

**The Impact of Industrial Agglomeration on the Economic,  
Technological and Environmental Performance of China's  
Manufacturing Industry**

by

**Shentu Yuan**  
(22010068)



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## DECLARATION

I hereby declare that the work presented in this thesis was conducted in full compliance with the regulations of Universiti Malaysia Sarawak (UNIMAS). Except where proper acknowledgment is given, this work is solely the effort of the author. This thesis has not been accepted for the award of any other degree and is not being **concurrently** submitted for any other academic qualification.

Signature Shentu Yuan  
Student Name: Shentu Yuan  
Matric No: 22010068  
Date: 11 March 2026

**Faculty of Economics and Business**  
Universiti Malaysia Sarawak (UNIMAS)

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# **The Impact of Industrial Agglomeration on the Economic, Technological and Environmental Performance of China's Manufacturing Industry**

## **ABSTRACT**

Industrial agglomeration is a defining feature of China's manufacturing sector, yet its multidimensional consequences remain insufficiently understood. Existing studies rarely integrate economic, technological, and environmental dimensions within a unified spatial econometric framework, often overlooking the trade-offs between competing regional objectives and the distinction between local impacts and spatial spillover effects. This thesis addresses this gap by systematically examining how industrial agglomeration reshapes regional manufacturing performance through both local and spillover channels. Using provincial panel data from 2008 to 2022 and spatial econometric models (e.g., the Spatial Durbin Model, SDM), this study evaluates the impacts of alternative agglomeration measures, including specialization, industrial concentration, and employment density. The results reveal a clear “triple-effect” pattern. Agglomeration generally enhances economic performance, but the spillover benefits are spatially uneven and geographically bounded. In contrast, higher agglomeration—especially in more concentrated configurations—is associated with weaker technological innovation, consistent with a spatial “siphoning effect” in which innovation-related capacity becomes more unevenly distributed across regions. Environmental impacts are heterogeneous: specialization-based clustering tends to improve local environmental outcomes, whereas high-density concentration can generate negative spillovers to neighboring regions, implying cross-regional governance externalities. The novelty of this research lies in constructing an integrated spatial econometric framework that jointly evaluates economic, technological, and environmental outcomes and clarifies why “one-size-fits-all” agglomeration policies may fail in a spatial economy. The findings support differentiated regional industrial strategies, improved spatial allocation of innovation factors, and stronger cross-regional environmental coordination to advance sustainable and high-quality manufacturing development in China.

**Keywords:** Industrial agglomeration; manufacturing industry; economic performance; technological performance; environmental performance

# ***Kesan Aglomerasi Perindustrian terhadap Prestasi Ekonomi, Teknologi dan Alam Sekitar Industri Pembuatan China***

## ***ABSTRAK***

*Aglomerasi perindustrian merupakan ciri penentu sektor pembuatan China, namun akibatnya yang pelbagai dimensi masih belum difahami dengan secukupnya. Kajian sedia ada jarang mengintegrasikan dimensi ekonomi, teknologi dan alam sekitar dalam kerangka kerja ekonometrik spatial yang bersatu, selalunya terlepas pandang tentang pertukaran antara objektif serantau yang bersaing dan perbezaan antara impak tempatan dan kesan limpahan spatial. Tesis ini menangani jurang ini dengan mengkaji secara sistematik bagaimana aglomerasi perindustrian membentuk semula prestasi pembuatan serantau melalui saluran tempatan dan limpahan. Menggunakan data panel wilayah dari 2008 hingga 2022 dan model ekonometrik spatial (contohnya, Model Durbin Spatial, SDM), kajian ini menilai impak langkah aglomerasi alternatif, termasuk pengkhususan, kepekatan perindustrian, dan kepadatan pekerjaan. Keputusan menunjukkan corak "kesan tiga kali ganda" yang jelas. Aglomerasi secara amnya meningkatkan prestasi ekonomi, tetapi faedah limpahan tidak sekata secara spatial dan terbatas secara geografi. Sebaliknya, aglomerasi yang lebih tinggi—terutamanya dalam konfigurasi yang lebih tertumpu—dikaitkan dengan inovasi teknologi yang lebih lemah, selaras dengan "kesan penyedutan" ruang di mana kapasiti berkaitan inovasi menjadi lebih tidak sekata di seluruh wilayah. Impak alam sekitar adalah heterogen: pengelompokan berasaskan pengkhususan cenderung untuk meningkatkan hasil alam sekitar tempatan, manakala kepekatan berketumpatan tinggi boleh menghasilkan limpahan negatif ke wilayah jiran, yang membayangkan luaran tadbir urus merentas wilayah. Pembaharuan penyelidikan ini terletak pada pembinaan rangka kerja ekonometrik ruang bersepadu yang bersama-sama menilai hasil ekonomi, teknologi dan alam sekitar serta menjelaskan mengapa dasar aglomerasi "satu saiz untuk semua" mungkin gagal dalam ekonomi ruang. Penemuan ini menyokong strategi perindustrian serantau yang berbeza, peruntukan ruang faktor inovasi yang lebih baik dan penyelarasan alam sekitar merentas wilayah yang lebih kukuh untuk memajukan pembangunan pembuatan yang mampan dan berkualiti tinggi di China.*

**Kata Kunci:** Penggabungan perindustrian; industri pembuatan; prestasi ekonomi; prestasi teknologi; prestasi alam sekitar

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## LIST OF ABBREVIATIONS

CBAM	Carbon Border Adjustment Mechanism
CGS	Centre for Graduate Studies
citylevel	Share of Urban Population in Regional Population
CNC	Computer Numerical Control
CNIPA	China National Intellectual Property Administration
CPC	Communist Party of China
CPI	Consumer Price Index
EBM	Epsilon-Based Measure model
ED	Employment Density
EKC	Environmental Kuznets Curve
EPI	Environmental Performance Index
fdi	Foreign Enterprise Direct Investment
FMS	Flexible Manufacturing System
fund	Volume of Scientific Research Funding
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
gov	Financial Expenditure on Science and Technology
GTFP	Green Total Factor Productivity
h	Level of Human Capital
HHI	Herfindahl-Hirschman Index
insti	Institutional Quality
k	Capital Investment Per Capita
LM	Langrange Multiplier
LQ	Location Quotient
NEC	National Economic Industry Classification
NEIC	National Economic Industry Classification
NRN	National Research Network
OECD	Organisation for Economic Co-operation and Development
pgdp	Per Capita Gross Domestic Product
PLC	Programmable Logic Controller
regu	Size of Manufacturing Firms
SCP	Structure-Conduct-Performance

SDGs	Sustainable Development Goals
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SLM	Spatial Lag Model
staff	Number of manufacturing personnel
TMT	Technology, Media, Telecommunications
UNIDO	United Nations Industrial Development Organization
UNIMAS	Universiti Malaysia Sarawak
WLB	Weighted Least Binary

CHAPTER 1:  
**INTRODUCTION**

## **1.1 Background of Study**

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Recent research and policy-oriented analyses highlight the strategic importance of upgrading China's manufacturing sector toward advanced and high-quality development, particularly in the context of supply-side restructuring and productivity improvement (Liu & Zhu, 2024). The manufacturing sector is a backbone of China's economy. According to official statistics, industry value added accounted for 33.6% of GDP in 2023, with manufacturing constituting the core component (National Bureau of Statistics of China, 2024). However, manufacturing development remains spatially concentrated in the eastern/coastal region, contributing to persistent regional disparities (National Bureau of Statistics of China, 2023). This spatial concentration is closely related to industrial agglomeration, because manufacturing activities tend to cluster in a limited number of core provinces and then shape the scale and structure of surrounding regions through interprovincial linkages. This concentration is accompanied by substantial environmental pressure, as industry has consistently accounted for more than 65% of national energy consumption in recent years (National Bureau of Statistics of China, 2023), highlighting the urgent need for a transition toward high-quality and sustainable development. Resource constraints further reinforce this urgency; despite hosting about 21% of the world's population, China has only about 6% of the world's freshwater resources (World Bank, 2018).

In addition to the east-west imbalance, manufacturing activity is unevenly distributed across provinces, implying substantial cross-provincial heterogeneity in industrial scale and structure. Given the spatial focus of this thesis, the Introduction provides only a brief overview of this heterogeneity, while detailed province-level evidence and discussions are presented in the Findings chapter to avoid redundancy. The manufacturing industry is the leading force of economic growth and transformation, the concentration of the level of productivity, and important support for economic and social development, and

people rely on the survival and development of basic industries. Since the establishment of the People's Republic of China, the manufacturing industry has experienced rapid development due to the introduction of advanced management concepts, science, and technology, resulting in an expansion of the industry's scale and improved scientific and technological content (Zhang & Yu, 2018).

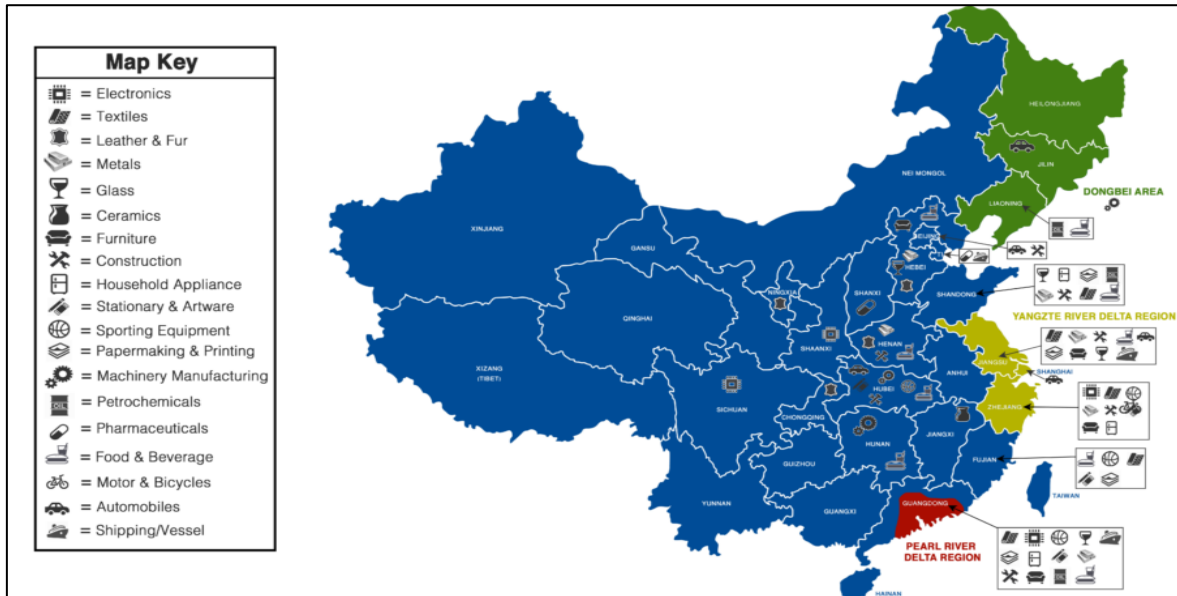
The regional architecture of China's manufacturing industry is characterized by imbalance, which is here to stay for the foreseeable future. Furthermore, the overall center of gravity for manufacturing development exhibits a shifting southwest-northeast-northwest pattern (Wang et al., 2021). The manufacturing sector in China is typified by uneven regional development and homogeneous clustering. Manufacturing inequalities are mostly caused by intra-regional variances, with the eastern region making the largest contribution, the western region coming in second, and the center region making the least (Meng & Cui, 2022).

These regional disparities are closely linked to the spatial concentration of manufacturing activities (industrial agglomeration). As firms cluster, they may generate productivity gains and resource sharing, but also create uneven innovation outcomes and environmental pressures across provinces, making agglomeration a central factor in explaining China's manufacturing performance differences. In practice, agglomeration can operate through multiple channels that differ across provinces, such as knowledge spillovers and specialized labor markets that raise innovation, supply-chain co-location that improves efficiency, and shared infrastructure that lowers production costs (Marshall, 2009). At the same time, clustering may intensify factor competition, widen gaps in innovative capacity, and amplify environmental burdens when pollution-intensive activities concentrate in a limited number of locations (Krugman, 1991). Importantly, these effects need not be confined within provincial borders, because interprovincial linkages can transmit both benefits and costs to neighboring regions, and environmental impacts may also exhibit spatial spillovers (Feng et al., 2019).

Cao and Wei (2024) identified that there are significant regional differences in the energy efficiency of China's manufacturing industry, with the energy efficiency in the eastern region generally higher than that in the central and western regions. This difference mainly stems from the differences in technology level, industrial structures and policy environments among regions. Many goods are produced in China, where the country is quite large and has a widely dispersed industrial sector. A map of China's manufacturing distribution in Figure

1-1, showing the locations of various industries' production facilities across the country's provinces, may be found below.

**Figure 1-1:  
Map of China Manufacturing Distribution**



Source: Berkeley Sourcing Group (2016).

Based on Zhang (2025), the current manufacturing landscape can be summarized into four key trends:

**(1) Digital Transformation**

The manufacturing industry is undergoing a digital transformation, utilizing technologies like IoT, big data, and artificial intelligence to enhance efficiency and product quality. This technological advancement not only boosts the industry's competitiveness but also encourages the growth of related industrial chains.

**(2) Rise of Emerging Markets**

Numerous developing nations have advanced in the manufacturing sector and grown to be significant participants in the global manufacturing industry. These nations are drawing the investment of numerous international corporations due to their enormous market potential and relatively cheap workforce. The worldwide manufacturing market is now more diversified as a result of this development.

### (3) Customized Production

Manufacturing businesses are gradually shifting to online sales channels as a result of the e-commerce industry's explosive growth. Customers may now personalize items to suit their demands, increasing product personalization and user experience. This is known as customized production, and it has grown popular in the manufacturing sector.

### (4) Green Manufacturing.

Nowadays, the core principles of sustainable development govern the industrial industry. The manufacturing industry is adopting environmentally friendly materials and green manufacturing techniques, automating processes at a rate never seen before, reducing resource waste and carbon emissions, and attaining sustainable development.

**Table 1-1:  
China Manufacturing Technology Development Path**

Stage	Marker	Zeitgeist	Production Pattern	Technical Characteristics	Manufacturing Equipment and Systems
<b>Industry 1.0</b>	Steam power	Steam Age	Small batch	Mechanization	Mechanization
<b>Industry 2.0</b>	Electricity and power	Electric Age	Mass-production	standardized, rigid automation	General machine tools, combined machine tools
<b>Industry 3.0</b>	Digital information	Information Age	Flexible production	Flexible automation, digitization, networking	CNC machine tools, composite machine tools, FMS, CIMS
<b>Industry 4.0</b>	New generation information	Intelligent Age	Networked collaboration, mass personalization	Human-machine-object interconnection, self-perception, self-analysis, self-decision, self-execution	Intelligent Equipment, Additive Manufacturing, Hybrid Manufacturing, Cloud Manufacturing, Cyber-Physical Production Systems

Source: China People's Daily (various years).

Based on the Table 1-1, after three rounds of mechanization, electrification, and informatization, China's manufacturing sector is currently transitioning to Industry 4.0, the fourth stage of intelligent development. From workshop-style mechanized manufacturing that depended on the talents of the workers to basic rigid automation and product uniformity, Industry 1.0 to Industry 2.0 achieved a change. In order to enable variable batch adaptable manufacturing, Industry 2.0 to Industry 3.0 accomplished more complicated automation with agile automation through the use of robotics, PLCs, advanced CNC machine tools, and industrial control systems. Industry 3.0 to Industry 4.0 realizations of these shifts include moving from a single manufacturing scenario to multiple hybrid manufacturing scenarios, from experience-based to evidence-based decision making, from visible problem solving to invisible problem avoiding, and from control-based machine learning to rich data-based deep learning.

In the past few years, China's relevant departments have persisted in putting relevant policies into action to support the growth of the manufacturing sector. In Table 1-2, the 14th Five-Year Plan (2021-2025), which was released in 2023 and focuses primarily on intelligent manufacturing as a national strategy, aims to increase the manufacturing sector's capacity for innovation and to promote the integration of the two sides. The overall layout of the construction of digital China plan is proposed in relation to agriculture, industry, finance, and education. The goal of the 2023 release of the Overall Layout Plan for the Construction of Digital China is to rapidly innovate and apply digital technology in vital sectors such as energy, transportation, healthcare, finance, and agriculture, while also guiding the trend of digital transformation. The following list of policy papers touches on the economic, technological, and environmental elements of China's manufacturing sector.

**Table 1-2:  
China's Manufacturing-Related Policies**

Times	Policy	Highlights
2023	Guidance on the promotion of casting and forging industry high-quality exhibition	By 2025, the overall level of the casting and forging industry will be further improved, and the ability to guarantee the security and stability of the supply chain of the equipment <b>manufacturing industry</b> chain will be significantly enhanced. The industrial structure will be more reasonable, and the industrial layout and production factors will be more synergistic.
2023	Action Plan for the Development of the Intelligent Testing Equipment Industry (2023-2025)	By 2025, intelligent testing <b>technology</b> to meet the needs of user areas of manufacturing processes, core components, special parts, and equipment supply capacity of the machine significantly improve the key areas of intelligent testing equipment demonstration and scale of the application of the effectiveness of the initial formation of the industrial ecosystem, and meet the needs of the development of intelligent manufacturing.
2023	Overall Layout Planning for the Construction of Digital China	Promote the deep integration of digital <b>technology</b> and the real <b>economy</b> , and accelerate the application of digital <b>technology innovation</b> in key areas such as agriculture, industry, finance, education, medical care, transportation, and energy. Support the development and growth of digital enterprises, improve the integration of large, medium, and small enterprises and innovation mechanisms, and play a "green light" investment case to guide the role of the platform to promote the standardized and healthy development of enterprises.
2022	A Guide to Digital Transformation for SMEs	In order to support the high-quality development of the real <b>economy</b> through the digital transformation of small and medium-sized enterprises (SMEs), the CPC Central Committee and State Council's decision-making and deployment processes are being put into practice. Policy synergy is being strengthened, scientific guidance is being reinforced, transformation cognition is being deepened, and work cohesiveness is being enhanced.
2022	The 14th Five-Year Plan for the Development of the Digital Economy	Based on the characteristics and differentiated needs of different industries, we will promote the digital transformation of traditional industries in an all-round and whole-chain manner, and improve the total factor productivity. Deeply implement intelligent manufacturing projects, vigorously promote equipment digitization, carry out intelligent manufacturing pilot demonstration special actions, and improve the national <b>intelligent manufacturing</b> standard system.
2021	The 14th Five-Year Development Plan for the Integration of Industrialization and Informatization	Digital transformation of the manufacturing industry as a key project, to promote raw materials, equipment manufacturing, consumer goods, electronic information, <b>green manufacturing</b> , safety production, and other key industry sectors to accelerate the digital transformation.

Source: China Association of Manufacturing Enterprises (various years).

China's manufacturing subsectors are classified according to the National Economic Industry Classification (NEIC); the detailed sector codes (C1–C30) are provided in Appendix Table 1.

According to Table 1-3, China's manufacturing sector shows an upward trend in the number of firms in all manufacturing subsectors between 2021 and 2022, indicating that China's manufacturing sector is still growing. In terms of total assets, although there are individual industries showing a downward trend, the overall state has risen. To provide descriptive evidence of manufacturing scale expansion, Table 1-3 reports enterprise counts and total assets by subsector.

**Table 1-3: Number of Enterprises and Total Asset Value of Manufacturing Segments in China, 2021-2022**

Industry	2021		2022		Change	
	Number	Value (billions)	Number	Value (billions)	Number	Value (billions)
C1	23128	33422.0	24289	36106.0	1161	2684.09
C2	8874	19040.2	9489	21256.3	615	2216.11
C3	5665	20521.3	5765	22452.6	100	1931.31
C4	122	11702.6	132	10726.0	10	-976.68
C5	19774	21840.8	20413	22120.4	639	279.56
C6	13168	11633.9	13618	11160.4	450	-473.52
C7	8308	7045.6	8555	6124.6	247	-920.94
C8	11205	5689.6	11992	6172.8	787	483.19
C9	7149	6957.6	7299	6956.0	150	-1.64
C10	7189	15922.1	7526	16387.9	337	465.80
C11	6579	7012.6	6840	7380.3	261	367.64
C12	9989	9561.6	10603	9449.3	614	-112.34
C13	2229	41344.1	2288	40972.4	59	-371.65
C14	23146	87710.0	24381	101194.3	1235	13484.35
C15	8629	44053.1	9231	47898.5	602	3845.39
C16	2084	10278.4	2224	11228.5	140	950.08
C17	23278	27449.4	25037	29197.5	1759	1748.08
C18	44086	73304.3	47220	80279.0	3134	6974.74
C19	5640	69199.8	5929	71697.2	289	2497.37
C20	8395	44470.7	9074	48161.0	679	3690.23
C21	31287	40862.0	34294	40559.7	3007	-302.33
C22	30511	56217.8	33114	59346.9	2603	3129.08
C23	23812	50541.9	25850	56851.6	2038	6309.70
C24	17254	89241.3	18108	99553.6	854	10312.27
C25	5646	31477.4	5957	32832.1	311	1354.70
C26	30305	89975.4	32626	107991.9	2321	18016.59
C27	24160	153315.6	26410	175815.0	2250	22499.43
C28	6032	13173.3	6644	14997.5	612	1824.24
C29	1956	3543.0	2149	4433.7	193	890.70
C30	2657	4666.7	3241	5983.3	584	1316.65
<b>Total</b>	<b>412257</b>	<b>1101173.9</b>	<b>440298</b>	<b>1205286.1</b>	<b>28041</b>	<b>104112.20</b>

Note: See Appendix 1 for the sectoral industrial classification.

Source: China Statistical Yearbook (2023).

Total asset value is employed as a key descriptive metric because it is a commonly used and relatively stable proxy for a sector's production capacity and capital accumulation, and is less volatile than annual profits. In this context, rising sectoral assets and enterprise counts are used to describe the expansion of manufacturing scale and capacity, which typically underpins growth in manufacturing output. As shown in Table 1-3, the aggregate assets of China's manufacturing sector increased by 104,112.20 billion (approximately 9.45%) from 2021 to 2022, alongside an increase of 28,041 enterprises, indicating continued expansion in industrial scale. Notably, asset growth is more pronounced in technology-intensive segments such as Electronic Equipment (14.68%) and Electrical Machinery (20.02%), which is consistent with the broader trend of upgrading toward higher value-added and more advanced manufacturing. It should be noted that total assets may also be influenced by valuation changes and restructuring; therefore, this indicator is used to describe broad scale and structural patterns rather than to measure productivity directly. To provide basic provincial context for the study sample, Appendix Table 2 summarizes key 2022 provincial manufacturing statistics; detailed province-level discussions are presented in the Findings chapter to avoid redundancy.

To provide a rigorous analytical foundation, this thesis conceptualizes manufacturing performance through three interconnected dimensions: economic, technological, and environmental. Industrial agglomeration influences these dimensions through (i) productivity-enhancing externalities, (ii) innovation spillovers versus resource siphoning, and (iii) environmental scale/abatement effects versus congestion and pollution spillovers, operating both locally and across regions.

Economic performance is operationalized using the efficiency/quality of manufacturing production factors, reflecting the effectiveness of factor utilization and production capacity. Industrial agglomeration is expected to shape economic performance via Marshallian externalities—such as labor market pooling, input sharing, and lower transaction costs (Marshall, 2009; Glaeser, 2010). Technological performance is proxied by the number of effective invention patents, capturing a region's independent innovation capacity. While proximity may facilitate knowledge spillovers, excessive agglomeration can also be associated with a spatial “siphoning effect,” whereby innovation-related resources become more concentrated in dominant hubs, potentially widening interregional innovation gaps (Jaffe et al., 1993; Audretsch & Feldman, 2019; Carlino & Kerr, 2015). Environmental

performance is measured by carbon intensity (the ratio of CO<sub>2</sub> emissions to GDP). Agglomeration may reduce carbon intensity through economies of scale, cleaner production, and shared abatement facilities, yet it may also increase local environmental pressure and generate transboundary spillovers under congestion effects (Fujita & Hu, 2001; Copeland & Taylor, 2013).

Together, these definitions and channels motivate an integrated assessment of trade-offs and spatial spillover logic when evaluating the net effects of industrial agglomeration on China's manufacturing development.

## **1.2 Problem Statement**

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China's manufacturing sector is navigating a critical transition toward high-quality growth, yet this process is increasingly constrained by uneven economic efficiency, weak innovation capacity, and mounting environmental pressures across provinces (Yu, 2023; Yang et al., 2022). Industrial agglomeration has emerged as a defining spatial feature of this restructuring; however, its net effects on manufacturing performance remain ambiguous when economic, technological, and environmental outcomes are considered jointly (Huang et al., 2022; Nie et al., 2023; Zhu et al., 2025).

Prior research tends to assess agglomeration effects in a single dimension and often without a unified spatial framework, leaving critical multidimensional trade-offs and spillover mechanisms inadequately addressed (Li et al., 2023). In the economic dimension, while agglomeration can foster industrial optimization and efficiency (Hui & Han, 2016), excessive concentration may exceed regional carrying capacity, intensifying competition for resources and eroding enterprise profitability (Sun et al., 2013). Moreover, existing studies predominantly focus on local effects, largely overlooking spatial interdependencies whereby high agglomeration in one region may impede neighboring development through resource siphoning (Su, 2020; Yanping, 2022).

In the technological dimension, the role of agglomeration in driving innovation remains mixed and contested (Xu et al., 2019; Kafetzopoulos, 2015). Although intended to facilitate knowledge spillovers, intense competition and weak intellectual property protection within clusters often result in technology imitation and "innovation lock-in," dampening firms' incentive to innovate and hindering genuine technology diffusion (Meiling & Chao, 2025; Xie, 2020; Xin, 2021; Meng, 2025).

In the environmental dimension, the relationship between manufacturing agglomeration and environmental performance is characterized by a duality of outcomes (Wu et al., 2022). Agglomeration may reduce pollution per unit output through economies of scale (Ming et al., 2023), yet concentrated industrial activities simultaneously exacerbate local ecological stress and shift environmental burdens to neighboring areas (Sun et al., 2021). Current literature insufficiently captures these externalities, particularly through quantitative spatial spillover analysis, leaving a critical gap in coordinating industrial layout with ecological protection (Chen & Ma, 2023; Chen et al., 2023).

To address these gaps, this study adopts a spatial econometric perspective to investigate how different forms of industrial agglomeration shape economic, technological, and environmental performance, with explicit attention to spatial dependence and cross-regional spillover effects.

### **1.3 Research Questions**

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The research questions for this study are as follows:

Q1: To what extent does industrial agglomeration affect the economic performance of China's manufacturing sector, and how do the local effects differ from spatial spillover effects across provinces?

Q2: Does industrial agglomeration enhance or inhibit technological performance, and to what extent does it generate a cross-regional "siphoning effect" through spatial spillovers?

Q3: Under what conditions does industrial agglomeration improve or worsen environmental performance, and to what extent are there cross provinces environmental spillovers?

### **1.4 Objectives of the Study**

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The primary objective of this study is to systematically evaluate the effects of industrial agglomeration on the multidimensional performance (economic, technological, and environmental) of China's manufacturing sector using a Spatial Durbin Model to account for spatial interdependencies and regional heterogeneity.

- 1) To measure the direct impact and spatial spillover effects of industrial agglomeration on the economic performance of the manufacturing industry.
- 2) To analyze the direct impact and spatial spillover effects of industrial agglomeration on technological performance of manufacturing industry.
- 3) To assess the direct impact and spatial spillover effects of industrial agglomeration on the environmental performance of the manufacturing industry.

## **1.5 Scope of the Study**

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This study aims to explore the impact of industrial agglomeration on the technological, economic, and environmental performance of China's manufacturing sector. To assess the relationship between industrial agglomeration and various performance indicators of China's manufacturing sector, this study collected manufacturing data from 30 provinces and cities in China excluding Tibet, Hong Kong, Taiwan and Macao that were publicly available from 2008 to 2022. These three regions are excluded due to the unavailable data.

### **1.5.1 Study Area: Reasons for Selection**

China (Figure 1-2) has a land area of about 9.6 million square kilometers, with a continental coastline of more than 18,000 kilometers in the east and south, and a total sea area of about 4.73 million square kilometers. By the end of 2020, China had 34 provincial-level administrative regions (including 23 provinces, 5 autonomous regions, 4 municipalities directly under the central government, and 2 special administrative regions).

China is a large country with a varied and complicated topography. As a result, different geographic factors influence industrial growth differently, and different sectors are appropriate for development in different regions. Geographical conditions determine the distribution of resources. China's abundant natural resources provide the basis for industrial development. For example, the wealth of coal and iron ore resources in the northeastern region provides an advantage for the local iron and steel industry.

Geographical conditions in China impact transportation and logistics. Eastern coastal regions have favorable sea and land conditions, fostering export-oriented economies and

manufacturing industries, while the western region faces complex terrain and poor transportation, hindering industrial growth.

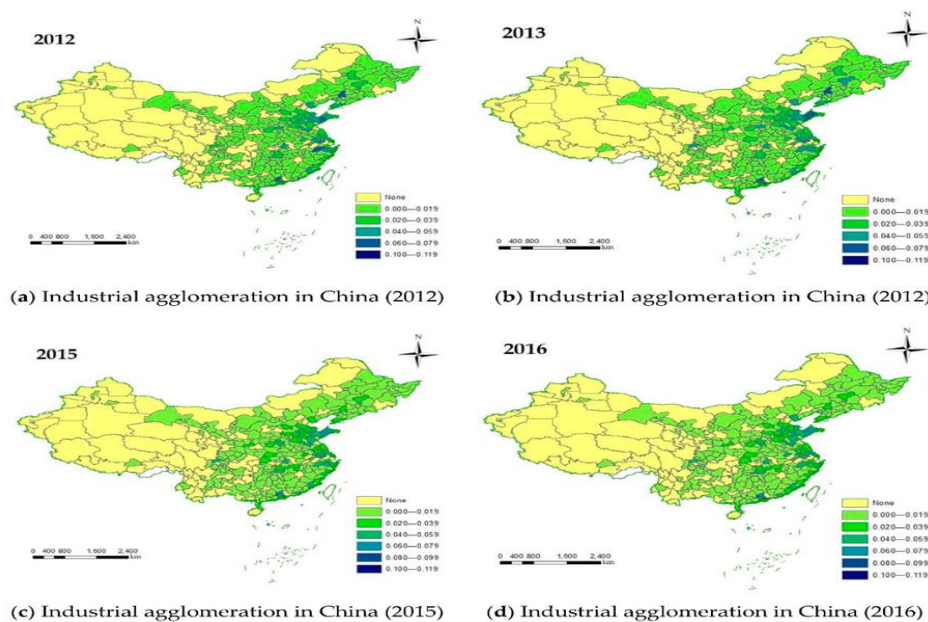
**Figure 1-2:  
Map of China**



Source: Ministry of Natural Resources of the People's Republic of China (2020).

Figure 1-3 shows that the spatial distribution characteristics of China's industrial agglomeration did not change significantly from 2012 to 2016, indicating that the distribution characteristics of China's industrial agglomeration are relatively stable, and also reflecting the distribution of China's industries in various regions.

**Figure 1-3:  
Spatio-Temporal Distribution of Industrial Agglomeration in China**



Source: (Dai & Lin, 2021).

Different provinces have developed 14th Five-Year Plans related to their own industries according to their own industrial agglomeration. Table 1-4 shows the 14th Five-Year Plan industrial policies and key development industries in selected cities.

Table 1- compares the key industrial policies of Shanghai, Beijing, Shenzhen, Chongqing, and Guangzhou during the 14th Five-Year Plan period: Shanghai focuses on cutting-edge technology, Beijing develops high-end industries, Shenzhen strengthens its advantages in electronics and information technology, Chongqing promotes the upgrading of traditional industries, and Guangzhou concentrates on the consumer goods industry. Policy documents indicate that the first three cities prioritize technological innovation, while the latter two focus more on manufacturing upgrades. This reflects both the potential for regional industrial synergy and the possibility of industrial competition. This strategic layout not only highlights the potential for regional industrial collaboration but also points to potential competitive issues arising from overlapping industries, providing a foundational framework for future research into the effectiveness of regional industrial policies.

**Table 1-4:  
Fourteenth Five-Year Industrial Policy and Key Development Industries in Some Region**

<b>Region</b>	<b>Key Industries</b>	<b>Policy Paper</b>
<b>Shanghai</b>	New Energy Vehicles, High-end Equipment, Aerospace, Information Communication, New Materials, Emerging Digital Industries Pilot Industries: Photonic Chips and Devices, Gene and Cell Technology,	Shanghai's 14th Five-Year Plan for the Development of Strategic Emerging Industries and Pilot Industries
<b>Beijing</b>	Integrated Circuits, Intelligent Networked Vehicles, Intelligent Manufacturing and Equipment, Green Energy and Energy Saving and Environmental Protection, Innovative Linkage Industry Technology Services	Beijing's 14th Five-Year Plan for the Development of High Precision Industries
<b>Shenzhen</b>	Electronic information, high-end manufacturing equipment, green low-carbon, new materials, biomedicine and health	Shenzhen Science and Technology Innovation 14th Five-Year Plan
<b>Chongqing</b>	Biomedicine, advanced materials, green environmental protection, automobiles and motorcycles, equipment manufacturing, consumer goods, raw materials	The 14th Five-Year Plan for High-Quality Development of Chongqing Manufacturing Industry
<b>Guangzhou</b>	Textile and apparel, beauty and daily necessities, smart home appliances, jewelry, food and beverages	Guangzhou Industry and Information Technology Development 14th Five-Year Plan

Source: Official website of government agencies (various years).

Therefore, the study of industrial agglomeration in China's manufacturing industry needs to be categorized into China as a whole as well as individual regions, and the importance of studying industrial agglomeration is demonstrated by examining the impact of industrial agglomeration on the performance of different geographic regions.

To align the scope of this thesis with the measurement of industrial agglomeration, three complementary indicators are introduced as the core explanatory variables, namely Location Quotient (LQ), Employment Density (ED), and the Herfindahl–Hirschman Index (HHI). Location Quotient (LQ) measures a province's manufacturing specialization relative to the national average, indicating whether manufacturing activity is disproportionately concentrated in that province in comparative terms. Employment Density (ED) is defined as the intensity of manufacturing employment within a given geographic space (e.g., manufacturing employment per unit area), capturing how tightly manufacturing jobs are spatially packed within a province. This indicator directly relates to the study scope because it reflects labour pooling and possible congestion pressures that may shape provincial manufacturing economic, technological, and environmental performance. HHI captures the internal concentration structure of manufacturing by summarizing how concentrated (or diversified) the industrial composition is within a province. Together, LQ (specialization), ED (spatial intensity), and HHI (structural concentration) allow the thesis to examine how different dimensions of agglomeration are associated with manufacturing triple performance across 30 Chinese provinces over 2008–2022. Detailed variable construction, equations, data sources, and the spatial weight matrix are provided in Chapter 3.

## **1.6 Significance of Study**

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By studying the impact of industrial agglomeration on the economic performance, technological performance, and environmental performance of China's manufacturing industry, the study will further explore the deep-rooted reasons for the low level of performance of China's manufacturing industry, and provide certain theoretical support and practical guidance for realizing the enhancement of China's manufacturing industry's performance level, and promoting the development of China's manufacturing industry's innovation-driven development and energy-saving and emission reduction.

Industrial agglomeration is a significant trend in China's manufacturing industry, impacting its performance in both positive and negative ways. The spatial heterogeneity of

industrial agglomeration leads to differences in manufacturing performance levels (Yuan et al., 2023). Therefore, it is crucial to study the intrinsic mechanisms of industrial agglomeration's influence on China's manufacturing industries' performance in economic activities, scientific and technological innovation activities, and environmental protection activities. China's manufacturing industry struggles with low performance, hindering its transformation from big to strong. Optimizing industrial layout and agglomeration is crucial for improving performance (Fuyuan et al., 2020).

This study holds significant value both theoretically and practically. Theoretically, by constructing a three-dimensional analytical framework of “economy-technology-environment,” it overcomes the limitations of traditional research that focuses on single performance indicators, deepens our understanding of the complex mechanisms underlying industrial agglomeration externalities, and provides new empirical evidence for spatial economics and new economic geography theories. Methodologically, the innovative application of the Spatial Durbin Model to decompose local effects and spatial spillover effects overcomes the shortcomings of traditional measurement methods that neglect spatial dependence, providing more precise analytical tools for regional industrial research.

At the practical level, the research findings offer a scientific foundation for government departments to formulate diversified regional industrial policies. Such policies may include the optimization of environmental regulation in agglomeration areas, the promotion of technological spillover, and the coordination of regional industrial layout. This has significant guiding value for promoting the coordinated development of China's manufacturing industry with high quality and the construction of an ecological civilization.

## **1.7 Organization of Study**

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The report is organized into seven chapters. The chapters are organized as follows:

Chapter 1	Provides an overview of China’s manufacturing industry, outlines relevant policies, and explains the background of industrial agglomeration, economic, technological, and environmental performance. Clarifies the problem statement, research questions, research objectives, scope of study, and significance of study.
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- Chapter 2            The system reviewed theories and empirical literature related to the research objectives, identified research gaps, and constructed a conceptual framework of the study.
- Chapter 3            Focus on research methodology, including methods for measuring industrial agglomeration, economic performance, technological performance, and environmental performance, then setting of research hypotheses, and the construction of relevant models and analysis.
- Chapter 4            A systematic empirical analysis was conducted on the impact of manufacturing agglomeration on economic, technological, and environmental performance. Through model robustness testing, data analysis, research findings, and in-depth discussion, conclusions were ultimately drawn.
- Chapter 5            This thesis summarizes the main conclusions of this study, discusses its contributions to research on the concentration of China's manufacturing industry, its theoretical and policy implications, and points out its limitations. It also offers directional suggestions for future related research.

# LITERATURE REVIEW

## 2.1 Introduction

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This chapter firstly briefly reviews the theory of industrial agglomeration and the theory of manufacturing performance, and then collates, analyzes and reviews the domestic and foreign research on industrial agglomeration and manufacturing economic performance, technological performance, environmental performance and other systematic research, describes the contents of China's manufacturing industry, and finally puts forward the research gaps that exist at present.

## 2.2 Theoretical Literature

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Industrial agglomeration first emerged in the early 1800s, and industries such as iron and steel, cars, handicrafts, and other manufacturing sectors are more prone to establish industrial spatial agglomeration. Western scholars first became interested in industrial agglomerations at the end of the 19th century. After hundreds of years of research by numerous scholars, academics in the area have developed a wealth of theoretical results. As a result, economic geography, regional economics, management, and industrial economics have gradually become hotspots for research.

### 2.2.1 Industrial Location Theory

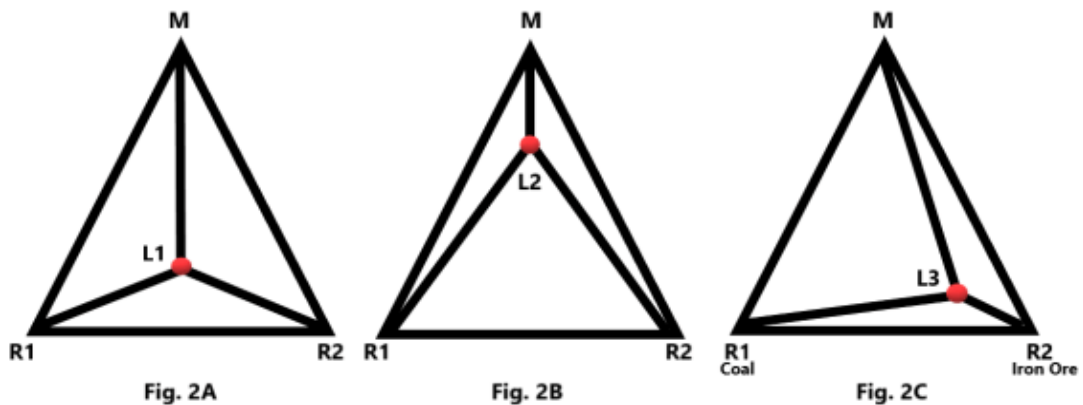
Industrial location theory focuses on the optimal location of industrial facilities, taking into account factors such as proximity to resources, markets and labor. The theory emphasizes the importance of place in industrial development because place influences the capacity of industry and resource. Although this perspective was originally developed to explain firms' location choices, it also implies that manufacturing activity and performance will be geographically uneven because production costs and market access vary across space.

However, much of the classic location literature pays greater attention to cost-minimizing location decisions than to how location-driven clustering generates interregional performance gaps, which is precisely the empirical concern of this thesis. In this thesis, the “importance of place” is operationalized as cross-provincial differences in manufacturing performance and industrial agglomeration.

Weber formulated his famous theory of industrial location in 1909. Weber developed the concept of the location triangle, which emphasizes the strategic positioning of factories between raw material sources and markets to optimize production and distribution (Church, 2023). Weber classified the factors affecting industrial distribution into two broad types: (1) Regional factors or primary causes of regional distribution of industries. (2) Agglomeration and fragmentation factors or secondary causes of industrial redistribution. Weber states that labor costs and transportation costs are the two main regional factors that have an impact on production costs. Building on this distinction, this thesis treats (i) regional conditions (e.g., factor endowments and development level) as the spatial background captured through controls and fixed effects, whereas (ii) agglomeration forces are the core explanatory mechanism shaping manufacturing performance. Nonetheless, Weber’s framework is primarily cost-oriented and does not explicitly model modern channels such as innovation spillovers or environmental externalities; thus, the thesis extends the location logic by examining whether agglomeration generates multidimensional outcomes (economic, technological, environmental) and whether these effects diffuse across provincial boundaries through spatial spillovers.

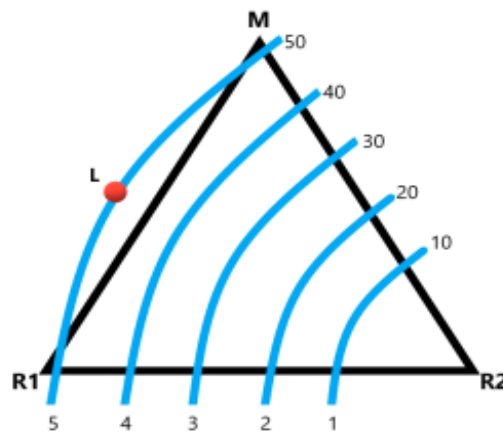
Figure 2-1 illustrates Weber's Location Triangle model, which shows three scenarios with two raw materials and one market. It demonstrates how factories choose locations to minimize total costs—particularly transportation—by balancing distances to inputs and markets. Although this thesis does not directly estimate transportation-cost minimization, the location triangle provides an intuitive justification for why provinces differ in industrial placement and why manufacturing performance varies across space, which motivates the use of a spatial framework to capture heterogeneity and spillovers.

**Figure 2-1:  
Weber's Location Triangle**



Weber makes the assumption that although worker salaries fluctuate, labor supply is consistent across places, as seen in Figure 2-2. Changes in wage rates will also affect industrial location. Weber thinks that placing the industry at point L5 is a cost-effective and lucrative position when taking labor and transportation expenses into account. In this thesis, this logic is reflected by treating factor-cost differences and regional conditions as part of the spatial background, while focusing empirically on how agglomeration relates to performance.

