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Research article

Towards a low-carbon economy: How can green technological innovation affect carbon productivity in China?

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ABSTRACT

Green technological innovation (GTI) has emerged as a central mechanism for advancing energy efficiency, mitigating carbon emissions, and facilitating the broader shift toward sustainable economic development in China. Utilizing panel data encompassing 269 prefecture-level Chinese cities from 2008 to 2021, we systematically investigate how GTI affects carbon productivity. Our findings reveal that GTI contributes positively to local carbon productivity while simultaneously exerting a positive influence on adjacent regions. This spatial diffusion, however, is subject to decay over geographic distance. Further analysis highlights pronounced heterogeneity in GTI's impact, shaped by variations in resource endowment and urban scale. The positive impact of GTI is particularly remarkable in cities that are not reliant on natural resources and in those classified as medium to large. In addition, structural optimization and factor allocation are effective pathways through which GTI drives improvements in carbon productivity. Finally, the low-carbon transition effect of GTI exhibits significant spatial threshold characteristics with respect to marketization. Only when marketization reaches a certain level can GTI effectively boost carbon productivity both locally and in neighboring regions. These results offer critical implications for formulating policies aimed at achieving carbon neutrality and fostering sustainable urban development in China.

1. Introduction

Since the reform and opening-up, China's "high-speed + high-imbalance" growth model, driven by resource input, has propelled the country's economic takeoff while simultaneously contributing to a qualitative decline in environmental conditions. According to data from the *Statistical Review of World Energy*, China emitted approximately 11.218 billion metric tons of carbon dioxide in 2023, accounting for 31.93 % of the global total, further solidifying its position as the world's largest emitter (Sun, 2022; Zhang and Liu, 2022). In response to mounting ecological concerns and the need to transition toward sustainable development, the Chinese government formally committed in 2020 to achieving peak carbon emissions by 2030 and carbon neutrality by 2060. In July 2024, it further emphasized the implementation of a dual-control carbon emission system during the 15th Five-Year Plan period, focusing primarily on intensity control with supplementary total volume control, to ensure the timely attainment of the carbon peaking target. Within this policy framework, decoupling economic growth from carbon emissions has become a strategic imperative. As a result, carbon productivity, defined as economic output per unit of carbon dioxide emitted, has emerged as a critical metric for assessing not only the efficiency of energy use but also the structural quality of economic growth (Li et al., 2025b). As a composite indicator, carbon productivity reflects an economy's capacity to sustain development while minimizing its environmental footprint, serving as a benchmark for evaluating the effectiveness of green transition policies. Prioritizing the improvement

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of carbon productivity is therefore not only essential for advancing ecological modernization but also instrumental in laying the foundation for high-quality, low-carbon development in China (Wei et al., 2025).

Realizing China's dual carbon objectives, while advancing Chinese-style modernization, critically depends on the transformative potential of GTI (Zeng et al., 2024). However, despite its strategic prominence, the empirical and theoretical literature remains divided on the precise role that GTI plays in enhancing carbon productivity. A prevailing perspective holds that GTI serves as a catalyst for both decarbonization and economic upgrading. Scenario analyses by the International Energy Agency (IEA) support this view, suggesting that over 60 % of the targeted emission reductions in its 450 pathways could be attributed to technological advancements, emphasizing the centrality of GTI in global low-carbon strategies (Birol, 2013). As an integral dimension of technological progress, GTI is believed to yield significant positive externalities by improving both environmental quality and firm-level productivity (Guo et al., 2018). It also contributes to structural transformation by facilitating industrial upgrading and enhancing energy efficiency (Xu et al., 2021). Empirical studies across emerging economies support these findings. For example, Khattak et al. (2024) demonstrated that GTI has helped curb carbon emission intensity across BRICS countries over the past three decades. Provincial-level analyses in China have further confirmed that GTI facilitates regional low-carbon transitions (Xu et al., 2021; Su et al., 2023; Cheng and Yao, 2021). However, some scholars hold opposing views. First, GTI is subject to accumulation effects and threshold effects. In the absence of a well-established foundational technological system, absorbing cutting-edge technology requires substantial investments in advanced equipment and talent cultivation, posing significant challenges to the local economic base (Keller, 1996). Du and Li (2019) found that while GTI is generally conducive to carbon productivity enhancement, its benefits are concentrated in high-income countries, with limited significance in lower-income contexts. Similarly, Razzaq et al. (2023) documented substantial cross-country variation in GTI effectiveness, particularly across different income quartiles. Another line of concern pertains to the energy rebound effect, where technological progress reduces energy costs and inadvertently induces higher energy consumption. This counterintuitive outcome, often referred to as carbon lock-in, undermines GTI's intended benefits (Shao et al., 2019). Wang et al. (2024a) argued that energy-augmenting innovations disproportionately increase the marginal productivity of energy relative to other inputs, thereby incentivizing greater energy use and diminishing carbon productivity. Such dynamics are particularly acute in resource-dependent regions, where the inertia of carbon-intensive development pathways intensifies the lock-in effect.

Although the role of GTI in facilitating low-carbon transformation has attracted growing scholarly attention, existing research remains insufficient both in depth and breadth, thus requiring more systematic exploration and theoretical refinement:

First, in the context of accelerating regional integration and increasingly fluid factor mobility, the cross-regional diffusion and spillover effects triggered by GTI have emerged as a critical lens through which to understand the divergent trajectories of urban low-carbon transitions. While prior studies generally affirm the existence of positive spatial externalities associated with GTI (Su et al., 2023; Zeng et al., 2024), most analyses focus narrowly on confirming whether such spillovers exist (Lu and Lu, 2024). As a result, they often neglect the nonlinear attenuation of spillover intensity with geographic distance and fail to delineate the effective range or critical decay threshold of green innovation diffusion. These omissions limit the formulation of more refined insights into regional coordination mechanisms and policy synergies.

Second, regarding the mechanisms of impact, extant literature has largely emphasized how GTI improves environmental performance through enhanced energy efficiency and end-of-pipe pollution control (Xu et al., 2021). However, such perspectives often remain external to core production processes and fall short of capturing the systemic reconfiguration of resources initiated by green innovation. Although a growing body of research has begun to recognize GTI's structural and factor-level transformative potential, most studies concentrate on single-channel mechanisms, such as industrial upgrading or energy substitution (Zhao et al., 2024; Lin and Ma, 2022), and overlook a systematic analysis of underlying pathways.

Third, the extent to which GTI can fully realize its ecological efficiency potential is often significantly constrained by the functioning of market mechanisms. While prior work has highlighted the link between market conditions and innovation performance (Boubaker et al., 2024; Aghion et al., 2005), few studies have conceptualized market environment as threshold variables, nor have they explored their spatially contingent moderating effects on the regional impacts of GTI (Zeng et al., 2024; Lin and Ma, 2022). Given that GTI is inherently characterized by high uncertainty and elevated risk, the market plays an irreplaceable role in alleviating information asymmetries, guiding resource allocation, and shaping societal expectations (Hall and Lerner, 2010). Neglecting the influence of the market environment on technological spillovers and innovation outcomes may lead to a misjudgment of the marginal effects of green innovation policies, thereby distorting resource allocation and weakening policy effectiveness.

In light of the above, this study aims to comprehensively explore how GTI impacts carbon productivity in China, as well as the underlying mechanisms, focusing on the following three aspects: First, from a spatial perspective, we aim to identify the diffusion patterns and influence radii of GTI across regions, and examine whether its spatial spillover effects exhibit boundary decay characteristics; second, we construct a "structural optimization-factor allocation" theoretical framework to clarify how GTI enhances carbon productivity through structural adjustments and the reorganization of resource factors; third, by introducing a spatial threshold model, we explore the nonlinear regulatory mechanism of marketization levels in the process through which GTI affects carbon productivity, and investigate the role boundaries and threshold conditions for enabling low-carbon transformation through technological innovation. Through both theoretical construction and empirical testing from multiple perspectives, this paper seeks to provide more targeted and systematic theoretical support for green development policy formulation and regional collaborative governance.

The remainder of this paper is structured as follows. Section 2 introduces the theoretical foundation of the study. Section 3 details the empirical strategy, including the econometric techniques and data sources applied. Section 4 presents the core empirical results and provides an integrated discussion of their implications. Section 5 further analyzes the external regulatory factors of low-carbon transformation through GTI. Section 6 concludes the study by summarizing the findings and proposing policies.

2. Theoretical mechanism analysis

2.1. Direct mechanism of GTI on carbon productivity

Technological progress has long been recognized as a fundamental driver of sustained economic development. When manifested as GTI, it assumes a pivotal role in reconciling economic expansion with environmental constraints. Beyond traditional productivity gains, GTI enhances carbon productivity by improving energy efficiency and lowering carbon intensity across production systems.

The central function of GTI lies in its capacity to optimize energy systems and accelerate the diffusion of clean technologies. These transformations reduce reliance on high-emission production models and foster a systemic transition toward low-carbon development. As innovation trajectories increasingly favor environmentally benign technologies, the historically positive association between economic growth and carbon emissions can be weakened, enabling a process of decoupling that allows economies to grow while emissions decline.

Acemoglu et al. (2012) formalized this concept within a dynamic theoretical framework, demonstrating that policy instruments can steer technological change toward green innovation, achieving substantial emission reductions without compromising economic performance. In practice, GTI facilitates the substitution of carbon-intensive technologies with cleaner alternatives, promoting widespread adoption of energy-efficient and renewable solutions. This shift reduces the environmental externalities associated with economic activity while simultaneously increasing the economic value extracted per unit of carbon emitted (Khattak et al., 2024). The underlying mechanism is consistent with the "technological effect" described by the Environmental Kuznets Curve, which suggests that as economies advance and technological capabilities improve, resource allocation becomes more efficient, energy intensity declines, and pollution is brought under control (Grossman and Krueger, 1995). Accordingly, GTI functions not merely as an incremental enhancement of production systems, but as a transformative force that reshapes the relationship between growth and environmental impact. It offers a viable technological pathway for advancing carbon productivity, thereby supporting the dual imperatives of economic development and ecological sustainability.

