



OPEN ACCESS

EDITED BY
Huaping Sun,
Jiangsu University, China

REVIEWED BY
Menglan Liu,
Tongji University, China
Qiang Yin,
Jishou University, China
Chaoqun Wang,
Lanzhou University, China

*CORRESPONDENCE
Qing Shao
✉ shaoqingsx@126.com

RECEIVED 06 April 2025
ACCEPTED 11 August 2025
PUBLISHED 29 August 2025

CITATION
Zhang S, Ding J, Ji C, Shao Q and Chen W
(2025) The impact of population
agglomeration in urban agglomerations on
green total factor productivity: insights from
China. *Front. Sustain. Cities* 7:1606754.
doi: 10.3389/frsc.2025.1606754

COPYRIGHT
© 2025 Zhang, Ding, Ji, Shao and Chen. This
is an open-access article distributed under the
terms of the [Creative Commons Attribution
License \(CC BY\)](#). The use, distribution or
reproduction in other forums is permitted,
provided the original author(s) and the
copyright owner(s) are credited and that the
original publication in this journal is cited, in
accordance with accepted academic practice.
No use, distribution or reproduction is
permitted which does not comply with these
terms.

The impact of population agglomeration in urban agglomerations on green total factor productivity: insights from China

Songlin Zhang¹, Jia Ding¹, Chunli Ji², Qing Shao^{1*} and
Weihong Chen¹

¹Business School, Shaoxing University, Shaoxing, China, ²Centre for Gaming and Tourism Studies,
Macao Polytechnic University, Macau, Macao SAR, China

Enhancing Green Total Factor Productivity (GTFP) is crucial for achieving sustainable development goals. While existing studies have largely focused on the impact of city-specific factors on GTFP, the influence of factors at the urban agglomeration scale has been overlooked. Given the ongoing trend of population agglomeration in urban agglomerations, the role of cross-city population agglomeration dynamics at the urban scale has become increasingly significant. This study investigates the impact and mechanisms of population agglomeration in urban agglomerations on GTFP, using panel data from 282 prefecture-level and above cities in China spanning the period 2011–2022. The findings indicate that population agglomeration in urban agglomerations can improve GTFP. Mechanism analysis reveals that population agglomeration in urban agglomerations enhances GTFP by strengthening knowledge spillover effects, increasing market potential, and promoting the upgrading of the human capital structure. Further research shows that when population agglomeration in urban agglomerations reaches a certain scale, a unified functional network can be formed within the urban agglomeration, leading to a more substantial increase in GTFP. Heterogeneity analysis suggests that the positive impact of population agglomeration in urban agglomerations on GTFP varies across different cities. Specifically, such agglomeration improves GTFP more effectively in central cities than in peripheral cities; this effect is significant in the southeast region, in cities with stronger environmental regulation, and resource-based cities, but is insignificant in the northwest region, in cities with weaker environmental regulation, and non-resource-based cities. These findings provide novel policy pathways for cultivating urban agglomerations as engines of green economic transformation in an era of escalating spatial population agglomeration.

KEYWORDS

population agglomeration, urban agglomerations, green total factor productivity, knowledge spillovers, market potential, human capital structure upgrading

1 Introduction

The agglomeration of populations in regions with economic development advantages reflects an objective and enduring trend in socioeconomic development (Liu and Lyu, 2025). In recent years, this trend has become especially evident within urban agglomerations (Zheng et al., 2024). As critical spatial carriers, urban agglomerations

have increasingly concentrated large populations. For instance, in the world's two largest economies—the United States and China—striking examples emerge: by 2023, the New York-Newark-Jersey City metropolitan area, comprising just 0.17% of U.S. land area, accounted for 5.82% of the national population. Similarly, in China, five major urban agglomerations—Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, Chengdu-Chongqing, and Middle Yangtze River—spanning approximately 12% of the national territory, were home to 46% of the population. While conventional studies have predominantly focused on population concentration within individual cities, urban agglomerations represent a fundamentally distinct and more complex spatial organizational form (Fang and Yu, 2017; Derudder et al., 2022). This is because population agglomeration in urban agglomerations transcends single administrative boundaries, involving intricate cross-city flows of people, capital, and information, and fostering interdependencies that are not merely additive sums of individual cities (Rozenblat, 2020). In particular, such cross-regional population agglomeration plays a critical role in promoting sustainable development (Cai et al., 2023). Consequently, analyzing population dynamics at this aggregated, multi-city scale is crucial for understanding unique regional development patterns and their implications for sustainability, a perspective often overlooked by single-city level analyses.

However, the rapid economic expansion accompanying urban agglomerations has intensified negative externalities, such as rising energy consumption and pollution emissions, presenting formidable challenges to sustainable development (Abbasi et al., 2021; Dong et al., 2022). While single mega-cities often face escalating congestion and environmental burdens with increasing density, urban agglomerations, through their polycentric structure and integrated functional networks, offer a potential pathway to mitigate these issues while still capturing agglomeration benefits. Within this context, Green Total Factor Productivity (GTFP), a vital metric for assessing economic sustainability, has gained prominence as a key mechanism for achieving sustainable development goals (Wang and Guo, 2023; Zheng et al., 2023). Therefore, against the backdrop of persistent population agglomeration in urban agglomerations and accelerating global ecological degradation, examining the impact of population agglomeration in urban agglomerations on GTFP becomes imperative. Should population agglomeration in urban agglomerations enhance GTFP, what mechanisms underpin this relationship? A thorough investigation of these questions is essential not only for elucidating effective strategies to elevate GTFP but also for positioning urban agglomerations as central hubs of green economic growth amidst ongoing population agglomeration.

Research on GTFP has predominantly focused on urban-level determinants, including urban energy consumption transitions, green policies, and carbon emissions (Wang S. et al., 2021; Wang et al., 2022; Zeng et al., 2025). In contrast, analyses of factors at the urban agglomeration level remain comparatively scarce. Urban agglomerations, which serve as pivotal frameworks for regional economic development, play a crucial role in improving GTFP. From an internal structural perspective, scholars argued that central cities within urban agglomerations efficiently integrate production functions, enhancing resource utilization

efficiency across the agglomeration (Zheng and Du, 2020). Peripheral cities, meanwhile, leverage producer services from central cities to advance green technologies and improve energy efficiency (Burger et al., 2015; Akinyemi et al., 2019). From the perspective of regional coordinated development, scholars assert that polycentric spatial structures within urban agglomerations mitigate the over-concentration of resources in central cities, thereby reducing inefficiencies (Fujita and Thisse, 2003). Furthermore, well-developed transportation and communication infrastructure fosters interconnected urban networks, enabling resource sharing and cross-boundary collaborations that spur innovation (Brezzi and Veneri, 2015; Tang and Cui, 2023). Recent studies have empirically confirmed that inter-city coordination within agglomerations alleviates resource misallocation, thereby enhancing GTFP (Wu et al., 2023).

Numerous studies have addressed the impact of urban-scale population agglomeration on GTFP. On the positive side, urban-scale population agglomeration attracts high-quality and high-skill talents, facilitating knowledge diffusion and technological innovation (Yan and Huang, 2022). This promotes green technology upgrading and application, and thereby enhances GTFP (Wang and Guo, 2023). Additionally, it also effectively promotes the free flow and rational allocation of production factors, promotes the further agglomeration of the service industry and optimization of industrial structure, to help reduce the intensity of pollution emissions and improve green total factor productivity (Yan and Huang, 2022; Guo et al., 2024). Conversely, population agglomeration can generate congestion effects, leading to excessive resource consumption and aggravated environmental pollution, which undermines GTFP. This negative impact is particularly pronounced in single cities with limited local space (Broersma and Oosterhaven, 2009; Brinkman, 2016).

However, the current research frontier highlights a significant gap: the underexplored role of population agglomeration in urban agglomerations in shaping GTFP. While population, labor, and talent are crucial elements for regional economic and social development, the specific dynamics of how their agglomeration at the multi-city scale influences GTFP remain largely unexamined. In fact, population agglomeration in China's cross-administrative urban agglomerations not only provides high-quality human capital but also promotes the emergence of knowledge spillover effects and the formation of regional market integration (Cai et al., 2023). Critically, these mechanisms operate with distinct characteristics and often greater effectiveness at the urban agglomeration scale due to unique factors such as inter-city specialization, integrated regional markets, and polycentric structures that can collectively enhance GTFP beyond what is achievable within a single urban boundary. Yet, empirical evidence specifically examining these nuanced aspects is still lacking. Therefore, focusing on China's urban agglomerations, this study seeks to systematically examine the impacts and underlying mechanisms of population agglomeration in urban agglomerations on GTFP, offering theoretical insights and practical implications for sustainable development.

Relative to prior studies, this paper offers the following contributions: First, while existing studies primarily focus on the impact of urban-level specific factors on GTFP, they often

neglect the influence of urban agglomeration-level factors. This paper emphasizes the impact of population agglomeration in urban agglomerations on GTFP and its mechanisms, which provides a new theoretical perspective for improving GTFP at the level of urban agglomerations. Second, our research provides a deeper theoretical and empirical understanding of the mechanisms linking population agglomeration to GTFP. While previous literature has identified these mechanisms in a general sense, our study unpacks them within the specific context of an urban agglomeration, exploring how inter-city specialization facilitates green knowledge spillovers, how integrated regional markets enhance market potential for green goods and services, and how a polycentric talent pool upgrades human capital for eco-innovation. This provides a more nuanced and context-specific theoretical framework. Third, we introduce a threshold effect analysis, demonstrating that the positive impact of population agglomeration on GTFP becomes significantly more pronounced after a specific scale is reached. This finding highlights the importance of fostering a “unified functional network”—a developmental phase in which cities within an urban agglomeration are deeply interconnected and interdependent through seamless, multidirectional flows of resources, information, goods, and services. Such integration is typically facilitated by coordinated regional governance and comprehensive infrastructure systems, and it carries significant policy implications for the strategic planning and development of urban agglomerations. Fourth, it provides empirical evidence to support China’s choice of cross-regional urban agglomeration as a priority for future regional growth. Particularly, against the backdrop of accelerating global ecological degradation and the growing concentration of population in urban agglomerations, population agglomeration in urban agglomerations is particularly significant for better utilizing the advantages of China’s mega-markets, promoting internal circulation, and achieving sustainable development.