**Figure 2-2:  
Impact of Labor Cost on Industrial Location**

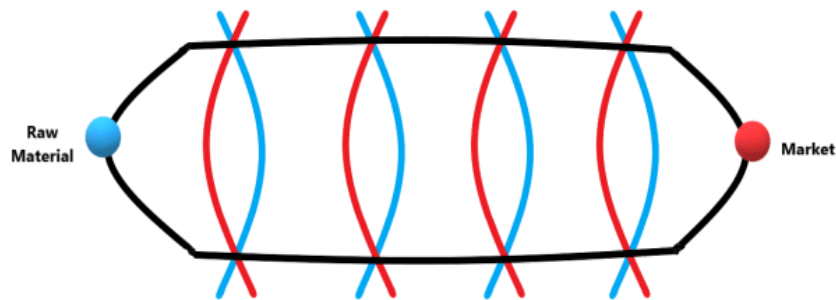


Weber further demonstrates the effect of industrial agglomeration through Isodapane (Figure 2-3), which connects locations with equal total costs (transportation + labor). Weber argues that agglomeration can reduce costs of labor, raw materials, technology, and transportation through externalities. This “agglomeration externalities” argument directly links to this thesis, agglomeration may enhance economic performance via cost reduction

and resource sharing; however, it may also generate congestion and excessive competition, reducing profitability. This duality provides the theoretical motivation for testing both positive and negative effects and for distinguishing local effects from spatial spillovers.

Nonetheless, industrial location theory has notable limitations. In particular, it may overemphasize transportation costs and understate the roles of government policy, institutions, and political factors in shaping industrial patterns. These critiques are relevant to this thesis because they justify moving beyond a single-cost explanation toward a broader spatial framework that allows for policy, regional conditions, and interregional interactions to shape outcomes.

**Figure 2-3:  
Isodapane**



McCann and Van Oort (2019) argue that production costs and agglomeration in addition to transportation costs, industrial location examines the impact of two other factors on site selection, spatial variation in production costs and agglomeration economies. The theory of industrial location should also articulate several issues around this concept, including the historical context, the declining importance of transportation costs, and local labor force characteristics and local agglomeration economy characteristics. However, this also implies that “location” is no longer explained by transport costs alone but by multi-factor spatial forces. Consistent with this view, the thesis treats industrial agglomeration as a spatial economic force and explicitly tests whether its impacts extend beyond the province through spillover effects, which cannot be captured by a purely local (non-spatial) approach.

Zhou et al. (2022) spotlight Chinese firms' investments in European industry clusters. Starting from the industrial location theory and knowledge base perspective, it explores how knowledge-related characteristics of TMTs, such as educational background, overseas

experience, and R&D experience, affect firms' overseas direct investment decisions in industrial clusters. This knowledge-base perspective connects to the technological dimension of this thesis, in that agglomeration may facilitate knowledge diffusion and innovation, yet may also concentrate high-level innovation resources in core provinces, potentially creating spatial “siphoning” and uneven technological performance. Therefore, the thesis explicitly considers spatial dependence when evaluating technological outcomes.

Balletto et al. (2019) apply the theory of industrial localization and puts it into the context of modern building construction and the circular economy debate. Their study explores the application of the theory to a real case study involving stadium construction, contributing to the development of an improved model of industrial localization based on circular economy principles. Nonetheless, the study confirms that Weber's industrial localization theory lacks consideration of circular economy principles and focuses primarily on material sourcing and waste disposal. This critique motivates incorporating environmental considerations in evaluating manufacturing development. In this thesis, environmental performance (e.g., carbon intensity) is treated as a core outcome rather than an external afterthought.

Sorting out the environmental theories of industrial siting with a focus on determining the optimal location for a business, the importance of considering environmental factors in industrial siting decisions is discussed, mainly environmental regulations, ecological impacts, climatic factors, transportation infrastructure, and community relations, emphasizing how these factors can affect the overall sustainability and efficiency of a business (Shankar, 2023). This supports the environmental channel of the thesis, agglomeration may improve environmental performance via cleaner technology diffusion and shared abatement, but conversely it may also intensify local environmental pressure and create cross-boundary spillovers—therefore environmental outcomes must be evaluated jointly with economic and technological outcomes.

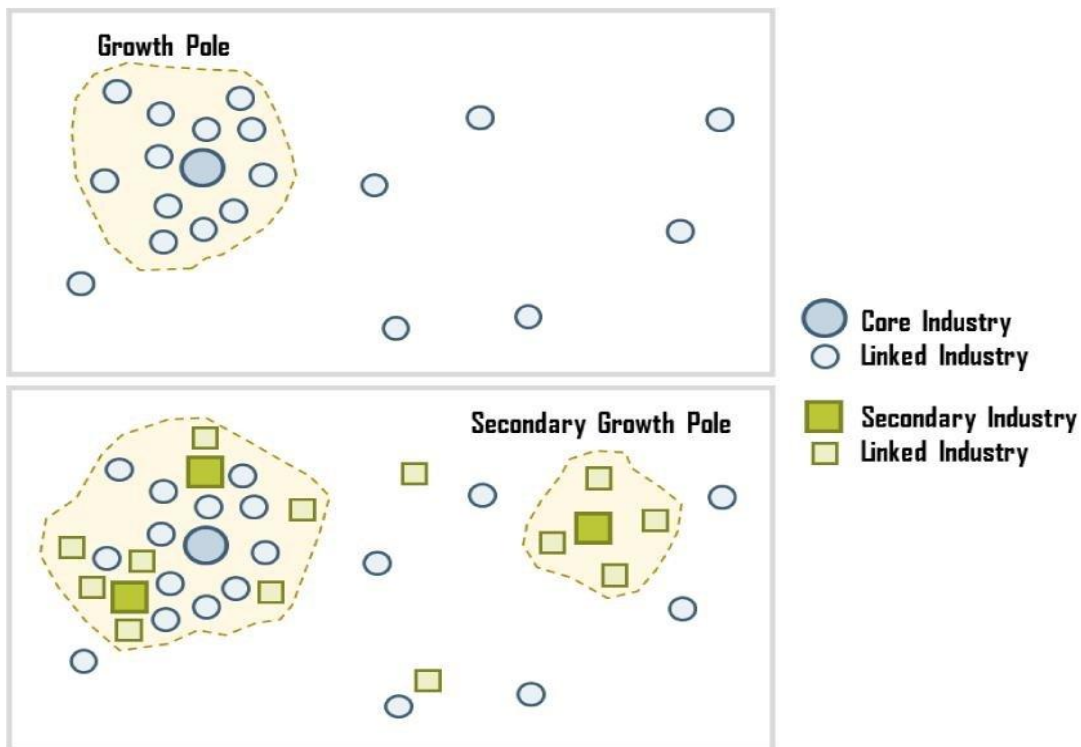
Overall, industrial location theory explains why manufacturing activities and performance outcomes are spatially uneven across provinces and why “place” matters. Weber’s agglomeration externalities provide the theoretical basis for testing the effects of industrial agglomeration on economic performance, while knowledge-base arguments motivate the technological mechanism, and environmental siting/circular economy perspectives motivate the environmental mechanism. Taken together, these perspectives justify not only the choice of a spatial econometric model, but also the thesis’s integrated

“economic–technological–environmental” framework and the explicit estimation of spatial spillovers in the empirical model.

### 2.2.2 Growth Pole Theory

Perroux created the growing pole idea in 1555. According to this theory, growth poles are the main forces behind a region's development and economic activity are its growth poles. The fundamental tenet of this theory is that, as a result of the trade of products and services, the expansion of a major city propels the growth of all surrounding areas. As shown in Figure 2-4 below, a growth pole represents an abstract area of the economy that serves as a center from which industries then radiate to peripheral areas and products are attracted to the center to add value. The three main characteristics of growth poles are homogeneous space, economic plan, and centrifugal and centripetal forces emanating from the growth pole (Perroux, 1955). In this study, outward effects correspond to diffusion/spillover (technology, capital, supply-chain linkages), while inward effects correspond to siphoning (resource and talent concentration). Therefore, this directly motivates testing spatial spillovers in the empirical model, especially to identify whether outward diffusion or inward siphoning dominates across provinces in each performance dimension.

**Figure 2-4:  
Growth Pole Theory**



Growth pole theory is based on Schumpeter's theory on the role of innovation and large firms in economic growth, with a major emphasis on the development of innovative technologies. According to Schumpeter (1942), the spread of technical advancements causes business clusters with connections between industries to arise. Since innovations are rarely single occurrences, they are not dispersed equally throughout time; rather, they typically occur in groups or clusters. Therefore, this provides the theoretical basis for using technological performance (e.g., patents) as a key dimension and for expecting innovation to cluster spatially rather than distribute evenly across provinces, which aligns with this thesis's spatial focus on technology spillovers and possible innovation polarization.

According to Perroux (1955), growth poles are groups of sectors that trade commodities with one another. Many benefits or externalities are provided to new enterprises by this agglomeration. A company's inventions are shared by other firms and sectors, contributing to the general expansion of the economy. Businesses and industries also expand quickly and are very inventive. However, most growth-pole applications emphasize economic expansion, whereas this thesis extends these arguments to a three-dimensional performance framework (economic–technological–environmental), asking whether the same agglomeration dynamics that boost productivity and innovation may also create environmental pressures and transboundary externalities.

Benedek et al. (2022) elucidated the utilization of the growth pole idea in scholarly domains including regional economics and spatial planning, with a focus on Central and Eastern Europe. Along with the need for more creative and transformative approaches to spatial planning in order to achieve sustainable development goals in metropolitan areas, the impact and efficacy of growth pole policies in addressing spatial inequalities and promoting balanced regional development were underscored. In this sense, this supports the policy relevance of our analysis, identifying whether agglomeration reduces or widens inter-provincial gaps via spatial spillovers.

Based on the growth pole theory, Liu et al. (2022) proposed a theoretical framework and hypotheses on the relationship between environmental rights trading policies, government competition, market competition and regional green innovation. Their study provides rich experience in the promotion and application of environmental rights trading policies, and offers a policy basis for realizing the goals of peak carbon and carbon neutrality. Importantly, this links to our environmental performance dimension by highlighting that

environmental outcomes and green innovation are shaped by interregional interactions—consistent with our spillover-focused empirical design, and motivating the inclusion of spatial dependence when evaluating environmental effects.

Eraydın (2020) discussed the shift from regional focus to clusters and nodes, and the shift from development to growth challenges. She highlighted anticipated changes in the global economy, including automation, artificial intelligence, digitalization, public service changes, and labor market changes. Taken together, these insights contextualize why China’s manufacturing upgrading may intensify “pole effects” in leading regions, reinforcing the need to test heterogeneity and spillovers rather than assuming uniform impacts.

Overall, Growth Pole Theory provides the spatial mechanism for this thesis by linking industrial agglomeration to core–periphery dynamics and diffusion versus siphoning effects across provinces. Although the thesis extends the growth-pole literature beyond economic growth by jointly evaluating economic, technological, and environmental performance and their spatial spillovers.

### **2.2.3 Agglomeration Economies Theory**

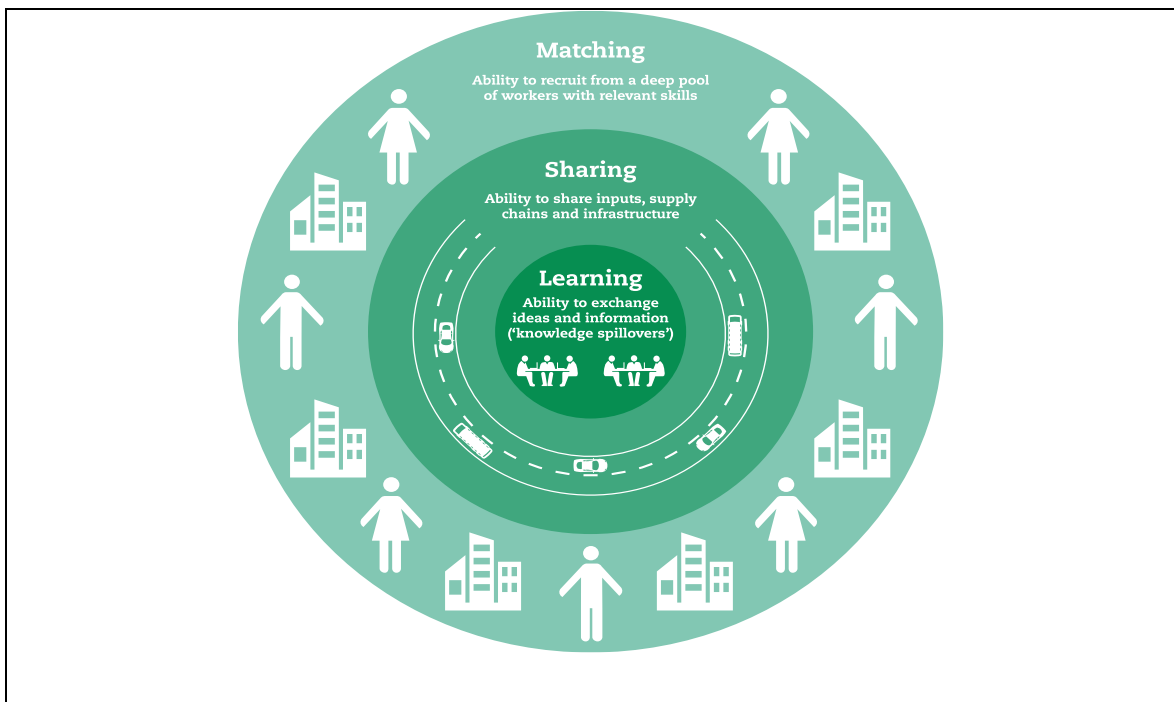
Agglomeration economies are the cost benefits that businesses and sectors experience when they are located adjacent to one another. Businesses can take advantage of various external economies of scale due to their close proximity, which boosts innovation, productivity, and total economic growth in a particular region. In this thesis, agglomeration economies provide the core theoretical rationale for expecting industrial agglomeration to affect manufacturing performance, and they motivate a spatial framework in which these effects may extend beyond provincial borders through spillovers.

Gomez-Lievano and Fragkias (2025) explored agglomeration economies from an economic and complex systems perspective, arguing that agglomeration corresponds to urban growth, resulting in productivity gains in the form of increasing returns to scale and generating positive externalities. Agglomeration economies bring higher productivity to firms and workers. The benefits of agglomeration increase with size because as the size of the market increases, so does the opportunity to achieve better economic outcomes. This supports the thesis’s focus on testing whether agglomeration structures deliver performance gains, and whether these gains diffuse spatially rather than remaining purely local.

Agglomeration economies offer benefits for urban production through sharing, matching, and learning. They reduce fixed costs by sharing facilities, intermediate suppliers,

workers, and consumers, encourage specialization, and pool risk. Markets facilitate easy interaction between different types of workers and employers, leading to faster job-worker matching. Agglomeration economies also facilitate the transfer of information, knowledge, and skills, and the creation of new ideas. As shown in Figure 2-5 below. These three channels directly align with the mechanisms examined in this thesis: (i) sharing and matching underpin economic performance improvements, (ii) learning supports technological performance (innovation), and (iii) intensified production may also create environmental pressures, implying potential trade-offs and cross-regional externalities that the spatial model is designed to capture.

**Figure 2-5:  
The Benefits of Agglomeration**



In the mid-1980s, Paul Romer studied the relationship between innovation and economic growth and argued that innovation has a very different intrinsic characteristic from commodities, which is its non-rivalry, i.e., innovations are not exclusive to the innovating firms, and other firms benefit from technological spillovers; and that the payoffs of innovations to the firms' factor accumulation are constant, but the payoffs to the nation's total factor accumulation are incremental. Romer incorporated these unique attributes of innovation into his model of economic growth, from which the new theory of economic growth emerged (Jiguang & Guangen, 2005). Building on this spillover logic, this thesis treats technological performance (e.g., effective invention patents) as a core outcome and

expects that innovation gains may extend beyond provincial borders—however, whether such benefits actually diffuse, and how far they travel, is ultimately an empirical question that requires a spatial framework.

Consistent with this mechanism-based view, Bolter and Robey (2020) argued that the advantages of an agglomeration economy can be recounted in three ways: (1) Sharing infrastructure is more efficient for firms, lowering transportation costs and making logistics easier. (2) Agglomeration brings in a large pool of laborers with specialized knowledge, which allows for a better match with corresponding firms. (3) Agglomeration produces knowledge spillovers, whereby Workers advance while firms advance. They believed that the most important factors driving agglomeration are an educated labor force and a skilled labor pool. This directly informs the thesis's control and mechanism logic, human capital is treated as a key driver that can strengthen the productivity and innovation effects of agglomeration, and the spatial framework allows us to assess whether these benefits are concentrated in leading provinces or diffuse to neighboring regions.

Empirical evidence further suggests that spillovers are often geographically bounded. Jofre-Monseny et al. (2011) discussed mechanisms related to agglomeration economies and the mechanisms that induce firms to coexist geographically, identifying three agglomeration mechanisms, namely labor market agglomeration, input sharing, and knowledge spillovers. The results suggested that labor market agglomeration is the most important agglomeration mechanism and that knowledge spillovers may also be relevant, but only at a very local level. Keller (2002) empirically verified that technology diffusion and R&D spillovers have strong spatial limitations, which decay with increasing geographical distance. These findings justify two key design choices in this thesis: (i) adopting a spatial econometric model (SDM) to distinguish local effects from spillovers, and (ii) allowing spillovers to depend on geographic proximity (via the spatial weight matrix), consistent with the idea that knowledge/technology spillovers weaken as distance increases.

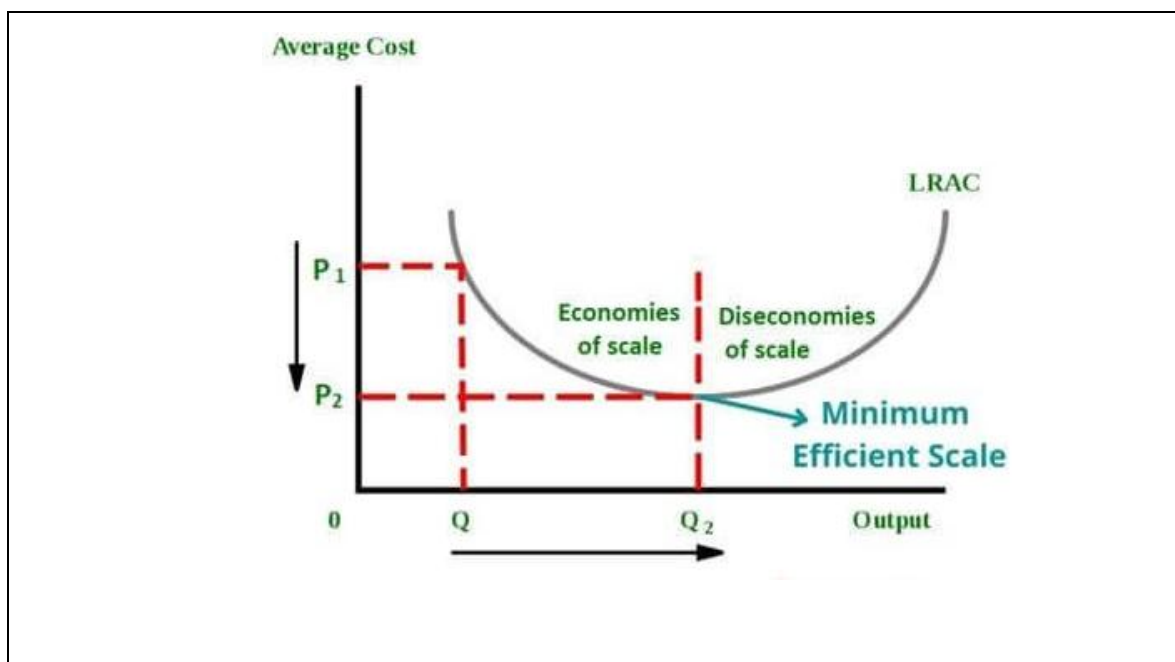
#### **2.2.4 Economies of Scale Theory**

Marshall (2009) introduced two important concepts, namely internal economies of scale and external economies of scale. The concept of external economies of scale refers to cost advantages accruing to firms in a region due to industrial clustering. By examining the phenomenon of enterprise clusters in some traditional industries in the United Kingdom,

Marshall found that there is a close connection between external scale economies and enterprise clusters, he believed that enterprise clusters are formed on the basis of external scale economies. Marshall argued that external economies of scale and internal economies of scale are equally important and effective industrial organization. Such economies can usually be obtained by concentrating many small enterprises of a similar nature in a particular place, which is often referred to as the regional distribution of industries. In this thesis, Marshall's external economies provide the core mechanism linking industrial agglomeration to manufacturing performance, because clustering can lower unit costs and improve efficiency (economic performance) and may also diffuse benefits across neighboring provinces through spatial spillovers. Nonetheless, the same concentration can also intensify competition for labor, land, and inputs, implying that the net effect is empirical rather than universally positive—hence the need to test both local and spillover effects.

As shown in Figure 2-6, economies of scale are the cost efficiencies that firms gain by expanding production. This benefit is due to the allocation of fixed costs incurred as the number of units produced increases. In this study, economies of scale are used to justify why agglomerated provinces may achieve higher manufacturing efficiency and output quality, motivating the empirical test of local effects and spillover effects.

**Figure 2-6:  
Economies of Scale**



Marshall emphasized the advantages of mass production in economies of scale, including economies of technology, machinery, and raw materials. Large firms have access to efficient machinery, enhancing productivity. Machine economies provide low prices and efficient transportation, while aggregation of firms reduces labor costs. Information spillovers make clustered firms more productive, and regional knowledge spillovers facilitate regional knowledge exchange. Although this classic view highlights efficiency gains, it tends to treat spillovers as broadly beneficial and does not fully address potential crowding or unequal diffusion across places. Beyond economic efficiency, these spillovers also imply potential links to technological performance (innovation diffusion) and, under scale expansion, possible environmental pressures—therefore requiring a multidimensional assessment rather than a single economic outcome.

Prior studies also show that cost efficiency and productivity improvements can be achieved through scale-related mechanisms; however, much of this evidence is firm-level and does not examine cross-regional spillovers, which is the focus of this thesis.

Buchi et al. (2018) highlighted the impact of Industry 4.0 technologies on productivity and economic outcomes in mass production environments. Kariel and Savagar (2024) explore the link between economies of scale and total productivity, emphasizing the importance of economies of scale for businesses and policymakers to enhance efficiency and competitiveness. Despite these contributions, existing studies are often confined to economic/productivity outcomes and pay less attention to the joint technological and environmental consequences under spatial dependence. Building on these insights, this thesis extends the scale-economy logic to a spatial setting by testing whether agglomeration-driven efficiency gains (economic) are accompanied by innovation outcomes (technological) and environmental consequences (environmental), including potential spillovers across provincial boundaries.

Overall, Marshall's scale-economy framework explains why agglomeration can improve manufacturing efficiency through external economies, while this thesis extends the logic by examining whether such gains—and related knowledge spillovers—translate into technological and environmental outcomes and diffuse across provinces under spatial dependence.

## 2.3 Brief Review of Performance

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Although prior studies provide useful definitions of performance from different angles—such as input–output efficiency and objective attainment (Pepall et al., 2014), job/behavioral outcomes (Bernardin & Kane, 1993; Rong & Mingli, 2011), innovation-related contributions at the employee level (Janssen & Van Yperen, 2004), and management-oriented “hard vs. soft” performance indicators (Guangshun, 2010)—these perspectives were largely developed for organizations or individuals rather than for comparing regional manufacturing performance across provinces.

Nonetheless, the literature consistently implies two common pillars, namely effectiveness (achievement of goals) and efficiency (output relative to inputs) (Chao, 2011; Haochang, 2018). Conversely, environmental-performance studies offer more explicit measurement logic (e.g., eco-efficiency and technology components) (Kortelainen, 2008), but they often treat environmental outcomes separately from economic and innovation outcomes. Therefore, consistent with the multidimensional view that “performance” depends on the observation perspective and measurement choice (Bates & Holton, 1995), this thesis synthesizes these strands by defining manufacturing performance as a measurable, province-level multidimensional outcome. It is operationalized through economic, technological, and environmental indicators to support cross-provincial comparison and subsequent spatial analysis.

### 2.3.1 Manufacturing Performance Study

For a very long time, the major driver of economic expansion has been the real economy, which is represented by manufacturing. Maintaining global competitiveness therefore requires attention to manufacturing performance and its determinants. The Consumer Price Index (CPI) used to assess industrial performance was developed by the United Nations Industrial Development Organization (UNIDO). It covers key dimensions such as manufacturing production capacity, export capacity, impact on world manufacturing value added and trade, and export quality.

Nevertheless, Hongjiao et al. (2009) measured manufacturing performance using three indicators, manufacturing labor productivity, the global share of manufacturing value added, and the average annual growth rate of manufacturing value added, capturing development level, scale strength, and growth potential. Similarly, Zhenxing and Shougui

(2011) constructed a manufacturing performance index using total profits and taxes, total assets, gross industrial product, and employment, and compared regional performance using two cross-sections (1998 and 2008) with cluster analysis to identify changes across regions.

Lishu and Xiujian (2013) used profit margin, industrial output per capita, and main business income per capita to represent manufacturing performance, and found positive spillovers from multinational retailers to consumer goods manufacturing. They suggest strengthening product innovation and differentiation to enhance competitiveness. Xiangui et al. (2010) compared Sichuan and Guangdong using relative efficiency indicators (e.g., development speed, scale, efficiency, employment absorption, and international competitiveness) through comparative analysis and multivariate methods, and argued for complementary cooperation to promote regional manufacturing development.

Jie and Tian (2016) measured manufacturing performance using comparative labor productivity (output value per 1% of manufacturing labor relative to GDP). They argue that servitization requires both stronger service inputs into manufacturing and deeper manufacturing–service integration. According to Wei and Yong (2004), industrial performance is shaped by multiple structural factors, including industry concentration, entry barriers, industry growth, diversification, geographic differences, strategic groups, risk, buyer concentration, and foreign trade. This broad structure–performance view is useful for framing why industrial outcomes vary across space and industries; however, it remains largely descriptive and does not clarify which factors dominate under different regional contexts or how they interact spatially. In particular, while foreign trade is argued to strengthen China’s linkage with the world economy and potentially upgrade industrial chains, the mechanism is often discussed at a macro level, leaving limited evidence on whether these gains are evenly distributed across provinces or whether they generate spatial divergence.

Ting and Hua (2013) examined manufacturing servitization and industry performance using panel-data regression, and their results suggest that service–manufacturing integration can matter for performance outcomes. Nonetheless, the analysis is centered mainly on the service sector and “integration effects” within industries, rather than treating manufacturing performance as a geographically interconnected system. As a result, it remains unclear whether servitization-driven benefits diffuse across regions or concentrate in leading hubs, which represents a key gap for spatially oriented manufacturing research.

Conversely, Chengxin (2014) found that improvements in circulation industry performance can promote manufacturing upgrading, but the specialization level of circulation does not significantly enhance manufacturing performance. This mixed evidence implies that not all upgrading-related channels translate into measurable performance gains, and the effectiveness may depend on complementary conditions (e.g., local industrial base, factor endowments, or regional coordination). Taken together, these studies highlight that performance drivers may be conditional and uneven across space, motivating a more integrated framework that can distinguish local effects from cross-regional spillovers and assess multidimensional outcomes rather than a single performance metric.

## **2.4 Study of Industrial Agglomeration and Manufacturing Performance**

Industrial agglomeration is a phenomenon that has been extensively studied in the context of China's manufacturing industries. Wen (2004) explored the spatial concentration of Chinese manufacturing and found that industrial agglomeration is driven by transaction and production agglomeration effects. Lu and Tao (2009) further investigated the trends and determinants of China's industrial agglomeration, highlighting the role of local protectionism and Marshallian externalities in obstructing or facilitating the process. Building on these studies, this thesis clarifies how agglomeration translates into outcomes by organizing the mechanisms into three channels—(i) cost and productivity gains through sharing and matching, (ii) innovation gains (or lock-in) through learning and knowledge spillovers, and (iii) environmental impacts through scale/abatement effects and pollution spillovers—each of which may operate both locally and across provincial borders.

De Blasio and Di Addario (2005) focused on the benefits accruing to workers in industrial clusters, using data from the Cluster Mapping Project of the Italian National Statistical Institute to examine wage and labor mobility differentials. Moreover, Dong et al.(2020) investigated whether industrial agglomeration promotes pollution agglomeration in China, suggesting strategies to optimize high-tech industrial agglomeration and strengthen regional linkages to improve environmental quality. Finally, Liu and Zhang (2021) studied the relationship between industrial agglomeration, technological innovation, and carbon productivity in China, emphasizing the importance of spatial reforming of industrial agglomerations to enhance economic growth and increase total carbon productivity in the

long run. Together, these studies imply that agglomeration can generate multi-dimensional effects (economic–technological–environmental) and that spatial linkages may produce diffusion (spillover) or concentration (siphoning), which motivates the spatial spillover analysis in this thesis.

#### **2.4.1 Industrial Agglomeration and Economic Performance**

According to the index of economic performance of the manufacturing industry defined in the previous section as manufacturing labor productivity, this thesis elaborates on the related literature on the research of the impact of industrial agglomeration on economic performance (manufacturing labor productivity). Economically, agglomeration is expected to affect labor productivity mainly through (i) sharing (specialized suppliers, infrastructure, and services), (ii) matching (labor pooling and improved firm–worker fit), and (iii) reduced transaction costs. However, when clustering exceeds local capacity, congestion and resource competition may weaken productivity gains. These mechanisms may also spill over across provinces via factor mobility and interregional supply chains.

Ciccone (2002) estimated the agglomeration effect for five European countries, empirically employed the 2SLS estimation procedure and concluded that industrial agglomeration has a significant positive contribution to labor productivity in the European region. Fafchamps and Hamine (2017) used data on the Moroccan manufacturing sector from 1985 to 2001; they found finds that both specialization and diversity of industrial agglomeration significantly contribute to regional labor productivity.

Graham et al. (2010) estimated panel data vector autoregressions for different sectors of the economy using a dynamic panel model of the Generalized Method of Moments (GMM) in order to test for bi-directional causality between productivity and industrial agglomeration economies. The results suggest that agglomeration economies are not strictly unidirectional, and that industrial agglomeration can increase labor productivity. This bi-directionality highlights a key identification issue for economic performance, productive provinces may attract more firms (reverse causality), which motivates spatial econometric designs and robustness checks in this thesis.

Melo et al. (2017) found that urban agglomeration has a positive effect on labor productivity, with elasticity values ranging between 0.07 and 0.10. Their paper also examined the spatial decay of productivity gains from urban agglomeration and found that

the agglomeration effect diminishes as travel time increases. This spatial decay provides a conceptual basis for expecting productivity spillovers to weaken with distance, consistent with spatial interaction settings. Otsuka et al. (2010) explored the relationship between production efficiency and agglomeration economies. The study showed that agglomeration economies and market access have a positive impact on the productivity of manufacturing and non-manufacturing industries in Japan, but public finance transfers have a negative impact on productivity, providing important policy insights for policymakers.

Rizov et al. (2012) used a semiparametric algorithm to estimate firm-specific in 2-digit industries such as agriculture, manufacturing, construction, trade, and services; calculated overall productivity for three types of regions in the Netherlands according to the level of urbanization and the density of economic activity; and used a Probit model with a polynomial or kernel to estimate the relationship between agglomeration and productivity. The paper highlights the benefits of agglomeration, such as greater diversity and specialization of production processes, co-location of firms in the same industry, and positive effects on productivity due to constant returns, positive externalities, and beneficial specialization.

Jin et al. (2011) examined the spatial agglomeration effect of the creative class. Their study showed that industrial agglomeration has a significant positive effect on labor productivity, while the indirect effect suggests that creative class agglomeration affects regional labor productivity through regional technological innovation, urbanization level, and industrial structure. This supports the mechanism view that agglomeration can raise productivity directly (cost or matching) and indirectly (innovation and structural upgrading), which this thesis tests within a spatial framework.

Overall, the empirical literature largely supports a positive association between agglomeration and manufacturing productivity, while also indicating potential spatial decay and bidirectional causality. To clarify *why* agglomeration can raise economic performance in a spatial setting, it is necessary to articulate the underlying mechanisms. The link between industrial agglomeration and economic performance is primarily sustained by labour pooling and input sharing within the classic Marshallian framework (Marshall, 2009). Industrial concentration creates a deep market for specialized labour, improving job-worker matching efficiency and reducing recruitment and search costs (Overman & Puga, 2010). At the same time, co-location enables firms to access specialized intermediate suppliers and shared

public infrastructure, thereby lowering transaction and logistics costs and generating both internal and external economies of scale (Glaeser,2010). Together, these channels improve manufacturing efficiency and labour productivity through cost reduction and operational upgrading, and they can extend beyond the focal province when factor markets and supply chains are spatially connected—providing a clear rationale for testing both local effects and spatial spillovers in the empirical model.

While these mechanisms explain productivity gains, agglomeration may also reshape regional innovation capacity through spatially bounded knowledge flows. The next subsection reviews how industrial agglomeration influences technological performance.

#### **2.4.2 Industrial Agglomeration and Technological Performance**

Technologically, agglomeration may improve innovation performance via knowledge spillovers, specialized R&D services, and talent pooling (“learning”); however, excessive clustering may create “lock-in,” crowd out smaller innovators, or increase imitation incentives under weak IP protection. These effects may diffuse to neighboring provinces (spillover) or concentrate in core hubs (siphoning).

Siqi (2023) constructed a model and concluded that high-tech industrial agglomeration promotes technological innovation efficiency. The study further identified regional heterogeneity in these effects among the four major economic regions and the eight comprehensive economic zones. Similarly, Yong (2013) found that the growth rate of capital input and the growth rate of total factor productivity in each region of China are obviously regionally differentiated, with a decreasing trend from east to west, and that the level of human capital, the degree of opening up to the outside world, and the degree of industrialization have a more significant impact on the regional innovation level. This indicates that the innovation channel of agglomeration is likely to be conditional on local absorptive capacity (e.g., human capital), which motivates heterogeneity analysis.

Beaudry and Breschi (2003) conducted an empirical study using patent, firm, and employment data for high-tech industries in Italy and the UK. They found that industrial agglomeration and innovation performance show a positive correlation; however, this relationship is not uniform across sectors. Greunz (2004) constructed a model combining diversity and specialization measures and found that both specialization and diversification externalities significantly affect regional innovation performance across 153 European

regions. Nonetheless, the coexistence of specialization and diversification effects implies potential non-linearity or threshold conditions.

Dos Santos Silvestre and Dalcol (2009) analyzed empirical data from the Brazilian oil and gas cluster and concluded that geographic proximity has a positive impact on innovative activity. However, their findings also indicate that proximity effects may be selective and not automatically generalizable. Li et al. (2023) found that the spatial spillover effects of industrial agglomeration in Chinese cities are phased, early stages manifest as polarization effects, while later stages evolve into trickle-down effects. This suggests that innovation outcomes are dynamic and spatially uneven.

Fu and Wang (2024) revealed an inverted U-shaped relationship between industrial agglomeration and carbon emissions, identifying green technological innovation as a mediator. Similarly, Liu and Wu (2023) found that high-tech industrial agglomeration significantly improves green innovation efficiency, with specialization agglomeration exhibiting an inverted U-shaped relationship, while diversification agglomeration continues to play a positive role. Despite the overall positive association, the inverted-U pattern implies diminishing or reversing innovation gains beyond a certain agglomeration level.

Tao et al. (2024) showed that industrial agglomeration promotes efficiency and green performance, and financial agglomeration can also promote green transformation through capital allocation. He et al. (2022) found that manufacturing agglomeration boosts a city's Green Total Factor Productivity (GTFP). Yuan et al. (2023) further revealed that industrial synergy clusters enhance technology–environment performance and exhibit significant spatial spillovers. These studies collectively support the thesis expectation that innovation outcomes from agglomeration may be non-linear and spatially dependent, which justifies modeling both direct and spillover effects.

Although most of the literature shows that industrial agglomeration has a certain promotion effect on technological innovation performance, some scholars suggest that industrial agglomeration has no effect or even a negative effect on technological performance. Kai et al. (2007) found that the high-tech industry agglomeration in China at this stage has not realized the real industrial agglomeration, thus failing to give full play to its role in enhancing innovation performance. eration and thus cannot give full play to its role in enhancing innovation performance. Conversely, this suggests that measured

agglomeration may not always reflect effective innovation clustering, which helps explain mixed or negative findings.

Jin et al. (2013) integrated three theoretical perspectives—agglomeration economic theory, resource-based view theory, and institutional theory—and explored the relationship between industrial agglomeration and innovation using 221 samples of China's high-tech industries. They found that the impact of industrial agglomeration on innovation varies at different levels, at lower levels, specialization is conducive to innovation while diversification inhibits it; on the contrary, at higher levels, specialization is not conducive to innovation while diversification promotes it. This provides direct theoretical support for testing threshold/non-linear innovation responses to agglomeration.

Existing evidence suggests that agglomeration can foster innovation, but the direction and magnitude may vary by region, stage of clustering, and type of agglomeration, implying that innovation effects are not uniformly positive. The technological outcome of agglomeration is mainly driven by knowledge spillovers within innovation clusters. Geographic proximity facilitates the exchange of tacit knowledge—informal “know-how” that is difficult to codify—through repeated face-to-face interactions, inter-firm learning, and labour mobility (Jaffe et al., 1993; Audretsch & Feldman, 2019). This learning environment accelerates the diffusion of new technologies across firm boundaries and supports higher patenting and R&D outcomes (Carlino & Kerr, 2015). However, because spillovers decay with distance and innovation resources can be attracted toward leading hubs, agglomeration may also generate a spatial siphoning pattern that widens interregional innovation gaps. These mechanisms justify modelling technological performance with explicit spatial dependence and spillover channels, rather than assuming innovation benefits remain purely local. Beyond productivity and innovation, agglomeration can also alter environmental outcomes through scale expansion, shared abatement, and cross-border pollution externalities. The following subsection reviews this environmental dimension.

### **2.4.3 Industrial Agglomeration and Environmental Performance**

At present, the study of environmental performance from the perspective of industrial agglomeration is still in its infancy. Environmentally, agglomeration influences performance through two competing effects: (i) a scale effect (more concentrated production may increase total emissions and local pressure), and (ii) a technique/abatement effect (shared treatment facilities, cleaner technology diffusion, and stricter monitoring in clusters may reduce

emissions intensity). In addition, pollution can cross boundaries, creating spatial spillovers (diffusion) or relocation patterns (pollution transfer). Regarding the existing relevant literature at local and abroad, the research conclusions are quite divergent, and the views are mainly divided into the following two:

**1) Industrial agglomeration facilitates environmental performance**

Yuanyuan and Kunwang (2010) hypothesized that industrial agglomeration can improve energy performance. Through a regression analysis of 25 industrial sectors in China from 2001 to 2007, they found that industrial agglomeration effectively improves energy performance. Feng et al. (2014) constructed spatial externality indicators and econometric models based on Marshallian theory to examine the impact of economic activity on environmental energy performance. Their results showed that urban performance is affected by the spatial effects of specialized labor, intermediate inputs, and technology spillovers. They concluded that intermediate inputs and technological outflows promote efficiency, while specialized labor in neighboring districts is not conducive to local environmental improvement.

Haojun and Shujin (2016) applied a panel threshold model to test the relationship between manufacturing agglomeration and environmental governance performance across 21 industries. Their results show that manufacturing agglomeration has a promoting effect on green technology efficiency and environmental governance performance. Similarly, Fu and Kunrong (2012) synthesized an EBM model using China's capital, human capital, and energy consumption data from 1952 to 2010. They found that industrial agglomeration improves energy performance through technology spillovers and infrastructure sharing. These findings correspond to the technique/abatement channel, clustering can lower per-unit abatement costs and speed up clean-technology diffusion.

Wang et al. (2022) further found that there is a two-way promotional relationship between high-tech industrial agglomeration and urban ecological efficiency, accompanied by significant spatial spillover effects. This finding indicates that there is not a one-way causal relationship between economic and environmental performance, but rather an interactive mechanism. Meanwhile, Yang and Jiang (2024) revealed that the synergistic clustering of manufacturing and productive services through spatial interaction mechanisms can significantly improve urban green energy efficiency, with significant differences between resource-based and non-resource-based cities. This supports the thesis emphasis on

spatial dependence, environmental outcomes in one province may be affected by neighboring provinces' agglomeration and industrial structure.

**2) Industrial agglomeration may have negative impacts on environmental performance or other non-linear linkages.**

Zhonghua et al. (2017) selected the panel data of 285 prefecture-level and above cities in China from 2004 to 2013 to analyze and used the EBM model to measure the total factor environmental energy performance in the presence of undesired outputs. The results showed that at the national level, manufacturing agglomeration significantly inhibits the improvement of environmental energy performance. At the sub-regional level, they identified an inverted U-shaped relationship between the impact of manufacturing agglomeration on environmental energy performance in the eastern region, manufacturing agglomeration inhibits the improvement of environmental energy performance in the central region, and manufacturing agglomeration has a significant negative impact on environmental energy performance in the western region.

However, these findings imply strong regional heterogeneity, suggesting that the environmental effect of agglomeration is not uniformly “good” or “bad,” but varies by development stage and regional conditions. Yin et al. (2021) analyzed the relationship between the degree of industrial agglomeration and environmental performance using Chinese provincial panel data and tested the heterogeneity of the relationship between industrial agglomeration and environmental performance based on environmental regulation, technological innovation level, and the degree of marketization in different regions. The results showed that: (1) the relationship between industrial agglomeration and environmental performance is inverted N, with two inflection points; (2) the environmental regulation in different regions affects the relationship between the two, and the relationship between the two is still in N when the environmental regulation is weak, and the relationship between the two is in U when the environmental regulation is strong. Nonetheless, the key implication is that regulation and innovation capacity can shift the sign and shape of the relationship, which helps explain why empirical conclusions differ across studies.

Wang and Wang (2019) studied the impact of industrial agglomeration at the municipal level using DEA window analysis. Their results showed a nonlinear, U-shaped relationship, where environmental performance deteriorates in the early stages of

agglomeration and improves as clustering proceeds. These results align with the scale-versus-technique trade-off and suggest that the net environmental effect depends on agglomeration level and regulatory/innovation conditions—consistent with the thesis’s non-linear and heterogeneous expectations.

Ding et al. (2022) pointed out that industrial clusters integrating manufacturing and productive services significantly promote regional green development through spatial spillover mechanisms. Han et al. (2023) used a Spatial Durbin Model to reveal the complex interrelationships between industrial agglomeration, air pollution, and economic development. Zhang et al. (2025) found that industrial agglomeration and pollution exhibit an inverted U-shaped relationship with significant spatial spillover effects. Similarly, Miao et al. (2024) that agglomeration significantly affects air pollution levels, while An et al. (2025) revealed that high-tech green innovation efficiency is significantly concentrated spatially. Furthermore, Xu and Xu (2024) noted that synergistic clustering helps promote urban Green Total Factor Productivity (GTFP) and exhibits significant spatial spillover characteristics. The environmental literature remains more contested than the productivity and innovation strands, with findings ranging from improvement in environmental efficiency to deterioration or non-linear relationships across regions and stages of clustering.

