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THE IMPACT OF MANUFACTURING AGGLOMERATION ON GREEN DEVELOPMENT: EMPIRICAL EVIDENCE FROM 287 CITIES IN CHINA

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Abstract. Amid global carbon-neutrality pledges and sustainable development agendas, balancing green transformation with manufacturing competitiveness has become a core challenge for the world economy. However, whether Manufacturing Agglomeration (MA) promotes or inhibits Green Development (GD) remains debated. Using panel data from 287 Chinese prefecture-level cities (2011–2023), this study employs econometric models to explore the overall, mediating, spatial, and threshold effects of MA on GD. Findings show that China's urban GD index rose from 0.118 to 0.232, with a spatial pattern of "higher in the east and south, lower in the west and north." Overall, MA significantly suppresses GD, a result robust to multiple tests. Mechanism analysis reveals that MA inhibits GD through the mediating effect of artificial intelligence industry agglomeration, while green technological innovation partly offsets this negative impact. Moreover, MA produces negative spatial spillovers, as environmental pressure and low-end lock-in spread through factor flows and supply-chain linkages. Threshold effects indicate the inhibition is strongest at moderate MA but weakens at higher levels, while heterogeneity analysis shows stronger suppression in the east, within urban clusters, and in higher-tier cities. This study enriches understanding of the MA-GD nexus and offers policy insights for advancing industrial green transformation and sustainable development.

Keywords: manufacturing agglomeration, green development, spatial spillover, threshold regression, China.

JEL Classification: C23, R11, Q56.

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1. Introduction

Sustainable growth and improved environmental performance have become global priorities (Li et al., 2024; Wang et al., 2023). Since the second half of the 20th century, developed countries have gradually shifted from high-speed industrialization to green transformation (Guo et al., 2024). For instance, the European Union has promoted low-carbon development through its emissions trading system and the "Green Deal" (Achasova & Achasov, 2024), while the United States has relied on market mechanisms and technological innovation to optimize its energy structure (Joshi, 2021). By contrast, many developing countries are still exploring Green Development (GD) models suited to their own conditions under the dual pressures of economic growth and ecological protection (Li et al., 2022). The United Nations' 2030

Agenda for Sustainable Development further highlights "inclusive growth," "climate action," and "ecosystem protection" as global goals, underscoring the strategic importance of green transition as the new trajectory of world economic development (Weiland et al., 2021).

Against this backdrop, China has achieved remarkable growth over four decades of reform and opening, but long-term reliance on factor-driven expansion and extensive resource use has created persistent challenges, including high energy consumption, heavy emissions, resource misallocation, and structural imbalances (Feng et al., 2022; Guan & Zhang, 2025). Under the "dual-carbon" targets and the high-quality development strategy, the traditional growth model has become unsustainable, making a fundamental transformation imperative. In this context, GD – characterized by carbon reduction, pollution abatement, ecological enhancement, and growth – has evolved from a policy vision into a systematic national strategy (Yang & Ran, 2024). It is now embedded in planning, investment, energy restructuring, technological innovation, and industrial upgrading, reflecting both China's domestic priorities and its role in the global green transition.

Manufacturing, as a pillar of the national economy, is critical for stabilizing growth, securing employment, fostering innovation, and enhancing competitiveness (Herman, 2016). Manufacturing Agglomeration (MA), a major organizational form of modern manufacturing (Fang, 2019), can raise productivity and promote upgrading through specialization, knowledge diffusion, factor matching, and capability accumulation (Baptista, 2001). Yet MA may also generate congestion costs, homogenized competition, and path dependence, leading to resource misallocation and environmental pressures. Its overall effect on GD is therefore context-dependent and spatially heterogeneous (Cao et al., 2024). Systematically identifying the mechanisms and spatial effects of how MA shapes GD is thus of both academic and policy relevance.

In recent years, China has promoted manufacturing clusters through industrial and regional policies. MA has, to some extent, supported green transition by facilitating technology diffusion, collaborative governance, and cleaner production (Guo et al., 2023). However, under regional decentralization and growth-oriented performance evaluation, local competition has also led to over-agglomeration, redundant construction, and policy homogeneity, undermining green transition (Zhang et al., 2025). This coexistence of positive and negative effects highlights the need for empirical and context-specific investigation.

Given China's pivotal role in global manufacturing, clarifying the mechanisms and spatial effects of MA on GD is crucial for advancing new industrialization, strengthening regional coordination, and offering lessons for other developing economies and the global green transition. Grounded in evolutionary economic geography, this study builds a multi-level empirical framework using panel data from 287 Chinese cities (2011–2023). Specifically, we first employ a two-way fixed effects model to test the overall impact of MA on GD. Second, we introduce a mediation model to uncover the transmission mechanisms of Artificial Intelligence (AI) industry agglomeration and Green Technological Innovation (GTI). Third, we apply a Spatial Durbin Model (SDM) to examine cross-city spatial spillovers. Fourth, we utilize a threshold panel model to identify potential nonlinear characteristics. Finally, we conduct heterogeneity analyses across regions, urban clusters, and city hierarchies.

This study makes four contributions. First, by integrating the UN Sustainable Development Goals with China's "dual-carbon" strategy, we construct a GD index system covering carbon reduction, pollution abatement, ecological enhancement, and growth, providing a comprehensive tool to measure GD. Second, empirical analysis based on a large panel dataset of Chinese cities shows that MA significantly suppresses GD at the current stage, accompanied by negative spatial spillovers. This finding not only reveals the environmental costs of industrialization but also provides new empirical evidence for research on agglomeration externalities. Third, in mechanism testing, unlike previous studies that mainly examined the mediating roles of industrial upgrading and general technological innovation, this study shows that the impact of MA on GD is dual. On the one hand, MA reinforces its inhibitory effect through AI industry agglomeration, and on the other hand, it partly offsets it by fostering GTI. Finally, threshold and subgroup analyses show that the inhibitory effect of MA is strongest at moderate levels but weakens at higher levels, and that negative effects are more pronounced in the eastern region, within urban clusters, and in higher-tier cities. These findings suggest that policymakers should adopt place-based approaches and implement differentiated green industrial policies and governance instruments.