2.2. Transmission mechanism of GTI on carbon productivity

GTI can influence carbon productivity through multiple channels. This paper seeks to elucidate its impact mechanisms from two perspectives: the structural optimization effect and the factor allocation effect.

From a structural perspective, GTI acts as a catalyst for the refinement of both industrial composition and energy consumption patterns. In terms of industrial restructuring, GTI facilitates the transition of traditional, energy-intensive sectors by promoting technological upgrades that enhance energy efficiency and reduce environmental impact. This transformation supports industrial upgrading while simultaneously enabling the expansion of green emerging industries. The development of sectors such as renewable energy, environmental protection, and the circular economy introduces novel engines of growth and diversification (López and Montalvo, 2015; Zeng et al., 2024), contributing to a more resilient and sustainability-oriented economic system. Within the energy sector, GTI serves as a pivotal driver in reducing capital expenditures for renewable energy systems and improving the efficiency of energy conversion processes. Such technological progression systematically strengthens the market penetration capacity of decarbonized energy sources while accelerating the phased substitution of carbon-intensive fuels, as corroborated by extant empirical studies (Li and Lin, 2016). As clean energy becomes more viable, GTI reshapes the structure of energy supply, weakening the dominance of conventional carbon-intensive sources and supporting the systemic shift toward renewables (Dauda et al., 2021; Lin and Li, 2022). This transformation accelerates the decarbonization of the energy system, reduces dependence on high-carbon energy, and contributes to a measurable decline in carbon intensity.

In terms of factor allocation effects, this encompasses both labor and capital elements. GTI increases the demand for green-skilled labor and contributes to human capital development, as firms require highly skilled workers to implement new green technologies (Hunjra et al., 2024). Empirical studies find that green innovations tend to be labor-friendly, especially increasing demand for workers with higher skills and education (Kunapatarawong and Martínez-Ros, 2016). The enhancement of labor capabilities through GTI can in turn reduce energy consumption and promote a low-carbon economy. For example, evidence from OECD countries suggests that greater human capital is associated with significant reductions in overall energy use, specifically curbing fossil fuel consumption while boosting renewables, which facilitates a transition to a low-carbon economy (Alvarado et al., 2021). GTI also helps reallocate capital more efficiently by reducing "lock-in" of capital in carbon-intensive industries and easing financing constraints for green projects (Du et al., 2025). By spurring cleaner technologies, GTI diminishes reliance on polluting assets and encourages investors and banks to shift funds toward green sectors. In fact, studies indicate that green finance instruments can alleviate financing constraints and redirect financial resources toward cleaner production and innovation (Lin and Zhong, 2024). Investors are able to reallocate capital from polluting to green sectors as GTI creates attractive opportunities in clean industries. Notably, large-scale shifts in investment portfolios, such as fossil-fuel divestment campaigns, have already mobilized trillions of dollars away from carbon-intensive assets toward green ventures (Trinks et al., 2020). This trend reflects how GTI, by improving the risk-return profile of clean technologies, allows investors to move capital out of polluting industries and into sustainable ones (Trinks et al., 2020).

2.3. Mechanism of marketization process on the low-carbon transition of GTI

Marketization aims to regulate the flow and allocation of resources through market supply-demand dynamics and price mechanisms, thereby achieving optimal resource utilization. As the marketization process deepens, institutional arrangements are improved, factor market distortions are mitigated, and a more competitive environment is created for enterprises. For this reason, an enhanced level of marketization has been regarded by some scholars as a "remedy" for addressing innovation-related challenges (Guo et al., 2023).

The advancement of marketization is crucial for nurturing and developing factor markets, as it can effectively direct production factors toward genuine innovation activities, thereby improving the level of GTI in cities. In contexts characterized by low levels of marketization, administrative approvals and market entry restrictions imposed by governments tend to suppress healthy competition among firms, leading to reduced efficiency in the allocation of innovation resources. Excessive government intervention, which often results in market monopolies and factor market distortions, severely constrains the dynamism of innovation and hampers the effective development of innovative activities (Ren et al., 2024). However, the deepening of marketization can substantially curb inappropriate local government interventions. Through mechanisms of competition and risk-taking, markets are able to achieve optimal resource allocation and facilitate a more rational distribution of innovation resources across society, thereby significantly enhancing urban GTI (Boubaker et al., 2024).

Concurrently, market liberalization facilitates product market maturation, creating an optimized institutional ecosystem that enhances GTI viability. Given the high risk and uncertainty associated with green innovation investment, market participants tend to exhibit cautious behavior (Hall and Lerner, 2010). However, as marketization advances, competitive mechanisms in product markets become more mature, and market information becomes significantly more transparent. This helps alleviate the undervaluation of innovation investment caused by information asymmetry and prevents the misallocation of resources (Burks et al., 2018), thereby stimulating urban innovation vitality and promoting the continuous evolution of green technologies. In addition, the advancement of marketization enhances the maturity of product markets, raising the standards for product quality and technological content. Under the pressure of intense competition, firms are compelled to increase investment in innovation to maintain their competitive edge (Aghion et al., 2005). At this stage, clearer and more effective price mechanisms better reflect the supply–demand dynamics of the market, enabling innovators to more accurately identify market needs and conduct targeted technological research and development. Ultimately, this facilitates the transformation of green innovation into productive capacity and promotes the improvement of urban carbon productivity (Acemoglu et al., 2012).

3. Material and methods

3.1. Model construction

3.1.1. Basic model

Following the analytical approach proposed by Fisher-Vanden et al. (2004), this study assumes that production activities require inputs such as capital, labor, and energy. Based on a cost-minimization framework, the Cobb-Douglas cost function is specified as follows:

$$C(P_K, P_L, P_E, Q) = A^{-1} P_K^{\alpha_K} P_L^{\beta_L} P_E^{\gamma_E} Q \tag{1}$$

Where $C(\cdot)$ denotes the cost function; P_K, P_L, P_E represent the prices of capital, labor, and energy inputs, respectively; α_k, β_L, γ_E correspond to the output elasticities of these inputs; Q stands for output; A indicates technological progress; captures the negative relationship between technological progress and production costs, and A^{-1} reflecting that higher levels of technological progress imply lower production costs (Fisher-Vanden et al., 2004). Assumes a positive correlation between GTI and technological progress, expressed as follows:

$$A = A_0 + \delta G \tag{2}$$

Where $\delta > 0$, G and denotes the level of GTI.

According to Shephard's lemma, under the assumption that producers behave in a cost-minimizing manner, the demand for a production input can be determined by taking the partial derivative of the cost function with respect to the price of that input. Consequently, the energy demand is obtained by taking the partial derivative of the cost function with respect to the price of energy. Denoting energy demand as E, thus we have:

$$E = \frac{\partial C}{\partial P_E^{\gamma_E}} = = \gamma_E (A_0 + \delta G)^{-1} P_K^{\alpha_K} P_L^{\beta_L} P_E^{\gamma_E - 1} Q \tag{3}$$

Assuming complete product homogeneity and a perfectly competitive market structure, firms act as price-takers in the market. Under these market conditions, an individual firm cannot influence market prices through its own production decisions; rather, it must adjust its output level and cost structure according to the prevailing market price. Consequently, in the long-run equilibrium, firms cannot earn economic profits, implying that total revenue equals total cost. This relationship can be represented as follows:

$$C = P_Q Q \tag{4}$$

where P_Q denotes the product price, which is determined by the prices of the three input factors, as follows:

$$P_Q = P_K^{\alpha_K} P_L^{\beta_L} P_E^{\gamma_E} \tag{5}$$

Where $\alpha_K + \beta_L + \gamma_E = 1$, and under conditions of perfect market competition, P_Q represents the general price level. Substituting equation (5) into equation (3), we obtain:

$$E = \frac{\gamma_E P_Q Q}{(A_0 + \delta G) P_E} \tag{6}$$

By rearranging terms, equation (6) can be further transformed into:

$$\frac{Q}{E} = \frac{\gamma_E^{-1} (A_0 + \delta G) P_E}{P_Q} \tag{7}$$

The analytical framework adopts a first-order linear coupling between energy usage and carbon emissions (Xu and Lin, 2023), formalized through the equation:

$$E = \lambda CO_2 \tag{8}$$

where λ is a positive parameter, and CO_2 represents the carbon dioxide emissions. Substituting equation (8) into equation (7), we obtain:

$$CPR = \frac{Q}{CO_2} = \frac{\lambda (A_0 + \delta G) P_E}{\gamma_E P_Q} \tag{9}$$

Building upon the above analysis, this study first employs a fixed effects panel model to examine the direct impact of GTI on carbon productivity, expressed as follows:

$$CPR_{it} = a_0 + a_1 GTI_{it} + a_2 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{10}$$

Where i denotes the city and t denotes the time period. The dependent variable is carbon productivity (*CPR*), and the core explanatory variable is green technological innovation (*GTI*). X denotes a vector of control variables, a represents the corresponding parameter estimates. The model includes city-specific fixed effects, denoted by u_i, and time-fixed effects, represented by γ_t, to control for unobserved heterogeneity across units and over time. The term ε_{it} captures the idiosyncratic error component.

3.1.2. Spatial Durbin Model

Given the mobility of carbon emissions and the potential for interregional technological spillovers, variations in carbon productivity within one region are likely to be shaped by activities in adjacent areas (Zeng et al., 2024). Moreover, adjacent regions in China tend to adopt imitative development strategies, and the country has made significant progress in transportation infrastructure in recent years, further amplifying spatial interdependence (Huang et al., 2017). As Elhorst (2014) has argued, neglecting spatial dependence may lead to biased model estimates. It is therefore imperative to incorporate spatial correlation into empirical analyses when examining issues related to carbon productivity.

