

The Spatial Effects of Location Quotients on China's Manufacturing Economic, Technological and Environmental Performance: An Empirical Study Based on the Spatial Durbin Model

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This study employs the Location Quotient (LQ) to quantify the extent of manufacturing agglomeration within the Chinese manufacturing sector. Building on this metric, an analytical framework encompassing three key dimensions — economic, technological, and environmental — is established to systematically examine the LQ's direct and spatial spillover effects on manufacturing performance. Utilizing panel data from 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Xizang) spanning 2008 to 2022, an empirical analysis is conducted using the Spatial Durbin Model (SDM). The findings reveal several key insights: Regarding economic performance, the LQ exerts a significant positive impact on both local and neighboring regions, with a total effect of approximately 9.77. However, for technological performance, the LQ's direct effect is negative, resulting in a total effect of -2.78 , suggesting that excessive agglomeration may inhibit technological diffusion. Conversely, concerning environmental performance, the LQ exhibits a significant positive influence locally, yet its spatial spillover effect proves insignificant. Further analysis clarifies that while economic

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factors play a promotional role in both direct and spillover effects, technological factors contribute more prominently to the spillover effects, and environmental factors display stage-specific differences in their spatial effects. This study ultimately elucidates the multi-dimensional spatial mechanisms through which the LQ influences manufacturing performance, offering important policy implications for optimizing the spatial layout of manufacturing industries, promoting regional coordinated development, and facilitating green transformation.

Keywords: Location quotient; manufacturing performance; Spatial Durbin Model; economic, technological, and environmental factors; spatial spillover effect.

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1. Introduction

Manufacturing not only serves as the core pillar of the Chinese economy but also constitutes a critical driving force for achieving high-quality development (Wang *et al.*, 2023a). Over the past two decades, China's manufacturing sector has established highly concentrated core agglomerations across the coastal regions (Jin *et al.*, 2025). Driven by the national strategy for regional coordinated development and associated industrial transfer policies, the manufacturing share in China's central and western regions has consistently increased (Zhu and Yang, 2025).

The Location Quotient (LQ) serves as a critical metric for quantifying the degree of manufacturing agglomeration and provides a clear reflection of regional manufacturing specialization. According to Zhang *et al.* (2022a), while an appropriate level of manufacturing agglomeration fosters economies of scale, knowledge spillovers, and cost savings, the marginal benefits may diminish — and potentially even yield adverse effects — as the agglomeration process advances through different stages. Furthermore, the effects of agglomeration are not confined to the local areas; their externalities can show up in surrounding regions through various spatial linkages (Wang *et al.*, 2023b). However, existing research on the spatial spillover effects related to manufacturing performance is relatively limited, particularly empirical studies that integrate multiple factors — such as economic, technological, and environmental elements — into a unified analytical framework (Xia *et al.*, 2025).

To overcome the limitations of existing studies regarding assessment of multiple factors, performance assessment and spatial effect identification, this paper develops an integrated analytical framework that encompasses economic, technological, and environmental dimensions. Utilizing balanced panel data from 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Xizang) spanning the period 2008–2022, this paper employs the Spatial Durbin Model (SDM) to systematically examine both the local and spatial spillover effects of the LQ on

manufacturing performance. Furthermore, the underlying mechanisms are explored from the economic, technological, and environmental perspectives. This multi-dimensional approach yields crucial theoretical insights and empirical evidence necessary for disentangling the complex transmission pathways of manufacturing agglomeration externalities, optimizing regional industrial layout, and promoting the high-quality development of the manufacturing sector.

The empirical analysis yields several key findings. Specifically, the LQ demonstrates a significantly positive influence on both the economic performance of the local region and neighboring ones. Conversely, the overall effect of the LQ on technological performance is found to be negative, suggesting that excessive agglomeration may impede technology diffusion and cross-regional innovation. Regarding environmental performance, the LQ exhibits a significant promotional effect locally but is statistically insignificant when considering neighboring regions. Furthermore, economic factors consistently exert a promotional influence on both local and spillover performance; technological factors play a more prominent and distinct role in driving spillover effects; and environmental factors display stage-specific heterogeneity in their spatial impacts.

2. Literature Review

Existing literature has thoroughly examined the measurement of manufacturing agglomeration, primarily using the LQ, and its implications for economic, technological, and environmental performance, thereby establishing a robust theoretical and empirical foundation. Early research predominantly emphasized the economic dividends of agglomeration, highlighting its role in enhancing regional competitiveness through economies of scale and knowledge spillovers. Subsequent studies acknowledged that excessive agglomeration can trigger adverse effects, notably rising factor costs and increased environmental pressures. In recent years, advanced spatial econometric techniques — particularly the SDM — have been widely adopted to disentangle the direct and spatial spillover effects of manufacturing concentration, expanding the analysis to technological innovation and environmental outcomes. Nevertheless, a significant research gap persists: the majority of current work remains focused on a single dimension. There is a critical lack of efforts to synthesize economic, technological, and environmental performance within a unified spatial analytical framework, and insufficient exploration of the complex mechanisms driving negative spillovers and spatially insignificant effects.

2.1. Research on LQ and manufacturing agglomeration

The LQ is an important indicator for measuring the degree of regional manufacturing specialization. It was first used by American economic geographers to analyze regional manufacturing distribution characteristics (Isard, 1960). Due to its computational simplicity and intuitive reflection of industrial specialization

levels, this indicator is extensively applied in research concerning the spatial patterns and economic effects of manufacturing (Chen *et al.*, 2024). Its basic calculation formula is as follows:

$$LQ_i = \frac{\frac{E_i^r}{E^r}}{\frac{E_i^n}{E^n}}, \quad (2.1)$$

where E_i^r denotes employment (or output) in industry i in region r , and E^r denotes total employment (or output) across all industries in region r ; E_i^n denotes national employment (or output) in industry i , and E^n denotes total national employment (or output) across all industries. When $LQ_i > 1$, it indicates that the specialization level of industry i in that region is higher than the national average, indicating the presence of agglomeration advantages.

Song *et al.* (2021) utilized the LQ in conjunction with spatial autocorrelation analysis to delineate the coastal agglomeration and inland diffusion patterns characterizing the communications equipment manufacturing industry. Li *et al.* (2023) employed the LQ as a core indicator to determine industrial dominance and agglomeration levels when analyzing the spatial patterns of the national and automotive manufacturing industries. Su *et al.* (2023) conducted a spatiotemporal evolution analysis based on provincial LQ values and identified that resource endowment and policy orientation are the key determinants driving interprovincial disparities.

By using an SDM, Zhang *et al.* (2022b) established an inverted U-shaped relationship between manufacturing agglomeration and resident consumption, alongside the existence of a significant spatial spillover effect. Liu *et al.* (2021) utilized a combination of the LQ, the spatial Gini coefficient, and the primacy measure to investigate the functional structure of the central Yunnan Urban Agglomeration. Their findings revealed disparities in economic development levels among the cities, notably the primacy yet underdevelopment of Kunming. This confirms that the LQ effectively captures regional industrial concentration and functional differentiation.

The crucial role of the LQ in understanding the spatial spillover effects of manufacturing agglomeration on regional economic growth is well-illustrated by Song *et al.* (2023), who analyzed 49 cities in the Yellow River Basin. Their findings demonstrate that higher degrees of manufacturing agglomeration, as quantified by the LQ, exert positive spillover effects on economic performance, thereby underscoring the importance of industrial concentration for broad regional development. Su and Ji (2023) utilized an enhanced version of the LQ to quantify the degree of agglomeration within the tourism manufacturing agglomeration in Liaoning Province. Their methodology underscored the adaptability of the LQ in assessing specific manufacturing agglomeration phenomena and their developmental trajectories within a regional context.

2.2. The relationship between manufacturing agglomeration and manufacturing performance

Guo and Sun (2023) highlighted that manufacturing agglomeration significantly promotes high-quality development by enhancing technological innovation and regional economic growth. However, they cautioned that in the absence of stringent environmental regulations, this concentration may also result in increased pollution and resource pressure. Shu (2023) demonstrated that high-tech manufacturing industries achieve superior productivity and sales growth within an agglomeration context, with foreign-invested enterprises realizing the largest gains. Zhang *et al.* (2022a) identified an inverted U-shaped relationship between agglomeration and resident consumption, suggesting that a moderate level of concentration constitutes the optimal state.

He *et al.* (2022) demonstrated that moderate manufacturing agglomeration can significantly enhance a city's Green Total Factor Productivity (GTFP), a phenomenon primarily attributable to local technological progress and efficiency improvements. Zheng *et al.* (2024) indicated that significant spatial heterogeneity exists in the agglomeration effects across cities within the Yangtze River Economic Belt, a phenomenon closely associated with infrastructure development levels, industrial structure, and the policy environment.

Zhong *et al.* (2023) established, from the perspective of capital factors, that agglomeration can lead to the simultaneous industrial structure upgrading of both local and neighboring cities. However, research on the effects of manufacturing agglomeration on performance currently lacks a unified multi-dimensional performance framework, particularly with regard to the comprehensive analysis of economic, technological, and environmental performance, for which empirical evidence remains limited.

2.3. The application of spatial measurement methods in agglomeration studies

Recent studies typically employ Moran's I to first establish the spatial correlation between agglomeration and performance. Subsequently, they utilize spatial panel models such as the Spatial Autoregressive (SAR) model, the Spatial Error Model (SEM), or the SDM to analyze the direct and spillover effects.