2. Literature review

Regarding the connotation and evaluation of GD, there is still no unified standard in the academic community, and existing research mainly follows three approaches. First, from the perspective of capital stock, some scholars incorporate natural resources and environmental factors into national wealth accounting, using indicators such as green Gross Domestic Product (GDP) or ecological footprint to assess sustainability (Wei et al., 2025). However, due to their one-dimensional nature, these indicators cannot fully capture the complex interactions among the economy, society, and the environment. Second, based on efficiency theory, many studies measure GD through green total factor productivity, which balances economic output and environmental constraints and has been widely applied at city, regional, and industry levels (Yang & Ni, 2022). Yet this approach remains limited by input-output variable selection, especially the neglect of ecosystem services and technological innovation (Yang et al., 2022). Third, from a systems perspective, GD is treated as a complex whole comprising economic, social, resource, and environmental subsystems (Aziz & Bakoben, 2024). This line of research often employs multi-dimensional subsystem decomposition to build comprehensive evaluation systems, emphasizing holism and dynamics but requiring higher data quality and stronger methodological integration (Pan et al., 2024). Overall, these three approaches reflect the influence of sustainability and ecological modernization theories in GD measurement, signaling a shift from single-factor assessment toward systemic and dynamic evaluation.

As for the relationship between MA and GD, existing research is relatively extensive but remains inconclusive. Broadly, three perspectives can be identified. The first argues that MA promotes GD (Guo & Sun, 2023). Through economies of scale and specialization, MA can lower unit costs and resource use (Chavas & Kim, 2010). Knowledge and technology spillovers, along with collaborative networks, further accelerate the diffusion of green technologies and the adoption of cleaner production, thereby improving resource allocation efficiency and environmental governance (Chyi et al., 2012). The second perspective contends that MA inhibits GD (Cheng, 2016). Excessive agglomeration magnifies negative externalities, such as intensive resource consumption, concentrated emissions, higher congestion costs, and intensified homogeneous competition (Guo et al., 2020). Moreover, under local competition and policy homogeneity, firms may cut back on green investment, generating a pollution haven effect that worsens resource misallocation and environmental degradation (Hu & Li, 2024). The third perspective highlights the nonlinear nature of the MA-GD nexus (Yuan et al., 2020). Many studies report U-shaped relationships, suggesting that MA is a dynamic process shaped by the interplay of positive and negative externalities. The direction and strength of its effects depend on thresholds and the relative weight of factors such as technological diffusion, governance capacity, and environmental carrying capacity (Zheng et al., 2024). This perspective aligns with the Environmental Kuznets Curve hypothesis, indicating that the impact of MA evolves with development stages and institutional contexts.

In terms of mechanisms, existing literature widely confirms the mediating roles of technological innovation and industrial structure upgrading. On the one hand, MA promotes inter-firm knowledge exchange, technological cooperation, and factor matching, thereby expanding the scale and efficiency of green innovation and improving environmental governance performance (Zhao et al., 2025). On the other hand, under certain conditions, MA supports industrial structure upgrading toward more advanced and cleaner sectors, reducing the share of resource-dependent and highly polluting industries and thus enhancing overall green performance (Yuan et al., 2020). In addition, spatial spillover effects have drawn increasing attention. The spatial concentration of economic activities suggests that MA not only affects local GD but also generates spillovers in neighboring regions through factor mobility, technology demonstration, governance linkages, and pollution transfer (Fang et al., 2020). While specialization and diversification externalities can produce positive demonstration and diffusion effects, siphoning and pollution relocation may impose negative shocks on surrounding areas (Cao et al., 2024). As a result, the spatial effects of MA often involve both positive and negative outcomes, with the net effect shaped by regional development stage, governance capacity, and environmental carrying capacity. This aligns with the analytical framework of new economic geography, which highlights spatial spillovers and agglomeration economies, as well as evolutionary economic geography, which emphasizes path dependence and dynamic adaptation (Henning, 2019).

Although existing studies have made important progress in examining the relationship between MA and GD, several gaps remain. First, there is no consensus on the direction of MA's impact: some studies argue that MA promotes GD through scale economies and technological diffusion, while others emphasize its potential to create environmental stress and low-end lock-in, underscoring the need for further empirical evidence. Second, nonlinear features are insufficiently explored, as most studies rely on linear models, making it difficult to capture marginal effects at different stages of agglomeration or to detect threshold effects. Third, regarding mechanisms, the literature has largely focused on industrial upgrading or general technological innovation, while neglecting the roles of emerging industries such as AI and of GTI, leading to a partial understanding of mediating pathways. Finally, most research remains at a macro level, with limited systematic comparison across regions, urban clusters, and city hierarchies, which constrains both external validity and policy relevance. Against this backdrop, this study conducts a comprehensive analysis along five dimensions – overall effects, mediating mechanisms, spatial spillovers, nonlinear features, and regional heterogeneity – to further clarify the internal logic of how MA influences GD and to provide more targeted empirical evidence and theoretical insights for differentiated, precision-oriented policy design.

3. Methodology and data

3.1 Entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method (EWTM)

The EWTM assigns indicator weights objectively through the entropy approach, effectively avoiding subjective bias in weight determination. By combining this with the TOPSIS technique, which approximates the ideal solution, it provides a comprehensive reflection of the relative performance of cities across multiple dimensions, making it well-suited for measuring GD within a composite indicator system (Yan et al., 2024b). This evaluation involved carrying out six consecutive steps.

(1) The initial data was subjected to a standardization procedure.

Positive indicators:

$$C_{ij} = \left(V_{ij} - V_{j\min}\right) / \left(V_{j\max} - V_{j\min}\right). \tag{1}$$

Negative indicators:

$$C_{ij} = \left(V_{j\max} - V_{ij}\right) / \left(V_{j\max} - V_{j\min}\right). \tag{2}$$

(2) Establish the weights.

$$B_j = -1/\ln m \sum_{i=1}^{m} \left(C_{ij} / \sum_{i=1}^{m} C_{ij} \right) \ln \left(C_{ij} / \sum_{i=1}^{m} C_{ij} \right), \tag{3}$$

$$W_j = 1 - B_j / \sum_{j=1}^{n} \left(1 - B_j\right). \tag{4}$$

(3) Weighted normalization matrix.

$$Q_{ij} = C_{ij} \times W_j. \tag{5}$$

(4) Identify the ideal solution as well as the suboptimal one.

$$\begin{aligned} Q^{+} &= \left\{ \max Q_{ij} \mid j = 1,2,\cdots,n \right\} = \left\{ Q_1^{+}, Q_2^{+}, \cdots Q_n^{+} \right\}; \\ Q^{-} &= \left\{ \min Q_{ij} \mid j = 1,2,\cdots,n \right\} = \left\{ Q_1^{-}, Q_2^{-}, \cdots Q_n^{-} \right\}. \end{aligned} \tag{6}$$

(5) Determine the Euclidean distance separating the optimal and least favorable solutions.