Among various spatial econometric models, the Spatial Durbin Model (SDM) is widely adopted due to its structural advantages. Unlike the Spatial Autoregressive Model (SAR), which accounts only for the spatial lag of the dependent variable, or the Spatial Error Model (SEM), which captures spatial autocorrelation in the error term, the SDM simultaneously includes spatial lags of both the dependent and independent variables. This dual-lag structure allows the SDM to more comprehensively capture the spatial transmission mechanisms of exogenous shocks and the cross-regional feedback effects of endogenous responses, thereby enhancing both flexibility and theoretical interpretability. Accordingly, this study incorporates a spatial weight matrix into equation (10) and employs the SDM to empirically examine the relationship between GTI and carbon productivity. The specific formula is as follows:

$$CPR_{it} = b_0 + \rho \sum_{j=1}^{N} w_{ij} CPR_{jt} + b_1 GTI_{it} + b_2 X_{it} + \sum_{j=1}^{N} w_{ij} GTI_{jt} b_3 + \sum_{j=1}^{N} w_{ij} X_{jt} b_4 + \mu_i + \gamma_t + \varepsilon_{it} \tag{11}$$

where w represents the spatial weight matrix, for which three types are constructed in this study—adjacency (W_1), geographic distance (W_2), and economic geographical matrices (W_3). ρ denotes the spatial autocorrelation coefficient, and b refers to the parameters to be estimated.

3.1.3. Threshold effect model

To elucidate how marketization conditions the effectiveness of GTI in enhancing carbon productivity, this study adopts the panel threshold regression methodology introduced by Hansen (2000). This analytical approach enables the identification of non-linearities in the marginal impact of GTI as the degree of market development changes. To illustrate, a single-threshold specification is adopted, and the corresponding panel model is established:

$$CPR_{it} = c_0 + c_1 GTI_{it} I(MAR_{it} \le \lambda) + c_2 (MAR_{it} > \lambda) + c_3 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{12}$$

Where $I(\cdot)$ is the indicator function, *MAR* represents the marketization threshold variable, λ denotes the threshold value, and c refers to the parameters to be estimated.

3.1.4. Spatial threshold model

As demonstrated in the preceding analysis, GTI exhibits both significant threshold and spatial effects on carbon productivity. Therefore, to further examine this complex interaction, this study adopts the spatial threshold modeling framework introduced by Yuan et al. (2020). This model integrates the foundational principles of threshold effect model and SDM, simultaneously accounting for threshold effects and spatial dependence. It is designed to evaluate how the impact of GTI on carbon productivity varies with different levels of market development. The specification of the spatial threshold model with a single threshold is as follows:

$$\begin{aligned} CPR_{it} = {} & d_0 + \rho\sum_{j=1}^{N} w_{ij}CPR_{jt} + d_1GTI_{it}I(MAR_{it}\le\lambda) + d_2GTI_{it}I(MAR_{it}>\lambda) + d_3X_{it} \\ & + d_4\sum_{j=1}^{N} w_{ij}GTI_{jt}I(MAR_{it}\le\lambda) + d_5\sum_{j=1}^{N} w_{ij}GTI_{jt}I(MAR_{it}>\lambda) + d_6\sum_{j=1}^{N} w_{ij}X_{jt}I(MAR_{it}\le\lambda) \\ & + d_7\sum_{j=1}^{N} w_{ij}X_{jt}I(MAR_{it}>\lambda) + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{13}$$

3.2. Variable description

(1) Explanatory variable: *Green technological innovation (GTI)*. In empirical studies of GTI, the number of patents is frequently employed as a proxy indicator (Luo et al., 2023; Többelmann and Wendler, 2020). While patent counts offer a standardized and accessible measure, they often reflect the codification of knowledge rather than its practical application. Many patented technologies are not commercially implemented or may not yield measurable environmental benefits (Du and Li, 2019). Moreover, the classification of patents into "green" and "non-green" categories remains imprecise at the city level, limiting the reliability of this measure for urban-scale analyses (Zeng et al., 2024). To overcome these challenges, recent research has advanced production-based approaches to evaluating GTI performance. Among these, the Slack-Based Measure (SBM) model has gained prominence for its ability to account for undesirable outputs while addressing input-output slacks (Liu et al., 2020). However, as a non-parametric efficiency model, SBM faces limitations when multiple decision-making units reach the frontier of efficiency. Specifically, when the efficiency score equals one, the model cannot further distinguish among units on the boundary (Tone, 2002). To address this methodological constraint, we employ the super-efficiency SBM model, which enables ranking of efficient units beyond the conventional frontier. The study constructs a composite input-output system for measuring GTI following the frameworks established (Li et al., 2025a; Zeng et al., 2024). Inputs include research and development expenditures and investments in human capital. Green patent applications are employed as the desirable output, whereas emissions of industrial wastewater, solid waste, and waste gases represent the undesirable outputs.

Based on the calculation results, this paper presents distribution maps of GTI across 269 Chinese cities for the years 2008 and 2021, as shown in Fig. 1. To better distinguish the differences in GTI levels among cities, this study adopts thresholds of M + T/2, M, and M-T/2 (where M is the overall mean and T is the overall standard deviation) to classify cities into four categories: leading, advancing, catching-up, and lagging. This classification helps to clearly identify the stage and characteristics of GTI in each city. As shown in the figure, darker-colored regions gradually increase over time, indicating a significant improvement in the overall level of GTI in China. Specifically, in 2008, most cities exhibited relatively low levels of GTI, primarily falling into the lagging and catching-up categories. Leading and advancing cities were mainly concentrated in the eastern region, particularly in provinces such as Guangdong, Jiangsu, and Zhejiang. By the year 2021, the count of cities categorized as leading and advancing had increased more than twofold relative to 2008 levels. Eastern cities maintained a clear dominance, comprising approximately 53.0 % of the national total of leading and advancing cities. The central region accounted for 35.7 %, and the western region represented 11.3 %. However, cities in the central and western regions still constituted a large proportion of the catching-up and lagging categories. These areas generally have weaker economic foundations and more homogeneous industrial structures, relying

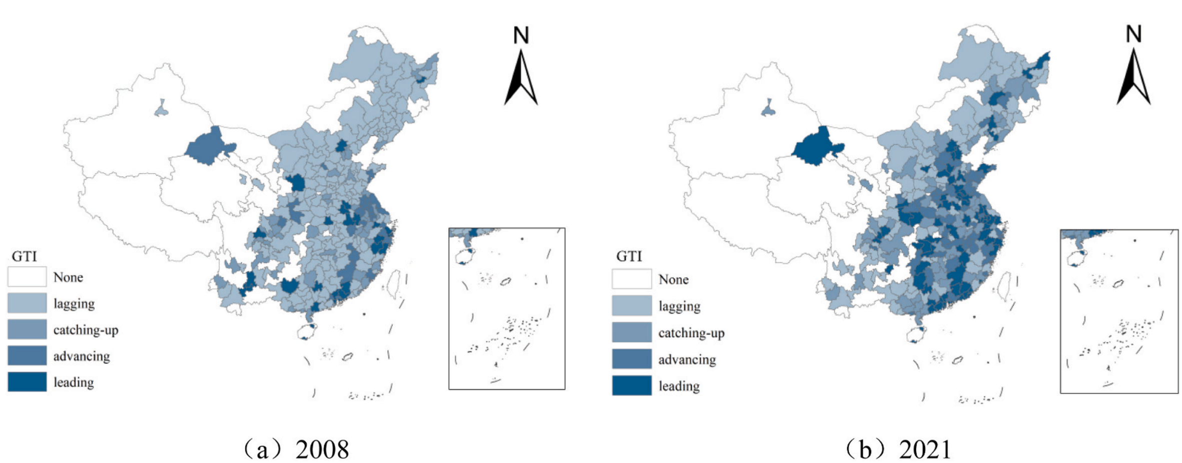


Fig. 1. Distribution of GTI of 269 cities in China, 2008 and 2021.

heavily on resource-based and heavy industries, which makes the green transition more challenging.

(2) Dependent variable: *Carbon Productivity (CPR)*. CPR initially articulated by Kaya and Yokobori (1997), refers to economic output measured as GDP generated per unit of carbon dioxide emissions. Consistent with this definition, the current study quantifies urban CPR as the ratio of GDP to aggregate carbon emissions. For estimating carbon emissions at the municipal level, the study adopts a carbon accounting approach drawing from Wu et al. (2016) and Xiang et al. (2024), utilizing consumption data from natural gas, liquefied petroleum gas, electricity, and thermal energy. Specifically, in terms of electricity consumption, the relatively low price of coal results in a high dependence on coal-fired power generation. Among all power generation methods, coal-fired electricity has the highest associated carbon dioxide emissions. Therefore, estimating carbon emissions from coal-based electricity generation provides greater accuracy and policy relevance. In the context of urban thermal energy, raw coal continues to serve as the primary fuel source for district heating systems. To estimate emissions from thermal energy use, the calculation first determines the volume of raw coal required based on the total heat supplied, the thermal efficiency of the heating system, and the calorific value of raw coal. This raw coal consumption is then converted into a standard coal equivalent using established conversion factors, thereby enabling the estimation of carbon emissions from urban heating activities.

(3) Mediating variable:
- *Structural optimization*

Industrial structure upgrading (IS): The tertiary sector, relative to the secondary sector, is generally characterized by greater capital and labor intensity, while the bulk of carbon emissions continues to originate from secondary industrial activities (Wu et al., 2021). Consequently, an increasing economic share of the service-oriented tertiary sector is often indicative of progress in decarbonizing industrial structures. Therefore, we measure it using the ratio of value-added in the tertiary sector to that of the secondary sector.