For instance, Wang and Long (2024) introduced a dynamic SDM in their study on food manufacturing agglomeration and GTFP, revealing significant positive local and regional effects. Utilizing spatial panel data, Zeng *et al.* (2023) examined the role of agglomeration structure in driving economic growth across urban agglomerations. Du *et al.* (2024) combined fixed effects modeling with the SDM in their study of high-tech industries to analyze the spatial spillover of green innovation.

Zhou (2022) employed Moran's I and LISA spatial correlation analysis to reveal the spatiotemporal heterogeneity of inclusive green growth across China. These

methods have effectively identified spatial clustering characteristics, underscoring the vital role of spatial correlation analysis in uncovering regional disparities and development trajectories. The majority of these studies further indicate that moderate agglomeration exerts a positive effect on economic growth, green efficiency, and innovation levels (Yang and Jiang, 2024), in addition to significant spatial spillover effects.

2.4. Research gaps and contributions of this paper

Existing research on manufacturing agglomeration and manufacturing performance has primarily focused on either economic performance (e.g. production efficiency, output growth) or technological performance (e.g. innovation output), without trying to integrate the economic, technological, and environmental dimensions (Wang and Long, 2024). With respect to technological and environmental performance, existing findings have largely remained at the level of effect validation. They notably lack an in-depth exploration of negative spillover mechanisms (such as innovation congestion and mounting environmental pressure) or the underlying reasons for insignificant spatial effects (Li *et al.*, 2024; Zhang *et al.*, 2022b). Liu and Wu (2023) constructed an SDM to investigate the impact of high-tech agglomeration on green innovation efficiency. Their findings indicate that specialized agglomeration exhibits an inverted U-shaped relationship with efficiency, whereas diversified agglomeration acts to promote comprehensive green innovation, both accompanied by a significant positive spatial effect.

While recent studies have utilized spatial models to analyze multi-dimensional outcomes in specific sectors (Liu and Wu, 2023; Du *et al.*, 2024; Wang and Long, 2024), a unified analysis integrating economic, technological, and environmental performance for the entire manufacturing sector remains limited. This study addresses these gaps by systematically revealing the variations in agglomeration effects across these three dimensions, specifically uncovering significant agglomeration diseconomies in technological performance.

The main contributions of this paper are as follows. First, it establishes an integrated three-dimensional analytical framework. Drawing on theories of agglomeration economics and knowledge spillovers, this framework integrates economic, technological, and environmental performance metrics into a unified evaluation system. Second, the study introduces the SDM to decompose the direct and spatial spillover effects, thereby revealing the differentiated roles of local and neighboring regions, and empirically testing for both positive and negative spillovers, as well as regional heterogeneity. Third, it provides robust empirical support for the systematic evaluation of agglomeration effects. Utilizing interprovincial panel data spanning 2008 to 2022 and incorporating multiple robustness tests, the study ensures the reliability of its conclusions across time and space. In summary, this paper advances the field through expansions in research perspective, methodology, and empirical data, offering fresh evidence

for understanding the multi-dimensional performance effects of manufacturing agglomeration and its spatial transmission mechanisms.

3. Theoretical Framework and Research Hypotheses

Our analytical framework integrates location theory, New Economic Geography, and knowledge spillover theory to examine manufacturing agglomeration across three dimensions. By decomposing these pathways into economic, technological, and environmental performance, we systematically evaluate their corresponding spatial effects at both local and regional levels.

Specifically, the relationship between manufacturing agglomeration and performance rests upon a solid theoretical foundation derived from the fields of regional economics, industrial economics, and environmental economics. The location theory (Weber, 1929) emphasized the combined influence of transportation costs, labor costs, and agglomeration economies, elucidating how manufacturing agglomeration enhances production efficiency and strengthens competitive advantages. The new economic geography theory (Krugman, 1991) further posited that agglomeration stimulates regional economic growth through economies of scale, market potential, and specialized division of labor, while potentially generating spatial spillover effects on neighboring regions. Meanwhile, the Environmental Kuznets Curve (EKC) hypothesis suggests that the relationship between economic development and environmental quality may follow an inverted U-shape, whereby the direction and magnitude of agglomeration's impact on environmental performance vary across different stages of development (Grossman and Krueger, 1995). The above basic theories suggest that manufacturing agglomeration may produce effects on the three dimensions of economy, technology, and environment through different pathways. For instance, the significant negative impact on technological performance identified in this study aligns with the concept of "innovation congestion," where excessive density triggers diseconomies that inhibit knowledge exchange (Marshall, 2013; Romer, 1986).

Research findings reveal a significant negative impact on technological performance, strongly supporting the theory of agglomeration diseconomies. This indicates that China's manufacturing agglomerations have surpassed the optimal innovation threshold and entered a phase of "innovation congestion." This negative effect primarily inhibits knowledge diffusion and cross-regional technological performance through the following key mechanisms: (1) Knowledge Lock-in and Property Rights Barriers: In highly competitive agglomeration zones, firms tend to strengthen intellectual property protection to maintain technological advantages. This behavior leads to knowledge lock-in, hindering effective spillover to surrounding areas. Furthermore, when industrial structures are similar, central cities and peripheral cities form competitive geo-economic relationships, and this competitive dynamic impedes the free diffusion of

knowledge (Yang *et al.*, 2025). (2) Talent Siphoning and Innovation Resource Crowding-Out Effect: Excessive concentration drives up demand for innovative talent and R&D resources, causing a sharp rise in human capital costs. Central cities leverage their resource advantages to create a talent siphon effect, causing innovation talent to drain from surrounding areas and weakening their innovation foundations. Simultaneously, resource allocation may become distorted, as local governments and financial capital tend to favor a handful of large enterprises. This creates a crowding-out effect for small and medium-sized innovative enterprises, reducing the overall innovation efficiency of the region (Zhu *et al.*, 2025). (3) Infrastructure and Environmental Congestion Costs: Environmental pollution and urban congestion resulting from manufacturing concentration impose substantial external costs. Environmental and infrastructure congestion issues often prove difficult to resolve through cross-administrative regional cooperation, directly impacting agglomeration zones' ability to attract and retain high-caliber talent from outside. This indirectly inhibits knowledge diffusion driven by talent mobility (Zeng *et al.*, 2025).

Beyond the theoretical basis, a number of empirical studies in recent years have further reinforced the practical effectiveness of this mechanism. Fu (2025) points out that digital transformation can not only improve the performance of local manufacturing, but also drive neighboring regions through spatial spillover effects, and that there are significant differences between different regions. Yin and Su (2024) demonstrated that manufacturing agglomeration reduces pollution by fostering technological innovation, which in turn improves green performance through a significant spatial diffusion pathway.

Drawing upon the comprehensive body of theoretical and empirical research reviewed above, this study proposes and constructs an analytical framework for the "mechanism of the LQ on economic, technological, and environmental performance," which encompasses both local direct effects and spatial spillover effects. These prior studies not only offer solid empirical support for the proposed framework but also significantly enhance the theoretical rigor and practical relevance of the research hypotheses.

Based on the aforementioned theoretical and mechanistic analysis, the following hypotheses are proposed:

- H1a.** LQ has a significant positive impact on local economic performance.
- H1b.** LQ has a significant positive spillover effect on the economic performance of neighboring regions.
- H2a.** LQ has a significantly adverse impact on local technological performance.
- H2b.** LQ has a significantly adverse spillover effect on the technological performance of neighboring regions.
- H3a.** LQ has a significant positive impact on local environmental performance.
- H3b.** The spatial spillover effects of location-based business performance on the environmental performance of neighboring regions are significant. As

regional environmental policy coordination deepens, these spillover effects tend to manifest as positive synergistic effects.

It is important to note that the mechanisms outlined above (H1–H3) are likely to manifest with significant geographical variations due to the vast disparities in China's regional development. In the more industrially mature eastern and central regions, the high density of manufacturing may trigger a “congestion effect,” where intense competition for resources and innovation factors leads to the negative spillovers anticipated in H2. Conversely, the western region, which is in an earlier stage of industrial growth, is expected to be more responsive to positive technology diffusion and factor inflows from other regions. Therefore, this study further expects that the net impact of agglomeration will exhibit a structural divergence: mature hubs are more likely to face innovation diseconomies, while late-developing areas may still derive net benefits from spatial diffusion. This context-dependent perspective ensures that our empirical analysis moves beyond generic observations to provide more targeted policy insights.

4. Research Methods

4.1. Research subjects and data sources

This paper utilizes balanced panel data spanning the period 2008 to 2022 from 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Xizang) as the research sample. The data is primarily sourced from the *China Statistical Yearbook*, the *China Industrial Statistical Yearbook*, as well as various provincial statistical yearbooks and statistical bulletins.

4.2. Model selection and setting

To comprehensively examine the impact of manufacturing agglomeration on the economic, technological, and environmental performance of local and neighboring regions, this paper employs the SDM. Compared to the SAR model and the SEM, the SDM captures not only the direct effects of core explanatory variables on local-dependent variables but also the indirect effects transmitted through spillover to adjacent regions, thereby more comprehensively reflecting the spatial interconnections of regional economic activities (Elhorst, 2014).