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(Q_{ij} - Q_j^{+} \right)^2}; \quad S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(Q_{ij} - Q_j^{-} \right)^2}. \tag{7}$$

(6) Assess the proximity of each evaluation item to the optimal solution.

$$GD_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}, \tag{8}$$

where, GD_i denotes the level of GD in city *i*.

3.2. Benchmark model

Following Yan et al. (2025), this study employs a two-way fixed effects model on city-year panel data to identify the impact of MA on GD. The model is specified as follows:

$$GD_{it} = \lambda_0 + \lambda_1 MA_{it} + \lambda_2 X_{it} + year_t + city_i + \varepsilon_{it}, \tag{9}$$

where, i and t represent city and year, respectively; GD_{it} denotes the level of GD; MA_{it} measures the degree of MA; X_{it} is the vector of control variables; α_0 is a constant; $year_t$ and $city_i$ capture year and city fixed effects; and ε_{it} denotes the error term.

3.3. Mediation effect model

To investigate the mediating role of AI industry agglomeration and GTI in the relationship between MA and GD, this study employs a mediation effect model, following the approach of Wen and Ye (2014), to empirically test the proposed transmission mechanism. The model is constructed as follows.

$$GD_{it} = c_1 MA_{it} + \gamma X_{it} + \mu_i + \nu_t + \varepsilon_{it}; \tag{10}$$

$$MV_{it} = \alpha MA_{it} + \gamma X_{it} + \mu_i + \nu_t + \varsigma_{it}; \tag{11}$$

$$GD_{it} = c_2 MA_{it} + \beta MV + \gamma X_{it} + \mu_i + \nu_t + \delta_{it}, \tag{12}$$

where, MV_{it} denotes mediator variable; c_1 represents the total effect, c_2 the direct effect, and $\alpha \times \beta$ the mediating effect.

3.4. SDM

To accurately identify the impact of MA on GD and its spillover mechanisms, it is necessary to incorporate spatial factors into the analysis (Chen & Liu, 2025). Based on spatial econometrics, this study employs a SDM and introduces city and year fixed effects to capture the interdependence between the dependent variable, the core explanatory variable, and their spatial lags, while controlling for time-invariant heterogeneity and common shocks. The model is specified as follows.

$$GD_{it} = \rho \sum_j w_{ij} GD_{jt} + \psi_1 MA_{it} + \psi_2 X_{it} + \theta_1 \sum_j w_{ij} MA_{jt} + \theta_2 \sum_j w_{ij} X_{jt} + \mu_i + \nu_t + \varepsilon_{it}, \tag{13}$$

where, i and t denote city and year, j represents neighboring regions, ρ is the spatial autoregressive coefficient, μ_i denotes city fixed effects, ν_t denotes time fixed effects, ε_{it} is the random error term, and w_{ij} represents the spatial weight matrix. To capture multidimensional spatial correlations and conduct robustness checks, this study constructs two types of spatial weight matrices: a geo-economic nested distance matrix and an inverse geographic distance matrix.

3.5. Threshold effect model

To further examine whether the impact of MA on GD exhibits nonlinear characteristics, this study introduces potential threshold variables to capture the differentiated effects of agglomeration across different stages (Yu et al., 2023). The model is specified as follows.

$$GD_{it} = \zeta_1 MA_{it} \times I\left(Thv_{it} \leqslant \gamma\right) + \zeta_2 MA_{it} \times I\left(Thv_{it} > \gamma\right) + \phi X_{it} + year_t + city_i + \varepsilon_{it}, \tag{14}$$

where, Thv_{it} denotes the threshold variable; γ represents the threshold value to be estimated. The function I (·) is an indicator function, which takes the value of 1 if the condition inside the parentheses is satisfied, and 0 otherwise.

3.6. Description of the variables

3.6.1. Dependent variable

Drawing on relevant literature (Han et al., 2022; Li et al., 2025; Tang et al., 2024; Zheng et al., 2022) and guided by the requirements of aligning with China's "dual-carbon" and green high-quality development goals, capturing the full chain of GD, and ensuring long-term comparability across cities, this study constructs an indicator system with four dimensions – carbon reduction, pollution abatement, ecological enhancement, and growth – to measure GD (Table 1). In the carbon reduction dimension, carbon dioxide (CO_2) emissions per unit of GDP and per capita CO_2 emissions are selected to measure emission intensity and individual burden, thereby reflecting the degree of decoupling between economic growth and carbon emissions (Zang et al., 2018). In the pollution abatement dimension, indicators including the comprehensive utilization rate of industrial solid waste, the harmless treatment rate of domestic waste, the centralized treatment rate of wastewater, and $PM_{2.5}$ concentration are

Table 1. GD indicators evaluation system

Dimension	Indicator	Attribute	Weight
Carbon reduction	CO_2 emissions per unit of GDP	Negative	0.004
	Per capita CO_2 emissions	Negative	0.003
Pollution abatement	Comprehensive utilization rate of industrial solid waste	Positive	0.038
	Harmless treatment rate of domestic waste	Positive	0.008
	Centralized treatment rate of wastewater	Positive	0.010
	$PM_{2.5}$ concentration	Negative	0.019
Ecological enhancement	Per capita park green space	Positive	0.035
	Green coverage ratio of built-up areas	Positive	0.005
	NDVI	Positive	0.017
Growth	GDP growth rate	Positive	0.006
	Per capita retail sales of consumer goods	Positive	0.179
	Per capita disposable income of urban residents	Positive	0.081
	Number of granted invention patents per 10,000 people	Positive	0.540
	Digital Inclusive Finance Index	Positive	0.058

adopted to combine governance performance with environmental quality outcomes (Yan et al., 2024a). In the greening dimension, per capita park green space, green coverage ratio of built-up areas, and the Normalized Difference Vegetation Index (NDVI) are employed to capture the accessibility, coverage, and ecological baseline of green infrastructure (Yang & Ran, 2024). Finally, in the growth dimension, GDP growth rate, per capita retail sales of consumer goods, per capita disposable income of urban residents, the number of invention patents granted per 10,000 people, and the Digital Inclusive Finance Index are employed to capture high-quality development in terms of growth speed, consumption demand, livelihood improvement, innovation capacity, and the digital economy (Pan et al., 2021).