Energy structure transformation (ES): China's 14th Five-Year Plan for Modern Energy System Development outlines an ambitious roadmap for energy transition, with a specific goal of raising the proportion of electricity generated from non-fossil fuel sources to approximately 39 % by 2025. Consequently, increasing the consumption and generation share of clean energy has become a key pathway toward optimizing the energy structure (Shi et al., 2024). Despite the absence of publicly available and consistently reported data on city-level clean energy consumption, this study draws on the methodology of Destek and Aslan (2017) and measures energy structure transformation using the proportion of clean energy in total electricity consumption at the city level.

- *Factor allocation* includes both *labor allocation (LA)* and *capital allocation (CA)*.

Higher resource allocation efficiency implies a lower degree of factor misallocation. Accordingly, this study uses the *labor misallocation index (LMIS)* and the *capital misallocation index (KMIS)* to measure the efficiency of labor and capital allocation across cities.

$$\gamma_{li} = \frac{1}{1 + LMIS_i} \tag{14}$$

$$\gamma_{ki} = \frac{1}{1 + KMIS_i} \tag{15}$$

Where γ_{li} and γ_{ki} denote the absolute distortion coefficients of labor and capital prices, respectively, reflecting the markup under conditions of no relative resource distortion. In empirical estimation, these are typically approximated using relative price distortion coefficients, as expressed by:

$$\gamma_{li} = \left(\frac{l_i}{l}\right) \Big/ \left(\frac{s_i \beta_{li}}{\beta_l}\right) \tag{16}$$

$$\gamma_{ki} = \left(\frac{k_i}{k}\right) \Big/ \left(\frac{s_i \beta_{ki}}{\beta_k}\right) \tag{17}$$

where $s_i = y_i / Y$ represents the share of industry y_i in city i in total economic output Y; l_i / l and k_i / k denote the proportion of total labor and capital, respectively, utilized by the city; β_l and β_k refer to the output-weighted contributions of labor and capital, respectively; and β_{li} and β_{ki} represent the output elasticities of labor and capital for each city, respectively.

(4) Moderating variable: *Marketization (MAR)*. The level of marketization reflects the extent to which market forces influence resource allocation and determines both the sensitivity and responsiveness of market demand to GTI. Moreover, market-oriented mechanisms, through price signals and competitive dynamics, can effectively incentivize enterprises to enhance their green innovation performance, thereby promoting the simultaneous advancement of economic performance and environmental sustainability. Drawing on the methodological approaches of Fan et al. (2018) and Fu et al. (2025), we construct a composite index to quantify marketization at the municipal level. The index incorporates five distinct components, namely, government-market relations, growth of the non-state economic sector, product market sophistication, factor market development, and the provision of market-oriented services and intellectual property rights protection. The marketization index for each city is then calculated using a scoring method.

(5) Control variable:
- *Economic development (ED)*. While economic development is often associated with higher energy consumption and increased environmental pressure (Obobisa et al., 2022), it also provides essential resources for investing in green technologies and low-carbon solutions, thereby positively influencing carbon productivity. Therefore, this study used economic development (level of GDP per capita) as a control variable.
- Urbanization *(UR)*. As centers of economic activity, cities benefit from agglomeration effects and economies of scale, often yielding higher economic returns. However, rapid urban expansion is typically accompanied by increased energy consumption (Shahbaz et al., 2012). Additionally, rising production and living costs associated with population density may lead to "congestion effects," which can hinder low-carbon economic development. Following prior studies, this study includes urbanization as a control variable, operationalized as the ratio of urban to total population.
- *Energy price (EP)*. Variations in energy prices alter the relative cost of energy compared to other production inputs, thereby influencing substitution behavior and affecting overall energy intensity. These changes have important implications for carbon productivity. To account for this effect, energy price is incorporated as a control variable in the empirical model. Following the methodology of Lin et al. (2025), energy price is measured using a composite index of energy costs, calculated as a weighted average based on the energy consumption structure of each prefecture-level city and the corresponding prices of different energy sources.
- *Trade openness (TO)*. Trade liberalization is believed to enhance the cross-border diffusion of advanced technologies and

capital, thereby contributing to environmentally sustainable growth (Chen et al., 2020). However, increased openness may give rise to the "pollution haven" phenomenon. Ahmed et al. (2017) argue that heightened trade activity may stimulate additional energy demand, potentially exacerbating carbon emissions. Following the empirical approach suggested (Acheampong et al., 2019), we operationalize trade openness as the ratio of total import and export volumes to gross domestic product.

- *Population density (PD).* Population density exerts a multifaceted influence on environmental and economic dynamics. Higher density levels are often associated with intensified economic activity, which can result in greater resource consumption, elevated waste generation, and increased ecological pressure (Li et al., 2019). Conversely, densely populated regions frequently provide fertile ground for technological advancement and institutional innovation, both of which can contribute to lower carbon emissions and the promotion of green development (Shao et al., 2017). Population density is operationalized as the resident count per square kilometer in this study.
- *Infrastructure construction (IC).* Infrastructure development serves as a foundational component in promoting carbon productivity and facilitating the transition toward green and low-carbon growth. Investments in energy-efficient transportation, energy systems, and buildings contribute to lowering greenhouse gas emissions while enhancing both environmental quality and economic performance. In line with the approach adopted by Xu et al. (2021), we use per capita road area as a proxy indicator for it.

3.3. Data sources and descriptive statistics

This study investigates the relationship between GTI and carbon productivity using a panel dataset comprising 269 prefecture-level cities in China over the period from 2008 to 2021. Data are compiled from multiple authoritative sources, including the China City Statistical Yearbook, China Urban Construction Statistical Yearbook, Wind Database, EPS Database, China Research Data Services Platform (CNRDS), and the CSMAR Database. In instances where data for specific indicators is unavailable for certain years, linear interpolation is applied to fill the gaps and ensure continuity. Summary statistics for all relevant variables are reported in Table 1.

4. Estimation results and discussion

4.1. Analysis of spatial correlation

To assess the suitability of applying spatial econometric methods, this study begins by evaluating the spatial dependence of carbon productivity using Moran's I statistic. The results indicate that the global Moran's I values for carbon productivity are consistently positive and highly significant, indicating that carbon productivity across cities is far from spatially independent; rather, it displays strong positive spatial autocorrelation. Furthermore, to visually capture the spatial clustering patterns of carbon productivity, this study plots the local Moran scatter diagrams for the years 2008 and 2021, as illustrated in Fig. 2. The results suggest a clear presence of local spatial agglomeration of carbon productivity, with the trend line located in the first and third quadrants. From 2008 to 2021, this clustering pattern has become increasingly pronounced, with a significant rise in the number of cities in High-High (first quadrant) clustering regions, highlighting a strengthened positive spatial dependence. In summary, the evidence of strong spatial autocorrelation justifies the application of spatial econometric model in the subsequent empirical analysis.

4.2. Analysis of the impact of GTI on carbon productivity

4.2.1. Spatial regression results

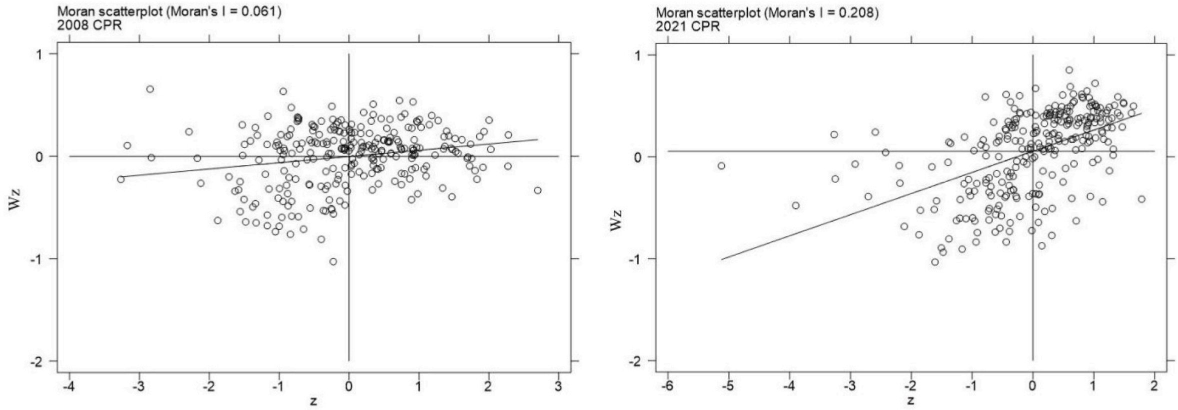
To ensure robust estimation, this study conducts diagnostic checks for multicollinearity and cross-sectional dependence prior to panel regression. As shown in Table 2, GTI is positively correlated with carbon productivity, and all explanatory variables exhibit weak pairwise correlations and VIF values well below critical thresholds, indicating no multicollinearity concerns. Tests by Pesaran, Friedman, and Frees confirm significant cross-sectional dependence, prompting the use of Driscoll-Kraay standard errors to correct for heteroscedasticity and interdependence (Bekun et al., 2021). As shown in Table 4, the estimation yields a statistically significant coefficient of 0.0569 for GTI, implying that each one-percentage-point increase in GTI corresponds to an improvement of at least 0.0569 percentage points in carbon productivity. Nevertheless, since conventional panel regression models do not capture spatial effects, this study proceeds to incorporate spatial factors into the subsequent analysis.

To identify the most suitable spatial model, this study conducts a sequence of diagnostic tests prior to regression analysis, with results summarized in Table 3. Residuals from standard panel regressions exhibit significant spatial autocorrelation under adjacency, distance, and economic geography weight matrices, with all LM-lag and LM-error tests yielding p-values below 0.01. Further LR and Wald tests reject the simplification of SDM to SAR or SEM. Finally, Hausman tests across all

Table 1
Descriptive statistics of the variables.

