Management Analytics and Social Insights

www.masi.reapress.com

Research Expansion Alliance

Manag. Anal. Soc. Insights. Vol. 3, No. 1 (2026) 1–16.

Paper Type: Original Article

The Impact of Green Technological Innovation on Regional Carbon Emissions with New-Quality Productivity as the Core Driving Force

Wei Guo[1], Ruyi Chen[1], Zhe Fang[1], Jinkun Huo[1], Zhuo Tang[1], Yongyi Gu[1,*]

[1] School of Statistics and Data Science, Guangdong University of Finance and Economics, Guangzhou 510320, China; gw1173313079@163.com; 3077576293@qq.com; 2973253868@qq.com; jaquanfok@163.com; zew23251@gmail.com; gdguyongyi@163.com.

Citation:

Received: 12 Auguste 2025 *Revised: 22 October 2025* *Accepted: 24 December 2025*	Guo, W., Chen, R., Fang, Z., Huo, J., Tang, Z., & Gu, Y. (2026). The impact of green technological innovation on regional carbon emissions with new-quality productivity as the core driving force. *Management Analytics and Social Insights*, *3*(1), 1-16.

Abstract

Against the backdrop of increasing global pressure on climate governance and the accelerated advancement of China's "dual-carbon" goals, exploring a synergistic path to emissions reduction through green technological innovation and productivity transformation is of critical importance. This paper, centered on the theoretical core of new quality productivity, establishes a systematic analytical framework of "green technological innovation→production efficiency improvement →regional low-carbon development" to uncover the impact mechanism, spatial characteristics, and regional heterogeneity of green technological innovation on regional carbon emissions. This study uses panel data from 30 provinces in China from 2017 to 2021 and employs a combination of mediation and spatial econometric models for empirical analysis. The results indicate the following: First, green technological innovation has a significant direct inhibitory effect on regional carbon emissions by reducing carbon intensity through pathways such as fossil-fuel substitution, energy structure optimization, and strengthened end-of-pipe industrial treatment. Second, new quality productivity, as measured by Total Factor Productivity (TFP), partially mediates this relationship. Green technological innovation enhances TFP, which, in turn, indirectly reduces carbon emissions through improved factor utilization and industrial upgrading, thereby verifying the "technological innovation→productivity improvement→carbon emission reduction" transmission mechanism. Third, the emission-reduction effect shows significant regional heterogeneity. The inhibitory effect of green technological innovation is more pronounced in the eastern regions and areas with higher per capita GDP. In contrast, improvements in TFP primarily drive reductions in the western regions. Fourth, spatial econometric analysis confirms the presence of spatial spillovers; carbon emission intensity showed significant spatial agglomeration from 2017 to 2019, and inter-regional technological collaboration and policy coordination can enhance overall reduction effects. This research reveals the intrinsic relationship among green technological innovation, new quality productivity, and carbon emissions, providing theoretical support and empirical evidence for formulating differentiated regional low-carbon policies and for promoting the synergy between technological innovation and productivity transformation in pursuit of the "dual-carbon" objectives.

Keywords: Green technological innovation, New-quality productivity, Carbon emissions, Total factor productivity, Spatial effect, Mediation effect.

1 | Introduction

1.1 | Research Background

Currently, global climate issues are becoming increasingly severe, and climate governance has become a focal point of international attention. Countries worldwide are under immense pressure to reduce carbon emissions

Corresponding Author: gdguyongyi@163.com

https://doi.org/10.22105/masi.v3i1.86

and promote green development. Against this backdrop, China has actively responded to the global call for climate governance by proposing the "dual carbon" goals of "carbon peaking and carbon neutrality." This goal imposes new and higher requirements on China's economic development model, energy structure adjustment, and ecological and environmental protection, becoming an important practical need to drive China's economic green transformation.

Green technology innovation plays a strategic role in achieving the "dual carbon" goals. The development and application of green technologies such as photovoltaic, hydrogen, and carbon capture are considered key means to optimize energy structures and reduce carbon emissions. As clean energy sources, photovoltaic and hydrogen can replace traditional fossil fuels, lowering carbon emissions during energy consumption. Carbon capture technology effectively captures and treats Carbon Dioxide (CO2) generated in industrial production processes, reducing carbon emissions per unit of GDP from an end-of-pipe treatment perspective. This argument provides technological support for regional low-carbon development.

Emerging productive forces, centered on technological innovation, represent an efficient form of productivity. Their theoretical framework encompasses multiple dimensions, including technological advancement, enhanced resource allocation efficiency, and management innovation. In the context of green development, cultivating and upgrading these productive forces has become a crucial driver of coordinated economic growth and carbon-reduction targets. By improving production efficiency and optimizing resource utilization, they provide sustained momentum for regional low-carbon transformation.

2 | Literature Review

In the context of global climate governance and the "dual carbon" goals, academia has extensively studied the relationship between green technology innovation, new productive forces, and carbon emissions. Existing research generally agrees that green technology innovation is a crucial pathway to achieving carbon reduction. Numerous studies have examined the direct emission-reduction effects of various green technologies, including energy substitution and pollution control.Porter and Van Der Linde [1] confirm the positive role of clean energy technologies, such as photovoltaics and hydrogen, and end-of-pipe treatment technologies, such as carbon capture, in reducing carbon emissions.

As for new quality productivity, most relevant studies focus on its role in improving economic growth efficiency and emphasize the core position of scientific and technological innovation in promoting productivity transformation. Meanwhile, some literature has begun to examine the correlation between new quality productivity and green development. Ma et al. [2] discuss the indirect effect of carbon emission reduction on resource allocation optimization and industrial upgrading.