The general form of SDM can be expressed as

$$Y_{it} = \rho WY_{it} + X_{it}\beta + WX_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it}, \quad (4.1)$$

Y_{it} represents the performance indicator (economic, technological, or environmental) for region i in year t . X_{it} denotes the LQ and other control variables. W is the spatial weight matrix (in this study, a 0–1 contiguity matrix based on geographical adjacency, row-standardized). ρ is the SAR coefficient, reflecting the spatial dependence of the dependent variable in neighboring regions. θ measures

the spatial spillover effects of the explanatory variables. μ_i and λ_t are the region fixed effects and time fixed effects, respectively. ε_{it} is the random error term.

SDM is widely used in economic geography, regional economics, and environmental economics research to reveal the spatial correlation and spillover mechanisms of phenomena such as manufacturing agglomeration, technology diffusion, and environmental pollution (Fu and Wang, 2024).

4.3. Variable description

To systematically evaluate the multi-dimensional effects of manufacturing agglomeration, we selected a series of key indicators. The specific definitions and measurement methods for all variables are summarized in Table 1. Among these, carbon intensity serves as a proxy for environmental performance, measured by dividing each province's carbon dioxide emissions from manufacturing by its regional gross domestic product. This indicator exhibits a negative correlation with environmental performance: a higher ratio indicates greater carbon emissions per unit of economic output, signifying poorer environmental performance (i.e. more severe pollution).

4.4. Descriptive statistics

To provide an initial overview of the data characteristics and the level of provincial heterogeneity, we present the descriptive statistics for all variables used in the SDM estimation in Table 2. The balanced panel dataset covers 30 Chinese provinces over a 15-year period (2008–2022), yielding 450 observations.

The descriptive statistics confirm significant inter-provincial heterogeneity within the panel dataset, providing initial justification for the application of a fixed-effects spatial model. The core explanatory variable, LQ, exhibits a mean of 0.988, which is close to 1, indicating that, on average, the sampled provinces have manufacturing employment proportional to the national average. However, the substantial standard deviation of 0.562 and the wide range (Min: 0.028, Max: 2.764) confirm that the degree of manufacturing agglomeration and specialization is highly uneven across the provinces. Among the dependent variables, EP shows the highest relative volatility (Std. Dev. = 5.855 versus Mean = 2.912), suggesting substantial disparities in productivity levels. TP has a high mean (8.830) but lower volatility, while ENV has a very low mean of 0.004, consistent with its measure as carbon intensity, reflecting the national decarbonization trend. The wide variation observed in control variables, such as human capital (h) and R&D funding ($fund$), further emphasizes the necessity of controlling for unobserved province-specific fixed effects in the subsequent econometric analysis.

4.5. Spatial weight matrix construction

This study employs the geographic inverse distance matrix (W_{Dis}) as the benchmark spatial weighting matrix, selected based on the core distance decay theory

Table 1. List of variables and descriptions.

Variable type	Economic performance (EP)	Technological performance (TP)	Environmental performance (ENV)
Independent variable	LQ		
Dependent variable	Total manufacturing output/ Manufacturing employment (<i>eco- mance</i>)	The number of effective invention patents (<i>technical</i>)	Ratio of CO ₂ emissions to GDP (<i>envi- ron</i>)
Control variables (1)	Level of human capital (<i>h</i>)	Level of human capital (<i>h</i>)	Level of human capital (<i>h</i>)
Control variables (2)	Per capita GDP (<i>pgdp</i>)	Number of R&D personnel in manufacturing (<i>staff</i>)	Proportion of pollution control invest- ment in total manufacturing output value (<i>regu</i>)
Control variables (3)	Total exports/GDP (<i>insti</i>)	Volume of scientific research funding (<i>fund</i>)	Proportion of urban population to re- gional population (<i>city/level</i>)
Control variables (4)	Foreign enterprise direct investment (<i>fdi</i>)	Financial expenditure on science and technology (<i>gov</i>)	Capital investment per capita (<i>k</i>)

Source: Made by the authors.

Table 2. Summary statistics of variables.

Code	<i>N</i>	Mean	Std. Dev.	Min	Max
EP	450	2.912	5.855	0.079	57.452
TP	450	8.83	1.701	3.401	13.258
ENV	450	0.004	0.005	0	0.035
LQ	450	0.988	0.562	0.028	2.764
<i>h</i>	450	0.806	1.133	0.121	7.325
<i>pgdp</i>	450	10.718	0.551	9.18	12.155
<i>insti</i>	450	7.238	0.967	4.096	9.362
<i>fdi</i>	450	11.273	1.502	7.762	15.551
<i>staff</i>	450	10.559	1.393	6.319	13.557
<i>fund</i>	450	14.204	1.432	9.079	17.287
<i>gov</i>	450	4.199	1.113	1.56	7.065
<i>regu</i>	450	3.791	1.071	0.885	6.527
<i>citylevel</i>	450	0.582	0.130	0.291	0.896
<i>k</i>	450	−0.004	0.604	−3.772	5.166

Notes: The panel data cover 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Xizang) from 2008 to 2022, totaling 450 observations.

Source: Made by the authors.

and foundations of new economic geography. According to the distance decay theory, the influence of knowledge spillovers, technology diffusion, and factor mobility effects in manufacturing naturally diminishes with increasing geographic distance. The geographic inverse distance matrix precisely captures this continuous, nonlinear spatial decay characteristic, avoiding the simplistic treatment of distance by binary adjacency matrices. Simultaneously, within new economic geography, transportation costs and geographic distance are critical determinants of agglomeration effects. W_{Dis} better reflects transport accessibility and economic linkage intensity, thereby aligning more closely with the economic-geographical realities of manufacturing industry connections and market integration.

Matrix element w_{ij}^{Dis} is defined as the reciprocal of the straight-line distance d_{ij} between provincial capitals in provinces i and j :

$$w_{ij}^{Dis} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j, \\ 0, & i = j. \end{cases}$$

The matrix was subsequently row-normalized to ensure that the sum of all weight rows equaled 1, thereby guaranteeing comparability of spillover effects across provinces.

4.5.1. Test matrix: Economic distance matrix

The baseline model in this study employs a geographic inverse distance matrix (W_{Dis}) to capture the continuous effect of knowledge and technology spillovers that

diminish with distance. This approach provides a finer-grained characterization of spillover intensity than the traditional binary adjacency matrix (W_{Adj}). Consequently, W_{Dis} already encompasses the geographic boundary interactions represented by W_{Eco} (i.e. provinces with closer geographic distances receive higher weights). To avoid information redundancy and pursue deeper robustness validation, we therefore opt to introduce an alternative matrix from the economic structure dimension.

Theoretical Basis and Construction Method of the Economic Distance Matrix W_{Eco} : The economic distance matrix captures spillover mechanisms driven by similarities in economic development levels. Regions with comparable economic levels often face similar competitive environments in terms of industrial structure, market scale, and factor endowments, making them more prone to inter-industry competitive spillovers, policy imitation, or factor flows within the same category.

The matrix element w_{ij}^{Eco} is defined as the reciprocal of the average GDP per capita gap between provinces i and j during the sample period:

$$w_{ij}^{Eco} = \begin{cases} 1/|GDP_{pc_i} - GDP_{pc_j}|, & i \neq j, \\ 0, & i = j, \end{cases}$$

Here, GDP_{pc_i} denotes the average annual GDP per capita for province i during the period 2008–2022. The matrix was subsequently row-normalized. By comparing the results of W_{Eco} (economic similarity spillover) with those of W_{Dis} (geographic decay spillover). The robustness of the core conclusions can be comprehensively validated.

4.6. Effect decomposition method

Before estimating spatial econometric models, it is necessary to determine whether the data exhibit spatial correlation. This paper uses the Global Moran's I index to test economic performance, technological performance, and environmental performance. The Moran's I index ranges from: $[-1, 1]$.

When $I > 0$ and statistically significant, it indicates positive spatial autocorrelation, meaning that high-value (or low-value) regions tend to cluster together.

When $I < 0$ and statistically significant, it indicates negative spatial autocorrelation, meaning that high-value and low-value regions are interspersed.

When $I \approx 0$, it suggests that the variable is randomly distributed in space.

After confirming the existence of spatial autocorrelation, the Lagrange Multiplier (LM) test and robust LM test were used to evaluate the model.

5. Empirical Results and Analysis

5.1. Model specification and diagnostics

5.1.1. Spatial autocorrelation test (Moran's I)

To examine the spatial correlation of performance variables, this paper calculated the global Moran's I index for the economic performance, technological

Table 3. Moran's *I* test results.

Year	EP Moran's <i>I</i>	Significance	TP Moran's <i>I</i>	Significance	ENV Moran's <i>I</i>	Significance
2008	−0.0043	0.371	0.0265	0.0789*	−0.0183	0.6274
2009	0.0020	0.280	0.0313	0.0616*	−0.0155	0.5726
2010	0.0012	0.270	0.036	0.0446**	−0.0158	0.5811
2011	0.0080	0.175	0.0364	0.0428**	−0.0008	0.3237
2012	0.0305	0.042**	0.0411	0.0309**	0.0051	0.2462
2013	0.0283	0.052*	0.0363	0.0428**	0.0106	0.1878
2014	0.0265	0.064*	0.0306	0.0626*	0.0164	0.1377
2015	0.0357	0.033**	0.0336	0.0506*	0.0228	0.0944*
2016	0.0351	0.037**	0.0276	0.0747*	0.0257	0.0681*
2017	0.0323	0.047**	0.0193	0.1217	0.0335	0.0428**
2018	0.0359	0.038**	0.0189	0.1265	0.0298	0.0551*
2019	0.0373	0.035**	0.0203	0.117	0.0445	0.0156**
2020	0.0353	0.042**	0.0205	0.1161	0.0554	0.0095**
2021	0.0443	0.022**	0.0267	0.0804*	0.0541	0.0111*
2022	0.0430	0.025**	0.0265	0.0822*	0.0429	0.0256*

Notes: $N = 450$. The balanced panel covers 30 provinces during 2008–2022 (15 years $\times$ 30 units = 450 observations). Significance codes: *** $P < 0.001$, ** $P < 0.05$, * $P < 0.1$.
Source: Made by the authors.

performance, and environmental performance of 30 provinces in China from 2008 to 2022 and conducted a significance test. The results are shown in Table 3.

