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Spatial spillovers, mediating mechanisms and moderating effects of industrial agglomeration in promoting green total factor productivity

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Industrial agglomeration (AGG) reshapes industrial green transformation through the dynamic interplay of economies of scale and congestion effects, yet its nonlinear relationship with green total factor productivity (GTFP) is continuously reconfigured by deepening spatial linkages, energy efficiency evolution, and iterative green economic policies. Leveraging panel data from 279 Chinese prefecture-level cities spanning 2011–2023, this study constructs a Spatial Durbin Model (SDM) and employs comprehensive robustness checks and endogeneity treatments to ensure causal validity. Our findings reveal: (1) a significant U-shaped AGG-GTFP nexus, wherein low-level agglomeration suppresses GTFP while high-level agglomeration fosters it; (2) positive spatial spillovers of GTFP, with neighboring AGG exerting inverted U-shaped effects on local GTFP; (3) energy efficiency serving as a partial mediator; and (4) markedly heterogeneous policy moderating effects—National Pilot Program of Low-Carbon Cities and National Big Data Comprehensive Pilot Zone Policy Green Finance Reform and Innovation Pilot Policy flatten the U-shaped curve, Green Finance Reform and Innovation Pilot Policy steepens it, and Emissions Trading Scheme Pilot Policy demonstrate insignificant moderation. These results furnish theoretical and empirical foundations for staged agglomeration regulation, cross-regional coordinated governance, and precision policy design.

Keywords Industrial agglomeration, Green total factor productivity, Spatial spillover effects, Energy efficiency, Policy heterogeneity

The rapid expansion of global industrial economies has precipitated extraordinary environmental pressures, rendering the green transformation of industry an imperative rather than an option. The International Energy Agency (IEA) released its latest Global Energy Review report, indicating that global energy demand grew by 2.2% year-on-year in 2024[1]. Emerging markets and developing economies accounted for 80% of the growth in global energy demand. China's energy consumption in 2024 reached 5.96 billion tons of standard coal equivalent (https://baijiahao.baidu.com/s?id=1825282672983550576&wfr=spider&for=pc). Against this backdrop, reconciling economic growth with environmental constraints has emerged as the central challenge confronting industrial development[2,3,4]. Green Total Factor Productivity (hereinafter referred to as GTFP) transcends the limitations of conventional productivity measures by incorporating energy consumption and pollution emissions into input-output frameworks, thereby offering a comprehensive assessment of the green effects of economic activity[5,6]. Consequently, enhancing GTFP has become the pivotal metric for industrial green development.

Industrial agglomeration (hereinafter referred to as AGG), as the fundamental spatial configuration of industrial economic evolution[7], influences green transformation through the dynamic equilibrium between economies of scale and congestion effects. On the one hand, scale economies enhance efficiency by reducing technology diffusion costs and facilitating collaborative pollution abatement. On the other hand, congestion effects intensify environmental loads, with their interaction exhibiting pronounced nonlinear dynamics[8],

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forming a long-standing academic debate between "agglomeration dividends" and "congestion effects". This dual-attribute dynamic balance positions AGG as a critical research agenda for coordinating industrial economic growth with ecological protection[9,10]. Notwithstanding the substantial scholarly accumulation in this domain, industrial agglomeration is by no means a static or obsolete subject; it remains continuously reshaped by emerging variables—including technological innovation[11], the digital economy[12], and policy updates[13]—that fundamentally alter the interplay between scale economies and congestion effects. Therefore, investigating how these evolving dynamics affect green economic efficiency retains irreplaceable academic value and practical significance within the context of global green development transitions[14].

Crucially, AGG is inherently characterized by geographical spatial correlation[15]. This spatial attribute reshapes nonlinear relationships through multiple dimensions: first, technological innovation in geographically proximate regions may enhance local GTFP through knowledge spillovers[16]; second, spatial displacement of pollutants may amplify local environmental costs[3]; third, agglomeration levels in neighboring regions influence local GTFP through competitive and demonstration effects[17]. This spatial dimension renders industrial agglomeration simultaneously an engine of efficiency enhancement and an amplifier of environmental pressure, thereby engendering potential spatial spillovers or siphon effects[18]. Hence, constructing spatial econometric models is essential. However, previous spatial studies often focus on a single spatial lag or overlook the potential spatial spillover of the agglomeration itself. By employing the Spatial Durbin Model (SDM), this study complements existing literature by simultaneously capturing the local and neighboring effects of both AGG and GTFP.

Energy efficiency serves as the critical nexus connecting AGG with green development (IEA, 2014)[19,20]. Improvements in energy efficiency, driven primarily by technological innovation and infrastructure sharing[21], directly reduce resource consumption intensity and pollution emission per unit of output. Importantly, during the process of enterprise agglomeration, dynamic changes in energy efficiency often function as precursor signals for nonlinear transitions in GTFP[13]. However, despite the dual effects of AGG elaborated above[22], existing research has paid insufficient attention to the mediating mechanisms through which AGG influences energy efficiency via nonlinear pathways[23,24]—a significant oversight that this study aims to address.

Green economic policies remain indispensable for promoting industrial green development. Enterprises, driven by profit maximization, frequently neglect environmental costs, manifesting as pollution emissions and resource overconsumption that generate accumulated negative externalities[25], with pollution transfer particularly elevating social marginal costs. As industrial economies undergo profound transformations toward intelligentization and low-carbon development, governments have dynamically iterated policy instruments to foster green industrial development, encompassing policies related to the digital economy, carbon emission trading, and financial instruments. Yet, a critical limitation pervades existing research: an overreliance on singular indicators[26,27], such as environmental regulation intensity or single government policy[13,28,29], to crudely measure government intervention, failing to systematically elucidate the differentiated moderating effects. Existing literature predominantly relies on singular policy indicators, leaving a critical gap in understanding how diverse policy paradigms, including digital transformation to green finance, heterogeneously reshape the AGG-GTFP nexus.

Building upon the foregoing analysis, this study focuses on examining the varying patterns of the nonlinear relationship between AGG and GTFP within a spatial correlation framework, taking into account the spatial impacts of neighboring AGG and GTFP on local GTFP. We further investigate the mediating role of energy efficiency and how the AGG-GTFP relationship is affected by four different types of green economic policies. The contributions of this research are twofold. First, we describe how the nonlinear effects of agglomeration change when spatial correlation is included. Second, we examine the moderating effects of government policies, which helps clarify how different policy tools influence the green outcomes of industrial agglomeration.

Theoretical framework

Mechanisms of industrial agglomeration affecting GTFP

Industrial agglomeration influences GTFP through the dynamic interaction between economies of scale and congestion effects. **On the one hand**, geographical proximity reduces inter-firm technology diffusion costs, facilitating knowledge spillovers and synergistic green innovation[30]; deepened division of labor along industrial chains improves the sharing of environmental infrastructure, achieving scale economies in pollution abatement[4,31]. **On the other hand**, concentration of production factors may intensify resource competition, compelling firms to adopt non-clean production methods, while localized pollutant accumulation exceeds environmental carrying capacity[32]. Congestion effects dominate and suppress GTFP, whereas scale economies enhance GTFP. The relative intensity of these two effects varies dynamically with agglomeration levels[33].

Furthermore, the green effects of industrial agglomeration exhibit spatial correlation, transmitted through two distinct mechanisms. **First**, **GTFP in neighboring regions affects local GTFP.** Neighboring GTFP influences local development through spatial spillover mechanisms: geographical proximity facilitates the diffusion of green innovation technologies[34,35] along supply chain networks, generating positive technology spillovers that significantly enhance GTFP[36]; simultaneously, pollutants undergo cross-boundary transfer through atmospheric and hydrological systems, resulting in negative pollution spillovers that continuously increase local environmental governance costs[16,37]. Technology spillover intensity may decay with distance, whereas pollution spillover intensity correlates with ecological connectivity. Together, these constitute a spatial dependence pattern encompassing both technological dividends and environmental risks, shaping the systematic linkage characteristics of inter-regional green development. **Second**, **neighboring AGG affects local GTFP.** The scale of the surrounding industrial agglomeration affects local green development pathways through competitive and demonstration effects. **The competitive effect** manifests as high-agglomeration areas leveraging resource siphon capabilities to extract critical transformation factors—labor and capital—from surrounding regions, diluting their investments in green technology R&D and industrial layout, thereby weakening green transformation capacity[15]. **The demonstration effect** operates through regional environmental regulation alliances that dismantle institutional barriers via policy coordination[38], utilizing paradigms such as carbon emission trading networks to reduce trial-and-error costs for green transformation in neighboring areas, thereby facilitating experience replication and enhancing overall governance efficacy. The relative intensity of these two effects depends on regional economic disparities and administrative coordination levels: greater economic gaps strengthen competitive effects, while smoother administrative coordination amplifies demonstration effects. The interplay between these forces ultimately determines the directional impact of the surrounding industrial agglomeration on local GTFP. **Based on the above analysis**, **we propose the first hypothesis**:

H1: The effect of AGG on GTFP exhibits a nonlinear relationship, **and spatial correlation exists between the two.**

Mediating mechanism of energy efficiency

Industrial agglomeration exerts nonlinear effects on energy efficiency through sharing mechanisms. **At low agglomeration stages**, dispersed industry layouts result in insufficient infrastructure sharing—such as weak dispatching capacity of independent power grids and substantial heat loss from decentralized heating systems—thereby reducing energy utilization efficiency. **When agglomeration reaches a certain scale**, centralized heating, shared power grids, and similar facilities achieve scale economies, reducing energy consumption per unit of output through "sharing of indivisible facilities"[20,39].

Energy efficiency affects GTFP growth through cost and environmental effects. **The cost-effect** manifests as energy-saving technologies reducing energy costs per unit of output[28], thereby freeing resources for green technology innovation and factor optimization. **The environmental effect** appears as pollution abatement, reducing environmental regulation costs, such as declining CO_2 intensity[40]. Accordingly, we propose the second hypothesis:

H2: Energy efficiency mediates the effect of AGG on GTFP.

Role of green economic policies

Government intervention through policy instruments constitutes an imperative for correcting market failures arising from environmental externalities[41]. Environmental resources exhibit non-excludability and non-rivalry characteristics, and firm production costs fall significantly below social costs, resulting in excessive pollution emissions and insufficient green technology investment. This necessitates the internalization of environmental costs through policy instruments to reconstruct the Pareto-optimal pathway for industrial economic development[38,42].