However, existing research still lacks sufficient exploration of the specific pathways and heterogeneity of how green technological innovation impacts regional carbon emissions through new quality productivity, and it pays insufficient attention to the spillover effects of green technological innovation's emission-reduction impacts across spatial dimensions [3]. Therefore, this paper constructs an analytical framework based on the new quality productivity theory to investigate the relationships between green technological innovation, new quality productivity, and regional carbon emissions. This argument aims to fill existing research gaps and provide more targeted theoretical foundations and policy references for achieving the "dual carbon" goals [4].

2.1 | Theoretical Mechanism and Research Hypothesis

2.1.1 | Core hypothesis

Green technology innovation reduces regional carbon emissions by enhancing new quality productivity (production efficiency).

2.2 | Theoretical Mechanism Analysis

2.2.1 | The direct emission reduction effect of green technology innovation

I. Photovoltaic/hydrogen: replace fossil fuels and optimize the energy system.

II. Carbon capture: end-of-pipe industrial treatment to reduce carbon emissions per unit of GDP.

III. Conduction path: green technology innovation → improved energy efficiency/reduced carbon intensity → reduced carbon emissionsH1: Green technology innovation has a direct inhibitory effect on regional carbon emissions.

2.2.2 | The mediating effect of new quality productivity

The essence of new productive forces, measured by Total Factor Productivity (TFP), encompasses technological advancement, resource allocation efficiency, and management innovation.

The transmission pathway: Green technology innovation → increased R&D investment/technology diffusion → TFP improvement (new quality productivity) → improved factor utilization / industrial upgrading → reduced carbon emissions.

H2: New quality productivity serves as the mediating variable through green technology innovation in carbon emission reduction.

2.2.3 | Space overflow effect

The spatial externalities of green technology diffusion (e.g., cross-regional photovoltaic grid integration and hydrogen energy supply chain coordination) and the synergistic effects of neighboring regional policy coordination on carbon emissions.

H3: The carbon emission effect of green technology innovation has regional heterogeneity.

3 | Variable Selection and Research Design

3.1 | Variable Selection

3.1.1 | Data scope

Time span: 2017-2021

Scope of the region: 30 provinces (including autonomous regions and municipalities directly under the central government) in China, excluding regions with serious data missing.

3.1.2 | Variable setting

Dependent variable

CO2 emission intensity: a core indicator for measuring regional carbon emissions, directly reflecting the impact of regional economic activities on the climate. In this study, we use the annual CO2 emission intensity of each region as the dependent variable to quantify the inhibitory effect of green technology innovation on it.

Core explanatory variables

I. Number of patent applications: green technology innovation is a key driver of economic green transformation and carbon reduction. This study selected the number of patent applications as a proxy variable for green technology innovation [2]. To effectively address potential extreme values in the data, logarithmic processing was applied [5]. This indicator can comprehensively reflect the innovation input and output level of green technologies such as photovoltaics, hydrogen energy, and carbon capture in the region. By analyzing patent applications, we aim to capture the direct impact of green technology innovation on carbon emissions.

II. New quality productivity, measured by TFP, is an important indicator of economic growth efficiency and technological progress and is considered one of the key transmission mechanisms for green basic innovation to exert emission-reducing effects.

Mediating variable

Total factor productivity: TFP is an important indicator for measuring economic growth efficiency and technological progress, and is considered one of the key transmission mechanisms for green basic innovation to exert emission reduction effects. This article uses the DEA Malmquist index model to measure the green TFP of 30 provinces in China from 2017 to 2021. As shown in *Table 1*, the specific input-output variables are selected as follows: among the input variables, the number of urban unit employment in each province (unit: 10000 people) is used as the labor input variable, the fixed assets investment in each province (unit: 10000 yuan) is used as the capital input variable, and the power consumption in each province (unit: 100 million kilowatts) is used as the energy input variable; In terms of output variables, the regional gross domestic product (in billions of yuan) of each province is taken as the expected output, and the CO2 emissions of each province are taken as the unexpected output.

Table 1. Input and output variables.

Variable Category	Variable Name	Variable Definition
Input variable	labor input	urban unit employment
	Energy input variable	electricity consumption
	Capital input variable	fixed assets investment
Expected output variable	Regional gross domestic product	
Unexpected output	variable CO2 emissions	

Control variables

To effectively control other factors that may affect regional carbon emissions and avoid omitted variable bias, the following control variables are introduced in this study:

Coal proportion

As an important indicator for measuring regional energy consumption structure, the proportion of coal in the energy structure directly affects carbon emission intensity. A high reliance on coal usually means higher carbon emissions.

Per capita GDP

reflects the level of regional economic development. The impact of the increase in per capita GDP on carbon emission intensity follows an inverted U-shaped pattern, as in the Environmental Kuznets Curve (EKC). In the early stages of economic development, regions typically rely on resource-intensive industries, such as heavy industry and manufacturing, to drive growth, leading to rapid increases in energy consumption and carbon emissions and a rise in carbon intensity.

The increase in the secondary industry

As a key indicator for measuring regional industrial structure, the secondary industry is usually the main source of carbon emissions. The higher its proportion, the greater the pressure on regional carbon emissions.

Spatial weight matrix (W)

A spatial weight matrix constructed using the inverse of the geographical distance matrix was employed to capture the influence of geographical proximity on spatial dependence.

