, however, policy efforts should focus on strengthening

foundational capacities, including subsidizing technology introduction and fostering local capabilities, to overcome barriers to technology diffusion.

Table 5: Quantile regression results

	(1) Gec 25%	(2) Gec 50%	(3) Gec 75%	(4) Gec 90%
GT	0.0334* (1.8032)	0.0396*** (3.1727)	0.0452*** (2.8571)	0.0494** (2.2390)
Controls	Yes	Yes	Yes	Yes
Id FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	360	360	360	360

Source: Authors' own calculations

To further identify the heterogeneous effects of *GT* on *Gec*, this study conducts grouped regression analyses based on the median value of regional openness level (*Open*) (Xiaobao *et al.*, 2024). The results in Columns (1) and (2) of Table 6 show that the coefficient of *GT* is significantly positive at the 1% level in the high-openness group, while it is statistically insignificant in the low-openness group. This indicates that a higher degree of openness strengthens the low-carbon transition effect of green innovation through mechanisms such as trade facilitation, cross-border technology spillovers, and enhanced factor mobility. Regions with greater openness are more capable of absorbing advanced international clean technologies and equipment, thereby improving energy allocation efficiency. In contrast, regions with lower openness exhibit weaker *GT* effects due to limited technology diffusion. Therefore, highly open regions should deepen international collaboration in green technology and promote the alignment of green standards with global benchmarks. Less open regions, however, need to strengthen local *GT* capabilities and infrastructure connectivity to gradually integrate into the global green technology system.

Table 6: Heterogeneity analysis

	(1) <i>Open_High</i> <i>Gec</i>	(2) <i>Open_Low</i> <i>Gec</i>	(3) <i>Dige_High</i> <i>Gec</i>	(4) <i>Dige_Low</i> <i>Gec</i>
<i>GT</i>	0.0538*** (4.9447)	−0.0318 (−0.7093)	0.0491*** (4.1438)	0.0523 (0.5160)
_cons	1.7782*** (3.0237)	7.4410*** (19.9778)	1.7582** (2.1495)	5.3858*** (7.8410)
Controls	Yes	Yes	Yes	Yes
Id FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	180	180	180	180
adj. <i>R</i>²	0.9435	0.9178	0.9532	0.9108
Chow test	10.1925		4.2679	
<i>p</i>-value	0.0001		0.0148	

Source: Authors' own calculations

Furthermore, this study examines the heterogeneous impact of *GT* on *Gec* based on the level of digital economic development (*Dige*), as shown in Columns (3) and (4) of Table 6. Drawing on the methodology of Zhang *et al.* (2023), *Dige* is constructed as a composite index of the digital economy based on two dimensions: internet development and digital financial development. The sample is divided into high- and low-level groups according to the median value of this index. The regression results indicate that the promoting effect of *GT* on *Gec* is more pronounced in regions with a higher level of digital economic development, suggesting that the digital economy significantly amplifies the emission reduction effects of green technologies by enhancing data flow, accelerating technology penetration, and optimizing industrial ecosystems. In contrast, regions with lower digital economic development exhibit limited *GT* potential due to constraints in infrastructure and technological application capacity. Therefore, digitally advanced regions should promote the deep integration of green and digital technologies, such as by establishing energy big data platforms and industrial internet energy-saving demonstration projects. Less developed regions, however, should prioritize the deployment of digital infrastructure such as 5G and IoT to strengthen the digital foundation for green technology application.

4.5 Robustness tests

Following the approach of Chen *et al.* (2023) and Xu *et al.* (2024), this study employs an instrumental variable (*IV*) method to address potential endogeneity concerns. Specifically, the interaction term between lagged green innovation and terrain ruggedness is used as the instrumental variable. Terrain ruggedness, as a natural geographic characteristic, influences the applicability of green technologies and the spatial layout of energy infrastructure. While it is correlated with green innovation, it is unlikely to be associated with the random disturbance term of current energy structure decarbonization, thereby satisfying the exogeneity requirement. Lagged green innovation helps mitigate reverse causality between current green innovation and the energy structure, ensuring relevance to the endogenous regressor. The inclusion of the interaction term further captures the heterogeneous expression of technology diffusion under geographic constraints, thus improving the instrument's identification strength. As shown in Table 7, the first-stage regression results indicate that the *IV* has a significantly positive effect on *GT*, confirming a strong correlation between the instrument and the endogenous variable. The weak instrument test rejects the null hypothesis of weak instruments, validating the effectiveness of the *IV*. In the second-stage regression, the coefficient of *GT* remains significantly positive. This confirms the causal robustness of the positive impact of *GT* on *Gec*.