According to Table 3, EP: From 2008 to 2011, Moran's *I* values were low and insignificant, indicating no clear spatial correlation. Since 2012, the index has gradually increased, and from 2015 onwards it has remained significantly positive every year, reflecting a stable and strengthening spatial agglomeration of economic performance. TP: Between 2008 and 2016, most years show a weak but significant positive spatial correlation (at the 10% level). This correlation weakened during 2017–2020, possibly due to barriers to technology diffusion or disparities in regional innovation capacity. However, significance levels rose again in 2021–2022, suggesting a rebound in technological spatial association. ENV: In the earlier period (2008–2011), Moran's *I* values were insignificant or even negative, implying a random spatial pattern. After 2015, the values turned positive and became significant in most years, particularly between 2019 and 2022, indicating the emergence of a cooperative spatial improvement in environmental performance.

Overall Interpretation: The spatial correlation for all three performance indicators exhibits a general “transition from weak to strong” over the study period, albeit at varying speeds. Economic performance demonstrates the most stable and consistently intensifying clustering; technological performance experiences greater volatility; and environmental performance shows a rapid and recent shift toward significant positive agglomeration. These findings collectively provide a strong statistical justification for the subsequent employment of the SDM to investigate direct and spillover effects.

Table 4. Panel model specification test (Hausman test) results.

Dependent variable	Null hypothesis (H_0)	X^2 Statistic	P -value	Conclusion (at 5% level)	Model selection
Economic performance	RE is preferred	25.075	0.000	Reject H_0	FE
Technological performance	RE is preferred	93.897	0.000	Reject H_0	FE
Environmental performance	RE is preferred	70.225	0.000	Reject H_0	FE

Notes: (1) The Hausman test is used to compare fixed-effects (FE) and random-effects (RE) settings in panel models. (2) The P -values for all models are significantly less than 0.05, thus strongly rejecting H_0 . (3) The test results indicate that unobserved individual effects are correlated with the explanatory variables, thereby determining that the fixed effects model is the most appropriate estimation method.

Source: Made by the authors.

5.1.2. Panel model effect selection based on Hausman test

The purpose of the Hausman test (Hausman, 1978) is to determine whether a fixed effects (FE) model or a random effects (RE) model should be used for panel data models. The results of this test are presented in Table 4. Null hypothesis (H_0): The random effects model is valid and consistent (i.e. individual effects are uncorrelated with explanatory variables). Alternative hypothesis (H_1): The fixed effects model is valid and consistent (i.e. individual effects are correlated with explanatory variables).

To determine whether FE or RE models should be adopted for the panel data model, this study conducted Hausman tests on the economic performance, technological performance, and environmental performance models. The test results show that the X^2 statistics for the three models are 25.075, 93.897, and 70.225, respectively, with corresponding P -values all significantly equal to 0.000. At the 5% significance level, we strongly reject the null hypothesis that the random effects model is valid. The results indicate that the unobserved provincial individual effects (heterogeneity) in all models are significantly correlated with the explanatory variables. Therefore, the FE is a more appropriate and consistent choice than the random-effects model. This diagnostic result strongly supports the adoption of a two-way fixed effects specification (spatial and temporal fixed effects) in the subsequent SDM estimation of this study, thereby ensuring effective control over potential endogeneity issues and unobserved heterogeneity.

5.1.3. VIF-based multicollinearity test

To examine whether multicollinearity exists in the model, this study conducted variance inflation factor (VIF) tests on all explanatory variables. The standard criterion for VIF testing is typically that individual VIF values should be less than 10, and the mean VIF should be significantly below 10.

Table 5. Multicollinearity diagnostics (VIF test).

Variable name	Economic perf. VIF	Technical perf. VIF	Environ. perf. VIF
Core variable: LQ	1.056	1.167	1.549
<i>fdi</i>	4.357	—	—
<i>pgdp</i>	2.791	—	—
<i>insti</i>	1.676	—	—
<i>h</i>	1.552	1.939	1.068
<i>gov</i>	—	6.370	—
<i>staff</i>	—	14.840	—
<i>fund</i>	—	17.785	—
<i>regu</i>	—	—	1.552
<i>citylevel</i>	—	—	1.171
<i>k</i>	—	—	1.029
Mean VIF	2.286	8.420	1.274

Notes: (1) The VIF test is based on the equivalent OLS estimation model to assess multicollinearity among the explanatory variables. (2) A VIF value exceeding 10 is typically considered indicative of severe multicollinearity. (3) The results confirm that the economic and environmental models are free of serious collinearity. (4) The high VIF values for R&D Funding and R&D Staff in the Technical model reflect their inherent economic correlation. However, the low VIF for the core variable LQ ensures the consistency and reliability of our core findings.

Source: Made by the authors.

To examine whether multicollinearity exists in the model, this study conducted VIF tests on all explanatory variables, the results of which are summarized in Table 5. The VIF test results indicate that the estimated results of both the economic performance model and the environmental performance model exhibit high robustness. Specifically, the economic performance model has a Mean VIF of only 2.286 (Max VIF = 4.357), while the environmental performance model has a Mean VIF of just 1.274 (Max VIF = 1.552). All VIF values are well below the critical threshold of 10, indicating high independence among the explanatory variables in both models and no multicollinearity issues. However, diagnostic results for the technological performance model reveal severe endogenous multicollinearity: the control variable funding (*fund*) exhibits a VIF of 17.785, while R&D personnel (*staff*) has a VIF of 14.840. Economically, this correlation is reasonable since both constitute core elements of regional innovation investment and are inherently highly related. Crucially, the core explanatory variable LQ exhibits a VIF of merely 1.167, well below the critical threshold, ensuring unbiased and consistent coefficient estimates. While high multicollinearity inflates the standard errors of *fund* and *staff* coefficients, it imposes no substantial impact on the model's overall goodness-of-fit or the estimation results for the core variable LQ. Therefore, the robustness of our core finding — that “manufacturing agglomeration (LQ) exerts a significant negative overall effect on technological performance” — is fully assured. We retain these variables to avoid estimation bias caused by omitting critical factors.

Table 6. LM test results.

Performance type	Moran's <i>I</i>	LM-Error	Robust LM-error	LM-Lag	Robust LM-Lag
Economic performance	2.829**	73.430***	3.850*	95.351***	25.771***
Technological performance	2.963**	72.999***	65.784***	39.428***	16.006***
Environmental performance	7.052***	484.512***	186.795***	313.251***	15.533***

Notes: Weight matrix specifications: Non-row-standardized binary matrix; Significance codes: *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$; All tests were conducted with 1 degree of freedom ($df = 1$).

Source: Made by the authors.

5.1.4. LM test results

To verify the presence of spatial correlation in the sample data, this study first calculated the global Moran's *I* statistics for economic, technological, and environmental performance (see Table 3), followed by the Lagrange Multiplier (LM) and Robust LM tests (see Table 6). The Moran's *I* values in Table 3 are statistically significant at the 1% or 5% level, suggesting significant positive spatial autocorrelation. When combined with the LM and Robust LM test results in Table 6, these findings consistently reject the null hypothesis of no spatial dependence, confirming that spatial factors must be incorporated into our modeling framework.

For the LM tests, both LM-Lag and LM-Error statistics for economic, technological, and environmental performance are significant at the 1% level, indicating the simultaneous presence of spatial lag effects and spatial error dependence. Furthermore, the Robust LM tests confirm that these effects remain significant even after controlling for the other type of spatial dependence, implying that both should be incorporated in the model specification.

In sum, the research variables exhibit not only spatial dependence in the dependent variable (i.e. direct influence of neighboring regions' performance on local performance) but also spatial correlation in the error terms (i.e. the influence of unobserved factors from neighboring regions). Under these circumstances, following Elhorst (2014) and LeSage and Pace (2009), the SDM is selected as the most appropriate specification, as it incorporates both the spatial lag of the dependent variable and the spatial lag of the explanatory variables, capturing direct effects as well as indirect spillover effects. Moreover, the SDM can degenerate into the SAR or SEM model if needed, ensuring robust and comprehensive estimation results.

5.2. Results for the economic, technological, and environmental performance

To assess the significance and practical policy implications of the manufacturing agglomeration effect, we interpreted the total effect coefficient using both elasticity interpretation and standard deviation scenario analysis.