2 Theoretical analysis and research hypothesis

Distinct from population agglomeration within individual cities, this study focuses on population agglomeration across administrative boundaries in urban agglomerations composed of multiple cities with diverse scales and functions. As a higher-order spatial organizational form, population agglomeration in urban agglomerations differs significantly from that in single cities. In individual cities, congestion effects arise from population agglomeration within confined local spaces. However, cities can leverage their membership in urban agglomerations to expand development space, diverting population flows from overcrowded central cities to multiple urban centers within the agglomeration. This spatial redistribution mitigates congestion effects caused by excessive population agglomeration in single cities (Li and Zhang, 2021). A critical advantage of population agglomeration in urban agglomerations, particularly compared to uncontrolled growth in a single mega-city, is its inherent capacity to mitigate these negative congestion effects (such as traffic congestion, pollution accumulation, and strain on public services) through

its polycentric and integrated structure. Unlike a monocentric mega-city where pressure concentrates at a single core, urban agglomerations often comprise multiple urban centers. This polycentricity effectively disperses population and economic activities, thereby decentralizing the load of traffic, infrastructure use, and resource consumption across several nodes, preventing the extreme bottlenecks seen in single-core cities (Burger and Meijers, 2016; Volkmann and Münter, 2022). This structure also enables the development of specialized regional infrastructure, such as inter-city public transport and regional green infrastructure networks, that efficiently connect specialized areas without overwhelming core city infrastructure. Furthermore, the multi-city framework encourages and often necessitates coordinated environmental policies, joint pollution control efforts, and shared green space planning, which are more challenging to implement within a single administrative boundary dealing with localized problems. For instance, pollution from one city can be mitigated by green belts or air quality monitoring systems established cooperatively across the agglomeration. While congestion effects can still exist, the inherent structure of urban agglomerations, when effectively managed through regional planning and cooperation, offers a systemic advantage in addressing these challenges. Consequently, population agglomeration in urban agglomerations may amplify the positive impacts of population agglomeration at the single-city level by alleviating congestion effects, thereby enhancing GTFP. Based on this theoretical foundation, we propose our first hypothesis:

Hypothesis 1: Population agglomeration in urban agglomerations positively impacts GTFP.

This positive direct effect is, however, not a simple linear outcome of increased density. Instead, it is the result of the urban agglomeration’s unique structure, which systematically amplifies traditional agglomeration benefits and mitigates their associated negative externalities. Specifically, the polycentric and integrated nature of urban agglomerations, which allows for congestion mitigation, simultaneously enhances the flow of resources and information, creating a fertile ground for the three key mechanisms discussed below to operate with greater effectiveness and a stronger link to green sustainable development. It can be seen that population agglomeration in urban agglomerations influences GTFP through three primary mechanisms:

Firstly, in terms of knowledge spillover effects, Population agglomeration in urban agglomerations enhances GTFP by strengthening knowledge spillover effects. From the perspective of individual cities, population agglomeration in urban agglomerations enables central cities to attract high-quality and high-skill labor, fostering knowledge exchange through the sharing of cutting-edge research outcomes and market dynamics (Roca and Puga, 2017; Zheng et al., 2024). Peripheral cities benefit from low-cost access to central cities’ knowledge and technologies, facilitating knowledge diffusion and application. At the agglomeration level, population agglomeration in urban agglomerations drives infrastructure upgrades that encourage labor mobility, thereby enhancing knowledge spillover effects (Ren et al., 2022; Yu and Xu, 2022). However, at the urban agglomeration scale, knowledge spillovers are not merely amplified

by larger overall density; they are critically enhanced by the complementarity and diversity of specialized industries and human capital distributed across multiple interconnected cities. A single large city, while dense, might suffer from industrial homogeneity, limiting the scope for diverse knowledge interaction. An urban agglomeration, conversely, often features a polycentric structure where different cities or urban cores specialize in distinct economic sectors. This inter-city specialization facilitates cross-sectoral green knowledge flow and “cross-pollination” of ideas, leading to novel combinations and eco-innovations that drive GTFP. For example, a technology developed in a research hub in one city focusing on renewable energy can quickly find application in manufacturing firms in a neighboring city specializing in industrial production, facilitated by integrated regional transport and information networks. This form of ‘inter-city knowledge spillover’ is distinct from intra-city spillovers, fostering a broader base for green technological advancement and the widespread adoption of sustainable practices by leveraging the collective intellectual assets dispersed across the entire agglomeration. Strengthened knowledge spillovers enable firms to absorb and apply new knowledge rapidly, fostering deeper intra- and inter-industry linkages. This integration of green technological knowledge accelerates green innovation and improves GTFP (Chen et al., 2021; Wang and Guo, 2023), and concurrently contributes to the upgrading of human capital by exposing individuals to new skills and expertise.

Secondly, concerning market potential, Population agglomeration in urban agglomerations improves GTFP by expanding market potential. From the demand side, population agglomeration increases labor wages, stimulating sustained growth in consumer demand and expanding consumption markets (Li and Zhang, 2021; Li S. et al., 2023). It also drives the development of tertiary industries, further enlarging domestic demand (Duranton and Puga, 2020; Comin et al., 2021). From the supply side, population agglomeration in urban agglomerations creates a diverse and abundant labor resource pool with a complex division of labor, generating sufficient employment opportunities and ensuring market supply (Liu et al., 2024). Expanding market scale allows firms to efficiently adjust production, reduce average costs, and enhance market potential (Wang et al., 2024). While a single mega-city offers a large internal market, an urban agglomeration presents a unique form of market potential derived from the integration of multiple, often specialized, city-level markets into a single, expansive regional market. This is primarily achieved by significantly reducing inter-city trade costs and barriers, both physical and institutional. Integrated regional infrastructure, such as high-speed rail and regional logistics hubs, along with harmonized market regulations, enables goods, services, and factors to flow almost as seamlessly between cities within the agglomeration as they would within a single large city. Rising market potential incentivizes investments in production equipment and technological improvements, particularly in green sectors where surging demand for eco-friendly products and services promotes the adoption of efficient, energy-saving, and pollution-reducing production methods, thereby contributing to the improvement of green total factor productivity (Ghisetti and Quatraro, 2017). The emergence of such an integrated regional green market also provides a broader

testing ground and larger demand base for new green technologies and innovations, further stimulating knowledge spillovers toward sustainable practices.

Finally, regarding human capital structure, Population agglomeration in urban agglomerations improves GTFP by advancing the human capital structure. It enhances labor skills and knowledge through knowledge spillovers while attracting high-quality workforce inflows, driving human capital upgrading (Black and Henderson, 1999; Li and Zhang, 2021). At the urban agglomeration scale, this effect is magnified and diversified. The presence of multiple specialized cities within an agglomeration creates a broader and more resilient regional labor market, where individuals with particular skills can find opportunities in various cities without needing to relocate residence, fostering a more dynamic and competitive talent pool. This polycentric labor market also facilitates access to diverse educational and training opportunities, as different cities may host specialized universities or vocational training centers. Collectively, these institutions contribute to a higher overall skill level across the agglomeration. Importantly, the agglomeration attracts a broader range of skilled individuals, including environmental scientists, green technology engineers, and policy experts, whose varied expertise can collectively drive eco-innovation and resource efficiency improvements, thereby promoting GTFP through a more comprehensive and adaptable human capital base. An advanced human capital structure promotes green technological innovation, enabling the design of more efficient and environmentally friendly production processes that reduce resource consumption and pollution (Wang K. H. et al., 2021; Lin and Ma, 2022). It also strengthens firms’ compliance with green standards and regulations and promotes the establishment of green management systems (Cai et al., 2024; Chen et al., 2024). Moreover, a higher-quality human capital pool is essential for identifying and capitalizing on new market opportunities in the green economy, thereby reinforcing the market potential for green products and services. These mechanisms lead us to propose the following hypothesis:

Hypothesis 2: Population agglomeration in urban agglomerations improves GTFP through enhanced knowledge spillover effects, expanded market potential, and upgraded human capital structure.

After population agglomeration in urban agglomerations reaches a critical scale, the formation of a unified functional network within the agglomeration begins to exert significant effects, leading to substantial improvements in GTFP. This phenomenon is theorized as follows: a critical mass of population, economic activity, and infrastructure development acts as a catalyst. At a certain threshold, the costs of fragmented governance and uncoordinated inter-city interactions begin to outweigh the benefits of independent development, pushing policymakers and market forces toward deeper integration. This triggers a qualitative shift from a simple division of labor to the formation of a unified functional network. This network is not merely about physical proximity; it represents a new stage of development characterized by highly interdependent, multi-directional flows of factors, information, goods, and services, facilitated by coordinated

regional governance and integrated infrastructure systems. This transition to a unified functional network reduces transaction costs and information asymmetry across administrative boundaries, fosters collaborative innovation, and optimizes the regional allocation of resources (Zhang et al., 2024). Consequently, the efficiency gains are more substantial than those achievable at a lower level of agglomeration, leading to a more pronounced improvement in GTFP. Given these insights, we propose the following hypothesis:

Hypothesis 3: Population agglomeration in urban agglomerations achieves increasingly significant positive impacts on GTFP after reaching a critical threshold.

Figure 1 illustrates the theoretical framework of this paper.

3 Model formulation and data

3.1 Econometric model settings

To investigate the impact of population agglomeration in urban agglomerations on GTFP, we specify the following panel fixed-effects model:

$$GTFP_{it} = \beta_0 + \beta_1 clust_{it} + \gamma X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

Where i and t denote city and year, respectively. $GTFP$ represents urban Green Total Factor Productivity, while $clust$ measures population agglomeration in urban agglomerations. The vector X_{it} includes control variables. λ_i and μ_t capture city-specific and time-fixed effects, respectively. Finally, ε_{it} is the error term, with standard errors clustered at the city level.