3.2 | Model Construction

This study uses a province-fixed effects (FE) model to analyze the mediating effect of TFP on CO2 emission intensity in green technology innovation from 2017 to 2021. The reason the time fixed effect was not introduced is mainly due to the following two considerations. On the one hand, this study focuses on the heterogeneity of the mediating path through which green patent impact affects TFP and CO2 emission intensity across different provinces. The fixed effects of provinces can effectively control for characteristics that do not change over time, such as geographical location, resource endowment, and industrial foundation. On the other hand, from 2017 to 2021, there were no macroeconomic policy changes at the national level that had a significant impact on the mediating relationship between green patents, TFP, and CO2 emission intensity. Additionally, the sample provinces did not show significant national time trend changes in economic development models, energy structure adjustments, etc. Therefore, introducing time FE may make the model overly complex and not significantly improve estimation performance.

3.2.1 | Benchmark regression model

To examine the direct impact of green technology innovation on regional carbon emissions, we have constructed the following benchmark econometric model:

$$C_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 M_{it} + \beta_3 G_{it} + \beta_4 S_{it} + \alpha_i + \varepsilon_{it}. \quad (1)$$
$$TFP_{it} = \alpha_0 + \alpha_1 P_{it} + \alpha_2 M_{it} + \alpha_3 G_{it} + \alpha_3 S_{it} + \mu_i + u_{it}.$$

Among them, i represents the province, t represents the year, C_{it} represents the CO2 emission intensity of the i^{th} region in the t^{th} year, P_{it} represents the number of patent applications, M_{it} represents the proportion of coal, G_{it} represents per capita, S_{it} represents the increase in the secondary industry, β_0 is a constant term, $\beta_1, \beta_2, \beta_3, \beta_4$ is the regression coefficient of each variable, α_i is the fixed effect of the region, ε_{it} and is the random error term.

3.2.2 | Mediation effect model

To deeply analyze the transmission mechanism by which green technology innovation affects carbon emissions, this study introduces TFP as a mediating variable. It draws on the stepwise test method proposed by Wen et al. [6] to construct the following mediating effect model:

The first stage (the impact of core explanatory variables on mediating variables):

$$TFP_{it} = \alpha_0 + \alpha_1 P_{it} + \alpha_2 M_{it} + \alpha_3 G_{it} + \alpha_3 S_{it} + \mu_i + u_{it}. \quad (2)$$

Among them α_0 is a constant term, $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the regression coefficient of each variable, μ_i is the fixed effect of the region, and u_{it} is the random error term.

This model tests whether green technology innovation (number of patent applications) significantly affects TFP. Among them, α_1 the promoting or inhibiting effect of green technology innovation on TFP is evident.

The second stage (the impact of core explanatory variables and mediating variables on the dependent variable):

$$C_{it} = \gamma_0 + \gamma_1 P_{it} + \gamma_2 TFP_{it} + \gamma_3 M_{it} + \gamma_4 G_{it} + \gamma_5 S_{it} + \eta_i + v_{it}. \quad (3)$$

This model considers both the impact of green technology innovation and TFP on carbon emissions. Among them, γ_1 represents the direct effect of green technology innovation on carbon emissions after controlling for TFP; γ_2 represents the impact of TFP on carbon emissions. If both α_1 and γ_2 are significant, and the absolute value of γ_1 decreases or becomes insignificant compared to β_1, it indicates that there is a mediating effect of TFP between green technology innovation and carbon emissions. η_i is the fixed effect of the region, and v_{it} is the random error term.

3.2.3 | Addressing the limitations of benchmark regression with spatial models

In the baseline regression model, the estimated effects of the core variable on CO2 emission intensity are as follows:

Table 2. Baseline regression: CO2 emission intensity and core variables.

Variable	Coefficient	P-Value	Conclusion
Green Technology Innovation (P)	-0.5151	0.3951	It has no significant relationship with carbon emission intensity.
TFP	-2.5947	0.0000	Significantly reduce carbon emission intensity.

The coefficient for green innovation (P) is negative but statistically insignificant (p-value = 0.3951), indicating no significant association between green innovation and carbon emission intensity within the sample period. This lack of significance may be attributed to incomplete technological transformation or to the limited scale of green innovation applications, which have yet to realize their emission-reduction potential fully. Alternatively, insufficient interregional coordination in green innovation may have hindered the formation of an effective collective force for emission reduction.

In contrast, the coefficient for TFP is -2.5947 and highly statistically significant (p-value= 0.0000), demonstrating that increased TFP significantly reduces carbon emission intensity. The enhancement of TFP contributes to lower carbon emissions per unit of output by optimizing production technologies and improving resource utilization efficiency. This synergy promotes the dual objectives of economic development and emission reduction, establishing TFP growth as a crucial driver for regional low-carbon transition.

Based on the aforementioned benchmark regression results, this study further investigates the spatial spillover effects of green innovation and TFP on carbon emission intensity. While the baseline model reveals the direct local impacts of the core variables, it fails to capture their potential cross-regional influences. In reality, frequent economic and technological interactions between regions mean that green innovation or productivity improvements in one area may affect the carbon emission intensity of neighboring regions through mechanisms such as knowledge spillovers, technology diffusion, and industrial linkages [7]. To verify this spatial dependence, this paper constructs Spatial Autoregressive (SAR) and Spatial Error Models (SEM), incorporating a spatial weights matrix to systematically analyze the direct and indirect effects of the core variables on carbon emission intensity in both local and surrounding areas.