This study selected four policies to represent the paradigm evolution of China's green economic policy instruments: the National Pilot Program of Low-Carbon Cities in the energy conservation and emission reduction dimension; the Emissions Trading Scheme Pilot Policy in the carbon trading dimension; the Green Finance Reform and Innovation Pilot Policy in the financial dimension; and the National Big Data Comprehensive Pilot Zone Policy in the digital economy dimension. The mechanisms through which these policies operate are elaborated as follows:

(1) National Pilot program of low-carbon cities

Initiated by the National Development and Reform Commission in 2010 and expanded in 2012 and 2017, this policy centers on formulating low-carbon development plans, establishing low-carbon industrial and consumption systems, and improving greenhouse gas emission target assessment systems. The low-carbon city pilot policy reshapes the nonlinear relationship between factor agglomeration and GTFP through dual pathways of institutional constraint and technology-driven transformation. **Institutional constraints** decompose emission reduction tasks to administrative districts and enterprises, promoting factor flows from high-carbon to low-carbon sectors and optimizing resource allocation. **Technological innovation** explicitly requires accelerated R&D and application of low-carbon technologies[17], guiding the deep integration of factor agglomeration with technology to foster low-carbon economic development.

(2) Emissions trading scheme pilot policy

Launched by the National Development and Reform Commission in 2011 across seven provinces and municipalities, including Beijing. This policy establishes a closed-loop mechanism encompassing total quantity control, quota allocation, and trading supervision, which emphasizes setting emission targets, allocation schemes, trading platforms, and regulatory systems to achieve market-based emission reduction and industrial upgrading. The carbon trading pilot influences factor allocation efficiency and productivity through quota allocation and market mechanisms. **Quota trading** impacts the flow of carbon emission rights toward low-carbon enterprises[13]; **innovation-driven mechanisms** utilize carbon price signals to incentivize technology investment, with collaborative supervision reducing costs and enhancing marginal output efficiency of factors[43].

(3) National big data comprehensive pilot zone policy

Approved and launched in March 2016 by the National Development and Reform Commission and relevant ministries, this policy centers on establishing data resource sharing and open access systems, promoting cross-regional data circulation and trading, and deepening industrial applications and ecosystem construction—such as industrial big data and trusted data spaces. This policy optimizes green transformation pathways through market-oriented allocation of data factors and industrial integration innovation.

Its mechanisms operate as follows: **data factor empowerment** reduces information asymmetry, promoting the directed agglomeration of capital and technology toward green industries[44]; **innovation synergy mechanisms** enhance resource utilization efficiency through key technology R&D, reducing energy consumption and pollution emissions[45].

(4) Green finance reform and innovation pilot policy

In 2017, the People's Bank of China and six other ministries jointly issued the "Overall Plan for Green Finance Reform and Innovation Pilot Zones," conducting pilots across eight locations in five provinces. The policy core involves constructing green financial organizational systems, innovating credit and bond products, exploring environmental rights pledge financing and green insurance, and guiding resource flows from high-pollution industries to green sectors. **The green finance pilot** catalyzes technological leaps in green industries through resource-directed agglomeration and risk diversification mechanisms[46]. **Resource direction** channels capital, technology, and talent toward concentrated deployment in green sectors[28]; **innovation risks are** dispersed through green insurance and transition bonds, promoting technology spillovers and efficiency enhancement.

Based on the foregoing, we propose the third hypothesis:

H3: Green economic policies moderate the nonlinear effect of AGG on GTFP.

The theoretical research framework of this study is illustrated in Fig. 1.

Figure 1 illustrates the integrated theoretical framework of this study. The internal logic of the AGG-GTFP relationship is rooted in the dynamic interaction between scale economies and congestion effects, which defines the fundamental nonlinear path. This baseline relationship is further situated within a broader spatial context, where spatial spillover theory accounts for the regional interdependencies of technology and pollution. Furthermore, the framework incorporates energy efficiency as an internal mediating pathway that facilitates the green transformation process. Finally, recognizing that the impacts of these mechanisms are contingent upon the external institutional environment, the model introduces green economic policies as moderators that influence the relative intensity of agglomeration forces. By synthesizing these theoretical strands into a coherent system, this framework provides a structured, logical basis for the subsequent hypotheses.

Research methodology

Spatial econometric model

General form

The spatial econometric model is a statistical method used to capture the spatial interrelationships between economic variables. This interconnection is described through spatial autocorrelation and spatial dependence[47]. The spatial econometric model can be generally represented in its universal form, as displayed in Eqs. (1) and (2).

$$Y = \rho Wy + X\beta + WX\theta + \varepsilon \tag{1}$$

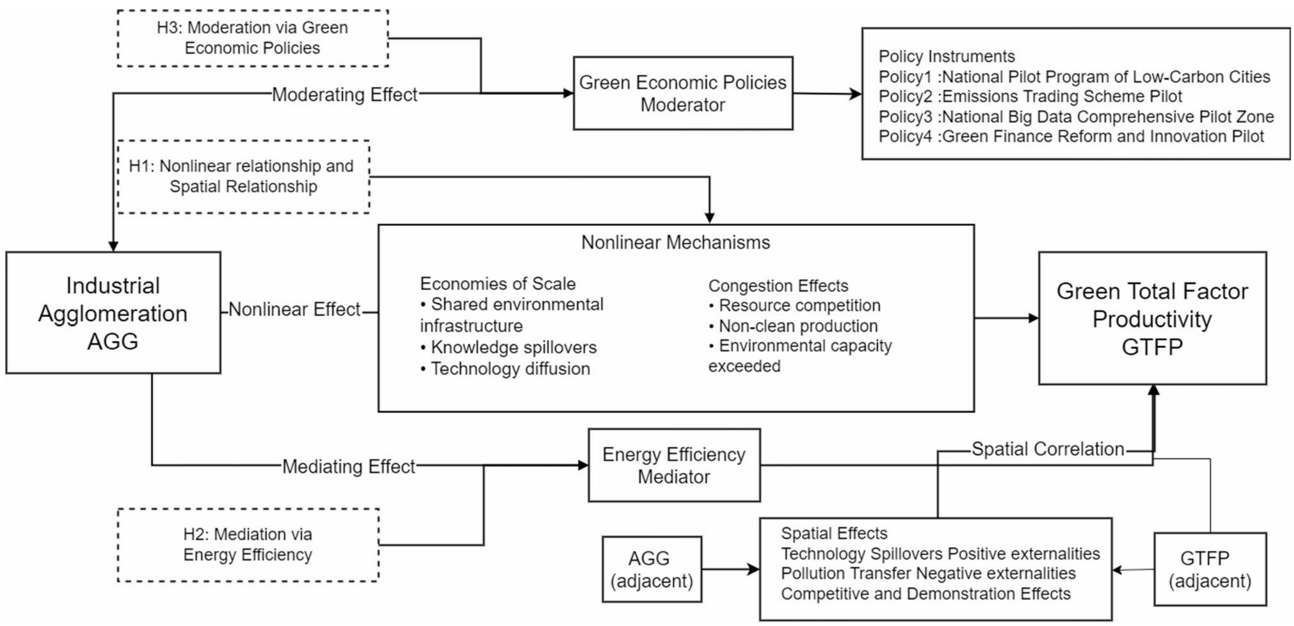

Fig. 1. Theoretical research framework.

$$\varepsilon = \lambda W \varepsilon + \nu \tag{2}$$

Where y represents the dependent variable; ρ denotes the spatial autoregressive coefficient; *W* is the spatial weight matrix, reflecting the spatial structure of the data; *X* represents the matrix of explanatory variables; *β* is the vector of coefficients for the explanatory variables; *θ* is the coefficient for the spatial lag of the explanatory variable; *ε* is the error term; *λ* represents the spatial autocorrelation coefficient of the error term; υ is the independently and identically distributed error term.

The spatial weight matrix is a distinguishing feature of spatial econometric models, as it describes the spatial relationships between variables using geographical or economic indicators[48]. The Formula (3)–(6) display the common types of spatial weight matrices, including the adjacency matrix (W1), which describes whether two locations are adjacent (Cliff et al., 1981); the inverse distance matrix (W2) and the inverse distance squared matrix (W3) which represent spatial relationships based on geographical distance[49]; the economic distance matrix (W4), which incorporates economic factors into the spatial matrix[50]. To ensure the results' generalizability, this study employs a spatial econometric model and comprehensively analyzes the data using the above spatial weight matrices.

$$W1_{ij} = \begin{cases} 1 & \text{if i and j our neighbors} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$W2_{ij} = \frac{1}{d_{ij}} \tag{4}$$

$$W3_{ij} = \frac{1}{d_{ij}^2} \tag{5}$$

$$W4_{ij} = \frac{1}{|GDP_i - GDP_j|} \tag{6}$$

Model design
Grounded in the previous mechanism analysis, this study first constructs a basic panel regression model to investigate the role of AGG, see equation:

$$GTFP_{it} = \alpha + \beta_1 AGG_{it} + \beta_2 AGG_{it}^2 + \gamma X_{it} + \mu_i + \eta_t + \epsilon_{it} \tag{7}$$

Note: $GTFP_{it}$ is the Green Total Factor Productivity of the i region during the t period; AGG_{it} is the industrial agglomeration of the i region during the t period; X_{it} is the set of the control variables; μ_i is the individual effect; η_t is the time effect; ε_{it} is the error term.

Then, this study introduces spatial factors into the above model to construct a Spatial Autoregressive Combined (SAC) model, as the following Eqs. (8, 9):

$$GTFP_{it} = \rho WGTFP_{it} + \beta_1 AGG_{it} + \beta_2 AGG_{it}^2 + \gamma X_{it} + \theta WX_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{8}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \upsilon_{it} \tag{9}$$

Where $\rho WGTFP_{it}$ is the spatial lag of the dependent variable, representing the influence of neighboring regions' GTFP on the local GTFP; θWX_{it} is the spatial lag of the control variables, indicating the impact of neighboring regions' AGG on the local GTFP; $\lambda W\varepsilon_{it}$ is the spatial autocorrelation of the error term, reflecting the influence of neighboring regions' error terms on the current region; υ_{it} is the random error term.

Mediation effect model
In the mediation analysis, we designated X_{it} as the independent variable (AGG), Y_{it} as the dependent variable (GTFP), and M_{it} as the mediating variable (energy efficiency), constructing a three-step mediation model as specified in Eqs. (10)–(12).

$$M_{it} = \alpha_1 + \theta_1 X_{it} + \gamma_1 Z_{it} + \mu_i + \lambda_t + \varepsilon_{1it} \tag{10}$$

$$Y_{it} = \alpha_2 + \theta_2 X_{it} + \theta_3 M_{it} + \gamma_2 Z_{it} + \mu_i + \lambda_t + \varepsilon_{2it} \tag{11}$$

$$Y_{it} = \alpha_3 + \theta_2^{\prime X_{it}} + \theta_3^{\prime\prime M_{it}} + \gamma_3 Z_{it} + \mu_i + \lambda_t + \varepsilon_{3it} \tag{12}$$

Moderating effect model
The moderating effect model is used to observe how the relationship between variables is influenced by a third variable[51]. The general expression of the moderating model is presented in Eq. (13).

$$Y_{it} = \alpha + \beta_1 X_{it} + \beta_2 M_{it} + \beta_3 (X_{it} \times M_{it}) + \gamma Z_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{13}$$

The coefficient β_3 of the interaction term ($X_{it} \times M_{it}$) reflects this relationship. If β_3 has the same sign as β_1 (both positive or both negative), it indicates that the moderating variable M_{it} has a positive moderating effect, meaning M_{it} enhances the influence of X_{it} on Y_{it}. Conversely, if β_3 has the opposite sign to β_1, it indicates that the moderating variable M_{it} has a negative moderating effect, meaning M_{it} weakens the influence of X_{it} on Y_{it}[52].