Environmental consequences are determined by the tension between shared abatement and congestion effects. In the early or moderate stages of clustering, firms may share pollution-control infrastructure, specialized environmental services, and monitoring systems, reducing the marginal cost of abatement and improving environmental efficiency. In contrast, over-concentration may increase energy use and emissions intensity and exceed local ecological carrying capacity, generating congestion externalities and environmental degradation (Verhoef & Nijkamp, 2002). Moreover, when environmental regulations tighten in core regions, firms may relocate pollution-intensive activities to neighbouring provinces, producing pollution leakage and transboundary externalities (Copeland & Taylor, 2013). These mechanisms jointly motivate (i) potential non-linear effects of agglomeration on environmental performance and (ii) the need to estimate spatial spillovers rather than treating environmental impacts as confined within administrative borders.

Taken together, the economic (labour pooling/input sharing), technological (knowledge spillovers/innovation clustering), and environmental (shared abatement vs congestion and leakage) channels provide a coherent theoretical basis for adopting a spatial

econometric framework to decompose direct and spillover effects across provinces. To enhance synthesis, Table 2-1 provides a comparative summary of key studies, highlighting differences in measures, methods, and whether spatial spillovers/nonlinearities are considered.

**Table 2-1:  
Comparative Summary of Key Literature on Agglomeration and Manufacturing Performance**

<b>Author</b>	<b>Focus (Dimension)</b>	<b>Method / Data</b>	<b>Key finding</b>	<b>Gap / Link to this thesis</b>
Wen (2004)	Agglomeration patterns	China manufacturing spatial evidence	Agglomeration driven by transaction/production effects	Motivates China context + spatial perspective
Lu & Tao (2009)	Determinants of agglomeration	China evidence	Local protectionism & Marshallian externalities matter	Justifies controls + institutional context
De Blasio & Di Addario (2005)	Economic (wages/worker gains)	Cluster mapping / labor outcomes	Clusters yield wage & mobility differentials	Micro evidence; thesis tests province-level spatial effects
Ciccone (2002)	Economic (productivity)	2SLS / density	Agglomeration labor productivity	Mostly local; thesis separates direct vs spillover (SDM)
Fafchamps & Hamine (2017)	Economic (TFP & costs)	Morocco manuf. 1985–2001	Specialization & diversity raise productivity	Firm-level; thesis adds cross-province spillovers
Graham et al. (2010)	Economic (bi-directional)	Dynamic panel (GMM)	Productivity ↔ agglomeration (two-way)	Motivates endogeneity awareness + spatial framework
Melo et al. (2017)	Economic (elasticity & decay)	US metros	Positive effect; decays with distance/time	Supports distance-based spillovers (W matrix)
Otsuka et al. (2010)	Economic (efficiency)	SFA / Japan	Agglomeration & market access efficiency	Mostly single-country local; thesis adds spillovers
Rizov et al. (2012)	Economic (productivity)	Semi-parametric + Probit	Diversity/specialization & co-location productivity	Helps justify multiple agglomeration measures
Jin et al. (2011)	Economic→Tech channel	China provinces	Indirect effects via innovation/urbanization/structure	Supports mechanism link: agglomeration → innovation → productivity
Beaudry & Breschi (2003)	Tech (innovation)	Patents + employment	Agglomeration correlates with innovation	Sector heterogeneity; thesis tests broad manuf. patterns
Greunz (2004)	Tech (specialization vs diversity)	153 regions, 16 sectors	Both specialization & diversity externalities matter	Supports comparing different agglomeration forms
Dos Santos Silvestre & Dalcol (2009)	Tech (cluster innovation)	Case evidence (Brazil O&G)	Proximity supports innovation for some firms	Micro evidence; thesis tests macro spatial spillovers
Siqi (2023)	Tech (innovation efficiency)	Sys-GMM + threshold	High-tech agglomeration ↑innovation; threshold/heterogeneity	Supports nonlinearity & heterogeneity expectations
Li et al. (2023)	Tech spillovers dynamics	China cities	Polarization early → trickle-down later	Supports stage-dependent spillovers
Kai et al. (2007)	Tech (null/negative)	China high-tech regions	Agglomeration not “true cluster” → weak innovation	Shows mixed evidence → motivates careful testing

Author	Focus (Dimension)	Method / Data	Key finding	Gap / Link to this thesis
Liu & Wu (2023)	Green innovation	China high-tech	Specialization inverted-U; diversity positive	Supports nonlinearity + “type of agglomeration matters”
Fu & Wang (2024)	Environment (carbon)	China evidence	Inverted-U; green innovation/talent as channels	Supports mechanism + nonlinearity
Dong et al. (2020)	Environment (pollution agglom.)	China evidence	Agglomeration may promote pollution agglomeration	Motivates environmental spillover concern
Yuanyuan & Kunwang (2010)	Environment (energy perf.)	China sectors	Agglomeration can improve energy performance	Suggests “shared abatement/infrastructure” mechanism
Feng et al. (2014)	Environment (energy efficiency)	Spatial externality indicators	Spillovers via inputs/tech outflows affect env. efficiency	Direct support for spatial environmental spillovers
Haojun & Shujin (2016)	Environment (threshold)	Panel threshold	Agglomeration promotes green efficiency under conditions	Supports threshold/nonlinear modeling logic
Zhonghua et al. (2017)	Environment (regional heterogeneity)	EBM / 285 cities	Nationally negative; regionally nonlinear/heterogeneous	Motivates heterogeneity across regions
Yin et al. (2021)	Environment (regulation heterogeneity)	Provincial panel	Nonlinear (inverted-N); regulation changes shape	Supports policy-regime heterogeneity
Wang & Wang (2019)	Environment (U-shape)	DEA window	Early deterioration → later improvement	Fits scale–technique trade-off narrative
Han et al. (2023)	Environment + spatial	SDM	Agglomeration–pollution–growth interlinked / spillovers	Direct justification for SDM approach
Ding et al. (2022)	Green development	Spillover mechanism	Manuf.+services clusters promote green development / spillovers	Supports “synergy + spillover” argument
He et al. (2022)	GTFP	City-level	Manuf. agglomeration GTFP; synergy strengthens	Supports multi-dimension “green productivity” link
Tao et al. (2024)	Green transformation	Finance + manuf.	Agglomeration improves green performance; capital allocation channel	Supports multi-channel mechanism
Yuan et al. (2023)	Tech–env synergy	Spatial spillover & heterogeneity	Synergy clusters enhance tech–env performance; spillovers	Supports integrated framework + heterogeneity
Zhang et al. (2025)	Pollution nonlinearity + spillover	Multi-city clusters	Inverted-U; pollution has spatial spillovers	Supports nonlinearity + cross-region externalities
Miao et al. (2024)	Air pollution + policy	Spatial dynamics	Agglomeration affects pollution; policy intervention matters	Supports governance/policy context
Xu & Xu(2024)	GTFP spillovers	Synergistic clustering	Promotes GTFP with spatial spillovers	Supports spillover-focused design
An et al. (2025)	Green innovation efficiency	3-stage SBM	Strong spatial concentration & regional differences	Supports spatial heterogeneity

Note: This table synthesizes evidence across economic, technological, and environmental dimensions, and the need to estimate both direct and spatial spillover effects (SDM) at the provincial level.

## 2.5 Research Gap

Industrial agglomeration and economic growth have a complicated and well-researched relationship. Policymakers are increasingly concerned with how to promote industrial agglomeration through industrial policy to achieve economic growth and competitiveness (Aiginger & Rodrik, 2020). Recent studies have explored how spatial agglomeration can drive regional economic growth by promoting knowledge spillovers and

innovation. For example, research often focuses on how industry clusters in a given region affect growth through specialization and diversification externalities.

With the development of technology, several literatures have examined how technological advances affect the shape and effects of industrial agglomeration and how these changes further affect economic development (Song et al., 2023). Yu et al. (2021) examined how industrial agglomeration affects the quality of FDI. In emerging market economies, industrial agglomeration attracts higher-quality FDI by providing good infrastructure and industrial ecosystems.

However, despite these advances, existing studies leave an important gap when the research focus shifts from “growth” to “manufacturing performance” in a broader sense. For example, Wang et al. (2022) identified a nonlinear relationship between agglomeration and green efficiency using IV and GMM approaches, yet their analysis remains largely at an aggregate geographic level and provides limited insight into how effects differ across regions and performance dimensions. Similarly, Li (2020) examined the relationship between industrial agglomeration and regional economic growth within a Cobb-Douglas framework utilizing data from 30 Chinese provinces. Using a panel threshold model, the study indicated that beneficial effects increase at greater degrees of industrial progress. Nevertheless, the study examined the industry only as a whole and did not break it down by sector. Ding et al. (2022) used panel data from 30 provinces and introduced the Spatial Durbin Model (SDM) to accurately reflect temporal and spatial spillover effects. The literature still tends to treat spillovers as a general phenomenon rather than differentiating which dimensions (economic, technological, environmental) experience positive versus negative spillovers and under what regional conditions.

Based on the above literature, three major gaps remain in research on industrial agglomeration and manufacturing performance. First, existing evidence remains largely single-dimensional, lacking a systematic “economy–technology–environment” assessment. Most studies focus on either economic outcomes or environmental performance (e.g., green efficiency) in isolation, making it difficult to identify whether agglomeration generates synergies or trade-offs across dimensions. Moreover, technological performance is often treated as a channel rather than an outcome, leaving limited empirical clarity on how agglomeration simultaneously shapes innovation/upgrading alongside economic and environmental outcomes.

Second, spatial dependence and spatial spillover mechanisms are still insufficiently specified. While some studies have introduced spatial models, spillovers are often reported in aggregate terms without clarifying what type of spillover occurs and in which performance dimension. In particular, prior work rarely differentiates positive technological spillovers (through knowledge diffusion) versus negative environmental spillovers (through pollution transfer), thereby limiting mechanism-based interpretation.

Third, regional heterogeneity is acknowledged but not rigorously examined. Substantial cross-provincial differences in development stages, industrial structure, and environmental regulation intensity likely condition whether agglomeration produces upgrading effects or lock-in/congestion effects. However, much of the existing evidence treats regions too homogeneously, leaving insufficient answers to where agglomeration works best and for which performance dimension.

To address these gaps, this study develops a three-dimensional framework and employs a Spatial Durbin Model to estimate both direct and spatial spillover effects, while further examining regional heterogeneity to provide more targeted evidence for coordinated regional development.

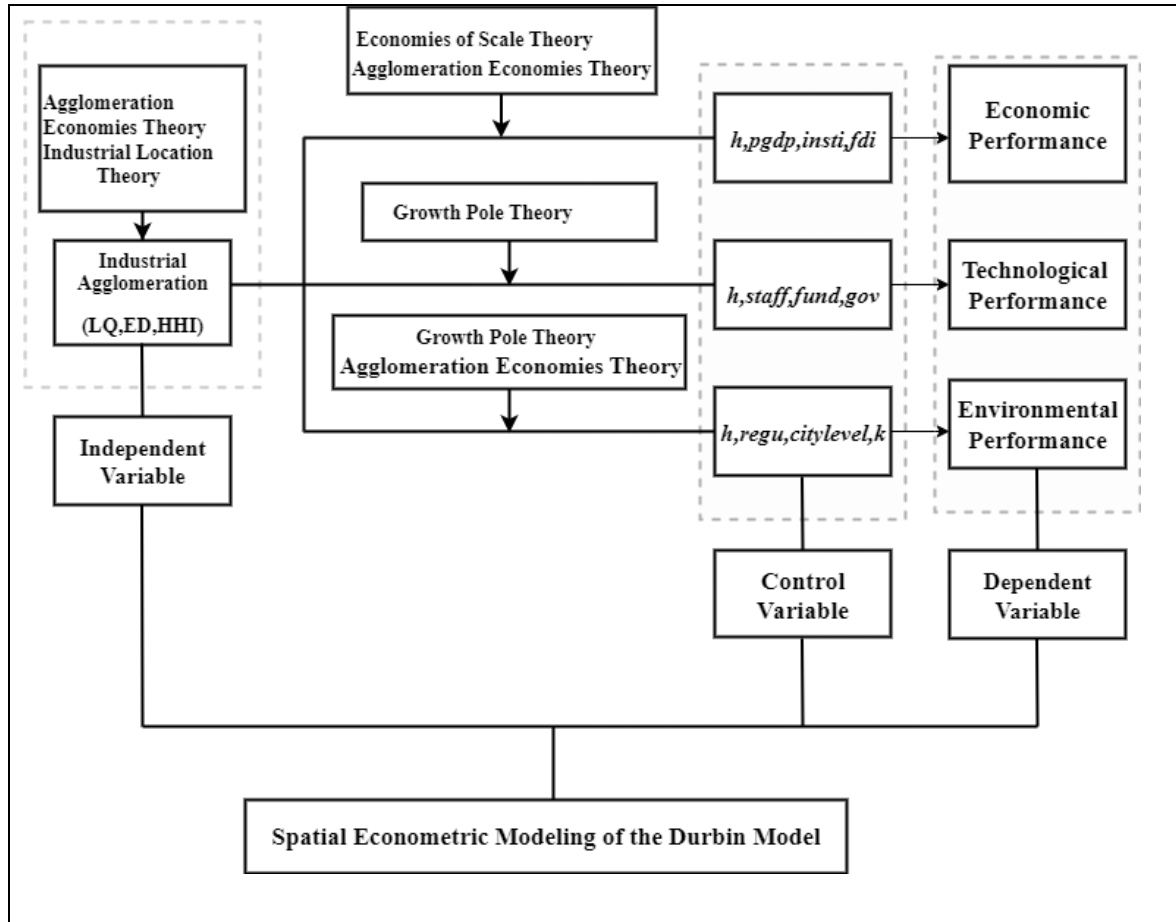
## **2.6 Conceptual Framework**

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This study is conceptualized based on four major studies, the Industrial Location Theory proposed by Weber (1909) and Church (2023) used the Agglomeration Economies Theory to further explain the concept of the independent variable industrial agglomeration; Perroux (1955) proposed Growth Pole Theory based on Industrial Location Theory to clarify the importance of technological performance and environmental performance in the study, and Liu et al (2022), based on Growth Pole Theory, proposed the relationship between industrial agglomeration and environmental policy, and technological innovation relationship theoretical framework to identify the link between manufacturing agglomeration and manufacturing performance in China. Marshall's (2009) Economies of Scale Theory also deals with the importance of economic performance in the process of industrial agglomeration. Based on the combination of these four theories, this study has been developed based on the Spatial Durbin Model to investigate the impact of industrial agglomeration on the performance of manufacturing industry, mainly in three aspects,

economic performance, technological performance, and environmental performance. The specific construction framework is shown in Figure 2-7.

**Figure 2-7:  
Conceptual Framework**



In the context of China's pursuit of high-quality development, industrial agglomeration has emerged as a critical factor shaping regional economic, technological, and environmental performance. Recent empirical studies have significantly enriched the theoretical foundations of this subject by unveiling the complex mechanisms, spatial dynamics, and nonlinear relationships underpinning industrial agglomeration. The conceptual framework captures the multifaceted influence of industrial agglomeration, incorporating mediating mechanisms, spillover effects, and contextual variables.

Industrial agglomeration, traditionally understood as the geographic concentration of industries, has been found to exert both direct and indirect effects on regional development. Li et al. (2023), through a study of Chinese cities, observed that the spatial spillover effects of agglomeration evolve over time. In the early stages, they manifest as polarization effects,

accelerating growth in core regions. Over time, however, these effects shift toward trickle-down benefits, supporting development in peripheral areas.

The relationship between industrial agglomeration and environmental outcomes is particularly nuanced. Fu and Wang (2024) established an inverted U-shaped relationship between industrial agglomeration and carbon emissions, suggesting that agglomeration initially exacerbates emissions but later supports green transformation through green innovation and talent agglomeration. Liu and Wu (2023) found a similar pattern for specialization agglomeration, while diversification agglomeration maintains a positive impact on green innovation efficiency. These findings highlight the dual environmental effect of agglomeration, where it can both enhance and undermine environmental quality, depending on the scale and structure of agglomeration.

Recent studies underscore the interdependence of industrial agglomeration with economic growth, technological advancement, and environmental performance. Wang et al. (2022) noted a bidirectional relationship between high-tech industrial agglomeration and urban ecological efficiency, indicating that improvements in one domain reinforce the other. Yang and Jiang (2024) further demonstrated that the clustering of manufacturing and productive services significantly boosts urban green energy efficiency, though with varied impacts between resource-based and non-resource-based cities.

The synergy between different forms of agglomeration is increasingly recognized. Tao et al. (2024) found that both industrial and financial agglomeration contribute to green transformation, while He et al. (2022) emphasized that manufacturing agglomeration independently boosts a city's Green Total Factor Productivity (GTFP). These effects are magnified when industrial clusters combine manufacturing and services, as shown by Yuan et al. (2023), who revealed that such clusters drive technology-environment performance through innovation and exhibit regional heterogeneity.

In a similar vein, Ding et al. (2022) and Han et al. (2023) provided evidence of spatial spillover effects and complex interrelations among industrial clustering, pollution, and development. Zhang et al. (2025) further confirmed an inverted U-shaped relationship between agglomeration and pollution and highlighted spatial variations across city clusters. These findings underscore the necessity of spatially sensitive policy responses.

Spatial dynamics and policy interventions are central to understanding the mechanisms through which industrial agglomeration affects regional performance. Miao et al. (2024) stressed that air pollution outcomes of agglomeration are influenced by policy mechanisms, while An et al. (2025) showed that green innovation efficiency in high-tech industries is spatially concentrated and regionally differentiated. Xu and Xu (2024) also emphasized the role of synergistic clustering in promoting GTFP and noted significant spatial spillover effects.

Collectively, these studies demonstrate that industrial agglomeration is not a one-dimensional growth strategy but a dynamic force with varying implications across time, space, and sectors. This necessitates a more nuanced analytical framework to fully capture its multifaceted effects.

Based on the reviewed literature, a conceptual framework is proposed to analyse the relationship between industrial agglomeration and regional development outcomes. This framework is structured around the following elements. The study includes various forms of agglomeration, such as high-tech, manufacturing, financial, and synergistic clusters of manufacturing and services. Key mechanisms include the growth pole effect and agglomeration economies, which enhance productivity, innovation, and resource allocation. Additionally, spatial spillovers and nonlinear effects—especially inverted U-shaped relationships—mediate the effects of agglomeration on environmental and technological outcomes. This study includes the dimensions of economic performance such as growth, productivity, competitiveness and foreign direct investment. In the technological performance the study will emphasize on the innovation efficiency and R&D concentration of the provinces. Nevertheless, in environmental performance, the study focuses on enhancing green outcomes through innovation and efficiency. The framework emphasizes regional heterogeneity and temporal evolution (e.g., from polarization to trickle-down effects), acknowledging that the impact of agglomeration varies across city types and development phases.

The framework integrates recent empirical findings into a multidimensional conceptual framework that links industrial agglomeration with economic, technological, and environmental performance. By incorporating spatial spillovers, nonlinear effects, and mediating mechanisms such as green innovation and synergistic clustering, the framework provides a more holistic understanding of agglomeration dynamics. This approach not only

deepens theoretical insights but also offers practical guidance for policy formulation aimed at achieving sustainable and regionally balanced industrial development in China.

## **2.7 Chapter Summary**

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This chapter first reviews, analyzes, and comments on the theories related to industrial agglomeration, and then sorts out the literature related to industrial agglomeration, economic performance, technological performance, and environmental performance. Finally, it points out the existing research gaps and proposes the conceptual framework of this study based on the research.

# RESEARCH METHODOLOGY

## 3.1 Introduction

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This chapter focuses on the calculation methods and formulas of industrial agglomeration, economic performance, technological performance and environmental performance. A spatial econometric model is used to measure the relationship between industrial agglomeration and economic performance, technological performance and environmental performance.

## 3.2 Source of Data

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The data used in this thesis are multi-regional panel data from China's manufacturing industry from 2008 to 2022. Economic performance indicators (total manufacturing output and employment) are sourced from the China Statistical Yearbook and provincial and municipal statistical yearbooks. Such data are widely used to measure regional economic output and labor productivity (Lu et al., 2021). Technical performance indicators (number of valid invention patents, full-time equivalent R&D personnel, R&D expenditure, and government science and technology expenditure) are taken from the China Science and Technology Statistics Yearbook and patent statistics published by the China National Intellectual Property Administration (CNIPA). The number of invention patents is widely regarded as a core indicator for measuring technological innovation output, and existing studies have adopted this indicator in research on industrial agglomeration and green innovation (Liu & Wu, 2023). Environmental performance indicators (sulfur dioxide emissions and industrial pollution control investment) are sourced from the China Environmental Statistics Yearbook published by the Ministry of Ecology and Environment. Sulfur dioxide emission intensity is often regarded as an important proxy variable for environmental performance (He et al., 2022).

In addition, industrial agglomeration indicators (Locational Quotient, Employment Density, and the Herfindahl-Hirschman Index) are calculated based on relevant data from the China Statistical Yearbook, China Industrial Statistics Yearbook, and China Urban Construction Statistics Yearbook. These indicators have been widely used to measure the degree of regional industrial agglomeration and spatial spillover effects (Xie & Li, 2021). Control variables such as per capita GDP, total exports as a percentage of GDP, foreign direct investment, urbanization level, and fixed asset investment are mainly sourced from the China Statistical Yearbook, the China Education Statistics Yearbook, and statistical data published by the Ministry of Commerce and the Ministry of Finance. All data are annual figures covering the period from 2008 to 2022, ensuring comparability and consistency across regions and years. The data sources are authoritative national and provincial statistical yearbooks and publicly available information released by government departments, ensuring high reliability and authority.

### **3.3 Methodology for Measuring Industrial Agglomeration**

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Assessing the level of industrial agglomeration has consistently been a significant area of interest for scholars. Some of the widely used techniques for determining the degree of industrial agglomeration have emerged after 1990 as a result of the theory of industrial agglomeration's development and ongoing refinement. These techniques are described below.

#### **3.3.1 Gini Coefficient**

Gini Coefficient, a concept proposed by Italian economist Corrado Gini in 1912, is a measure that can be applied to describe the degree of concentration/dispersion in a distribution and is widely known for measuring inequality in income or wealth distribution. In this thesis, the Gini concept is introduced in a spatial context to describe the geographic concentration (agglomeration) of industrial activity across provinces, rather than interpersonal income inequality. An important index in economic research, it is widely used in distributional and concentration analysis in national economy, wealth disparity research, and financial management and other fields. However, it should be noted that the indicator discussed here is a “spatial Gini” used for industrial concentration, not the traditional Lorenz-based income Gini.

Basic calculation formula:

$$G = \sum_i (S_i - X_i)^2 \quad \text{Equation 3.1}$$

G: the Gini coefficient;

$S_i$ : the proportion (share) of the target industry's output value in province  $i$  relative to the national output value of that industry;

$X_i$ : the proportion (share) of province  $i$ 's total industrial output value relative to national total industrial output value (benchmark distribution);

$G=0$ : the industry is evenly distributed in space. The larger the value of G (up to 1), the higher the degree of regional industrial agglomeration (spatial concentration).

As a spatial concentration indicator, this Gini-type measure has the following advantages: First, it is easy to calculate and intuitive to express, condensing complex distribution conditions into a value between 0 and 1, which facilitates cross-regional and cross-period comparisons, as well as rapid response in policy analysis (Blesch et al., 2022). Secondly, the Gini coefficient has become a standard tool used by important international institutions, including the World Bank and the United Nations, to compare income disparities, ensuring a high degree of international comparability and widespread use (Haddad et al., 2024). Second, it provides a simple descriptive summary of whether an industry's spatial distribution deviates from a benchmark distribution, which helps motivate the need for spatial analysis in this thesis. However, it is clarified that this spatial Gini is introduced only as background/alternative measurement and is not used in the empirical estimation in this thesis; the main agglomeration indicators adopted in the models are ED, LQ, and HHI.

However, the Gini coefficient also has many limitations. First, First, when used as a spatial concentration summary, a single index may mask different underlying spatial patterns (i.e., different spatial configurations can generate similar index values)(Gavilan-Ruiz et al., 2024). Second, the index may have different sensitivity across provinces depending on the distribution of industrial activity and the benchmark structure, which may lead to limited discrimination for extreme concentration cases (Sittthiyot & Holasut, 2020). In addition, the Gini coefficient may produce biases when the underlying distribution is highly skewed or

when there are measurement inconsistencies across regions, and it may be unstable when estimated in non-normal (fat-tailed) distributions (Inoua, 2021). Furthermore, recent studies have pointed out that the Gini coefficient may be “stagnant” and insensitive in long-term time series, unable to reflect the evolution of concentration caused by institutional changes or economic restructuring (Au, 2023). Given these considerations and for consistency with the research objectives and SDM effect decomposition, ED, LQ, and HHI are used as the main agglomeration measures in the empirical analysis of this thesis.

### 3.3.2 Concentration Ratio of Industry

Concentration ratio of industry is measured by the share of an industry related value (output value, output, sales volume, number of employees, total assets, etc.) in the entire market in the largest companies.

$$CR_n = \frac{\sum_{i=1}^n X_i}{\sum_{i=1}^{N_{\text{total}}} X_i} \quad \text{Equation 3.2}$$

Calculation formula:

$CR_n$ : is the concentration degree of China's different industry;

$X_i$ : the output value, output, sales volume, number of employees, total assets, etc., of the  $i$ -th company (ranked from largest to smallest by  $X$ );

$n$ : is the number of top companies included in the calculation (typically 4 or 8, i.e., CR4 or CR8);

$N_{\text{total}}$ : is the total number of companies in the sample (all companies).

In theory, if the percentage value is greater than 10, the industry shows concentration, and the larger the  $CR_n$  value, the greater the degree of concentration.

The concentration ratio Liu et al. (2020) is a classic method for measuring market structure and degree of competition, offering the advantages of being intuitive and easy to use. First, conclusions can be drawn based solely on the market share of the top few companies, which facilitates cross-industry and cross-period comparisons (Martin, 2001). At the same time, concentration ratio Liu et al.(2020) is highly practical in policy-making, and antitrust agencies often use it as an important signal to determine whether an industry is becoming oligopolistic(Carree & Thurik, 1999).

However, CR also has significant limitations. First, it only considers leading companies and ignores the market share distribution of small and medium-sized enterprises, which may lead to an underestimation of the degree of competition in the industry (Davies & Lyons, 1996). Secondly, CR cannot reveal the differences in market share among leading companies. For example, if the top four companies in two industries all have a 60% market share, this could mean either “four equal players” or “one dominant player,” but the competitive landscape in each industry would be completely different (Tirole, 1988). In addition, CR's insufficient sensitivity to market segment differences may mask local monopolies or structural competitive pressures (Lipczynski et al., 2005).

Recent studies have further revealed the limitations of CR. Grullon et al. (2019) found that industry concentration in the United States has risen significantly over the past few decades, but CR struggles to capture firm-level heterogeneity and the market power effects brought about by “super firms.” Similarly, De Loecker et al. (2020) point out that although CR can show an upward trend in concentration, it cannot reflect differences in corporate productivity, and therefore falls short when explaining the expansion of market power and macroeconomic consequences. In contrast, indicators such as the Herfindahl–Hirschman Index (HHI) are more advantageous in reflecting the continuity of market concentration and differences between companies.

### **3.3.3 Herfindahl-Hirschman Index**

Herfindahl-Hirschman Index is hereinafter referred to as HHI. Herfindahl-Hirschman Index is a comprehensive index to measure industrial concentration, which refers to the sum of squares of the total revenue or total assets of each market competitor in an industry and is used to measure the change of market share, that is, the dispersion of the scale of manufacturers in the market. The theoretical basis of the Herfindahl-Hirschman Index actually comes from Bain's structure-conduct-performance, which is the Structure-Conduct-Performance (SCP) framework that lays down the theoretical economics of industrial organization and is also the basic theoretical framework of the Harvard School. The theory is that the market structure affects the operation of the firm and ultimately determines the performance of the firm. With the concentration of market share, manufacturers will tend to adopt collusion strategies, and the final price will deviate from the perfectly competitive market price.

$$HHI = \sum_{i=1}^N Z_i^2 = \sum_{i=1}^N \left(\frac{X_i}{X}\right)^2 \quad \text{Equation 3.3}$$

Basic calculation formula:

$X$ : total market size of China's different industry (employment or output value);

$X_i$ : the scale of  $j$  enterprise;

$Z_i = \frac{X_i}{X}$ : the market share of enterprise  $I$ ;

$N$ : the number of enterprises in the Chinese different industry.

The larger the Herfindahl-Hirschman Index, the higher the degree of industrial agglomeration.

Its advantage lies in its ability to comprehensively reflect the market share distribution of all enterprises in the industry, taking into account not only leading enterprises but also capturing the impact of small and medium-sized enterprises on the market structure (Rhoades, 1993). Compared to the Concentration Ratio Liu et al (2021), the HHI is more sensitive because it can distinguish between a market situation where there is “balanced competition among multiple companies” and one where “one company dominates.” Grullon et al. (2019) found that the HHI of US industries has risen significantly over the past few decades, indicating increasing market power concentration, a trend that is difficult to clearly reflect in CR. Similarly, De Loecker et al. (2020) point out that the expansion of market power in the US is highly consistent with changes in the HHI at the macroeconomic level, demonstrating its advantage in explaining long-term trends. The study by Autor et al. (2020) also shows that the rise in HHI is closely related to the emergence of “super firms” and is an important tool for understanding the decline in labor's share and industrial concentration.

In addition to traditional manufacturing and service industries, HHI has also demonstrated strong explanatory power in research on banking and financial markets. Benmelech et al. (2022) found that the HHI effectively explains the relationship between credit market concentration and Small and Medium-sized Enterprises financing conditions, demonstrating its potential application in financial research. Similarly, Akcigit and Ates (2021) used the HHI in a cross-national comparison to reveal differences in industrial concentration trends among countries, demonstrating its universality in international

industrial competition research. These latest studies not only reinforce the academic value of the HHI but also expand its interdisciplinary application scenarios.

### 3.3.4 Employment Density

Employment density refers to the number of persons employed per unit area or per unit population and is one of the most important indicators of the degree of concentration of employment. The calculation of employment density can reflect the employment situation and economic development level of a region.

$$ED_i = M_i/S_i \quad \text{Equation 3.4}$$

The specific formula:

$M_i$ : Indicates the number of people employed in an industry in the regio

$S_i$ : Indicates the total area of the region

The larger the value of  $ED_i$ , the higher the degree of industry concentration in the region.

Employment density, as a core indicator of agglomeration effects, can effectively reflect the impact of spatial agglomeration on productivity. The Özgüzel (2020) used UK city data to find that a 10% increase in employment density is significantly correlated with a 0.9–1.0% increase in productivity, and this correlation remains robust even after controlling for worker self-selection. This suggests that employment density is an intuitive and reliable indicator of urban agglomeration intensity.

The classic study by Ciccone and Hall (1993) has demonstrated that employment density is positively correlated with knowledge spillovers, and regions with higher density tend to have higher innovation output. Subsequent studies have further confirmed this point. For example, Liu et al. (2020) used data on the distribution of employment in high-rise buildings in New York to find that employment density can enhance interaction between enterprises and the spillover of innovation. Combes et al.,(2019) demonstrated in their urban economics research that laborers and businesses in areas with high employment density are more efficiently matched, which not only improves the quality of business recruitment but also improves laborers' career mobility and wage levels.

Nevertheless, the application of employment density still has shortcomings. First, its relationship with economic performance may be distorted by the “ranking effect.” Knaap and Rey (2024) studied metropolitan areas in the United States and found that different spatial division methods significantly alter employment density values, leading to the “variable spatial unit problem” and thereby affecting the robustness of empirical conclusions. In addition, with the development of remote working, the link between employment density and productivity is weakening. Althoff et al. (2022) found that the prevalence of remote working in the United States has made urban population density highly correlated with the potential for remote working, thereby weakening the explanatory power of a single employment density indicator for agglomeration effects.

The above literature indicates that employment density has multiple advantages, it not only provides a direct measure of agglomeration effects but also significantly promotes productivity growth Özgüzel (2020), fosters innovation and knowledge spillovers Liu et al. (2020), and improves labor market matching efficiency (Combes et al., 2019).

### 3.3.5 Location Quotient

The Location Quotient, the index of regional concentration or specialization of production, first proposed by P. Haggett and used in location analysis. It is used to measure the spatial distribution of a certain regional element, reflect the degree of specialization of a certain industrial sector, and the status and role of a certain region in the high-level region. In the study of industrial structure, it is usually used to analyze the status of regional dominant specialized sectors. Calculation formula:

$$LQ_{ij} = \frac{q_{ij}/q_j}{q_i/q} \quad \text{Equation 3.5}$$

$LQ_{ij}$ : the location quotient of each province's different industry in the country;

$q_{ij}$ : relevant indicators of the different industry in each province (e.g. output value, employment number, etc.);

$q_j$ : relevant indicators for all industries in each province;

$q_i$ : national different industry related indicators;

$q$ : relevant indicators for all industries in the country.

The higher the Location Quotient, the higher the level of regional industrial agglomeration. Generally speaking, when  $LQ_{ij} > 1$ , the researcher believe that the regional economy of the province has an advantage in the whole country; When  $LQ_{ij} < 1$ , the researcher believe that the regional economy of the province is disadvantageous in the whole country.

Isard (1966) first systematized the use of LQ in his classic work on regional analysis, pointing out that it can reveal the degree of concentration of a region in a specific industry through simple proportional comparisons. This characteristic allows it to provide researchers with an effective reference for industrial comparative advantage and specialization levels even in the absence of detailed statistical data. In recent years, scholars have continued to emphasize the value of LQ in revealing regional specialization and comparative advantage. Martínez-Alpañez et al. (2023) used regional data from Spain to find that LQ remains an important indicator for measuring industrial spatial agglomeration and comparative advantage, especially for cross-regional comparisons and industrial structure analysis.

LQ has also demonstrated its importance in input-output analysis and regional economic modeling. The improved location quotient proposed by Flegg et al. (2021) demonstrates higher accuracy in small-area input-output table estimation and is better able to capture interregional industrial linkages than traditional methods. Similarly, Buendía et al. (2022) validated the applicability and robustness of the improved LQ in regional forecasting and policy analysis through empirical research. This indicates that LQ is not only applicable to static comparisons, but also provides reliable support in modeling and policy simulation.

Furthermore, the application of LQ in emerging fields demonstrates the flexibility of the methodology. Anaman and Shaibu (2024) found that the modified RLQ was more effective in analyzing the spatial distribution of non-traditional industries when comparing different LQ variants, indicating that the LQ framework can be adapted to different research needs. This finding means that the application of LQ is no longer limited to traditional manufacturing or employment research.

However, since the calculation of LQ depends on proportional relationships, if the overall scale of a region is small, even a small number of companies entering or exiting the market can significantly alter the value of LQ, leading to misjudgments about the level of industrial specialization. Pominova et al. (2021) pointed out in a study on industrial

agglomeration in the United States that small-area LQ is highly sensitive to data fluctuations, and relying solely on its results in policy-making may mislead regional industrial layout. Iglesias (2021) found that in highly concentrated regions, LQ tends to overestimate the degree of industrial specialization, while in diversified regions, it may underestimate the agglomeration effect. This means that if there are significant differences in industrial structure and scale between different regions, direct comparison of LQ results may lead to erroneous conclusions. Therefore, it is necessary to combine other indicators or control variables to conduct robustness tests.

As a relative indicator for a single industry, LQ cannot reveal the input-output relationship between industries, nor does it take into account the economic spillover effects between regions. Fukui (2025) pointed out in a comparison of different regional input-output estimation methods that traditional LQ has obvious shortcomings in dealing with complex interactions between industries, especially when analyzing cross-industry value chains and regional integration, and needs to be used in combination with other methods (such as HHI, input-output analysis, or employment density indicators).

### **3.4 Methodological Options for Measuring Industry Agglomeration**

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Indicators used to measure industrial agglomeration can be broadly divided into spatial specialization (such as location quotient LQ), spatial intensity (such as employment density), market structure (such as HHI and CR), and distribution imbalance (such as Gini coefficient). Among these, LQ intuitively depicts the relative professional advantages of a certain region compared to the national average; employment density directly measures the intensity of employment/activity per unit area and is closely related to outcome variables such as productivity and wages; HHI, as a market concentration indicator, can sensitively reflect changes in the share of the top segment and facilitates cross-industry comparisons. In contrast, CR only looks at the top few companies and is not sensitive to “tail” information; the Gini coefficient is an indicator of income/wealth inequality and is not essentially a measure of industrial spatial agglomeration, so it can be distorted when used as a proxy for agglomeration. Therefore, in “industrial agglomeration” research, a more reasonable combination is LQ , Employment Density, HHI(Anaman & Shaibu, 2024; Buendía et al., 2022; Flegg et al., 2021).

Different measurement methods reflect different contents and have different advantages and disadvantages. The following is a comparative analysis of the commonly used measurement methods of industrial agglomeration mentioned above, together with their advantages and disadvantages, so as to select the appropriate method from among them. The Gini coefficient has the benefit of being straightforward, simple to comprehend, and capable of visualizing the level of income distribution disparity. The Gini coefficient may also be used as a tool for policy formation by comparing the income distribution across various nations, regions, and demographic groupings. Its disadvantage is that it does not take into account differences in the size of firms, nor does it take into account specific industrial organization and regional differences, and therefore tends to contain spurious elements in the representation of the degree of industrial agglomeration. It is not possible to distinguish whether industrial agglomeration comes from industrial structure or from geographical concentration caused by natural advantages and spillovers (Shan et al., 2007).

Herfindahl-Hirschman Index (HHI) visualizes the size distribution of all firms in an industry, but it cannot describe the relationship between regions, especially spatial linkages and interdependence. Another problem is that the Herfindahl-Hirschman Index (HHI) can only measure the absolute concentration but not the relative concentration, and to compare the degree of aggregation among different industries, using the Herfindahl-Hirschman Index (HHI) will yield unrealistic results.

The advantage of Location Quotient is that the calculation process is simple and convenient, which can better analyze the degree of industrial agglomeration from a regional perspective and make a greater contribution to the sustainable development and construction of the city. The disadvantage is that it cannot effectively reflect the absolute concentration level of an industry and may be sensitive to the choice of benchmark when regions have very different industrial structures. The main advantages of the Employment Density method are that it is simple and convenient to calculate, produces relatively stable results, and reflects industrial specialization and agglomeration effects. However, it ignores industry differences and tends to mistake congestion and inefficiency for efficiency. Nevertheless, LQ remains appropriate for cross-regional comparison, especially when regions differ substantially in size and development level, because it is constructed as a relative share measure (a region's industry share benchmarked against the national share), which helps reduce scale distortions caused by large cross-regional differences in overall economic size (U.S. Bureau of

Economic Analysis, 2008). Accordingly, LQ is widely used as a basic tool in regional analysis to identify relative specialization under heterogeneous regional conditions (Miller et al., 1991).

As can be seen from the above, single indices often have their own shortcomings, employment density only reflects “employment per unit of land” and ignores industry structure; location quotient emphasizes ‘specialization’ but is unable to measure differences in enterprise scale; Herfindahl-Hirschman Index (HHI) is good at depicting “concentration” but does not include a spatial dimension. Therefore, this thesis constructs a complementary system within a “region-industry-firm” three-dimensional framework, combining the “employment density index (regional dimension) + location quotient index (industry dimension) + Herfindahl-Hirschman Index (firm dimension).”

By incorporating three types of indicators into a spatial econometric model, this study overcomes the information gaps associated with using a single indicator and enables analysis within the same framework, providing a quantitative basis for assessing the stability of China's manufacturing clusters. This chapter will use the employment density method, location quotient method, and Herfindahl-Hirschman Index to estimate the degree of industrial agglomeration in China's manufacturing sector across different regions from 2008 to 2022. Using ED, LQ, and HHI jointly captures different facets of agglomeration (spatial intensity, specialization, and concentration), reducing reliance on any single indicator and providing a more robust basis for subsequent spatial effect estimation.

### **3.5 Economic Performance Measurement in Manufacturing**

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Manufacturing economic performance essentially refers to manufacturing economic efficiency, which is measured by manufacturing factor productivity. Manufacturing factor productivity is an important variable that reflects the quantitative relationship between inputs and outputs in manufacturing economic activities. The following are methods for measuring manufacturing factor productivity (manufacturing economic performance level).

Factor Productivity in the manufacturing industry is the labor productivity in the manufacturing industry measured only by using the labor factors in the manufacturing industry's economic activities as input factors and economic output as output factors, similar to the manufacturing industry's per capita labor output, which is the average labor

productivity in the manufacturing industry. It is similar to the average labor output of the manufacturing industry. Its specific calculation formula is:

$$SFP = \frac{Y}{L} \quad \text{Equation 3.6}$$

*SFP*: manufacturing Factor Productivity;

*Y*: total manufacturing output;

*L*: manufacturing labor input, i.e., manufacturing employment.

### **3.5.1 The Influence Mechanism of Industrial Agglomeration on the Economic Performance of Manufacturing Industry**

Industrial agglomeration has both significant positive and negative effects on the manufacturing industry's economic performance. In other words, while it can help to raise the industry's level of economic performance within the agglomeration area, it can also have some inhibitory effects.

The positive influence mechanism of the industrial agglomeration on the economics performance can be seen from three effects known as competitive effect, synergistic effect and spillover effect. Industrial agglomeration increases the degree of competition in the market, facilitates easier communication between businesses, concentrates enterprise space, and allows homogeneous products to continue emerging. As a result, businesses are able to continuously update their production technology and equipment and optimize the region's industrial structure (Ding & Zhang, 2020). Fierce competition will lead to the continuous improvement of production efficiency, product quality and price reduction, which in turn will continue to expand the market outside the region, increase the market share of enterprises in the region, and promote the development of the regional economy.

Industrial agglomeration can promote regional economic development through synergistic cooperation among enterprises. Businesses can communicate and work together more easily since industries are heavily concentrated in one area. In the region, there are a lot of businesses of the same kind, and as trade grows, so does the division of work between them. By reducing needless expenses like knowledge transmission, technology exchange, and transportation, the businesses in the area would not only experience returns on scale

from increased production efficiency but also become more competitive in the marketplace (Zhang & Wang, 2019).

The market mechanism requires industries to have a finer division of labor, and competitive advantages will attract similar enterprises and factors of production to gather in this region, including labor, capital, technology, etc., which also expands the scale of the factor market. Upstream and downstream industrial chains have been continuously extended in the region, and business-to-business synergy has grown stronger. This has led to the gradual development of industry associations and regional brands, which in turn have regulated the production and sales practices of local businesses.

Industrial agglomeration has both significant positive and negative effects on the manufacturing industry's economic performance. In other words, while it can help to raise the industry's level of economic performance within the agglomeration area, it can also have some inhibitory effects. Both the aggregation and crowding effects are produced when a manufacturing industry agglomeration forms in a given area. The aggregation effect refers to external economies of scale, technological externality, and competitive externality in manufacturing industries, resulting from labor market sharing, intermediate product input sharing, transaction cost reduction, local market demand, and industrial linkages.

The crowding effect is a phenomenon where a large number of manufacturing enterprises in a region or industry converge, leading to industrial blind over-agglomeration. This occurs when the economic development of the region exceeds a critical value, resulting in excessive competition for raw materials, labor, capital, and infrastructure. This leads to a decline in corporate profitability, hindering regional economic performance improvement.