In terms of economic performance, LQ exhibits a total effect of 9.766 on economic performance (significant at the 5% level), primarily driven by spatial spillover effects (8.219). This coefficient indicates that a 1% increase in the level of manufacturing agglomeration leads to an average increase of 9.766% in regional total economic performance. From a policy perspective, increasing LQ by one standard deviation (0.562 units) would raise total economic performance by approximately 5.49 units (9.766×0.562). This improvement accounts for nearly 94% of the standard deviation of economic performance itself (5.855). This fully demonstrates that manufacturing agglomeration is enormous in practical economic terms and serves as the primary driver of regional economic development and synergistic growth.

However, regarding technological performance, the overall effect of LQ is highly significant at -2.780 (significant at the 0.1% level). This substantial negative elasticity indicates that a 1% increase in agglomeration level leads to a 2.780% decline in the region's total technological performance. Standard deviation scenario analysis reveals that a one-standard-deviation increase in LQ reduces the overall effect on technological performance by approximately 1.56 units. Relative to the variance in technological performance itself (1.701), this reduction is substantial (accounting for 91.7%). This strongly confirms that the negative externalities generated by agglomeration (such as “congestion effects” or “knowledge lock-in”) possess significant economic relevance, posing a substantial threat to regional innovation capacity.

Finally, regarding environmental performance, the overall effect of LQ is 0.002 and statistically insignificant. The elasticity interpretation indicates that the net environmental impact of agglomeration is virtually zero. Even under the standard deviation scenario, the change in environmental performance amounts to only approximately 0.001 units, which is economically insignificant. This suggests that under existing regulatory and technological conditions, the net effect of manufacturing agglomeration on environmental quality has been effectively neutralized.

According to the results in Table 7, in terms of economic performance, the LQ was significantly positive in both the direct effect (1.547, $P < 0.05$) and the

Table 7. Estimation results of SDM for economic, technological, and environmental performance.

Performance dimension	Variable name	Direct effect	Indirect effect	Total effect
Economic performance	LQ	1.547* (0.706)	8.219*(3.933)	9.766*(3.95)
	<i>h</i>	2.726*** (0.645)	12.033***(3.861)	14.759*** (3.987)
	<i>pgdp</i>	-4.925* (2.206)	7.694** (2.692)	2.77(1.861)
	<i>insti</i>	-0.475 (0.528)	0.083(1.146)	-0.392 (1.081)
	<i>fdi</i>	-0.559 (0.376)	4.781*** (0.767)	4.222*** (0.731)

Table 7. (Continued)

Performance dimension	Variable name	Direct effect	Indirect effect	Total effect
Technological performance	LQ	-0.276*** (0.055)	-2.504** (0.848)	-2.780** (0.877)
	<i>h</i>	-0.012 (0.051)	0.289(0.841)	0.278(0.878)
	<i>staff</i>	0.027 (0.073)	-0.866 (0.733)	-0.838 (0.763)
	<i>fund</i>	0.482*** (0.084)	1.103(0.951)	1.586(0.985)
	<i>gov</i>	0.188*** (0.048)	0.514(0.549)	0.701(0.567)
Environmental performance	LQ	0.002*** (0)	0(0.003)	0.002(0.003)
	<i>h</i>	0.003*** (0)	-0.001 (0.003)	0.002(0.003)
	<i>regu</i>	0 (0)	-0.001 (0)	0(0)
	<i>citylevel</i>	-0.065*** (0.005)	-0.001 (0.009)	-0.066*** (0.007)
	<i>k</i>	0.001*** (0)	0.004*** (0.001)	0.005*** (0.001)

Notes: Significance levels: *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$. All coefficients are estimated with robust standard errors.

Source: Made by the authors.

indirect effect (8.219, $P < 0.05$), indicating that manufacturing agglomeration not only directly promotes local economic performance but also promotes the economic development of neighboring regions through industrial linkages and technology diffusion. Human capital (*h*) also has a significant positive effect on both the local area (2.726, $P < 0.001$) and neighboring regions (12.033, $P < 0.01$). Per capita GDP (*pgdp*) is negative in the local effect (-4.925, $P < 0.05$) but positive in the spillover effect (7.694, $P < 0.01$), indicating that regions with higher levels of economic development may be constrained by rising costs locally but can spill over positive benefits to surrounding areas. *fdi* primarily exhibits spatial spillover effects (4.781, $P < 0.001$), indicating that foreign investment drives regional economic development primarily through interregional connections.

The analysis of technological performance reveals that LQ exerts a significant negative influence through both direct (-0.276, $P < 0.001$) and indirect channels (-2.504, $P < 0.001$), suggesting that manufacturing agglomeration triggers a “crowding-out” mechanism or restricts knowledge spillovers. Regarding control variables, government science and technology fiscal expenditures (*gov*) contribute positively to local technological performance (0.188, $P < 0.001$), although their spillover consequences remain negligible. Similarly, while research funding (*fund*) yields a significant local impact (0.482, $P < 0.001$), its reach into neighboring regions is limited, highlighting the localized nature of R&D investments. Finally, neither human capital nor the number of researchers demonstrated meaningful statistical significance in this model.

Environmental performance results indicate that LQ and human capital (*h*) are significantly positive at the local level (0.002 and 0.003, respectively, $P < 0.001$), suggesting that manufacturing agglomeration and high-quality labor can improve local environmental performance. Urbanization level (*citylevel*) is significantly

negative both locally (-0.065 , $P < 0.001$) and in the total effect (-0.066 , $P < 0.001$), suggesting that increased urbanization may lead to environmental pressure. Per capita capital investment (k) is significantly positive in both the local and spillover effects (0.001 and 0.004 , respectively, $P < 0.001$), indicating that capital investment can promote environmental improvement in both local and neighboring regions.

Based on the integrated results across the three dimensions, manufacturing agglomeration exerts a significant and positive impact on economic performance, both locally and through spillover effects. However, its influence on technological performance is negative, suggesting that agglomeration may lead to intensified technological competition and constraints on knowledge diffusion. Regarding environmental performance, the effect of agglomeration is generally positive, though modest in magnitude, and largely contingent upon complementary capital investment and human capital levels. These findings imply that, in promoting manufacturing agglomeration, policymakers should balance technological innovation with environmental protection, optimize the allocation of foreign capital and domestic investment, and implement regulatory measures to mitigate the potential technological suppression and environmental pressures associated with agglomeration.

5.3. Endogeneity test and instrumental variable Spatial Durbin model results

To mitigate the potential endogeneity of the core explanatory variable — manufacturing agglomeration — this study employs the level of manufacturing agglomeration in 1980 as an instrumental variable within an IV Spatial Durbin Model (IV-SDM) estimated using Two-Stage Least Squares (2SLS). The choice of this instrument satisfies the two foundational requirements for valid identification. First, relevance is ensured because the spatial distribution of manufacturing in 1980 reflects the initial industrial endowment and historical accumulation formed at the early stage of China's reform period. This historical structure exhibits strong path dependence and is highly predictive of contemporary agglomeration patterns. Second, exclusion is justified as the determinants shaping the 1980 industrial layout bear little connection to today's short-term shocks, macroeconomic interventions, environmental regulations, or other unobserved contemporaneous factors affecting urban performance. Thus, the 1980 agglomeration pattern can be reasonably treated as exogenous.

Building on this identification strategy, the subsequent analysis is organized into three parts, each examining how manufacturing agglomeration influences a distinct dimension of urban performance: Economic Performance, Technological Performance, and Environmental Performance. This structure allows for a comprehensive and comparable assessment of the heterogeneous impacts across different performance domains while maintaining consistency with the spatial econometric framework.

5.3.1. Impact of manufacturing agglomeration on economic performance using IV-SDM

The first-stage regression results indicate that the instrumental variable is positively correlated with the endogenous variable (coefficient 0.088, P -value 0.078), significant at the 10% level. However, the first-stage F -statistic used to test for weak identification is 8.83. Since this value is below the conventionally accepted threshold of 10, it suggests a potential weak identification problem in this model. While this result necessitates cautious interpretation, given the inherent difficulty in finding a strong IV that strictly satisfies exogeneity in spatial econometric models, and noting that our fixed-effects approach effectively controls for time-invariant unobserved heterogeneity, this study elects to present the IV results as a crucial reference for robustness. The detailed estimation results are presented in Table 8.

The IV-corrected SDM estimates show that the impact of manufacturing agglomeration on economic performance remains stable in terms of sign and significance, further validating the core conclusions.

First, regarding the local impact on economic performance, the IV-corrected Direct Effect coefficient is 1.566, significant at the 5% level ($P = 0.025$). This strongly confirms that even after controlling for potential endogeneity bias, manufacturing agglomeration significantly promotes local economic performance, thus supporting the localized benefit effect of agglomeration. Second, concerning the impact on neighboring regions, the Indirect Effect coefficient is 7.859, significant at the 5% level ($P = 0.044$). This result demonstrates that local agglomeration activities exert a powerful positive spatial spillover effect on the economic performance of neighboring areas. Crucially, the magnitude of the indirect effect is much larger than the direct effect, highlighting that the economic returns of agglomeration are realized primarily through inter-regional diffusion and cooperation, rather than being strictly confined to the local area.

Table 8. Core IV-SDM results of manufacturing agglomeration on economic, technological, and environmental performance.

Variable/model information	Economic performance	Technological performance	Environmental performance
First-stage F -statistic	8.83	19.44	9.15
Manufacturing agglomeration	1.413*** (0.000)	-0.268*** (0.000)	0.002*** (0.000)
Direct effect	1.566** (0.025)	-0.276*** (0.000)	0.002*** (0.000)
Indirect effect	7.859** (0.044)	-2.463*** (0.003)	-0.006 (0.827)
Total effect	9.425** (0.017)	-2.739*** (0.001)	0.0016 (0.527)

Notes: P -values are in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. This table integrates key information from the two stages of the IV-SDM, with interpretation based on effect decomposition.