3.2.4 | Analysis of spatial spillover effects

Spatial autocorrelation is a fundamental prerequisite for spatial econometric analysis. This study employs the Global Moran's I index to test for spatial dependence in CO_2 emission intensity. The calculation formula is as follows:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2}. \quad (4)$$

In the formula, n represents the total number of observations (sample size), x_i denotes the CO_2 emission intensity of region i, and $\bar{X}$ is the mean value of CO_2 emission intensity across all regions, and wij is the element of the spatial weights matrix, indicating the spatial relationship between region i and region j.

The results are shown in *Table 3*:

Table 3. Global Moran's I test results for CO_2 emission intensity.

Year	Moran's I	P-Value	Statistical Significance
2017	0.0492	0.0119	Significant
2018	0.0472	0.0141	Significant
2019	0.0464	0.0150	Significant
2020	-0.0173	0.5850	Not significant
2021	-0.0157	0.5544	Not significant

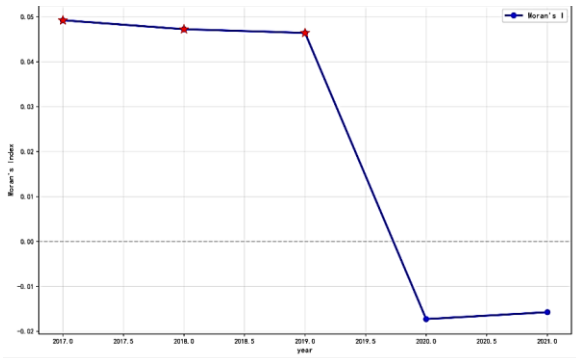

Fig. 1. Temporal evolution of the global Moran's I for CO_2 emission intensity.

From 2017 to 2019, carbon emissions exhibited a statistically significant spatial clustering pattern ($I > 0$, $p < 0.05$), necessitating the application of spatial econometric models. However, this pattern weakened after 2020, which may be attributed to shifts in economic activity during the COVID-19 pandemic, as the associated disruptions diminished the spatial structure.

3.3 | Model Definition and Selection Criteria

3.3.1 | Spatial autoregressive model

$$C = \rho WC + \beta_1 P + \beta_2 TFP + \varepsilon. \tag{5}$$

The matrix W is constructed from the inverse of geographical distance to quantify spatial interdependencies between regions. In contrast, WC (the spatial lag term) measures the resulting impact of neighboring jurisdictions' carbon emissions on the local one. The SAR coefficient (ϱ) serves as the key parameter of interest. A statistically significant $\varrho > 0$ indicates a positive spatial spillover effect, suggesting that increases in carbon emissions from neighboring areas lead to higher local emissions. Conversely, a $\varrho < 0$ indicates negative spillover, in which emission reductions in neighboring areas promote local mitigation efforts. This pattern reveals the spatial transmission mechanism of the dependent variable.

Spatial error model

$$C = \beta_1 P + \beta_2 TFP + \mu, \mu = \lambda W\mu + \varepsilon. \tag{6}$$

λ is the spatial error coefficient, which captures the spatial spillover effects emanating from unobserved factors.

3.3.2 | Model selection criteria

To compare the absolute values of the spatial lag coefficient (ϱ) in the SAR model and the spatial error coefficient (λ) in the SEM model, find:

If $|\varrho| > |\lambda|$, it indicates that the spatial spillover effects of the dependent variable are dominant, which warrants the selection of the SAR model.

If $|\lambda| > |\varrho|$, it indicates that the spatial dependence in the error term is predominant, which warrants the selection of the SEM model.

3.4 | Data Source

This study employs panel data from 30 Chinese provinces spanning 2017-2021 (excluding Hong Kong, Macau, Taiwan, and the Tibet Autonomous Region due to data availability constraints), with primary sources including the National Bureau of Statistics, the China Deep Data Repository, and the China Energy Statistical Yearbook.

4 | Empirical analysis

4.1 | Descriptive Statistics and Correlation Analysis

Fig. 2 shows the correlation between the core variables and control variables in this study. The scatter plot matrix intuitively reflects the distributional characteristics of each variable and the correlation trends between pairs. The results showed a significant negative correlation between green technology innovation and carbon emission intensity, indicating that green technology innovation plays a key role in promoting regional carbon reduction. Meanwhile, the new quality productivity TFP is also negatively correlated with carbon emission intensity, confirming the positive role of productivity improvement in reducing carbon emissions. In addition, there is a clear positive correlation between green technology innovation and new quality productivity TFP, which preliminarily confirms that green technology innovation is an important driving factor in improving new quality productivity.