3.2 Variable selection and description

3.2.1 GTFP

Drawing on Li T. et al. (2023), this study employs a super-efficiency Slack Based Measure (SBM) model incorporating undesirable outputs to measure GTFP. While traditional SBM models reduce radial and angular biases by integrating undesirable outputs, standard SBM efficiency scores remain ≤ 1 , limiting discrimination among efficient Decision Making Units (DMUs). The super-efficiency SBM model addresses this limitation by allowing efficiency scores > 1 for effective DMUs, enabling further differentiation among them. The measurement formula is specified as follows:

$$E = \min \left(\frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{r0}} + \sum_{k=1}^{q_2} \frac{s_k^-}{b_{k0}} \right)} \right) \quad (2)$$

$$s.t. \begin{cases} \sum_{j=1, j \neq j_0}^n x_j \lambda_j - s_i^- \leq x_0 (i = 1, 2, \dots, m) \\ \sum_{j=1, j \neq j_0}^n y_j \lambda_j + s_r^+ \geq y_0 (r = 1, 2, \dots, q_1) \\ \sum_{j=1, j \neq j_0}^n b_j \lambda_j - s_k^- \leq b_0 (k = 1, 2, \dots, q_2) \\ 1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{r0}} + \sum_{k=1}^{q_2} \frac{s_k^-}{b_{k0}} \right) > 0 \\ \lambda_j, s_i^-, s_r^+, s_k^- \geq 0 (j = 1, 2, \dots, n, j \neq j_0) \end{cases}$$

In Equation 2, E represents the efficiency value determined by the Super-efficiency Slacks-Based Measure model, which accounts for undesirable outputs. The parameters m , q_1 , and q_2 denote the number of input, desirable output, and undesirable output variables associated with each DMU, respectively, while n indicates the total number of DMUs. x_j , y_j , and b_j represent the input, desired output, and undesired output matrices of the j -th DMU, respectively. The

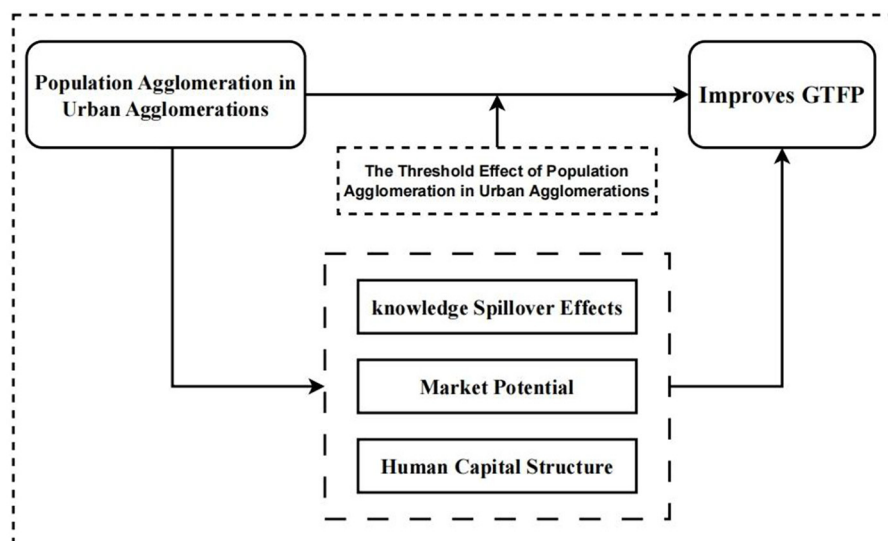


FIGURE 1
Theoretical framework diagram.

slack variables s_i^- , s_r^+ , and s_k^- correspond to the inputs, desirable outputs, and undesirable outputs, respectively, and λ_j denotes the weight variable.

After calculating the efficiency score E under the Constant Returns to Scale (CRS) assumption, this study further employs the Global Malmquist index, which possesses the advantage of inter-temporal comparability, to measure the dynamic change rate of GTFP. The calculation formula for the Global Malmquist index is as follows:

$$GML_0^{t,t+1} = \frac{E_0^g(x^{t+1}, y^{t+1}, b^{t+1})}{E_0^g(x^t, y^t, b^t)} = \frac{E_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{E_0^t(x^t, y^t, b^t)} \times \left[\frac{E_0^g(x^{t+1}, y^{t+1}, b^{t+1})}{E_0^{t+1}(x^t, y^t, b^t)} \times \frac{E_0^t(x^{t+1}, y^{t+1}, b^{t+1})}{E_0^g(x^t, y^t, b^t)} \right] \quad (3)$$

In Equation 3, $GML_0^{t,t+1}$ represents the rate of change in GTFP for a city from period t to period $t + 1$. $E_0^g(x^{t+1}, y^{t+1}, b^{t+1})$ is the efficiency value in period $t + 1$, and $E_0^g(x^t, y^t, b^t)$ represents the efficiency value in period t . To convert this rate of change into actual GTFP values, we adopt the methodology proposed by Wang and Guo (2023), using 2010 as the base year and cumulatively quantifying GTFP for each subsequent year.

Following the framework established by Li T. et al. (2023), this study incorporates capital, labor, and energy as inputs, with real GDP as the expected output. Industrial wastewater discharge, industrial soot and dust emissions, and industrial sulfur dioxide emissions are designated as undesirable output variables. There are two reasons for choosing the three pollutant emissions. First, they are usually the more comprehensive variables for measuring pollution levels and can thus reflect the region's pollution situation to a great extent (Tian and Pang, 2022). Second, the government has strictly controlled and monitored these indicators. Specifically, for the measurement of capital input, this study refers to the methodology of Zhang et al. (2004) and employs the perpetual inventory method to estimate the real capital stock of each city, with 2006 set as the base year. In the perpetual inventory method, the total fixed asset investment of each region is selected as the investment indicator and deflated using the fixed asset investment price index of each province over the years. Furthermore, the depreciation rate is uniformly set at 9.6%. Energy input is proxied by the city's total annual electricity consumption, while labor input is measured by the number of employed persons at the end of the year.

3.2.2 Population agglomeration in urban agglomerations

This study, drawing on Cai et al. (2023), constructs the following indicators to measure population agglomeration in urban agglomerations:

$$clust_{it} = \sum_{K \in D, K \neq i} \frac{size_{kt}}{d_{ki}^\delta} \quad (4)$$

Where D represents the set of cities within a certain geographical distance from city i . $clust$ denotes the degree of

population agglomeration in city i in the urban agglomeration in year t . $size_{kt}$ indicates the year-end resident population of city k in year t . d_{ki} represents the geographical distance between city k and city i , calculated using the spherical distance formula based on the latitude and longitude information of the municipal government locations. δ is the distance decay parameter, assigned a value of 1.

Given that the average distance between a given city and the remaining cities within the 19 urban agglomerations outlined in China's policy planning documents is approximately 198 km, D is defined as the set of cities within a 200-km radius centered on city i . Furthermore, to address potential heteroscedasticity in the data, the population agglomeration in urban agglomerations is subjected to logarithmic transformation.

3.2.3 Control variables

To mitigate potential omitted variable bias, this paper, drawing upon Wang and Guo (2023), selects the following variables that may influence GTFP as control variables:

Green Credit (GC): Green credit is designed to channel funds toward energy conservation and environmental protection industries, fostering green investment and providing essential capital factors for green economic growth. Following the measurement approach of Dai et al. (2024), this study uses the ratio of total urban environmental protection project loans to total urban loans to measure the level of green credit.

Industrial Structure (Ins): The optimization and upgrading of industrial structure can incentivize enterprises to continuously increase investment in research and development and the application of green technologies to maintain market competitiveness. These green technologies can not only improve production efficiency but also effectively reduce environmental pollution and ecological damage. This paper uses the sum of the primary industry's share, twice the secondary industry's share, and three times the tertiary industry's share in GDP to measure industrial structure.

Foreign Direct Investment Level (Fd): Foreign direct investment (FDI) often brings advanced technologies and management expertise, which are typically more environmentally friendly and efficient. The inflow of FDI enables domestic enterprises to learn, imitate, and absorb these advanced factors, thereby improving their own production efficiency and resource utilization efficiency, and ultimately enhancing GTFP. This paper measures the level of FDI using the proportion of FDI to regional GDP.

Infrastructure Level (lnRod): Improvements in infrastructure play a critical role in reducing the transportation and transaction costs of production factors. These improvements foster the development of urban economies of scale and industrial agglomeration. The infrastructure level is measured using the natural logarithm of per capita road area.

Informationization Level (lnInf): Elevating the level of informationization accelerates the spillover effects of knowledge and technology, leading to effective reductions in transaction costs and energy consumption per unit of output. This, in turn, strengthens manufacturing capabilities and efficiency, providing a powerful impetus for the growth of GTFP. The

TABLE 1 Descriptive statistics for variables.

Variable	Mean	SD	Min	Max	N
GTFP	1.234	0.416	0.225	6.454	3,384
<i>clust</i>	3.113	1.103	−1.091	4.944	3,384
<i>Gc</i>	0.050	0.018	0.007	0.111	3,384
<i>Ins</i>	2.308	0.146	1.821	2.836	3,384
<i>Fd</i>	0.022	0.166	0.000	6.296	3,384
<i>lnRod</i>	2.829	0.438	0.315	4.096	3,384
<i>lnInf</i>	6.493	0.578	2.698	9.379	3,384

informationization level is quantified using the natural logarithm of per capita telecommunication business volume. To ensure temporal consistency, all monetary values in the dataset are adjusted for inflation, with 2010 serving as the base year.

Descriptive statistics for the main variables are summarized in Table 1.

3.3 Sample selection and data sources

To ensure the integrity and consistency of the dataset, counties and county-level cities with inadequate data continuity were excluded. Consequently, panel data from 282 cities spanning the period from 2011 to 2022 were selected. The urban data were primarily sourced from the “China Urban Construction Statistical Yearbook” and the “China Urban Statistical Yearbook”. For missing data, relevant city statistical yearbooks, annual statistical bulletins, and interpolation methods were used to address the gaps, resulting in a total of 3384 observations.

4 Empirical results and discussion

4.1 Baseline regression results

Table 2 presents the regression results examining the impact of population agglomeration in urban agglomerations on GTFP. The results in Column (1) demonstrate that the regression coefficient for population agglomeration in urban agglomerations is significantly positive. Column (2) includes only city fixed effects, controlling for time-invariant city-level characteristics. The regression coefficient for population agglomeration in urban agglomerations is 2.018 and statistically significant. Column (3), however, adds year fixed effects to Column (2)’s specification to account for time-varying macro shocks, with the coefficient declining to 0.870 while remaining significantly positive. This notable reduction suggests that part of the impact originally attributed to population agglomeration in urban agglomerations may be related to year-specific factors. For instance, green technology breakthroughs or industrial policy adjustments in specific years could have concurrently driven both population agglomeration in urban agglomerations and GTFP improvement. In Column (4), the analysis further incorporates control variables, and the regression results continue to show a significantly positive coefficient for population agglomeration in urban agglomerations,

TABLE 2 Baseline regression results.