Using the natural breaks (Jenks) method and ArcGIS 10.2 (Figure 1a–d), this study classifies urban GD into five categories. From 2011 to 2023, China's urban GD rose steadily, with the average index increasing from 0.118 to 0.232 (5.8% annual growth). The spatial pattern shows "higher in the east and south, lower in the west and north." The Yangtze River Delta and Pearl River Delta consistently formed stable high-value cores, while inland provincial capitals (e.g., Wuhan, Zhengzhou, Chengdu) and transport hubs upgraded from low or medium to higher levels, driving the emergence of ring- and belt-shaped transitional zones. Low-value clusters in the northwest and southwest gradually contracted into scattered patches. Further local spatial autocorrelation tests based on ArcGIS 10.2 (Figure 1e–h) reveal significant and persistent positive autocorrelation. High-high clusters are concentrated in developed eastern coastal regions, while low-low clusters remain in the underdeveloped west, showing a northward shift. High-low and low-high outliers are mainly distributed along transitional belts and transport corridors (e.g., the Beijing–Guangzhou line, Shanghai-Wuhan-Chengdu axis), suggesting uneven and heterogeneous cross-regional diffusion of GD.

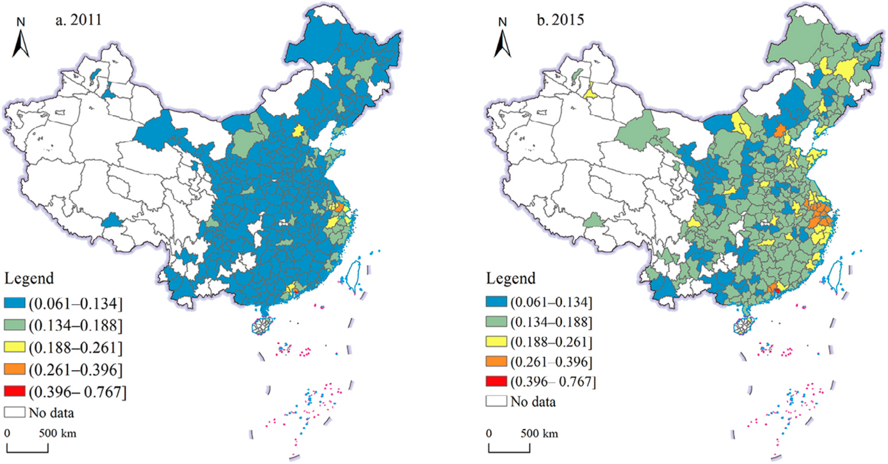

Figure 1. *Continued on next page*

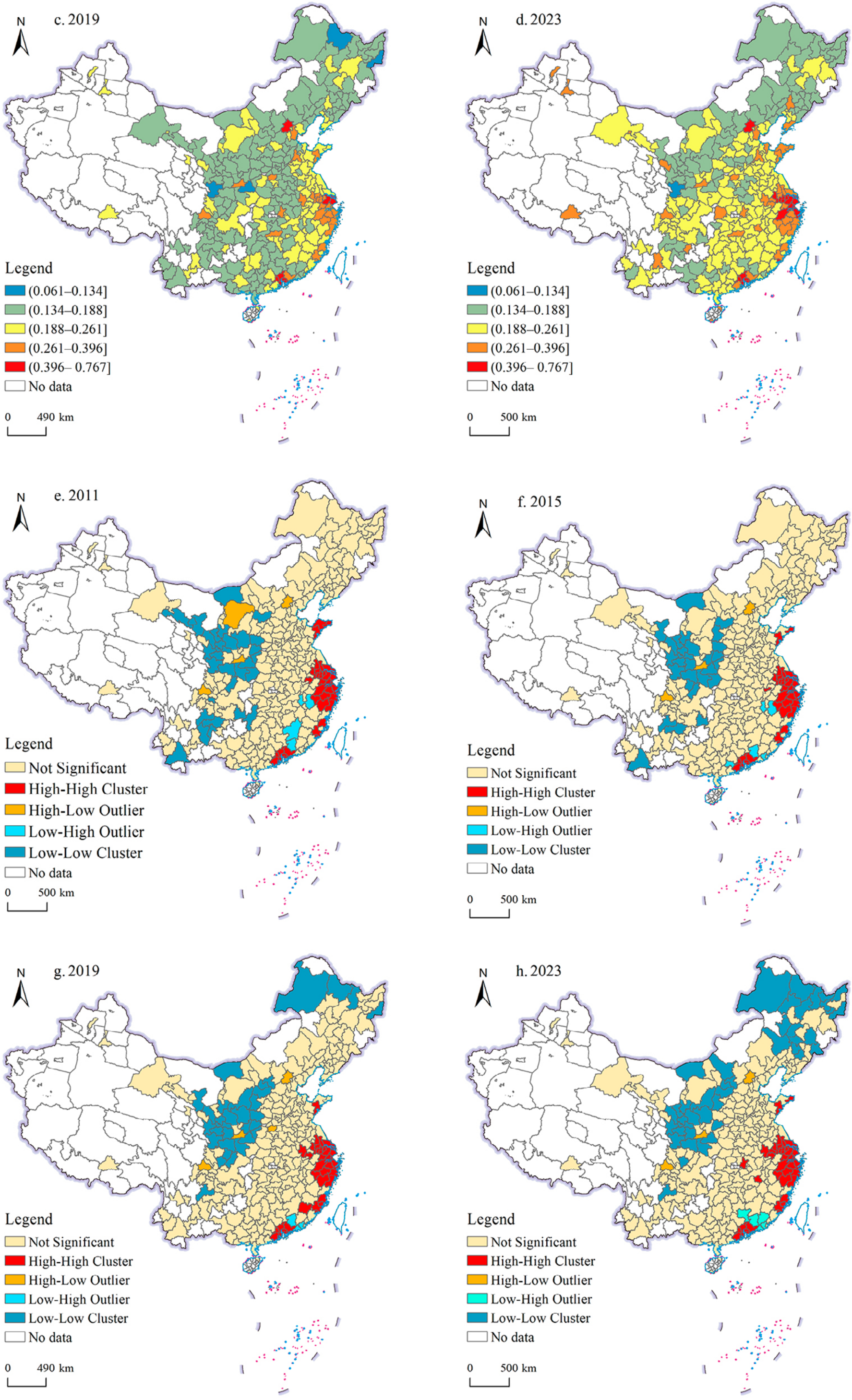

Figure 1. Spatial evolution and local spatial autocorrelation of urban GD in China (2011–2023)

3.6.2. Core explanatory variable

Given that Location Quotient (LQ) effectively measures the degree of industrial specialization and relative concentration within a region, this study follows Yuan et al. (2020) and employs LQ to construct the MA index, which is calculated as follows.

$$MA_{ij} = \frac{H_{ij} / H_i}{H_j / H}, \tag{15}$$

where, MA_{ij} denotes the LQ index. H_{ij} represents the number of firms in industry j within region i; H_i is the total number of firms in region i; H_j denotes the total number of firms in industry j nationwide; and H is the total number of firms in the country.