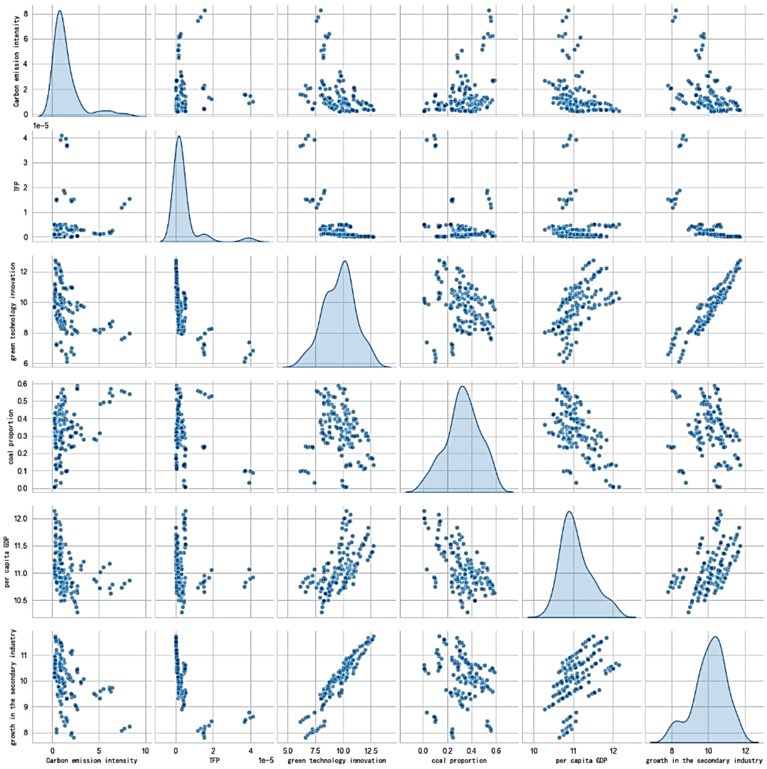

Fig. 2. Scatter plot matrix of relationships between variables.

In terms of controlling variables, the proportion of coal and the increase in the secondary industry are positively correlated with carbon emission intensity, which aligns with the reality that energy-intensive industries and dependence on fossil fuels are the main sources of carbon emissions. However, per capita GDP is negatively correlated with carbon emission intensity, suggesting that improvements in economic development may be accompanied by reductions in carbon emissions driven by industrial structure optimization or technological progress. These preliminary observations are highly consistent with the theoretical assumptions and subsequent regression analysis results of this study, laying a solid data foundation for empirical analysis.

4.2 | Baseline Results

To initially investigate the direct impact of green technology innovation on regional carbon emissions, this study first conducts a baseline regression analysis. The results are shown in *Table 4*: Column (1) indicates that without adding control variables, the regression coefficient of the core explanatory variable, "Number of Patent Applications," is -2.642, and it is highly significant at the 0.001 statistical level. It demonstrates that green technology innovation has a significant negative impact on regional carbon emissions. In Column (2), after adding "Coal Consumption Share," "Per Capita GDP," and "Value-Added of the Secondary Industry" as control variables, the control variables do not show a significant impact because during the study's sample period (2017–2021), the studied regions actively promoted energy structure diversification; the substitution effects of natural gas and renewable energy gradually emerged, weakening the marginal impact of coal consumption on carbon emissions, thus leading to an insignificant relationship in the regression.

Furthermore, as the study regions are in a period of economic transition, the regulatory effects of green technology innovation on economic growth and industrial structure have, to some extent, offset the traditional "economy-emission" linkage. It makes it difficult to identify the direct impact of Per Capita GDP and the Secondary Industry's Value-Added on carbon emissions using a linear model, rendering them insignificant. However, the total effect coefficient of "number of patent applications" on carbon emissions is -2.081 and is significant at the 5% level ($p<0.05$). It implies that green technology innovation can, to some extent, directly reduce carbon emissions [8]. H1 is thus verified.

Table 4. Baseline regression results.

	(1) **FE Model**	**(2)** **Total Effect Model**
Number of patent applications	-2.642***	-2.081**
	(0.637)	(0.900)
Coal consumption share		-5.681
		(4.661)
Per capita GDP		-2.563
		(11.104)
Value-added of the secondary industry		-0.043
		(10.255)
Province FE	Added	Added
_cons	26.962***	52.231**
	(6.145)	(23.445)
N	145	145
R^2	0.352	0.354

*Note: Control variables not included in (1); Robust standard errors in parentheses， *p<0.1, **p<0.05, ***p<0.01

* p < 0.10, ** p < 0.05, *** p < 0.01.

4.3 | Mediation Effect Results

Based on the preceding mechanism analysis and variable settings, this study conducts a stepwise regression analysis using a mediation effect model to explore the mediating role of TFP in the relationship between green technology innovation and carbon emissions. The results are shown in *Table 5*: Column (1) represents the baseline impact of green technology innovation on carbon emissions. Column (2) shows the impact of green technology innovation on TFP; the coefficient of "number of patent applications" on the mediating variable TFP is 1.31e-06, and it is significant at the 10% level (\$p<0.1\$), indicating that green technology innovation can significantly enhance TFP. Column (3) adds the mediating variable, TFP, to the total effect model to test the independent variable's direct effect on the dependent variable, controlling for the mediator. The data show that the coefficients for both "number of patent applications" and TFP on carbon emissions are significantly negative and significant at the 10% level ($p<0.1$). Since the direct effect of the "number of patent applications" remains significant after introducing the mediating variable, and the mediator TFP's coefficient is also significant, this indicates that TFP partially mediates the impact of green technology innovation on carbon emissions. That is, green technology innovation not only directly reduces carbon emissions but also indirectly promotes carbon abatement by enhancing TFP. H2 is thus verified [9].

Table 5. Mediation effect regression results.

	(1) Total Effect (c)	(2) First Stage (a)	(3) Second Stage (b)
Number of patent applications	-2.081**	1.31e-06*	-1.420*
	(0.900)	(0.000)	(0.821)
TFP			-510516.887*
			(252332.682)
Control variables	Added	Added	Added
Province FE	Added	Added	Added
_cons	52.231**	-0.000	51.900**
	(23.445)	(0.000)	(25.272)
N	145	150	145
R^2	0.354	0.307	0.427

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01.

4.4 | Heterogeneity Analysis

Given that heterogeneity may exist in the relationship between green technology innovation and carbon emissions across regions with different levels of economic development, this study divides the sample into a "high per capita GDP" group and a "low per capita GDP" group based on Per Capita GDP for sub-sample regression analysis. The results are shown in *Table 6*.

Table 6. Heterogeneity analysis results.