Xie (2013) analyzed the panel data of three regions, namely coastal, central and western China, and concluded that industrial agglomeration has a negative effect on regional economic growth. In addition, there are some scholars believe that industrial agglomeration on regional economic growth is not a simple linear relationship, but shows an inverted U-shaped relationship, that is, the beginning of the first to promote economic growth, to a certain extent, after the negative relationship on economic growth, that is, to verify the establishment of the Williamson hypothesis.

### *3.5.1.1 Spillover Effect*

The spillover effect refers to the process by which economic activities in a certain region or enterprise indirectly influence other regions or enterprises through technology diffusion, knowledge sharing, market connections, or environmental externalities (Grossman & Helpman, 1991). In industrial economics, spillover effects typically manifest as externalities in areas such as technological progress, productivity improvements, environmental enhancements, or social welfare gains. Their impacts can be positive (e.g., increased productivity) or negative (e.g., pollution dispersion). In recent years, with the development of the digital economy, global value chains, and regional integration, the spatial transmission pathways and mechanisms of spillover effects have become increasingly complex, making them an indispensable perspective in the study of industrial agglomeration and regional development (Audretsch & Belitski, 2022).

Industrial agglomeration often brings about productivity spillover effects through knowledge sharing, labor mobility, and market division of labor. Zhang & Yang (2022) conducted an empirical study on the manufacturing industry in Malaysia and found that industries with a high concentration of foreign-owned enterprises are able to transfer technology and management experience to local enterprises, thereby improving overall productivity. However, in industries with a low concentration of foreign-owned enterprises, this spillover effect is not significant. This result indicates that industrial agglomeration enhances the overall competitiveness of regional industries through externalities, thereby promoting the growth of local enterprises.

In the context of the digital economy, the spillover effects of industrial agglomeration are exhibiting new characteristics. Liu and Lian (2025) point out that the digital economy not only increases local tax revenue, but also promotes tax revenue growth and economic vitality in surrounding cities through spatial diffusion effects. At the same time, Teng et al. (2024) found that the development of digital finance can significantly improve regional green economic efficiency through spillover mechanisms and transmit sustainable development experiences and models across regions. This indicates that digital industrial clusters not only play a role locally, but also have positive spillover effects across regions.

The externalities of industrial agglomeration are also reflected in infrastructure investment. Yin et al. (2024) found in their study based on the spatial Durbin model that China's transportation infrastructure construction not only significantly promoted local

economic growth but also drove the development of surrounding areas through spatial spillover effects. This shows that infrastructure improvements brought about by industrial agglomeration can transcend geographical boundaries and create cross-regional synergies, thereby enhancing the overall economic coordination of the region.

Industrial agglomeration not only influences economic and technological development, but also exhibits significant spillover effects in structural upgrading and environmental governance. Tao et al. (2025) found that industrial upgrading in Chinese cities not only promotes local economic growth, but also drives industrial transformation in surrounding areas through spatial spillover effects. At the same time, Zhang and Sun (2025) emphasizes that the technology finance ecosystem has a significant spatial spillover effect on carbon emission reduction, providing impetus for regional green development. Therefore, industrial agglomeration plays a key role in promoting regional sustainable development through spillover effects.

In summary, the spillover effects of industrial agglomeration are a multidimensional and comprehensive mechanism. First, it promotes the improvement of local enterprise productivity and enhances overall industrial competitiveness through knowledge diffusion and technology transfer. Second, digital transformation has expanded the spatial scope of spillover effects, promoting cross-regional tax growth and improvements in green economic efficiency (Teng et al., 2024). At the same time, infrastructure construction has strengthened agglomeration externalities, not only promoted local economic development but also driven growth in neighboring areas through transportation and network connections (Yin et al., 2024). Finally, industrial agglomeration also exhibits significant spatial spillover effects in terms of structural upgrading and environmental governance, helping to promote industrial transformation and green, low-carbon development across regions (Tao et al., 2025). Therefore, the spillover effects of industrial agglomeration are not only an important driver of economic growth, but also play a key role in technological progress, regional coordination, and sustainable development, providing a solid theoretical basis for understanding regional economic evolution and policy regulation.

#### ***3.5.1.2 Research Hypothesis on the Impact of Industrial Agglomeration on Manufacturing Economic Performance***

This section firstly describes the positive and negative influence mechanisms of industrial agglomeration on the economic performance of the manufacturing industry from

the theoretical level, and finally puts forward the research hypotheses in this section on the basis of the existing theoretical analyses. Based on the above theoretical analysis, this section proposes the following research hypotheses on the impact of industrial agglomeration on the economic performance of the manufacturing industry:

- H1: The higher the level of industrial agglomeration, the more significant the economic performance of the region.
- H2: Industrial agglomeration has a negative impact on economic performance, and excessive agglomeration reduces regional economic performance.
- H3: Industrial agglomeration not only improves the economic performance of the region itself, but also has a significant spatial spillover effect on the economic performance of neighboring regions.

### 3.5.2 Empirical Modeling of The Impact of Industrial Agglomeration on The Economic Performance of Manufacturing Industry

In order to study the impact of industrial agglomeration on economic performance, the study import several control variables, introduce a spatial matrix, and take the economic performance of the manufacturing industry as a dependent variable, and then derive a Spatial Durbin Model of country economic growth:

$$\ln \text{ecomance}_{it} = \beta_0 + \alpha_1 \ln \text{agglo}_{it} + \alpha_2 \ln X_{it} + \alpha_3 W_{ij} \ln \text{agglo}_{it} + \alpha_4 W_{ij} \ln X_{it} + \eta_i + \eta_t + \varepsilon$$

Equation 3.7

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} & \text{When region " i" and region " j" share a common boundary} \\ 0 & \text{,When there is no common boundary between region " i" and region " j" or " i=j"} \end{cases}$$

Where  $\beta_0$  denotes the intercept term,  $i$  represents time,  $t$  represents region,  $\text{agglo}_{it}$  denotes the industrial agglomeration index of a province in a certain year,  $X_{it}$  is the control variable,  $\eta_i, \eta_t$  denote the regional effect, time effect, and  $\varepsilon$  denotes the random interference term,  $W_{ij}$  is the inverse geographic distance spatial weight matrix,  $d_{ij}$  denotes the geographic distance between regions  $i$  and  $j$ , and  $\alpha_1, \alpha_2, \alpha_3,$  and  $\alpha_4$  denote the regression coefficients of the variables, respectively.

### 3.5.2.1 Selection of Variables and Description of Indicators Related to Economic Performance and Industrial Agglomeration

Table 3-1 illustrates the variable selections in relation to economic performance and industrial agglomeration, along with their definitions. These indicators are included to address Objective 1 (economic performance) by (i) measuring industrial agglomeration through complementary dimensions (ED, LQ, HHI), and (ii) controlling for key regional factors (*h*, *pgdp*, *insti*, *fdi*) that may jointly affect agglomeration and manufacturing performance, so that the SDM can identify both direct (local) and indirect (spatial spillover) effects more reliably.

**Table 3-1:  
Variable Selection and Definition (Economic Performance)**

Variable type	Variable Symbol	Variable Definition
<b>dependent variable</b>	<i>ecomance</i>	Manufacturing production factors
<b>independent variable (agglomeration)</b>	<i>ED</i>	Employment Density
	<i>LQ</i>	Location Quotient
	<i>HHI</i>	Herfindahl-Hirschman Index
<b>control variable</b>	<i>h</i>	Human capital level (average years of schooling per employed person).
	<i>pgdp</i>	Per capita gdp
	<i>insti</i>	Institutional openness (trade openness), measured by merchandise exports as a percentage of regional GDP.
	<i>fdi</i>	Foreign enterprise direct investment

***h***: Human capital is an important determinant of labor productivity. Generally speaking, regions with high levels of human capital have relatively high labor productivity. This argument is well supported by human capital theory and empirical productivity and regional performance studies, which commonly use education-based proxies of human capital to explain productivity differences across regions (Becker, 1964; Barro, 1991; Mankiw et al., 1992).

Higher human capital enables local enterprises to accumulate numerous excellent talents, allowing them to hire labor quickly and with minimal wage increases. This reduces waiting times and recruitment costs, lowering manufacturing costs and increasing labor productivity. Higher human capital levels also lead to higher worker quality, stronger

employability, and creativity. This results in more value created per unit of time, thereby increasing labor productivity. Therefore, a higher level of human capital is crucial for successful business operations. Thus, human capital is also a key factor influencing the economic performance of the manufacturing sector. Accordingly,  $h$  is included to isolate the agglomeration effect from workforce-quality differences across provinces, which is essential for answering Objective 1. In addition, provincial-level evidence for China has also highlighted the role of human capital in explaining productivity differences across provinces (Wei & Hao, 2010).

In this section the study uses years of schooling per employed person to measure the level of human capital. It is measured as follows:

$$h = \frac{H}{L} \quad \text{Equation 3.8}$$

where:  $H$  denotes the sum of years of schooling for each employed person in the region, and  $L$  denotes the total number of employed persons in the region.  $H$  is generally obtained by adding the product of the number of employed persons with various levels of education multiplied by the corresponding number of years of schooling, i.e.

$$H = \sum L_i H_i \quad \text{Equation 3.9}$$

Where:  $L_i$  denotes the number of employed persons with the  $i$  level of education, and  $H_i$  denotes the coefficient of years of schooling with the  $i$  level of education.

This can be further derived by substituting equation (3.9) into equation (3.8)

$$\begin{aligned} h &= \frac{\sum L_i H_i}{L} \\ &= \sum \frac{L_i}{L} H_i \end{aligned} \quad \text{Equation 3.10}$$

$\frac{L_i}{L}$ : the proportion of employed persons with the first level of education.

According to the basic academic system of modern education in China, it can be obtained that: ratio of average years of schooling/higher education (percentage of university education).

So human capital level ( $h$ )=(Number of persons with elementary school education\*6+Number of persons with lower secondary school education\*9+Number of

persons with upper secondary school and middle school education\*12+Number of persons with college and bachelor's degree or higher education\*16)/ Total population over 6 years of age.)/ higher education (percentage of university education).

***pgdp***: GDP (gross domestic product) or GDP per capita (*pgdp*) are two ways to measure the degree of economic development. The primary rationale for selecting the per capita gross domestic product (*pgdp*) indicator in this section is its superior ability to represent the real output per capita status of a region in comparison to gross domestic product (*gdp*)(Liu & Xu, 2010). Additionally, it is more effective in reflecting the region's level of economic development. Greater per capita GDP (*pgdp*) is a sign of more advanced economic development in a given area. *pgdp* is included because regional development level affects manufacturing productivity and may also correlate with agglomeration; controlling for *pgdp* helps answer Objective 1 by reducing omitted-variable bias.

***insti***: Institutions are also an important factor in the economic performance of an organization. In addition, North (1990) contended that institutions and institutional change are key variables among the numerous others influencing economic success. According to Fujita and Hu (2001), the theory of new economic geography posits that international trade plays a significant role in the exporting country's regional specialization due to market forces. This, in turn, affects the manufacturing firms' financial performance in the exporting country.

The opening up to the outside world is the most significant institutional shift in China's economy as a result of its reform and opening up. China's economic structure has progressively opened up to the outside world, transitioning from a planned economy to a market one. Greater degrees of economic opening up are associated with easier access to foreign capital, greater export rates, better employment and economic development rates, and improved manufacturing company performance. Consequently, the study adds the open-door system to its list of control variables. In keeping with previous research, the study gauges the regional open-door policy in this chapter by looking at the value of merchandise exports as a percentage of regional GDP. Therefore, “*insti*” in this study captures institutional openness (trade openness), which is important for answering Objective 1 because openness can directly affect manufacturing productivity and competitiveness and may also be correlated with agglomeration.

*fdi*: Due to the knowledge and technology spillover effect, foreign direct investment (FDI) can, on the one hand, improve the energy utilization efficiency of the manufacturing enterprises in the host country and reduce environmental pollution by bringing advanced process equipment, energy-saving, and emission-reduction technologies to the host country through the demonstration and imitation effect, personnel training effect, competition effect, and linkage effect (Hatzipanayotou et al., 2008). *fdi* is also closely linked to manufacturing productivity and upgrading, and agglomerated regions may attract more *fdi*; therefore, *fdi* is included to isolate the net effect of agglomeration on economic performance (Objective 1). FDI in manufacturing is expressed as the gross output value of manufacturing firms/gross manufacturing output value, based on research by (Han et al., 2015).

Human capital (*h*), per capita GDP (*pgdp*), institutional openness (*insti*), and foreign direct investment (*fdi*) capture key drivers of manufacturing economic performance that may also be correlated with industrial agglomeration and generate cross-provincial externalities. Controlling for these factors helps reduce omitted-variable bias and avoids attributing performance differences stemming from workforce quality, development level, openness, or technology spillovers to agglomeration itself. This improves identification of both the local effects and spatial spillover effects of industrial agglomeration on manufacturing economic performance.

### **3.6 Technological Performance Measurement in Manufacturing**

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Industrial agglomeration significantly contributes to economic development by fostering technological innovation, concentrating talent and capital, creating an innovative environment, and facilitating knowledge transfer. Competition and collaboration among enterprises in the same industry enhance the efficient flow of information, technology, and talent. According to Schumpeter, industrial agglomeration contributes to innovation and innovation depends on industrial agglomeration.

#### **3.6.1 The Influence Mechanism of Industrial Agglomeration on the Technological Performance of Manufacturing Industry**

First, explain the positive impact of industrial agglomeration on technological performance from two perspectives. The network of knowledge, technology, and information exchange created by industrial agglomeration is helpful in fostering the spread

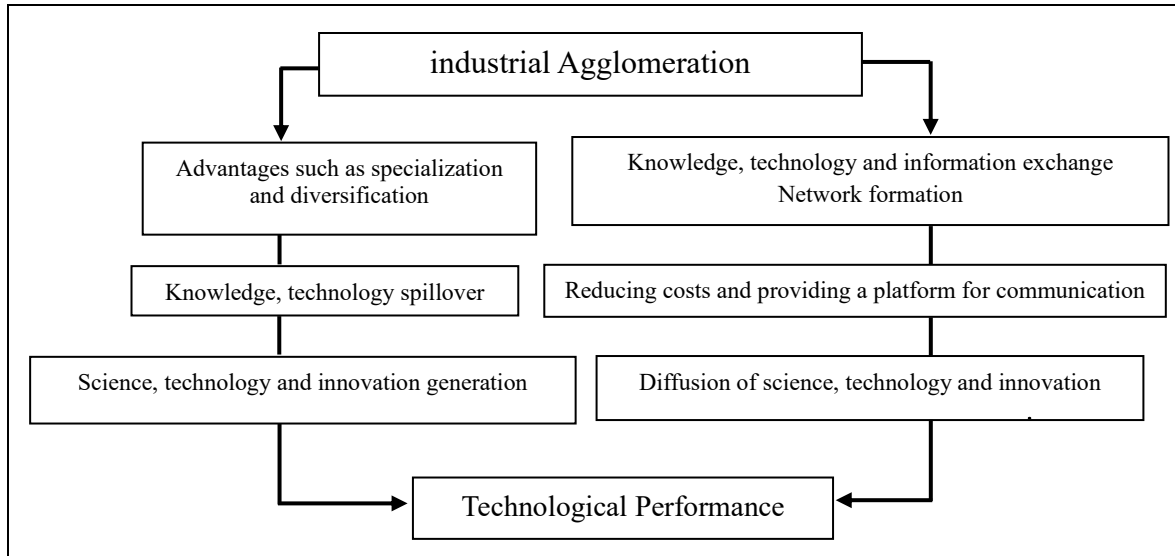
of advances in science and technology. Industrial agglomeration helps to lower the transaction costs associated with the diffusion of scientific and technological innovations among manufacturing enterprises in industrial agglomeration zones (Yang & Zhang, 2002).

This helps to accelerate the diffusion of innovations among manufacturing enterprises and, as a result, encourages the ongoing enhancement of the technological performance of manufacturing in industrial agglomeration zones. In addition to offering more platforms for mutual exchanges between various manufacturing enterprises, the ideal knowledge, technology, and information exchange network in the industrial agglomeration area can also provide more and better dissemination channels for the diffusion of scientific and technological innovation achievements among manufacturing enterprises. This will help to accelerate the diffusion of these achievements and raise the level of manufacturing technological performance in this industrial agglomeration area (Cheng & Li, 2008).

The advantages of industrial agglomeration, such as specialization and diversification, are conducive to the promotion of scientific and technological innovations. Through the close agglomeration of talents, enterprises, and industries, manufacturing industrial agglomerations achieve interdependence, collaboration and complementarity, a finely tuned division of labor, information sharing, and resource integration. These factors collectively promote the overflow of knowledge and technology, stimulate the generation of scientific and technological innovations, and advance the sustained enhancement of enterprises' technological performance.

In the meantime, intense competition within the industrial agglomeration area drives people and businesses to concentrate on their areas of expertise, boosts the effectiveness of scientific and technological innovation, encourages the flow of knowledge and technology, quickens the pace at which innovation results are produced, and, in the end, raises the technological performance of the entire industrial agglomeration area.

**Figure 3-1:  
Positive Influence Mechanism of Industrial Agglomeration on Manufacturing  
Innovation Performance**



Agglomeration of manufacturing industries may be detrimental to the realization of knowledge or technology spillovers. A large spatial agglomeration of the same type or the same manufacturing industry will frequently lead to intense homogenized and vicious competition among manufacturing enterprises. In regions with a high degree of manufacturing industry agglomeration, the degree of competition is also typically stronger.

In addition to the weak awareness of intellectual property protection, there are occasional instances of technology imitation and copying. These occurrences will negatively affect manufacturing enterprises' enthusiasm for technological innovation, which will hinder or prevent the play of knowledge and technology spillover effect. Consequently, technology performance will negatively affect the manufacturing industry.

### **3.6.2 Research Hypothesis on the Impact of Industrial Agglomeration on Manufacturing Technological Performance**

H4: The higher the level of industrial agglomeration, the more significant the technological performance of the region.

H5: Excessive industrial agglomeration can inhibit regional technological performance.

H6: Industrial agglomeration not only improves the technological performance of the region itself, but also has a significant spatial spillover effect on the technological performance of neighboring regions.

### **3.6.3 Methods for Measuring the Technological Performance of the Manufacturing Industry**

Manufacturing technology performance essentially refers to manufacturing innovation capacity. Measurement of manufacturing innovation capacity can be broadly categorized into measurement of manufacturing innovation inputs and measurement of manufacturing innovation outputs (Huang et al., 2013).

This thesis argues that innovation output can be categorized as the output of scientific research in the manufacturing industry and the output of products in the manufacturing industry. The number of patents awarded is the primary metric used to quantify the output of scientific research and shows up as a non-market innovation performance indicator. Xiao and Lin (2014) indicate that the amount of product output reflects the level of market-oriented manufacturing innovation performance; new product sales or output are the primary measures used to assess performance in China.

The measurement of manufacturing output outcomes is often done by counting the number of patents in the manufacturing sector as a sign of the results of scientific research conducted in the sector, or by looking at sales figures or the output value of new goods. By avoiding the issue of multiple covariance between the control variables and allowing for a range of decision-making elements in each period, this method reduces the impact of measurement results on the quality of the data in this thesis and improves the usability of the research findings in the case of statistical data in the presence of year-specific or regional deficiencies of the problem. Additionally, it compares the input efficiency across periods and provides a visual comparative analysis of input-output ratios in each period. This thesis uses the number of valid invention patents in each province's manufacturing industry to measure technological performance.

### 3.6.4 Empirical Modeling of The Impact of Industrial Agglomeration on The Technological Performance of Manufacturing Industry

The technological performance of the manufacturing industry is used as the dependent variable in order to derive the spatial Durbin model of the impact of industrial agglomeration on technological performance. The study import multiple control variables, introduce the spatial matrix, and study the relationship between industrial agglomeration and technological performance.

$$\ln technical_{it} = \beta_0 + \alpha_1 \ln aggro_{it} + \alpha_2 \ln X_{it} + \alpha_3 W_{ij} \ln aggro_{it} + \alpha_4 W_{ij} \ln X_{it} + \eta_i + \eta_t + \varepsilon$$

Equation 3.11

$$\text{Where, } W_{ij} = \begin{cases} \frac{1}{d_{ij}} & \text{When region " i" and region " j" share a common boundary} \\ 0 & \text{,When there is no common boundary between region " i" and region " j" or " i=j"} \end{cases}$$

#### 3.6.4.1 Selection of Variables and Description of Indicators Related to Technological Performance and Industrial Agglomeration

Table 3-2 illustrates the variable selections in relation to technological performance and industrial agglomeration, along with their definitions. These indicators are included to address Objective 2 (technological performance) by (i) measuring industrial agglomeration through complementary dimensions (ED, LQ, and HHI), and (ii) controlling for key innovation inputs and institutional supports (human capital, R&D personnel, research funding, and government S&T expenditure) that directly shape patenting outcomes and may also correlate with agglomeration. Within the Spatial Durbin Model (SDM), the selected variables allow the estimation of both direct (local) effects and indirect (spatial spillover/cross-regional) effects of industrial agglomeration on technological performance, which directly corresponds to the research objective.

**Table 3-2:  
Variable Selection and Definition (Technological Performance)**

Variable type	Variable symbol	Variable Definition
<b>dependent variable</b>	<i>technological</i>	The number of effective invention patents
<b>independent variable (agglo)</b>	<i>ED</i>	Employment Density
	<i>LQ</i>	Location Quotient
	<i>HHI</i>	Herfindahl-Hirschman Index
<b>control variable</b>	<i>h</i>	Human capital level (average years of schooling per employed person).
	<i>staff</i>	R&D personnel input (number of R&D personnel in manufacturing, per capita / normalized by regional size as used in this study)
	<i>fund</i>	Volume of scientific research funding (R&D expenditure of manufacturing enterprises)
	<i>gov</i>	Financial expenditure on science and technology (proxy for government support for innovation)

**h:** Human capita is included because human capital enhances firms' absorptive capacity and innovative capability, which directly affects invention patent output. Controlling for h helps isolate the innovation effect of agglomeration from underlying differences in workforce quality across provinces, which is essential for answering Objective 2.

**staff:** In general, the manufacturing industry benefits from a greater number of scientific and technical people contributions, a greater supply of scientific and technological human resources, and a better degree of innovation performance. This is supported by empirical innovation studies showing that R&D inputs (including R&D personnel) are strongly associated with patenting and innovation outputs (Pakes & Griliches, 1984; Crépon et al., 1998). In general, the manufacturing industry's degree of innovation performance increases with the amount of scientific and technical personnel invested in the sector. This is because the manufacturing sector has a greater supply of scientific and technology human resources. This chapter uses the number of R&D employees in manufacturing companies as a proxy for the contribution of scientific and technology workers to the manufacturing sector. The use of R&D personnel as an innovation-input measure is also consistent with standard R&D statistical guidelines (OECD, 2015). Accordingly, staff is included as a key innovation-input control because regions with higher R&D personnel typically generate more patents and may also be more agglomerated; controlling for staff helps identify the net direct and spillover effects of agglomeration on technological performance (Objective 2). This helps

ensure that the estimated agglomeration effect is not confounded by cross-regional differences in R&D input intensity (Crépon et al., 1998).

*fund*: Investment in manufacturing science and technology has a significant impact on the technological performance of the manufacturing sector. This is because investment in this area indicates the level of scientific and technological activity that goes into the sector. The more money invested in this area, the more of a role it plays in enhancing the technological performance of the manufacturing sector. The R&D expenditure of manufacturing companies is used in this chapter to gauge the contribution of science and technology to the manufacturing sector (Yang, 2018). *fund* is included because R&D expenditure is a direct driver of patenting and innovation output, and omitting it may bias the estimated agglomeration effect if agglomerated regions systematically invest more in R&D.

*gov*: Government support for R&D and innovation in manufacturing enterprises, including R&D subsidies and tax breaks, increases the scale of funds for these activities. This boosts enthusiasm for R&D and innovation, provides sufficient financial support for large-scale activities, and promotes technological performance enhancement in manufacturing enterprises. This support method is conducive to overall economic growth. The government is focusing on supporting R&D innovation in manufacturing enterprises through subsidies and tax breaks, screening projects based on strategic significance, efficiency, and novelty. This aims to guide R&D innovation and improve dynamic innovation performance levels. This research, which is based on Yu (2009), gauges the level of government support for science and technology by looking at the percentage of government money in total funds raised for S&T initiatives. *gov* is included because public S&T expenditure can directly stimulate firm innovation and can also interact with agglomeration (e.g., policy support is often concentrated in key industrial clusters); controlling for *gov* supports a cleaner identification of agglomeration's direct and spillover effects on technological performance (Objective 2).

Human capital (*h*), R&D personnel (*staff*), R&D expenditure (*fund*), and government support (*gov*) are included as core innovation-input controls when examining how industrial agglomeration affects manufacturing technological performance. Specifically, *h* captures provinces' absorptive capacity and underlying workforce quality; *staff* and *fund* represent the intensity of private R&D inputs that directly drive patenting; and *gov* reflects public

support that can stimulate innovation and is often concentrated in key clusters. Controlling for these factors reduces confounding from cross-provincial differences in innovation resources and policy support, allowing the estimated effects to more cleanly reflect agglomeration's direct impact and spatial spillover effects on technological performance.

Human capital (*h*), environmental regulation (*regu*), urbanization (*citylevel*), and capital investment (*k*) are controlled because each can affect manufacturing CO<sub>2</sub> intensity independently of agglomeration and may also co-vary with clustering across provinces. Including them helps avoid attributing regulation, urbanization, or capital-driven changes in emissions to agglomeration, thereby allowing a cleaner assessment of agglomeration's direct effects and spatial spillover effects on environmental performance.

### **3.7 Environmental Performance Measurement in Manufacturing**

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Assessing the environmental efficiency of different countries or regions not only helps people to understand the differences in environmental performance among them, but also provides a favorable reference for improving the level of environmental performance Song et al. (2012). Industrial agglomeration has a multifaceted impact on environmental performance. Through knowledge spillovers, economies of scale, and competitive impacts, it improves the manufacturing sector's performance in green innovation. There is an ideal agglomeration point, though, beyond which agglomeration may have unfavorable consequences. As such, this improvement is not infinite.

#### **3.7.1 The Influence Mechanism of Industrial Agglomeration on the Environmental Performance of Manufacturing Industry**

Industrial agglomeration can reduce governance costs through economies of scale, enhance green production efficiency through labor and infrastructure intensification, and accelerate the diffusion of clean technologies through knowledge and technology spillovers, thereby promoting overall environmental performance improvement.

The most significant element in the process of an industrial agglomeration's establishment is the scale economy impact. Industrial agglomeration may efficiently lower the inputs of capital, labor, and energy per unit of output through the creation of economies of scale. This lowers the average cost of production, lowers energy consumption, and improves energy usage efficiency. As an industrial agglomeration forms and grows, manufacturing firms' production scales will also continue to expand, leading to an increase

in the overall output of these businesses and the eventual establishment of economies of scale.

This has the potential to not only enable large-scale production by the manufacturing enterprises in the industrial agglomeration area, but also to assist in bringing about the incremental effect of returns to scale through the reduction of manufacturing enterprises' average cost of production. As a result, the degree of industrial agglomeration will be accompanied by an increase in a variety of factors, including energy consumption, and output per unit of output will significantly decline. Energy efficiency is significantly improved by urbanization and industrial agglomeration (Shi & Shen, 2012).

Due to the effect of economies of scale, manufacturing enterprises' input of capital, labor, energy, and other resources will be significantly reduced in order to produce the same number of products, which is conducive to reducing energy consumption and improving energy use efficiency. Alternatively, if manufacturing enterprises input the same amount of capital, labor, energy, and other resources, the authors will produce a greater number of products, which is conducive to improving the energy output efficiency and thereby promoting the local industrial agglomerations. The industrial agglomeration area's manufacturing businesses will consistently increase their energy efficiency.

The formation of an industrial agglomeration due to economies of scale also makes it possible for large-scale centralized treatment of pollutants generated by manufacturing enterprises. This helps lower the cost and energy input of treating pollutants at the manufacturing enterprise unit, which in turn lowers pollution emissions and energy consumption, ultimately promoting the manufacturing enterprises' environmental performance to continue improving. Manufacturing companies within the same industry or type have comparable demands for labor, public infrastructure, and market networks. By assembling multiple manufacturing companies within the same industry or type in a particular region for production, industrial agglomeration facilitates the sharing of labor, infrastructure, and information. By allowing public infrastructure to be produced on a large scale and used collectively, labor, infrastructure, and information sharing helps prevent the duplication of related public infrastructure in industrial agglomerations. This lowers the average cost of production and energy consumption of manufacturing enterprises within the agglomerations (Ji & Zhao, 2016).

In industrial agglomerations, labor, infrastructure, and information sharing prevents the duplication of related public infrastructure and enables the production of public infrastructure on a large scale for joint use, lowering the average production cost and energy consumption of the agglomeration's manufacturing businesses. The quantity of energy used by manufacturing companies per unit of production may be efficiently decreased by increasing worker productivity through the sharing of labor, infrastructure, and knowledge. In addition to improving the energy performance of manufacturing firms in the industrial agglomeration area, this enables manufacturing enterprises in the agglomeration area to effectively reduce the inputs of labor, capital, and energy while maintaining a specific level of output (Liu, 2022). Combining manufacturing companies of the same kind or upstream and downstream with backward and forward linkage can reduce labor costs, search times, and intermediate input costs. It can also shorten the distance between manufacturing companies and minimize intermediate input loss during transit, which lowers the price of intermediate inputs and lowers transportation and use costs. Ultimately, this lowers energy consumption and increases manufacturing companies' efficiency in using energy. efficiency of energy use.

Knowledge and technology spillover effects are important mechanisms arising from the formation of industrial agglomerations. By generating externalities such as knowledge and technology spillovers, industrial agglomeration is conducive to accelerating technological progress and technology diffusion, thereby improving technological efficiency and, consequently, environmental performance. Industrial agglomeration is driven by knowledge and technology spillovers, which also give manufacturing firms the opportunity to generate their own knowledge and technology spillovers. However, externalities like technological advancements and technology spillovers are primarily responsible for the effective improvement of environmental performance, or energy performance (Xu, 2009).

The establishment of industrial agglomerations gives rise to significant processes, including the spillover effects of technology and knowledge. Industrial agglomeration contributes to the acceleration of technical advancement and dissemination through the generation of externalities like information and technology spillovers. This, in turn, improves technological efficiency and, ultimately, environmental performance. It is evident from the study above that industrial agglomeration enhances the manufacturing sector's environmental performance. However, there is a drawback to industrial agglomeration that

also affects the manufacturing sector's environmental performance. To put it another way, there is a negative externality associated with industrial agglomeration.

The majority of industrial agglomerations in China are shaped by the government rather than emerging naturally from the market. On the one hand, the lack of rational and scientific layout planning for manufacturing firms in agglomerations makes it challenging to create structural optimization and technological knowledge spillover effects amongst enterprises, which not only results in resource waste and other wastes but also increases the likelihood of cross-regional pollutants superposing. Some governments have introduced a large number of low-end manufacturing enterprises eliminated by developed countries, which are high in energy consumption, high in emissions, high in pollution and low in efficiency, thus becoming a paradise for enterprises that take refuge in pollution, resulting in huge energy loss and serious environmental damage, which has led to a decrease in the environmental performance level of the manufacturing industry. This has resulted in huge energy losses and serious environmental damage, which in turn has led to a decline in the environmental performance of the manufacturing sector (Zhu et al., 2010).

The creation of industrial agglomerations will, on the one hand, enable manufacturing companies to expand their production scale, but, on the other hand, these researchers will also result in higher energy consumption and a notable rise in pollutant emissions (Verhoef & Nijkamp, 2002). This will impede the manufacturing sector's ability to improve its environmental performance. Industrial agglomeration also causes monopolization of resources, which leads to distortion of resource allocation and inefficient use of energy Fan and Wang (2013), and thus inhibits further improvement of the environmental performance of the manufacturing industry.

The spatial aggregation of industries in specific areas can lead to "free-riding" behavior in manufacturing enterprises, resulting in government policies failing. These enterprises may enjoy preferential policies but not prioritize energy conservation and environmental improvement. This makes it difficult to achieve the desired level of intensive energy use and centralized environmental management in the aggregation area, resulting in a reduction in the overall environmental performance of the manufacturing industry.

Industrial agglomeration leads to cost savings, technological progress, and diffusion through the sharing of labor, infrastructure, and information. However, these benefits require

frequent exchanges and personnel mobility between enterprises in long-term competition and cooperation. These exchanges and mobility take time to have a significant impact on the environmental performance of enterprises, indicating that the positive effects of industrial agglomeration on environmental performance have a significant lag in their effect.

### **3.7.2 Research Hypothesis on the Impact of Industrial Agglomeration on Manufacturing Environmental Performance**

H7: The higher the level of industrial agglomeration, the more significant the environmental performance of the region.

H8: Excessive industrial agglomeration reduces the environmental performance of a region.

H9: Industrial agglomeration not only improves the environmental performance of the region itself, but also has a significant spatial spillover effect on the environmental performance of neighboring regions.

### **3.7.3 Methods for Measuring the Environmental Performance of the Manufacturing Industry**

In past research, a lot of single-factor environmental efficiency measures were utilized to evaluate environmental performance. The ratio of environmental pollution emissions to an economic variable is used as an indication for the single-factor environmental efficiency, much like it is for the single-factor energy efficiency.

For example, Kaya and Yokobori (1997) propose an indicator of carbon productivity (i.e., the ratio of GDP to carbon dioxide emissions) to reflect the environmental cost of pursuing economic growth in a country or region. Mielnik and Goldemberg (1999) proposed carbon dioxide emissions per unit of energy consumption as a criterion for evaluating the efforts of developing countries to combat climate change. Sun (2005) argues that carbon intensity (the ratio of carbon dioxide emissions to GDP) is a suitable indicator for evaluating a country or region's energy policy and the effectiveness of emission reduction.

One advantage of single-factor efficiency indicators is that they are simple and easy to describe. In this case, decomposition techniques related to energy intensity can also be used to analyze the reasons behind changes in environmental performance. Through a single

economic variable, environmental performance can be quantified intuitively, reducing the complexity of data acquisition and analysis. Therefore, this study uses the ratio of carbon dioxide emissions to GDP to measure environmental performance.

### 3.7.4 Empirical Modeling of The Impact of Industrial Agglomeration on The Environmental Performance of Manufacturing Industry

The manufacturing sector's environmental performance is used as the dependent variable to create the spatial Durbin model of how industrial agglomeration affects environmental performance. To investigate the connection between industrial agglomeration and environmental performance, the study imports many control variables and build a geographical matrix.

$$\ln environ_{it} = \beta_0 + \alpha_1 \ln agglo_{it} + \alpha_2 \ln X_{it} + \alpha_3 W_{ij} \ln agglo_{it} + \alpha_4 W_{ij} \ln X_{it} + \eta_i + \eta_t + \varepsilon$$

Equation 3.12

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} & \text{When region " i" and region " j" share a common boundary} \\ 0 & \text{,When there is no common boundary between region " i" and region " j" or " i=j"} \end{cases}$$

#### 3.7.4.1 Selection of Variables and Description of Indicators Related to Environmental Performance and Industrial Agglomeration

Table 3-3 illustrates the variable selections in relation to environmental performance and industrial agglomeration, along with their definitions. These indicators are included to address Objective 3 (environmental performance) by (i) measuring industrial agglomeration through complementary dimensions (ED, LQ, and HHI), and (ii) controlling for key determinants of regional environmental outcomes—human capital, environmental regulation intensity, urbanization, and capital investment—that may directly affect CO<sub>2</sub> intensity and may also correlate with agglomeration. Within the Spatial Durbin Model (SDM), the selected variables allow the estimation of both direct (local) effects and indirect (spatial spillover/cross-regional) effects of industrial agglomeration on environmental performance, which directly corresponds to the research objective.

**Table 3-3:  
Variable Selection and Definition (Environmental Performance)**

Variable type	Variable Symbol	Variable Definition
dependent variable	<i>environ</i>	Ratio of CO <sub>2</sub> emissions to GDP
independent variable (agglo)	<i>ED</i>	Employment Density
	<i>LQ</i>	Location Quotient
	<i>HHI</i>	Herfindahl-Hirschman Index
control variable	<i>h</i>	Human capital level (average years of schooling per employed person).
	<i>regu</i>	Proportion of pollution control investment in total manufacturing output value
	<i>citylevel</i>	Proportion of urban population to regional population
	<i>k</i>	Capital investment per capita, Manufacturing fixed asset investment/manufacturing employment

*h*: Human capital is controlled for because regions with higher human capital tend to adopt cleaner technologies and have stronger environmental awareness and governance capacity, which can affect CO<sub>2</sub> intensity independently of agglomeration. Controlling for *h* therefore helps isolate the net direct and spillover effects of agglomeration on environmental performance (Objective 3).

*regu*: Environmental regulation is a key determinant of environmental performance and is included to capture policy stringency that can directly reduce emissions intensity and also interact with agglomeration. A further significant factor influencing the environmental (energy) performance of industry is environmental legislation. Porter's hypothesis states that proper environmental regulation can effectively encourage regulated manufacturing companies to further optimize resource allocation efficiency and raise technology standards despite shifting constraints. It can also encourage the innovation compensation effect, which can enhance energy performance while also compensating manufacturing companies. In addition to offsetting the "compliance cost" for industrial companies, this may also significantly increase productivity (Porter, 1998), which in turn enhances the companies' energy and environmental performance. Drawing on the study of Wang et al. (2014) , the

proportion of investment in pollution control to the total output value of the manufacturing industry is used to express the intensity of environmental regulation, while the existence of the Porter's hypothesis is further tested through empirical analysis. Accordingly, *regu* is included to avoid attributing regulation-driven emission reductions to agglomeration.

*citylevel*: Urbanization is included because it affects energy demand, transport patterns, and industrial structure, thereby influencing CO<sub>2</sub> intensity and potentially correlating with agglomeration. Urbanization can increase productive energy use while reducing per capita residential energy consumption. Urbanization has varying effects on energy consumption depending on income level: it decreases energy consumption in the low-income group, increases energy consumption in the lower-middle-income and high-income groups significantly, and has no discernible effect on the upper-middle-income group (Li & Lin, 2015). This study uses the share of urban population in regional population to measure the level of urbanization. Controlling for *citylevel* helps identify agglomeration's direct/local and spillover impacts on environmental performance (Objective 3).

*k*: Capital investment is included because it can change the scale and technology composition of manufacturing production, thereby affecting emissions intensity and possibly co-moving with agglomeration. This is consistent with the capital accumulation (capital deepening) view in production theory, where capital investment expands production capacity and can influence productivity and the input–output structure (Solow, 1956). Empirical studies on China also commonly treat investment—especially fixed-asset investment—as an important determinant/control variable when explaining CO<sub>2</sub> emissions or emissions-related outcomes. For example, Zhao et al. (2022) find that investment has significant positive effects on CO<sub>2</sub> emissions, and they cite evidence that fixed-asset investment is a key factor in China's CO<sub>2</sub> emissions dynamics. In addition, He et al. (2017) explicitly note that many studies focus on FDI and fixed asset investment when examining the investment–carbon emissions linkage. Similarly, Chen et al. (2022) include (log) total fixed-asset investment among their control variables in a provincial-panel spatial model of carbon emissions. The environmental performance of the manufacturing industry is influenced by both agglomeration degree and per capita capital investment. Capital investment is a key driver of economic development and affects the performance of regional manufacturing enterprises' inputs and outputs. This section uses per capita fixed asset investment as a proxy variable for per capita capital investment in the manufacturing industry and measures it using the

ratio of fixed asset investment to the number of manufacturing industry employment. Accordingly, controlling for  $k$  helps avoid confounding agglomeration effects with capital-deepening effects when assessing environmental performance (Objective 3).

### **3.8 Spatial Econometric Model**

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One statistical method for examining how geography affects economic events is spatial econometric modeling. By accounting for geographical elements, it overcomes the drawbacks of conventional economic models and offers a crucial tool for more precisely examining regional economic disparities and developing successful policy initiatives. While traditional economic models usually assume that observations are independent of each other, spatial econometric models recognize that geographically proximate regions are often economically linked and interact with each other. For example, the levels of economic development of neighboring regions may affect each other, or the formation of industrial clusters in one region may have a radiation effect on neighboring regions.

Spatial econometric modeling has been widely used in many fields such as economics, geography, and regional science. For example, it is applied to analyze regional economic growth differences, helping identify which factors lead to economic growth differences in different regions, such as geographic location, natural resource endowment, and industrial structure. It is also used to study economic policy effects and assess the regional impacts of economic policies, such as fiscal policy, monetary policy, and industrial policy. Identifying industrial cluster effects is another common application, helping identify the formation mechanisms of industrial clusters and their impacts on regional economic development. Looking ahead, spatial econometric models are increasingly combined with other statistical methods for more in-depth economic analysis and to support more targeted recommendations for regional economic policy formulation.

Spatial econometric models have been widely used in various studies to analyze the impact of spatial factors on economic phenomena. Henry et al. (2001) compared different spatial econometric approaches for estimating multi-equation models of small region development, specifically focusing on rural community growth in France. Anselin (2003) discussed spatial externalities, spatial multipliers, and spatial econometrics, highlighting the importance of considering spatial effects in economic analysis. Di Giacinto (2003) emphasized the differential regional effects of monetary policy using a geographical SVAR

approach, indicating the increasing attention given to studying asymmetric effects at a spatially disaggregated scale.

### **3.8.1 Spatial Lag Models**

Spatial lag models have been widely used in various fields to account for spatial dependence effects in data analysis. Piras (2005) proposed the use of panel data econometrics models that incorporate spatial lag among explanatory variables, known as the spatial lag model. This approach allows for a more accurate representation of spatial autocorrelation effects in the data. Longhi and Nijkamp (2007) evaluated the ability of spatial error and spatial lag models to correct for misspecifications due to neglected spatial autocorrelation in regional labor market data. Wang et al. (2005) applied the spatial lag model in estimating net primary production of Chinese forest ecosystems, highlighting the importance of considering spatial non-stationarity in regression models. Similarly, Garretsen and Peeters (2009) tested the relevance of spatial linkages for Dutch foreign direct investment (FDI) by estimating a spatial lag model for Dutch FDI to 18 host countries. They applied a spatial regression approach to study the relationship between tobacco outlet density and demographic factors in New Jersey, USA.

In environmental studies, spatial regression models have been used to analyze pollutant emissions and heavy metal concentrations. Li et al. (2014) conducted a spatial econometric analysis of SO<sub>2</sub> and COD emissions in China, providing policy recommendations for regions facing environmental challenges. Wu et al. (2020) identified influencing factors controlling the spatial variation of heavy metals in suburban soil using spatial regression models, highlighting the importance of considering spatial autocorrelation in environmental data analysis. Krisztin and Piribauer (2023) further advanced the estimation techniques of spatial autoregressive (models by proposing a Bayesian method for estimating the weight matrix. Their approach focuses on binary prior matrices before row normalization, facilitating a feasible estimation process and improving the accuracy of spatial interaction modeling. These methods are essential for accurately capturing the spatial dependence structure inherent in complex datasets.