In this line of thinking, this study constructed a moderating model, as shown in Eq. (13), which can reveal the role of government intervention.

$$\mathrm{GTFP_{it}} = \boldsymbol{\alpha} + \boldsymbol{\beta}_1\mathrm{AGG_{it}} + \boldsymbol{\beta}_2\mathrm{AGG_{it}^2} + \boldsymbol{\beta}_3\mathrm{P_{it}} + \boldsymbol{\beta}_4\left(\mathrm{AGG_{it}} \times \mathrm{P_{it}}\right) + \boldsymbol{\beta}_5\left(\mathrm{AGG_{it}^2} \times \mathrm{P_{it}}\right) + \boldsymbol{\gamma}\mathrm{X_{it}} + \boldsymbol{\mu}_\mathrm{i} + \boldsymbol{\lambda}_\mathrm{t} + \varepsilon_\mathrm{it} \quad (14)$$

In this framework, β_2 represents the baseline curvature of the U-shaped relationship, and β_5 captures the policy-driven adjustment to this curvature. Specifically, if β_2 and β_5 share the same sign, government intervention amplifies the quadratic effect, resulting in a more pronounced U-shaped trajectory. Conversely, opposite signs indicate that the policy attenuates the non-linear intensity, thereby smoothing the transition toward industrial green development.

Variable definition and data description

Dependent variable

The dependent variable in this study is GTFP, which measures the comprehensive performance of resource use efficiency and environmental impact in economic activities. Considering the advantages of various Data Envelopment Analysis (DEA) models[5] this study employs the super-efficiency SBM-DEA model to measure GTFP, as manifested in Formula (15) [53]. Rooted in relevant studies, the input and output indicators are set as follows:

Economic input indexes include (1) Capital, which is represented by the net value of fixed assets; (2) Labor, which is explained by the average annual number of employees; and (3) Energy, which is expressed by total energy consumption. Environmental input indicators include (4) industrial waste gas, which is represented by SO2 emissions; (5) Industrial wastewater, which is measured by Chemical Oxygen Demand (COD) emission; (6) CO2 emission from Global Atmospheric Research (EDGAR). The output indicator refers to the economic output indicator, which is represented by industrial output.

$$\min\rho = \frac{1}{\mathrm{m}}\sum\nolimits_{\mathrm{i=1}}^{\mathrm{m}}\frac{\mathrm{x_{io}} - \mathrm{s_i^-}}{\mathrm{x_{io}}},\ \text{Subject to}\ \begin{array}{c} \sum\nolimits_{\mathrm{j=1}}^{\mathrm{n}}\lambda_{\mathrm{j}}\mathrm{x_{ij}} + \mathrm{s_i^-} = \mathrm{x_{io}}, i = 1,2,\ldots,m \\ \sum\nolimits_{\mathrm{j=1}}^{\mathrm{n}}\lambda_{\mathrm{j}}\mathrm{y_{rj}} - \mathrm{s_r^+} = \rho\,\mathrm{y_{ro}}, r = 1,2,\ldots,s \\ \sum\nolimits_{\mathrm{j=1}}^{\mathrm{n}}\lambda_{\mathrm{j}}\mathrm{b_{tj}} + \mathrm{s_t^u} = \mathrm{b_{to}}, t = 1,2,\ldots,u \\ \sum\nolimits_{\mathrm{j=1}}^{\mathrm{n}}\lambda_{\mathrm{j}} = 1 \\ \lambda_{\mathrm{j}} \geq 0, j = 1,2,\ldots,n \\ \mathrm{s_i^-}, \mathrm{s_r^+}, \mathrm{s_t^u} \geq 0 \end{array} \quad (15)$$

$\mathrm{s_i^-}$: Input slack variable, representing the adjustment amount for the $\mathrm{i_{th}}$ input. $\mathrm{s_r^+}$: Output slack variable, representing the adjustment amount for the $\mathrm{r_{th}}$ output.

It is noteworthy that, when measuring the capital input indicator for GTFP, the perpetual inventory method is used to calculate the capital stock to more accurately reflect the economic value of the capital stock. This method accounts for capital depreciation and helps analyze the long-term trend of capital stock changes. The Formulas (16) and (17) are used for calculating the capital stock.

$$\mathrm{K_t} = \mathrm{K_{t-1}} + \mathrm{I_t} - \mathrm{cc}\delta\mathrm{K_{t-1}} \quad (16)$$

$$\mathrm{I_t^{real}} = \frac{\mathrm{I_t}}{\mathrm{P_t}} \quad (17)$$

Where $\mathrm{I_t^{real}}$ is the fixed asset investment in period t calculated at base period prices; $\mathrm{I_t}$ is the fixed asset investment in period t calculated at current period prices; $\mathrm{P_t}$ is the price index in period t.

Figure 2 illustrates the spatial distribution of GTFP across Chinese cities in 2023. High GTFP cluster regions were predominantly concentrated in two major agglomerations: the Yangtze River Delta area, centered on Shanghai, Jiangsu, and Zhejiang; and the western regions, centered on Chongqing and Chengdu. These regions leveraged technology spillovers and industrial cluster advantages to achieve higher efficiency in production factor allocation, forming a mutually reinforcing spatial pattern characterized by high GTFP. Low GTFP cluster regions were primarily distributed in central and western China, including portions of Shanxi, Henan, Gansu, and Ningxia. These areas, constrained by heavy industrial structures and resource-dependent development, exhibited lower efficiency in green technology transformation and factor coordination, resulting in spatially correlated clusters with depressed GTFP.

Figure 3 presents the spatial distribution of AGG in 2023, revealing a markedly uneven geographical pattern. High industrial agglomeration characterized the developed eastern regions, specifically the Beijing-Tianjin-Hebei region, the Greater Bay Area, and the Yangtze River Delta. These areas attracted substantial enterprise clustering and production factor concentration through superior geographical location, well-developed infrastructure, abundant R&D resources, and favorable policy support, thereby forming robust industrial clusters. In contrast, the high industrial agglomeration observed in Northeast China primarily stemmed from historical accumulation as the nation's traditional industrial base; the heavy industrial systems established through early national strategic planning—including equipment manufacturing and energy chemical industries—laid the foundation for modern industrial clusters. Conversely, central and western regions exhibited lower industrial agglomeration. These areas demonstrated significant gaps in economic scale and industrial agglomeration compared with eastern regions, attributable to remote geographical location, lagging transportation and other infrastructure, human resource outflow, and insufficient policy support.

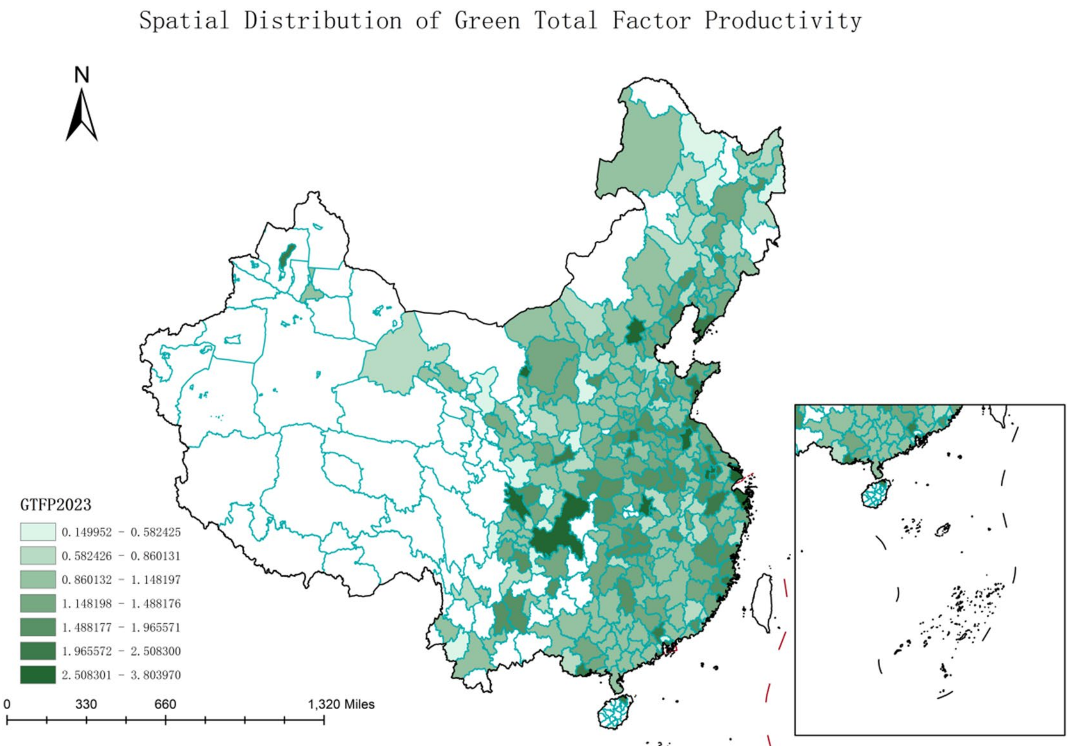

Fig. 2. The spatial distribution of GTFP in 2023 (Generated using ArcGIS Desktop 10.7, version. 10.7.0.10450, https://www.esri.com).