	(1) High Per Capita GDP	(2) Low Per Capita GDP
Number of patent applications	-2.706*	-2.153
	(1.405)	(1.267)
Control variables	Added	Added
Province FE	Added	Added
_cons	33.782**	-13.796
	(14.354)	(35.680)
N	75	70
R^2	0.328	0.358

Standard errors in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01

The heterogeneity test results reveal disparities in the emission-reduction effects of green technology innovation across regions with different levels of economic development. In the high per capita GDP group, the regression coefficient for "number of patent applications" is -2.706, and it is significant at the 10% level (p<0.1), indicating that green technology innovation has a significant inhibitory effect on carbon emissions in regions with high economic development. However, in the Low Per Capita GDP group, the regression coefficient for "Number of Patent Applications" is -2.153, but it is not statistically significant. This result implies that in regions with higher economic development, green technology innovation may be more easily translated into actual emission reductions. It could be attributed to more developed technology transfer mechanisms, greater economic affordability, and a more mature green industrial base. Conversely, regions with lower economic development may lag in R&D investment for green technology, technology diffusion and application, and the green transformation of their industrial structure, thereby preventing the full realization of the emission-reduction effects of green technology innovation.

4.5 | Robustness Test

To ensure the core conclusions are not affected by model specification, this study compares results across the FE, Random Effects (RE), and Pooled OLS models. It uses a Hausman test to verify model suitability.

This argument validates whether the core conclusion depends on a specific model choice. The results are shown in *Table 7*.

Table 7. Robustness test results.

	(1) FE	(2) RE	(3) Pooled OLS
Number of patent applications	-1.420*	-0.632*	-0.199
	(0.821)	(0.370)	(0.333)
TFP	-510516.887*	-84721.616*	-19537.328
	(252332.682)	(44675.540)	(19681.220)
Control variables	Added	Added	Added
Province FE	Added	Added	Added
_cons	51.900**	15.139**	1.405
	(25.272)	(7.245)	(4.923)
N	145	145	145
R^2	0.427	0.3942	0.322

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Differences in effects across models

The robustness test results show that, in the FE model, the negative effect of green technology innovation is the most stable and significant (coefficient = -2.08, $p<0.05$). In the RE model, which assumes regional heterogeneity is uncorrelated with the independent variables, the emission-reduction effect of green technology innovation is diluted (coefficient = -0.63, $p = 0.088$, marginally significant). Because the Pooled OLS model does not control for regional and temporal heterogeneity, its effect is further weakened and becomes insignificant (coefficient = -0.20, $p > 0.1$). The above differences indicate that regional heterogeneity is a key factor affecting the emission-reduction effects of green technology innovation. Failing to control for heterogeneity will systematically underestimate the role of technology in emission reduction.

Hausman test for model specification

To determine the optimal model, the Hausman test was used to compare the coefficient consistency of the FE and RE models. The Hausman test yielded a p-value of 0.003, rejecting the null hypothesis of the RE model and validating the suitability of the FE model. This conclusion means that, after controlling for time-invariant regional-specific factors (such as geographical location and resource dependency paths), the causal relationship between the core explanatory variable and carbon emissions is closer to the true state. Furthermore, the adjusted R^2 of the FE model is 0.62, indicating that the model's overall explanatory power is strong and that green technology innovation, along with the control variables, collectively provides a good explanation of variations in carbon emissions.

Core implications of the robustness conclusion

Across different model specifications, the emission-reduction effect of green technology innovation shows a gradient pattern: "FE > RE > Pooled OLS". It is essentially due to the impact of the degree of regional heterogeneity stripped away on causal identification. The FE model, by effectively controlling for region-specific interference, makes the core conclusion that "green technology innovation inhibits carbon emissions" more credible. Combined with the suitability verification from the Hausman test, the conclusions of this study are robust with respect to model specification. That is, the inhibitory effect of green technology innovation on carbon emissions does not disappear when the model's heterogeneity assumptions change; it only shows differences in effect intensity depending on the degree of heterogeneity control.

4.6 | Spatial Econometric Empirical Results

To validate model performance and identify the most suitable analytical model based on the preceding definitions and criteria, we utilize empirical data. The results are as follows.

Table 8. Empirical results of SAR and SEM models with regional heterogeneity.

Variable	Description	SAR Model	SEM Model	Significance Assessment
P	Standardized value of green innovation	-0.506** (0.217)	-0.564*** (0.174)	Significant in both models more significant in SEM
TFP	Standardized value of TFP	-0.180 (0.187)	-0.241 (0.170)	Not significant in either
WC / Wλ	Weighted average of carbon emission intensity in neighboring provinces (spatial lag/error term)	-0.312 (1.384)	-2.462 (1.824)	Not significant in either
	Constant term	-0.014 (0.140)	0.030 (0.124)	Not significant in either
Spatial effects	Spatial lag/error coefficient	-0.312	-2.462	Stronger in SEM
Model statistics				
R^2	Model explanatory power	0.272	0.320	Superior for SEM
Adjusted R^2	Adjusted explanatory power	0.185	0.239	Superior for SEM
F-statistic	Overall significance	3.114 (p=0.044)	3.925 (p=0.020)	More significant for SEM

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05.