Overall, the ability to capture spatial dependency effects and increase the precision of data analysis has been demonstrated by the application of spatial lag models in a variety of study domains. In an effort to better comprehend complicated geographical interactions

in various datasets and solve spatial autocorrelation, researchers are still investigating the applications of spatial regression models.

### **3.8.2 Spatial Error Models**

Spatial Error Model (SEM) has gained significant attention in recent econometric research due to its ability to account for spatial dependence in data. The theoretical and methodological foundations of SEM were further elaborated by Cañaveral et al. (2021) and others, who reviewed the application of spatial econometric modeling in environmental pollution studies. They emphasize the growing interest in spatial analysis, driven by advances in communication technologies and econometric methods, and point out that SEM is particularly useful in addressing the socio-economic drivers of spatial phenomena. Zeug-Žebro (2021) also considers SEM in their analysis of investment activity in Poland, comparing SEM with spatial lag models to understand the spatial dependence.

Spatial error models have been widely used in various fields such as economics, ecology, and social sciences. Ward and Gleditsch (2008) discuss spatial regression models, highlighting the importance of considering spatial dependence in OLS models. Mueller and Loomis (2008) specifically address spatial dependence in hedonic property models, using robust testing procedures to identify spatial dependence. Garretsen and Peeters (2009) examined spatial linkages in Dutch foreign direct investment, estimating a spatial lag model for FDI to different host countries. Bhattacharjee and Jensen-Butler (2013) focused on the estimation of the spatial weights matrix under structural constraints, emphasizing the importance of identifying the spatial weights in spatial error models. Li et al. (2014) conduct a spatial econometric analysis of pollutant emissions in China, providing policy recommendations based on their findings. López-Hernández (2013) introduced a second-order polynomial spatial error model to capture spatial dependence at different levels in unemployment data in Andalusia.

Cellmer (2014) discussed the use of spatial autocorrelation in building regression models for transaction prices in the land property market. Darmofal (2015) provided insights into spatial analysis for the social sciences, emphasizing the relevance of spatial modeling in social research. Hamylton et al. (2015) compared empirical and optimization methods for deriving high-resolution bathymetry from satellite imagery, highlighting the importance of geographical error analysis and spatial autocorrelation in model performance evaluation.

Overall, SEM are important tools for capturing spatial dependencies in a variety of fields, from regional economic growth to environmental studies, and are supported by rigorous testing and inference methods. These models contribute to a fine-grained understanding of spatial processes, ensuring more accurate and reliable econometric analyses in the context of spatial data.

### **3.8.3 Spatial Durbin Models**

Spatial Durbin Model (SDM) has been increasingly used to analyze regional interactions and spillovers in various environmental technology and economic areas in China. Several studies have utilized SDM to explore the spatial dynamics affecting energy efficiency, technological innovation, industrial structure and environmental regulation. Spatial Durbin Model has been widely used in various studies to analyze different phenomena. Elhorst and Fréret (2009) proposed a two-regime Spatial Durbin Model with fixed effects to test for political yardstick competition in France. This model aims to exclude other explanations that might produce spatial interaction effects among the variables. Elhorst (2010) highlighted the importance of the Spatial Durbin Model in spatial econometrics and emphasized the use of indirect effects to test for significant spatial spillovers. The study also discussed the use of Bayesian posterior model probabilities to determine the best spatial weights matrix for the data. In a study by Elhorst et al. (2010), a spatial Durbin model was used to test hypotheses about the impact of relative location on economic growth and well-being. The study incorporated space and time dynamics into an extended Solow-Swan neoclassical growth model.

Li and Wu (2017) employed a spatial Durbin model to investigate the effects of local and civil environmental regulations on green total factor productivity in China. The study found that environmental regulations inhibit the original technological innovation of enterprises. Feng et al. (2019) explored the impacts of environmental regulation, FDI, and their interaction on urban innovation in China using a spatial Durbin model. The study emphasized the importance of driving urban innovation through the cooperation of environmental regulation and FDI. Dai et al. (2021) used a dynamic spatial Durbin model to analyze the relationship between industrial clustering, technological innovation and carbon productivity. Their findings suggest that spatial reforms in industrial clusters can optimize efficiency and promote long-term carbon productivity, emphasizing the model's ability to capture spatial spillovers in industrial and environmental contexts. In addition, Wang and

Zhang (2021) explored the interactive effects of environmental regulation on carbon dioxide emissions using a two-regime spatial Durbin model, demonstrating how regional governance behaviors can affect the emission levels of neighboring regions through spatial dependence. Liu and Song (2020) used a spatial Durbin model to analyze the relationship between financial development and carbon emissions in China since the recent world financial crisis. The study concluded that carbon emission reductions in China may not be solely attributed to financial resources channeled into emission-reduction technologies or high value-added firms.

In the field of technological innovation and economic development, Peng et al. (2021) applied SDM to assess the spatial spillover effects of green innovation on the quality of urban economic development. Their analysis reveals significant spatial effects, suggesting that green innovation in one city can positively affect the economic output of neighboring cities. Similarly, Xie et al (2021) used SDM to investigate the impact of financial agglomeration on green total factor productivity and found significant direct and spillover effects, highlighting the importance of regional financial agglomeration in promoting sustainable growth. Wang and Gao (2021) applied stochastic frontier analysis and Malmquist index methods to estimate provincial green total factor productivity in China. The study highlighted the importance of green technology innovation in improving green total factor productivity and achieving sustainable development goals.

Lastly, Zhao et al. (2022) used an epsilon-based measure data envelopment analysis model with undesirable outputs and a Spatial Durbin Model to estimate transportation sector carbon dioxide emissions efficiency in Chinese provinces. The research indicated that most regions still require improvements in terms of carbon emissions efficiency.

In this study, the SDM is selected as the proposed methodology because it offers clear advantages over alternative approaches. Compared with conventional (non-spatial) panel models, the SDM explicitly accounts for spatial dependence across provinces, which helps avoid biased or inefficient estimates when manufacturing performance and agglomeration are spatially correlated. Compared with the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), the SDM is more general because it includes spatial lags of both the dependent variable and the explanatory variables. This enables the estimation and decomposition of impacts into direct (local) effects and indirect (spillover/cross-regional) effects within a unified framework, which aligns directly with the study objectives that

emphasize both local and cross-regional impacts of industrial agglomeration. Moreover, combining ED–LQ–HHI provides a complementary measurement system of agglomeration (spatial intensity, specialization, and concentration), reducing reliance on any single index and strengthening the robustness and interpretability of the SDM-based effect estimates.

### 3.9 Empirical Technique

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#### 3.9.1 Descriptive Analysis

Descriptive analysis was conducted to assess the distributional characteristics of the variables used in the empirical model. This involved calculating measures of central tendency and dispersion, including the mean, standard deviation, minimum, and maximum values. The analysis aimed to evaluate the variability, spread, and potential anomalies in the dataset, which informs the selection and specification of appropriate econometric techniques (Gujarati & Porter, 2009; Wooldridge, 2016). It also helps identify the presence of outliers, data volatility, and distributional patterns that may influence model robustness or require further statistical adjustments in subsequent analysis (Field, 2024; Hair et al., 2019).

#### 3.9.2 Moran's I Analysis

The Moran's I was proposed by Australian statistician Patrick Alfred Pearce Moran in 1950 as an important indicator for measuring spatial autocorrelation (Moran, 1950). The formula is as follows:

$$Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad \text{Equation 3.13}$$

In this formula,  $n$  is the number of observations,  $w_{ij}$  is an element of the spatial weight matrix, representing the spatial proximity relationship between spatial units  $i$  and  $j$ ,  $x_i$  and  $x_j$  are the observations,  $\bar{x}$  is the mean of the observations and  $S^2$  is the variance of the observations. The application of Moran's I in spatial analysis has been prominently featured across various studies, emphasizing its utility in measuring spatial autocorrelation and understanding regional disparities. The Moran index ranges from  $[-1, 1]$ . When the value is positive, it indicates spatial positive correlation, meaning that similar observations tend to cluster together; when the value is negative, it indicates spatial negative correlation, meaning that dissimilar observations tend to cluster together; when the value is close to 0, it indicates spatial random distribution.

Moran's I is a widely utilized measure of spatial autocorrelation, with foundational work establishing its exact distribution in small samples. Tiefelsdorf and Boots (1995) demonstrated that the exact distribution of Moran's I, akin to the Durbin-Watson statistic, can be derived through algebraic and theoretical methods, enabling precise inference for normally distributed variables. This development enhances the statistical rigor in assessing spatial patterns, especially in small datasets. The decomposition of the global Moran's I into local contributions has benefited from the development of local spatial association indicators, Jofre-Monseny et al. (2011) proposed a class of local indicators that can be used to identify specific spatial units that contribute to overall autocorrelation, thereby enabling detailed spatial pattern analysis at the local level.

Wang et al. (2022) investigated the spatial heterogeneity and correlation networks of green innovation efficiency in China using Moran's I, analyzing data from 2009 to 2017. Their findings emphasized the importance of spatial correlation in green innovation efficiency, revealing the existence of spatial heterogeneity and interconnections among provinces. Similarly, Duran (2022) used Moran's I as part of a series of spatial dependence tests such as Geary's C and the spatial LM test to assess the validity of Okun's law in the context of spatial dependence and cyclicity. This study emphasizes the importance of considering spatial dependence to avoid estimation distortion, demonstrating the usefulness of Moran's I in detecting global spatial autocorrelation. Yamada (2024) discussed how to extend Moran's I index to measure spatial autocorrelation in multivariate spatial data and established its theoretical properties. Multivariate spatial data analysis provides a new tool and a theoretical basis for further research. In the same year, the Moran index was re-examined, and new perspectives and theoretical improvements were proposed. Through mathematical derivation and matrix theory, the representation of the Moran coefficient was revised and expanded, providing new insights and calculation methods.

In the context of environmental efficiency, Liu et al. (2021) estimated the environmental efficiency of public buildings in various provinces of China, employing spatial analysis techniques that may incorporate spatial autocorrelation measures similar to Moran's I in order to understand regional variations. The study by Wang and Zhang (2021), while focusing primarily on green total factor productivity, emphasizes the importance of spatial analysis in evaluating regional performance, which can be complemented with Moran's I to understand spatial dependence. Ma (2021) applied Moran's I to analyze the

spatial correlation between transportation infrastructure and economic growth within the Pearl River West Economic Zone. The results of the study confirmed the existence of spatial autocorrelation, suggesting that infrastructure development and economic performance exhibit spatial spillover effects, which is crucial for regional planning. Moran's I is a widely used global spatial autocorrelation statistic, while Local Moran's I is used to assess the spatial autocorrelation of each observation point, enabling the detection of spatial clusters and spatial outliers. However, interpreting Local Moran's I statistics can be complex, especially in an exploratory analysis environment, where it is crucial to quickly understand the results (Mason et al., 2024).

In industrial agglomeration research, the Global Moran's I is often used to test whether a particular industry exhibits significant spatial agglomeration within a region as a whole. If the index is significantly positive, it indicates that the industry exhibits “clustering” characteristics in terms of spatial distribution. Tsui et al. (2022) used Global Moran's I to examine the spatial concentration of different industrial activities across the Netherlands while researching the waste recycling industry, demonstrating that this method can effectively characterize the overall spatial pattern of industrial activities. Similar methods are equally applicable in manufacturing and innovation activity research, revealing whether there are significant spatial concentration trends in the industry.

Local Moran's I further reveals the “geographical location of industrial agglomeration.” For example, at the regional level, some areas may form “high-high” agglomeration zones (industrial clusters) for manufacturing, while others may exhibit a “low-low” distribution. Pregi and Novotný (2024) used Local Moran's I to analyze migration and economic activity in Slovakian towns, identifying areas of spatial concentration and marginalization. In industrial agglomeration research, this method can help researchers identify the core clusters and peripheral areas of manufacturing or high-tech industries, revealing the spatial structure of industrial development polarization. In addition, Chen et al. (2023) derived the mathematical structure of Moran's I from a statistical modeling perspective, clarifying how the index captures spatial interactions through a spatial weight matrix. This is particularly important for research on industrial agglomeration, as the spatial distribution of manufacturing industries is influenced not only by location factors but also by spillover effects from neighboring regions. By combining Global Moran's I and Local Moran's I, researchers can verify the significant existence of agglomeration at the macro

level, while revealing the specific location and spatial interaction mechanisms of clusters at the micro level, thereby gaining a more comprehensive understanding of the spatial evolution process of industrial agglomeration.

Overall, these studies show that Moran I is an important statistical tool for detecting and quantifying spatial autocorrelation across multiple domains, including green innovation, environmental security, consumer behavior and economic analysis. Its application contributes to a deeper understanding of regional disparities, spatial clustering and the interconnectedness of spatial units, thereby informing targeted policy interventions and regional development strategies. Global Moran's I is suitable for testing the overall significance of industrial agglomeration at the national or regional level, while Local Moran's I is more suitable for identifying “hot spots” and “cold spots” to help determine the spatial location of industrial clusters. Combined, the two can effectively support research on manufacturing agglomeration, spatial evolution, and policy intervention.

### 3.9.3 Specification of the Moran's I Analysis Model of the study

To ensure consistency with the economy–technology–environment framework adopted in this thesis, Global Moran’s I is specified and calculated separately for the three performance dimensions, namely economic, technological, and environmental. This dimension-specific specification allows the study to examine whether spatial autocorrelation is a general feature of manufacturing performance or whether it varies across economic outcomes, innovation outcomes, and environmental outcomes. In addition, using the same analytical structure for the three indicators improves comparability across dimensions and provides a coherent statistical basis for interpreting subsequent empirical results within a unified performance system.

$$I_{ecomance} = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (ecomance_i - ecom\bar{ance}) (ecomance_j - ecom\bar{ance})}{S_{ecomance}^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad \text{Equation 3.14}$$

$$I_{technological} = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (technological_i - technol\bar{ogical}) (technological_j - technol\bar{ogical})}{S_{technological}^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad \text{Equation 3.15}$$

$$I_{\text{environ}} = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (\text{environ}_i - \text{env}\bar{\text{iron}}) (\text{environ}_j - \text{env}\bar{\text{iron}})}{S_{\text{environ}}^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad \text{Equation 3.16}$$

Notation.  $I_{\text{ecomance}}$ ,  $I_{\text{technological}}$ , and  $I_{\text{environ}}$  denote the Global Moran's I statistics for the economic, technological, and environmental performance dimensions, respectively.  $n$  is the number of cross-sectional units (provinces).  $i$  and  $j$  index provinces ( $i, j = 1, \dots, n$ ).  $w_{ij}$  is the  $(i, j)$ -th element of the spatial weight matrix, describing the linkage strength between province  $i$  and province  $j$ , with  $w_{ii} = 0$ .  $\text{ecomance}_i$ ,  $\text{technological}_i$ , and  $\text{environ}_i$  represent the observed values of each performance indicator for province  $i$ .  $\text{ecom}\bar{\text{ance}}$ ,  $\text{technol}\bar{\text{ogical}}$ , and  $\text{env}\bar{\text{iron}}$  are the corresponding sample means across all provinces.  $S_{\text{ecomance}}^2$ ,  $S_{\text{technological}}^2$ , and  $S_{\text{environ}}^2$  are the corresponding sample variances. The term  $\sum_{i=1}^n \sum_{j=1}^n w_{ij}$  is the sum of all spatial weights and serves as a normalizing factor in the statistic.

This unified specification ensures that spatial autocorrelation is assessed in a comparable way across the three dimensions, providing a consistent diagnostic basis for the subsequent spatial econometric analysis.

### 3.9.4 Lagrange Multiplier Test

The LM test is a statistical test method based on the Lagrange multiplier principle, widely used in structural equation modeling, time series analysis, fixed effects modeling, and selection modeling. It provides important statistical evidence for the significance of model parameters by testing the validity of constraints. Compared with other test methods, the LM test has unique advantages in certain application scenarios. The following are standard Lagrange multiplier (LM) test formulas used in spatial econometrics to detect spatial error autocorrelation and spatial lag dependence.

$$\begin{aligned} & \text{LM test for spatial error dependence (Anselin, 1988):} \\ & LM_{\text{err}} = [(e^T W e) / \hat{\sigma}^2]^2 / T \end{aligned} \quad \text{Equation 3.17}$$

$$\begin{aligned} & \text{LM test for spatial lag dependence:} \\ & LM_{\text{lag}} = [(e^T W y) / \hat{\sigma}^2]^2 / (R \hat{\sigma}^2 + Q) \end{aligned} \quad \text{Equation 3.18}$$

$$\begin{aligned} & \text{Robust LM (error):} \\ & LM_{\text{err}^*} = [(e^T W e) / \hat{\sigma}^2 - T \cdot LM_{\text{lag}} / Q]^2 / [T (1 - T \cdot R / Q)] \end{aligned} \quad \text{Equation 3.19}$$

$$\text{Robust LM (lag):} \\ \text{LMlag}^* = [ (e^T W y) / \hat{\sigma}^2 - R \cdot \text{LMerr} / T ]^2 / [ R + Q - R^2 / T ] \quad \text{Equation 3.20}$$

The Lagrange Multiplier (LM) test is a widely utilized statistical procedure for assessing model specification and detecting various forms of misspecification across different econometric contexts. Hosking (2018) emphasized the utility of overfitting as a method for testing the correctness of a model, where the null hypothesis of correct specification is tested against an alternative that encompasses additional parameters, with the LM test serving as a key tool in this framework. In the context of model evaluation and item response theory, Glas (1999) demonstrated that violations of certain models, such as the 2-PL and nominal response models, can be effectively diagnosed using the LM test or the equivalent score test. These diagnostics serve both as item-specific tools and as measures of overall model fit.

The versatility of the LM test extends to models with complex structures, as shown by Baltagi and Li (1990), who develop a LM test tailored for error components models with incomplete panels. This highlights the test's adaptability to panel data settings and models with specific error structures. The utility of LM tests extends to panel data analysis as seen in the study by Bashir et al. (2021), where panel data estimation techniques including LM tests are used to assess the relationship between current asset management and financial efficiency in the textile industry of Pakistan. LM tests help in determining the appropriateness of the fixed or random effects model to ensure the robustness of econometric inferences.

The scope of the LM test also encompasses diagnostic assessments for model fit and misspecification due to spatial dependence and heterogeneity. Anselin (1988) develops diagnostics based on the LM principle to evaluate spatial autocorrelation and heteroskedasticity, starting from a general spatial model that incorporates lagged variables and residual autocorrelation, thereby extending the application of LM tests to spatial econometrics. In the context of macroeconomic and financial interdependence, Sivarethinamohan et al. (2021) tested the existence of heteroskedasticity and serial correlation using the LM test to analyze the impact of macroeconomic variables on stock market returns in India. The application of the test confirms the validity of the model assumptions and facilitates reliable inferences about the relationship between macroeconomic indicators and stock indices.

Overall, the literature underscores the LM test's broad applicability across various econometric models and its effectiveness in diagnosing model misspecification, functional form issues, and dependence structures, making it a fundamental tool in econometric analysis.

### 3.9.5 Specification of the Lagrange Multiplier Test of the study

To ensure that model selection is fully consistent with the three-dimensional performance framework of this thesis, the Lagrange Multiplier (LM) diagnostics are implemented separately for economic, technological, and environmental. Specifically, for each performance dimension, a baseline (non-spatial) regression is first estimated, and the residual vector from that regression is used to construct LM statistics. Following the standard diagnostics in spatial econometrics (Equations 3.17–3.20), two complementary tests are computed. The LM test for spatial error dependence (LMerr), which examines whether remaining dependence is reflected in the disturbance term, and the LM test for spatial lag dependence (LMlag), which examines whether dependence is transmitted through the dependent variable. When the standard LM tests suggest that both forms of dependence may coexist, the robust versions reported in Equations 3.19–3.20 are used to support a clearer diagnostic judgment. This dimension-by-dimension specification avoids mixing information across outcome types and ensures that the diagnostic evidence used in later modelling directly corresponds to each performance indicator.

(1) economic dimension

$$LMerr_{ecomance} = \frac{\left[ \frac{(e_{ecomance}^T W e_{ecomance})}{\hat{\sigma}_{ecomance}^2} \right]^2}{T} \quad \text{Equation 3.21}$$

$$LMlag_{ecomance} = \frac{\left[ \frac{(e_{ecomance}^T W y_{ecomance})}{\hat{\sigma}_{ecomance}^2} \right]^2}{R\hat{\sigma}_{ecomance}^2 + Q} \quad \text{Equation 3.22}$$

(2) technological dimension

$$LMerr_{technological} = \frac{\left[ \frac{(e_{technological}^T W e_{technological})}{\hat{\sigma}_{technological}^2} \right]^2}{T} \quad \text{Equation 3.23}$$

$$LMlag_{technological} = \frac{\left[ \frac{(e_{technological}^T W y_{technological})}{\hat{\sigma}_{technological}^2} \right]^2}{R\hat{\sigma}_{technological}^2 + Q} \quad \text{Equation 3.24}$$

(3) environmental dimension

$$LMerr_{environ} = \frac{\left[ \frac{(e_{environ}^T W e_{environ})}{\hat{\sigma}_{environ}^2} \right]^2}{T} \quad \text{Equation 3.25}$$

$$LMlag_{environ} = \frac{\left[ \frac{(e_{environ}^T W y_{environ})}{\hat{\sigma}_{environ}^2} \right]^2}{R \hat{\sigma}_{environ}^2 + Q} \quad \text{Equation 3.26}$$

Notation.  $y_d$  denotes the dependent-variable vector for dimension  $d$ ,  $e_d$  is the residual vector from the corresponding baseline regression, and  $\hat{\sigma}_d^2$  is the estimated residual variance. The scalars  $T$ ,  $R$ , and  $Q$  follow the same definitions as in Equations 3.17–3.20. In this thesis, the LM statistics are interpreted as diagnostic evidence for whether spatial dependence should be explicitly modelled for each performance dimension. If LMerr is significant while LMlag is not, the dependence is more consistent with an error-type process; if LMlag is significant while LMerr is not, the dependence is more consistent with a lag-type process. If both standard LM tests are significant, the robust LM tests (Equations 3.19–3.20) are used to support a clearer decision, reducing the risk of misclassification when both dependence channels may be present. This interpretation rule is applied consistently to the economic, technological, and environ dimensions so that subsequent spatial model specification is grounded in comparable diagnostic criteria across outcomes.

### 3.10 Chapter Summary

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This chapter focuses on the economic, technological, and environmental performance of the manufacturing industry, analyzing the positive and negative impacts of industrial agglomeration on these three types of performance and proposing corresponding research hypotheses and models. Based on this, spatial econometric methods are further introduced to characterize the spatial characteristics of agglomeration effects through spatial lag models, spatial error models, and spatial durbin models, and combined with Moran's I and LM tests for verification, thereby providing theoretical and methodological support for subsequent empirical analysis. Compared with conventional (non-spatial) panel models, the proposed Spatial Durbin Model (SDM) explicitly accounts for spatial dependence across provinces and enables the decomposition of impacts into direct (local) and indirect (spatial spillover/cross-regional) effects, which aligns with the study objectives that emphasize both local and cross-regional impacts. Moreover, the combined ED–LQ–HHI indicators capture complementary facets of industrial agglomeration (spatial intensity, specialization, and concentration), reducing reliance on any single index and strengthening the robustness and interpretability of the subsequent spatial effect estimates.

## FINDINGS AND DISCUSSIONS

### 4.1 Introduction

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This chapter deeply studies the influence of three indicators of industrial agglomeration (Location Quotient, Employment Density and Herfindahl-Hirschman Index) on economic, technological and environmental performance, and provides comprehensive empirical evidence through systematic research methods and rigorous analysis process. Firstly, Moran's I test is performed to determine the existence of spatial autocorrelation. Subsequently, LM test is used to evaluate the applicability of Spatial Durbin Model. Through detailed data analysis, the complex relationship between industrial agglomeration and economic, technological and environmental performance is revealed. Finally, this chapter summarizes the main conclusions of this thesis, puts forward suggestions for future research directions, and emphasizes the importance of further exploring the influence of industrial agglomeration on the development of different economic sectors and regions.

### 4.2 Descriptive Analysis

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Descriptive statistics for the variables used in the empirical analysis are shown in Table 4-1. The results of descriptive statistics show that among the core variables, ecomance (mean=2.91, standard deviation=5.85) and ED (mean=20.80, standard deviation=23.42) have a high degree of dispersion, which indicates that there is a large difference between different observations in the sample, while Herfindahl-Hirschman Index (mean=0.18, standard deviation=0.04) and citylevel (mean=0.58, standard deviation=0.13) have relatively concentrated distributions. Technological variables (e.g., technological, insti) have smaller mean to standard deviation ratios (e.g., technological mean= 8.83, standard deviation =1.70), suggesting lower data volatility. In addition, some of the variables (e.g., k) have means close to zero and negative values (minimum=-3.77). Overall, the extreme deviation

(the difference between the maximum and minimum values) is large for all variables, such as pgdp (maximum value = 12.15, minimum value=9.18) and fdi (maximum value = 15.55, minimum value=7.76), reflecting the wide sample coverage.

**Table 4-1:  
Descriptive Statistics for Variables**

<b>Variables</b>	<b>Maximum</b>	<b>Minimum</b>	<b>Mean</b>	<b>Std. Dev.</b>
<i>ecomance</i>	57.4522	0.0791	2.9119	5.8549
<i>technological</i>	13.2579	3.4012	8.8296	1.7012
<i>environ</i>	0.0353	0.000003	0.0039	0.0051
<i>LQ</i>	2.7635	0.0284	0.9884	0.5615
<i>ED</i>	126.8585	0.6279	20.8015	23.4153
<i>HHI</i>	0.3099	0.0727	0.1756	0.03625
<i>h</i>	7.3252	0.1210	0.8060	1.1330
<i>pgdp</i>	12.1547	9.1797	10.7180	0.5513
<i>insti</i>	9.3619	4.0963	7.2383	0.9674
<i>fdi</i>	15.5508	7.7622	11.2735	1.5016
<i>staff</i>	13.5575	6.3190	10.5587	1.3934
<i>fund</i>	17.2868	9.0790	14.2044	1.4323
<i>gov</i>	7.0646	1.5602	4.1988	1.1128
<i>regu</i>	6.5270	0.8846	3.7906	1.0712
<i>citylevel</i>	0.8958	0.2912	0.5818	0.1304
<i>k</i>	5.1656	-3.7724	-0.0038	0.6040

Note: Std. Dev.= standard deviation.

### **4.3 Empirical Findings on The Influence of Industrial Agglomeration on The Economic Performance of Manufacturing Industry**

#### **4.3.1 The Results of Moran's I Analysis**

##### **4.3.1.1 Yearly Economic Performance of Region in China Based on the Global Moran's I**

This study uses Moran's I global spatial autocorrelation analysis, based on provincial economic performance data from China between 2008 and 2022, to reveal the spatial dependency characteristics of regional economic development and its dynamic evolutionary patterns. The spatial dependency means that provincial economic performance is not independent across space which neighboring provinces tend to exhibit similar performance levels (e.g., high–high or low–low clustering). This dependence is typically driven by interregional linkages such as factor mobility, supply-chain connections, and spillover effects. The results of the test indicate that China's regional economic spatial structure has undergone a transformation in phases from random distribution to significant agglomeration, a process that is closely linked to the nation's regional development strategies and policy adjustments.

From Table 4-2, it can be found that Moran's I did not pass the significance test ( $P > 0.1$ ) during the period from 2008 to 2011, indicating that the spatial distribution of economic performance across regions during this period was relatively independent and had not formed a significant agglomeration pattern. This may reflect the divergent recovery paths of various regions following the global financial crisis, as well as the decentralized nature of regional development policies at the end of the 11th Five-Year Plan. However, from 2012 onwards, the Moran's I began to exhibit statistical significance ( $P < 0.05$ ) and has shown a consistent upward trend, peaking at 0.0443 in 2021 ( $Z = 2.288$ ,  $P = 0.022$ ). This turning point coincided with the implementation of the regional coordination development strategy emphasized in the 12th Five-Year Plan (2011-2015), particularly the promotion of urban agglomeration development and regional integration policies. These policies significantly strengthened economic ties and spatial interdependence among regions.

**Table 4-2:  
Moran's I Spatial Autocorrelation Test Results of Economic Performance From 2008 to 2022**

Year	Moran's I	Expected E(I)	Std. Dev.	Z-score	*P*-value
2008	-0.0043	-0.0345	0.0337	0.895	0.371
2009	0.0020	-0.0345	0.0337	1.081	0.280
2010	0.0012	-0.0345	0.0324	1.103	0.270
2011	0.0080	-0.0345	0.0313	1.357	0.175
2012	0.0305	-0.0345	0.0319	2.037	0.042**
2013	0.0283	-0.0345	0.0323	1.943	0.052*
2014	0.0265	-0.0345	0.0329	1.852	0.064*
2015	0.0357	-0.0345	0.0330	2.128	0.033**
2016	0.0351	-0.0345	0.0333	2.091	0.037**
2017	0.0323	-0.0345	0.0336	1.986	0.047**
2018	0.0359	-0.0345	0.0340	2.072	0.038**
2019	0.0373	-0.0345	0.0340	2.110	0.035**
2020	0.0353	-0.0345	0.0343	2.037	0.042**
2021	0.0443	-0.0345	0.0344	2.288	0.022**
2022	0.0430	-0.0345	0.0346	2.240	0.025**

Notes: See Equation (3.14) for the specification of Moran's I.

N = 450 (30 panels over 15 years). Significance codes: \*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

In-depth analysis shows that the actual Moran's I values for all years during the study period were significantly higher than the expected random distribution value ( $E(I) = -0.0345$ ), and the index maintained a steady annual growth rate of approximately 0.0015 from 2015 to 2022. This consistent increase in spatial positive correlation reflects, on one hand, the reduction of barriers to factor mobility, such as high-speed rail network development and

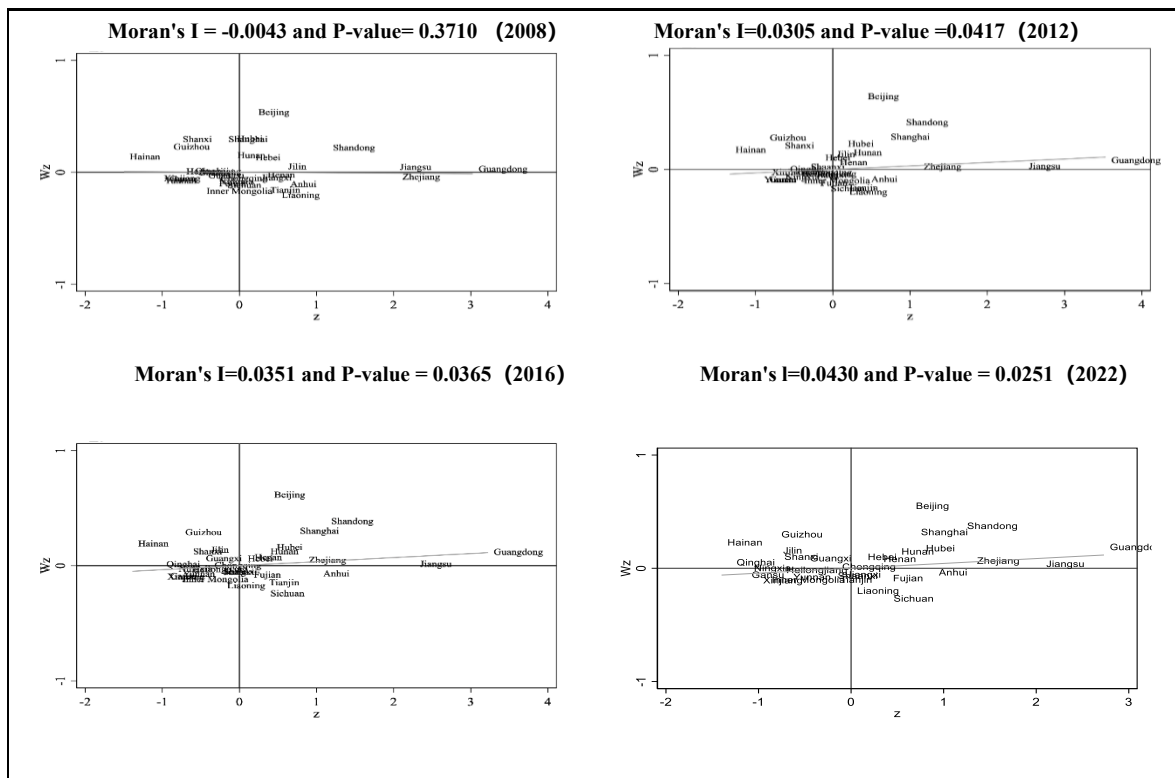
industrial relocation, and on the other hand, the ongoing enhancement of regional coordination mechanisms.

It is worth noting that during the epidemic period from 2020 to 2022, the Moran's I has remained at a high level. This may be due to new spatial connections emerging as a result of the rapid development of the digital economy. This may also be due to the fact that the economic spatial structure is being reorganized through regional joint prevention and control mechanisms during the epidemic response efforts.

#### 4.3.1.2 Economic Performance of Region in China based on Local Moran's I

As illustrated in Figure 4-1, four Moran's I scatter plots visually reveal the spatial evolution of regional economic performance from 2008 to 2022. To keep the presentation concise while capturing long-run evolution (2008–2022), the local Moran's I results are reported for four representative years (2008, 2012, 2016, and 2022) at four-year intervals.

**Figure 4-1:  
Time Evolution of Spatial Autocorrelation of Economic Performance: Moran Scatter Diagram (2008-2022)**



Source: Author's calculation based on provincial statistical data (2008–2022) using Stata. See Chapter 3 for details on data sources and spatial weight matrix construction.

In 2008, Moran's I  $\approx 0$  and  $P > 0.05$ , with scatter points distributed randomly; Starting in 2012, Moran's I became significantly positive (0.0305,  $P=0.042$ ), with eastern provinces

such as Beijing, Shanghai, Shandong, Jiangsu, and Zhejiang forming the first-quadrant high-high club, while central and western provinces such as Shanxi, Hebei, and Hainan fell into the third-quadrant low-low club; in 2016, Moran's I rose to 0.0351, further expanding the scope of the clubs; In 2022, Moran's I reached 0.0430 ( $P=0.025$ ), with the eastern high-high club and western low-low club differentiated along the  $45^\circ$  line, marking the highest spatial polarization level during the sample period. This validated the “spatial club convergence” hypothesis and highlighted the urgent need to break the path dependence of low-low agglomeration zones through differentiated revitalization policies.

Provinces showing High–High clustering (e.g., Beijing–Shanghai–Jiangsu–Zhejiang–Shandong–Guangdong) are typically coastal and core-market regions with stronger infrastructure, deeper industrial supply chains, and higher factor mobility, which reinforce inter-provincial spillovers and cumulative growth. In contrast, Low–Low clustering in parts of the central, western, and some southern provinces may reflect weaker connectivity, thinner industrial bases, and slower structural upgrading, which limit productivity gains and create persistent “core–periphery” differences.

Based on the local Moran's I of China's provincial economic performance in 2008, this study analyzes the spatial heterogeneity of regional economic development. The findings in Table 4-3 show that China's provincial economic performance displays a significant spatial differentiation pattern, but the overall spatial agglomeration effect is relatively modest. Specifically, at the  $\alpha=0.05$  significance level, only Shandong Province ( $I_i=0.2717$ ,  $P=0.0757$ ) exhibits a significantly high-high (HH) agglomeration characteristic, indicating that the province has formed a spatial cluster with relatively high economic development levels with its neighboring provinces. Guizhou Province ( $I_i=-0.2282$ ,  $P=0.0989$ ) exhibits marginally significant low-low (LL) clustering characteristics, reflecting that this region, together with its neighboring provinces, constitutes an area with relatively lagging economic development.

While most provinces did not demonstrate statistical significance in terms of local spatial autocorrelation, certain patterns of spatial distribution were still evident. Despite failing the significance test, the eastern coastline provinces—Beijing, Jiangsu, and Guangdong—all exhibit the high-high (HH) aggregation pattern, which suggests areas with potential advantages for economic growth. On the other hand, the central and western

provinces of Shanxi, Shanghai, Hainan, and others exhibit low-low (LL) agglomeration characteristics, which might be linked to historical issues of uneven regional growth.

**Table 4-3:**  
**Local Moran's I Analysis on the Economic Performance of Provinces in China (2008)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.0966	-0.0345	0.1783	0.7350	0.4623	HH	
Tianjin	-0.0495	-0.0345	0.1211	-0.1237	0.9015	LH	
Hebei	0.0196	-0.0345	0.1259	0.4298	0.6673	HH	
Shanxi	-0.2571	-0.0345	0.2099	-1.0607	0.2888	LL	
Inner	0.0810	-0.0345	0.2024	0.5703	0.5684	HL	
Liaoning	-0.0952	-0.0345	0.1321	-0.4595	0.6459	LH	
Jilin	0.0352	-0.0345	0.2079	0.3355	0.7373	HH	
Heilongjiang	-0.0152	-0.0345	0.1190	0.1619	0.8714	LL	
Shanghai	-0.0687	-0.0345	0.1600	-0.2137	0.8308	LL	
Jiangsu	0.1182	-0.0345	0.1351	1.1296	0.2586	HH	
Zhejiang	-0.0630	-0.0345	0.1464	-0.1950	0.8454	LH	
Anhui	-0.0573	-0.0345	0.1147	-0.1987	0.8425	LH	
Fujian	0.0318	-0.0345	0.1318	0.5026	0.6153	HL	
Jiangxi	-0.0078	-0.0345	0.0785	0.3402	0.7337	LH	
Shandong	0.2717	-0.0345	0.1724	1.7763	0.0757	HH	*
Henan	-0.0034	-0.0345	0.1343	0.2313	0.8171	LH	
Hubei	-0.0342	-0.0345	0.1548	0.0018	0.9985	LL	
Hunan	-0.0171	-0.0345	0.1121	0.1555	0.8764	LL	
Guangdong	0.1234	-0.0345	0.1776	0.8890	0.3740	HH	
Guangxi	0.0090	-0.0345	0.1369	0.3179	0.7506	HL	
Hainan	-0.2305	-0.0345	0.1280	-1.5315	0.1256	LL	
Chongqing	0.0141	-0.0345	0.1209	0.4014	0.6881	HL	
Sichuan	0.0247	-0.0345	0.1604	0.3689	0.7122	HL	
Guizhou	-0.2282	-0.0345	0.1174	-1.6504	0.0989	LL	*
Yunnan	0.0674	-0.0345	0.1303	0.7822	0.4341	HL	
Shaanxi	-0.0049	-0.0345	0.1468	0.2011	0.8406	LL	
Gansu	0.0494	-0.0345	0.1323	0.6341	0.5260	HL	
Qinghai	-0.0138	-0.0345	0.0964	0.2150	0.8298	LL	
Ningxia	0.0257	-0.0345	0.1691	0.3559	0.7219	HL	
Xinjiang	0.0483	-0.0345	0.2035	0.4067	0.6843	HL	

Notes: See Equation (3.14) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes:

\*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

Particularly noteworthy is the high-low spatial heterogeneity observed in Inner Mongolia, Fujian, and Guangxi provinces, which indicates that there are significant differences in economic development levels between these regions and their neighboring provinces. This "core-periphery" pattern may stem from differences in locational advantages or policy preferences that have led to divergent development trajectories. The research findings not only validate the existence of spatial dependence in regional economic

development but, more importantly, reveal the non-uniform distribution of this dependence, providing empirical evidence for the formulation of differentiated regional development policies.

Table 4-4 shows the Moran's I analysis of the economic performance of the provinces in China in 2012, revealing significant changes in the spatial agglomeration mode of regional economic development. Compared with 2008, 2012 exhibited more pronounced spatial polarization characteristics, specifically manifested as follows:

First, at the  $\alpha=0.05$  significance level, Shandong Province ( $I_i=0.3843$ ,  $P=0.016$ ) and Guangdong Province ( $I_i=0.3374$ ,  $P=0.037$ ) both exhibit significantly high-high (HH) clustering characteristics, indicating that the eastern coastal regions have formed more pronounced economic growth poles. In particular, Shandong Province's local Moran's I has significantly improved compared to 2008 (0.2717), reflecting the continued strengthening of spatial spillover effects in this region. Secondly, Guizhou Province ( $I_i=-0.2653$ ,  $P=0.067$ ) continues to show marginally significant low-low (LL) clustering characteristics, and the spatial autocorrelation strength has increased compared to 2008. This shows that the spatial lock-in effect of the lagging economic development in western regions may be intensifying. Notably, Hainan Province ( $I_i=-0.2515$ ,  $P=0.107$ ) also exhibits a similar low-value agglomeration trend, suggesting internal development imbalances within the southern coastal region. In addition, although Beijing ( $I_i=0.2550$ ) and Shanghai ( $I_i=0.2068$ ) have not reached statistical significance, the trend of high-high agglomeration has strengthened, indicating that the effects of metropolitan areas have initially taken shape. Compared to 2008, the number of provinces displaying a high-high concentration trend increased significantly in 2012 (with Hubei and Hunan provinces being newly added), while the low-low concentration area remained relatively concentrated in southwestern China. This spatial pattern of 'high in the east and low in the west' is closely related to China's regional development strategy. Specifically, it reflects the long-term "coastal priority" development approach and the subsequent shift toward coordinated regional development through major national strategies, including the Western Development Strategy (Go West), the Revitalize Northeast China Strategy, the Rise of Central China Strategy, and the 12th Five-Year Plan's regional coordination and urban-agglomeration

**Table 4-4:  
Local Moran's I Analysis on the Economic Performance of Provinces in China (2012)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.2550	-0.0345	0.1788	1.6195	0.105	HH	
Tianjin	-0.0186	-0.0345	0.1289	0.1228	0.902	LH	
Hebei	-0.0201	-0.0345	0.1329	0.1079	0.914	LL	
Shanxi	-0.1579	-0.0345	0.2072	-0.5957	0.551	LL	
Inner	0.0404	-0.0345	0.2004	0.3738	0.709	HL	
Liaoning	-0.0263	-0.0345	0.1383	0.0595	0.953	LH	
Jilin	-0.0035	-0.0345	0.2053	0.1510	0.880	LL	
Heilongjiang	0.0130	-0.0345	0.1272	0.3737	0.709	HL	
Shanghai	0.2068	-0.0345	0.1625	1.4848	0.138	HH	
Jiangsu	0.1022	-0.0345	0.1409	0.9706	0.332	HH	
Zhejiang	0.0405	-0.0345	0.1506	0.4976	0.619	HH	
Anhui	-0.0327	-0.0345	0.1236	0.0145	0.988	LH	
Fujian	0.0256	-0.0345	0.1380	0.4352	0.663	HL	
Jiangxi	0.0116	-0.0345	0.0949	0.4850	0.628	HL	
Shandong	0.3843	-0.0345	0.1735	2.4138	0.016	HH	**
Henan	0.0012	-0.0345	0.1401	0.2548	0.799	HH	
Hubei	0.0295	-0.0345	0.1579	0.4052	0.685	HH	
Hunan	0.0324	-0.0345	0.1214	0.5509	0.582	HH	
Guangdong	0.3374	-0.0345	0.1781	2.0885	0.037	HH	**
Guangxi	0.0075	-0.0345	0.1424	0.2952	0.768	HL	
Hainan	-0.2515	-0.0345	0.1347	-1.6108	0.107	LL	
Chongqing	0.0065	-0.0345	0.1288	0.3180	0.751	HL	
Sichuan	0.0166	-0.0345	0.1628	0.3134	0.754	HL	
Guizhou	-0.2653	-0.0345	0.1258	-1.8342	0.067	LL	*
Yunnan	0.0783	-0.0345	0.1367	0.8252	0.409	HL	
Shaanxi	-0.0120	-0.0345	0.1510	0.1487	0.882	LL	
Gansu	0.0721	-0.0345	0.1384	0.7696	0.442	HL	
Qinghai	-0.0085	-0.0345	0.1087	0.2387	0.811	LL	
Ningxia	0.0399	-0.0345	0.1705	0.4363	0.663	HL	
Xinjiang	0.0106	-0.0345	0.2014	0.2238	0.823	HL	

Notes: See Equation (3.14) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

The research results not only confirm the increasing spatial dependence of economic growth but also reveal the spatial solidification trend of regional development gaps, which has important implications for the optimization of regional coordinated development strategies in the new period.