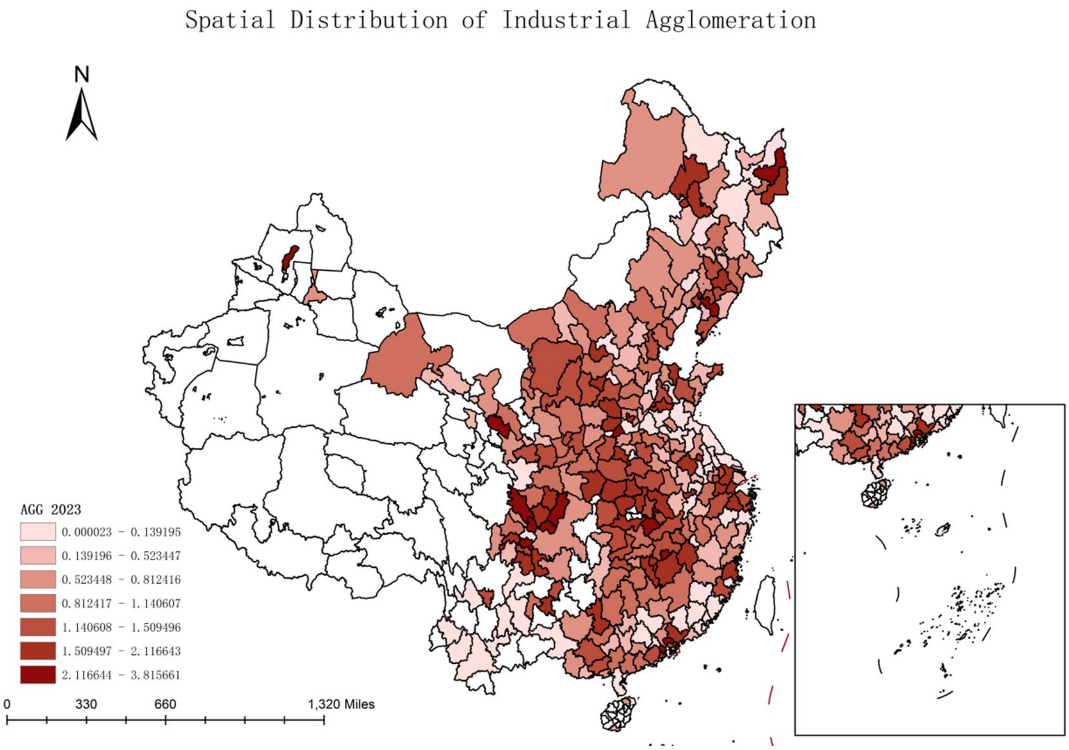

Fig. 3. The spatial distribution of AGG in 2023 (Generated using ArcGIS Desktop 10.7, version. 10.7.0.10450, https://www.esri.com).

Visual inspection suggests that AGG and GTFP were not spatially isolated but exhibited pronounced regional interdependence. Whether this spatial association generates positive spillover effects or siphon effects on GTFP requires further investigation through spatial econometric modeling.

The explanatory variable in this study is AGG. As previously mentioned, AGG is measured using the location quotient, as shown in Formula (18). Following previous research, the number of industrial employees at the end of the year is used as an indicator, as it captures the regional distribution characteristics of the labor market and economic activities[54].

$$\mathrm{Agg_i} = \frac{\frac{\mathrm{E_{i,r}}}{\mathrm{E_r}}}{\frac{\mathrm{E_{i,n}}}{\mathrm{E_n}}} \tag{18}$$

Where $\mathrm{Agg_i}$ presents the location quotient of the $\mathrm{i_{th}}$ industry; $E_{\mathrm{i,r}}$ presents employment of the $\mathrm{i_{th}}$ industry in a specific region r; E_{r} presents total employment in a specific region r; $E_{\mathrm{i,n}}$ presents employment of the $\mathrm{i_{th}}$ industry in the entire region n; E_{n} presents total employment in the entire region n.

To ensure the robustness of our findings, this study employed the industrial density index (**aggdens**) as an alternative proxy for the core explanatory variable AGG. This index effectively captures the relative degree of industrial spatial agglomeration; higher values indicate greater industrial concentration and more pronounced agglomeration advantages in a given region.

The industrial density index was computed through the following three steps, as shown in Formulas (19)–(21):

$$\mathrm{step1:\ dens\_local_{it}} = \frac{\mathrm{secgdp_{it}}}{\mathrm{area_i}} \tag{19}$$

$$\mathrm{step2:\ dens\_mean_t} = \frac{\sum_{i=1}^{N} \mathrm{secgdp_{it}}}{\sum_{i=1}^{N} \mathrm{area_i}} \tag{20}$$

$$\mathrm{step\ 3{:}aggdens_{it}} = \frac{\mathrm{secgdp_{it}} \cdot \sum_{i=1}^{N} \mathrm{area_i}}{\mathrm{area_i} \cdot \sum_{i=1}^{N} \mathrm{secgdp_{it}}} \tag{21}$$

Where $\mathrm{dens\_local_{it}}$ denotes industrial density, $\mathrm{secgdp_{it}}$ represents industrial value-added; $\mathrm{area_i}$ indicates geographical area; $\mathrm{dens\_mean_t}$ refers to national average industrial density; $\mathrm{aggden_{it}}$ signifies the relative density index; and N represents the total number of regions nationwide.

Control variables

Drawing upon prior research, this study incorporated variables closely associated with industrial green development as controls, encompassing human capital, industrialization, population density, economic development, technological innovation, financial deepening, and environmental regulation(Li et al., 2019). Human capital was measured as average years of schooling per capita[55], capturing its role in enhancing labor productivity and reducing environmental pollution through improved environmental awareness and technical skills. Industrialization was operationalized as the share of secondary industry value-added in GDP[56], reflecting its effects of promoting economic efficiency while potentially intensifying environmental pollution and energy consumption. Population density was measured as the logarithm of population per square kilometer[57], capturing its influence on resource allocation and environmental pressure. Economic development was measured as the logarithm of GDP per capita, representing a critical determinant of GTFP given the association between affluent regions and superior technological innovation capacity and environmental investment. Technological innovation was operationalized as the logarithm of green utility patent grants[58], capturing its potential to enhance GTFP through clean technology adoption and production process improvements. Financial deepening was characterized as the ratio of financial institution deposits and loans to GDP[59], reflecting its influence on GTFP through optimized resource allocation and guided green investment. Environmental regulation was represented by the centralized treatment rate of sewage treatment plants[60], capturing its effect on GTFP through mandatory pollution abatement investment and induced industrial upgrading.

Mediating variable

As previously elaborated, energy efficiency was posited to function as a mediating variable, enhancing GTFP through optimized energy input-output ratios. In this study, energy efficiency was measured as GDP output per unit of electricity consumption.

Moderating variables

Grounded in the theoretical mechanisms outlined above, this study selected four green economy-related policies as moderating variables. All policy variables were operationalized as dummy variables, coded 1 for pilot cities and 0 otherwise, specifically including: The National Low-Carbon Province and Low-Carbon City Pilot Policy (Policy1), The Carbon Emission Trading Pilot Policy (Policy2), The National Big Data Comprehensive Pilot Zone Policy (Policy3), and The Green Finance Reform and Innovation Pilot Policy (Policy4). Definitions and descriptions for all variables are presented in Table 1.

Variable type	Variable name	Variable symbol	Variable description	Unit
Explained variable	Green Total Factor Productivity	GTFP	Calculated using the super-efficiency SBM-DEA model	/
Explanatory variable	Industrial agglomeration	AGG	Calculated using the location entropy method	/
Mediating variable	Energy efficiency	energ	GDP created per unit of electricity consumption	10,000 yuan/kWh
Moderator variable	National Pilot Program of Low-Carbon Provinces and Cities	Policy1	pilot_city = 1 if the city is a pilot city, 0 otherwise	/
	Emissions Trading Scheme Pilot Policy	Policy2	pilot_city = 1 if the city is a pilot city, 0 otherwise	/
	National Big Data Comprehensive Pilot Zone Policy	Policy3	pilot_city = 1 if the city is a pilot city, 0 otherwise	/
	Green Finance Reform and Innovation Pilot Policy	Policy4	pilot_city = 1 if the city is a pilot city, 0 otherwise	/
Control variable	Human resources	edu	The average years of education per capita	years
	Industrialization	gdp2p	measured as the share of secondary industry value added to GDP	/
	Population density	popden	Ratio of registered population to the area of the administrative region	/
	Economic development	lngdppc	logarithm of GDP per capita	/
	Technological innovation	lngutupat	Logarithm of green utility model patent quantity	/
	Financial deepening	fin	Ratio of financial institutions' deposit and loan balances to GDP	/
	Environmental regulation	trate	Centralized treatment rate of sewage treatment plants	/

Table 1. Explanation of variables.

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.	VIF
gtfp1	3627	1.027	0.34	0.15	5.424	2.465	18.998	-
gtfp2	3627	0.92	0.236	0.109	2.996	1.139	8.427	-
agg	3627	0.938	0.385	0	3.816	0.449	5.742	1.332
aggdens	3627	0.929	1.437	0.013	8.818	3.461	16.707	2.645
edu	3627	9.223	0.806	6.634	12.36	0.592	3.639	2.545
popden	3627	434.851	306.905	10	1460	0.842	3.31	1.27
energ	3627	26.598	24.158	2.994	151.556	2.9	13.384	1.151
lngdppc	3627	10.819	0.562	9.497	12.101	0.067	2.592	2.41
gdp2p	3627	44.57	10.934	10.68	89.34	-0.16	3.379	1.717
lngutupat	3627	4.308	1.81	0	9.302	-0.158	3.141	1.614
fin	3627	2.624	1.189	1.037	6.898	1.376	4.87	2.039
trate	3627	0.89	0.141	0	1	-3.106	15.989	1.164

Table 2. Descriptive statistics.

Data sources
This study utilized panel data covering 279 prefecture-level cities in mainland China from 2011 to 2023. Certain prefecture-level cities with severe data missingness that failed to meet analytical requirements were excluded due to data availability. Data were compiled from multiple authoritative sources, including the China Statistical Yearbook, statistical yearbooks of individual prefecture-level cities and provinces, the China Environmental Statistical Yearbook, the Emissions Database for Global Atmospheric Research (EDGAR), the China Industrial Statistical Yearbook, and other officially released datasets.

To eliminate inflationary effects, all value-based variables were deflated using the 2000 price index. To ensure data completeness, missing values were imputed through linear interpolation. Additionally, winsorization was applied at the 1st and 99th percentiles for selected continuous variables to mitigate outlier effects.

Table 2 presents the descriptive statistics. The panel data exhibited relatively balanced properties with no detectable outliers. The mean variance inflation factor (VIF) was 1.888, indicating the absence of severe multicollinearity. Table 3 reports the correlation coefficients among variables, demonstrating statistically significant relationships. To ensure econometric rigor, this study performed panel unit root tests as stated in Table 4. The cointegration test results show that the ADF statistics for the Kao and Pedroni tests are 8.5551 and – 18.0919, respectively, both significant at the 1% level. This confirms a stable long-term equilibrium relationship

Variables	(gtfp1)	(agg)	(edu)	(popden)	(energ)	(lngdppc)	(gdp2p)	(lngutupat)	(fin)	(trate)
gtfp1	1.000									
agg	0.012	1.000								
edu	0.310***	0.166***	1.000							
popden	0.258***	0.247***	0.203***	1.000						
energ	0.125***	-0.072***	-0.230***	-0.048***	1.000					
lngdppc	0.341***	0.309***	0.679***	0.262***	-0.278***	1.000				
gdp2p	-0.027*	0.386***	-0.053***	0.105***	0.127***	0.152***	1.000			
lngutupat	0.156***	0.261***	0.431***	0.434***	-0.176***	0.485***	0.005	1.000		
fin	0.194***	-0.089***	0.528***	0.086***	-0.240***	0.246***	-0.494***	0.271***	1.000	
trate	0.072***	0.076***	0.186***	0.091***	-0.208***	0.296***	-0.113***	0.248***	0.140***	1.000

Table 3. Pairwise correlation coefficients. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Variables	LLC Adjusted t*	HT Z-statistic	IPS Z-statistic
gtfp1	−16.92***	−15.01***	−8.40***
agg	−12.89***	24	16.95
d_agg	−45.23***	0.592	−19.46***
edu	−16.91***	−28.21***	/
popden	−170.00***	−8.02***	−14.84***
energ	−20.66***	−14.84***	−14.87***
lngdppc	−18.05***	−1.89**	−9.16***
gdp2p	−18.73***	7.33	−4.52***
lngutupat	26.81	−1.35*	12.03
fin	−26.42***	−1.10	−1.90**
trate	−22.61***	−16.66***	−9.66***
gtfp2	−17.04***	0.462 **	7.66
aggdens	−18.76***	0.55	/
d_aggdens	−35.27***	0.151***	/

Table 4. Unit root tests. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

among the variables, ensuring the statistical robustness of the regression analysis in the empirical model and effectively ruling out the risk of spurious regression.