	Variable symbol	Obs	Mean	Std. dev.	Min.	Q1	Median	Q3	Max.
Dependent variable	CPR	3766	2.5420	2.1679	0.0987	1.2401	1.9058	3.0345	27.3395
Independent variable	GTI	3766	0.2797	0.2707	0.0002	0.0794	0.1987	0.3968	1.9348
Mediating variable	IS	3766	2.2677	0.1597	1.8312	2.1569	2.2651	2.3702	2.9677
	ES	3766	0.2055	0.0559	0.0165	0.1677	0.1998	0.2539	0.3178
	LA	3766	3.7440	1.8381	0.0234	2.5351	3.5174	4.6292	23.6004
	CA	3766	0.9503	0.8802	0.0001	0.3207	0.7227	1.3013	8.0021
Moderating variable	MAR	3766	11.4838	2.6884	3.9306	9.5502	11.4286	13.3814	20.2253
Control variable	ED	3766	10.5599	0.6740	4.5951	10.1315	10.5613	11.0132	13.0557
	UR	3766	0.5444	0.1551	0.0990	0.4335	0.5268	0.6431	0.9981
	EP	3766	4.6175	0.1950	3.7860	4.4968	4.5918	4.7298	5.4103
	TO	3766	0.2049	0.3843	0.0001	0.0321	0.0856	0.2207	8.1339
	PD	3766	5.7990	0.8969	0.6831	5.2646	5.9472	6.4870	7.8816
	IC	3766	16.9691	7.3765	0.1356	11.8400	15.5650	21.3300	60.0700

Note: Obs represents the number of observations. The mean denotes the arithmetic average of the variable, while Std. dev. refers to the standard deviation, indicating the degree of dispersion. Min and Max represent the minimum and maximum values, respectively. Q1, Median, and Q3 refer to the 25th percentile, 50th percentile, and 75th percentile, respectively.



（a）2008　　　　（b）2021

Fig. 2. Local Moran's I scatter plot for carbon productivity, 2008 and 2020.
Note: The z-axis represents standardized carbon productivity, and the Wz-axis is the spatially lagged term. The vertical and horizontal lines indicate $z = 0$ and $Wz = 0$, respectively. The slanted line is the regression fit, whose slope equals the global Moran's I. Each circle denotes one city observation. The four quadrants correspond, in order, to the spatial association patterns High-High, Low-High, Low-Low, and High-Low.

Table 2
Tests of correlation and multicollinearity.

	CPR	GTI	ED	UR	EP	TO	PD	IC	VIF
CPR	1.000								
GTI	0.087****	1.000							1.28
ED	−0.207***	0.278***	1.000						2.16
UR	−0.387***	0.316***	0.672***	1.000					2.02
EP	−0.081***	0.279***	0.308***	0.350***	1.000				1.01
TO	−0.152***	−0.058***	−0.022	0.010	0.018	1.000			1.21
PD	0.045***	0.351***	0.198***	0.154***	0.224***	−0.006	1.000		1.17
IC	−0.043***	0.127***	0.346***	0.110***	0.086***	0.031*	0.076***	1.000	1.18
Pesaran	210.836***		Friedman	1053.647***		Frees	50.427***		

Note: ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

Table 3
Results of model screening tests.

	W_1	W_2	W_3
LM-l	601.116***	1654.087***	182.814***
LM-e	676.928***	4402.340***	231.175***
Wald-l	61.50***	51.39***	69.95***
Wald-e	95.57***	75.34***	99.05***
LR-l	62.13***	53.96***	20.78***
LR-e	83.07***	78.23***	42.05***
Hausman	80.91***	74.21***	80.33***

Note: (1) LM-l and LM-e refer to the Lagrange Multiplier tests for spatial lag and spatial error dependence, respectively. Wald-l and Wald-e are Wald statistics testing the necessity of spatial lag and spatial error terms. LR-l and LR-e represent the likelihood ratio tests for spatial lag and error models. The Hausman test is used to choose between fixed effects and random effects specifications. (2) ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

spatial matrices yield p-values of 0.000, supporting the fixed-effects model. Taken together, the diagnostic outcomes provide robust statistical justification for employing the fixed-effects SDM in the subsequent empirical investigation.

According to the regression results (Table 4), the spatial lag coefficients of carbon productivity are positive and remarkable at the 1 % level under different spatial weight settings, demonstrating a robust positive spatial spillover effect. The competition and imitative behaviors of local governments are key drivers of this spatial spillover in carbon productivity (Brueckner, 2003). In their efforts to simultaneously advance economic performance and control carbon emissions, local authorities often replicate the successful policy frameworks implemented in more developed cities, resulting in a "mutual benefit" spatial spillover effect in carbon productivity. Furthermore, regression outcomes under the adjacency, geographic, and economic-geographic weight matrices yield GTI coefficients that are consistently positive and statistically significant, with values of 0.0482, 0.0421, and 0.0442, respectively. The significant impact of GTI reflects a broader "technology dividend" that underpins China's transition to a low-carbon economy. This dividend is largely driven by targeted advances in clean technologies, which simultaneously lower carbon intensity and generate long-term productivity improvements. These benefits are particularly pronounced in the restructuring of carbon-intensive industries and the widespread adoption of energy-efficient production practices (Popp, 2002; Dechezleprêtre et al., 2013).

Among the control variables, economic development exhibits a significant positive relationship with carbon productivity, indicating its role as a key enabler of low-carbon growth. While it may increase energy consumption, it also provides vital resources and market incentives for low-carbon technologies, promoting structural upgrades and facilitating the shift toward sustainable, low-carbon growth. In contrast, urbanization is found to be significantly negatively associated with carbon productivity. This suggests that, within the context of China's rapid urban expansion, the scale and intensity of construction-related energy use may outweigh the potential efficiency gains associated with urban agglomeration. The result implies that, under current patterns of urban development, higher levels of urbanization tend to suppress improvements in carbon productivity. Rising energy prices exert a strong positive effect on carbon productivity, primarily because higher energy costs incentivize more efficient and cleaner energy use. As energy becomes more expensive, firms and consumers are more likely to adopt energy-saving measures and seek alternative energy sources, thereby improving energy efficiency and reducing carbon emissions. In addition,

Table 4
Regression results.

	Driscoll-Kraay	SDM		
		W_1	W_2	W_3
GTI	0.0569*** (0.0545)	0.0482*** (0.0042)	0.0421*** (0.0042)	0.0442*** (0.0042)
ED	0.1196 (0.0849)	0.1420*** (0.0234)	0.1359*** (0.0234)	0.1331*** (0.0233)
UR	−0.2090*** (0.1928)	−1.8044*** (0.0967)	−1.9118*** (0.0891)	−1.8090*** (0.0899)
EP	−0.0139 (0.0557)	0.2290*** (0.0874)	0.2574*** (0.0877)	0.2387*** (0.0879)
TO	0.2326 (0.1831)	0.0164 (0.0295)	−0.0053 (0.0286)	−0.0056 (0.0287)
PD	0.0102 (0.0414)	−0.0784*** (0.0173)	−0.0663*** (0.0151)	−0.0845*** (0.0154)
IC	0.0014 (0.0058)	−0.0002 (0.0015)	−0.0023 (0.0015)	−0.0020 (0.0015)
W*GTI		0.0198*** (0.0076)	0.1460*** (0.0376)	0.0905** (0.0387)
W*ED		−0.0891** (0.0352)	0.1610 (0.1751)	0.0779 (0.1826)
W*UR		−0.0373 (0.1756)	−0.6573 (0.9541)	−3.4554*** (1.0115)
W*EP		0.1172* (0.0697)	−0.4292 (0.9763)	−0.5987 (1.0432)
W*TO		−0.0814 (0.0572)	−0.7707** (0.3052)	−0.1099 (0.2659)
W*PD		0.1046*** (0.0232)	0.3509*** (0.1294)	0.6294*** (0.1415)
W*IC		0.0003 (0.0021)	−0.0130 (0.0149)	−0.0162 (0.0136)
ρ		0.1829*** (0.0207)	0.6966*** (0.0695)	0.5694*** (0.0887)
R^2	0.3446	0.3211	0.3527	0.3507
Log-likelihood		−3087.6078	−3069.1249	−3075.4000
N	3766	3766	3766	3766

Note: ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors are reported in parentheses.

Table 5
Estimation results of the decomposition effects.

	variable	W_1	W_2	W_3
LR_Direct	GTI	0.0495*** (0.0042)	0.0444*** (0.0042)	0.0453*** (0.0042)
	ED	0.1386*** (0.0223)	0.1383*** (0.0220)	0.1335*** (0.0221)
	UR	−0.1809*** (0.0091)	−0.1927*** (0.0083)	−0.1835*** (0.0085)
	EP	0.2342*** (0.0855)	0.2527*** (0.0847)	0.2337*** (0.0849)
	TO	0.0130 (0.0275)	−0.0153 (0.0270)	−0.0069 (0.0271)
	PD	−0.0745*** (0.0164)	−0.0622*** (0.0142)	−0.0796*** (0.0146)
	IC	−0.0002 (0.0015)	−0.0025 (0.0015)	−0.0021 (0.0016)
LR_Indirect	GTI	0.0325*** (0.0080)	0.5970*** (0.1886)	0.2731*** (0.1052)
	ED	−0.0693* (0.0382)	0.9253 (0.6301)	0.3990 (0.4303)
	UR	−0.0429** (0.0188)	−0.6902* (0.3666)	−1.0846*** (0.3358
	EP	0.1762** (0.0801)	−1.0348 (3.4430)	−1.2515 (2.5972)
	TO	0.1762 (0.0801)	−2.6460** (1.2658)	−0.2524 (0.6486)
	PD	0.1039*** (0.0220)	1.0397** (0.4784)	1.3884*** (0.4186)
	IC	0.0002 (0.0024)	−0.0502 (0.0526)	−0.0415 (0.0331)

Note: ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors are reported in parentheses.

population density displays a significantly negative coefficient at the 1 % level, indicating that high population concentration places considerable pressure on local environmental and resource systems. In densely inhabited areas, strong aggregate energy demand frequently leads to increased carbon emissions, offsetting gains in productivity. Finally, the regression coefficients for trade openness and infrastructure development are not statistically significant.