3.6.3. Mediating variables

This study selects AI industry agglomeration and GTI as mediating variables. Specifically, AI industry agglomeration is measured by the LQ of the AI industry (Wang et al., 2025), while GTI is proxied by the number of granted green patents, following the approach of Khan et al. (2024).

3.6.4. Control variables

To isolate the influence of other factors on GD and enhance empirical validity, five categories of control variables are introduced with reference to prior studies (Ding & Luo, 2024; Ma & Zhu, 2022; Tao et al., 2023) and data availability: Population Density (PD), Urbanization Rate (UR), Number of New Enterprises (NNE), Per Capita Road Freight (PCRF), and Per Capita Postal Services (PCPS). All control variables are expressed in natural logarithms to address scale differences, correct skewed distributions, limit the impact of extreme values, and facilitate elasticity interpretation.

3.7. Data processing

This study uses panel data from 287 prefecture-level cities in China during 2011–2023. Socioeconomic indicators are drawn from the *China Urban Statistical Yearbook* and city yearbooks. Firm-level microdata come from Tianyancha, where enterprises are screened by the *Industrial Classification for National Economic Activities* (GB/T 4754–2017), retaining those with registered capital ≥20 million RMB and “active/in operation” status. After deduplication and outlier removal, 3020677 valid firm records remain, including 474293 in manufacturing, aggregated by year and city. Patent data are obtained from CNRDS. PM2.5 data come from the Dalhousie University global gridded dataset. NDVI is derived from MOD13A3, with annual composites generated by the maximum value method. Carbon emissions are taken from the EDGAR gridded dataset. All price-related variables are deflated to 2011 real values using the GDP deflator. Missing or abnormal socioeconomic indicators are interpolated and corrected. Multicollinearity tests show variance inflation factors below 3 for all variables. Descriptive statistics are reported in Table 2.

Table 2. Descriptive statistics of variables

Variables	Observation	Mean	Standard deviation	Minimum	Maximum
GD	3731	0.183	0.077	0.061	0.891
MA	3731	1.125	0.468	0.105	3.143
lnPD	3731	5.737	0.939	1.628	8.159
lnUR	3731	6.315	0.268	5.201	6.908
lnNNE	3731	6.977	0.673	4.702	10.843
lnPCRF	3731	10.051	0.764	2.484	13.930
lnPCPS	3731	12.044	1.117	9.146	16.502

4. Empirical results

4.1. Baseline regression

Column (1) of Table 3 reports the baseline regression results of MA on GD. The empirical results show that the coefficient of MA is significantly negative, indicating that MA exerts an inhibitory effect on GD. This finding suggests that, at China's current stage of development, MA has not yet fully realized its potential role in improving resource allocation efficiency. Instead, it imposes structural constraints on GD through mechanisms such as intensified homogeneous industrial competition, widespread low-end repetitive construction, declining factor allocation efficiency, and the concentration of pollutant emissions.

Regarding the control variables, the coefficients of PD, PCRF, and PCPS are significantly positive, indicating that improvements in population agglomeration, transportation, and information flows enhance scale economy effects in green infrastructure and public services, thereby promoting GD. By contrast, the coefficient of UR is significantly negative, suggesting that current urbanization is still driven by extensive expansion and factor inputs. The accompanying growth in construction land, infrastructure and real estate investment, and commuting congestion leads to high energy use and emissions, offsetting the potential green gains from scale economies and specialization.

4.2. Robustness check results

To further test robustness, Columns (2)–(6) of Table 3 report five checks: (1) winsorizing core variables at the 1% and 99% levels to reduce outlier influence; (2) excluding Beijing, Shanghai, Tianjin, and Chongqing to control for institutional advantages in resource allocation and policy support; (3) lagging the key explanatory variable by one period to mitigate potential endogeneity from reverse causality and contemporaneous shocks; (4) adding provincial fixed effects alongside city and year effects to capture unobserved heterogeneity in regional institutions and policies; and (5) removing 2020–2022 observations to avoid distortions from the COVID-19 pandemic. In all cases, the coefficient of MA remains significantly negative, confirming its inhibitory effect on GD. The direction and significance of control variables are also consistent with the baseline, leaving the statistical and economic implications unchanged.

Table 3. Robustness checks of the impact of MA on GD

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline regression	Excluding extreme observations	Excluding centrally administered municipalities	One-period lag of MA	High-dimensional fixed effects	Excluding COVID-19 years (2020–2022)
MA	−0.032***	−0.033***	−0.028***		−0.032**	−0.027***
	(−3.10)	(−2.86)	(−2.78)		(−2.49)	(−2.81)
Lag1(MA)				−0.031***		
				(−2.80)		
lnPD	0.192***	0.123***	0.192***	0.194***	0.192***	0.134***
	(5.27)	(5.44)	(5.15)	(5.01)	(3.37)	(5.05)
lnUR	−0.051***	−0.048***	−0.048***	−0.050***	−0.051***	−0.037***
	(−6.47)	(−6.00)	(−6.30)	(−6.22)	(−4.53)	(−5.52)
lnNNE	−0.001	0.004	0.001	0.001	−0.001	−0.006**
	(−0.32)	(1.61)	(0.09)	(0.13)	(−0.24)	(−2.33)
lnPCRF	0.002*	0.002*	0.002*	0.003**	0.002	0.001
	(1.76)	(1.67)	(1.83)	(2.32)	(1.19)	(1.42)
lnPCPS	0.010***	0.010***	0.009***	0.008***	0.010***	0.010***
	(4.17)	(4.92)	(3.89)	(3.77)	(4.38)	(4.19)
Constant	−0.755***	−0.414***	−0.783***	−0.762***	−0.692**	−0.422***
	(−3.76)	(−3.18)	(−3.86)	(−3.48)	(−2.46)	(−2.72)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	No	No	No	No	Yes	No
Observations	3731	3731	3679	3444	3731	2870
R-squared	0.843	0.856	0.845	0.822	0.951	0.958

Notes: ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate *t*-statistics. Lag1(MA) represents the one-period lag of manufacturing agglomeration.