Overall, the panel data employed in this study maintained balanced properties and satisfied the requirements for statistical analysis.

Empirical analysis
Spatial autocorrelation tests and model selection
In spatial econometrics, establishing spatial dependence among variables is essential, which is assessed through Moran's I index[61]. The Moran's I results presented in Table 5 reveal that both the AGG index and GTFP exhibited positive spatial autocorrelation across most years[62]. These findings indicate significant spatial clustering of both variables across regions, consistent with prior research[63].

Table 6 presents the results of a comprehensive series of model diagnostic tests.

The selection of the spatial econometric model specification was determined through LM and robust LM tests. The test statistics for both spatial error and spatial lag components were statistically significant at the 1% level, indicating the presence of spatial correlation. Furthermore, the LR test and Wald test results corroborated the existence of spatial dependence and rejected the possibility of reducing the SDM model to either SAR or SEM specifications, demonstrating the necessity of simultaneously accounting for both spatial error and lag effects.

The BP and Hausman test results were employed to examine model fixed effects. The results indicated that fixed effects were preferable to random effects, ensuring model stability and consistency. The LR test further clarified whether fixed effects were individual fixed, time fixed, or both. The results demonstrated that both time and individual factors played critical roles in the model specification.

Ultimately, based on these rigorous diagnostic tests, the SDM model with fixed effects (time and individual fixed effects) was adopted to investigate the impact of AGG on GTFP, thereby providing more precise and reliable analytical results.

Table 6 presents the results of a comprehensive series of model diagnostic tests to ensure the econometric rigor of the spatial analysis. First, the selection of the spatial econometric model specification was initially screened through the Lagrange Multiplier (LM) and Robust LM tests. The test statistics for both spatial error and spatial lag components are statistically significant at the 1% level (Table 6), indicating that ignoring spatial

Variables	W1	W2	W3	W4
AGG2011	7.303***	10.119***	8.531***	4.111***
AGG2012	7.228***	10.972***	8.827***	3.936***
AGG2013	7.917***	13.470***	10.340***	3.709***
AGG2014	8.209***	15.869***	11.568***	3.720***
AGG2015	8.920***	16.538***	11.950***	3.500***
AGG2016	8.942***	16.875***	12.242***	3.887***
AGG2017	9.930***	18.655***	13.245***	3.585***
AGG2018	10.178***	21.008***	14.367***	4.135***
AGG2019	9.255***	17.152***	12.241***	3.610***
AGG2020	7.924***	11.143***	9.038***	2.977***
AGG2021	6.609***	7.019***	6.513***	2.616***
AGG2022	6.077***	6.510***	5.959***	1.885*
AGG2023	5.486***	6.489***	5.570***	1.211
GTFP2012	-1.888**	1.888**	1.258	0.214
GTFP2013	-1.15	-0.034	-0.317	1.107
GTFP2014	1.344*	2.162**	1.596*	1.342*
GTFP2015	2.386***	2.158**	1.871**	1.989**
GTFP2016	2.681***	2.996***	2.941***	0.419
GTFP2017	1.135	1.967**	0.852	0.14
GTFP2018	-0.11	-0.815	-0.858	-0.238
GTFP2019	2.354***	4.100***	2.112**	-0.943
GTFP2020	1.980**	2.792***	1.640*	-0.424
GTFP2021	2.469***	5.621***	3.194***	0.306
GTFP2022	2.545***	5.746***	3.839***	0.717
GTFP2023	2.227**	4.687***	3.524***	1.648*

Table 5. Moran's I results. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Test	Statistic
U test for agg	3.22*
LM test spatial error	915.544***
Robust LM test spatial error	387.928***
LM test spatial lag	540.444***
Robust LM test spatial lag	12.828***
LR Test spatial lag	44.64***
LR Test spatial error	46.78**
Wald Test spatial lag	44.85***
Wald Test spatial error	46.69***
BP test	3826.83***
Hausman test	173.00**
LR Test fixed effects	21.14***

Table 6. Diagnosis test results. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

interdependencies would lead to biased estimations and that traditional OLS is inappropriate. Crucially, to address the preference for the Spatial Durbin Model (SDM), we performed both Likelihood Ratio (LR) and Wald tests. The results (Table 6) significantly reject the null hypotheses that the SDM could be simplified or reduced to either the Spatial Autoregressive (SAR) or the Spatial Error (SEM) models. This validates the necessity of adopting the SDM, as it simultaneously accounts for the complex spatial spillover effects arising from both the dependent and independent variables. Regarding model effects, the BP and Hausman test results indicate that fixed effects are preferable to random effects, ensuring the consistency of the parameter estimates. Furthermore, the LR test for fixed effects clarifies that a double fixed effects (time and individual fixed effects) specification is superior to a single fixed effect. Ultimately, based on these rigorous diagnostic tests, the SDM with double fixed effects was adopted to provide the most precise and reliable analytical results for investigating the AGG-GTFP relationship.

Table 7 presents the baseline regression results for five model specifications: OLS regression, fixed effects panel regression, SEM, SAR, and SDM, corresponding to columns (1)–(5), respectively.

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	SEM	SAR	SDM
agg	-0.229***	-0.282***	-0.200***	-0.191***	-0.200***
	(-5.94)	(-8.47)	(-6.28)	(-6.07)	(-6.10)
agg2	0.069***	0.097***	0.063***	0.061***	0.063***
	(4.09)	(6.86)	(4.68)	(4.49)	(4.65)
edu	0.043***	0.260***	0.126***	0.116***	0.121***
	(4.37)	(6.73)	(3.10)	(3.01)	(3.14)
popden	0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(13.65)	(-3.46)	(-3.66)	(-4.07)	(-4.01)
energ	0.004***	0.006***	0.007***	0.007***	0.007***
	(16.72)	(29.97)	(32.86)	(32.81)	(32.87)
lngdppc	0.205***	0.346***	0.163***	0.146***	0.151***
	(14.62)	(16.48)	(5.37)	(5.00)	(5.15)
gdp2p	-0.001*	0.001	0.004***	0.004***	0.004***
	(-1.78)	(1.34)	(4.29)	(4.44)	(4.13)
lngutupat	-0.017***	-0.025***	-0.015***	-0.015***	-0.016***
	(-4.77)	(-7.67)	(-2.80)	(-2.94)	(-3.04)
fin	0.027***	0.009	-0.042***	-0.040***	-0.040***
	(4.48)	(1.04)	(-4.10)	(-3.97)	(-4.00)
trate	-0.014	-0.125***	-0.094***	-0.095***	-0.095***
	(-0.37)	(-3.46)	(-2.78)	(-2.84)	(-2.82)
_cons	-1.580***	-4.842***			
	(-13.82)	(-16.47)			
Spatial					
lambda			0.221***		
			(4.65)		
rho				0.205***	0.210***
				(4.87)	(4.89)
Variance					
sigma2_e			0.039***	0.039***	0.039***
			(42.53)	(42.52)	(42.52)
Wx					
agg					0.245**
					(2.03)
agg2					-0.116**
					(-2.16)
Inflection point	1.659	1.454	1.587	1.566	1.587
N	3627.000	3627.000	3627.000	3627.000	3627.000
ll	-722.879	606.149	749.989	751.059	753.389
aic	1467.757	-1190.299	-1475.978	-1478.118	-1478.778
bic	1535.915	-1122.141	-1401.624	-1403.764	-1392.032

Table 7. Baseline regression results. t statistics in parentheses* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Regarding the core variables, the coefficient on agg was consistently negative and statistically significant across all models, while the coefficient on agg2 was significantly positive. These findings indicate a robust U-shaped relationship between AGG and GTFP, with this nonlinearity remaining stable under different estimation specifications.

With respect to the key spatial parameters, the spatial autoregressive coefficient (rho) in the SAR model was significantly positive; the spatial error coefficient (lambda) in the SEM model was likewise significantly positive; and the spatially lagged dependent variable coefficient Wxagg2 in the SDM model was statistically significant. These results collectively demonstrate that spatial effects play a substantively important role in this study, providing strong empirical justification for the adoption of spatial econometric methods.

Based on the comprehensive diagnostic tests and model comparisons presented above, the SDM specification was determined to be the most appropriate choice. Subsequent analyses were conducted using a spatial inverse distance-squared weighting matrix (W3), with economic interpretations derived from the SDM regression results.

To accurately assess the marginal impacts of industrial agglomeration, we decomposed the spatial effects into direct and indirect components.

As shown in Table 7, the direct effect of AGG on GTFP exhibits a significant U-shaped pattern locally. This confirms that the initial "crowding effect" and rising factor costs constrain local GTFP[64], while subsequent economies of scale and synergy effects foster green innovation[15].

More importantly, the indirect effect (spatial spillover) of AGG displays a distinct inverted U-shaped characteristic. The negative spatial lag coefficient of agg2 reveals that at lower levels of neighboring agglomeration, the local region benefits from vertical specialization and industrial chain collaboration, fostering resource complementarity. However, as neighboring AGG surpasses the inflection point (1.587), a powerful "siphon effect" dominates. Neighboring regions with superior infrastructure and productivity drain high-quality labor and capital from the local area, intensifying resource shortages and suppressing local GTFP. The numerical dominance of the indirect effect over the direct effect underscores the critical role of spatial interdependencies in China's green development. This disparity is primarily driven by deepening regional economic integration and high factor mobility across city boundaries. In a highly integrated spatial network, the cumulative externalities generated by the collective industrial trajectories of neighboring regions exert a more potent influence on local GTFP than isolated internal industrial adjustments alone. This confirms that cross-regional resource allocation and technical coordination act as the primary catalysts for fostering green technical progress.

Furthermore, the spatial lag coefficient of GTFP is significantly positive. This indicates that GTFP in geographically adjacent regions generates positive spillover effects on local green development through channels such as technology diffusion and demonstration effects[65]. These findings collectively underscore the complex non-linear spatial interdependencies between industrial agglomeration and green technical progress. These findings collectively validate Hypothesis 1.

Regarding the control variables, all achieved statistical significance at varying confidence levels.