4.2.2. Spatial spillover results

This study further disaggregates the influence of GTI on carbon productivity into direct and indirect components, with results presented in Table 5. For the direct effects, the estimated coefficients of GTI under the adjacency, geographic distance, and economic-geographic spatial weight matrices are 0.0495, 0.0444, and 0.0453, respectively, all of which are significant at the 1 % level. These findings underscore the essential contribution of local green innovation efforts to advancing sustainability, consistent with the theory of directed technical change, which posits that innovation guided by environmental goals can enhance productivity while reducing carbon intensity (Acemoglu et al., 2012).

With regard to the indirect effects, the estimated coefficients for the spillover effect of GTI range from 0.0325 to 0.5970 and are all statistically significant at the 1 % level. This suggests that GTI in one city can enhance the carbon productivity of surrounding areas through mechanisms such as technology diffusion, knowledge spillovers, industrial chain cooperation, and factor mobility. Spatial externalities arising from GTI assume particular relevance given China's pronounced regional disparities in innovation capacities and environmental governance. Effective regional innovation diffusion and policy coordination can thus mitigate these disparities through cross-regional learning and adoption of best practices. As noted by Rodríguez-Pose (2015), institutional and technological diffusion can help lagging regions catch up when innovation flows are well-connected. In this case, the spillover effects from GTI reflect the networked nature of green transformation, where urban centers of innovation serve as hubs of technological dissemination, raising the overall carbon productivity frontier across regions. These results collectively highlight that GTI is not only a local engine of low-carbon development but also a regional public good, whose benefits transcend administrative boundaries and reinforce collaborative pathways to ecological modernization.

Table 6
Tests of endogeneity.

variable	Lewbel	GS2SLS	
	(1)	(2)	(3)
GTI	0.0339** (0.0141)	0.0127*** (0.0045)	0.0125*** (0.0050)
ED	0.0820*** (0.0218)	0.1501*** (0.0285)	0.1531*** (0.0286)
UR	−0.2207*** (0.0104)	−0.1208*** (0.0119)	−0.1187*** (0.0119)
EP	0.0435 (0.0313)	0.4587*** (0.0608)	0.4669*** (0.0604)
TO	−0.4832*** (0.0528)	−0.1528*** (0.0276)	−0.1539*** (0.0275)
PD	0.0422** (0.0166)	−0.0241 (0.0257)	−0.0143 (0.0249)
IC	−0.0033** (0.0015)	−0.0086*** (0.0017)	−0.0082*** (0.0017)
_cons	2.9573*** (0.3167)	−2.3161*** (0.4131)	−2.3853*** (0.4142)

Note: ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors are reported in parentheses.

4.2.3. Endogeneity test

Although this study controls for a range of relevant variables, the potential omission of important factors may still result in endogeneity issues. Additionally, a bidirectional causal relationship may exist between GTI and carbon productivity, which constitutes another source of endogeneity. To address this concern and avoid estimation bias, the study employs both the Lewbel instrumental variable approach and the Generalized Spatial Two-Stage Least Squares (GS2SLS) method. (i) The Lewbel instrumental variable approach overcomes the conventional requirement that valid instruments must be exogenous by proposing a method to construct instruments from heteroskedasticity in the absence of suitable external instruments (Lewbel, 2012). As reported in Table 6, the estimated coefficient on GTI remains significantly positive, in line with the baseline results. (ii) GS2SLS approach utilizes both the explanatory variables and their spatially lagged terms as instrumental variables, thereby estimating spatial econometric models on the basis of the conventional Two-Stage Least Squares framework. This method effectively addresses endogeneity bias stemming from potential reverse causality and yields robust parameter estimates (Wang et al., 2024b). In the empirical analysis, spatial regression is conducted using both geographical and geo-economic weight matrices. The analysis, detailed in Table 6, confirms that GTI significantly boosts carbon productivity, demonstrating full alignment with baseline regression estimates under all model specifications.

4.2.4. Robustness test

To ensure the robustness and reliability of the empirical results, the study conducts a series of robustness checks using four distinct strategies: alternative model specification, substitution of the explanatory variable, adjustment of the dependent variable, and consideration of policy impacts arising from the Low-Carbon City Pilot Program. The outcomes of these robustness checks are systematically presented in Table 7. Specifically, (i) an alternative SAR model (Model 1) is applied to examine whether the spatial spillover assumptions remain valid; (ii) the explanatory variable is replaced with the number of green patent applications (Model 2) to assess measurement consistency; (iii) the dependent variable is re-estimated using a super-efficiency SBM model (Model 3) to test the stability of the carbon productivity indicator; and (iv) the effects of policy shocks are addressed by incorporating the Low-Carbon City Pilot Program (Model 4). A multi-period Difference-in-Differences approach is employed, based on the timing of the pilot program launches in 2010, 2012, and 2017. The convergence of multiple validation frameworks collectively attests to the methodological rigor and empirical generalizability underpinning our principal findings.

Table 7
Tests of robustness.

	(1)	(2)	(3)	(4)
GTI	0.0515*** (0.0038)	0.0761*** (0.0082)	0.0075*** (0.0018)	
DID				0.0563** (0.0233)
ED	0.1291*** (0.0211)	0.0768*** (0.0242)	0.1567*** (0.0101)	0.1774*** (0.0393)
UR	−0.1999*** (0.0083)	−0.2033*** (0.0093)	−0.0225*** (0.0039)	−0.0735*** (0.0186)
EP	0.2416*** (0.0874)	0.2661*** (0.0883)	0.0081 (0.0379)	0.4853*** (0.0819)
TO	−0.0056 (0.0268)	−0.0224 (0.0290)	0.0124 (0.0124)	−0.1828** (0.0770)
PD	−0.0123 (0.0110)	−0.1200*** (0.0161)	0.0110* (0.0066)	−0.2132*** (0.0568)
IC	0.0005 (0.0014)	−0.0023 (0.0015)	0.0032*** (0.0007)	−0.0124*** (0.0024)
ρ	0.8122*** (0.0449)	0.7789*** (0.0531)	0.7737*** (0.0543)	

Note: ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors are reported in parentheses.

4.3. Analysis of the spatial spillover decay boundary

The realization of spatial spillover effects is often constrained by geographical distance, a phenomenon well documented in spatial economics and innovation diffusion theory. In the context of GTI, its positive externalities on carbon productivity may exhibit distance-decay characteristics, whereby the intensity of spillover effects diminishes as the physical distance between cities increases. To capture this spatial attribute, this study draws upon the theoretical foundation of spatial decay (Paci and Usai, 2009), which posits that the dissemination of knowledge, technology, and environmental impacts is geographically bounded, and such effects tend to attenuate with increasing distance due to frictions in information flow, institutional heterogeneity, and differences in regional absorptive capacity. Specifically, this study constructs a spatial weight matrix based on equidistant threshold increments, enabling a nuanced investigation of how the spatial spillover effects of GTI manifest across varying geographical scales. By doing so, the study aims to delineate the effective radiation range and identify the decay boundary of spillover effects. It is assumed that the inter-city distance is denoted by w_{ij}^d, and the threshold distances are set as follows:

$$w_{ij}^d = \begin{cases} \dfrac{1}{d_{ij}}, d_{ij} \geq d \\ 0, d_{ij} < d \end{cases} \tag{18}$$

The analysis of the spatial spillover decay boundary primarily focuses on examining whether the spatial correlation coefficients exhibit a gradual decline as the distance increases. To this end, this study employs a stepwise approach with a 100-km interval to estimate the spatial spillover coefficients of GTI. For each distance threshold, the corresponding p-values and 95 % confidence intervals are also documented. The results are then visually presented in Fig. 3.

Overall, as the geographic threshold increases, the indirect effects of GTI exhibit a nonlinear trajectory characterized by an initial rise followed by a subsequent decline. Specifically, when the geographical threshold is less than 400 km, GTI has a significant promotional effect on the carbon productivity of neighboring cities, indicating that strong knowledge spillover and technological synergy effects have formed within close proximity between regions. As the geographical threshold further expands to 400 km or more, this positive effect significantly weakens and gradually turns negative, reaching a negative peak at 800 km. This reflects that the long-distance diffusion of green technology may trigger negative externalities such as misallocation of resources and insufficient technological adaptability. When the geographical

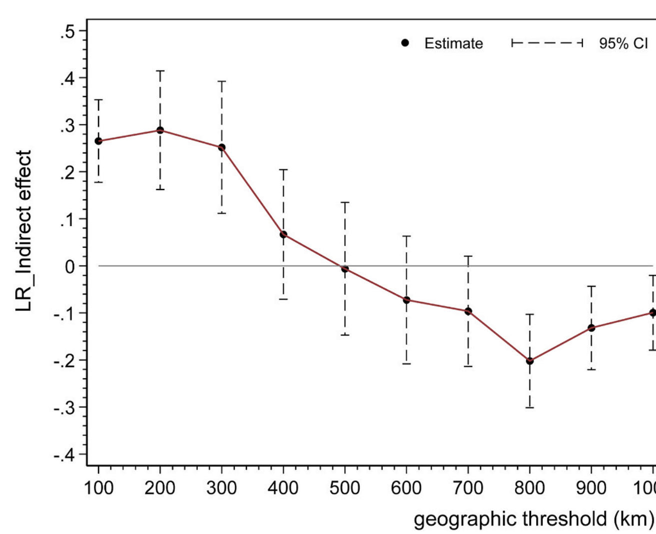


Fig. 3. Spatial decay process of GTI affecting carbon productivity.

threshold exceeds 800 km, although the indirect effect slightly rebounds, it still fails to return to the positive range, indicating that GTI faces significant spatial diffusion boundaries. This evolving pattern reflects several structural constraints in the spatial transmission of green technologies in China, including regional imbalances, institutional frictions, and the absence of effective interregional coordination mechanisms. To mitigate the geographic decay of GTI spillovers and facilitate the broader diffusion of its low-carbon benefits, policy efforts should prioritize the development of cross-regional collaboration platforms and resource-sharing frameworks tailored to the green economy.