4.3. Endogeneity test

To mitigate potential endogeneity between MA and GD arising from omitted variables and reverse causality, this study adopts a Two-Stage Least Squares (2SLS) estimation strategy (Table 4). Following the approach of Zhang (2025), we use the interaction term of topographic relief and the one-period lag of MA as the Instrumental Variable (IV). The rationale is that topographic relief is an exogenous natural geographic attribute that is unlikely to be influenced in the short run by GD or related policy shocks, thereby satisfying the exogeneity condition. Meanwhile, MA exhibits strong path dependence and is shaped by long-term geographic endowments, and their interaction generates exogenous variation in current MA that is independent of the error term. The first-stage results show that the IV has a significantly positive effect on MA at the 1% level. Moreover, the Kleibergen-Paap rk LM statistic equals 71.457, rejecting the null of under-identification, while the rk Wald F statistic is 1987.210, well above the Stock-Yogo 10% critical value of 16.38, thereby ruling out weak instrument concerns. In the second-stage regression, the coefficient of MA remains significantly negative at the 1% level, indicating that even after controlling for potential endogeneity, MA exerts a robust inhibitory effect on GD.

Table 4. IV estimation of the impact of MA on GD

Variable	(1) First stage	(2) Second stage
	MA	GD
MA^{IV}	0.118^{***}	
	(44.57)	
MA		-0.047^{***}
		(–3.97)
Controls	Yes	Yes
City fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Kleibergen-Paap rk LM	71.457^{***}	
Kleibergen-Paap rk Wald F	1987.210	
Observations	3444	3444

Notes: *** represent statistical significance at the 1% levels. Figures in parentheses indicate *t*-statistics.

4.4. Mechanism analysis

To examine the transmission mechanisms of AI industry agglomeration and GTI in the MA-GD nexus, we employ a three-step mediation model (Table 5). Column (1) shows that MA significantly promotes AI industry agglomeration through factor clustering, industrial linkages, and knowledge spillovers, generating demand traction and technological diffusion. Column (2) indicates that when both MA and AI agglomeration are included, their effects on GD remain significantly negative, consistent with partial mediation. The inhibitory role of AI agglomeration may reflect short-term pressures from intensive computing power, concentrated energy demand, and infrastructure construction. The Sobel test ($z = -2.124$, $p = 0.033$) and Bootstrap test (indirect effect = –0.005, 95% CI [–0.010, –0.001]) both confirm this pathway.

Column (3) shows that MA significantly enhances GTI via knowledge spillovers, factor concentration, and active R&D. Column (4) further reveals that GTI significantly promotes GD, while MA's coefficient remains negative, again indicating partial mediation. Both the Sobel test ($z = 2.844$, $p = 0.005$) and the Bootstrap test (indirect effect = 0.002, 95% CI [0.001, 0.004]) validate this effect. Overall, AI agglomeration and GTI act as key mediators: the former reinforces MA's inhibitory impact on GD, while the latter partly offsets and alleviates it.

Table 5. Mediation effects of MA on GD

Variables	(1)	(2)	(3)	(4)
	lnAI	GD	lnGTI	GD
MA	0.201***	−0.027***	0.435***	−0.034***
	(3.21)	(−2.79)	(2.96)	(−3.32)
lnAI		−0.022***		
		(−3.05)		
lnGTI				0.004***
				(5.72)
Constant	−0.7174	−0.7714***	−6.376***	−0.727***
	(−0.89)	(−3.85)	(−3.26)	(−3.60)
Controls	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
R-squared	0.102	0.846	0.640	0.845
Observations	3731	3731	3731	3731

Note: *** represent statistical significance at the 1% levels. Figures in parentheses indicate *t*-statistics.

4.5. Spatial spillover effect analysis

Following the approach of Yan et al. (2024b), we sequentially conduct the LM, robust LM, Wald, and Hausman tests (Table 6). The results show that both LM-lag and LM-error are significant, indicating the presence of spatial lag dependence as well as spatial error correlation. The Wald and LR restriction tests significantly reject the null hypotheses that the SDM can be reduced to either the Spatial Lag Model (SLM) or the Spatial Error Model (SEM), suggesting that the SDM provides a better fit and more appropriately captures spatial spillovers. Furthermore, the Hausman test supports the fixed-effects specification. Based on these findings, this study ultimately adopts the fixed-effects SDM as the baseline model.

Given that coefficients in the SDM are not equivalent to marginal effects, we follow the partial derivative decomposition approach proposed by LeSage and Pace (2008) to identify the "direct-indirect-total effects" of MA (Table 7). Under the spatial weight matrices constructed with both the geo-economic nested distance matrix and the inverse distance matrix, the direct, indirect, and total effects of MA are all significantly negative, indicating that agglomeration not only suppresses local GD but also transmits adverse impacts to neighboring

Table 6. Spatial econometric model correlation test results

Inspection method	Statistical values	Inspection method	Statistical values
LM lag	833.136***	Wald spatial lag	36.10***
LM error	1003.847***	Wald spatial error	95.74***
R-LM lag	142.064***	Hausman	499.93***
R-LM error	312.775***		

Note: *** represent statistical significance at the 1% levels.

or similar cities through factor mobility and industrial linkages. The potential mechanisms include, first, MA increases demand for upstream intermediate goods and intensifies downstream processing, thereby driving energy and material consumption as well as pollution and carbon emissions to spill over along input-output networks, and second, regions with high levels of MA tend to siphon capital, labor, and producer services, leading to insufficient green investment and lagging innovation in adjacent or similar cities.

Regarding the control variables, PD and PCPS show significant positive spatial spillovers, indicating that population agglomeration and improved logistics networks help spread the fixed costs of environmental governance and green infrastructure, creating economies of scale and shared benefits that diffuse to nearby areas through commuting and service networks. In contrast, UR and PCRF exhibit significant negative spillovers. Rapid urbanization drives construction land expansion and traffic emissions, transmitting these externalities to surrounding areas via factor flows and spatial linkages, thereby weakening regional GD. Likewise, higher PCRF intensifies local traffic-related pollution while extending environmental pressures along interregional transport routes, further constraining green performance in neighboring cities.

Table 7. Effect decomposition of SDM

Variables	Geographic-economic nested matrix			Inverse distance matrix		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
MA	–0.022***	–0.064**	–0.086***	–0.040***	–0.554**	–0.594**
	(–6.87)	(–2.29)	(–2.90)	(–11.46)	(–2.22)	(–2.37)
lnPD	0.140***	0.586***	0.725***	0.138***	0.590**	0.728***
	(26.37)	(10.65)	(12.76)	(23.21)	(2.57)	(3.16)
lnUR	–0.023***	–0.149***	–0.173***	–0.034***	–0.300**	–0.334**
	(–7.73)	(–6.32)	(–6.94)	(–10.69)	(–2.20)	(–2.44)
lnNNE	0.001	–0.005	–0.003	–0.005***	–0.087	–0.092
	(1.47)	(–0.58)	(–0.38)	(–5.11)	(–1.51)	(–1.60)
lnPCRF	0.002***	–0.013**	–0.011*	0.001	–0.145***	–0.145*
	(2.91)	(–2.41)	(–1.94)	(0.29)	(–2.85)	(–2.83)
lnPCPS	0.007***	0.029***	0.036***	0.007***	0.221***	0.228***
	(9.57)	(4.46)	(5.20)	(8.74)	(3.18)	(3.27)

Notes: ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Figures in parentheses indicate *t*-statistics.