To further mitigate potential endogeneity bias, this study leverages the exogenous shock of the carbon emission trading pilot policy by constructing a difference-in-differences (DID) model for verification. Provinces included in the carbon trading pilot launched in 2013 were designated as the treatment group, while non-pilot provinces served as the control group. A DID term, generated by interacting province and time dummy variables, was incorporated into the regression. As shown in Column (1) of Table 8, after controlling for this policy shock, the coefficient of *GT* remains significantly positive at the 1% level, indicating that the core conclusion – that *GT* promotes the low-carbon transition of energy consumption structure – exhibits strong robustness.

Table 7: Instrumental variable regression results

	First stage Gec	Second stage Gec
IV	0.3855*** (5.4460)	
GT		0.0938*** (4.3793)
Controls	Yes	Yes
Id FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen–Paap rk LM statistic	5.0917**	
Kleibergen–Paap Wald rk F statistic	29.7610 [16.38]	
p-value of the endogeneity test		0.0269

Note: The values in [] represent the critical thresholds for the Stock–Yogo weak instrument test at the 10% significance level.

Source: Authors' own calculations

Furthermore, to ensure the reliability of the key findings, additional robustness tests were conducted by replacing variables and adjusting the sample period, as summarized in Table 8. First, in Column (2), green total factor productivity (*GT1*) was used as an alternative measure for *GT*. The results show that the coefficient of *GT1* is significantly positive, confirming that the direction and significance of the core conclusion remain consistent across different measures of green innovation. Second, in column (3), the *Gec* is replaced with the coal consumption ratio (*Gec1*). The coefficient of *GT* is significantly negative at the 1% level, confirming that *GT* directly reduces reliance on high-carbon energy. This result forms a logical complement to the baseline model, where *GT* positively influences the low-carbon index. Finally, in column (4), to account for the potential influence of municipalities with unique policy and economic conditions, the four provincial-level municipalities – Beijing, Shanghai, Tianjin, and Chongqing – are excluded from the sample. The coefficient of *GT* remains significantly positive, indicating that the results are not driven by outliers or region-specific characteristics.

Table 8: Additional robustness checks

	(1)	(2)	(3)	(4)
	<i>Gec</i>	<i>Gec</i>	<i>Gec1</i>	<i>Gec</i>
<i>DID</i>	0.0612*** (3.6540)			
<i>GT</i>	0.0371*** (4.1852)		−0.0082*** (−2.8945)	0.0509** (2.1901)
<i>GT1</i>		0.4735** (2.2202)		
<i>_cons</i>	4.2047*** (9.9078)	4.3942*** (9.3047)	1.4197*** (7.5603)	4.7906*** (15.2498)
Controls	Yes	Yes	Yes	Yes
Id FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	360	360	360	312
adj. <i>R</i>²	0.9375	0.9355	0.9540	0.9237

Source: Authors' own calculations

5. Discussion of Results

This research empirically examines the impact of green innovation on the low-carbon transition of energy consumption structure and its underlying mechanisms. The main findings can be summarized as follows:

First, green innovation serves as a core driver promoting the low-carbon transition of energy consumption structure. This finding aligns with the conclusions of Ramzan *et al.* (2023) and Z. Y. Zhao *et al.* (2024), indicating that green technologies effectively facilitate the decarbonization of the energy system by improving energy efficiency and promoting the substitution of clean energy.

Second, this study identifies industrial structure upgrading as a significant mediating mechanism through which green innovation influences energy transition. This result resonates with the findings of Y. Zhang *et al.* (2025), suggesting that green innovation indirectly advances

the low-carbon transition of energy consumption structure by driving the industrial system toward higher-value and cleaner production. Furthermore, the confirmed moderating effect of government environmental attention highlights the critical role of institutional environments in the transformation of green technologies. This observation is consistent with the research of Xu *et al.* (2023) on the synergistic effects of environmental regulations and green innovation.

The quantile regression analysis reveals that the promoting effect of green technology on energy structure transition intensifies with the level of regional low-carbon development, demonstrating a clear dependency on existing low-carbon foundations. This finding extends the research of Jiang *et al.* (2024) on the path dependency of green technology diffusion, indicating that the structural transformation effect of green innovation is more fully realized in regions with a stronger low-carbon foundation.

The heterogeneity analysis yields results that resonate with existing literature, showing a stronger low-carbon transition effect of green innovation in regions characterized by greater openness and digital economic development. This regional disparity echoes Dai *et al.* (2025)'s insights on green technology absorption through trade openness and reinforces the enabling mechanism of the digital economy proposed by Wu *et al.* (2025).