Table 4-5 presents an analysis of China's provincial economic performance in 2016 using the local Moran's I, revealing further developments in the spatial model of regional economic development. The results demonstrate that the spatial agglomeration

characteristics of China's regional economy are strengthening and exhibiting new development trends.

First of all, at the significance level of  $\alpha = 0.05$ , Shandong Province ( $I_i=0.4597$ ,  $P=0.004$ ) and Guangdong Province ( $I_i=0.4360$ ,  $P=0.008$ ) showed more obvious high-high (HH) clustering characteristics than in 2012, indicating that the radiation effects of economic growth poles in the eastern coastal areas continued to strengthen. Notably, Shanghai ( $I_i=0.2308$ ,  $P=0.099$ ) first exhibits marginally significant high-value clustering characteristics, reflecting the emerging synergistic development effects within the core region of the Yangtze River Delta urban agglomeration. Secondly, new changes have emerged in the spatial differentiation pattern. Hainan Province showed a significant low-low (LL) clustering pattern ( $I_i=-0.2913$ ,  $P=0.048$ ), while Guizhou Province unexpectedly changed to a low-value clustering pattern with significant edges ( $I_i=0.2424$ ,  $P=0.082$ ). This may be related to the intensification of internal development and differentiation in western regions during this period. Meanwhile, although Beijing ( $I_i=0.2435$ ) has not reached statistical significance, its high-value clustering trend remains stable.

It is noteworthy that the spatial scope of high-value clusters underwent a substantial expansion in 2016. Although Jiangsu, Zhejiang, Hubei and Hunan provinces did not attain statistical significance, they all exhibited a high-high clustering trend. Conversely, low-value agglomeration regions exhibited a "southward and westward expansion" pattern, extending from the southwest region to the southern coastal areas and certain parts of the northwest. This evolution in spatial patterns is closely linked to the regional coordination development strategy implemented during the 13th Five-Year Plan period (2016-2020), particularly the advancement of urban agglomeration construction and industrial transfer policies, which have reshaped China's regional economic development spatial structure. This transition is closely associated with the Western Development Strategy, the Rise of Central China Plan, the Yangtze River Economic Belt, and the Beijing–Tianjin–Hebei (BTH) Coordinated Development initiatives, which promoted infrastructure connectivity, industrial relocation, and regional integration.

**Table 4-5:**  
**Local Moran's I Analysis on the Economic Performance of Provinces in China (2016)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-	Cluster	Significance
Beijing	0.2435	-0.0345	0.1784	1.5579	0.119	HH	
Tianjin	-0.0436	-0.0345	0.123	-0.0739	0.941	LH	
Hebei	0.0025	-0.0345	0.1276	0.2894	0.772	HH	
Shanxi	-0.0951	-0.0345	0.2092	-0.2896	0.772	LL	
Inner	0.0896	-0.0345	0.2019	0.6145	0.539	HL	
Liaoning	0.0391	-0.0345	0.1336	0.5509	0.582	HL	
Jilin	-0.0693	-0.0345	0.2072	-0.1679	0.867	LL	
Heilongjian	0.0139	-0.0345	0.121	0.3994	0.69	HL	
Shanghai	0.2308	-0.0345	0.1606	1.6513	0.099	HH	*
Jiangsu	0.0605	-0.0345	0.1366	0.6959	0.487	HH	
Zhejiang	0.0501	-0.0345	0.1474	0.5739	0.566	HH	
Anhui	-0.0621	-0.0345	0.1169	-0.2358	0.814	LH	
Fujian	-0.0079	-0.0345	0.1333	0.1994	0.842	LH	
Jiangxi	0.0124	-0.0345	0.0828	0.5669	0.571	HL	
Shandong	0.4597	-0.0345	0.1727	2.8621	0.004	HH	**
Henan	0.0106	-0.0345	0.1357	0.3321	0.74	HH	
Hubei	0.0727	-0.0345	0.1556	0.6892	0.491	HH	
Hunan	0.0455	-0.0345	0.1144	0.6988	0.485	HH	
Guangdong	0.436	-0.0345	0.1777	2.6477	0.008	HH	**
Guangxi	-0.0396	-0.0345	0.1382	-0.037	0.971	LL	
Hainan	-0.2913	-0.0345	0.1297	-1.981	0.048	LL	*
Chongqing	-0.0061	-0.0345	0.1229	0.2312	0.817	LL	
Sichuan	-0.0778	-0.0345	0.161	-0.269	0.788	LH	
Guizhou	0.2424	-0.0345	0.1195	1.7402	0.082	LL	**
Yunnan	0.0502	-0.0345	0.1319	0.6424	0.521	HL	
Shaanxi	0.0122	-0.0345	0.1479	0.3156	0.752	HL	
Gansu	0.081	-0.0345	0.1338	0.8628	0.388	HL	
Qinghai	-0.0243	-0.0345	0.0995	0.1023	0.919	LL	
Ningxia	0.0127	-0.0345	0.1694	0.2783	0.781	HL	
Xinjiang	0.0898	-0.0345	0.203	0.6122	0.54	HL	

Notes: See Equation (3.14) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

In particular, the southward and westward expansion of low-value (LL/LH) areas indicates that economically weaker provinces were no longer concentrated only in the traditional southwest core, but gradually formed a broader inland belt stretching toward the south and further west/northwest. This pattern can be explained by three mutually reinforcing mechanisms. First, during the 13th Five-Year Plan period, interregional industrial transfer accelerated from the eastern coast to inland provinces; however, transferred industries were often more resource- and energy-intensive and had lower value-added, which can weaken local economic performance in receiving areas when upgrading

capacity and supporting services lag behind. Second, uneven connectivity and market access continued to shape regional outcomes. Provinces with weaker transport-logistics advantages and greater distance to major consumption/export markets faced higher transaction costs, making it harder to attract high-end manufacturing and producer services, thereby reinforcing a “core–periphery” gradient. Third, differences in factor endowments and human capital constrained inland catch-up. Compared with coastal growth poles, some inland provinces faced persistent shortages in skilled labor, innovation platforms, and advanced supplier networks, so spillovers from core regions were not strong enough to offset structural disadvantages, resulting in a wider geographic spread of low-performance clustering. Overall, the “southward and westward expansion” reflects not only locational disadvantages but also the combined effects of industrial-structure lock-in and uneven upgrading capacity across provinces under the national regional coordination framework.

The Moran's I analysis of China's provincial economic performance in 2022 reveals the latest evolutionary characteristics of regional economic development patterns (Table 4-6). The results demonstrate that China's regional economic spatial differentiation exhibits a polarized trend of "the strong get stronger", which is manifested in three prominent characteristics.

Firstly, at the  $\alpha=0.05$  significance level, Guangdong Province ( $I_i=0.5359$ ,  $p=0.001$ ), Shandong Province ( $I_i=0.4634$ ,  $P=0.004$ ), and Beijing Municipality ( $I_i=0.3644$ ,  $P=0.025$ ) all exhibited significant high-high (HH) clustering characteristics. It is noteworthy that Guangdong Province's local Moran's I has seen a further increase in comparison with 2016 (0.4360), indicating that the spatial spillover effects of the Guangdong-Hong Kong-Macao Greater Bay Area continue to strengthen, thus forming the most prominent economic growth pole in the country. Secondly, low-value agglomeration regions demonstrate a "south-fixed, north-expanding" trend. Hainan Province ( $I_i=-0.3331$ ,  $P=0.016$ ) and Guizhou Province ( $I_i=0.2545$ ,  $P=0.051$ ) continue to demonstrate significant or marginally significant low-value agglomeration characteristics, and the spatial autocorrelation intensity has increased further in comparison with the preceding period. Concurrently, provinces in Northeast China, including Jilin Province ( $I_i=-0.1314$ ), have begun to manifest low-value agglomeration trends, thereby reflecting novel changes in regional development imbalances.

**Table 4-6:**  
**Local Moran's I Analysis on the Economic Performance of Provinces in China (2022)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-	Cluster	Significance
Beijing	0.3644	-0.0345	0.1781	2.2398	0.025	HH	**
Tianjin	0.0186	-0.0345	0.1169	0.4541	0.65	HL	
Hebei	0.0124	-0.0345	0.1221	0.3836	0.701	HH	
Shanxi	-0.084	-0.0345	0.2112	-0.2344	0.815	LL	
Inner	0.0941	-0.0345	0.2034	0.632	0.527	HL	
Liaoning	-0.0004	-0.0345	0.1289	0.2648	0.791	LH	
Jilin	-0.1314	-0.0345	0.2091	-0.4632	0.643	LL	
Heilongjian	0.0102	-0.0345	0.1146	0.3897	0.697	HL	
Shanghai	0.2302	-0.0345	0.1587	1.6673	0.096	HH	*
Jiangsu	0.087	-0.0345	0.1321	0.9196	0.358	HH	
Zhejiang	0.0929	-0.0345	0.1442	0.8831	0.377	HH	
Anhui	-0.0312	-0.0345	0.1099	0.0302	0.976	LH	
Fujian	-0.0345	-0.0345	0.1285	0.0002	1	LH	
Jiangxi	0.0063	-0.0345	0.0686	0.5937	0.553	HL	
Shandong	0.4634	-0.0345	0.1718	2.8975	0.004	HH	**
Henan	0.025	-0.0345	0.1312	0.4537	0.65	HH	
Hubei	0.1381	-0.0345	0.1532	1.1265	0.26	HH	
Hunan	0.0748	-0.0345	0.107	1.0209	0.307	HH	
Guangdong	0.5359	-0.0345	0.1773	3.2175	0.001	HH	***
Guangxi	-0.0475	-0.0345	0.134	-0.0972	0.923	LL	
Hainan	-0.3331	-0.0345	0.1244	-2.4004	0.016	LL	**
Chongqing	-0.0026	-0.0345	0.1167	0.2735	0.784	LL	
Sichuan	-0.1087	-0.0345	0.1591	-0.4665	0.641	LH	
Guizhou	0.2545	-0.0345	0.1129	1.9499	0.051	LL	*
Yunnan	0.0535	-0.0345	0.1269	0.6938	0.488	HL	
Shaanxi	0.0138	-0.0345	0.1447	0.3334	0.739	HL	
Gansu	0.0656	-0.0345	0.1291	0.7751	0.438	HL	
Qinghai	-0.0726	-0.0345	0.0895	-0.4263	0.67	LL	
Ningxia	-0.0047	-0.0345	0.1683	0.177	0.86	LL	
Xinjiang	0.109	-0.0345	0.2046	0.7014	0.483	HL	

Notes: See Equation (3.14) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\* \*p\* < 0.001, \*\* \*p\* < 0.05, \* \*p\* < 0.1.

Finally, the synergistic effects of the core area of the Yangtze River Delta urban agglomeration have become increasingly evident. Shanghai (Ii=0.2302, P=0.096) maintains a marginally significant high-value agglomeration, while provinces such as Jiangsu and Zhejiang, though not statistically significant, continue to show a strengthening trend toward high-value agglomeration. This indicates that the region has established a relatively mature spatial coordination mechanism for development. It is noteworthy that the high-value agglomeration index of central provinces, such as Hubei Province (Ii=0.1381), has

undergone a substantial enhancement, which may be attributable to the comprehensive execution of the Yangtze River Economic Belt strategy.

The evolution of this spatial pattern is closely related to the new regional coordination mechanism emphasized in the 14th Five-Year Plan. In particular, under the dual circulation development pattern, the agglomeration effect of advantageous regions has been further strengthened, while the spatial lock-in effect of some underdeveloped regions has not yet been fundamentally changed.

### 4.3.2 Economic Performance based on Lagrange Multiplier Test

The spatial dependency characteristics of the relationship between economic performance and Location Quotient (LQ) were systematically evaluated through the spatial autocorrelation diagnostic test in Table 4-7. The results of the test indicate that the research model exhibits significant spatial effects, as evidenced by the following three key findings:

**Table 4-7:  
Spatial Autocorrelation Diagnosis of Economic Performance and Location Quotient**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	2.829	1	0.005	**
	Lagrange Multiplier	73.430	1	<0.001	***
	Robust LM	3.850	1	0.050	*
<b>Spatial Lag</b>	Lagrange Multiplier	95.351	1	<0.001	***
	Robust LM	25.771	1	<0.001	***

Notes: See Equations (3.21)– (3.22) for the specification of the LM tests.  
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).

Firstly, the results of Moran's I test indicate significant spatial autocorrelation (I=2.829, P=0.005), confirming that economic performance is not randomly distributed spatially but exhibits distinct clustering characteristics. This finding is consistent with the results of a previous local Moran's I analysis, which collectively support the existence of spatial dependence in regional economic development.

Secondly, the Lagrange multiplier tests for both the Spatial Lag Model (SLM) and the Spatial Error Model (SEM) reached extremely significant levels (LM-lag=95.351, P<0.001; LM-error=73.430, P<0.001). It is noteworthy that the statistical significance of the spatial lag term in the robust LM test was even more pronounced (Robust LM-lag=25.771, P<0.001). This comparative advantage suggests that the spatial dependence of economic

performance primarily manifests as direct spillover effects between regions (spatial lag effects) rather than the spatial transmission of unobservable factors (spatial error effects).

Thirdly, the findings of the test results, based on the non-standardized binary weight matrix (WLB), demonstrate that the explanatory power of the spatial lag effect is significantly superior to that of the spatial error effect. This finding is of significant importance for the selection of models, and subsequent studies should prioritize the Spatial Durbin Model (SDM) in order to reveal the interactive relationships between regions. The research results confirm the existence of significant spatial spillover channels in economic performance and reveal that this spatial dependency primarily stems from direct economic interactions between regions. This provides new empirical evidence for understanding the formation mechanisms of China's regional economic development patterns.

The results presented in Table 4-8 illustrate the spatial correlation characteristics between economic performance and Employment Density (ED). The findings, derived from the non-standardized binary spatial weight matrix (WLB), reveal a notable degree of spatial dependence in regional economic performance (Moran's I=5.510,  $P < 0.001$ ). This provides substantial evidence to support the development of subsequent spatial econometric models.

**Table 4-8:  
Spatial Autocorrelation Diagnosis of Economic Performance and Employment**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	5.510	1	<0.001	***
	Lagrange Multiplier	290.957	1	<0.001	***
	Robust LM	170.217	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	126.356	1	<0.001	***
	Robust LM	5.616	1	0.018	*

Notes: See Equations (3.21)– (3.22) for the specification of the LM tests.

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).

Further spatial dependency diagnostic tests revealed two key findings: firstly, the Lagrange multiplier test statistic for the spatial error model (LM=290.957,  $P < 0.001$ ) was significantly higher than that for the Spatial Lag Model (SLM) (LM=126.356,  $P < 0.001$ ). Robustness tests (robust LM error=170.217,  $P < 0.001$ ) further confirmed this result. The findings of this study suggest that the spatial dependence of economic performance is predominantly attributable to the spatial transmission effects of unobservable factors, as opposed to direct regional economic spillovers. Secondly, while the robustness test for spatial lag effects (Robust LM-lag=5.616,  $p = 0.018$ ) also reached statistical significance, its

statistic was significantly smaller than that of the error model, suggesting relatively weak direct economic interaction effects between regions.

From a methodological perspective, the research results support the use of the Spatial Error Model (SEM) or the Spatial Durbin Model (SDM), which simultaneously incorporates error and lag effects, for subsequent analysis. From a policy perspective, the results indicate that regional economic performance differences are not only influenced by observable economic factors but are also significantly affected by spatially related unobservable factors.

A detailed analysis was conducted on the spatial correlation characteristics between economic performance and the Herfindahl-Hirschman Index (HHI), as presented in Table 4-9. The results of the test, based on the non-standardized binary spatial weight matrix (WLB), indicate the following.

**Table 4-9:  
Spatial Autocorrelation Diagnosis of Economic Performance and Herfindahl-Hirschman Index**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	2.226	1	0.026	*
	Lagrange Multiplier	41.359	1	<0.001	***
	Robust LM	18.120	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	74.503	1	<0.001	***
	Robust LM	51.265	1	<0.001	***

Notes: See Equations (3.21)– (3.22) for the specification of the LM tests.

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).

Moran's, I test demonstrates that economic performance exhibits significant spatial autocorrelation ( $I=2.226$ ,  $P=0.026$ ), thereby confirming that regional economic development is subject to spatial dependence. Further spatial dependency diagnostic tests revealed important finding. The Lagrange multiplier test statistic for the Spatial Lag Model (SLM) ( $LM=74.503$ ,  $P<0.001$ ) is significantly higher than that for the Spatial Error Model (SEM) ( $LM=41.359$ ,  $P<0.001$ ). It is imperative to note that the robustness tests (Robust LM-lag= $51.265$ ,  $P<0.001$ ; Robust LM-error= $18.120$ ,  $P<0.001$ ) serve to further substantiate the preeminent role of spatial lag effects.

The results indicate that the spatial dependence of economic performance primarily manifests as direct spillover effects between regions. These effects may stem from economic interaction processes such as industrial agglomeration and factor mobility. From a methodological perspective, the research findings support the use of Spatial Lag Models

(SLM) or Spatial Durbin Models (SDM) for subsequent analysis. From a policy perspective, this finding emphasizes the importance of enhancing regional economic cooperation and suggests measures such as the promotion of the free flow of factors and the optimization of industrial spatial layout to reinforce positive spatial spillover effects.

#### ***4.3.2.1 The Impact of Location Quotient on Economic Performance***

The present study employs a Spatial Durbin Model (SDM) to analyze the impact of Locational Quotients (LQ) and other variables on regional economic performance, while examining both direct (local) effects and indirect (spatial spillover) effects. The findings presented in Table 4-10 demonstrate that the model test signifies moderate explanatory power within the group ( $R^2=0.337$ ). However, the spatial autoregression coefficient ( $\rho=-0.138$ ,  $P=0.394$ ) is not significant, indicating weak global spatial dependence.

The Location Quotient (LQ) has been shown to exhibit a significant positive direct effect (coefficient=1.583,  $P=0.019$ ) and a stronger positive spatial spillover effect (coefficient=9.208,  $P=0.035$ ). The total long-run effect of Location Quotient on economic performance remains significant (coefficient=9.766,  $P=0.013$ ), implying that both local industrial specialization and its spillovers to neighboring regions enhance economic outcomes.

The human capital level (h) is a measure of the total value of the workforce within a given economy. The findings indicate that both the direct effect (2.843,  $P<0.001$ ) and the indirect effect (13.877,  $P<0.001$ ) are significant, suggesting a positive impact on both the local and surrounding economies. The per capita GDP (pgdp) is a measure of the economic output of a country's population. The direct effect is negative (-5.034,  $P=0.026$ ), but the spatial spillover effect is positive (8.233,  $P=0.003$ ), possibly reflecting both economic convergence within the region and divergence between regions. Although the local effect of foreign direct investment (fdi) is insignificant, its spatial spillover effect is significantly positive (5.268,  $P<0.001$ ), suggesting that fdi contributes to regional development by fostering interregional collaboration.

**Table 4-10:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Location Quotients**

Model Diagnostics: Panel structure: 30 provinces  $\times$  15 years (balanced);  $R^2$ : within=0.337, between=0.214, overall=0.018; Log-likelihood = -1164.043; Mean of fixed-effects = -110; Variance ( $\sigma^2$ ): 10.326\*\*\* (0.689)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>LQ</i>	1.583**	0.675	2.34	0.019	0.259	2.907
	<i>h</i>	2.843***	0.676	4.21	<0.001	1.518	4.167
	<i>pgdp</i>	-5.034*	2.258	-2.23	0.026	-9.459	-0.608
	<i>insti</i>	-0.459	0.545	-0.84	0.399	-1.527	0.608
	<i>fdi</i>	-0.515	0.394	-1.31	0.191	-1.287	0.257
<b>Spatial Effects</b>	<i>LQ</i>	9.208*	4.374	2.11	0.035	0.637	17.78
	<i>h</i>	13.877***	3.767	3.68	<0.001	6.493	21.261
	<i>pgdp</i>	8.233**	2.796	2.94	0.003	2.753	13.713
	<i>insti</i>	-0.06	1.286	-0.05	0.963	-2.581	2.46
	<i>fdi</i>	5.268***	1.015	5.19	<0.001	3.279	7.257
<b>Spatial Parameter</b>	$\rho$	-0.138	0.162	-0.85	0.394	-0.456	0.18
<b>Long-Run Effect</b>							
<b>Direct</b>	<i>LQ</i>	1.547*	0.706	2.19	0.028	0.164	2.93
	<i>h</i>	2.726***	0.645	4.22	<0.001	1.461	3.99
	<i>pgdp</i>	-4.925*	2.206	-2.23	0.026	-9.247	-0.602
	<i>insti</i>	-0.475	0.528	-0.9	0.368	-1.51	0.56
	<i>fdi</i>	-0.559	0.376	-1.49	0.137	-1.295	0.178
<b>Indirect</b>	<i>LQ</i>	8.219*	3.933	2.09	0.037	0.51	15.929
	<i>h</i>	12.033**	3.861	3.12	0.002	4.465	19.601
	<i>pgdp</i>	7.694**	2.692	2.86	0.004	2.419	12.97
	<i>insti</i>	0.083	1.146	0.07	0.942	-2.163	2.33
	<i>fdi</i>	4.781***	0.767	6.23	<0.001	3.278	6.284
<b>Total</b>	<i>LQ</i>	9.766*	3.95	2.47	0.013	2.025	17.507
	<i>h</i>	14.759***	3.987	3.7	<0.001	6.945	22.573
	<i>pgdp</i>	2.77	1.861	1.49	0.137	-0.878	6.418
	<i>insti</i>	-0.392	1.081	-0.36	0.717	-2.51	1.726
	<i>fdi</i>	4.222***	0.731	5.77	<0.001	2.789	5.656

Notes: See Equation (3.7) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = -0.138 (P=0.394); All standard errors are robust standard errors.

#### 4.3.2.2 The Impact of Employment Density on Economic Performance

The results of the estimation of the Spatial Durbin Model (SDM) are presented in Table 4-11. The model examines the impact of Employment Density on regional economic performance. The model is predicated on 15 years of balanced panel data from 30 provinces, the analysis of which considers both the direct effects and spatial spillover effects of employment density.

The direct effects reveal that employment density (ED) exerts a significant positive influence on local economic development, with a coefficient of 0.271 ( $P < 0.001$ ). Human capital (H) shows an even stronger positive effect (3.330,  $P < 0.001$ ). In contrast, foreign direct investment (fdi) demonstrates a significant negative impact (-0.989,  $P < 0.01$ ). Meanwhile, the direct effects of per capita GDP (pgdp) and institutional quality (insti) are statistically insignificant.

The spatial spillover effect indicates that employment density (ED) has a significant negative impact on neighboring regions, with a spatial coefficient of -0.295 ( $P < 0.01$ ). Human capital (h) exhibits a significant positive spatial externality (8.617,  $P < 0.05$ ), while foreign direct investment (fdi) also produces a significant positive spatial spillover effect (3.647,  $P < 0.01$ ). However, the spatial autoregression coefficient ( $\rho = 0.129$ ) is not statistically significant.

The long-term decomposition results show that the direct effects are consistent with the main effects (ED: 0.271,  $P < 0.001$ ; h: 3.375,  $P < 0.001$ ). The indirect effects indicate that the negative spatial spillover of employment density (ED) remains significant (-0.291,  $P < 0.05$ ), whereas the positive spatial spillover of human capital (h) becomes stronger (10.391,  $P < 0.05$ ). In terms of the total effects, the combined influence of human capital (h) (13.766,  $P < 0.01$ ) and foreign direct investment (fdi) (3.129,  $P < 0.05$ ) is found to be significant.

The model diagnostics indicate a satisfactory fit (intraclass  $R^2 = 0.439$ ), with significant variance components ( $\sigma^2 = 8.691$ ,  $P < 0.001$ ). The fixed-effects model is an effective means of controlling for unobserved heterogeneity across provinces and years.

**Table 4-11:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Employment Density**

Model Diagnostics: Panel structure: 30 provinces × 15 years (balanced) ; R<sup>2</sup>: Within=0.439, Between=0.365, Overall=0.355; Log-likelihood = -1125.233; Mean of fixed-effects = -76.7868; Variance

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>ED</i>	0.271***	0.029	9.31	<0.001	0.214	0.328
	<i>h</i>	3.330***	0.629	5.29	<0.001	2.097	4.562
	<i>pgdp</i>	-0.617	2.016	-0.31	0.76	-4.568	3.334
	<i>insti</i>	-0.517	0.494	-1.05	0.295	-1.484	0.451
	<i>fdi</i>	-0.989**	0.369	-2.68	0.007	-1.711	-0.266
<b>Spatial Effects</b>	<i>ED</i>	-0.295**	0.108	-2.73	0.006	-0.507	-0.084
	<i>h</i>	8.617*	3.589	2.4	0.016	1.583	15.65
	<i>pgdp</i>	4.123	2.914	1.42	0.157	-1.588	9.833
	<i>insti</i>	0.903	1.147	0.79	0.431	-1.345	3.15
	<i>fdi</i>	3.647**	1.163	3.14	0.002	1.368	5.927
<b>Spatial Parameter</b>	$\rho$	0.129	0.143	0.9	0.369	-0.152	0.41
<i>Long-Run Effect</i>							
<b>Direct</b>	<i>ED</i>	0.271***	0.03	9.1	<0.001	0.212	0.329
	<i>h</i>	3.375***	0.612	5.52	<0.001	2.176	4.574
	<i>pgdp</i>	-0.403	1.918	-0.21	0.834	-4.163	3.357
	<i>insti</i>	-0.521	0.47	-1.11	0.268	-1.442	0.401
	<i>fdi</i>	-0.969**	0.349	-2.78	0.005	-1.653	-0.286
<b>Indirect</b>	<i>ED</i>	-0.291*	0.124	-2.35	0.019	-0.533	-0.049
	<i>h</i>	10.391*	4.698	2.21	0.027	1.182	19.6
	<i>pgdp</i>	4.322	3.327	1.3	0.194	-2.198	10.843
	<i>insti</i>	1.069	1.288	0.83	0.406	-1.455	3.593
	<i>fdi</i>	4.098***	1.237	3.31	0.001	1.673	6.523
<b>Total</b>	<i>ED</i>	-0.02	0.133	-0.15	0.879	-0.281	0.24
	<i>h</i>	13.766**	4.899	2.81	0.005	4.165	23.367
	<i>pgdp</i>	3.919	3.032	1.29	0.196	-2.024	9.861
	<i>insti</i>	0.549	1.269	0.43	0.665	-1.938	3.035
	<i>fdi</i>	3.129*	1.286	2.43	0.015	0.608	5.65

Notes: See Equation (3.7) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.129 (P=0.369); All standard errors are robust standard errors.

#### 4.3.2.3 The Impact of Herfindahl-Hirschman Index on Economic Performance

The estimation results of the Spatial Durbin Model (SDM) are presented in Table 4-12. The model examines the impact of the Herfindahl-Hirschman Index (HHI) on regional economic performance. The model is predicated on 15 years of balanced panel data from 30 provinces, the analysis of which considers both the direct effects and spatial spillover effects of industrial concentration. The following key findings are presented:

The direct effects reveal that the Herfindahl-Hirschman Index (HHI) has a significant positive impact on local economic development, with a coefficient of 18.624 ( $P < 0.01$ ). Human capital (h) exerts an even stronger positive effect (2.978,  $P < 0.001$ ), whereas per capita GDP (pgdp) shows a marginally significant negative effect (-3.814,  $P < 0.1$ ). Moreover, the results indicate that institutional quality (insti) and foreign direct investment (fdi) are not significantly associated with local economic development.

The spatial spillover effects indicate that the spatial coefficient of the Herfindahl-Hirschman Index (HHI) is not statistically significant (6.664,  $P > 0.1$ ), suggesting that industrial concentration does not generate notable spillover effects across regions. In contrast, the spatial externalities of human capital (h) are significant (15.348,  $P < 0.001$ ), while both per capita GDP (pgdp) (8.448,  $P < 0.01$ ) and foreign direct investment (fdi) (4.646,  $P < 0.001$ ) display significant positive spatial spillovers. However, the spatial autoregression coefficient ( $\rho = -0.109$ ) is not statistically significant.

The long-term effect decomposition indicates that the direct effect of the Herfindahl-Hirschman Index (HHI) has strengthened (18.951,  $P < 0.05$ ), while human capital (h) continues to exert a highly significant influence (2.873,  $P < 0.001$ ). For the indirect effects, the spatial spillover effects of human capital (h) (13.820,  $P < 0.01$ ) and per capita GDP (pgdp) (7.862,  $P < 0.01$ ) are both significant. In terms of the total effects, the combined contributions of human capital (h) (16.693,  $P < 0.001$ ), per capita GDP (pgdp) (4.187,  $P < 0.05$ ), and foreign direct investment (fdi) (3.828,  $P < 0.001$ ) are also found to be significant.

The model diagnostics indicate a reasonable fit (intraclass  $R^2 = 0.334$ ) and significant variance components ( $\sigma^2 = 10.409$ ,  $P < 0.001$ ). The fixed-effects model is an effective means of controlling for unobservable heterogeneity across provinces and years.

**Table 4-12:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Herfindahl-Hirschman Index**

Model Diagnostics: Panel structure: 30 provinces × 15 years (balanced) ; R<sup>2</sup>: Within=0.334, Between=0.153, Overall=0.004; Log-likelihood = -1165.759; Mean of fixed-effects =-110; Variance ( $\sigma^2$ ):

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>HHI</i>	18.624**	7.156	2.6	0.009	4.599	32.649
	<i>h</i>	2.978***	0.679	4.39	<0.001	1.648	4.309
	<i>pgdp</i>	-3.814*	2.183	-1.75	0.081	-8.092	0.463
	<i>insti</i>	-0.121	0.54	-0.22	0.823	-1.18	0.938
	<i>fdi</i>	-0.456	0.395	-1.15	0.249	-1.231	0.319
<b>Spatial Effects</b>	<i>HHI</i>	-6.664	14.507	-0.46	0.646	-35.098	21.769
	<i>h</i>	15.348***	3.924	3.91	<0.001	7.657	23.04
	<i>pgdp</i>	8.448**	2.73	3.09	0.002	3.098	13.799
	<i>insti</i>	0.518	1.268	0.41	0.683	-1.967	3.003
	<i>fdi</i>	4.646***	0.987	4.71	<0.001	2.713	6.58
<b>Spatial Parameter</b>	$\rho$	-0.109	0.161	-0.68	0.498	-0.426	0.207
<i>Long-Run Effect</i>							
<b>Direct</b>	<i>HHI</i>	18.951*	7.39	2.56	0.01	4.466	33.435
	<i>h</i>	2.873***	0.649	4.43	<0.001	1.601	4.144
	<i>pgdp</i>	-3.675*	2.11	-1.74	0.082	-7.811	0.461
	<i>insti</i>	-0.134	0.517	-0.26	0.795	-1.148	0.879
	<i>fdi</i>	-0.487	0.379	-1.29	0.198	-1.23	0.255
<b>Indirect</b>	<i>HHI</i>	-7.352	13.405	-0.55	0.583	-33.625	18.921
	<i>h</i>	13.820***	4.19	3.3	0.001	5.609	22.032
	<i>pgdp</i>	7.862**	2.613	3.01	0.003	2.74	12.984
	<i>insti</i>	0.591	1.15	0.51	0.607	-1.663	2.846
	<i>fdi</i>	4.315***	0.782	5.52	<0.001	2.783	5.848
<b>Total</b>	<i>HHI</i>	11.599	11.636	1	0.319	-11.208	34.405
	<i>h</i>	16.693***	4.328	3.86	<0.001	8.211	25.175
	<i>pgdp</i>	4.187*	1.913	2.19	0.029	0.438	7.936
	<i>insti</i>	0.457	1.089	0.42	0.675	-1.677	2.591
	<i>fdi</i>	3.828***	0.763	5.02	<0.001	2.333	5.323

Notes: See Equation (3.7) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) =-0.109 (P=0.498); All standard errors are robust standard errors.

## 4.4 Empirical Findings on the Influence of Industrial Agglomeration on the Technological Performance of Manufacturing Industry

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### 4.4.1 The Results of Moran's I analysis

#### 4.4.1.1 Yearly Technological Performance of Region in China Based on the Global Moran's I

The global Moran's I is used to measure the spatial autocorrelation within the entire study area, that is, the overall clustering or dispersion degree between spatial units. This study is based on panel data from 30 provinces in China from 2008 to 2022. It uses Moran's I to systematically test the spatial autocorrelation of regional technological performance. The main findings are as follows:

The results of the Moran's I test (Table 4-13) indicate that technological performance exhibited a significant positive spatial correlation during the study period (all Moran's I values were positive). Specifically, the spatial autocorrelation index ranged from 0.0189 to 0.0411 between 2008 and 2022, with an average value of 0.0287, and most years (9/15) reached statistical significance ( $P < 0.1$ ). This finding confirms the important role of spatial spillover effects of technological innovation in China's regional development, consistent with previous research conclusions on knowledge externalities and innovation diffusion.

The spatial agglomeration of technological performance manifests distinct phased characteristics. The period from 2008 to 2012 exhibited an ascending phase, characterized by Moran's I values that exhibited a steady increase from 0.0265 to 0.0411 (representing an average annual growth rate of 9.1%), accompanied by a continuous improvement in the level of significance (attaining  $P < 0.05$  starting in 2010). This phenomenon may be indicative of the policy implications of strengthened regional innovation system construction towards the conclusion of the 11th Five-Year Plan period. From 2013 to 2020, there was a fluctuating decline: the index value fell from 0.0363 to 0.0205 (an average annual decrease of 6.3%) and even lost statistical significance between 2017 and 2020 ( $P > 0.1$ ). This change may be related to the implementation of the regional coordinated development strategy since the 12th Five-Year Plan and the decentralized distribution of innovation resources. From 2021 to 2022, a slight rebound was observed, with the index value rising to approximately 0.0265 and regaining marginal significance ( $P < 0.1$ ). This may suggest a spatial restructuring of new technology diffusion patterns in the post-pandemic era.

The results of the Z-value test (range 1.528–2.158) clearly indicate that in significant years, the Z-values all exceeded the critical value of 1.65 ( $P < 0.1$ ), with 2010–2013 and 2015 exceeding 1.96 ( $P < 0.05$ ). This proves that the spatial distribution of technological performance exhibits significant non-randomness. Spatial clustering intensity reached its peak in 2012 ( $Z=2.158$ ), when the spatial dependence of technological performance was highest; 2018 was the year with the weakest spatial association ( $Z=1.528$ ), but it still exceeded the expected value for a completely random distribution.

**Table 4-13:**  
**Moran's I Spatial Autocorrelation Test Results of Technological Performance From 2008 to 2022**

Year	Moran's I	Expected E(I)	Std. Dev.	Z-score	*P*-value
2008	0.0265	-0.0345	0.0347	1.7569	<b>0.0789*</b>
2009	0.0313	-0.0345	0.0352	1.869	<b>0.0616*</b>
2010	0.036	-0.0345	0.0351	2.0083	<b>0.0446**</b>
2011	0.0364	-0.0345	0.035	2.0256	<b>0.0428**</b>
2012	0.0411	-0.0345	0.035	2.1584	<b>0.0309**</b>
2013	0.0363	-0.0345	0.0349	2.0258	<b>0.0428**</b>
2014	0.0306	-0.0345	0.035	1.8621	<b>0.0626*</b>
2015	0.0336	-0.0345	0.0348	1.955	<b>0.0506*</b>
2016	0.0276	-0.0345	0.0348	1.7822	<b>0.0747*</b>
2017	0.0193	-0.0345	0.0348	1.5477	0.1217
2018	0.0189	-0.0345	0.0349	1.528	0.1265
2019	0.0203	-0.0345	0.0349	1.5674	0.117
2020	0.0205	-0.0345	0.035	1.5712	0.1161
2021	0.0267	-0.0345	0.035	1.7485	<b>0.0804*</b>
2022	0.0265	-0.0345	0.0351	1.738	<b>0.0822*</b>

Notes: See Equation (3.15) for the specification of Moran's I.

N = 450 (30 panels over 15 years). Significance codes: \*\*\*  $P < 0.001$ , \*\*  $P < 0.05$ , \*  $P < 0.1$ .

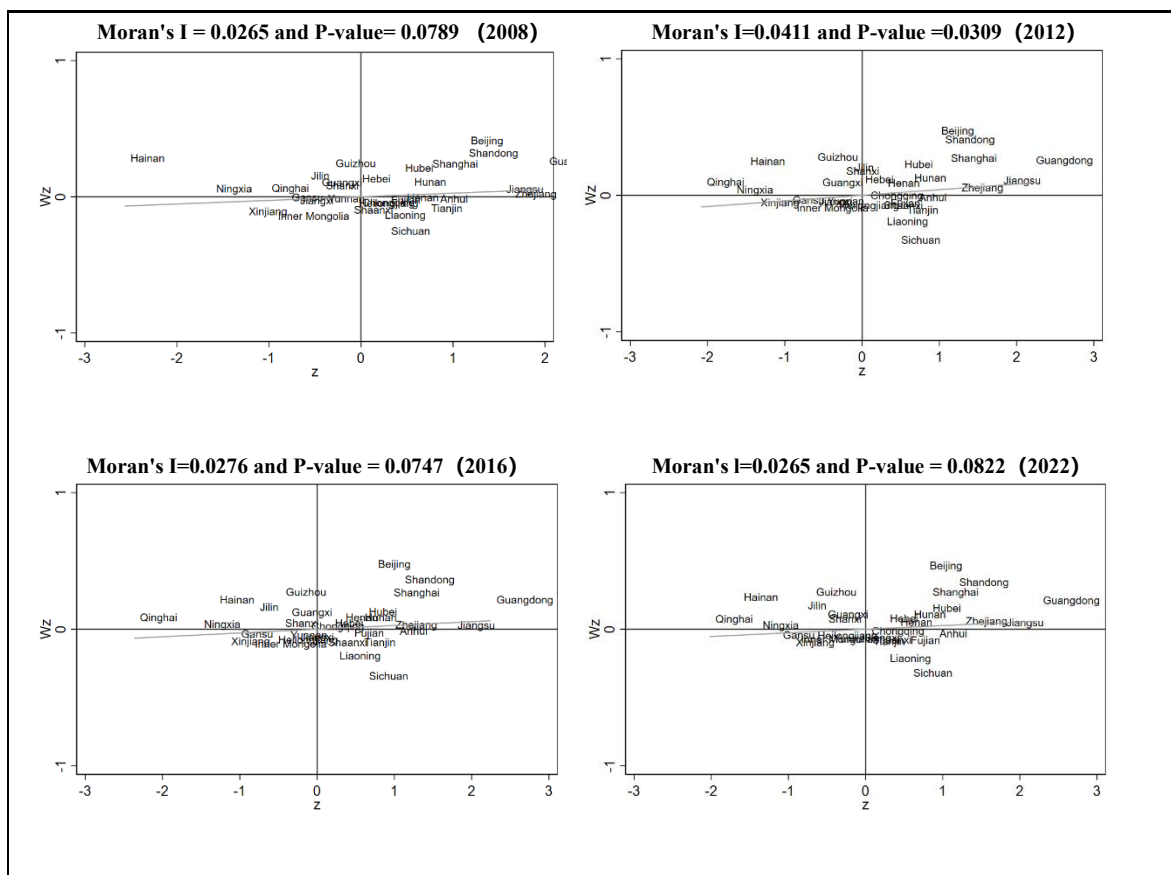
#### **4.4.1.2 Technological Performance of Region in China based on Local Moran's I**

The local Moran's I is used to measure the local spatial autocorrelation of a single spatial unit and can identify the specific location and type of spatial clustering. In this study, a visual analysis of the spatial autocorrelation characteristics of China's regional technological performance from 2008 to 2022 was conducted using Moran's scatter plot (see Figure 4-2). The primary conclusions that can be drawn from this analysis are as follows, the Moran scatter plot demonstrates that technological performance exhibited a significant positive spatial correlation pattern during the study period, with Moran's I indices for all years being positive (0.0265-0.0411). This spatial dependency characteristic indicates that provinces with high technological performance tend to be adjacent to provinces with similar

performance (first quadrant), while provinces with low technological performance also exhibit spatial clustering (third quadrant), confirming the spatial spillover effects of technological innovation activities.

These clustering patterns are consistent with China’s uneven innovation geography. High–high clusters are mainly observed in coastal and core provinces where manufacturing bases are stronger, innovation infrastructure and R&D resources are denser, and market access and transport connectivity facilitate knowledge diffusion. In contrast, low–low clusters tend to appear in inland or peripheral regions with weaker industrial foundations, lower R&D capacity, and higher barriers to factor mobility, which reinforces persistent regional technology gaps.

**Figure 4-2:**  
**Time Evolution of Spatial Autocorrelation of Technological Performance: Moran Scatter Diagram (2008-2022)**



Source: Author’s calculation based on provincial statistical data (2008–2022) using Stata. See Chapter 3 for details on data sources and spatial weight matrix construction.

As shown in Figure 4-2, in 2008 Moran’s I was 0.0265 (P=0.0789), indicating marginally significant spatial clustering, with the scatter plot demonstrating that eastern coastal provinces were mainly distributed in the high–high clustering quadrant. By 2012,

spatial autocorrelation reached its peak ( $I=0.0411$ ,  $P=0.0399$ ), and the high–high clustering zone expanded, reflecting the initial concentration of innovation factors during the early stage of the 12th Five-Year Plan. In 2016, the index declined to 0.0276 ( $P=0.0747$ ), with some provinces shifting from the high–high to the low–high quadrant, suggesting the beginning of regional technology diffusion. By 2022, the index stabilized at 0.0265 ( $P=0.0822$ ), but new high–high clustering areas emerged, potentially reflecting spatial restructuring driven by the application of digital technologies.

A comparison of the scatter plots for 2012 and 2022 reveals that the number of high-high agglomeration provinces has remained stable, but their specific composition has changed, with some traditional innovation centres being replaced by emerging cities. The spatial scope of low-low agglomeration areas has diminished, with provinces in the central region demonstrating an upward migration trend. Spatial heterogeneity has increased, with the presence of more high-low and low-high outliers, indicating that regional technological gaps are showing new signs of differentiation.