4.6. Threshold effect analysis

To further assess the nonlinear impact of MA on GD, this study employs Hansen's (1999) panel threshold regression. The procedure involves two steps: first, using a bootstrap with 1,000 replications to test threshold significance and obtain p-values; second, comparing single- and double-threshold models under different constraints to determine the optimal specification. The results (Table 8) show that with MA as the threshold variable, both single- and double-threshold effects are significant, with optimal thresholds identified at 0.585 and 2.039. This indicates that the effect of MA on GD differs across agglomeration levels, presenting a clear threshold-type nonlinear pattern.

Table 8. Threshold effect tests of the impact of MA on GD

Threshold type	Threshold value	*F* value	*P* value	Crit 10	Crit 5	Crit 1
Single threshold	0.585	167.59	0.000	43.647	52.032	77.967
Double threshold	2.039	111.13	0.067	41.114	143.521	234.580

Notes: "Crit 10", "Crit 5", and "Crit 1" represent the critical values at the 10%, 5%, and 1% significance levels, respectively, obtained via bootstrap sampling.

Based on the estimation results in Table 9, when the level of MA is less than or equal to 0.585, the coefficient of MA is negative but not significant, indicating that at a relatively low level of agglomeration, its inhibitory effect on GD is not evident. When MA is greater than 0.585 but less than 2.039, the coefficient is significantly negative (–0.042), suggesting that at a moderate level of agglomeration, MA significantly suppresses GD. When MA is greater than or equal to 2.039, the coefficient of MA remains significantly negative (–0.029), but its absolute value is smaller than in the moderate interval, implying that at a high level of agglomeration, although the inhibitory effect persists, its intensity is mitigated. Overall, across all threshold intervals, MA does not exert a positive effect on GD; rather, the strongest negative effect occurs at the moderate level, while the inhibitory effect becomes relatively weaker at the high level of agglomeration.

Table 9. Threshold fixed effects regression results

Variables	GD
MA (MA ≤0.585)	−0.003
	(−0.21)
MA (0.585 < MA < 2.039)	-0.042^{***}
	(−4.34)
MA (MA ≥ 2.039)	-0.029^{***}
	(−3.20)
Controls	Yes
City fixed effect	Yes
Time fixed effect	Yes
Observations	3731
R-squared	0.853

Note: *** stand for the significance of 1% levels. *t* statistics in parentheses.

4.7. Heterogeneity analysis

To further identify the heterogeneous impacts of MA across different types of cities, this study conducts subgroup regressions based on regional characteristics, urban agglomerations, and city hierarchies (Table 10). Following Yan et al. (2024a), Chinese cities are first divided into eastern and central-western regions to compare the differences in agglomeration effects across geographic locations. In addition, according to the 19 key urban agglomerations outlined in the *14th Five-Year Plan*, cities are further classified into those within and outside urban agglomerations to capture the moderating role of spatial organizational structure. Finally, based on administrative hierarchy, municipalities directly under the central government, provincial capitals, and sub-provincial cities are categorized as higher-level cities, while all others are defined as ordinary cities, in order to examine how differences in development foundations shape the effects of agglomeration.

Table 10. Heterogeneous effects of MA on GD

Variables	Eastern region	Central & Western region	Urban agglomeration	Non-agglomeration cities	Ordinary cities	Advanced cities
	(1)	(2)	(3)	(4)	(5)	(6)
MA	-0.033^{**}	-0.024^{***}	-0.033^{***}	−0.003	−0.010	-0.148^{***}
	(−1.99)	(−2.06)	(−2.61)	(−0.18)	(−0.96)	(−3.35)
Constant	-1.487^{***}	0.226^{*}	-0.703^{**}	−0.046	-0.553^{**}	−0.093
	(−4.47)	(1.78)	(−2.54)	(−3.31)	(−2.08)	(−0.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1560	2171	2756	975	3172	559
R-squared	0.955	0.940	0.953	0.915	0.940	0.961

Notes: ***, ** and * stand for the significance of 1%, 5% and 10% levels; *t* statistics in parentheses.

First, regarding regional heterogeneity, the coefficients of MA are significantly negative in both eastern and central-western samples, with stronger inhibition in the east. This reflects higher agglomeration and denser supply chains, where industrial overcrowding intensifies factor and environmental constraints, amplifies pollution spillovers, and, combined with diminishing returns to knowledge diffusion, causes negative externalities to outweigh benefits. Second, in terms of spatial organization, MA significantly suppresses GD within urban agglomerations but not outside them. In integrated agglomerations, intercity division of labor and factor mobility accelerate emission transmission, while competition for investment fosters a race to the bottom, further amplifying externalities. Finally, with respect to city hierarchy, MA significantly inhibits GD in higher-level cities but not in ordinary ones. In higher-level cities, additional agglomeration leads to factor crowding-out, higher governance costs, and lock-in of energy-intensive paths, making the net effect strongly negative. By contrast, in ordinary cities, lower agglomeration levels mean positive and negative effects largely offset each other. Overall, the heterogeneity analysis shows that in the east, within urban agglomerations, and in higher-level cities, policy should prioritize controlling scale, improving quality, and advancing green transformation to mitigate the dual pressures of over-agglomeration on environment and development.

5. Discussion

5.1. Regional pattern and practical logic of GD

This study shows that China's urban GD exhibits a clear spatial pattern of "higher in the east than in the west, and higher in the south than in the north," reflecting differences in development stage, industrial structure, and policy environment. The eastern region, with a mature industrial system, concentrated technology and capital, and stronger regulatory capacity, has consistently led in GD (Xia et al., 2022). High PD further generates governance demand and consumer pressure, accelerating green transition through combined policy and market forces (Schroeder, 2014). In contrast, the western region, despite favorable ecological conditions and abundant clean energy resources, remains dominated by resource-dependent and energy-intensive industries, with weak green innovation and governance capacity (Tian et al., 2023). Limited infrastructure and factor conversion mechanisms prevent resource endowments from being effectively transformed into GD drivers, creating the paradox of resource abundance but underutilization (Qiu & Zhang, 2023). Significant north-south differences also emerge. The south benefits from higher economic development, complete industrial chains, stronger green innovation, and richer renewable resources such as hydropower and biomass, enabling smoother green transformation. The north, dominated by heavy industry and higher energy intensity, faces greater GD pressure and overall lag (Hou et al., 2019).