Variable	(1)	(2)	(3)	(4)
<i>clust</i>	0.027* (0.014)	2.018*** (0.402)	0.870** (0.392)	0.838** (0.385)
<i>Gc</i>				−0.571 (0.564)
<i>Ins</i>				0.164 (0.242)
<i>Fd</i>				−0.036 (0.024)
<i>lnRod</i>				−0.070 (0.045)
<i>lnInf</i>				−0.006 (0.020)
Constant	1.150*** (0.048)	−5.048*** (1.251)	−1.474 (1.219)	−1.487 (1.238)
City-FE	×	✓	✓	✓
Year-FE	×	×	✓	✓
Observations	3,384	3,384	3,384	3,384
R ²	0.005	0.400	0.498	0.500

***, **, * Represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

suggesting a positive effect on GTFP. These findings indicate that population agglomeration in urban agglomerations enhances GTFP, thereby providing empirical support for Hypothesis 1. It is worth noting that control variables such as Green Credit and Industrial Structure are all insignificant. This may be because their impacts on GTFP are not direct but rather exerted through complex mediating mechanisms. Under the current model specification, capturing their significant direct effects is challenging. However, it is important to emphasize that the insignificance of control variables does not entirely imply that they do not influence the dependent variable; they still support the robustness of the model to a certain extent. It can be seen that population agglomeration in urban agglomerations can indeed improve GTFP. This insight suggests that city governments, when designing policies to boost GTFP, should consider not only local factors but also explore opportunities for advancement at the urban agglomeration level. This study’s conclusion offers a novel policy perspective by expanding the scope from the individual city scale to the broader urban agglomeration scale in efforts to elevate GTFP.

4.2 Robustness check

To further ensure the reliability of the baseline regression, this study conducts robustness tests by employing alternative indicators, adjusting the sample scope, and applying the winsorization technique. These tests verify the robustness of the baseline results.

TABLE 3 Robustness check results.

Variable	(1)	(2)	(3)	(4)	(5)
	Alternate explanatory variable	Alternate dependent variable	Exclusion of centrally administered municipalities	Exclusion of COVID-19 years	Winsorization
<i>clust</i>	0.323** (0.140)	0.825** (0.378)	0.829** (0.372)	0.756** (0.375)	0.706* (0.380)
Control	✓	✓	✓	✓	✓
City-FE	✓	✓	✓	✓	✓
Year-FE	✓	✓	✓	✓	✓
Observations	3,384	3,384	3,336	2,820	3,384
R ²	0.501	0.509	0.502	0.478	0.566

***, **, *Represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

4.2.1 Alternative variable

In this study, we refine the calculation of population agglomeration in urban agglomerations by adjusting the population scale data. The urban district, recognized as the area with concentrated economic activity and elevated business vitality, serves as the focal point of this modification. Accordingly, we replace the original population scale, which encompassed the entire city, with the population scale specific to the urban district, and subsequently recalculate population agglomeration in urban agglomerations. The regression results, reported in Column (1) of Table 3, indicate that the regression coefficient of population agglomeration in urban agglomerations is significantly positive. Furthermore, we replaced the dependent variable with that calculated by the traditional SBM (SBM without super-efficiency) model and re-conducted the model estimation, with the results presented in column (2). The coefficient of population agglomeration in urban agglomerations remains significantly positive.

4.2.2 Sample adjustment

Regarding cities, the four municipalities directly under the central government—Beijing, Shanghai, Tianjin, and Chongqing—are excluded due to their significant differences from other cities. Therefore, the sample excluding these four municipalities is reanalyzed. The regression results in Column (3) show that the regression coefficient of population agglomeration in urban agglomerations remains significantly positive.

Regarding the years, 2020–2021 are excluded. Mu et al. (2022) pointed out that during the full outbreak of COVID-19, strict epidemic prevention measures implemented by the government led to a sharp decline in population mobility. To eliminate the impact of this factor on the regression results, the city samples from 2020–2021 are excluded and reanalyzed. The regression results in Column (4) of Table 3 show that the regression coefficient of population agglomeration in urban agglomerations remains significantly positive.

4.2.3 Winsorization

To eliminate the impact of outliers, both the dependent variable and the core explanatory variable are subjected to a 1%

winsorization at both ends. The regression results in Column (5) of Table 3 show that the regression coefficient of population agglomeration in urban agglomerations remains significantly positive. It can be observed that the direction and significance of the regression coefficient of population agglomeration in urban agglomerations are consistent with the baseline regression results, indicating the robustness of the baseline regression results.

4.3 Endogeneity test

Endogeneity poses a significant challenge in evaluating the impact of population agglomeration in urban agglomerations on GTFP. To mitigate the estimation bias resulting from endogeneity, this study conducts the following two analyses.

Dependent variable lead by one period: To address potential endogeneity arising from reverse causality, we lead the dependent variable by one period. This approach introduces a temporal misalignment between the independent and dependent variables, thereby mitigating the endogeneity bias. Additionally, this method accounts for the possible time lag in the realization of GTFP. The regression results presented in Table 4 column (1), reveal a significantly positive coefficient of population agglomeration in urban agglomerations. This finding confirms the robustness of our baseline regression results.

Instrumental variable approach: While the incorporation of time fixed effects and city fixed effects can effectively mitigate the impact of omitted variables, the presence of endogenous variables may still introduce endogeneity bias into the regression estimates. To address this issue, we employ the instrumental variable (IV) method, following Zhang et al. (2024). This study constructs an instrumental variable for population agglomeration in urban agglomerations using the reciprocal of a city's average slope. The core logic underpinning the relevance and exogeneity of this instrumental variable is as follows: on the one hand, cities with steeper surface slopes and higher elevations face higher road construction and maintenance costs, which increase the unit transportation and time costs for factor mobility, thereby hindering population agglomeration in urban agglomerations. Thus, the reciprocal of a city's average slope is correlated with current population agglomeration in urban agglomerations. On the other hand, compared to the current pace of urban development

TABLE 4 Results of endogeneity tests.

Variable	(1)	(2)		(3)
	Leading dependent variable	Instrumental variable approach		
		<i>clust</i>		<i>GTFP</i>
<i>clust</i>	0.942** (0.411)			1.715*** (0.585)
<i>IV</i>		4.639*** (0.352)		
Control	✓	✓		✓
City-FE	✓	✓		✓
Year-FE	✓	✓		✓
LM statistic		45.585 [0.000]		
Wald F statistic		173.455 {16.38}		
Observations	3,102	3,102		3,102
<i>R</i> ²	0.523			

Values in [] represent *p*-values; values in {} represent the critical value for the Stock-Yogo weak identification test at the 10% level. ***, **, *Represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

and population agglomeration, geographic characteristic variables, as inherent geographic attributes of cities, have minimal impact on current GTFP, meeting the exogeneity requirement. Since geographic data are cross-sectional and are not directly applicable to panel data econometric analysis, this study utilizes the interaction term between the reciprocal of a city's average slope and the lagged value of the independent variable as an instrumental variable for population agglomeration in urban agglomerations.

The first- and second-stage regression results after introducing the instrumental variable are reported in columns (2) and (3) of Table 4. The results from the first-stage regression show [see column (2) of Table 4] that the Kleibergen-Paap rk LM statistic significantly rejects the null hypothesis of “under-identification of the IV” at the 1% significance level. Additionally, the Kleibergen-Paap rk Wald F statistic surpasses the critical threshold for the weak identification test at the 10% level, thereby rejecting the null hypothesis of “weak IV.” Furthermore, the coefficients of the instrumental variables in the first stage are significantly positive, fulfilling the requirement of relevance. Therefore, these findings substantiate the appropriateness of the chosen IV. The results from the second stage show [see column (3) of Table 4] that after accounting for endogeneity, the regression outcomes remain largely consistent with those reported earlier in the study, further affirming the robustness of the baseline regression results.

5 Further analysis

5.1 Mechanism analysis

The baseline regression results indicate that population agglomeration in urban agglomerations enhances GTFP. Theoretical analysis suggests that this effect is primarily

driven by three mechanisms: amplifying knowledge spillover effects, expanding market potential, and fostering the advancement of human capital structure. This study empirically examines these mechanisms. The empirical model is specified as follows:

$$MV_{it} = \beta_0 + \beta_1 clust_{it} + \gamma X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (5)$$

Specifically, MV_{it} denotes the mechanism variables, including knowledge spillovers ($lnKs$) in city i in year t , market potential ($lnMp$) in city i in year t , and the advanced structure of human capital (Hs) in city i in year t . $GTFP_{it}$ represents green total factor productivity, $clust_{it}$ denotes population agglomeration in urban agglomeration, X_{it} represents a series of control variables, λ_i and μ_t denote city and year fixed effects, respectively, and ε_{it} is the random disturbance term.

5.1.1 Knowledge spillover

Drawing on the methodology proposed by Wang and Liu (2024), this study constructs the following indicator to quantify knowledge spillover across cities:

$$Ks_{it} = \sum_{j=1}^j H_{ijt} \frac{k_{it}k_{jt}}{d_{ij}^2}, H_{ijt} = \frac{k_{it}}{k_{it} + k_{jt}} \quad (6)$$

Where Ks_{it} denotes the knowledge spillover for city i in year t , k_{it} and k_{jt} represent the knowledge stock of city i and city j in year t , respectively. d_{ij} is the geographical distance between city i and city j , calculated using the spherical distance formula based on the longitude and latitude coordinates of the municipal government locations for each prefecture-level city.

Drawing on the methodology of Sun et al. (2021), this study utilizes the total number of granted patents as an indicator to measure the local knowledge stock of a region. The calculation formulas are as follows:

$$K_{it0} = \frac{P_{it0}}{g + \delta} \quad (7)$$

$$K_{it} = p_{it} + (1 - \delta)k_{i(t-1)} \quad (8)$$

Here, p_{it} denotes the total number of patent grants in city i in year t , and p_{it0} represents the total number of patent grants in city i in the base year (2010). δ is the depreciation rate, set at 10%, and g is the geometric average growth rate of the total number of patent grants during the sample period. Furthermore, to reduce the impact of heteroscedasticity, the knowledge spillovers are logarithmically transformed.

5.1.2 Market potential

Market potential reflects the influence of the latent demand (e.g., market size and income levels) inherent in a city's overall market scale or spatial extent on its urban economy (Han and Ke, 2012). Building upon the work of Han and Ke (2012), this paper constructs the following indicator to measure urban market potential:

$$Mp_{it} = \sum_{j=1}^j \frac{Y_{jt}}{d_{ij}} \quad (9)$$

Where Y_{jt} denotes the total retail sales of consumer goods in city j during year t , and d_{ij} represents the geographical distance between city i and city j . This distance is calculated based on the latitude and longitude coordinates of each prefecture-level city's municipal government using the spherical distance formula. Furthermore, to mitigate potential heteroscedasticity issues, the market potential variable undergoes a logarithmic transformation.