4.4. Analysis of heterogeneity

The effectiveness of GTI in promoting carbon productivity is likely influenced by varying socioeconomic contexts. Given China's large-scale economy and substantial regional differences in economic scale, green technology capabilities, and resource endowments, the actual impact of GTI may differ substantially across localities. In light of the above, this study analyzes how GTI-carbon productivity relationships vary across areas by grouping samples based on two factors: resource availability and urban scale.

(i) During the transition toward a low-carbon economy, regional resource endowment has emerged as an important factor influencing patterns of economic development. Specifically, resource-rich regions tend to exhibit pronounced resource dependence, which often results in path-dependent development trajectories and carbon lock-in effects (Unruh, 2000). Furthermore, in order to protect the economic interests tied to resource-intensive and high-emission industries, local governments in such regions may be inclined to relax environmental regulations (Fredriksson and Wollscheid, 2007). To further investigate whether the impact of GTI on carbon productivity varies under different resource endowment conditions, this study adopts the classification framework outlined in the National Sustainable Development Plan for Resource-Based Cities (2013–2020) to categorize the sample. As detailed in Table 8, the impact of GTI on carbon productivity is significantly positive in non-resource-based cities. Conversely, the positive coefficient observed in resource-based cities lacks statistical significance, underscoring a considerably weaker impact. The underlying reasons lie in the structural and institutional differences between the two types of cities. Non-resource-based cities typically possess higher levels of industrial diversification and innovation capacity, coupled with more flexible resource allocation mechanisms. These conditions create a more conducive environment for GTI to support low-carbon development. Conversely, resource-based cities often depend heavily on energy-intensive industries and face greater obstacles in industrial restructuring. Their relatively rigid economic structures hinder the effective integration of green technologies into traditional sectors, resulting in lower innovation conversion efficiency. Furthermore, these cities are burdened by historical dependencies and entrenched development paths, which constrain the adaptability and scalability of GTI within their economic systems, ultimately weakening its effectiveness in improving carbon productivity.

(ii) City size, measured by population scale, serves as an important indicator of a city's level of economic development, overall competitiveness, and future growth potential. Differences in city size are not only reflected in their external influence but also in their responsiveness to policy measures and their capacity to adopt new technologies. Against this backdrop, it becomes essential to examine how GTI affects carbon productivity across cities of varying sizes. Following the categorization methodology proposed by Du et al. (2024), this study classifies cities based on their year-end registered populations into three groups: large cities with populations above 6.2 million, medium-sized cities with populations ranging from 2.55 to 6.2 million, and small cities with fewer than 2.55 million residents. The empirical findings, as detailed in Table 8, display varied impacts of GTI on urban carbon productivity by city size. The analysis shows that GTI significantly fosters the low-carbon transition in large and medium-sized cities. However, in small cities, the positive influence of GTI is not statistically significant, indicating that GTI's effectiveness in supporting low-carbon transformations may be constrained in these smaller urban settings. The primary reason lies in large and medium-sized cities concentrate abundant innovation resources, well-developed infrastructure, and strong fiscal capacity, creating favorable conditions for the development

Table 9
Regression results of the transmission mechanism of GTI on carbon productivity.

variable	structural optimization		factor allocation	
	IS	ES	LA	CA
GTI	0.0073***	0.0382*	−0.0308***	−0.0141*
	(0.0008)	(0.0215)	(0.0032)	(0.0080)
ED	0.1118***	0.2333	0.3030***	0.2245***
	(0.0046)	(0.1589)	(0.0182)	(0.0657)
UR	0.0158***	−0.1638***	−0.1416***	−0.0535**
	(0.0018)	(0.0633)	(0.0069)	(0.0240)
EP	0.0101	−4.3802***	0.0392	0.2362**
	(0.0172)	(0.2661)	(0.0681)	(0.0951)
TO	0.0136**	0.1576	−0.1725***	−0.1663***
	(0.0056)	(0.1275)	(0.0222)	(0.0457)
PD	0.0122	0.4523**	−0.0073	−0.1850**
	(0.0030)	(0.2078)	(0.0118)	(0.0749)
IC	−0.0025	0.0278***	0.0125***	−0.0032
	(0.0003)	(0.0084)	(0.0012)	(0.0030)
ρ	0.7549	0.1523***	0.6836***	0.8489***
	(0.0595)	(0.0301)	(0.0724)	(0.0382)

Note: ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors are reported in parentheses.

Table 8
Estimation results for heterogeneity.

	Resource Endowment		City Size		
	resource	non-resource	large	medium	small
GTI	0.0066 (0.0096)	0.0282*** (0.0044)	0.0212*** (0.0065)	0.0443*** (0.0053)	−0.0107 (0.0112)
ED	0.0423 (0.0534)	0.2324*** (0.0289)	0.1490** (0.0609)	0.2233*** (0.0404)	0.0309 (0.0887)
UR	−0.0599*** (0.0224)	−0.2075*** (0.0108)	−0.0241 (0.0214)	−0.1294*** (0.0146)	−0.0924*** (0.0298)
EP	0.6380*** (0.0944)	0.2697*** (0.1040)	0.2723** (0.1352)	0.2492** (0.1219)	0.4507*** (0.1253)
TO	−0.630***1 (0.1413)	−0.0421 (0.0279)	−0.0554 (0.0649)	−0.0985** (0.0386)	−0.3008*** (0.0554)
PD	−0.2345*** (0.0690)	0.0001 (0.0188)	−0.1070*** (0.0346)	0.0641*** (0.0195)	−0.2929*** (0.0737)
IC	−0.0082*** (0.0028)	−0.0071*** (0.0019)	0.0106*** (0.0022)	−0.0006 (0.0021)	−0.0156*** (0.0034)
ρ	0.2148* (0.1222)	0.6013*** (0.0844)	0.3794*** (0.0489)	0.2979*** (0.0461)	0.5731*** (0.0623)
N	1470	2296	910	1890	966

Note: ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors are reported in parentheses.

and application of green technologies and facilitating a positive cycle between GTI and industrial upgrading. In contrast, small cities face constraints in capital, technology, and talent, coupled with rigid, path-dependent industrial structures, limiting the effectiveness of GTI in driving their low-carbon transition.

4.5. Analysis of the transmission mechanism

To further elucidate the underlying transmission mechanisms, and building upon the preceding theoretical analysis as well as the empirical approach proposed by Dell (2010), this study investigates how GTI influences carbon productivity through the dual lenses of structural optimization and resource allocation. The corresponding estimation results are reported in Table 9.

4.5.1. Structural optimization

From the perspective of structural optimization, GTI exerts a significant positive influence on industrial upgrading, with its regression coefficient passing the 1 % significance level. This result highlights that industrial restructuring serves as an effective channel through which GTI drives improvements in carbon productivity. By fostering technological breakthroughs and advancing process innovations, GTI facilitates the transformation of traditional high-energy-consuming and heavily polluting industries toward low-carbon and intelligent development models. Simultaneously, it accelerates the rise of emerging sectors such as energy conservation, environmental protection, and renewable energy, promoting a leapfrog evolution of industrial structure and ultimately enhancing carbon productivity.

Secondly, a remarkable positive correlation exists among GTI and energy structure transformation, indicating that advances in green technologies can effectively promote improvements in carbon productivity by facilitating energy system optimization. Historically, China's energy structure has been dominated by coal and other high-carbon sources, a pattern that has not only intensified environmental pressures but also constrained sustained gains in carbon productivity. Against this backdrop, breakthroughs in GTI, particularly in the field of clean energy, have provided critical technological support for energy structure optimization. Specifically, by accelerating the development of renewable energy sectors such as solar and wind power and continuously improving the efficiency and application of energy storage technologies, China's energy system has gradually shifted from a traditional high-carbon model to a low-carbon and cleaner configuration, thereby effectively enhancing overall carbon productivity.

4.5.2. Factor allocation

The regression results reveal a significant negative association between GTI and both labor and capital distortions, with coefficients significant at least at the 10 % level. This finding indicates that GTI improves carbon productivity by alleviating inefficiencies in the allocation of production factors, confirming the critical role of GTI in optimizing resource utilization in the transition to a low-carbon economy. Against the backdrop of China's economic transformation and upgrading, the traditional development model, which has long relied on factor input-driven growth, has led to structural imbalances such as the excessive concentration of capital in high-carbon industries and the inefficient allocation of labor resources, thereby constraining the potential for improvements in carbon productivity. GTI has played a crucial role in addressing these challenges by redirecting capital flows toward emerging sectors such as energy conservation, environmental protection, and green manufacturing, while simultaneously encouraging labor resources to shift toward high value-added and green-intensive industries. These shifts have effectively mitigated factor misallocation across the economy. In parallel, advances in green technologies have reduced the technological risks and financing barriers associated with green projects, thereby enhancing the responsiveness of capital markets to green investments. Moreover, by fostering the development of green skills among the labor force, it has further promoted the optimization of human capital structures. As labor and capital factors are increasingly allocated more efficiently, resource utilization within the economic system has steadily improved, the share of green production activities has continued to expand, and ultimately, a sustained enhancement in carbon productivity has been achieved.