5.2. Dialectical relationship between MA and GD

Empirical results show that MA significantly inhibits GD, underscoring the tension between agglomeration economies and environmental sustainability in China's industrialization. New economic geography highlights potential benefits such as scale economies, knowledge spillovers, and labor pooling (Cao et al., 2024), yet under over-agglomeration these are offset by resource crowding, pollution, and "race-to-the-bottom" competition (Hong et al., 2020). Evolutionary economic geography further stresses path dependence and lock-in: highly concentrated, low-end, and homogeneous manufacturing chains hinder the shift toward high-tech, low-carbon development, aggravating emissions and pollution diffusion (Drechsler & Wätzold, 2020). The complementarity of these theories explains why negative effects dominate at high concentration. Notably, the inhibitory impact of MA is strongest at moderate levels but weakens at higher levels, suggesting that deeper agglomeration may enable some cities to mitigate externalities through technological upgrading and stronger governance.

5.3. Mediation mechanisms linking MA and GD

Mechanism analysis shows two main channels. First, AI industry agglomeration currently serves to boost efficiency and expand scale in traditional manufacturing, indirectly raising energy use and environmental stress, thus amplifying negative effects. Second, MA promotes GTI, which enhances GD, but this positive mediation remains limited and insufficient to offset the pressures of agglomeration. These results reveal the contradictory logic of the MA-GD nexus: emerging industries and green innovation have yet to fully realize their potential, while path dependence and short-term profit orientation remain dominant. Under the dual-carbon and high-quality development strategies, stronger institutional design is needed to integrate AI with green technologies, channel innovative resources toward low-carbon sectors, and expand the positive spillovers of agglomeration while curbing its negative externalities.

5.4. Spatial spillover effects of MA

MA not only suppresses local GD but also produces significant negative spillovers. Environmental regulations in agglomeration cores push polluting industries into neighboring regions, creating cross-regional pollution havens (Zheng & Shi, 2017). Intergovernmental competition and industrial homogeneity further misallocate resources and raise energy use (Hong et al., 2020). MA also siphons land, capital, and talent from surrounding areas, limiting green industry growth, while structural bias amplifies negative knowledge spillovers. Through supply-chain and environmental coupling, upstream emissions are transmitted downstream, intensifying green transition pressures (Zhou et al., 2023). These findings highlight the need for coordinated regional governance, supply-chain upgrading, and wider diffusion of green technologies.

5.5. Policy implications

The relationship between MA and GD is stage-dependent, nonlinear, and context-specific. Stronger support for green R&D, enhanced green finance, and closer industry-university-research collaboration can accelerate the shift from factor- to innovation-driven growth, promoting restructuring and upgrading. At the same time, coordinated environmental policies and cross-regional mechanisms are vital to harmonize standards, foster certification recognition, and avoid "race-to-the-bottom" competition and pollution transfer. Threshold management is also crucial: at low-to-moderate levels, policies should encourage cooperation and green innovation networks, while in highly agglomerated regions, stricter entry standards, dual energy-control measures, and land-use regulations are required to mitigate congestion and clustering. Differentiated regional strategies are equally important. Eastern and higher-level cities should lead in developing high-end manufacturing and green services to offset marginal costs, while central-western and smaller cities should avoid low-end lock-in, leverage clean energy endowments and late-mover advantages, and foster emerging green industries and value chains to turn resource advantages into GD momentum.

China's experience also offers lessons internationally. For developing economies in rapid industrialization, heavy reliance on resource- and factor-driven agglomeration risks entrenching high-emission trajectories. These countries should pursue green upgrading in tandem with agglomeration by attracting international green investment, embedding in global green value chains, and strengthening technology transfer and knowledge sharing. For developed economies, priorities lie in advancing green supply chain standards, implementing carbon border adjustment mechanisms, and promoting environmental technology cooperation to avoid shifting pollution burdens, while jointly building an international cooperation framework for GD and a just transition.

5.6. Limitations and future research

Despite providing a systematic empirical and mechanistic analysis, this study has several limitations. First, due to data constraints, the GD index system does not fully capture dimensions such as green innovation outputs or ecosystem services, which may limit the external validity of the findings. Second, the analysis is conducted mainly at the city level, with limited attention to firm-level mechanisms. Future research could address these issues by integrating multi-source data to improve the coverage and granularity of GD measurement, and by incorporating firm-level data to examine how MA influences green innovation, production efficiency, and emission behaviors at the micro level.

6. Conclusions

Based on panel data from 287 Chinese cities during 2011–2023, this study systematically investigates the relationship between MA and GD using fixed-effects, mediation, spatial Durbin, and threshold models. The results indicate that from 2011 to 2023, the overall GD level of Chinese cities rose steadily from 0.118 to 0.232, with an average annual growth rate of 5.8%, showing significant spatial autocorrelation and a clear spatial pattern of "higher in the east and south, lower in the west and north." Overall, MA significantly inhibits GD. Further analysis identifies a dual mechanism: MA amplifies its negative effect on GD through AI industry agglomeration, while partially offsetting it through the promotion of GTI. MA also generates negative spatial spillovers, with adverse effects diffusing to neighboring regions via factor flows and industrial linkages. Regarding intensity, the inhibitory effect is strongest at moderate levels but weakens at higher levels. Heterogeneity analysis reveals that the negative effect is more pronounced in the eastern region, within urban clusters, and in higher-level cities, underscoring the role of regional and hierarchical differences in shaping GD outcomes. In sum, the impact of MA on GD is complex and heterogeneous, highlighting the need for policymakers – when advancing the "dual-carbon" strategy and high-quality development – to remain alert to the potential externalities of agglomeration and to promote industrial upgrading, regional coordination, and differentiated governance to fully unlock the GD potential of MA.

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Author contributions

Mingtao Yan: conceptualization, methodology, data curation, validation, visualization, formal analysis, software, writing – original draft, writing – review & editing. Jianji Zhao: conceptualization, supervision, formal analysis, funding acquisition, Writing – review & editing. Mingyue Yan: conceptualization, methodology, data curation, validation, writing – review & editing.

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Data availability statement

Data will be made available on request.

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