5.1.3 Human capital structure

A defining characteristic of the advancement of human capital structure is the continuous transition from primary to advanced human capital (Liu et al., 2018). Following the approach of Liu et al. (2018), this study employs the vector angle method to measure the advancement of human capital structure. Notably, due to data constraints at the prefecture-level city level, this method is applied only to the provincial level. Given that the definition of human capital structure advancement emphasizes the dominant role of higher education, this paper further draws on the approach of Fan and Zhao (2019). Specifically, it uses the proportion of higher education students in a prefecture-level city relative to the total number of higher education students in its respective province as a weight. This weight is then multiplied by the provincial-level human capital structure advancement index to derive the human capital structure advancement index for each prefecture-level city. Following this rationale, the calculation process is outlined below:

First, human capital is categorized into five groups based on educational attainment: illiterate and semi-illiterate, primary school, junior high school, senior high school (including vocational secondary education), and tertiary education (including junior college, undergraduate, and postgraduate levels). The proportion of each category is treated as a component of a five-dimensional human capital spatial vector, denoted as $X_0 = (x_{0,1}, x_{0,2}, x_{0,3}, x_{0,4}, x_{0,5})$.

Second, the following basic unit vectors are selected as benchmark vectors: $X_1 = (1, 0, 0, 0, 0)$, $X_2 = (0, 1, 0, 0, 0)$, $X_3 = (0, 0, 1, 0, 0)$, $X_4 = (0, 0, 0, 1, 0)$, $X_5 = (0, 0, 0, 0, 1)$, and measure the angles $\theta_j (j = 1, 2, 3, 4, 5)$ between the human capital space vector X_0 and these vectors sequentially:

$$\theta_j = \arccos \left(\frac{\sum_{i=1}^5 (x_{j,i} \cdot x_{0,i})}{\left(\sum_{i=1}^5 x_{j,i}^2 \right)^{1/2} \cdot \left(\sum_{i=1}^5 x_{0,i}^2 \right)^{1/2}} \right) \quad (10)$$

Where $x_{j,i}$ is the i -th component of $x_j (j = 1, 2, 3, 4, 5)$, and $x_{0,i}$ represents the i -th component of x_0 .

First, calculate the provincial-level human capital structure advancement Hs using the predetermined weights θ_j according to the following formula:

$$Hs = \sum_{j=1}^5 (W_j \cdot \theta_j) \quad (11)$$

Where W_j denotes the weight assigned to θ_j , with W_1, W_2, W_3, W_4, W_5 set to 5, 4, 3, 2, and 1, respectively. The term Hs_p represents the advancement of human capital structure for province p .

Second, estimate the human capital structure advancement at the prefecture-level city Hs_{it} using the following proportional allocation formula:

$$Hs_{it} = Hs_{pt} \frac{Sdu_{it}}{Sdu_{pt}} \quad (12)$$

Where Hs_{it} is the human capital structure advancement for city i in year t , Sdu_{it} denotes the number of higher education students in city i during year t , and Sdu_{pt} is the number of higher education students enrolled in province p in year t .

Table 5 presents the regression results for the mechanism tests of how population agglomeration in urban agglomerations affects GTFP. Column (1) demonstrates a significantly positive coefficient of population agglomeration in urban agglomerations, indicating that it enhances knowledge spillovers. Column (2) reveals a similarly positive and significant coefficient, suggesting that population agglomeration in urban agglomerations strengthens market potential. Column (3) confirms another statistically significant positive relationship, highlighting that population agglomeration in urban agglomerations advances human capital structure. These findings collectively validate Hypothesis 2: population agglomeration in urban agglomerations improves GTFP by (1) amplifying knowledge spillovers, (2) expanding market potential, and (3) accelerating the advancement of human capital structure.

This implies that population agglomeration in urban agglomeration scale leverages systemic advantages to achieve efficient resource integration and utilization, thereby elevating GTFP. To maximize these benefits, policymakers should prioritize strategies to optimize population agglomeration, focusing on three key pathways: (1) fostering knowledge spillovers through enhanced connectivity and collaboration, (2) unlocking market potential via infrastructure investment and institutional innovation, and (3) advancing human capital structure through targeted education and talent retention policies. Such measures will ensure that population agglomeration in

TABLE 5 Results of mechanism analysis.

Variable	(1)	(2)	(3)
	$\ln Ks$	$\ln Mp$	Hc
<i>clust</i>	2.068*** (0.705)	0.385*** (0.073)	0.683* (0.380)
Control	✓	✓	✓
City-FE	✓	✓	✓
Year-FE	✓	✓	✓
Observations	3384	3384	3384
R^2	0.988	0.993	0.991

***, **, * Represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

urban agglomeration contributes robustly to sustainable urban productivity growth.

5.2 Threshold model test

This study adopts the threshold regression framework proposed by Hansen (1999) to investigate the nonlinear threshold effects of population agglomeration in urban agglomerations on GTFP. Specifically, population agglomeration in urban agglomerations is designated as the threshold variable. The empirical procedure involves two sequential steps: First, identifying the magnitude and number of threshold values in the estimation equation; Second, determining the optimal functional form of the threshold model. It is noteworthy that the model is designed to prioritize capturing non-linear abrupt effects over explaining the full variation in the dependent variable. Even with a low R^2 , it retains practical relevance if threshold effects are significant, as verified by the Bootstrap test.

Due to the non-standard distribution of test statistics arising from the presence of unknown parameters, a bootstrap method with 500 replications is employed to approximate the asymptotic distribution of the test statistics, thereby rigorously evaluating the statistical significance of the threshold effects.

$$GTFP_{it} = \beta_0 + \beta_1 clust_{it} \times D(clust_{it} \leq \lambda_1) + \beta_2 clust_{it} \times D(\lambda_1 < clust_{it} < \lambda_2) \dots \beta_{n+1} clust_{it} \times D(\lambda_n \leq clust_{it}) + \gamma X_{it} + \varepsilon_{it} \quad (13)$$

Where i and t denote city and year, respectively; $GTFP$ represents urban green total factor productivity; and $clust$ represents population agglomeration in urban agglomerations. λ denotes the threshold value under investigation, X_{it} represents a vector of control variables, and ε_{it} is the random error term. D is an indicator function that equals 1 if the condition in the parentheses is true, and 0 otherwise.

The threshold test results are summarized in Table 6. For the single-threshold model using population agglomeration in urban agglomerations ($clust$) as both the independent and threshold variable, the p-statistic is statistically significant, rejecting the null hypothesis of a linear relationship. In contrast, the double-threshold model fails to demonstrate statistical significance in the second threshold test, indicating no evidence of a dual-threshold effect. Consequently, the single-threshold regression specification is adopted for further analysis.

Following the threshold test, the specific regression results are presented in Table 7. As shown in columns (1) and (2), when population agglomeration in urban agglomerations is below or equal to the threshold of 2.428, its regression coefficient is

0.691 and statistically significant at the 1% level. However, when population agglomeration in urban agglomerations exceeds the threshold of 2.428, the regression coefficient increases to 1.555, also statistically significant at the 1% level. This indicates that population agglomeration in urban agglomerations can more substantially enhance GTFP once a certain scale is reached, thereby confirming Hypothesis 3. According to our theoretical analysis, a key reason for this finding is that achieving a sufficient level of population agglomeration in urban agglomerations allows the spatial functional division of labor within urban agglomerations to evolve into a highly networked stage, thereby fostering a unified functional network internally. For instance, core cities in more developed urban agglomerations such as the Yangtze River Delta and Pearl River Delta (e.g., Shanghai and Shenzhen) have leveraged integrated initiatives—including convenient intercity commuting connectivity, co-construction and integration of industrial chains, and shared use of infrastructure—to drive the spatial functional division of labor within urban agglomerations toward a new stage of highly networked division. Within this highly networked division system, the multi-center collaborative innovation chains, supply chains, and ecological chains in urban agglomerations have been accelerated and organically integrated, which has strongly promoted the process of infrastructure integration and enabled the free and efficient flow of various production factors. These developments have fully unleashed the population agglomeration effect of urban agglomerations, thereby more significantly improving GTFP. Consequently, in promoting population agglomeration toward urban agglomerations, it is essential to fully leverage the scale effects generated, which in turn facilitates the formation of an integrated functional network within the urban agglomeration, leading to a more significant improvement in GTFP.

5.3 Analysis of the spatial spillover effect of GTFP

The impact of population agglomeration in urban agglomerations on GTFP may not be confined to local cities; it could also influence neighboring cities through spatial spillovers of GTFP. To mitigate estimation biases stemming from the neglect of such spatial spillover effects and to examine more profoundly and accurately how this agglomeration affects GTFP, this study further employs the spatial autoregressive (SAR) model for regression analysis. It is worth noting that, compared to the more generalized Spatial Durbin Model (SDM), the SAR model emphasizes the spatial autocorrelation of the dependent variable, namely GTFP. This characteristic renders the SAR model more congruent with the underlying logic of the present research.

TABLE 6 Results of threshold effect test.

Equation	Number of thresholds	F-statistic	P-value	Critical values at different significance levels		
				10%	5%	1%
Equation 13	Single threshold	97.227	0.006	50.027	61.214	89.725
	Double threshold	36.821	0.238	90.733	131.018	219.579

TABLE 7 Results of threshold and spatial dimensions.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Threshold model		SAR model		The influence scope of population agglomeration in urban agglomerations		
	$clust \leq 2.428$	$2.428 < clust$	Inverse distance geographic matrix	Queen-type adjacency matrix	100 km	200 km	300 km
<i>clust</i>	0.691***	1.555***	0.544***	0.734***	0.415	0.838**	0.647
	(0.210)	(0.199)	(0.188)	(0.187)	(0.322)	(0.385)	(0.453)
ρ			0.677***	0.093***			
			(0.078)	(0.022)			
Control	✓	✓	✓	✓	✓	✓	✓
Observations	3384		3384	3384	3384	3384	3384
R ²	0.095		0.006	0.005	0.498	0.500	0.499

***, **, *Represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

TABLE 8 Moran's I of GTFP.