Human capital (edu) demonstrated a positive and significant effect at the 1% level, indicating that human capital enhancement increased GTFP. An educated workforce facilitates innovation and environmental awareness, underscoring the necessity for increased educational investment[66].

Population density (popden) exhibited a significant negative correlation at the 1% level, likely attributable to diseconomies of scale resulting from excessive population concentration: infrastructure overload precipitated declines in energy efficiency, while pollution aggregation effects exceeded the benefits of intensification, thereby constraining GTFP improvement[67].

Economic development (lngdppc) yielded a positive and statistically significant coefficient at the 1% level, demonstrating that economic advancement enhanced GTFP. As economies expand, technological innovation and environmental governance measures generate positive impacts[68].

Industrialization level (indus) was positive and significant at the 1% level, indicating that industrialization fostered green development through enhanced production efficiency and resource utilization, highlighting the imperative of advancing industrialization[69].

Technical innovation (lnpaten) displayed a significant negative correlation at the 1% level, reflecting insufficient clean technology application: despite quantitative growth in green innovation, actual conversion rates of clean technologies remained low, failing to generate large-scale substitution effects[70]; simultaneously, high upfront R&D investments in green innovation crowded out productive resources in the short term, elevating comprehensive environmental costs and creating a transitional adjustment period.

Financial deepening (fin) exhibited a significant negative correlation at the 1% level, primarily stemming from capital concentration in short-term, high-return traditional pollution-intensive industries, which crowded out investments in green technological R&D.

Environmental regulation (trate) demonstrated a significant negative correlation at the 1% level, mainly attributable to mandatory pollution abatement requirements that substantially increased firm compliance costs, crowding out productive resources and suppressing innovation investment.

Robustness and endogeneity tests

To rigorously verify the stability of our findings, this study conducted five robustness checks. First, alternative spatial weighting matrices: adjusting the definition of spatial connectivity, other three spatial weighting matrices were applied to examine whether spatial effects remained robust, as shown in Columns (1)–(3) of Table 8, and Fig. 4 illustrates the nonlinear relationships between AGG and GTFP under other three spatial weighting matrices (W1, W2 and W4), confirming the robustness of the U-shaped pattern across different specifications. Second, key variable replacement: alternative indicators were utilized to verify whether conclusions depended on specific indicator selection; a new GTFP measure(gtfp2) was constructed with CO_2 as the undesirable output, and the industrial density index (aggdens) served as the alternative proxy for AGG, as illustrated in Columns (4)–(5) of Table 8. Third, municipality exclusion: samples from provincial-level municipalities with higher administrative status were removed to eliminate interference from extreme values or special groups, thereby examining the influence of sample composition on results, as reported in Column (1) of Table 9. Fourth, U-test implementation: it was employed to examine whether significant nonlinear relationships existed between variables[71], as presented in Column (2) of Table 9. Fifth, semiparametric model estimation: relaxing functional form assumptions to verify whether nonlinear model results remained robust, as illustrated in Column (3) of Table 9. The comprehensive robustness test results demonstrated that the U-shaped relationship between AGG and GTFP, as well as the spatial correlation between AGG and GTFP, remained robust across different confidence intervals.

To address endogeneity concerns, this study employed two approaches. First, lagged explanatory variables: explanatory variables were lagged by one period. Temporally, lagged variables precede the dependent variable, effectively circumventing endogeneity bias arising from reverse causality—for instance, prior states of industrial

	(1) W1	(2) W2	(3) W4	(4) gtfp2	(5) aggdens	(6) Lagged explanatory variables
agg	-0.213***	-0.189***	-0.180***	-0.165***	0.076*	-0.316***
	(-6.36)	(-5.81)	(-5.60)	(-8.70)	(1.83)	(-6.24)
agg2	0.061***	0.062***	0.059***	0.044***	0.008*	0.100***
	(4.42)	(4.56)	(4.33)	(5.61)	(1.75)	(4.36)
edu	0.118***	0.121***	0.117***	0.163***	0.097**	0.143***
	(3.04)	(3.12)	(3.04)	(7.28)	(2.46)	(3.03)
popden	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.67)	(-4.10)	(-3.96)	(-3.30)	(-3.62)	(-3.92)
energ	0.007***	0.007***	0.007***	0.005***	0.005***	0.004***
	(32.85)	(32.88)	(33.09)	(40.79)	(31.97)	(17.50)
lngdppc	0.136***	0.161***	0.159***	-0.001	0.104***	0.129***
	(4.64)	(5.37)	(5.49)	(-0.08)	(3.17)	(3.79)
gdp2p	0.005***	0.004***	0.005***	0.004***	0.002**	0.004***
	(4.82)	(4.03)	(4.80)	(7.60)	(2.25)	(3.84)
lngutupat	-0.016***	-0.015***	-0.017***	-0.008***	-0.020***	-0.034***
	(-3.15)	(-2.87)	(-3.45)	(-2.64)	(-4.00)	(-3.06)
fin	-0.041***	-0.043***	-0.039***	-0.044***	-0.044***	-0.033***
	(-4.09)	(-4.23)	(-3.86)	(-7.54)	(-4.29)	(-2.83)
trate	-0.098***	-0.091***	-0.102***	-0.089***	-0.097***	-0.309***
	(-2.91)	(-2.69)	(-3.05)	(-4.60)	(-2.86)	(-7.11)
Wx						
agg	0.056	0.738*	-0.446***	0.163**	-0.070	0.481***
	(0.97)	(1.79)	(-5.03)	(2.34)	(-0.75)	(2.64)
agg2	0.007	-0.437**	0.199***	-0.071**	0.034***	-0.187**
	(0.26)	(-2.33)	(5.08)	(-2.31)	(2.67)	(-2.18)
Spatial						
rho	0.099***	0.350***	-0.007	0.364***	0.172***	0.265***
	(4.44)	(3.11)	(-0.26)	(10.04)	(3.91)	(5.82)
Variance						
sigma2_e	0.039***	0.039***	0.039***	0.013***	0.039***	0.045***
	(42.50)	(42.54)	(42.59)	(42.45)	(42.54)	(40.85)
vN	3627	3627	3627	3627	3627	3348
ll	752.438	749.287	753.021	2731.356	734.298	422.552
aic	-1476.875	-1470.575	-1478.043	-5434.712	-1440.595	-817.104
bic	-1390.129	-1383.828	-1391.296	-5347.966	-1353.849	-731.478

Table 8. Robustness and endogeneity tests (I). t statistics in parentheses* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

agglomeration influence current-period GTFP but are not conversely affected by current-period GTFP, as shown in Column (6) of Table 8.

Second, instrumental variable two-stage least squares (2SLS) estimation: one-period lagged variables of agg and agg2 served as instrumental variables to alleviate endogeneity concerns. The selection rationale was as follows: Recognizing the practical constraints in identifying external instruments at the municipal level, this study adopts the lagged explanatory variables following the identification strategy common in economic research (Shao et al.,[33]. Instrument variables exhibit natural temporal correlation with current-period agg and agg2, satisfying the relevance condition; as historical data, they remain unaffected by disturbance terms in current-period GTFP, satisfying the exogeneity condition. Diagnostic tests confirmed that the underidentification test verified a significant correlation between instrumental variables and endogenous variables; the weak instrument test demonstrated adequate instrument strength; and the Hansen J test excluded risks of overidentification, as reported in Column (4) of Table 9. After accounting for endogeneity bias, AGG maintained significant nonlinear relationships with GTFP, reaffirming the core conclusions of this study.

5.4 Mediation Effects Results.

Based on the theoretical analysis presented above, energy efficiency constitutes the critical transmission nexus connecting AGG with GTFP; accordingly, this study designated energy efficiency as the mediating variable. The empirical results are presented in Table 10. The total effect of AGG on GTFP exhibited U-shaped characteristics; energy efficiency was likewise significantly positive, indicating that both AGG and energy efficiency exerted significant influences on GTFP, as shown in Column (1) of Table 10. The total effect decomposed into direct

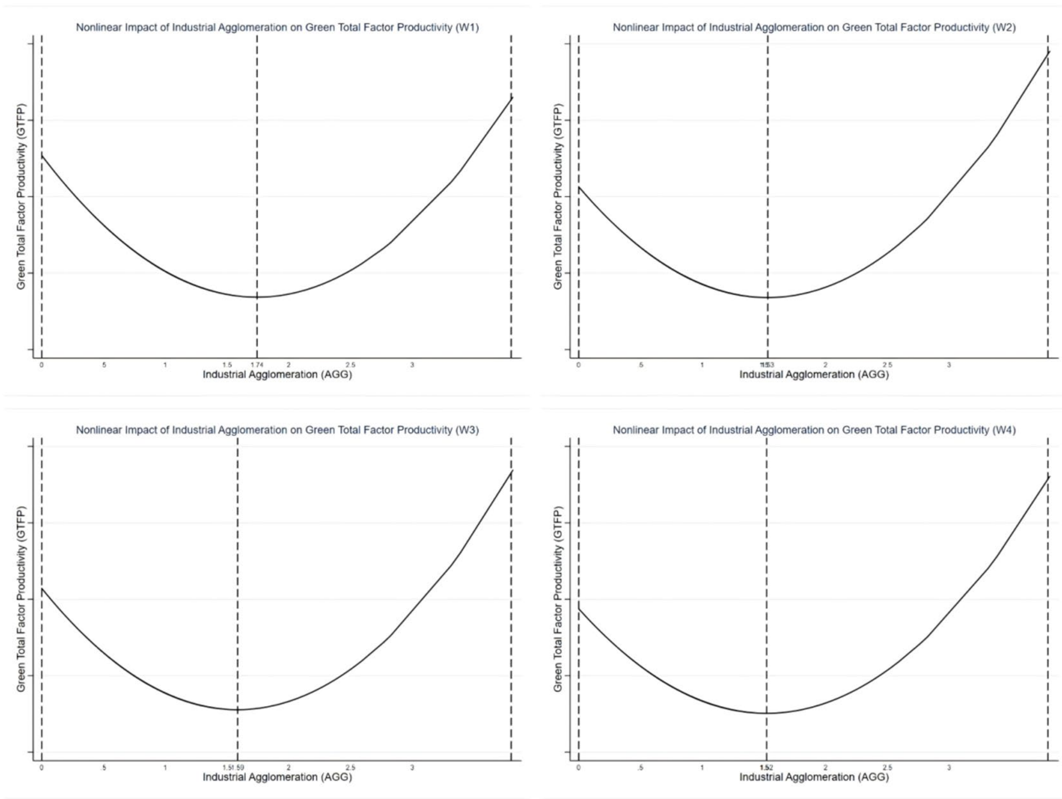

Fig. 4. U-shaped relationships under four spatial weighting matrices.

and indirect components: the direct effect of AGG on GTFP operated through pathways including technological innovation and managerial optimization, as presented in Column (2) of Table 10. Simultaneously, the indirect effect of AGG on GTFP was transmitted through the mediating role of energy efficiency, as reported in Column (3) of Table 10. The influence of AGG on energy efficiency similarly followed a U-shaped pattern, consistent with our theoretical expectations; this indicated that low agglomeration suppressed energy efficiency, whereas high agglomeration enhanced energy efficiency. This transmission mechanism originated from insufficient infrastructure sharing and absent technological coordination due to enterprise dispersion at low agglomeration stages, while high agglomeration stages achieved intensive energy utilization through centralized energy supply, concentrated pollution abatement, and technology spillovers. These findings indicate that energy efficiency serves as a partial mediator, thereby validating Hypothesis 2 of this study.