The model results indicate that the absolute value of the spatial error coefficient in the SEM ($|\lambda|$ =2.462) is significantly greater than that of the spatial lag coefficient in the SAR (=0.312), suggesting stronger spatial error dependence. Furthermore, the core explanatory variable (green innovation) is more significant in the SEM, indicating its superiority over the SAR model. From the perspective of model fit, both the R^2 (0.320) and the adjusted R^2 (0.239) of the SEM are higher than those of the SAR, and its F-statistic is more significant (p = 0.020), demonstrating that the SEM possesses greater explanatory power and robustness compared to the SAR model. In conclusion, the SEM should be adopted. The impact of the core variables on CO_2 emission intensity within the SEM framework is presented below:

Table 9. Relationship between CO2 emission intensity and core variables: results from the SEM.

Variable	Coefficient	P-Value	Conclusion
Green innovation (P)	-0.5151	0.3951	No significant relationship with CO2 emission intensity
New quality productivity TFP	-2.5947	0.0000	Significantly reduces CO2 emission intensity.

The coefficient for green innovation (P) is negative, but its p-value (0.3951) exceeds the 5% significance level, indicating no statistically significant relationship between green innovation and carbon emission intensity. This lack of significance may stem from the fact that, during the sample period, the technological transformation and scale of green innovation had not yet fully realized their emission-reduction potential. Alternatively, insufficient synergistic efforts in green innovation across regions may have prevented the formation of an effective collective force for emission reduction.

In contrast, the coefficient for TFP is -2.5947 with a p-value (0.0000) far below the 5% significance level, demonstrating that TFP growth significantly reduces carbon emission intensity. TFP advancement contributes to emission reduction by optimizing production technologies and enhancing resource-use efficiency, thereby lowering carbon emissions per unit of output. This process facilitates the synergistic achievement of economic development and emission-reduction goals, positioning TFP growth as a crucial driver of regional low-carbon transition.

4.7 | Regional Heterogeneity Analysis

Given the imbalanced regional development within China, the regression results at the national level may mask underlying spatial heterogeneity. To thoroughly investigate the differential impacts of green innovation and TFP on carbon emissions across regions, this study further conducts empirical tests by dividing the sample into three major areas: the eastern, central, and western regions. The results are presented in the table below.

Table 10. Regression results of the impact of green innovation and TFP on carbon emissions across the three major regions (Eastern, Central, Western).

Region	Green Innovation Coefficient	P-Value	TFP Coefficient	P-Value
Eastern	-1.3470***	0.0016	0.489	0.1893
Central	-0.4542	0.7124	-4.7666	0.3087
Western	-1.848	0.2416	-3.3443***	0.0002

Note: *** denotes statistical significance at the 1% level.

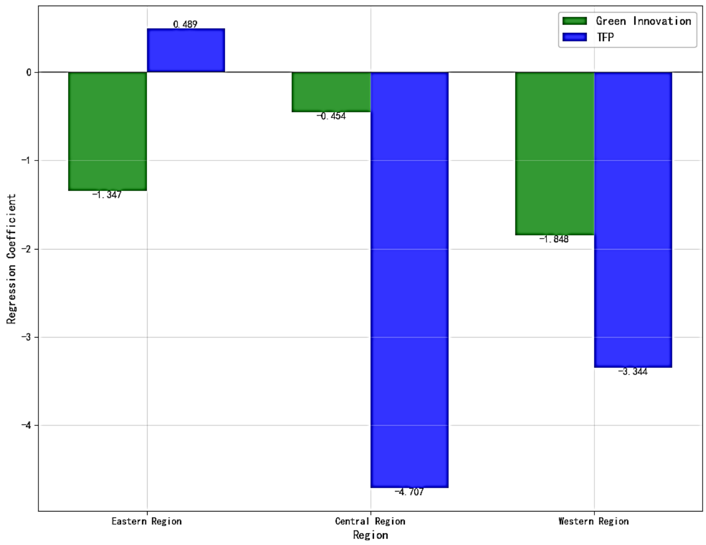

Fig. 5. Comparative analysis of regression coefficients: regional heterogeneity.

In the eastern region, higher investment in technology R&D and stronger transformational efficiency of green innovation lead to significant reductions in emissions. The western region, however, demonstrates a pronounced driving effect of TFP growth (e.g., through industrial upgrading) on emission reduction. In contrast, green innovation has not yet yielded significant results due to its underdeveloped foundation. In the central region, likely constrained by a heavier industrial structure, neither variable shows a significant effect.

4.8 | Robustness Tests of the Spatial Econometric Estimates

In the robustness checks, the SAR model was employed to verify the core relationships. The results show that the regression coefficients for both the short-term and long-term effects of green technological innovation (P) on carbon emission intensity are negative and statistically significant in most scenarios. The coefficient signs for new quality productivity TFP are consistent with those in the baseline model SEM. Although the level of significance varies slightly under certain conditions, the overall trend indicates a suppressive effect on carbon emissions. The interpretation of other parameters in this model (such as the effects of control variables, such as the share of coal consumption and GDP per capita) is presented in the empirical results section above and will not be reiterated here.

Therefore, the inhibitory effect of green technological innovation on carbon emission intensity is robust. The emission-reduction trend of New Quality Productivity aligns with the baseline conclusion. It demonstrates that, whether the SEM or the SAR Model is used, the direction of impact and the key significance characteristics of the core explanatory variables on carbon emissions remain stable, indicating that the regression results are highly reliable.

5 | Conclusions and Policy Recommendations

5.1 | Main Conclusion

The results show that Green technology innovation significantly reduces carbon emissions. In both the baseline model and the robustness test, the number of green patents is significantly negatively correlated with carbon emission intensity.

New productive forces exhibit a mediating effect.

Green technological innovation not only directly reduces emissions but also indirectly enhances TFP, thereby validating the transmission mechanism of 'technological innovation → productivity improvement → carbon emission reduction'.