Year	Moran'I	Z	P-value
2011	0.002	1.074	0.283
2012	0.005*	1.674	0.094
2013	0.016***	3.766	0.000
2014	0.020***	4.595	0.000
2015	0.012***	3.448	0.001
2016	0.027***	6.253	0.000
2017	0.018***	4.187	0.000
2018	0.009**	2.368	0.018
2019	0.042***	8.985	0.000
2020	0.037***	7.960	0.000
2021	0.021***	4.881	0.000
2022	0.018***	4.150	0.000

***, **, *Represent significance at the 1%, 5%, and 10% levels, respectively.

Specifically, population agglomeration in urban agglomerations impacts local GTFP and subsequently influences the GTFP of neighboring cities through spatial spillover effects. This framework not only prevents redundancy in spatial information but also precisely delineates the process by which the population agglomeration in urban agglomerations initiates a chain reaction, ultimately affecting the GTFP of adjacent areas.

Before conducting spatial econometric analysis, this study verified the presence of spatial correlation in GTFP. Moran's I statistic was employed to calculate the annual spatial effects using an inverse distance geographic matrix. As shown in Table 8, Moran's I for GTFP is positive and statistically significant in most years, indicating strong spatial autocorrelation of GTFP across Chinese cities.

Columns (3) and (4) of Table 7 present the estimation results of the SAR model with spatial-temporal two-way fixed effects, based on the inverse distance geographic matrix and Queen-type adjacency matrix, respectively. The results show that the

coefficients of population agglomeration in urban agglomerations are significantly positive, indicating that population agglomeration in urban agglomerations has a significant positive impact on GTFP. In addition, the spatial lag coefficients ρ are positive and pass the 1% significance level test, which confirms that there is indeed a positive spatial spillover effect of GTFP in geographical adjacency. This implies that while population agglomeration in urban agglomerations improves local GTFP, it can further affect the GTFP of neighboring cities through the spatial spillover effect of GTFP itself. Therefore, the government should take the overall development of urban agglomerations into consideration, take population agglomeration as a link, guide cities to share the spillover dividends of GTFP, promote the in-depth superposition of the population agglomeration effect of urban agglomerations and the spatial spillover effect of GTFP, and jointly empower urban green development.

5.4 Tests on the influence scope of population agglomeration in urban agglomerations

In the baseline regression, this paper adopts 200 kms as the geographic distance threshold for selecting neighboring cities. To further examine the scope of influence of population agglomeration in urban agglomerations, this paper extends the distance threshold and conducts separate regressions. As shown in columns (5), (6), and (7) of Table 7, within the range of 100–300 kms, the coefficient of population agglomeration in urban agglomerations is significantly positive only at the specific distance of 200 kms, and the coefficient value reaches the maximum at this point, indicating that the population agglomeration effect of urban agglomerations has a specific reasonable spatial scope. This also reflects the rationality and feasibility of the 200-km distance range in actual urban agglomeration planning. Therefore, constructing urban clusters by taking the average distance between a city and other cities within the 19 urban agglomerations specified in China's policy planning documents as the geographic distance threshold

(i.e., 200 kms) not only conforms to the spatial scope where the population agglomeration effect of urban agglomerations can be effectively exerted but also provides a relatively balanced and efficient green development space for cities within the urban agglomeration. This research conclusion offers new policy insights for the government to accurately understand the scope of policy implementation and maximize the population agglomeration efficiency of urban agglomerations in promoting the urban agglomeration strategy.

5.5 Heterogeneity analysis

5.5.1 Urban heterogeneity

To investigate the urban-level heterogeneity in the impact of population agglomeration in urban agglomerations on GTFP, this study adopts the classification framework from Zhao et al. (2020), categorizing municipalities, provincial capitals, and sub-provincial cities as core cities, while classifying other prefecture-level cities as peripheral cities. To address potential biases in direct cross-group coefficient comparisons, a Fisher permutation test is employed to statistically validate differences between subgroups.

Table 9 presents the regression results for the heterogeneity analysis of population agglomeration in urban agglomerations. Column (1) indicates that in core cities, the coefficient of population agglomeration in urban agglomerations is 2.498, significant at the 10% level. In contrast, Column (2) shows that for peripheral cities, the coefficient is 0.646, significant at the 5% level. A Fisher permutation test confirms that the difference between these coefficients is statistically significant at the 1% level. A comparison of the two coefficients shows that the promoting effect of population agglomeration in urban agglomerations on GTFP in core cities is approximately 3.87 times that in peripheral cities. The results indicate that population agglomeration in urban agglomerations exerts a more pronounced positive effect on GTFP in core cities compared to peripheral cities.

A plausible explanation for this disparity lies in the scale economies inherent to core cities. Their larger population bases enable more efficient resource allocation, knowledge

spillovers, and pollution mitigation infrastructure—factors that amplify the productivity-enhancing effects of agglomeration. Peripheral cities, however, may lack the institutional capacity, technological readiness, or infrastructure to fully capitalize on population agglomeration, resulting in diminished GTFP gains. This aligns with theories of agglomeration externalities, where core cities disproportionately benefit from cumulative advantages in innovation and environmental governance.

5.5.2 Regional heterogeneity

To further investigate the regional heterogeneity in the impact of population agglomeration in urban agglomerations on GTFP, this study builds on the research by Yin and Yuan (2019). We adopt the Hu Huanyong Line (commonly referred to as the Hu Line), a significant demographic boundary in China, to divide the sample into two distinct groups: one comprising regions along and to the northwest of the line, and the other encompassing regions to the southeast.

The regression results, presented in columns (3) and (4) of Table 9, reveal notable differences between these groups. In the southeast regions, population agglomeration in urban agglomerations exerts a positive and statistically significant effect on GTFP. In contrast, in the regions along and to the northwest of the Hu Line (Northwest Region), the effect of population agglomeration in urban agglomerations on GTFP is not statistically significant. Moreover, the difference in the coefficients of population agglomeration in urban agglomerations between these two groups is statistically significant at the 5% level. These findings suggest that population agglomeration in urban agglomerations significantly enhances GTFP only in the southeastern regions.

A likely explanation for this regional disparity is that, unlike cities in the northwest, those in the southeast constitute the core areas of China's urban agglomerations and urbanization (Chen et al., 2016, 2019). They exhibit a more optimized industrial structure, a high degree of economic extroversion, and more sophisticated transportation, communication, and public service facilities. These conditions can better facilitate the efficient

TABLE 9 Results of heterogeneity analysis.

Variable	(1) Core cities	(2) Peripheral cities	(3) Southeast region	(4) Northwest region	(5) Stronger environmental regulation	(6) Weaker environmental regulation	(7) Resource-based cities	(8) Non-resource-based cities
<i>clust</i>	2.498* (1.274)	0.646** (0.323)	0.941** (0.442)	−0.188 (0.835)	1.547** (0.612)	0.535 (0.473)	0.974* (0.553)	0.550 (0.487)
Control	✓	✓	✓	✓	✓	✓	✓	✓
Observations	420	2964	2676	708	1524	1860	1368	1992
<i>R</i> ²	0.612	0.492	0.497	0.533	0.514	0.491	0.463	0.524
<i>p</i> -value for inter-group coefficient difference	0.000***		0.017**		0.000***		0.013**	

The *p*-value for the inter-group coefficient differences is obtained through a bootstrap-based Fisher combination test, computed with 1,000 resampling iterations. ***, **, * Represent significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

operation of economic activities, fully leverage the population agglomeration effect of urban agglomerations, and thereby provide strong support for the improvement of GTFP.

5.5.3 Environmental regulation heterogeneity

For cities with different intensities of environmental regulation, the impact of population agglomeration in urban agglomerations on GTFP also varies. Drawing on the method proposed by Shao et al. (2024), this study gauges environmental regulation intensity by the ratio of words in sentences containing environmental protection keywords to the total word count of government work reports. Based on the annual average of urban environmental regulation intensity, the sample is split into a stronger environmental regulation group (above the overall sample average) and a weaker environmental regulation group (below the overall sample average), with separate regressions conducted thereafter.

Regression results in Columns (5) and (6) of Table 9 reveal that within the stronger environmental regulation subsample, population agglomeration in urban agglomerations positively affects GTFP. Conversely, within the weaker environmental regulation subsample, such agglomeration exerts no significant impact on GTFP. Moreover, the difference in the coefficients of this agglomeration between the two groups is statistically significant at the 1% level. This implies that this agglomeration exerts a significantly positive effect on GTFP only within the stronger environmental regulation subsample. A plausible explanation for this result is that a higher intensity of environmental regulation entails stricter environmental supervision by the government and greater pressure on enterprises regarding environmental costs, which motivates enterprises to engage more actively in green activities. Consequently, only under stronger environmental regulation, the population agglomeration effect in urban agglomerations is guided onto the path of green development, thereby effectively promoting the improvement of GTFP.

5.5.4 Resource endowment heterogeneity

According to the “National Sustainable Development Plan for Resource-Based Cities (2013–2020)” issued by the State Council of the People’s Republic of China, the sample is split into resource-based cities and non-resource-based cities for subgroup regression analysis. Regression results in Columns (7) and (8) of Table 9 show that within the resource-based city subsample, population agglomeration in urban agglomerations exerts a positive impact on GTFP. In contrast, within the non-resource-based city subsample, such agglomeration has no significant impact on GTFP. Furthermore, the difference in the coefficients of this agglomeration between the two groups is statistically significant at the 5% level. This indicates that population agglomeration in urban agglomerations only exerts a significantly positive effect on urban GTFP within the resource-based city subsample. A plausible explanation for this result is that, compared with non-resource-based cities, resource-based cities typically feature a homogeneous industrial structure, low efficiency in land and energy utilization,

and high carbon emissions. Such cities, therefore, urgently need to undergo green and intelligent transformation. Within urban agglomerations, population agglomeration can attract high-caliber talent, including technical and innovative professionals, into resource-based cities. Consequently, population agglomeration in urban agglomerations plays a crucial role in enhancing the GTFP of resource-based cities.

6 Discussion

6.1 Conclusions and policy implications

Against the backdrop of continuous population agglomeration in urban agglomerations, enhancing GTFP is of paramount importance for achieving sustainable development. This paper investigates the impact and mechanisms of population agglomeration in urban agglomerations on GTFP, using panel data from 282 cities in China spanning the period 2011–2022. The findings reveal that population agglomeration in urban agglomerations positively affects GTFP. This conclusion remains robust after various robustness checks, including addressing endogeneity, excluding partial samples, and replacing the explained variable. Mechanism analysis indicates that population agglomeration in urban agglomerations enhances knowledge spillover effects, increases market potential, and promotes the upgrading of the human capital structure, thereby improving GTFP. Threshold effect analysis demonstrates that population agglomeration in urban agglomerations can significantly boost GTFP once it reaches a certain scale. Heterogeneity analysis suggests that the positive impact of population agglomeration in urban agglomerations on GTFP varies across different cities. Specifically, such agglomeration improves GTFP more effectively in central cities than in peripheral cities; this effect is significant in the southeast region, in cities with stronger environmental regulation, and resource-based cities, but is insignificant in the northwest region, in cities with weaker environmental regulation, and non-resource-based cities.