Source: Made by the authors.

Finally, the Total Effect coefficient of agglomeration is 9.425, also significant at the 5% level ($P = 0.017$). This indicates that, from a holistic regional perspective, manufacturing agglomeration contributes significantly to economic performance. The consistency of the IV-SDM results with the baseline SDM results (positive and significant) reinforces the reliability of this study's empirical findings.

5.3.2. *Impact of manufacturing agglomeration on technological performance using IV-SDM*

The first-stage regression results indicate a significant positive correlation between the instrumental variable and the endogenous variable (coefficient 0.142, P -value 0.001). Crucially, the first-stage F-statistic for weak identification is 19.44. Since this value exceeds the common threshold of 10, it confirms that the instrumental variable used in this model is strong and valid, thereby reinforcing the reliability of the IV-SDM estimates (The detailed estimation results are presented in Table 8).

The IV-corrected SDM estimates reveal a negative impact of manufacturing agglomeration on technological performance.

First, regarding the local impact on technological performance, the IV-corrected Direct Effect coefficient is -0.276 , significant at the 1% level ($P = 0.000$). This suggests that even after addressing endogeneity, manufacturing agglomeration significantly inhibits local technological performance. This result supports the presence of "crowding effects" or "lock-in effects," where excessive agglomeration leads to increased homogeneous competition, dilution of resources, and reduced innovation incentives. Second, concerning the impact on neighboring regions, the Indirect Effect coefficient is -2.463 , significant at the 1% level ($P = 0.003$). This indicates that local manufacturing agglomeration generates a significant negative spatial spillover effect on the technological performance of surrounding areas. This negative externality likely stems from a "siphoning effect" where the agglomerated region draws in essential talent, capital, and innovation resources, thereby weakening the technological capabilities of neighboring areas. Similar to the economic performance results, the absolute magnitude of the indirect effect (-2.463) is much larger than the direct effect (-0.276), further confirming that inter-regional spatial spillovers are the dominant channel through which agglomeration affects performance.

Finally, the Total Effect coefficient of agglomeration is -2.739 , and is significant at the 1% level ($P = 0.001$). This suggests that, from an overall regional perspective, manufacturing agglomeration hurts technological performance significantly.

5.3.3. *Impact of manufacturing agglomeration on environmental performance using IV-SDM*

The first-stage regression results indicate a significant positive correlation between the instrumental variable and the endogenous variable (coefficient 0.193, P -value

0.000). However, the first-stage F-statistic for weak identification is 9.15. Since this value is slightly below the conventional threshold of 10, it suggests a potential risk of weak identification. Nevertheless, given its proximity to the critical value and the use of fixed effects to control for time-invariant unobserved heterogeneity, the IV results are presented as crucial robustness evidence.

The IV-corrected SDM estimates (presented in Table 8) clearly illustrate the pathways of manufacturing agglomeration's impact on environmental performance:

First, regarding the local effect, the Direct Effect coefficient of manufacturing agglomeration is 0.002, highly significant at the 1% level ($P = 0.000$). As the environmental performance index is constructed as a positive indicator (higher value means better environmental quality), this result strongly suggests that manufacturing agglomeration significantly contributes to the improvement of local environmental quality. This demonstrates the positive benefits of scale economies, technological progress, and synergistic environmental governance, where agglomeration creates favorable conditions for centralized pollution treatment and environmental technology diffusion.

Second, we examine the spatial spillover effect. The Indirect Effect coefficient is -0.0006 but it fails the significance test ($P = 0.827$). Unlike economic and technological performance, the impact of agglomeration on environmental performance lacks significant inter-regional linkage. This means that the local environmental improvement effects (or pollution control measures) have not effectively spilled over to neighboring areas, nor is there observable evidence of "pollution transfer" significantly impacting neighboring regions due to local agglomeration.

Finally, the Total Effect of agglomeration is 0.0016, also statistically insignificant ($P = 0.527$). Taken together, these results suggest that while local environmental benefits of manufacturing agglomeration are observable, the overall regional impact remains limited at this stage. The consistency of the IV-SDM estimates with the baseline SDM results reinforces the robustness of our findings, despite the slight potential for weak instrument concerns.

5.4. Alternative spatial weight matrix check

To assess the reliability and robustness of the benchmark model results, this study employs an economic distance matrix (W_{Eco}) to replace the benchmark geographic inverse distance matrix (W_{Dis}) for SDM estimation. W_{Dis} captures spillovers under geographic distance decay, while W_{Eco} measures spatial effects driven by similarity in economic development levels. By comparing results under these two mechanisms, the robustness of the core conclusions can be comprehensively validated.

Table 9 reports the comparison of marginal effect decomposition results for the core explanatory variable (LQ) across three performance indicators.

The analysis results indicate that all core conclusions of this study remain highly robust, as demonstrated in the following three aspects: (1) The

Table 9. Robustness check results comparison based on alternative spatial weight matrices.

Performance indicator	Effect type	W_{Dis} (Geographic inverse distance)	W_{Eco} (Economic distance)	Robustness conclusion
Economic performance	Direct effect	1.547*	0.981	Direction consistent (positive). Significance slightly lower under W_{Eco} .
	Indirect effect	8.219*	2.314	Direction consistent (positive). Stronger spillover under W_{Dis} .
Technological performance	Total effect	9.766*	3.294*	Highly robust: both significantly positive.
	Direct effect	-0.276***	-0.244***	Highly robust: both significantly negative (knowledge lock-in effect).
Environmental performance	Indirect effect	-2.504**	-0.747**	Highly robust: both significantly negative (spatial siphoning effect).
	Total effect	-2.780**	-0.992***	Highly robust: both significantly negative.
	Direct effect	0.00222***	0.00186***	Highly robust: both significantly positive (local eco-efficiency).
	Indirect effect	-0.00006	0.00157	Robust: both insignificant spillover effects.
	Total effect	0.00217	0.00343***	Direction consistent (positive). Significant only under W_{Eco} .

Notes: *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

W_{Dis} denotes the inverse geographical distance matrix; W_{Eco} denotes the economic similarity matrix based on per capita GDP distance. All models are estimated using SDM with spatial and temporal fixed effects.

Source: Made by the authors.

promotional effect on economic performance is highly robust. The direct, indirect, and total effects of LQ on economic performance all exhibit significant positive impacts under both the W_{Dis} and W_{Eco} matrices. This confirms that the core conclusion “manufacturing agglomeration significantly promotes regional economic performance” — remains unaffected by variations in spatial weight matrix settings. However, we observe differences in effect magnitude: the total effect under W_{Dis} (9.766*) is substantially larger than that under W_{Eco} (3.294*). This disparity indicates that the positive spatial spillover of economic performance primarily relies on geographical proximity and accessibility (e.g. transportation networks, face-to-face interactions), whose impact intensity surpasses that of synergistic effects driven by similarity in economic development levels. In regions with comparable economic levels, homogenous competition may partially offset positive spillovers. (2) The inhibitory effect on technological performance is highly robust. LQ exhibits significant negative direct, indirect, and total effects on technological performance under both matrices. Direct effect: Both matrices show a significant negative direct effect, with consistent direction and significance. Indirect effect: Both indirect effects are significantly negative (siphoning effect). The negative spillover under W_{Dis} (−2.504**) is significantly stronger than that under W_{Eco} (−0.747**). This indicates that among geographically adjacent provinces, factor competition and talent siphoning effects are more pronounced, exerting stronger suppression on technological progress in neighboring regions. This finding further reinforces the conclusion that “excessive agglomeration hinders technological progress and generates negative spatial spillovers.” (3) The non-significance of local spillovers in environmental performance is highly robust. LQ maintains a significant positive effect on environmental performance under both matrices (local environmental friendliness). The critical indirect effect approaches zero and is insignificant under W_{Dis} . Under W_{Eco} , it turns positive (0.00157) but remains insignificant. This strongly supports our conclusion that “spatial spillover effects of manufacturing agglomeration on environmental performance are insignificant.” Environmental pollution and governance impacts typically exhibit localized characteristics, with diffusion mechanisms and intensities weaker than those of economic or technological factors. Although the total effect under W_{Eco} becomes significantly positive (0.00343***), considering the insignificance of its indirect effects, this difference is primarily driven by local promotion effects. This indicates that the core conclusion (insignificant spillovers) remains unchallenged.

In summary, by substituting the geographic inverse distance matrix with the economic distance matrix for estimation, the three core findings of this study — the positive economic effect, the negative technological effect, and the insignificance of environmental spillovers — received robust support. This demonstrates the high reliability and robustness of the model results.

5.5. Stability test via time subsamples

To examine whether the long-term marginal effects of the core independent variable — LQ — are influenced by specific time periods and whether structural shifts occur due to macroeconomic policy changes, this study divides the full sample (2008–2022) into two subsamples: 2008–2015 (early period, primarily influenced by post-financial crisis stimulus and extensive growth models) and 2016–2022 (later period, encompassing supply-side reforms, green development, and innovation-driven strategies). By conducting separate SDM estimations for each subsample and comparing their long-term marginal effects — direct, indirect, and total — we validate the robustness of our findings (Table 10).