The results in Table 4-14 reveal the regional differentiation characteristics of the local spatial autocorrelation analysis of provincial technological performance in China in 2008. From the perspective of spatial agglomeration patterns, the eastern coastal regions formed distinct high-value technological agglomeration zones, with Beijing ( $I_i=0.4854$ ,  $P=0.0035$ ) and Guangdong ( $I_i=0.5391$ ,  $P=0.0012$ ) as the two major innovation hubs exhibiting extremely strong positive spatial correlation, while Shandong ( $I_i=0.3721$ ,  $P=0.0179$ ) emerges as a secondary hub with statistical significance. Meanwhile, Hainan ( $I_i=-0.7578$ ,  $P<0.001$ ) exhibits extremely significant low-value clustering characteristics. Although Guangxi, Guizhou, and other western provinces did not attain a significant level, they exhibited a low-low clustering trend. Spatial outlier analysis demonstrates that Inner Mongolia, Heilongjiang, and other provinces exhibit high-low outliers, while Anhui, Fujian, and others exhibit low-high outliers. This reflects the gradient transfer characteristics in the technology diffusion process.

**Table 4-14:  
Local Moran's I Analysis on the Technological Performance of Provinces in China  
(2008)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.4854	-0.0345	0.1781	2.9195	0.0035	HH	**
Tianjin	-0.0601	-0.0345	0.1163	-0.2203	0.8256	LH	
Hebei	-0.0069	-0.0345	0.1216	0.2269	0.8205	LL	
Shanxi	-0.0392	-0.0345	0.2114	-0.0224	0.9822	LL	
Inner	0.1363	-0.0345	0.2036	0.839	0.4015	HL	
Liaoning	-0.0263	-0.0345	0.1284	0.0634	0.9494	LH	
Jilin	-0.0993	-0.0345	0.2093	-0.3097	0.7568	LL	
Heilongjiang	0.0041	-0.0345	0.114	0.338	0.7354	HL	
Shanghai	0.1807	-0.0345	0.1586	1.3572	0.1747	HH	
Jiangsu	0.0951	-0.0345	0.1317	0.9838	0.3252	HH	
Zhejiang	0.0446	-0.0345	0.1439	0.5495	0.5827	HH	
Anhui	-0.0118	-0.0345	0.1092	0.2075	0.8356	LH	
Fujian	-0.0058	-0.0345	0.1281	0.2243	0.8226	LH	
Jiangxi	0.0176	-0.0345	0.0671	0.7751	0.4383	HL	
Shandong	0.3721	-0.0345	0.1718	2.3669	0.0179	HH	**
Henan	-0.0003	-0.0345	0.1307	0.2611	0.794	LH	
Hubei	0.0918	-0.0345	0.153	0.8256	0.4091	HH	
Hunan	0.0609	-0.0345	0.1063	0.8972	0.3696	HH	
Guangdong	0.5391	-0.0345	0.1772	3.2358	0.0012	HH	**
Guangxi	-0.0555	-0.0345	0.1336	-0.1573	0.875	LL	
Hainan	-0.7578	-0.0345	0.1239	-5.8376	0.0000	LL	***
Chongqing	0.002	-0.0345	0.1161	0.3141	0.7534	HL	
Sichuan	-0.0683	-0.0345	0.1589	-0.2126	0.8317	LH	
Guizhou	-0.0867	-0.0345	0.1122	-0.4653	0.6417	LL	
Yunnan	0.0035	-0.0345	0.1264	0.3007	0.7636	HL	
Shaanxi	0.0131	-0.0345	0.1444	0.3295	0.7418	HL	
Gansu	0.0023	-0.0345	0.1286	0.2862	0.7747	HL	
Qinghai	-0.0706	-0.0345	0.0885	-0.4081	0.6832	LL	
Ningxia	-0.1034	-0.0345	0.1682	-0.4095	0.6822	LL	
Xinjiang	0.1389	-0.0345	0.2047	0.847	0.397	HL	

Notes: See Equation (3.15) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes:  
\*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

From a statistical perspective, the spatial distribution of technological performance exhibits a typical "core-periphery" structure. The mean Ii value (0.272) of high-high aggregation provinces is significantly higher than that of low-low aggregation provinces (-0.071), with the top 5% of high-value provinces contributing over one-third of the spatial autocorrelation strength. It is noteworthy that spatial heterogeneity is pronounced, with the standard deviation of the Ii value (0.234) far exceeding the expected value (0.0345), and the Z-value range spanning 9.673, from -5.838 in Hainan to 3.236 in Guangdong. This

significant regional disparity indicates that China's provincial-level technological development exhibits pronounced spatial imbalance.

According to Table 4-15, the local spatial autocorrelation analysis of provincial-level technological performance in China in 2012 shows that technological innovation activities are exhibiting increasingly obvious spatial clustering characteristics. The eastern coastal areas with high-high concentration (HH) have been observed to continue to strengthen. Guangdong ( $I_i=0.5838$ ,  $P=0.0005$ ) has been found to have surpassed Beijing ( $I_i=0.4671$ ,  $P=0.0048$ ) and has become the most influential technological innovation area in China. As demonstrated by the  $I_i$  values of 0.3041 and 0.2066, respectively, alongside the corresponding  $p$  values of 0.0323 and 0.0651, both Shanghai and Jiangsu exhibited significant high-value clustering characteristics. Concurrently, the scope of the low-low (LL) cluster has expanded, with Hainan ( $I_i=-0.3948$ ,  $P=0.0033$ ) and Qinghai ( $I_i=-0.2177$ ,  $P=0.0333$ ) both exhibiting statistical significance. Although Guizhou ( $I_i=-0.1916$ ) did not attain statistical significance, it exhibited a discernible tendency towards low-value clustering. It is noteworthy that the spatial distribution patterns of high-low and low-high (LH) outliers have undergone significant changes compared to 2008, reflecting the dynamic evolution of technological innovation diffusion processes.

From the perspective of spatial pattern evolution, the spatial differentiation of technological performance in 2012 exhibited the following characteristics: Firstly, the spatial agglomeration intensity of the eastern coastal innovation belt increased overall in comparison with 2008, with particularly significant enhancements in Shanghai and Jiangsu in the Yangtze River Delta region. This indicates that the construction of regional innovation systems had achieved results during the initial phase of the 12th Five-Year Plan. Secondly, the spatial scope of low-value clusters has expanded westward, with western provinces such as Qinghai and Guizhou beginning to exhibit characteristics of technological lag, thereby exacerbating regional development imbalances. Thirdly, changes in the distribution of spatial outliers indicate that technological innovation diffusion is exhibiting more complex spatial patterns, with some central provinces beginning to transition from low-high (LH) to high-high (HH) types. This suggests that the technological gradient transfer effect is taking effect.

**Table 4-15:  
Local Moran's I Analysis on the Technological Performance of Provinces in China  
(2012)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.4671	-0.0345	0.178	2.8176	0.0048	HH	**
Tianjin	-0.0544	-0.0345	0.1149	-0.1737	0.8621	LH	
Hebei	-0.0044	-0.0345	0.1203	0.25	0.8026	LL	
Shanxi	-0.053	-0.0345	0.2119	-0.0874	0.9304	LL	
Inner	0.0861	-0.0345	0.2039	0.5913	0.5543	HL	
Liaoning	-0.0477	-0.0345	0.1273	-0.1039	0.9173	LH	
Jilin	-0.0351	-0.0345	0.2097	-0.0031	0.9975	LL	
Heilongjiang	0.0276	-0.0345	0.1125	0.5515	0.5813	HL	
Shanghai	0.3041	-0.0345	0.1581	2.1413	0.0323	HH	**
Jiangsu	0.2066	-0.0345	0.1307	1.8444	0.0651	HH	*
Zhejiang	0.0736	-0.0345	0.1432	0.7544	0.4506	HH	
Anhui	-0.0089	-0.0345	0.1076	0.2381	0.8118	LH	
Fujian	-0.0166	-0.0345	0.127	0.141	0.8879	LH	
Jiangxi	0.0274	-0.0345	0.0635	0.9752	0.3295	HL	
Shandong	0.4267	-0.0345	0.1716	2.6878	0.0072	HH	**
Henan	0.0247	-0.0345	0.1297	0.4563	0.6482	HH	
Hubei	0.1118	-0.0345	0.1524	0.9595	0.3373	HH	
Hunan	0.0809	-0.0345	0.1046	1.1037	0.2697	HH	
Guangdong	0.5838	-0.0345	0.1772	3.4901	0.0005	HH	***
Guangxi	-0.0588	-0.0345	0.1327	-0.1833	0.8546	LL	
Hainan	-0.3948	-0.0345	0.1227	-2.9369	0.0033	LL	**
Chongqing	0.0001	-0.0345	0.1147	0.3011	0.7633	HH	
Sichuan	-0.1433	-0.0345	0.1585	-0.6865	0.4924	LH	
Guizhou	-0.1916	-0.0345	0.1107	-1.4197	0.1557	LL	
Yunnan	0.0207	-0.0345	0.1253	0.4409	0.6593	HL	
Shaanxi	-0.0145	-0.0345	0.1437	0.1391	0.8893	LH	
Gansu	0.0336	-0.0345	0.1276	0.5334	0.5938	HL	
Qinghai	-0.2177	-0.0345	0.0861	-2.1281	0.0333	LL	**
Ningxia	-0.0744	-0.0345	0.168	-0.2375	0.8123	LL	
Xinjiang	0.0725	-0.0345	0.205	0.5217	0.6019	HL	

Notes: See Equation (3.15) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes:  
\*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

A study of local spatial autocorrelation in provincial-level technological performance in China, as shown in Table 4-16, reveals that the spatial pattern of China's technological performance in 2016 exhibited new evolutionary characteristics. The high-high cluster (HH) continues to demonstrate a substantial trend, with Guangdong (Ii=0.5083, P=0.0022) and Beijing (Ii=0.3534, P=0.0294) maintaining their status as the two primary innovation hubs. Shandong (Ii=0.4041, P=0.0106) exhibited a subsequent augmentation in its agglomeration intensity, while Shanghai (Ii=0.2565, P=0.0663) demonstrated a modest diminution in its pertinence. In the low-low (LL) clustering zone, Hainan (Ii =-0.2993, P=0.0320) and

Qinghai ( $I_i=-0.2175$ ,  $P=0.0369$ ) continue to exhibit significant low-value clustering characteristics, while western provinces such as Sichuan ( $I_i=-0.2097$ ) also show a clear trend of technological lag. The spatial distribution of outliers indicates an increase in the number of provinces classified as high-low and low-high (LH) types, reflecting the complex spatial interactions in the process of technological innovation diffusion.

**Table 4-16:**  
**Local Moran's I Analysis on the Technological Performance of Provinces in China (2016)**

Province	$I_i$	$E(I)$	$Sd(I)$	Z-Value	P-Value	Cluster	Significance
Beijing	0.3534	-0.0345	0.1781	2.1784	0.0294	HH	**
Tianjin	-0.0504	-0.0345	0.1158	-0.1373	0.8908	LH	
Hebei	0.0079	-0.0345	0.1211	0.3503	0.7261	HH	
Shanxi	-0.0234	-0.0345	0.2116	0.0523	0.9583	LL	
Inner	0.0957	-0.0345	0.2037	0.639	0.5228	HL	
Liaoning	-0.0424	-0.0345	0.128	-0.0621	0.9505	LH	
Jilin	-0.1396	-0.0345	0.2094	-0.5021	0.6156	LL	
Heilongjiang	0.0444	-0.0345	0.1135	0.6949	0.4871	HL	
Shanghai	0.2565	-0.0345	0.1584	1.8366	0.0663	HH	*
Jiangsu	0.0583	-0.0345	0.1314	0.7064	0.4799	HH	
Zhejiang	0.037	-0.0345	0.1437	0.4973	0.6189	HH	
Anhui	-0.0105	-0.0345	0.1087	0.2204	0.8255	LH	
Fujian	-0.0111	-0.0345	0.1277	0.1834	0.8545	LH	
Jiangxi	0.0163	-0.0345	0.0659	0.7708	0.4408	HL	
Shandong	0.4041	-0.0345	0.1717	2.5543	0.0106	HH	**
Henan	0.0272	-0.0345	0.1304	0.4728	0.6363	HH	
Hubei	0.0815	-0.0345	0.1528	0.7589	0.4479	HH	
Hunan	0.05	-0.0345	0.1057	0.7992	0.4242	HH	
Guangdong	0.5083	-0.0345	0.1772	3.0626	0.0022	HH	**
Guangxi	-0.0527	-0.0345	0.1333	-0.1368	0.8912	LL	
Hainan	-0.2993	-0.0345	0.1235	-2.1442	0.0320	LL	**
Chongqing	-0.0036	-0.0345	0.1156	0.2672	0.7893	LL	
Sichuan	-0.2097	-0.0345	0.1588	-1.1037	0.2697	LH	
Guizhou	-0.1365	-0.0345	0.1117	-0.9136	0.3609	LL	
Yunnan	0.0169	-0.0345	0.126	0.4077	0.6835	HL	
Shaanxi	-0.006	-0.0345	0.1442	0.1973	0.8436	LH	
Gansu	0.0342	-0.0345	0.1283	0.5353	0.5925	HL	
Qinghai	-0.2175	-0.0345	0.0877	-2.0871	0.0369	LL	**
Ningxia	-0.0641	-0.0345	0.1681	-0.1763	0.86	LL	
Xinjiang	0.1025	-0.0345	0.2048	0.6686	0.5038	HL	

Notes: See Equation (3.15) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\*  $*P* < 0.001$ , \*\*  $*P* < 0.05$ , \*  $*P* < 0.1$ .

As shown in Table 4-16, considering the dynamic evolution of the spatial pattern, the spatial distribution of technological performance in 2016 exhibits several salient features. Firstly, the overall spatial agglomeration intensity of the eastern coastal innovation belt has declined, particularly in Jiangsu ( $I_i=0.0583$ ) and Zhejiang ( $I_i=0.0370$ ) within the Yangtze River Delta region, which may be associated with the multi-centered diffusion of innovation resources. Secondly, low-value agglomeration zones have further consolidated in the western regions, where technological lag issues in provinces such as Qinghai and Sichuan have become more pronounced, underscoring persistent regional development imbalances. Thirdly, the distributional changes of spatial outliers indicate that technological innovation diffusion is evolving toward a more diversified spatial pattern. Specifically, certain central provinces are undergoing a transition from low-high (LH) to high-high (HH) clusters, while some traditional high-value provinces are showing signs of diffusion into neighboring areas.

The spatial pattern analysis of China's provincial-level technological performance in 2022 (Table 4-17) demonstrates that there is a novel trend of multi-center collaborative development in technological innovation activities. From the perspective of spatial agglomeration characteristics, a three-polar innovation pattern has emerged. Guangdong ( $I_i=0.4937$ ,  $P=0.0029$ ) continues to maintain its leading advantage, while Shandong ( $I_i=0.4076$ ,  $P=0.0099$ ) has significantly enhanced its agglomeration intensity and surpassed Beijing ( $I_i=0.3666$ ,  $P=0.0242$ ), emerging as a new technological innovation growth pole. Concurrently, the  $I_i$  values of Shanghai ( $I_i=0.2271$ ,  $P=0.0979$ ) and provinces such as Jiangsu and Zhejiang in the Yangtze River Delta region have exhibited an upward trend, signifying that regional innovation synergy effects are being reinforced.

With regard to spatial heterogeneity, a distinct "strong south, weak north" pattern emerges. Technological divergence is more pronounced in southern regions, with Hainan ( $I_i=-0.4076$ ,  $P=0.0023$ ) experiencing a worsening technological lag, and provinces such as Guizhou ( $I_i=-0.2031$ ) and Guangxi also exhibiting significant clustering of low values. Conversely, in the northern regions, with the exception of the Beijing-Tianjin-Hebei innovation triangle, provinces such as Inner Mongolia ( $I_i=0.0673$ ) and Heilongjiang ( $I_i=0.0308$ ) demonstrate comparatively balanced technological innovation activities. This north-south disparity may be indicative of the differing effectiveness of regional development strategies and economic structural adjustments.

**Table 4-17:**  
**Local Moran's I Analysis on the Technological Performance of Provinces in China (2022)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.3666	-0.0345	0.178	2.2534	0.0242	HH	**
Tianjin	-0.0023	-0.0345	0.1145	0.2808	0.7789	LH	
Hebei	0.0208	-0.0345	0.1199	0.4607	0.645	HH	
Shanxi	-0.0441	-0.0345	0.212	-0.0454	0.9638	LL	
Inner	0.0673	-0.0345	0.204	0.4988	0.6179	HL	
Liaoning	-0.0525	-0.0345	0.127	-0.1418	0.8872	LH	
Jilin	-0.1516	-0.0345	0.2098	-0.5583	0.5766	LL	
Heilongjiang	0.0308	-0.0345	0.1121	0.5821	0.5605	HL	
Shanghai	0.2271	-0.0345	0.158	1.6552	0.0979	HH	*
Jiangsu	0.0913	-0.0345	0.1304	0.9643	0.3349	HH	
Zhejiang	0.0785	-0.0345	0.143	0.7902	0.4294	HH	
Anhui	-0.0251	-0.0345	0.1071	0.0872	0.9305	LH	
Fujian	-0.0399	-0.0345	0.1267	-0.0428	0.9659	LH	
Jiangxi	0.0045	-0.0345	0.0624	0.6247	0.5321	HL	
Shandong	0.4076	-0.0345	0.1715	2.5776	0.0099	HH	**
Henan	0.0219	-0.0345	0.1294	0.4354	0.6633	HH	
Hubei	0.1309	-0.0345	0.1523	1.086	0.2775	HH	
Hunan	0.0636	-0.0345	0.104	0.9429	0.3457	HH	
Guangdong	0.4937	-0.0345	0.1771	2.9818	0.0029	HH	**
Guangxi	-0.065	-0.0345	0.1324	-0.2302	0.8179	LL	
Hainan	-0.4076	-0.0345	0.1223	-3.0498	0.0023	LL	**
Chongqing	0	-0.0345	0.1143	0.3013	0.7632	LH	
Sichuan	-0.1787	-0.0345	0.1584	-0.9105	0.3625	LH	
Guizhou	-0.2031	-0.0345	0.1102	-1.5296	0.1261	LL	
Yunnan	0.0346	-0.0345	0.1249	0.553	0.5803	HL	
Shaanxi	-0.0009	-0.0345	0.1435	0.2343	0.8148	LH	
Gansu	0.0449	-0.0345	0.1272	0.624	0.5326	HL	
Qinghai	-0.1668	-0.0345	0.0854	-1.5493	0.1213	LL	
Ningxia	-0.045	-0.0345	0.1679	-0.0627	0.95	LL	
Xinjiang	0.0937	-0.0345	0.2052	0.6247	0.5322	HL	

Notes: See Equation (3.15) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes:

\*\*\* \*p\* < 0.001, \*\* \*p\* < 0.05, \* \*p\* < 0.1.

From the perspective of dynamic evolution trends, significant changes in the spatial pattern of technological performance were observed between 2016 and 2022. Firstly, the distribution of innovation factors shifted from a single-pole dominance (Beijing, Guangdong) to a multi-center collaboration (with the addition of Shandong). Secondly, the scope of technological diffusion expanded from coastal areas to inland regions, with provinces such as Hubei. These changes indicate that the implementation of the regional coordinated development strategy and the innovation-driven development strategy is reshaping China's technological innovation geographical landscape.

#### 4.4.2 Technological Performance Based on Lagrange Multiplier Test

The results of the spatial autocorrelation diagnostic tests in Table 4-18 indicate that there is a significant spatial dependency between Location Quotient (LQ) and technological performance. The Moran's I of the Spatial Error Model (SEM) is 3.418 ( $P=0.001$ ), the Lagrange Multiplier test statistic is as high as 99.827 ( $P<0.001$ ), and the Robust LM test is 93.814 ( $P<0.001$ ). These statistics reach extremely significant levels, indicating that the model exhibits strong spatial error correlation. Furthermore, the Lagrange Multiplier test (22.019,  $P<0.001$ ) and Robust LM test (16.006,  $P<0.001$ ) for the spatial lag model were also significant, thus confirming the spatial spillover effects of technological performance.

It is important to note that the test statistic for the spatial error term is considerably larger than that for the spatial lag term. This feature suggests two things. Firstly, the spatial correlation of unobserved factors (such as institutional environment and innovation infrastructure) plays a more critical role in the relationship between locational quotient and technological performance. Secondly, the use of a non-standardized binary spatial weight matrix (WLB) may have reinforced the spatial influence effect of regions with more neighboring provinces. The "double significance" feature of the test results indicates that a simple spatial regression model may be inadequate in fully capturing the spatial dependency structure in the data. Subsequent analyses could adopt a Spatial Durbin Model (SDM) to simultaneously consider both endogenous and exogenous spatial dependency effects.

**Table 4-18:**  
**Spatial Autocorrelation Diagnosis of Technological Performance and Location Quotient**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	3.418	1	0.001	***
	Lagrange Multiplier	99.827	1	<0.001	***
	Robust LM	93.814	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	22.019	1	<0.001	***
	Robust LM	16.006	1	<0.001	***

Notes: See Equations (3.23)– (3.24) for the specification of the LM tests.

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 ( $df = 1$ ).

The results of the spatial autocorrelation diagnostic tests in Table 4-19 provide a foundation for the following significant conclusions regarding the spatial association between Employment Density (ED) and technological performance. The Moran's I of the Spatial Error Model (SEM) is 2.963 ( $P=0.003$ ), and the Lagrange multiplier test statistic is 72.999 ( $P< 0.001$ ). The robust LM test statistic is 65.784 ( $P< 0.001$ ). These results indicate

highly significant spatial error dependence. Furthermore, the Lagrange Multiplier test (39.428,  $P < 0.001$ ) and the robust LM test (16.006,  $P < 0.001$ ) for the Spatial Lag Model (SLM) are also highly significant, collectively confirming the presence of significant spatial spillover effects in technological performance.

The test results exhibit the following characteristics, the spatial error term is more significant (LM=72.999 vs.39.428), indicating that the spatial correlation of unobserved variables (such as innovation environment and institutional factors) is more prominent; the use of a non-row-standardized binary spatial weight matrix (WLB) may have strengthened the influence of neighboring provinces; consequently, the Spatial Durbin Model (SDM) was adopted to simultaneously capture spatial lag and error effect.

**Table 4-19:  
Spatial Autocorrelation Diagnosis of Technological Performance and Employment Density**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	2.963	1	0.003	**
	Lagrange Multiplier	72.999	1	<0.001	***
	Robust LM	65.784	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	39.428	1	<0.001	***
	Robust LM	16.006	1	<0.001	***

Notes: See Equations (3.23)– (3.24) for the specification of the LM tests.

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).

The results of the spatial autocorrelation diagnostic tests in Table 4-20 indicate a significant spatial dependence between the Herfindahl-Hirschman Index (HHI) and technological performance. The primary conclusions that can be drawn from this analysis are as follows, the Moran's I of the Spatial Error Model (SEM) is 2.556 ( $P = 0.011$ ), the Lagrange Multiplier test statistic is 50.946 ( $P < 0.001$ ), and the Robust LM test is 45.430 ( $P < 0.001$ ). All of these are statistically significant. The Lagrange Multiplier test (36.662,  $P < 0.001$ ) and Robust LM test (31.145,  $P < 0.001$ ) for the Spatial Lag Model (SLM) were also found to be significant. The findings suggest that the impact of industrial concentration on technological performance manifests distinct spatial spillover effects and spatial error correlations.

**Table 4-20:  
Spatial Autocorrelation Diagnosis of Technological Performance and Herfindahl-  
Hirschman Index**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	2.556	1	0.011	*
	Lagrange Multiplier	50.946	1	<0.001	***
	Robust LM	45.430	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	36.662	1	<0.001	***
	Robust LM	31.145	1	<0.001	***

Notes: See Equations (3.23)– (3.24) for the specification of the LM tests.

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).

The following analysis is concerned with the spatial effect. The spatial error term and the lag term are both found to be significant, yet the test statistic for the error term is found to be larger (50.946 vs. 36.662), indicating that the spatial correlation of unobserved factors is more prominent. The strength of spatial dependence is weaker than that in the Employment Density (ED) and Location Quotient (LQ) models, but it remains highly significant. Subsequent analysis may be undertaken using the Spatial Durbin Model (SDM). According to the results in Tables 4-18, 4-19 and 4-20 above, it can be seen that the results are significant, so the Spatial Durbin Model (SDM) can be used.

#### **4.4.3 Findings from the Spatial Durbin Model of Industrial Agglomeration and Technological Performance**

##### **4.4.3.1 The Impact of Location Quotient on Technological Performance**

The present study conducted an in-depth analysis of the relationship between Location Quotient (LQ) and technological performance based on the Spatial Durbin Model (SDM). The estimation results presented in Table 4-21 yield the following significant findings: Location Quotient (LQ) has been demonstrated to exert a substantial negative influence on technological performance, with a direct effect measuring -0.276 ( $P < 0.001$ ). This finding suggests that for every one-unit increase in industrial specialization, local technological performance experiences a decrease of 0.276 units. This result remains robust within the 95% confidence interval [-0.384, -0.168]. Of particular note is the spatial spillover effect of location quotient, which has been shown to be as high as -2.504 ( $P = 0.003$ ). This effect is nine times that of the direct effect, resulting in a total effect of -2.780 ( $P = 0.002$ ). The "siphoning effect" is theorized to operate via three mechanisms, unidirectional flow of innovation factors, intensified regional technological competition, and spatial misallocation of innovation resources.

**Table 4-21:  
Estimation Results of Spatial Durbin Model with Marginal Effects-Location  
Quotients**

Model Diagnostics: Panel structure: 30 provinces × 15 years (balanced); R<sup>2</sup>: Within=0.954, Between=0.960, Overall=0.908; Log-likelihood = 80.226; Mean of fixed-effects = -1.696; Variance ( $\sigma^2$ ): 0.039 \*\*\* (0.0026)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>LQ</i>	-0.209***	0.047	-4.44	<0.001	-0.302	-0.117
	<i>h</i>	-0.018	0.04	-0.45	0.655	-0.097	0.061
	<i>staff</i>	0.044	0.071	0.61	0.541	-0.096	0.184
	<i>fund</i>	0.460***	0.084	5.49	<0.001	0.296	0.624
	<i>gov</i>	0.175***	0.048	3.61	<0.001	0.08	0.269
<b>Spatial Effects</b>	<i>LQ</i>	-0.737**	0.29	-2.54	0.011	-1.305	-0.168
	<i>h</i>	0.112	0.251	0.45	0.656	-0.38	0.603
	<i>staff</i>	-0.316	0.253	-1.25	0.211	-0.812	0.18
	<i>fund</i>	0.053	0.316	0.17	0.866	-0.567	0.674
	<i>gov</i>	0.082	0.202	0.4	0.686	-0.315	0.478
<b>Spatial Parameter</b>	$\rho$	0.040***	0.003	14.85	<0.001	0.034	0.045
<b>Long-Run Effect</b>							
<b>Direct</b>	<i>LQ</i>	-0.276***	0.055	-5.01	<0.001	-0.384	-0.168
	<i>h</i>	-0.012	0.051	-0.22	0.822	-0.112	0.089
	<i>staff</i>	0.027	0.073	0.37	0.708	-0.116	0.171
	<i>fund</i>	0.482***	0.084	5.77	<0.001	0.318	0.646
	<i>gov</i>	0.188***	0.048	3.93	<0.001	0.094	0.281
<b>Indirect</b>	<i>LQ</i>	-2.504***	0.848	-2.95	0.003	-4.166	-0.842
	<i>h</i>	0.289	0.841	0.34	0.731	-1.36	1.938
	<i>staff</i>	-0.866	0.733	-1.18	0.237	-2.301	0.57
	<i>fund</i>	1.103	0.951	1.16	0.246	-0.76	2.967
	<i>gov</i>	0.514	0.549	0.94	0.35	-0.563	1.59
<b>Total</b>	<i>LQ</i>	-2.780***	0.877	-3.17	0.002	-4.498	-1.062
	<i>h</i>	0.278	0.878	0.32	0.752	-1.443	1.999
	<i>staff</i>	-0.838	0.763	-1.1	0.272	-2.333	0.656
	<i>fund</i>	1.586	0.985	1.61	0.108	-0.345	3.517
	<i>gov</i>	0.701	0.567	1.24	0.216	-0.41	1.813

Notes: See Equation (3.11) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.661 (P=0); All standard errors are robust standard errors.

In sharp contrast to the negative impact of Location Quotient (LQ), both R&D funding and government support exhibit significant positive effects. The direct effects are 0.482 (P<0.001) for R&D funding (fund) and 0.188 (P<0.001) for government (gov) support, but the spatial spillover effects are not significant (P>0.05). These findings suggest that the impact of R&D (fund) investment exhibits distinct localization characteristics, that the policy effects of government support are constrained by administrative boundaries and that the influence of human capital (h) and research staff (staff) do not reach significant levels.

The spatial autoregressive parameter  $\rho$  was found to be 0.040 ( $P < 0.001$ ), indicating that technological performance exhibits significant positive spatial dependence. The model demonstrates excellent goodness of fit (Within  $R^2 = 0.954$ ), with significant variance components ( $\sigma^2 = 0.039$ ,  $P < 0.001$ ). All standard errors have been robustly adjusted to ensure the reliability of the results.

#### ***4.4.3.2 The Impact of Employment Density on Technological Performance***

The results of Table 4-22 indicate that the impact of Employment Density (ED) on technological performance is not statistically significant. The direct effect coefficient is found to be insignificant ( $P = 0.949$ ), with a 95% confidence interval of  $[-0.004, 0.005]$ . The indirect effect coefficient is  $-0.009$  ( $P = 0.614$ ), with a confidence interval of  $[-0.046, 0.027]$ . The total effect coefficient is also  $-0.009$  ( $P = 0.639$ ), with a confidence interval of  $[-0.048, 0.03]$ . This finding indicates that, at the present stage of development, merely augmenting employment density is inadequate to efficaciously promote technological performance, and there may be a necessity to prioritize employment quality over quantity.

The volume of scientific research funding (fund) exhibits a significant positive impact. The direct effect coefficient reaches 0.493 ( $P < 0.001$ ), indicating that for every 1-unit increase in R&D investment, local technological performance improves by approximately 49.3%. The spatial spillover effect is marginally significant at 2.182 ( $P = 0.065$ ), and the total effect of 2.675 ( $P = 0.029$ ) indicates that R&D investment not only promotes local innovation but also drives the development of surrounding regions. This finding highlights the importance of continuously increasing R&D investment.

The influence of research staff (staff) exhibits a unique pattern. While the local effect is not significant ( $-0.044$ ,  $P = 0.543$ ), the spatial spillover effect is  $-2.260$  ( $P = 0.01$ ), and the total effect is  $-2.304$  ( $P = 0.011$ ). This negative spatial spillover effect may stem from talent siphoning and regional mismatches in innovation resources, suggesting the need to optimize the spatial distribution and mobility mechanisms of research staff.

Government support (gov) exhibited a substantial local effect (0.100,  $P = 0.037$ ), yet its spatial spillover effect proved non-significant (0.278,  $P = 0.684$ ). This finding suggests that the impact of government innovation policies is predominantly confined to the local administrative region, emphasizing the necessity for the enhancement of cross-regional

synergies. The establishment of more effective regional policy coordination mechanisms is imperative.

**Table 4-22:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Employment Density**

Model Diagnostics: Panel structure: 30 provinces  $\times$  15 years (balanced); R<sup>2</sup>: Within=0.946, Between=0.939, Overall=0.846; Log-likelihood = 67.282; Mean of fixed-effects = -1.674; Variance ( $\sigma^2$ ): 0.041\*\*\* (0.0028)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>ED</i>	0	0.002	0.17	0.865	-0.004	0.004
	<i>h</i>	-0.029	0.041	-0.7	0.483	-0.11	0.052
	<i>staff</i>	0.014	0.072	0.19	0.847	-0.127	0.155
	<i>fund</i>	0.437***	0.084	5.19	<0.001	0.272	0.602
	<i>gov</i>	0.092**	0.046	1.99	0.046	0.002	0.183
<b>Spatial Effects</b>	<i>ED</i>	-0.003	0.005	-0.66	0.509	-0.014	0.007
	<i>h</i>	0.035	0.271	0.13	0.898	-0.497	0.566
	<i>staff</i>	-0.647**	0.25	-2.59	0.01	-1.137	-0.157
	<i>fund</i>	0.292	0.326	0.89	0.371	-0.348	0.931
	<i>gov</i>	0.034	0.206	0.16	0.87	-0.37	0.437
<b>Spatial Parameter</b>	$\rho$	0.717***	0.054	13.31	<0.001	0.612	0.823
<b>Long-Run Effect</b>							
<b>Direct</b>	<i>ED</i>	0	0.002	0.06	0.949	-0.004	0.005
	<i>h</i>	-0.03	0.059	-0.51	0.611	-0.146	0.086
	<i>staff</i>	-0.044	0.073	-0.61	0.543	-0.187	0.099
	<i>fund</i>	0.493***	0.087	5.67	<0.001	0.323	0.664
	<i>gov</i>	0.100**	0.048	2.08	0.037	0.006	0.193
<b>Indirect</b>	<i>ED</i>	-0.009	0.019	-0.5	0.614	-0.046	0.027
	<i>h</i>	0.021	1.073	0.02	0.984	-2.081	2.123
	<i>staff</i>	-2.260**	0.881	-2.57	0.01	-3.986	-0.534
	<i>fund</i>	2.182*	1.181	1.85	0.065	-0.133	4.497
	<i>gov</i>	0.278	0.684	0.41	0.684	-1.062	1.618
<b>Total</b>	<i>ED</i>	-0.009	0.02	-0.47	0.639	-0.048	0.03
	<i>h</i>	-0.009	1.119	-0.01	0.994	-2.202	2.184
	<i>staff</i>	-2.304**	0.908	-2.54	0.011	-4.084	-0.524
	<i>fund</i>	2.675**	1.224	2.19	0.029	0.276	5.075
	<i>gov</i>	0.378	0.705	0.54	0.592	-1.004	1.759

Notes: See Equation (3.11) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.717 (P=0); All standard errors are robust standard errors.

The spatial autoregressive parameter  $\rho$  attained a maximum of 0.717 (P<0.001), signifying a robust positive spatial correlation in technological performance. This result is significantly higher than the spatial dependency intensity of traditional industrial indicators, potentially reflecting the growing trend toward regional clustering of innovative activities and the geographical limitations of knowledge spillover effects.

#### *4.4.3.3 The Impact of Herfindahl–Hirschman Index on Technological Performance*

The present study conducted an in-depth analysis of the relationship between the Herfindahl–Hirschman Index (HHI) and technological performance based on the Spatial Durbin Model (SDM). The estimation results presented in Table 4-23 yield the following significant findings:

The research findings suggest that the Herfindahl–Hirschman Index (HHI) has a negative impact on technological performance. The direct effect coefficient is -1.606 ( $P < 0.001$ ), with a 95% confidence interval of [-2.49, -0.721]. This indicates that, for every one-unit increase in industry concentration, local technological performance decreases by 1.606 units. Furthermore, the indirect effect is as high as -6.014 ( $P = 0.005$ ), with a confidence interval of [-10.245, -1.783], while the total effect is -7.620 ( $P < 0.001$ ), with a confidence interval of [-11.888, -3.351]. These results confirm that excessive industrial concentration has a 'double inhibition' effect, constraining local innovation and generating significant negative spillover effects in surrounding regions.

The volume of scientific research funding (fund) has a significant positive effect. The direct effect coefficient is 0.471 ( $P < 0.001$ ), meaning that local technological performance improves by 47.1% for every 1-unit increase in R&D investment. The spatial spillover effect is 2.493 ( $P = 0.011$ ) and the total effect is 2.964 ( $P = 0.004$ ). This indicates that R&D investment promotes local innovation and drives the development of surrounding regions through knowledge spillovers. These findings emphasize the strategic importance of continuously increasing R&D investment.

The influence of research staff (staff) exhibits a unique pattern. Although the local effect is insignificant (-0.036,  $P = 0.602$ ), the indirect effect is -2.310 ( $P = 0.001$ ) and the total effect is -2.346 ( $P = 0.001$ ). This significant negative spatial spillover effect may be due to one-way talent flows and regional imbalances in talent allocation. This suggests the need to improve mechanisms for the regional mobility and collaboration of research staff.

**Table 4-23:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Herfindahl-Hirschman Index**

Model Diagnostics: Panel structure: 30 provinces × 15 years (balanced); R<sup>2</sup>: Within=0.952, Between=0.943, Overall=0.842; Log-likelihood = 78.583; Mean of fixed-effects = -2.081; Variance ( $\sigma^2$ ): 0.040\*\*\* (0.0027)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>HHI</i>	-1.459***	0.447	-3.26	0.001	-2.335	-0.582
	<i>h</i>	-0.034	0.04	-0.85	0.396	-0.113	0.045
	<i>staff</i>	0.019	0.07	0.27	0.787	-0.119	0.157
	<i>fund</i>	0.410***	0.083	4.95	<0.001	0.247	0.572
	<i>gov</i>	0.102**	0.045	2.27	0.023	0.014	0.19
<b>Spatial Effects</b>	<i>HHI</i>	-1.217	0.87	-1.4	0.162	-2.921	0.487
	<i>h</i>	-0.045	0.25	-0.18	0.857	-0.535	0.445
	<i>staff</i>	-0.828***	0.246	-3.37	0.001	-1.311	-0.346
	<i>fund</i>	0.602*	0.328	1.84	0.066	-0.04	1.244
	<i>gov</i>	-0.14	0.204	-0.68	0.493	-0.54	0.26
<b>Spatial Parameter</b>	$\rho$	0.650***	0.063	10.39	<0.001	0.528	0.773
<b>Long-Run Effect</b>							
<b>Direct</b>	<i>HHI</i>	-1.606***	0.451	-3.56	<0.001	-2.49	-0.721
	<i>h</i>	-0.041	0.051	-0.8	0.422	-0.14	0.058
	<i>staff</i>	-0.036	0.07	-0.52	0.602	-0.173	0.1
	<i>fund</i>	0.471***	0.083	5.69	<0.001	0.309	0.633
	<i>gov</i>	0.095*	0.046	2.07	0.038	0.005	0.185
<b>Indirect</b>	<i>HHI</i>	-6.014**	2.159	-2.79	0.005	-10.245	-1.783
	<i>h</i>	-0.184	0.799	-0.23	0.818	-1.751	1.382
	<i>staff</i>	-2.310***	0.703	-3.29	0.001	-3.688	-0.932
	<i>fund</i>	2.493*	0.983	2.54	0.011	0.567	4.419
	<i>gov</i>	-0.253	0.602	-0.42	0.674	-1.433	0.926
<b>Total</b>	<i>HHI</i>	-7.620***	2.178	-3.5	<0.001	-11.888	-3.351
	<i>h</i>	-0.225	0.835	-0.27	0.788	-1.861	1.411
	<i>staff</i>	-2.346**	0.725	-3.23	0.001	-3.768	-0.925
	<i>fund</i>	2.964***	1.019	2.91	0.004	0.966	4.961
	<i>gov</i>	-0.158	0.62	-0.26	0.798	-1.373	1.056

Notes: See Equation (3.11) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.65 (P=0); All standard errors are robust standard errors.

Government support (*gov*) showed a significant local effect (0.095, P=0.038), but its spatial spillover effect was -0.253 (P=0.674) and not significant. This indicates that the effects of government innovation policies are mainly limited to the local administrative region, with insufficient cross-regional synergies, necessitating the establishment of a more effective regional policy coordination system.

The spatial autoregressive parameter,  $\rho$ , is 0.650 (P<0.001), which indicates a strong positive spatial correlation in technological performance. This result reflects the

geographical agglomeration of innovation activities and the spatial limitations of knowledge spillovers. It provides an important basis for formulating regional collaborative innovation policies.

The model demonstrates excellent fitting performance.  $R^2$  is 0.952 within, 0.943 between and 0.842 overall. The variance component,  $\sigma^2$ , is significant at  $p < 0.001$ , with a log-likelihood value of 78.583, and all standard errors have been robustly adjusted. Fixed-effects estimation was employed based on 15 years of balanced panel data from 30 provinces to ensure the reliability of the research results.

## **4.5 Empirical Findings on the Influence of Industrial Agglomeration on the Environmental Performance of Manufacturing Industry**

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### **4.5.1 The Results of Moran's I Analysis**

#### ***4.5.1.1 Yearly Environmental Performance of Region in China Based on the Global Moran's I***

As illustrated in Table 4-24, the spatial correlation of China's provincial environmental performance from 2008 to 2022 manifests a discernible three-stage evolutionary pattern. The initial stage extends from 2008 to 2014, during which Moran's I exhibited fluctuations between -0.0183 and 0.0164, with no values surpassing the significance threshold ( $P > 0.1$ ). This finding suggests that environmental performance during this period demonstrated a random spatial distribution pattern. The second stage commenced in 2015–2016, marking the initial success of regional collaborative governance, with the index demonstrating a significant positive correlation for the first time ( $I = 0.0228$  in 2015,  $P = 0.094$ ). From 2017 to 2022, the third phase witnessed the index's sustained rise, reaching a peak in 2020 ( $I = 0.0554$ ,  $P = 0.0095$ ), signifying the emergence of a substantial spatial clustering pattern in environmental governance.

The significance level of the Moran's I test shows clear temporal variation. Between 2008 and 2014, the p-values for all years were greater than 0.1, indicating that there was no significant spatial dependence in environmental performance. Marginal significance ( $P < 0.1$ ) began to emerge in 2015 and, from 2017 onwards, all years passed the 5% significance test ( $P < 0.05$ ), with 2020 reaching the highest level of significance ( $P < 0.01$ ). The trend in Z-values aligns with that of p-values, gradually increasing from below 1.96 in earlier years to above 2.0 in later years, which further validates the strengthening of spatial correlation.

A significant temporal coupling exists between the evolution of spatial patterns and the implementation of major environmental policies. The implementation of the "New Environmental Protection Law" in 2015 coincided with the first instance in which spatial correlation became significant ( $P < 0.1$ ). In the aftermath of the initiation of the "Pollution Prevention and Control Campaign" in 2018, spatial aggregation underwent a process of consolidation, and when the "carbon peak" target was proposed in 2020, spatial correlation attained its zenith during the study period ( $I = 0.0554$ ). This temporal correspondence provides novel spatial-dimensional evidence for evaluating the effectiveness of environmental policies, indicating that policy interventions play a crucial role in shaping the spatial patterns of environmental performance.

The spatial pattern demonstrated novel heterogeneous characteristics between 2019 and 2022. Despite a decline in spatial agglomeration intensity from its peak in 2020 ( $I = 0.0554$ ) to 0.0429 in 2022, statistical significance remained stable ( $P < 0.05$ ). This change may be indicative of uneven development in the process of regional collaborative governance, including regional differentiation in the intensity of environmental regulations, spatial restructuring of pollution caused by industrial relocation, and differentiated improvements in environmental governance capabilities across different regions.