In summary, structural optimization and factor allocation are effective pathways through which GTI drives improvements in carbon productivity.

5. Further analysis: spatial threshold effects of marketization on the low-carbon transition impact of GTI

As established in the preceding analysis, GTI can enhance carbon productivity through structural optimization and resource allocation effects. However, this enabling effect is not independent of the external market environment. In contexts where market signals are weak or distorted, GTI may encounter substantial barriers such as high implementation costs and technological constraints, thereby limiting its potential for large-scale adoption. Consequently, a comprehensive and systematic assessment of the impact of GTI on carbon productivity must incorporate the moderating role of the market environment. Against this backdrop, the present study employs a spatial threshold model to examine how the effects of GTI on carbon productivity vary across different levels of marketization. This approach also accounts for spatial spillover effects, allowing for a nuanced understanding of the spatial heterogeneity in the relationship between GTI and carbon productivity under varying degrees of market development.

5.1. Analysis of regression results for threshold effects

Table 10 presents the threshold value and relevant statistics estimated using 300 bootstrap samples. The F-statistic for the single threshold in marketization level is 45.52 with a p-value of 0.0233, indicating that the single-threshold model is statistically significant. In contrast, the double-threshold F-statistic is 22.41 with a p-value of 0.1367, suggesting that the dual-threshold model does not pass the significance test. These findings imply the presence of a single threshold effect for marketization level, with the corresponding threshold value being 13.0705.

Table 11 reports the threshold regression results for marketization level. When the marketization level is below the threshold value of 13.0705, the regression coefficient of GTI is −0.0085 and is statistically significant at the 10 % level, indicating that GTI inhibits the improvement of carbon productivity in low-marketization environments. However, once the marketization level surpasses the threshold, the effect of GTI shifts from a negative constraint to a positive driver, suggesting that higher levels of market development enable GTI to promote carbon productivity.

5.2. Analysis of regression results for spatial threshold effects

Building on the above findings, GTI exhibits both threshold effects and spatial spillover effects in its impact on carbon productivity. Therefore, this study further employs a spatial threshold model to investigate how external market environment factors influence the spatially heterogeneous impact of GTI on carbon productivity. The detailed regression results are presented in Table 12.

Direct effect: The regression results show that when the marketization index falls within the first interval, the coefficients of GTI under the adjacency, geographic, and economic-geographic spatial weight matrices fail to pass the significance test. However, when the marketization index lies within the second interval, the coefficients of GTI range from 0.0462 to 0.0620 and are all statistically significant at the 1 % level, indicating that higher levels of marketization significantly enhance the positive effect of GTI on carbon productivity. The

Table 10
Tests for threshold effects of marketization levels.

Model	Threshold	Lower	Upper	F	Prob	Crit10	Crit5	Crit1
single	13.0705	12.8982	13.0845	45.52	0.0233	33.3470	38.8543	49.6984
double	15.1101	14.8273	15.1434	22.41	0.1367	24.1161	28.0315	41.4725

Table 11
Threshold effect regression results of marketization level.

	CPR
GTI*I(MAR≤13.0705)	−0.0085* (0.0050)
GTI*I(MAR>13.0705)	0.0195*** (0.0056)
ED	0.1666*** (0.0327)
UR	−0.0693*** (0.0140)
EP	0.4885*** (0.0593)
TO	−0.1737*** (0.0284)
PD	−0.2335*** (0.0463)
IC	−0.0125*** (0.0019)
N	3766

Note: ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors are reported in parentheses.

Table 12
Spatial threshold regression results of marketization level.

		W_1	W_2	W_3
LR_Direct	GTI*I	0.0106	0.0014	0.0046
	(MAR≤13.0705)	(0.0176)	(0.0109)	(0.0118)
	GTI*I	0.0562***	0.0462***	0.0620***
	(MAR>13.0705)	(0.0042)	(0.0044)	(0.0041)
LR_Indirect	GTI*I	0.0182	0.0349	0.0136
	(MAR≤13.0705)	(0.0118)	(0.1135)	(0.0594)
	GTI*I	0.0348***	0.3549**	0.0200*
	(MAR>13.0705)	(0.0083)	(0.1557)	(0.0109)
LR_Total	GTI*I	0.0287	0.0363	0.0182
	(MAR≤13.0705)	(0.0251)	(0.1171)	(0.0654)
	GTI*I	0.0909***	0.4011***	0.0819***
	(MAR>13.0705)	(0.0085)	(0.1557)	(0.0120)
control variables		Yes	Yes	Yes
N		3766	3766	3766

Note: ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. Standard errors are reported in parentheses.

fundamental reason lies in the fact that regions with higher marketization levels typically enjoy more efficient competition mechanisms and flexible resource allocation systems, providing a solid institutional foundation for GTI. In such environments, firms are better able to detect market demand for green technologies, which stimulates their motivation and willingness to invest in innovation. Meanwhile, well-established property rights protections and incentive systems help reduce information asymmetries, facilitating the effective transformation and diffusion of green technologies. In contrast, regions with lower levels of marketization often suffer from distorted resource allocation and excessive government intervention, which weakens firms' innovation incentives and capabilities. Under such conditions, green technologies struggle to translate into measurable carbon reduction outcomes. Therefore, the key to promoting the integration of GTI and carbon productivity lies in further deepening market-oriented reforms, removing institutional barriers, and fostering a freer, more standardized, and more efficient market environment.

Spillover effect: When the marketization index is at a low level, the regression coefficients of GTI under the adjacency, geographic, and economic-geographic spatial weight matrices are not statistically significant, indicating that its positive spatial spillover effects have yet to emerge. In contrast, once marketization reaches a higher stage, the coefficients range from 0.0200 to 0.3549 and are significant at least at the 10 % level, suggesting that GTI can significantly boost the carbon productivity of neighboring regions. These results highlight that the spatial spillover effect of GTI is contingent upon the level of marketization. A higher degree of marketization helps dismantle regional barriers, facilitates the free flow of production factors, and promotes the cross-regional diffusion of green technologies, thereby enhancing interregional innovation linkages and collaborative mechanisms. In addition, a robust legal system and strong intellectual property protection provide institutional guarantees for technology transfer and industrial cooperation, effectively reducing the risks and transaction costs associated with innovation diffusion. In such an environment, neighboring regions not only benefit from the technological spillovers of GTI but also improve their own carbon productivity by adopting advanced management practices and production models. In contrast, regions with low levels of marketization often suffer from severe market fragmentation and weak diffusion channels, making it difficult to absorb the dividends of GTI. As a result, the capacity of green technologies to drive improvements in carbon productivity in adjacent areas is significantly constrained.

6. Conclusions and policy recommendations

GTI serves as a key driver for energy conservation, emissions reduction, and green growth, as well as for accelerating China's transition to a low-carbon economy. Against the backdrop of the in-depth implementation of the dual carbon strategy and the ongoing promotion of regional coordinated development, clarifying how GTI influences carbon productivity is not only crucial for enhancing the national innovation system and low-carbon governance framework, but also provides practical guidance for local governments to optimize green development policies and improve inter-city collaborative emissions reduction efficiency.

To address this, utilizing panel data from 269 prefecture-level Chinese cities spanning from 2008 to 2021, this study systematically investigates the impacts and underlying mechanisms through which GTI affects carbon productivity. The core findings and associated policy implications are as follows: (i) GTI generates significant technological dividends by enhancing local carbon productivity and inducing positive spatial spillovers to neighboring regions. However, this spillover effect diminishes progressively with increasing geographical distance; (ii) Considerable heterogeneity is observed in the effectiveness of GTI across regions with differing resource endowments and city sizes. Specifically, non-resource-based cities and medium to large cities exhibit a more pronounced enhancement in carbon productivity attributable to GTI; (iii) Structural optimization and efficient factor allocation emerge as key transmission channels linking GTI with carbon productivity gains; (iv) The positive impacts of GTI are subject to distinct spatial thresholds associated with regional marketization levels. Under conditions of low marketization, the effect of GTI remains limited, while surpassing a specific marketization threshold significantly amplifies GTI's positive contributions to local and neighboring carbon productivity.

Based on the empirical findings discussed, several targeted policy recommendations are proposed:

First, accelerate research and development, as well as the efficient conversion of GTI results, to establish a solid technological foundation for a low-carbon economy. The government should enhance support for original GTI innovations and breakthroughs in key core technologies by providing financial, tax, and credit incentives. At the same time, it should foster the creation of a multi-party collaborative innovation platform that includes enterprises, universities, research institutes, and industries across the entire supply chain, facilitating the transfer of technology, industry, and market knowledge, thereby improving the application efficiency and market responsiveness of green technology outcomes.

Second, promote regional collaborative governance and the rational allocation of green industries to achieve gradual improvements in carbon productivity. Given the differences in resource endowments, technological capabilities, and environmental carrying capacity across regions, a tiered and categorized policy support system should be developed. Within urban agglomerations, mechanisms for sharing green technology resources and coordinating policies should be implemented. Special attention should also be paid to guiding the development of green industries and supporting resource allocation in resource-dependent regions and small cities to prevent the "green technology divide" from worsening regional development disparities.

Third, accelerate market-oriented reforms and optimize the environment for the allocation of innovation resources. A unified, efficient, and orderly competitive factor market system should be established. Measures such as strengthening property rights protection, improving technology trading markets, and fostering the development of green financial instruments should be implemented to enhance the efficiency of resource flows between different economic entities. In particular, policy guidance should be used to stimulate the vitality of enterprises as green innovation drivers and encourage the formation of long-term, stable investment mechanisms in carbon emission reduction and energy conservation.

CRediT authorship contribution statement

Tengfei Li: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Gen Li:** Writing – original draft, Investigation, Data curation. **Shihong Zeng:** Writing – original draft, Resources. **Yu Hao:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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