Moderating mechanism analysis

Based on the theoretical mechanisms elaborated above, this study employed four policies closely associated with green development to capture government policy effects and examine their potential moderating roles in the AGG-GTFP relationship, including: National Pilot Program of Low-Carbon Cities (Policy 1), Emissions Trading Scheme Pilot Policy (Policy 2), National Big Data Comprehensive Pilot Zone Policy (Policy 3), and Green Finance Reform and Innovation Pilot Policy (Policy 4). Table 11 presents the moderating effect results for these four green economy policies (Table 12).

The interaction coefficient between policy1 and agg2 (policy1×agg2) was −0.046 and statistically significant at the 10% level, indicating that the policy attenuated the U-shaped relationship between AGG and GTFP. This finding suggests that the policy flattened the U-shaped curve by simultaneously suppressing negative externality releases during initial agglomeration stages and excessive scale expansion during later stages (see Fig. 5). Specifically, on the left side of the U-shaped curve, the policy formed hard constraints on high-carbon sectors by decomposing emission reduction tasks to administrative districts and key enterprises, promoting factor flows from low-efficiency high-carbon sectors to high-efficiency low-carbon sectors and thereby alleviating GTFP declines caused by resource misallocation. On the right side of the U-shaped curve, the policy requirements for accelerating low-carbon technology R&D and application guided the deep integration of factor agglomeration with low-carbon technologies, substituting technological progress for scale expansion and limiting diminishing marginal returns from excessive agglomeration. This synchronous constraint on both ends embodies the policy characteristic of maintaining stability, preventing both the extreme inefficiency of "pollute first, remediate later " and resource waste from excessive agglomeration.

The policy 2 exhibited no significant moderating effect on the relationship between AGG and GTFP; neither the linear (policy2×agg) nor the quadratic interaction coefficients (policy2×agg2) achieved statistical significance. This result stemmed from the limited coverage and depressed carbon prices during the sample period. The pilot

Variables	(1) Municipalities excluded	(2) utest	(3) Semiparametric estimation	(4) 2SLS
agg	-0.200***	-0.200***		-0.206**
	(-3.221)	(-3.221)		(0.080)
agg2	0.067***	0.067***		0.0652*
	(2.729)	(2.729)		(0.040)
edu	0.031	0.031	0.063	0.120**
	(0.564)	(0.564)	(0.713)	(0.050)
popden	-0.000***	-0.000***	-0.000	-0.000***
	(-3.554)	(-3.554)	(-0.952)	(0.000)
energ	0.007***	0.007***	0.008***	0.007***
	(18.624)	(18.624)	(9.219)	(0.000361)
lngdppc	0.149***	0.149***	0.169***	0.162***
	(4.348)	(4.348)	(3.250)	(0.040)
gdp2p	0.005***	0.005***	0.003***	0.005***
	(3.737)	(3.737)	(3.422)	(0.00108)
lngutupat	-0.013	-0.013	-0.003	-0.017*
	(-1.309)	(-1.309)	(-0.583)	(0.009)
fin	-0.034***	-0.034***	-0.030***	-0.040***
	(-2.776)	(-2.776)	(-2.633)	(0.014)
trate	-0.028	-0.028	0.121	-0.081
	(-0.562)	(-0.562)	(1.133)	(0.062)
Constant	-0.832	-0.832		
	(-1.395)	(-1.395)		
t-value		1.88**		
Underidentification (LM)				59.559 ***
Weak IV (Cragg-Donald)				3493.788
Weak IV (Kleibergen-Paap)				571.371
Overidentification (Hansen J)				0.000
Observations	3,575	3,575	3,300	3,348
R-squared	0.662	0.662	0.371	0.408
ID	YES	YES	YES	YES
YEAR	YES	YES	YES	YES

Table 9. Robustness and endogeneity tests (II). t statistics in parentheses* $p<0.1$ ** $p<0.05$ *** $p<0.01$.

phase incorporated only a few sectors, such as power generation, leaving most prefecture-level cities unregulated and rendering policy impacts difficult to penetrate the industrial agglomeration. Simultaneously, severe market illiquidity persisted: the 2024 national carbon market turnover rate was approximately 3.5%, substantially below the spot turnover rate and futures turnover rate in mature European and American carbon markets (https://business.sohu.com/a/926595652_120988533). Although the closing price in 2024 reached 97.49 CNY/ton, representing a 22.75% increase from 2023 (https://www.gov.cn/lianbo/bumen/202501/content_6996276.htm), China's carbon price remained at relatively low levels compared with other mature carbon trading markets, failing to generate effective emission reduction cost incentives. Consequently, enterprises lacked motivation to respond through spatial layout adjustments or technological innovation. This policy demonstrates an immature mechanism with limited efficacy, reflecting the universal predicament during initial institutional construction: the foundational framework has been preliminarily established, yet operational effectiveness requires continued temporal accumulation and practical optimization.

The interaction coefficient between policy3 and agg2 (policy3×agg2) was − 0.059 and statistically significant at the 10% level, weakening the nonlinear influence of AGG on GTFP. This policy flattened the U-shaped curve through market-oriented allocation of data factors and enhanced resource allocation efficiency (see Fig. 6). Specifically, on the left side of the U-shaped curve, the policy reduced firms' costs of accessing green technology information through improved digital infrastructure and increased internet penetration, alleviating resource allocation distortions caused by information barriers in low-agglomeration areas and thereby moderating GTFP declines. On the right side of the curve, the policy facilitated the spillover of data technology into industrial chains by attracting digital talent agglomeration and promoting the digital industry, substituting digital technology for traditional factor inputs and reducing the risk of diminishing marginal returns from excessive agglomeration,

	(1) Total effect	(2) Indirect effect	(3) Direct effect
agg	-0.200***	-10.462***	-0.272***
	(-6.10)	(-3.97)	(-7.29)
agg2	0.063***	3.709***	0.089***
	(4.65)	(3.40)	(5.74)
energ	0.007***		
	(32.87)		
edu	0.121***	-4.597	0.086*
	(3.14)	(-1.48)	(1.96)
popden	-0.000***	-0.012*	-0.000***
	(-4.01)	(-1.90)	(-4.31)
lngdppc	0.151***	-3.227	0.128***
	(5.15)	(-1.37)	(3.84)
gdp2p	0.004***	0.073	0.005***
	(4.13)	(0.94)	(4.26)
lngutupat	-0.016***	-2.547***	-0.033***
	(-3.04)	(-6.23)	(-5.67)
fin	-0.040***	-0.807	-0.043***
	(-4.00)	(-1.00)	(-3.79)
trate	-0.095***	-9.454***	-0.160***
	(-2.82)	(-3.51)	(-4.20)
Wx			
agg	0.245**	-8.982	0.160
	(2.03)	(-0.92)	(1.16)
agg2	-0.116**	4.244	-0.078
	(-2.16)	(0.98)	(-1.28)
Spatial			
rho	0.210***	0.214***	0.232***
	(4.89)	(4.41)	(5.07)
Variance			
sigma2_e	0.039***	250.255***	0.050***
	(42.52)	(42.51)	(42.51)
N	3627.000	3627.000	3627.000
ll	753.389	-1.52e + 04	279.869
aic	-1478.778	30356.466	-533.739
bic	-1392.032	30437.016	-453.189

Table 10. Mediation effect results. t statistics in parentheses* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

thereby stabilizing GTFP improvements. This dual role of information empowerment and efficiency optimization smoothed the differential green effects of industrial agglomeration across stages.

The interaction coefficient between policy4 and agg2 (policy4×agg2) was 0.069 and statistically significant at the 5% level, intensifying the U-shaped relationship between AGG and GTFP. This incentive-oriented policy exacerbated the "Matthew effect" of industrial agglomeration through differentiated allocation of financial resources, rendering the curve steeper[72] (see Fig. 7). Specifically, on the left side of the curve, green credit resources tilted toward green industries; however, low-agglomeration regions possessed weak foundations in green industries, making effective financial resource allocation difficult and instead aggravating resource misallocation, thereby amplifying GTFP declines. On the right side of the curve, where industrial agglomeration began exhibiting economies of scale, differentiated credit policies effectively identified and supported green projects, while innovative instruments such as green bonds broadened financing channels, generating more robust GTFP improvements. This mechanism of differentiated financial resource allocation magnified the nonlinear impact of AGG on GTFP. These findings demonstrate that green finance does not universally improve green efficiency across all regions; rather, through a screening mechanism, it accelerates the survival-of-the-fittest process of industrial agglomeration, intensifying the divergence between green growth poles and traditional lagging regions.

	(1) Policy 1	(2) Policy 2	(3) Policy 3	(4) Policy 4
agg	-0.249***	-0.203***	-0.197***	-0.161***
	(-6.49)	(-5.98)	(-5.59)	(-4.67)
agg#agg	0.078***	0.064***	0.072***	0.052***
	(-5.05)	(-4.48)	(-4.96)	(-3.61)
edu	0.125***	0.128***	0.137***	0.178***
	(-3.23)	(-3.25)	(-3.48)	(-4.45)
popden	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.98)	(-4.13)	(-3.88)	(-4.03)
energ	0.007***	0.007***	0.007***	0.007***
	(-32.84)	(-32.84)	(-32.78)	(-32.98)
lngdppc	0.154***	0.148***	0.150***	0.148***
	(-5.22)	(-5.05)	(-5.03)	(-5.05)
gdp2p	0.004***	0.004***	0.004***	0.003***
	(-4.18)	(-3.89)	(-4.26)	(-3.32)
lngutupat	-0.015***	-0.016***	-0.018***	-0.016***
	(-2.98)	(-3.09)	(-3.54)	(-3.04)
fin	-0.041***	-0.040***	-0.047***	-0.036***
	(-4.05)	(-4.03)	(-4.62)	(-3.61)
trate	-0.094***	-0.091***	-0.083**	-0.085**
	(-2.80)	(-2.70)	(-2.49)	(-2.54)
policy1	-0.092**			
	(-2.28)			
policy1×agg	0.139**			
	(-2.36)			
policy1×agg2	-0.046*			
	(-1.75)			
policy2		0.031		
		(-0.53)		
policy2×agg		0.052		
		(-0.62)		
policy2×agg2		-0.017		
		(-0.47)		
policy3			0.103**	
			(-2.53)	
policy3×agg			0.018	
			(-0.25)	
policy3×agg2			-0.059*	
			(-1.86)	
policy4				0.243***
				(-4.8)
policy4×agg				-0.229***
				(-3.01)
policy4×agg2				0.069**
				(-2.03)
Wx				
agg	0.186	0.241**	0.280**	0.337***
	(-1.51)	(-1.97)	(-2.32)	(-2.75)
agg2	-0.093*	-0.121**	-0.130**	-0.151***
	(-1.72)	(-2.24)	(-2.44)	(-2.80)
Spatial				
rho	0.204***	0.204***	0.220***	0.201***
	(-4.71)	(-4.68)	(-5.13)	(-4.61)
Variance				
sigma2_e	0.039***	0.039***	0.038***	0.038***
	(-42.52)	(-42.52)	(-42.51)	(-42.52)
Continued				

	(1)	(2)	(3)	(4)
	Policy 1	Policy 2	Policy 3	Policy 4
N	3627.000	3627.000	3627.000	3627.000
ll	756.535	756.863	769.229	766.925
aic	-1479.070	-1479.727	-1504.457	-1499.851
bic	-1373.735	-1374.392	-1399.122	-1394.516

Table 11. Moderating effects of four policies. t statistics in parentheses* $p<0.1$ ** $p<0.05$ *** $p<0.01$.