6. Conclusion and Recommendations

Employing panel data from Chinese provinces between 2011 and 2022, this paper empirically analyzes the effect of green innovation on the decarbonization of the energy mix and identifies its transmission channels. A quantile regression model is further employed to uncover the distributional characteristics of the green innovation effect. The findings show that green innovation significantly promotes the decarbonization of the energy structure. Industrial upgrading plays a partial mediating role in this process, while governmental environmental attention strengthens the emission reduction effects of green innovation. Moreover, the effect of green innovation becomes more pronounced as the level of decarbonization increases, reflecting a clear pattern of low-carbon foundation dependence. In addition, the institutional and technological environment further conditions this relationship: the low-carbon effect of green innovation is more significant in regions with higher degrees of openness and more advanced digital economy development.

The foregoing empirical findings lead to the following policy suggestions: First, establish a national-level special fund for green technology R&D and industrialization, prioritizing support for core technology breakthroughs and demonstration applications in critical fields such as clean energy, smart grids, and industrial energy efficiency. A market-oriented collaborative innovation mechanism led by enterprises and integrating industry, academia,

and research should be developed to foster synergistic advancements. Second, implement stringent industrial access and upgrade policies. Through differentiated measures in environmental protection, credit, land use, and other areas, forcefully phase out backward, high-carbon production capacity. Efforts should be geared toward facilitating the green upgrade of traditional manufacturing and cultivating new, high-value, low-carbon industries, supported by smooth factor mobility into these green sectors. Third, incorporate environmental governance efficacy as a core component of local government performance evaluation systems. Maintain the stability and predictability of environmental policies, and reduce corporate transition costs by expanding government green procurement and constructing public technical service platforms. Finally, promote differentiated implementation strategies based on regional endowments: Innovation-leading regions should focus on establishing international green technology trading centers and industrial innovation alliances, promoting the outward transfer of technologies, standards, and management models. Regions with a weak technological foundation and lagging transitions require central fiscal support through specific transfer payments for technology introduction and adaptive retrofitting. Enhanced targeted personnel training and infrastructure interconnectivity are also essential to solidify the foundation for green technology diffusion.

This study systematically investigates the mechanism through which green innovation drives the low-carbon transition of energy consumption structure, yet it has the following limitations. First, although the provincial-level panel data used offer valuable policy insights, they may obscure heterogeneous behaviors at the enterprise or industry level, such as differences in the efficiency of green technology development and application across industries and firms of varying sizes. Provincial data may fail to capture such micro-level dynamics. Future research could incorporate firm-level microdata to further elucidate the entire process from green technology innovation to emission reduction. Second, the study primarily relies on quantitative analysis, which, while revealing statistical relationships between variables, lacks qualitative insights into deeper factors such as institutional barriers and behavioral motivations in the practical promotion of green innovation. Future studies could adopt mixed-methods approaches, incorporating case studies, expert interviews, or policy text analysis, to deeply explore the implementation processes and contextual adaptability of green technologies across different regions and policy environments.

Appendix

Table A1: Variable definitions

Variable type	Name	Symbol	Definition	Data source
Dependent variables	Low-carbon transformation of the energy structure	Gec	Low-carbon energy structure index	China Energy Statistical Yearbook
		Gec1	Coal consumption / total energy consumption	
Independent variables	Green innovation	GT	Number of green patent applications per capita	National Intellectual Property Administration; China Statistical Yearbook
		GT1	Green total factor productivity	China Statistical Yearbook; China Energy Statistical Yearbook
Mediating variable	Industrial upgrading	Ris	Reciprocal of industrial structural deviation	China Statistical Yearbook
Moderating variable	Governmental environmental attention	ER	Ratio of environmental protection expenditure to total fiscal expenditure	
Control variables	Human capital	Edu	Number of enrolled students in higher education / total population	
	Social consumption level	Consum	Total retail sales of consumer goods / regional GDP	National Intellectual Property Administration
	Artificial intelligence development	AI	ln (Number of AI patent applications + 1)	
	Urban–rural income gap	Gap	Per capita disposable income of urban residents / that of rural residents	China Statistical Yearbook
	Government intervention	Gov	Fiscal expenditure / regional GDP	
	Urbanization level	Urb	Urban population / total population	
	Fiscal self-sufficiency	Govself	Fiscal revenue / fiscal expenditure	
	Informatization level	IT	Number of internet users / total population	

Source: Authors’ own calculations

The 30 Chinese provinces included in this study are: Beijing Municipality, Tianjin Municipality, Hebei Province, Shanxi Province, Inner Mongolia Autonomous Region, Liaoning Province, Jilin Province, Heilongjiang Province, Shanghai Municipality, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province, Henan

Province, Hubei Province, Hunan Province, Guangdong Province, Guangxi Zhuang Autonomous Region, Hainan Province, Chongqing Municipality, Sichuan Province, Guizhou Province, Yunnan Province, Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region.

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