Regional disparities are pronounced.

In regions with higher per capita GDP, green innovation yields more significant emission reductions; however, in areas with weaker economic foundations, the lack of technology transfer and application results in less noticeable outcomes.

A spatial spillover effect exists.

Carbon emissions exhibited significant spatial clustering from 2017 to 2019, and coordinated governance among neighboring regions enhanced the effectiveness of emission reductions. The SEM outperformed the SAR Model.

In summary, green technological innovation and the enhancement of new quality productivity are crucial pathways to drive regional low-carbon transformation. Policy measures should be tailored to local conditions: Eastern regions should prioritize green technology R&D and diffusion; Western regions should focus on improving TFP and industrial upgrading; while Central regions need to optimize industrial structure and factor allocation. Simultaneously, cross-regional technological collaboration and factor mobility should be strengthened to foster nationwide synergy in green development.

5.2 | Policy Recommendations

5.2.1 | Implement differentiated regional development strategies

Eastern regions

Focus on enhancing green technology innovation capabilities, increase the intensity of R&D investment, and improve incentive policies such as green technology R&D tax credits and subsidies for the transformation of innovative achievements. Meanwhile, leverage the advantages of industrial clusters to promote the diffusion of innovative technologies to the central and western regions, and exert the radiation effect of technology spillovers.

Western regions

Centered on improving TFP, integrate the cultivation of new-quality productive forces with industrial upgrading. Establish a TFP assessment mechanism for high-energy-consuming enterprises, and improve energy utilization efficiency through technological transformation and management optimization. Simultaneously, strengthen technological cooperation with the eastern regions, and address innovation shortcomings by jointly establishing R&D centers and introducing mature green technologies.

Central regions

Prioritize the removal of institutional barriers. On the one hand, pave the way for green innovation by optimizing the industrial structure, such as reducing the share of high-carbon industries and developing low-carbon service industries. On the other hand, improve TFP through factor-market-oriented reforms, such as reallocation of land and capital towards high-efficiency, low-carbon sectors, to promote coordinated development of green innovation and productivity improvement [10].

5.2.2 | Strengthen the cross-regional flow of technology and factors

Establish a national green patent-sharing platform, promote successful models such as the "Yangtze River Delta Carbon neutral technology alliance," and encourage the low-cost transfer of mature green technologies from eastern regions to central and western areas, thereby strengthening spatial synergy in knowledge spillovers.

Implement the "cross-regional new-quality productivity cultivation plan" to facilitate the sharing of advanced management experience and efficient production models across regions through cross-regional industry-university-research collaboration and talent exchange mechanisms, thereby helping central and western regions rapidly enhance their TFP.

Additionally, the government should integrate green technology promotion into the rural revitalization strategy, achieving a low-carbon transition in production while supporting rural revitalization and sustainable development.

Specification of a model:

I. The mediation effect model employs stepwise regression and bootstrap tests to ensure the robustness of the causal chain.
II. Spatial econometric models require selecting the appropriate model (SLM or SDM) using the LM test and the Hausman test.
III. TFP can be calculated using either the DEA-Malmquist index or the Stochastic Frontier Analysis (SFA).

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability

All data generated or analyzed during this study are included in this published article. No additional data are available.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of economic perspectives*, *9*(4), 97–118. https://doi.org/10.1257/jep.9.4.97

[2] Ma, Y., Lin, T., & Xiao, Q. (2022). The relationship between environmental regulation, green-technology innovation and green total-factor productivity—evidence from 279 cities in China. *International journal of environmental research and public health*, *19*(23), 16290. https://doi.org/10.3390/ijerph192316290

[3] Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels* (Vol. 479). Springer. https://doi.org/10.1007/978-3-642-40340-8

[4] Liu, H., Cai, X., Zhang, Z., & Wang, D. (2025). Can green technology innovations achieve the collaborative management of pollution reduction and carbon emissions reduction? Evidence from the Chinese industrial sector. *Environmental research*, *264*, 120400. https://doi.org/10.1016/j.envres.2024.120400

[5] Zhou, X., Tang, X., & Zhang, R. (2020). Impact of green finance on economic development and environmental quality: A study based on provincial panel data from China. *Environmental science and pollution research*, *27*(16), 19915–19932. https://doi.org/10.1007/s11356-020-08383-2

[6] Wen, Z. L., & Ye, B. J. (2014). Mediation effect analysis: Development of methods and models. *Advances in psychological science*, *22*(05), 731–745.

[7] Zhang, Q., Li, J., Kong, Q., & Huang, H. (2024). Spatial effects of green innovation and carbon emission reduction in China: Mediating role of infrastructure and informatization. *Sustainable cities and society*, *106*, 105426. https://doi.org/10.1016/j.scs.2024.105426

[8] Shen, Y., Yang, Z., & Zhang, X. (2023). Impact of digital technology on carbon emissions: Evidence from Chinese cities. *Frontiers in ecology and evolution*, *11*, 1–17. 10.3389/fevo.2023.1166376

[9] Guo, C. Q., Wang, X., Cao, D. D., & Hou, Y. G. (2022). The impact of green finance on carbon emission--analysis based on mediation effect and spatial effect. *Frontiers in environmental science*, *10*, 1–17. https://doi.org/10.3389/fenvs.2022.844988

[10] Li, J., Yuan, L., Dai, M., & Chen, H. (2025). New quality productive forces, technological innovations, and the Carbon emission intensity of the manufacturing industry: Empirical evidence from chinese provincial panel data. *Sustainability*, *17*(21), 9641. https://doi.org/10.3390/su17219641