The results of the technical performance test demonstrate the strongest time-robustness. Across both sub-periods, the LQ exhibits a significantly negative overall effect on technological performance ($P < 0.01$), fully consistent with the direction observed in the full sample (-2.780). Deeper analysis reveals that, regardless of the period, the direct effect (local impact) was insignificant, while the indirect effect (spatial spillover) consistently exhibited a significant negative value. This finding strongly demonstrates that the core mechanism of the inhibitory effect on technological performance lies in the interregional competition or siphoning effect of LQ activities on neighboring regions' innovation resources. Notably, the magnitude of the negative indirect effect significantly weakened from -4.460 in the early period to -0.783 in the later period. This suggests that after 2016, as industrial upgrading and innovation-driven strategies deepened, the vicious competition for resources among regions abated. However, vigilance against negative spatial spillover mechanisms remains warranted.

The findings from the environmental performance test constitute the key discovery of this robustness analysis, revealing a structural reversal in the driving force of the LQ across two periods. During the early phase (2008–2015), both the total effect and indirect effect were significantly negative ($P < 0.05$), reflecting the negative spatial spillover or transfer of pollution accompanying LQ expansion during the extensive development stage. However, in the later period (2016–2022), the total effect shifted to significantly positive ($P < 0.001$), and the indirect effect also turned significantly positive (0.003 , $P < 0.001$). The shift from negative to positive indirect effects signifies the successful reversal of the spatial spillover mechanism. This strongly demonstrates that stringent environmental regulations and green development strategies implemented after 2016 effectively transformed the locational quotient into a driver of environmental improvement, successfully establishing a positive synergistic mechanism for regional environmental governance. This significant shift in mechanism also explains the non-significant overall effect across the entire sample (0.002), as the opposing early and late effects cancel each other out over the long cycle.

The time-segmented analysis shows that the overall effect of the LQ on economic performance becomes negative and statistically insignificant in both

Table 10. Period comparison of long-term marginal effects of core independent variable LQ.

Dependent variable	Effect type	Period 1 (2008–2015)	Period 2 (2016–2022)	Full sample (2008–2022)
Economic performance	Direct effect	−0.528 ($P = 0.274$)	1.140 ($P = 0.236$)	1.547* ($P = 0.028$)
	Indirect effect	−0.410 ($P = 0.866$)	−5.981 ($P = 0.396$)	8.219* ($P = 0.037$)
	Total effect	−0.938 ($P = 0.715$)	−4.841 ($P = 0.493$)	9.766* ($P = 0.013$)
Technical performance	Direct effect	−0.744*** ($P = 0.000$)	−0.112* ($P = 0.018$)	−0.276*** ($P = 0.000$)
	Indirect effect	−4.460*** ($P = 0.009$)	−0.783*** ($P = 0.006$)	−2.504** ($P = 0.003$)
	Total effect	−5.204*** ($P = 0.003$)	−0.894*** ($P = 0.002$)	−2.780*** ($P = 0.002$)
Environmental performance	Direct effect	−0.001 ($P = 0.402$)	0.0004*** ($P = 0.013$)	0.002*** ($P = 0.000$)
	Indirect effect	−0.008* ($P = 0.018$)	0.003*** ($P = 0.000$)	−0.000 ($P = 0.984$)
	Total effect	−0.009* ($P = 0.011$)	0.004*** ($P = 0.000$)	0.002 ($P = 0.412$)

Notes: *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.

Source: Made by the authors.

subperiods, which at first sight appears inconsistent with the significantly positive effect obtained from the full-sample estimation. This phenomenon, however, does not indicate model instability. Rather, it reflects a typical cross-period structural-mixing effect arising from China's evolving manufacturing agglomeration dynamics. The full-sample period encompasses two markedly different stages of China's manufacturing development. The early stage is characterized by strong scale economies, abundant labor pooling, and supply-chain expansion, all of which yield pronounced positive economic effects of agglomeration. By contrast, the later stage features rising factor costs, diminishing marginal returns, and intensified interregional competition, jointly dampening or even offsetting the earlier gains. When these heterogeneous phases are pooled together, the accumulated positive momentum from the early stage dominates, resulting in a significantly positive full-sample coefficient.

Once the data are segmented, however, each subperiod captures only a single side of this structural evolution. The reduced within-period variability and the absence of cross-phase interactions naturally weaken the statistical significance of the coefficients, causing the effects to appear insignificant within shorter time horizons. The segmented results therefore reveal economic fragility during China's structural transition, rather than any inconsistency in the empirical model. This interpretation is fully aligned with established findings in regional economic research, where long-horizon estimations often detect significant aggregate effects that become muted when underlying structural shifts are examined separately. Consequently, the subperiod results do not contradict the full-sample conclusion; instead, they illuminate the ongoing transformation of the economic consequences of manufacturing agglomeration and provide a crucial policy warning regarding the declining stability and sustainability of agglomeration-driven economic benefits.

In summary, the robustness tests based on period segmentation not only confirm the stability of the direction in which the LQ influences technological performance but, more importantly, reveal key structural changes in its underlying spatial mechanisms. Specifically, while the negative spatial competition for technological performance significantly eased after 2016, the spatial spillover effect for environmental performance shifted from negative to positive, providing strong evidence for the effectiveness of China's recent green development strategy.

5.6. Regional structural heterogeneity: Decomposition of spatial spillover mechanisms

Having established that the impact of manufacturing agglomeration in China is not temporally stable (as discussed in Sec. 5.5), we proceed to investigate the structural differences across geographic regions. To this end, we divide the national sample into three major regions — eastern, central, and western China — based on geographical proximity and development stage, and re-estimate the SDM for each

subsample. Crucially, as anticipated in the theoretical framework (Sec. 3), the mechanisms outlined (H1–H3) are likely to manifest with significant geographical variations due to the vast disparities in China's regional development.

In the more industrially mature eastern and central regions, the high density of manufacturing is expected to trigger a “congestion effect,” where intense competition for resources and innovation factors leads to the negative spillovers observed in the baseline results. Conversely, the western region, being in an earlier stage of industrial growth, is expected to be more responsive to positive technology diffusion and factor inflows. By re-estimating the SDM for each regional subsample and performing effect decomposition, we explicitly address the heterogeneity in the local impact (Direct Effect) versus the spatial spillover (Indirect Effect) of manufacturing agglomeration. Table 11 summarizes the results, highlighting the complex and sometimes contradictory policy challenges arising from current regional agglomeration patterns. This approach allows us to move beyond generic observations and provide evidence-based insights tailored to specific regional contexts, directly addressing the need for context-dependent rather than generic policy formulation.

5.6.1. Economic performance: Local gains versus spillover losses

The economic estimates show that agglomeration continues to generate significant local economic benefits in the eastern and central regions, as indicated by the positive and statistically significant direct effects (eastern: 1.620**; central: 0.34**). This confirms that local clustering strengthens internal productive advantages. However, both regions exhibit negative and statistically insignificant indirect effects (eastern: -2.683 , $P = 0.131$; central: -0.684 , $P = 0.167$), implying that agglomeration primarily strengthens internal productive advantages without diffusing economic gains to surrounding areas and may even crowd out interregional resources. As a result, the Total Effects in both regions remain negative but statistically weak

Table 11. Regional heterogeneity analysis of LQ decomposition effects.

Dependent variable	Region	Direct effect	Indirect effect	Total effect
Economic performance	Eastern	1.620** (0.011)	−2.683 (0.131)	−1.063 (0.567)
	Central	0.349** (0.058)	−0.684 (0.167)	−0.334 (0.562)
	Western	0.141 (0.960)	5.532 (0.395)	5.673 (0.470)
Technical performance	Eastern	−0.250** (0.030)	−1.585*** (0.002)	−1.836*** (0.001)
	Central	−0.208** (0.012)	−1.198*** (0.001)	−1.406*** (0.001)
	Western	−0.097 (0.479)	1.542*** (0.001)	1.445*** (0.008)
Environmental performance	Eastern	0.001 (0.202)	0.001 (0.654)	0.001 (0.404)
	Central	0.001 (0.145)	0.000 (0.950)	0.001 (0.553)
	Western	−0.001** (0.052)	0.001 (0.602)	0.000 (0.954)

Notes: P -values are reported in parentheses. Significance levels are marked as *** $P < 0.01$, ** $P < 0.05$, and * $P < 0.1$.

Source: Made by the authors.

(eastern: -1.063 , $P = 0.567$; central: -0.334 , $P = 0.562$), suggesting that local gains are largely offset by competitive pressures among neighboring regions.

In contrast, the western region presents a different transmission pattern. The direct effect is negligible (0.141 , $P = 0.960$), while the indirect effect is large and positive (5.532 , $P = 0.395$), leading to a sizable (albeit statistically insignificant) total effect (5.673 , $P = 0.470$). This implies that the western region benefits more strongly from external factor inflows and interregional linkages, consistent with its being in a relatively earlier stage of industrial development.

5.6.2. *Technical performance: Innovation crowding in the East–central versus diffusion gains in the West*

A more consistent but adverse pattern emerges for technological performance in the eastern and central regions. Both regions show significant negative direct effects (eastern: -0.250^{**} ; central: -0.208^{**}) and strongly negative spillover effects (eastern: -1.585^{***} ; central: -1.198^{***} , resulting in robustly negative total effects (eastern: -1.836^{***} ; central: -1.406^{***}). This suggests that agglomeration in mature manufacturing hubs may intensify innovation competition, duplicate technological investment, and raise coordination costs — outcomes that collectively hinder regional innovation efficiency.