	(1)	(2)	(3)	(4)
	W1	W2	W4	GTFP4
policy1	-0.084**	-0.093**	-0.095**	-0.036
	(-2.09)	(-2.30)	(-2.38)	(-1.56)
policy1×agg	0.132**	0.138**	0.154***	0.061*
	(2.23)	(2.34)	(2.65)	-1.79
policy1×agg2	-0.040	-0.044*	-0.052**	0.000
	(-1.53)	(-1.65)	(-1.98)	(-0.00)
policy2	0.032	0.024	0.023	-0.063*
	(0.54)	(0.41)	(0.40)	(-1.86)
policy2×agg	0.034	0.052	0.052	0.137***
	(0.40)	(0.62)	(0.62)	-2.81
policy2×agg2	-0.009	-0.010	-0.011	-0.029
	(-0.24)	(-0.26)	(-0.32)	(-1.40)
policy3	0.105**	0.100**	0.100**	-0.043*
	(2.57)	(2.43)	(2.45)	(-1.83)
policy3×agg	0.007	0.024	0.027	0.145***
	(0.10)	(0.35)	(0.38)	(3.58)
policy3×agg2	-0.051	-0.060*	-0.061*	-0.056***
	(-1.59)	(-1.89)	(-1.92)	(-3.06)
policy4	0.247***	0.248***	0.238***	0.062**
	(4.93)	(4.88)	(4.77)	-2.13
policy4×agg	-0.248***	-0.245***	-0.232***	-0.038
	(-3.28)	(-3.22)	(-3.09)	(-0.86)
policy4×agg2	0.079**	0.081**	0.077**	0.034*
	(2.33)	(2.38)	(2.28)	-1.74

Table 12. Robustness tests for moderating effects. t statistics in parentheses* $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Conclusion, policy implications, and limitations

Conclusion

This study employed provincial panel data spanning 2011–2023 to investigate the dynamic nexus between industrial agglomeration and GTFP. Our findings reveal a U-shaped curvilinear relationship: AGG initially impedes GTFP at low agglomeration levels, subsequently promoting GTFP upon surpassing an inflection threshold. Further analysis demonstrates that GTFP exhibits significant positive spatial spillover effects, with local GTFP subject to nonlinear influences from neighboring AGG, specifically manifesting as an inverted U-shaped relationship. Mechanism tests confirm that energy efficiency serves as a critical mediating conduit between AGG and GTFP. Green economic policies form government exhibit markedly heterogeneous moderating effects: National Pilot Program of Low-Carbon Cities and National Big Data Comprehensive Pilot Zone Policy attenuate the AGG-GTFP nonlinearity; Emissions Trading Scheme Pilot Policy demonstrates insignificant effects; whereas Green Finance Reform and Innovation Pilot Policy intensifies the AGG-GTFP relationship.

Policy implications

Based on the empirical evidence, this study provides the following insights to optimize the relationship between industrial agglomeration and green growth: First, the U-shaped relationship between AGG and GTFP suggests the necessity of staged dynamic regulation. For regions below the inflection point, the targeted allocation of industrial support funds is recommended to promote scale economies through localized assistance. Conversely, for regions exceeding the threshold, policy focus should shift toward industrial upgrading and the extension of industrial chains into high-end manufacturing segments. Second, the presence of spatial spillovers necessitates cross-regional collaborative governance. Given the inverted U-shaped influence of neighboring agglomeration,

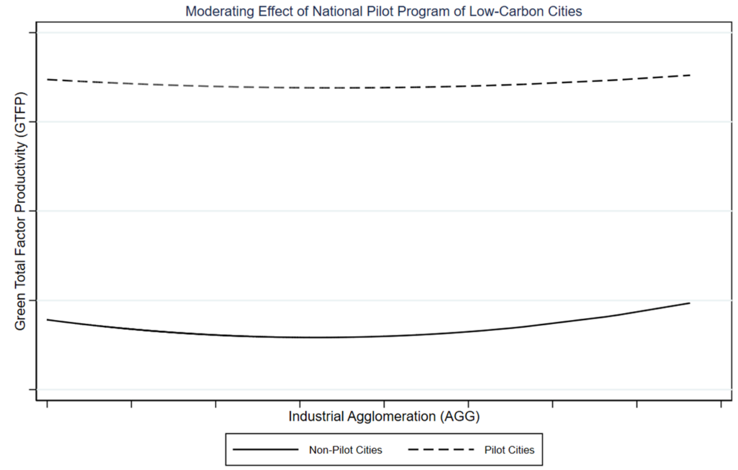

Fig. 5. Moderating effect of low-carbon city Pilot policy(Policy 1).

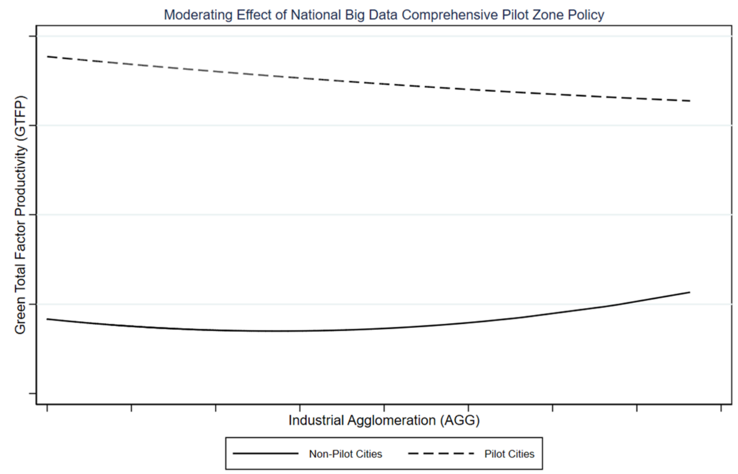

Fig. 6. Moderating effect of national big data comprehensive Pilot zone policy (Policy 3).

efforts should be directed toward harmonizing environmental standards and optimizing regional industrial layouts within urban clusters. Implementing resource-sharing models, such as the enclave economy, could effectively mitigate pressures arising from localized over-agglomeration. Third, the role of energy efficiency as a critical mediator underscores the importance of prioritizing energy conservation. This involves providing financial support for energy-saving technological R&D and integrating energy efficiency metrics into local government performance evaluations. Such measures are essential to incentivize a comprehensive green industrial transformation. Fourth, the heterogeneous effects of policy instruments call for differentiated optimization. Specifically, the Low-Carbon City Pilot should balance constraint and incentive effects based on local AGG levels, while the Carbon Emissions Trading Pilot should focus on expanding sectoral coverage and enhancing market liquidity. Furthermore, the Big Data and Green Finance pilots should prioritize infrastructure extension and financial instrument innovation, respectively, to guide precise resource allocation.

To summarize the aforementioned policy recommendations, this study suggests prioritizing energy efficiency improvements and cross-regional synergy as action priorities to generate immediate green dividends, while positioning carbon trading, digital infrastructure, and green finance as long-term strategic goals. Crucially, the implementation of various policies must be matched with local fiscal resources and administrative capacities, thereby ensuring the feasibility of these recommendations. Furthermore, a dynamic monitoring mechanism matched with local administrative capacities should be established. Specifically, periodic policy evaluations are essential to prevent excessive government intervention from imposing unnecessary administrative burdens on firms.

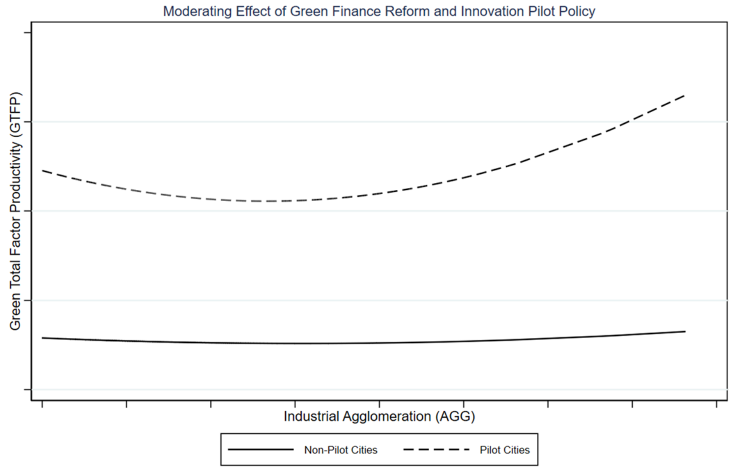

Fig. 7. Moderating effect of green finance reform pilot policy (Policy 4).

Limitations and future research

This study is constrained by the limited availability of firm-level microdata and the substantial challenges of cross-database matching, alongside time constraints that precluded comprehensive processing of complex data and models required for differentiated analysis across industrial subsectors. Consequently, our analysis has not penetrated to the firm micro-level, failing to uncover heterogeneous influence pathways across enterprises of varying scales and ownership structures, nor has it conducted differentiated analyses of agglomeration characteristics across manufacturing subsectors, potentially limiting the precision and generalizability of our conclusions.

Future research directions should incorporate firm-level data to investigate transmission mechanisms across different enterprise types; simultaneously, multidimensional heterogeneity analyses classified by industrial characteristics (e.g., energy-intensive versus high-technology industries)should be undertaken, thereby furnishing evidentiary foundations for differentiated policy formulation.

Data availability

The datasets used in this study are available from the corresponding author upon reasonable request.

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Author contributions

All authors contributed to the study design. The research framework was completed by Saifuzzaman Ibrahim and Xiaoming Mao. Data analysis and the first draft of the manuscript were completed by Jin Yin and Cheng Zhong. Revision and proofreading were done by Xinyu Zhang. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

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