Based on these findings, it is crucial to adopt an urban-agglomeration perspective to fully leverage the potential of population agglomeration in enhancing GTFP. The specific policy implications are as follows: Policymakers should focus on the entire urban agglomeration to actively promote and optimize population agglomeration. This will facilitate the scale effects generated by population agglomeration and foster the formation of a unified functional network within the urban agglomeration, thereby effectively improving GTFP. Beyond general encouragement for population concentration, policies should specifically focus on fostering multi-centric urban development within agglomerations, strategically directing population and industries toward new growth poles and peripheral cities to alleviate pressure on central cities while activating regional potential. This requires integrated spatial planning that considers the entire urban agglomeration as a functional unit, rather than a collection of isolated cities.

To achieve this, on the one hand, urban agglomerations should be treated as integrated entities, extending the scale of population agglomeration from the city level to the entire urban agglomeration

level, and actively promoting and optimizing this process to improve GTFP. First, when implementing urban agglomeration strategies, governments should rationally regulate the radiation scope of population agglomeration in urban agglomerations. For instance, they can define a 200-km functional radius for core cities and formulate graded population absorption plans according to urban carrying capacity. Therefore, this can preclude administratively driven unordered expansion and provide a relatively balanced and efficient green development space for cities in urban agglomeration. Second, governments ought to facilitate the in-depth integration of the population agglomeration effect and GTFP spatial spillover effect within urban agglomeration (e.g., establishing cross-city technology transfer mechanisms, jointly building green industrial parks), thereby fostering green high-quality development across the entire urban agglomeration.

On the other hand, the pathways through which population agglomeration in urban agglomerations improves GTFP should be continuously optimized. Our research shows that population agglomeration in urban agglomerations improves GTFP by strengthening knowledge spillovers, boosting market potential, and upgrading the human capital structure. Therefore, governments should enhance knowledge spillovers by establishing urban agglomeration innovation network platforms and facilitating the free flow of talent; boost market potential by optimizing the business environment and promoting market integration within the urban agglomeration; and promote the upgrading of the human capital structure by increasing investment in education and training and actively attracting high-end talent. Specifically, to enhance knowledge spillovers, policies should move beyond simply increasing R&D investment. Instead, they should focus on establishing cross-city innovation platforms and “green technology corridors” that explicitly connect research institutions, universities, and high-tech firms across different specialized cities within the agglomeration. This could involve joint funding for inter-city research projects, shared intellectual property rights frameworks, and specialized talent mobility programs designed to facilitate the flow of green innovation knowledge and high-skill labor between complementary urban centers. For market potential, policies should aim at institutionalizing truly integrated regional markets by dismantling administrative barriers and harmonizing market regulations across cities within the agglomeration. This includes streamlining inter-city business registration, standardizing environmental protection compliance, and developing unified logistics and distribution networks that minimize internal trade costs. Such measures will enable firms to fully exploit the vast, interconnected consumer and industrial demand of the entire agglomeration, incentivizing investments in green production methods and eco-friendly products. To promote the upgrading of human capital structure, strategies should emphasize developing inter-city talent sharing schemes and vocational training programs that cater to the diverse needs of green industries across the agglomeration. This could involve establishing regional human resource development centers, offering cross-city internships in green sectors, and providing incentives for environmental specialists and green tech professionals to work across different cities, fostering a highly

skilled and mobile workforce adapted to the evolving demands of a green economy.

Furthermore, our findings on the threshold effect underscore the importance of fostering a “unified functional network” once population agglomeration reaches a critical scale. Institutionalizing inter-city coordination is paramount for achieving this network state. This can be realized through the establishment of permanent joint planning commissions for urban agglomerations with delegated decision-making authority on regional infrastructure, environmental management, and industrial layout. Additionally, creating shared fiscal mechanisms for cross-city public goods (e.g., regional parks, joint waste treatment facilities) and developing harmonized environmental monitoring and enforcement protocols are crucial. Such institutional arrangements move beyond *ad-hoc* cooperation, embedding a systemic approach to regional governance that facilitates seamless factor flows and coordinated development, thereby maximizing the GTFP benefits of mature urban agglomerations.

Finally, our heterogeneity analysis reveals distinct challenges and opportunities for different types of cities within urban agglomerations and across regions. For peripheral cities, policies should focus on strengthening their functional linkages with central cities, for instance, by investing in rapid inter-city public transport to enhance commuter flows and facilitate access to central city knowledge and markets. Targeted support for green industrial transfers from central cities, coupled with capacity building for environmental governance in peripheral areas, can ensure more balanced green growth. For urban agglomerations in Northwest regions, where the positive impact of agglomeration on GTFP is less pronounced, policies must prioritize investment in foundational green infrastructure, ecological restoration projects, and the attraction of green industries through specific incentive packages. Meanwhile, for cities with weaker environmental regulation intensity, governments should further strengthen local environmental regulation and establish an effective deterrent effect of environmental supervision. This will urge enterprises to proactively comply with environmental regulations and engage in green production. Additionally, for non-resource-based cities, they can leverage their advantages in industrial flexibility to establish regional green standard certification systems. By setting environmental protection standards higher than the industry average, these cities can compel local enterprises to actively improve green technology in the process of population agglomeration in urban agglomerations. These differentiated strategies are essential to ensure that green development is inclusive and benefits all cities within the agglomeration, reducing regional disparities in environmental performance.

6.2 Limitations and future research

Despite achieving its research objectives, this study inevitably has certain limitations. Firstly, the theoretical analysis presented is not grounded in a unified mathematical model framework, and the empirical analysis does not utilize micro-level data. Future research could address this by developing a unified mathematical model to systematically analyze the impact and mechanisms of population

agglomeration in urban agglomerations on GTFP, followed by corresponding empirical tests using micro-level data. Secondly, this study does not decompose the GTFP index. This limitation opens an avenue for future research to decompose the GTFP index into technological progress and technological efficiency indices, thereby enabling a more in-depth and detailed exploration of the GTFP research topic. Finally, CO₂ emissions were not included in the selection of non-desired output indicators. While this maintains comparability with traditional studies, as China's carbon accounting system improves and the "dual-carbon" goals advance, future research should incorporate CO₂ emissions into the GTFP measurement framework to evaluate green total factor productivity more comprehensively.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SZ: Writing – original draft. JD: Writing – original draft. CJ: Writing – original draft. QS: Writing – original draft. WC: Writing – original draft.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was

supported by the National Social Science Foundation of China "Research on the Mechanism and Policy of Spatial Agglomeration in Urban Agglomerations Promoting Economic Growth (Grant Number: 22BJL070)".

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

- Abbasi, K. R., Hussain, K., Radulescu, M., and Ozturk, I. (2021). Does natural resources depletion and economic growth achieve the carbon neutrality target of the UK? A way forward towards sustainable development. *Resour. Policy* 74:102341. doi: 10.1016/j.resourpol.2021.102341
- Akinyemi, O., Efobi, U., Osabuohien, E., and Alege, P. (2019). Regional integration and energy sustainability in Africa: exploring the challenges and prospects for ECOWAS. *Afr. Dev. Rev.* 31, 517–528. doi: 10.1111/1467-8268.12406
- Black, D., and Henderson, V. (1999). A theory of urban growth. *J. Polit. Econ.* 107, 252–284. doi: 10.1086/250060
- Brezzi, M., and Veneri, P. (2015). Assessing polycentric urban systems in the OECD: country, regional and metropolitan perspectives. *Eur. Plan. Stud.* 23, 1128–1145. doi: 10.1080/09654313.2014.905005
- Brinkman, J. C. (2016). Congestion, agglomeration, and the structure of cities. *J. Urban Econ.* 94, 13–31. doi: 10.1016/j.jue.2016.05.002
- Broersma, L., and Oosterhaven, J. (2009). Regional labor productivity in the Netherlands: evidence of agglomeration and congestion effects. *J. Regional Sci.* 49, 483–511. doi: 10.1111/j.1467-9787.2008.00601.x
- Burger, M. J., and Meijers, E. J. (2016). Agglomerations and the rise of urban network externalities. *Pap. Reg. Sci.* 95, 5–16. doi: 10.1111/pirs.12223
- Burger, M. J., Meijers, E. J., Hoogerbrugge, M. M., and Tresserra, J. M. (2015). Borrowed size, agglomeration shadows and cultural amenities in North-West Europe. *Eur. Plan. Stud.* 23, 1090–1109. doi: 10.1080/09654313.2014.905002
- Cai, Q., Wang, S., Liu, H., and Shu, S. (2023). Does the population agglomeration of urban agglomerations promote local firm's innovation. *China Ind. Econ.* 41, 152–170. doi: 10.19581/j.cnki.ciejournal.2023.03.006
- Cai, X., Xiang, H., Neskoroedieva, I., and Durmanov, A. (2024). Interrelation between human capital management and ESG engagement: evidence from SandP 500 firms. *Hum. Soc. Sci. Commun.* 11:1654. doi: 10.1057/s41599-024-04189-6
- Chen, A., Chen, F., and Cheng, Y. (2021). Industry chain linkage and firm's innovation. *China Ind. Econ.* 39, 80–98. doi: 10.19581/j.cnki.ciejournal.2021.09.004
- Chen, D., Zhang, Y., Yao, Y., Hong, Y., Guan, Q., and Tu, W. (2019). Exploring the spatial differentiation of urbanization on two sides of the hu huanyong line—based on nighttime light data and cellular automata. *Appl. Geogr.* 112:102081. doi: 10.1016/j.apgeog.2019.102081
- Chen, L., Shen, Q., Yu, X., and Chen, X. (2024). Knowledge spillovers along the sustainable supply chain of China's listed companies: the role of long-term orientation. *J. Innov. Knowl.* 9:100478. doi: 10.1016/j.jik.2024.100478
- Chen, M., Gong, Y., Li, Y., Lu, D., and Zhang, H. (2016). Population distribution and urbanization on both sides of the hu huanyong line: answering the premier's question. *J. Geogr. Sci.* 26, 1593–1610. doi: 10.1007/s11442-016-1346-4
- Comin, D., Lashkari, D., and Mestieri, M. (2021). Structural change with long-run income and price effects. *Econometrica* 89, 311–374. doi: 10.3982/ECTA16317
- Dai, K., Yang, X., and Chen, A. (2024). How functional industrial policy promote the green innovation? Empirical evidence from manufacturing development strategy. *Mod. Econ. Sci.* 46, 116–131. doi: 10.20069/j.cnki.DJKX.202406009
- Derudder, B., Meijers, E., Harrison, J., Hoyle, M., and Liu, X. (2022). Polycentric urban regions: conceptualization, identification and implications. *Reg. Stud.* 56, 1–6. doi: 10.1080/00343404.2021.1982134
- Dong, F., Hu, M., Gao, Y., Liu, Y., Zhu, J., and Pan, Y. (2022). How does digital economy affect carbon emissions? Evidence from global 60 countries. *Sci. Total Environ.* 852:158401. doi: 10.1016/j.scitotenv.2022.158401