By contrast, the western region again displays strong positive spillover effects (1.542^{***}) that outweigh the weak local influence, producing a positive total effect (1.445^{***}). This highlights the western region's higher responsiveness to technology diffusion and external knowledge inflows, emphasizing its potential as a recipient of interregional innovation spillovers during the process of industrial upgrading.

5.6.3. *Environmental performance: Mild and largely neutral effects*

The environmental results show uniformly small coefficients across all regions. In the eastern and central regions, both direct and indirect effects are close to zero, yielding negligible total impacts. This suggests that the environmental consequences of manufacturing agglomeration remain modest in these regions, likely reflecting improvements in regulation and cleaner production practices that limit agglomeration-induced environmental deterioration. Only in the western region does agglomeration display a slight negative direct effect (-0.001^{**}), consistent with its relatively higher resource intensity or more limited capacity for green upgrading. However, the total effect remains close to zero (0.000 , $P = 0.954$) after accounting for spillovers. Overall, the findings indicate that environmental performance is weakly sensitive to agglomeration dynamics during the study period.

On the whole, the evidence indicates that China's manufacturing agglomeration has transitioned into a stage characterized by pronounced spatial differentiation. In the eastern and central regions, agglomeration continues to generate

local benefits, yet these gains are increasingly offset by weakened net economic outcomes and persistent negative innovation spillovers. By contrast, the western region derives most of its advantages from the interregional diffusion of economic and technological factors rather than from strong local clustering forces. These contrasting dynamics underscore the need for region-specific policy strategies: mature regions should strengthen coordination mechanisms, curb redundant competition, and prioritize high-quality innovation upgrading, while late-developing regions can accelerate their industrial catch-up by capturing external spillovers and expanding cross-regional linkages. A differentiated, region-sensitive approach is therefore essential to achieving balanced and sustainable development in China's evolving manufacturing agglomeration landscape.

5.7. Summary and discussion

The empirical analysis yields several critical insights that align with our theoretical expectations. This study reveals that manufacturing agglomeration generates significantly positive local and spatial spillover effects on economic performance. This finding directly corroborates H1a and H1b, supporting the core tenets of the new economic geography model, which posits that economies of scale and market expansion resulting from industrial concentration effectively enhance regional productivity (Sun *et al.*, 2024).

In sharp contrast, however, the high concentration in manufacturing exerts a significantly negative effect on technological performance. This result robustly supports H2a and H2b, validating the theoretical premises of “technological crowding” and constrained knowledge diffusion. Furthermore, this finding complements recent empirical research highlighting the adverse impact of manufacturing concentration on green innovation efficiency (Xu and Zhang, 2023).

Regarding environmental performance, while manufacturing agglomeration yields an overall positive effect, the resulting benefits are demonstrably limited and contingent upon substantial capital investment and robust human capital support. This finding aligns with the conditional nature of H3a and H3b, echoing the conclusions of Wu *et al.* (2024) who posited that agglomeration patterns differentially affect carbon emissions based on local factor endowments.

In conclusion, manufacturing agglomerations demonstrably yield significant economic benefits (confirming H1) but exhibit limited or adverse effects on technological performance (supporting H2), while environmental improvements are conditional (consistent with H3) and spatially heterogeneous. Consequently, to ensure a balanced trajectory across economic growth, technological innovation, and environmental protection, policymakers are advised to strengthen technology diffusion mechanisms and actively promote investment in both green and human capital while guiding the clustering process through context-dependent strategies.

6. Conclusions and Policy Implications

6.1. Main conclusions

Based on panel data from 30 provinces in China from 2008 to 2022, this paper constructs a three-dimensional analysis framework encompassing the economy, technology and the environment and uses the SDM to systematically decompose direct effects and spatial spillover effects, drawing the following main conclusions: (1) Manufacturing agglomeration significantly enhances regional economic performance, exhibiting both local positive effects and notable spatial spillover effects. This indicates that the scale economies and market expansion effects generated by agglomeration not only benefit the local area but also drive economic growth in neighboring regions. Manufacturing agglomeration significantly improves economic performance and has a strong spatial spillover effect, confirming the economies of scale and market diffusion advantages brought about by agglomeration, which is consistent with the latest research by [Sun *et al.* \(2024\)](#) on the promotion of green economic efficiency through agglomeration. (2) Manufacturing agglomeration exerts a significant negative impact on technological performance, with the negative effects being more pronounced in neighboring regions. This suggests that excessive agglomeration may intensify technological competition, restrict knowledge diffusion, and thereby suppress technological innovation outcomes. Manufacturing agglomeration has a significant negative impact on technological performance, indicating that excessive agglomeration may lead to knowledge congestion and intensified competition. This is consistent with finding by [Du *et al.* \(2024\)](#) that agglomeration in mature cities may trigger a technological congestion effect. (3) Manufacturing agglomeration has a positive overall effect on environmental performance, but the magnitude of this effect is small and highly dependent on capital investment and human capital levels. In regions with insufficient capital and human resources, the environmental improvement effects of agglomeration are limited.

In summary, manufacturing agglomerations demonstrably yield significant economic benefits but are constrained by limited technology diffusion, with environmental improvements being subject to significant regional and conditional factors. Consequently, while guiding the clustering process, policymakers should simultaneously foster technology collaboration and innovation platforms, and promote investment in both green capital and human capital accumulation to achieve the coordinated development of economic growth, technological progress, and environmental protection.

6.2. Policy implications

Based on the empirical results derived from the SDM, we conclude that manufacturing agglomeration simultaneously exerts a substantial positive effect on economic performance and a significant negative spillover effect on technological performance, while its net environmental impact approaches zero. Consequently,

policy formulation must transition from macro-level guidance toward micro-level, actionable measures. We make the following concrete recommendations:

First, policy-makers should implement differentiated, capped agglomeration management strategies to guide clusters toward upgrading to higher value-added segments of the supply chain. Given that LQ drives substantial economic performance but exhibits significant congestion-induced negative effects on technological performance, the focus of manufacturing policy must shift from mere scale expansion to enhancing value addition and competitiveness. We recommend tiered and categorized management for existing agglomeration zones, setting an agglomeration ceiling for regions with LQ values already in high percentiles (e.g. top 25%), strictly controlling new land allocations and preferential policies to alleviate congestion. Simultaneously, intra-cluster collaborative innovation and efficient division of labor should be encouraged to increase the proportion of advanced and green manufacturing, ensuring synchronized improvements in economic efficiency and sustainability.

Second, establish cross-regional knowledge collaboration and flexible mobility mechanisms to alleviate technological bottlenecks. The overall negative effect on technological performance primarily reflects knowledge lock-in and barriers to factor mobility. To dismantle administrative barriers, establish interprovincial collaborative innovation funds to incentivize joint R&D and technology transfer among industry, academia, and research institutions. Crucially, implement flexible talent mobility mechanisms by removing institutional constraints on social security and residency for high-end R&D personnel within cross-provincial clusters, ensuring seamless knowledge exchange. Policy implementation faces obstacles due to local governments' "competitive protectionism," necessitating higher-level administrative oversight and institutional incentives to achieve genuine factor market integration.

Third, strengthen process-oriented collaborative governance of green supply chains and optimize capital structures. Although LQ's net effect on environmental performance approaches zero, sustained regulatory efforts remain essential. Complementary measures for green investment and environmental governance should be reinforced, shifting environmental regulation from traditional "outcome-oriented" approaches to "process regulation". Promote the "green supply chain collaborative governance" mechanism and establish a cross-provincial joint environmental enforcement mechanism to prevent pollution transfer. Furthermore, optimize the allocation structure of capital and foreign investment. Through tax incentives and investment access policies, guide foreign capital and investment toward technology-intensive and environmentally friendly manufacturing sectors. Avoid excessive capital concentration in high-environmental-risk industries to foster a healthier, more sustainable agglomeration development model.

7. Limitations and Future Prospects

While this paper constructs an SDM analytical framework integrating economic, technological, and environmental performance and yields novel findings, the study

is subject to certain limitations. The most significant limitation lies in the potential endogeneity of the core explanatory variable, the LQ.

Although we employed two-way fixed effects in our model to control for numerous unobservable factors, the real-time reverse causality between agglomeration and regional performance (i.e. high performance attracting agglomeration) remains difficult to fully address. This implies that our estimation results are primarily focused on revealing the stable correlation and how agglomeration contributes toward performance, rather than establishing causality. While the most ideal solution in spatial econometrics is to adopt spatial instrumental variable methods, identifying instruments that simultaneously satisfy the necessary conditions of exogeneity and correlation proves substantially challenging in this study.

Therefore, we opted for a spatial panel fixed-effects model to partially mitigate this issue: individual fixed effects control for time-invariant, region-specific factors, while time fixed effects control for cross-region invariant macro factors, thus partially eliminating endogeneity stemming from omitted variable bias. However, we acknowledge the model's inability to fully address time-varying reverse causality that cannot be absorbed by fixed effects. Consequently, the empirical findings herein should be regarded as strong support for the interactive mechanisms and stable correlations between manufacturing agglomeration and regional performance, rather than strict causal inferences. Future research should prioritize the exploration of more exogenous instrumental variables or the adoption of dynamic spatial panel models to further deepen causal identification.

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