- Duranton, G., and Puga, D. (2020). The economics of urban density. *J. Econ. Perspect.* 34, 3–26. doi: 10.1257/jep.34.3.3
- Fan, Z., and Zhao, R. (2019). Does rule of law promote pollution control? Evidence from the establishment of the environmental court. *Econ. Res. J.* 65, 21–37.
- Fang, C., and Yu, D. (2017). Urban agglomeration: an evolving concept of an emerging phenomenon. *Landsc. Urban Plann.* 162, 126–136. doi: 10.1016/j.landurbplan.2017.02.014
- Fujita, M., and Thisse, J. F. (2003). Does geographical agglomeration foster economic growth? And who gains and loses from it? *Jan. Econ. Rev.* 54, 121–145. doi: 10.1111/1468-5876.00250
- Ghisetti, C., and Quatraro, F. (2017). Green technologies and environmental productivity: a cross-sectoral analysis of direct and indirect effects in Italian regions. *Ecol. Econ.* 132, 1–13. doi: 10.1016/j.ecolecon.2016.10.003
- Guo, X., Deng, M., Wang, X., and Yang, X. (2024). Population agglomeration in Chinese cities: is it benefit or damage for the quality of economic development? *Environ. Sci. Pollut. Res.* 31, 10106–10118. doi: 10.1007/s11356-023-25220-4
- Han, F., and Ke, S. (2012). Tracking the spatial sources of manufacturing agglomeration in China: an integrated perspective based on marshallian externalities and new economic geography. *Manag. World* 28, 55–70. doi: 10.19744/j.cnki.11-1235/f.2012.10.006
- Hansen, B. E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference. *J. Econom.* 93, 345–368. doi: 10.1016/S0304-4076(99)00025-1
- Li, P., and Zhang, X. (2021). Agglomeration externalities of city cluster: analysis from labor wage premium. *Manag. World* 37, 121–136. doi: 10.19744/j.cnki.11-1235/f.2021.0175
- Li, S., Shao, Y., Hong, M., Zhu, C., Dong, B., Li, Y., et al. (2023). Impact mechanisms of urbanization processes on supply-demand matches of cultivated land multifunction in rapid urbanization areas. *Habitat Int.* 131:102726. doi: 10.1016/j.habitatint.2022.102726
- Li, T., Qi, Y., Chen, M., Hui, B., and Su, Y. (2023). Sub-central city's green innovation in regional integration: can it be a bridgehead even if it is far away? *Ecol. Indic.* 154:110618. doi: 10.1016/j.ecolind.2023.110618
- Lin, B., and Ma, R. (2022). Green technology innovations, urban innovation environment and CO₂ emission reduction in China: fresh evidence from a partially linear functional-coefficient panel model. *Technol. Forecast. Soc.* 176:121434. doi: 10.1016/j.techfore.2021.121434
- Liu, S., Li, Y., Shen, Z., Yu, J., and Xu, Z. (2024). The impact of population agglomeration on economic resilience: evidence from 280 cities in China. *Int. Rev. Econ. Financ.* 94:103429. doi: 10.1016/j.jref.2024.103429
- Liu, Y., and Lyu, M. (2025). Regional vitality and population growth: the reality of the Yangtze River economic belt. *Financ. Res. Lett.* 74:106788. doi: 10.1016/j.frl.2025.106788
- Liu, Z., Li, H., Hu, Y., and Li, C. (2018). Human capital structure upgrading and economic growth: a reconsideration of disparities among China's Eastern, Central and Western regions. *Econ. Res. J.* 64, 50–63.
- Mu, X., Fang, C., Yang, Z., and Guo, X. (2022). Impact of the COVID-19 epidemic on population mobility networks in the Beijing-Tianjin-Hebei urban agglomeration from a resilience perspective. *Land* 11:675. doi: 10.3390/land11050675
- Ren, Y., Tian, Y., and Xiao, X. (2022). Spatial effects of transportation infrastructure on the development of urban agglomeration integration: evidence from the Yangtze River economic belt. *J. Transp. Geogr.* 104:103431. doi: 10.1016/j.jtrangeo.2022.103431
- Roca, J. D. L., and Puga, D. (2017). Learning by working in big cities. *Rev. Econ. Stud.* 84, 106–142. doi: 10.1093/restud/rdw031
- Rozenblat, C. (2020). *Extending the Concept of City for the Delineation of Large Urban Regions (LUR) for the Cities of the World [Preprint]*. Available at: doi: 10.20944/preprints202003.0213.v1
- Shao, S., Ge, L., and Zhu, J. (2024). How to achieve the harmony between humanity and nature: environmental regulation and environmental welfare performance from the perspective of geographical factors. *Manag. World* 40, 119–146. doi: 10.19744/j.cnki.11-1235/f.2024.0088
- Sun, H., Edziah, B. K., Kporsu, A. K., Sarkodie, S. A., and Taghizadeh-Hesary, F. (2021). Energy efficiency: the role of technological innovation and knowledge spillover. *Technol. Forecast. Soc.* 167:120659. doi: 10.1016/j.techfore.2021.120659
- Tang, J., and Cui, W. (2023). Does urban agglomeration affect innovation convergence: evidence from China. *Econ. Innov. New Tech.* 32, 563–578. doi: 10.1080/10438599.2021.1973896
- Tian, Y., and Pang, J. (2022). The role of internet development on green total-factor productivity—An empirical analysis based on 109 cities in yangtze river economic belt. *J. Clean. Prod.* 378, 134415. doi: 10.1016/j.jclepro.2022.134415
- Volgmann, K., and Münter, A. (2022). Understanding metropolitan growth in German polycentric urban regions. *Reg. Stud.* 56, 99–112. doi: 10.1080/00343404.2020.1807491
- Wang, C., Liu, Y., Liu, X., and Xia, H. (2024). How does the digital economy impact green manufacturing: a new perspective from the construction of a unified large market in China. *Hum. Soc. Sci. Commun.* 11:1705. doi: 10.1057/s41599-024-04258-w
- Wang, J., and Guo, D. (2023). Siphon and radiation effects of ICT agglomeration on green total factor productivity: evidence from a spatial Durbin model. *Energy Econ.* 126:106953. doi: 10.1016/j.eneco.2023.106953
- Wang, K.-L., Pang, S.-Q., Zhang, F.-Q., Miao, Z., and Sun, H.-P. (2022). The impact assessment of smart city policy on urban green total-factor productivity: evidence from China. *Environ. Impact. Assess.* 94:106756. doi: 10.1016/j.eiar.2022.106756
- Wang, K. H., Umar, M., Akram, R., and Caglar, E. (2021). Is technological innovation making world “Greener”? An evidence from changing growth story of China. *Technol. Forecast. Soc.* 165:120516. doi: 10.1016/j.techfore.2020.120516
- Wang, S., Chen, G., and Han, X. (2021). An analysis of the impact of the emissions trading system on the green total factor productivity based on the spatial difference-in-differences approach: the case of China. *Int. J. Env. Res. Pub. He.* 18:9040. doi: 10.3390/ijerph18179040
- Wang, Y., and Liu, X. (2024). Impact of knowledge spillover on regional innovation: an analysis based on innovation policies. *Sci. Res. Manag.* 45, 68–78.
- Wu, D., Lie, Y., Liu, L., Cheng, Z., Zhang, Y., Yang, Y., et al. (2023). City-level environmental performance and the spatial structure of China's three coastal city clusters. *J. Clean. Prod.* 422:138591. doi: 10.1016/j.jclepro.2023.138591
- Yan, Y., and Huang, J. (2022). The role of population agglomeration played in China's carbon intensity: a city-level analysis. *Energy Econ.* 114:106276. doi: 10.1016/j.eneco.2022.106276
- Yin, D., and Yuan, S. (2019). A study on 70 Years' change of china's population distribution: a spatial quantitative analysis based on hu's line. *Chin. J. Popul. Sci.* 33, 15–28.
- Yu, X., and Xu, Y. (2022). Impact of population agglomeration on urban entrepreneurship activities: effects and paths considering an agglomeration dynamic. *China Popul. Resour. Environ.* 32, 151–163.
- Zeng, S., Gu, Y., Su, B., and Li, T. (2025). Energy consumption transition and green total factor productivity in Chinese prefecture-level cities. *Energy Econ.* 142:108156. doi: 10.1016/j.eneco.2024.108156
- Zhang, J., Wu, G., and Zhang, J. (2004). The estimation of China's provincial capital stock: 1952–2000. *Econ. Res. J.* 50, 35–44.
- Zhang, S., Miao, X., Zheng, H., Chen, W., and Wang, H. (2024). Spatial functional division in urban agglomerations and carbon emission intensity: new evidence from 19 urban agglomerations in China. *Energy* 300:131541. doi: 10.1016/j.energy.2024.131541
- Zhao, T., Zhang, Z., and Liang, S. (2020). Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China. *Manag. World* 36, 65–76. doi: 10.19744/j.cnki.11-1235/f.2020.0154
- Zheng, H., Hsiao, C. Y.-L., Ho, H.-W., Ji, C., and Zhang, S. (2024). How the spatial functional division of labor in urban clusters affects urban population size? Evidence from 19 urban clusters in China. *Hum. Soc. Sci. Commun.* 11:1704. doi: 10.1057/s41599-024-04183-y
- Zheng, H., Wu, S., Zhang, Y., and He, Y. (2023). Environmental regulation effect on green total factor productivity in the Yangtze River Economic Belt. *J. Environ. Manag.* 325:116465. doi: 10.1016/j.jenvman.2022.116465
- Zheng, S., and Du, R. (2020). How does urban agglomeration integration promote entrepreneurship in China? Evidence from regional human capital spillovers and market integration. *Cities* 97:102529. doi: 10.1016/j.cities.2019.102529