**Table 4-24:  
Moran's I Spatial Autocorrelation Test Results of Environmental Performance From  
2008 to 2022**

Year	Moran's I	Expected E(I)	Std. Dev.	Z-score	*P*-value
2008	-0.0183	-0.0345	0.0333	0.4855	0.6274
2009	-0.0155	-0.0345	0.0337	0.5642	0.5726
2010	-0.0158	-0.0345	0.0338	0.5518	0.5811
2011	-0.0008	-0.0345	0.0342	0.9869	0.3237
2012	0.0051	-0.0345	0.0341	1.1596	0.2462
2013	0.0106	-0.0345	0.0343	1.3171	0.1878
2014	0.0164	-0.0345	0.0343	1.4845	0.1377
2015	0.0228	-0.0345	0.0343	1.6725	<b>0.0944*</b>
2016	0.0257	-0.0345	0.033	1.8246	<b>0.0681*</b>
2017	0.0335	-0.0345	0.0336	2.0255	<b>0.0428**</b>
2018	0.0298	-0.0345	0.0335	1.918	<b>0.0551*</b>
2019	0.0445	-0.0345	0.0327	2.418	<b>0.0156**</b>
2020	0.0554	-0.0345	0.0347	2.5937	<b>0.0095**</b>
2021	0.0541	-0.0345	0.0349	2.5394	<b>0.0111*</b>
2022	0.0429	-0.0345	0.0347	2.2317	<b>0.0256*</b>

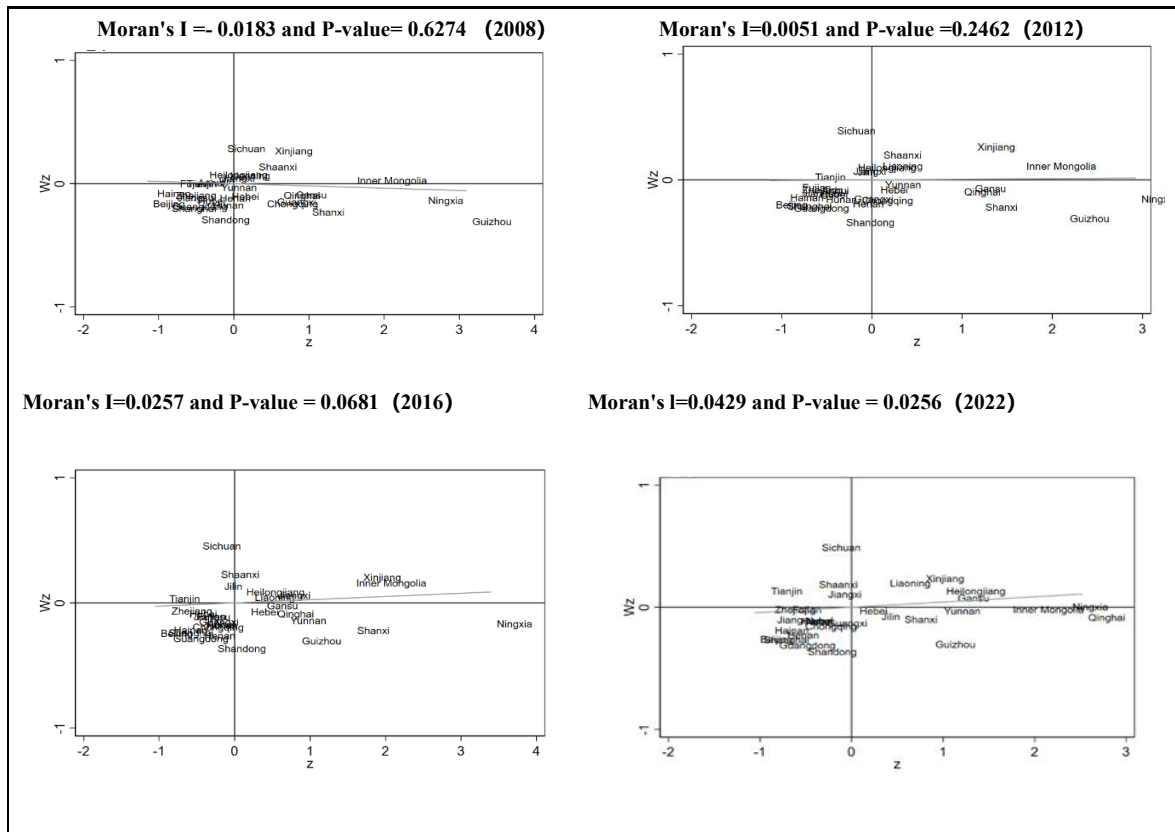
Notes: See Equation (3.16) for the specification of Moran's I.

N = 450 (30 panels over 15 years). Significance codes: \*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

#### 4.5.1.2 Environmental Performance of Region in China based on Local Moran's I

As can be clearly seen from the trend of the Moran I from 2008 to 2022 in Figure 4-3, the spatial autocorrelation of environmental performance across Chinese provinces shows a fluctuating upward trend. In 2008, the Moran's I was 0.0183 (P=0.6274), which did not achieve statistical significance, indicating that environmental performance exhibited a random spatial distribution pattern. By 2022, Moran's I had risen to 0.0429 (P=0.0236), which was significant at the 5% level, indicating a weak positive spatial clustering effect. This evolutionary process suggests that China's regional environmental governance may have gradually formed a spatially dependent pattern, with provinces demonstrating similar environmental performance exhibiting a geographical clustering trend.

**Figure 4-3:  
Time Evolution of Spatial Autocorrelation of Environmental Performance: Moran Scatter Diagram (2008-2022)**



Source: Author's calculation based on provincial statistical data (2008–2022) using Stata. See Chapter 3 for details on data sources and spatial weight matrix construction.

In the initial stage (2008–2012), Moran's I values were 0.0183 in 2008 and 0.0051 in 2012, with P-values exceeding 0.1, suggesting the absence of significant spatial autocorrelation. During this period, the spatial distribution of environmental performance among provinces appeared relatively independent. This was particularly evident in western

provinces such as Sichuan, Xinjiang, and Shaanxi (Figure 4-3), where clear spatial linkages in environmental governance outcomes had yet to emerge.

In the transition phase (2016), Moran's I rose to 0.0257 ( $P=0.0681$ ), reaching marginal significance at the 10% level. As illustrated in Figure 4-3, northern provinces such as Xinjiang and Inner Mongolia began to exhibit spatial clustering, while provinces like Guizhou remained within specific quadrants. These patterns suggest that regional environmental policies had begun to generate spatial spillover effects.

In the significant clustering phase (2022), Moran's I reached its highest value during the study period at 0.0429, which was statistically significant ( $P=0.0236$ ). The recurrent appearance of the "Xinjiang–Inner Mongolia" combination in the legend, together with the distinct position of Guizhou, indicates that China's environmental performance had evolved into a spatially differentiated pattern characterized by "high–high clustering in the north" and "low–low clustering in the southwest." This differentiation may be closely linked to variations in environmental regulations shaped by regional strategies such as the Beijing–Tianjin–Hebei Coordinated Development initiative and the Yangtze River Economic Belt.

These clustering patterns likely reflect differences in industrial structure, resource endowments, and policy intensity. Northern/northwestern provinces with energy- and heavy-industry bases may show spatially linked outcomes via cross-border pollution transport and coordinated regulation, whereas parts of the southwest can exhibit low–low clusters due to weaker environmental infrastructure/enforcement and more difficult terrain. Coastal core provinces may appear as HL outliers because upgrading and stricter regulation improve local performance faster than surrounding areas, while spillovers remain limited by boundary effects and industrial transfer.

The local spatial autocorrelation analysis (local Moran's I) of China's provincial environmental performance in 2008 shown in Table 4-25 indicates that most provinces did not exhibit significant spatial clustering patterns ( $P>0.05$ ), suggesting weak spatial dependence in environmental performance. Guizhou ( $I_i=-0.9722$ ,  $P<0.01$ ) and Ningxia ( $I_i=-0.3463$ ,  $P=0.0657$ ) were the only provinces to exhibit significant low-low (LL) clustering. This suggests that both provinces and their surrounding regions have relatively low levels of environmental governance, which may indicate regional delays in environmental governance.

High–high (HH) clustering regions are observed in Inner Mongolia ( $I_i=0.0445$ ), Shaanxi ( $I_i=0.0371$ ), and Xinjiang ( $I_i=0.1309$ ), reflecting relatively strong environmental performance in these provinces and their surrounding areas. However, the associations are not statistically significant ( $P>0.05$ ), suggesting only an emerging tendency toward collaborative environmental governance in the northwest region.

**Table 4-25:**  
**Local Moran's I Analysis on the Environmental Performance of Provinces in China (2008)**

Province	$I_i$	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.1898	-0.0345	0.1784	1.2572	0.2087	HL	
Tianjin	-0.0022	-0.0345	0.1228	0.2625	0.7929	LH	
Hebei	0.011	-0.0345	0.1275	0.3566	0.7214	HL	
Shanxi	-0.2274	-0.0345	0.2093	-0.9217	0.3567	LL	
Inner	0.0445	-0.0345	0.202	0.3911	0.6957	HH	
Liaoning	-0.0087	-0.0345	0.1335	0.1934	0.8466	LH	
Jilin	-0.008	-0.0345	0.2073	0.1276	0.8985	LH	
Heilongjiang	-0.0307	-0.0345	0.1208	0.0316	0.9748	LH	
Shanghai	0.1856	-0.0345	0.1606	1.3707	0.1705	HL	
Jiangsu	0.0972	-0.0345	0.1364	0.9655	0.3343	HL	
Zhejiang	0.0821	-0.0345	0.1473	0.7915	0.4286	HL	
Anhui	-0.0063	-0.0345	0.1167	0.2414	0.8093	LH	
Fujian	-0.0007	-0.0345	0.1332	0.2535	0.7999	LH	
Jiangxi	-0.0113	-0.0345	0.0824	0.2812	0.7786	LH	
Shandong	0.1513	-0.0345	0.1726	1.0759	0.282	HL	
Henan	0.0317	-0.0345	0.1356	0.4881	0.6255	HL	
Hubei	0.0796	-0.0345	0.1555	0.7334	0.4633	HL	
Hunan	0.0639	-0.0345	0.1142	0.8617	0.3889	HL	
Guangdong	0.1712	-0.0345	0.1777	1.1577	0.247	HL	
Guangxi	-0.0741	-0.0345	0.1381	-0.2869	0.7742	LL	
Hainan	0.0897	-0.0345	0.1295	0.9587	0.3377	HL	
Chongqing	-0.0604	-0.0345	0.1227	-0.2114	0.8326	LL	
Sichuan	-0.0484	-0.0345	0.1609	-0.0867	0.9309	LH	
Guizhou	-0.9722	-0.0345	0.1193	-7.8609	0	LL	***
Yunnan	0.0069	-0.0345	0.1317	0.3143	0.7533	HL	
Shaanxi	0.0371	-0.0345	0.1478	0.4843	0.6282	HH	
Gansu	-0.0678	-0.0345	0.1337	-0.2495	0.803	LL	
Qinghai	-0.0571	-0.0345	0.0992	-0.2282	0.8195	LL	
Ningxia	-0.3463	-0.0345	0.1694	-1.8407	0.0657	LL	*
Xinjiang	0.1309	-0.0345	0.203	0.8146	0.4153	HH	

Notes: See Equation (3.16) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\*  $P < 0.001$ , \*\*  $P < 0.05$ , \*  $P < 0.1$ .

Low–low (LL) clusters are concentrated in several western provinces, including Guizhou, Ningxia, Guangxi, Chongqing, Gansu, and Qinghai, where environmental

performance remains generally weak. Notably, Guizhou exhibits the largest absolute value of the local Moran's I ( $I_i = -0.9722$ ) with high statistical significance ( $P < 0.01$ ), suggesting that its level of environmental governance constitutes a distinct low-value cluster relative to neighboring provinces. This pattern may be shaped by factors such as regional economic development, industrial structure, and the stringency of policy implementation.

Table 4-25 also shows, High-Low and Low-High (LH) Heterogeneous Patterns: Beijing ( $I_i = 0.1898$ ), Shanghai ( $I_i = 0.1856$ ), Guangdong ( $I_i = 0.1712$ ), and other economically developed provinces exhibit an HL pattern where high values are surrounded by low values, but this pattern did not pass the significance test ( $P > 0.05$ ), indicating that while their environmental performance is higher than that of surrounding regions, the spatial spillover effects are limited. The LH pattern (low values surrounded by high values) in provinces such as Tianjin, Liaoning, and Jilin is also not significant, suggesting that spatial heterogeneity in environmental governance has not yet formed a stable structure.

Table 4-26 shows that Moran's I analysis for 2012 reveals significant changes in the spatial clustering patterns of provincial environmental performance in China compared to 2008. Guizhou ( $I_i = -0.6758$ ,  $P < 0.01$ ) and Ningxia ( $I_i = -0.4535$ ,  $P = 0.013$ ) continued to exhibit a significant "low-low" (LL) clustering pattern, indicating that the lag in environmental governance in western regions persists. It is noteworthy that the region of Xinjiang ( $I_i = 0.3012$ ,  $P = 0.0998$ ) demonstrated a substantial "high-high" (HH) clustering pattern at the 10% significance level for the first time, which may indicate that the northwestern region is undergoing favorable spatial interactions in environmental performance.

It is evident that high-value clustering regions are of significant importance. The regions of Xinjiang, Inner Mongolia ( $I_i = 0.1913$ ), and Liaoning ( $I_i = 0.0067$ ) have been identified as a potential HH clustering belt, suggesting the potential environmental benefits of the "Western Development" policy. As demonstrated in Figure 1, the regions of Beijing ( $I_i = 0.2276$ ), Shanghai ( $I_i = 0.2122$ ), and Guangdong ( $I_i = 0.2146$ ) have been observed to maintain HL characteristics; however, their radiation effects remain insignificant ( $P > 0.05$ ).

From Table 4-26, The low-value aggregation zone is defined as follows: Guizhou and Ningxia form a significant LL aggregation core. It is evident that Sichuan ( $I_i = -0.1822$ ) has undergone a transition from an LH type to a more pronounced low-value characteristic. Provinces such as Shanxi ( $I_i = -0.2629$ ) and Gansu ( $I_i = -0.0722$ ) continue to demonstrate a LL

trend. Coastal provinces in the east generally exhibit HL characteristics but are these patterns not statistically significant. Central regions (e.g., Hunan,  $I_i=0.0914$ ) begin to show signs of improved environmental performance.

**Table 4-26:  
Local Moran's I Analysis on the Environmental Performance of Provinces in China  
(2012)**

Province	$I_i$	$E(I)$	$Sd(I)$	Z-Value	P-Value	Cluster	Significance
Beijing	0.2276	-0.0345	0.1782	1.4704	0.1415	HL	
Tianjin	-0.0167	-0.0345	0.1192	0.1494	0.8813	LH	
Hebei	-0.0025	-0.0345	0.1242	0.2571	0.7971	LL	
Shanxi	-0.2629	-0.0345	0.2105	-1.0853	0.2778	LL	
Inner	0.1913	-0.0345	0.2029	1.1127	0.2658	HH	
Liaoning	0.0067	-0.0345	0.1307	0.3148	0.7529	HH	
Jilin	-0.015	-0.0345	0.2084	0.0937	0.9253	LH	
Heilongjiang	-0.0225	-0.0345	0.1171	0.1019	0.9188	LH	
Shanghai	0.2122	-0.0345	0.1595	1.5472	0.1218	HL	
Jiangsu	0.0898	-0.0345	0.1338	0.9291	0.3528	HL	
Zhejiang	0.0669	-0.0345	0.1455	0.6969	0.4858	HL	
Anhui	0.0516	-0.0345	0.1126	0.7645	0.4445	HL	
Fujian	0.0494	-0.0345	0.1304	0.6434	0.52	HL	
Jiangxi	-0.0195	-0.0345	0.0743	0.2021	0.8398	LH	
Shandong	0.1207	-0.0345	0.1721	0.9017	0.3672	HL	
Henan	0.053	-0.0345	0.1329	0.6582	0.5104	HL	
Hubei	0.0727	-0.0345	0.1541	0.6955	0.4868	HL	
Hunan	0.0914	-0.0345	0.1098	1.1457	0.2519	HL	
Guangdong	0.2146	-0.0345	0.1774	1.4038	0.1604	HL	
Guangxi	0.0408	-0.0345	0.1356	0.5555	0.5786	HL	
Hainan	0.1373	-0.0345	0.1264	1.3586	0.1743	HL	
Chongqing	0.0287	-0.0345	0.1191	0.5309	0.5955	HL	
Sichuan	-0.1822	-0.0345	0.1598	-0.9246	0.3552	LH	
Guizhou	-0.6758	-0.0345	0.1154	-5.5578	0	LL	***
Yunnan	-0.003	-0.0345	0.1288	0.2447	0.8067	LL	
Shaanxi	0.0135	-0.0345	0.1459	0.3289	0.7423	HH	
Gansu	-0.0722	-0.0345	0.1309	-0.288	0.7733	LL	
Qinghai	-0.0914	-0.0345	0.0934	-0.6094	0.5423	LL	
Ningxia	-0.4535	-0.0345	0.1687	-2.4833	0.013	LL	**
Xinjiang	0.3012	-0.0345	0.204	1.6457	0.0998	HH	*

Notes: See Equation (3.16) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\*  $P < 0.001$ , \*\*  $P < 0.05$ , \*  $P < 0.1$ .

The dynamic evolution characteristics show that, compared with 2008, significant changes appeared in 2012. The positive spatial association of Xinjiang's environmental performance strengthened, likely driven by environmental infrastructure development under the Belt and Road Initiative. The LL agglomeration intensity in Guizhou weakened (from  $I_i$

= -0.9722 to -0.6758), suggesting the initial effectiveness of environmental governance measures. At the same time, the performance gap between the eastern developed provinces and their surrounding regions gradually narrowed, reflecting a reduction in regional disparities.

**Table 4-27:  
Local Moran's I Analysis on the Environmental Performance of Provinces in China  
(2016)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.2639	-0.0345	0.1785	1.6716	0.0946	HL	*
Tianjin	-0.0352	-0.0345	0.1243	-0.0054	0.9957	LH	
Hebei	-0.0103	-0.0345	0.1288	0.1876	0.8512	LL	
Shanxi	-0.3485	-0.0345	0.2088	-1.5041	0.1326	LL	
Inner	0.2573	-0.0345	0.2016	1.447	0.1479	HH	
Liaoning	0.0096	-0.0345	0.1346	0.3275	0.7433	HH	
Jilin	-0.03	-0.0345	0.2068	0.0218	0.9826	LH	
Heilongjiang	0.0072	-0.0345	0.1224	0.3408	0.7333	HH	
Shanghai	0.2353	-0.0345	0.161	1.6751	0.0939	HL	*
Jiangsu	0.0686	-0.0345	0.1375	0.7496	0.4535	HL	
Zhejiang	0.0604	-0.0345	0.1481	0.6405	0.5219	HL	
Anhui	0.076	-0.0345	0.1183	0.9338	0.3504	HL	
Fujian	0.0646	-0.0345	0.1343	0.7375	0.4608	HL	
Jiangxi	0.0317	-0.0345	0.0855	0.7748	0.4385	HH	
Shandong	0.1134	-0.0345	0.1728	0.8558	0.3921	HL	
Henan	0.1292	-0.0345	0.1366	1.1982	0.2308	HL	
Hubei	0.0593	-0.0345	0.1561	0.601	0.5478	HL	
Hunan	0.0833	-0.0345	0.1159	1.0161	0.3096	HL	
Guangdong	0.2599	-0.0345	0.1778	1.6562	0.0977	HL	*
Guangxi	0.0848	-0.0345	0.1391	0.8576	0.3911	HL	
Hainan	0.1947	-0.0345	0.1307	1.7528	0.0796	HL	*
Chongqing	0.1258	-0.0345	0.1241	1.2915	0.1965	HL	
Sichuan	-0.236	-0.0345	0.1614	-1.2488	0.2117	LH	
Guizhou	-0.2533	-0.0345	0.1208	-1.8109	0.0702	LL	*
Yunnan	-0.0935	-0.0345	0.1329	-0.4438	0.6572	LL	
Shaanxi	-0.0613	-0.0345	0.1485	-0.1804	0.8569	LH	
Gansu	-0.0075	-0.0345	0.1348	0.2	0.8415	LL	
Qinghai	-0.0427	-0.0345	0.1015	-0.0806	0.9358	LL	
Ningxia	-0.5849	-0.0345	0.1696	-3.2443	0.0012	LL	**
Xinjiang	0.3498	-0.0345	0.2026	1.8961	0.0579	HH	*

Notes: See Equation (3.16) for the specification of Moran's I.

Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

From Table 4-27, A spatial analysis of China's provincial environmental performance in 2016 revealed that Xinjiang (Ii=0.3498, P=0.0579) and Inner Mongolia (Ii=0.2573) formed significant high-value clusters, indicating that the environmental governance collaboration under the Belt and Road Initiative is beginning to yield results in the

northwestern region. This finding lends further credence to the notion that regional development strategies have exerted a substantial influence on the spatial patterns of environmental performance, with western regions gradually forming a positive feedback mechanism for environmental governance.

Ningxia ( $I_i = -0.5849$ ,  $P = 0.0012$ ) and Guizhou ( $I_i = -0.2533$ ,  $P = 0.0702$ ) continue to exhibit significant low-value clusters; however, it is noteworthy that Guizhou's clustering intensity has weakened in comparison to 2012 ( $I_i = -0.6758$ ). This change may be indicative of the implementation effects of the "Western Development" and "Precision Poverty Alleviation" policies in the field of environmental governance, suggesting that targeted regional environmental policies are yielding positive outcomes. Beijing ( $I_i = 0.2639$ ,  $P = 0.0946$ ), Shanghai ( $I_i = 0.2353$ ,  $P = 0.0939$ ), and Guangdong ( $I_i = 0.2599$ ,  $P = 0.0977$ ) have for the first time exhibited statistically significant high-low clustering characteristics, a finding of significant importance. The findings suggest that the environmental governance levels of eastern developed cities have significantly surpassed those of surrounding areas, thereby forming distinct "high-performance zones" in environmental performance. However, this also reflects the need to strengthen the radiating and driving effects of these core cities.

Sichuan ( $I_i = -0.2360$ ) continues to demonstrate low-to-high anomaly characteristics, thereby serving as a transitional zone between the western low-value region and the eastern high-value region. This spatial pattern may be attributed to the province's distinct geographical location and level of economic development, as it is influenced by the lagging environmental governance in the west while also receiving industrial transfers from the east, resulting in significant spatial heterogeneity in its environmental performance.

From Table 4-27, The central region exhibits a differentiated development pattern, with provinces such as Henan ( $I_i = 0.1292$ ) and Hunan ( $I_i = 0.0833$ ) demonstrating enhanced environmental performance, while Shanxi ( $I_i = -0.3485$ ) persists in a state of suboptimal environmental performance. This divergent trend may be attributed to the varying implementation intensity of the "Central Region Rise" strategy and the differing progress of industrial structure adjustments across regions. The findings indicate that the implementation effects of regional coordination development strategies in the environmental sector demonstrate spatial imbalance.

From a dynamic perspective, the spatial pattern in 2016 demonstrated an expansion in the discrepancy in environmental performance between the eastern and western regions. On the one hand, western provinces such as Xinjiang have achieved notable success in environmental governance; on the other hand, regions such as Ningxia continue to be characterized by low-value agglomeration. This polarization underscores the necessity for greater emphasis on the balanced development of regional environmental governance, with a view to averting the solidification of a pattern of environmental inequality.

The analysis results for 2022 in Table 4-28 indicate that Beijing ( $I_i=0.2829$ ,  $P=0.0747$ ), Shanghai ( $I_i=0.2763$ ,  $P=0.0501$ ), and Guangdong ( $I_i=0.2707$ ,  $P=0.0852$ ) continued to exhibit significant high-low clustering characteristics, with Shanghai showing significance at the 5% level for the first time. This finding suggests that the environmental governance advantages of the core cities in the Yangtze River Delta, Beijing-Tianjin-Hebei, and Pearl River Delta metropolitan areas have been further consolidated, resulting in more pronounced gradient differences with surrounding regions. It is noteworthy that the enhanced significance level in Shanghai may be indicative of the impact of green development policies implemented within the Yangtze River Economic Belt, suggesting an augmentation in the demonstrative effect of megacities on environmental governance.

Guizhou ( $I_i=-0.2664$ ,  $P=0.0392$ ) and Qinghai ( $I_i=-0.2155$ ,  $P=0.0418$ ) form a significant low-low (LL) clustering zone, while Xinjiang ( $I_i=0.1848$ ) and Gansu ( $I_i=0.0904$ ) exhibit a high-high (HH) clustering trend. This spatial pattern is indicative of significant regional disparities in environmental governance outcomes across western China. On the one hand, environmental conditions in "Belt and Road" node provinces continue to improve; on the other hand, environmental governance in the ecologically fragile southwest region remains challenging. It is noteworthy that Ningxia has transitioned from a markedly low-value zone ( $I_i=-0.5849$ ) in 2016 to a non-significant high-value zone ( $I_i=0.0182$ ), which may be indicative of the impact of the ecological protection priority zone policy.

It is evident that certain provinces, including Henan ( $I_i=0.1785$ ,  $P=0.1037$ ) and Hainan ( $I_i=0.1753$ ,  $P=0.0910$ ), have demonstrated a marginal yet statistically significant enhancement in their environmental performance. This change can be attributed to the policy dividends of the "Central Region Rise" strategy and the construction of free trade ports, indicating that regional development strategies have played a positive role in improving environmental quality. In particular, the environmental improvements in Henan, a populous

and agriculturally significant province, hold significant implications for the balanced development of national environmental governance.

**Table 4-28:  
Local Moran's I Analysis on the Environmental Performance of Provinces in China  
(2022)**

Province	Ii	E(I)	Sd (I)	Z-Value	P-Value	Cluster	Significance
Beijing	0.2829	-0.0345	0.1781	1.7822	0.0747	HL	*
Tianjin	-0.1314	-0.0345	0.1166	-0.8319	0.4054	LH	
Hebei	-0.0006	-0.0345	0.1218	0.2778	0.7811	LL	
Shanxi	-0.0522	-0.0345	0.2113	-0.084	0.933	LL	
Inner	-0.0301	-0.0345	0.2035	0.0217	0.9827	LL	
Liaoning	0.0736	-0.0345	0.1286	0.8406	0.4006	HH	
Jilin	-0.0205	-0.0345	0.2092	0.0667	0.9469	LL	
Heilongjiang	0.1339	-0.0345	0.1143	1.4731	0.1407	HH	
Shanghai	0.2763	-0.0345	0.1586	1.9591	0.0501	HL	*
Jiangsu	0.0911	-0.0345	0.1319	0.9521	0.341	HL	
Zhejiang	0.0149	-0.0345	0.1441	0.3425	0.732	HL	
Anhui	0.0679	-0.0345	0.1095	0.9347	0.35	HL	
Fujian	0.0126	-0.0345	0.1283	0.3667	0.7138	HL	
Jiangxi	-0.0362	-0.0345	0.0678	-0.0252	0.9799	LH	
Shandong	0.2033	-0.0345	0.1718	1.3839	0.1664	HL	
Henan	0.1785	-0.0345	0.1309	1.627	0.1037	HL	
Hubei	0.0644	-0.0345	0.1531	0.6458	0.5184	HL	
Hunan	0.072	-0.0345	0.1066	0.9992	0.3177	HL	
Guangdong	0.2707	-0.0345	0.1773	1.7213	0.0852	HL	*
Guangxi	0.0435	-0.0345	0.1338	0.5829	0.56	HL	
Hainan	0.1753	-0.0345	0.1241	1.6901	0.091	HL	*
Chongqing	0.0901	-0.0345	0.1164	1.0705	0.2844	HL	
Sichuan	-0.1965	-0.0345	0.159	-1.019	0.3082	LH	
Guizhou	-0.2664	-0.0345	0.1125	-2.0621	0.0392	LL	**
Yunnan	-0.0261	-0.0345	0.1266	0.0666	0.9469	LL	
Shaanxi	-0.082	-0.0345	0.1445	-0.3289	0.7422	LH	
Gansu	0.0904	-0.0345	0.1288	0.9697	0.3322	HH	
Qinghai	-0.2155	-0.0345	0.0889	-2.0352	0.0418	LL	**
Ningxia	0.0182	-0.0345	0.1682	0.3128	0.7544	HH	
Xinjiang	0.1848	-0.0345	0.2046	1.0717	0.2839	HH	

Notes: See Equation (3.16) for the specification of Moran's I.  
Cluster Type: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High; Significance codes: \*\*\* \*P\* < 0.001, \*\* \*P\* < 0.05, \* \*P\* < 0.1.

Table 4-28 also shows that Heilongjiang (Ii=0.1339) exhibits a high-high clustering trend, while Liaoning (Ii=0.0736) and Jilin (Ii=-0.0205) demonstrate deficiencies in environmental performance. This spatial differentiation may be attributed to variations in the implementation priorities and progress of the Northeast Revitalization Strategy, which

reflects the uneven environmental governance during the transformation and upgrading of old industrial bases.

#### 4.5.2 Environmental Performance based on Lagrange Multiplier Test

The Lagrange Multiplier Test (LM test) is a statistical method used to test spatial autocorrelation, particularly widely used in spatial econometrics. It is mainly used to determine whether spatial data has spatial dependencies (i.e. spatial autocorrelation) and help select appropriate spatial econometric models.

Table 4-29 shows the results of the spatial autocorrelation diagnostic test, indicating that there is significant spatial dependence between environmental performance and location quotient. The Moran's I test statistic is 7.052 ( $p < 0.001$ ), strongly rejecting the null hypothesis that “there is no spatial autocorrelation.” This result confirms that there is obvious spatial interaction between provincial environmental performance, and traditional non-spatial econometric models may produce bias.

**Table 4-29:  
Spatial Autocorrelation Diagnosis of Environmental Performance and Location Quotient**

Test Category	Diagnostic Test	Statistic	df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	7.052	1	<0.001	***
	Lagrange Multiplier	484.512	1	<0.001	***
	Robust LM	186.795	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	313.251	1	<0.001	***
	Robust LM	15.533	1	<0.001	***

Notes: See Equations (3.25)– (3.26) for the specification of the LM tests.

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).

For the Spatial Error Model (SEM), both the Lagrange Multiplier test (LM = 484.512,  $P < 0.001$ ) and the Robust Lagrange Multiplier test (Robust LM=186.795,  $P < 0.001$ ) were highly significant, confirming the presence of spatial error autocorrelation in the model. For the Spatial Lag Model (SLM), the Lagrange Multiplier test (LM=313.251,  $P < 0.001$ ) was also strongly significant, while the Robust test (Robust LM=15.533,  $P < 0.001$ ) was comparatively smaller, indicating that spatial lag effects of the dependent variables are present.

As summarized in Table 4-29, the following three pieces of evidence support the Spatial Durbin Model (SDM) in this study: Firstly, the spatial error and spatial lag effects are both significant, which fulfills the conditions for applying the Spatial Durbin Model

(SDM); secondly, the Spatial Durbin Model (SDM) can simultaneously capture the spatial lag effects of the explained variable and the spatial spillover effects of the explanatory variable; thirdly, the Spatial Durbin Model (SDM) is more inclusive and can avoid model specification bias when the true data generation process is unknown.

The results of Moran's I test, based on the non-standardized binary spatial weight matrix (WLB) presented in Table 4-30, demonstrate the presence of a highly significant spatial autocorrelation between environmental performance and Employment Density (ED) ( $I=7.413$ ,  $p<0.001$ ). This finding provides substantial evidence to refute the null hypothesis that "there is no spatial dependence," thereby indicating the presence of a significant spatial spillover effect in provincial environmental performance. The utilization of conventional non-spatial econometric methodologies is liable to engender model specification bias.

**Table 4-30:  
Spatial Autocorrelation Diagnosis of Environmental Performance and Employment Density**

Test Category	Diagnostic Test	Statistic	Df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	7.413	1	<0.001	***
	Lagrange Multiplier	534.091	1	<0.001	***
	Robust LM	122.755	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	414.243	1	<0.001	***
	Robust LM	2.907*	1	0.088	

Notes: See Equations (3.25)– (3.26) for the specification of the LM tests.

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).

The Spatial Error Model (SEM) testing shows that both the Lagrange multiplier test (LM = 534.091,  $P<0.001$ ) and the robust test (Robust LM=122.755,  $P<0.001$ ) are highly significant, indicating the presence of unobserved spatial correlation factors in the model. The Spatial Lag Model (SLM) test shows that although the ordinary Lagrange multiplier test is significant (LM=414.243,  $P<0.001$ ), the robust test is only marginally significant (Robust LM=2.907,  $P=0.088$ ), suggesting that the spatial lag effects may be partly explained by interference from spatial error terms.

Based on the comprehensive test results, this study can adopt the Spatial Durbin Model (SDM) based on the following evidence: spatial error effects dominate (Robust LM=122.755 vs.2.907), but spatial lag effects still have some explanatory power (LM=414.243), and the SDM model can accommodate both types of spatial effects simultaneously.

The results of the spatial dependency test (see Table 4-31) demonstrate that the Moran's I test statistic is 5.524 ( $P < 0.001$ ), which strongly rejects the null hypothesis that "there is no spatial autocorrelation" at the 1% significance level. This finding suggests that environmental performance, as measured by Herfindahl-Hirschman Index (HHI), exhibits significant spatial dependency, with environmental performance across provinces demonstrating clear spatial correlation characteristics.

**Table 4-31:  
Spatial Autocorrelation Diagnosis of Environmental Performance and Herfindahl-Hirschman Index**

Test Category	Diagnostic Test	Statistic	Df	*P*-Value	Significance
<b>Spatial Error</b>	Moran's I	5.524	1	<0.001	***
	Lagrange Multiplier	282.825	1	<0.001	***
	Robust LM	77.257	1	<0.001	***
<b>Spatial Lag</b>	Lagrange Multiplier	205.997	1	<0.001	***
	Robust LM	0.429	1	0.513	

Notes: See Equations (3.25)– (3.26) for the specification of the LM tests.

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 ( $df = 1$ ).

The Spatial Error Model (SEM) testing shows that both the Lagrange multiplier test (LM = 282.825,  $P < 0.001$ ) and the robust Lagrange multiplier test (Robust LM=77.257,  $P < 0.001$ ) are highly significant. This result indicates the presence of substantial spatial error autocorrelation within the model, which may be due to the omission of spatially correlated explanatory variables or the existence of spatially correlated measurement errors. The Spatial Lag Model (SLM) testing shows that although the ordinary Lagrange multiplier test (LM = 205.997,  $P < 0.001$ ) is significant, the robust test (Robust LM=0.429,  $P = 0.513$ ) is not, suggesting that the apparent significance of the spatial lag effect is likely driven by interference from spatial error terms rather than a genuine spatial lag process. On the basis of these test results, this study adopts the Spatial Durbin Model (SDM).

### **4.5.3 Findings from the Spatial Durbin Model of Industrial Agglomeration and Environmental Performance**

#### ***4.5.3.1 The Impact of Location Quotient on Environmental Performance***

The findings presented in Table 4-32 demonstrate that both Location Quotient (LQ) and human capital (h) exert a substantial positive influence on environmental performance (LQ=0.002,  $P < 0.001$ ; h=0.003,  $P < 0.001$ ). This suggests that heightened industrial specialization and the accumulation of human capital can efficaciously enhance

environmental performance. It is noteworthy that city level (*citylevel*) demonstrates a substantial negative effect (-0.065,  $P < 0.001$ ), which may be indicative of the more pronounced environmental pressures and governance challenges encountered by large cities. Furthermore, capital stock (*k*) demonstrated a substantial positive effect (0.001,  $P = 0.001$ ), suggesting that augmented investment in environmental governance exerts a favorable influence.

**Table 4-32:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Location Quotients**

Model Diagnostics: Panel structure: 30 provinces  $\times$  15 years (balanced);  $R^2$ : Within=0.767, Between=0.326, Overall=0.338; Log-likelihood = 2154.996; Mean of fixed-effects=0.0375; Variance ( $\sigma^2$ ): 0.000004 \*\*\* (0.0000027)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>LQ</i>	0.002***	0	5.14	<0.001	0.001	0.003
	<i>h</i>	0.003***	0	7.35	<0.001	0.002	0.004
	<i>regu</i>	0	0	0.91	0.362	0	0.001
	<i>citylevel</i>	-0.065***	0.005	-12.04	<0.001	-0.075	-0.054
	<i>k</i>	0.001***	0	3.32	0.001	0	0.001
<b>Spatial Effects</b>	<i>LQ</i>	0	0.002	-0.15	0.883	-0.005	0.004
	<i>h</i>	-0.001	0.003	-0.49	0.622	-0.006	0.004
	<i>regu</i>	-0.001	0	-1.16	0.247	-0.001	0
	<i>citylevel</i>	0.003	0.011	0.31	0.759	-0.018	0.024
	<i>k</i>	0.004***	0.001	3.03	0.002	0.001	0.006
<b>Spatial Parameter</b>	$\rho$	0.059	0.140	0.42	0.674	-0.215	0.333
<b>Long-Run Effect</b>							
<b>Direct</b>	<i>LQ</i>	0.002***	0	5.07	<0.001	0.001	0.003
	<i>h</i>	0.003***	0	7.47	<0.001	0.002	0.004
	<i>regu</i>	0	0	1.06	0.289	0	0.001
	<i>citylevel</i>	-0.065***	0.005	-12.07	<0.001	-0.075	-0.054
	<i>k</i>	0.001***	0	3.49	<0.001	0	0.001
<b>Indirect</b>	<i>LQ</i>	0	0.003	-0.02	0.984	-0.005	0.005
	<i>h</i>	-0.001	0.003	-0.44	0.663	-0.007	0.004
	<i>regu</i>	-0.001	0	-1.27	0.204	-0.001	0
	<i>citylevel</i>	-0.001	0.009	-0.08	0.933	-0.018	0.016
	<i>k</i>	0.004***	0.001	3.11	0.002	0.001	0.006
<b>Total</b>	<i>LQ</i>	0.002	0.003	0.82	0.412	-0.003	0.007
	<i>h</i>	0.002	0.003	0.63	0.527	-0.004	0.007
	<i>regu</i>	0	0	-0.89	0.372	-0.001	0
	<i>citylevel</i>	-0.066***	0.007	-9.17	<0.001	-0.08	-0.052
	<i>k</i>	0.005***	0.001	3.53	<0.001	0.002	0.007

Notes: See Equation (3.12) for the specification of the model.  
\*\*\*  $P < 0.001$ , \*\*  $P < 0.01$ , \*  $P < 0.05$ ; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.0588 ( $P = 0.674$ ); All standard errors are robust standard errors.

In terms of spatial effects, capital stock (k) exhibits a significant positive spatial spillover effect (0.004, P=0.002), indicating that environmental governance investments in one region not only improve local environmental performance but also have a positive impact on neighboring regions. However, the spatial effects of other variables were not significant (P>0.05), particularly the spatial autoregression coefficient  $\rho$ , which was not significant (0.059, P=0.674).

Long-term effect analysis shows that in terms of direct effects, the positive effects of LQ (0.002, P< 0.001), h (0.003, P<0.001), and k (0.001, P<0.001) remain significant, while the negative effect of citylevel remains significant (-0.065, P<0.001). In terms of indirect effects, only capital stock (k) exhibits a significant positive spatial spillover effect (0.004, P=0.002). In the total effects, citylevel (-0.066, P< 0.001) and k (0.005, P< 0.001) remain significant, while the total effects of other variables are not significant.

As can be seen from Table 4-32, the model demonstrated good goodness-of-fit (Within R<sup>2</sup>=0.767) and a high log-likelihood value (2154.996). The variance component was significant ( $\sigma^2=0.000004$ , P<0.001), indicating that the model was appropriately specified. It is worth noting that the spatial autoregressive parameter is not significant (0.0588, P=0.674), suggesting that subsequent studies may consider using a spatial error model as a robustness test.

#### ***4.5.3.2 The Impact of Employment Density on Environmental Performance***

From the results shown in Table 4-33, the Employment Density (ED) demonstrated a significant yet modest positive influence on environmental performance (0.0001, P=0.001). This finding suggests that economic growth may facilitate environmental enhancement, although the efficacy of this relationship appears to be limited. The positive impact of human capital (h) is found to be more significant (0.0033, P<0.001), thus emphasizing the critical role of talent accumulation in environmental governance. The negative effect of city level (citylevel) is significant at the 0.001 level, as indicated by the negative coefficient of -0.0621.

This suggests that large cities are more likely to face severe environmental challenges. However, the positive impact of capital stock (k) is significant at the 0.05 level, as indicated by the positive coefficient of 0.0006. This suggests that environmental protection investments are effective. It is evident that the impact of environmental regulations (regu) is not significant (P=0.998). This finding suggests that current regulatory policies may be

characterized by enforcement weaknesses or design flaws. Employment Density (ED) exhibits significant negative spatial spillover (-0.0002, P= 0.004), suggesting a potential “race to the bottom” in environmental governance between neighboring regions. Meanwhile, capital stock (k) exhibits positive spatial spillover (0.0037, P=0.002), indicating that environmental protection investment has regional synergistic effects. However, the spatial autoregressive coefficient ( $\rho$ ) is not significant (0.0385, P=0.788).

**Table 4-33:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Employment Density**

Model Diagnostics: Panel structure: 30 provinces  $\times$  15 years (balanced); R<sup>2</sup>: Within=0.762, Between=0.320, Overall=0.359; Log-likelihood = 2150.644; Mean of fixed-effects=0.043; Variance ( $\sigma^2$ ): 0.000004 \*\*\* (0.000000278)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
<b>Main Effects</b>	<i>ED</i>	0.0001**	0.0000	3.22	0.001	0.0000	0.0001
	<i>h</i>	0.0033***	0.0004	7.97	<0.001	0.0025	0.0041
	<i>regu</i>	0.0000	0.0002	-0.00	0.998	-0.0003	0.0003
	<i>citylevel</i>	-0.0621***	0.0053	-11.80	<0.001	-0.0724	-0.0518
	<i>k</i>	0.0006**	0.0002	3.14	0.002	0.0002	0.0010
<b>Spatial Effects</b>	<i>ED</i>	-0.0002**	0.0001	-2.91	0.004	-0.0003	-0.0001
	<i>h</i>	-0.0040	0.0026	-1.54	0.123	-0.0091	0.0011
	<i>regu</i>	0.0003	0.0005	0.65	0.513	-0.0007	0.0014
	<i>citylevel</i>	-0.0018	0.0106	-0.17	0.865	-0.0226	0.0190
	<i>k</i>	0.0037**	0.0012	3.10	0.002	0.0014	0.0060
<b>Spatial Parameter</b>	$\rho$	0.0385	0.1432	0.27	0.788	-0.2422	0.3192
<b>Long-Run Effect</b>							
<b>Direct</b>	<i>ED</i>	0.0001**	0.0000	3.15	0.002	0.0000	0.0001
	<i>h</i>	0.0033***	0.0004	8.08	<0.001	0.0025	0.0041
	<i>regu</i>	0.0000	0.0002	0.11	0.909	-0.0003	0.0003
	<i>citylevel</i>	-0.0621***	0.0052	-11.95	<0.001	-0.0723	-0.0519
	<i>k</i>	0.0006**	0.0002	3.29	0.001	0.0002	0.0010
<b>Indirect</b>	<i>ED</i>	-0.0002**	0.0001	-2.88	0.004	-0.0003	-0.0001
	<i>h</i>	-0.0042	0.0029	-1.45	0.147	-0.0098	0.0015
	<i>regu</i>	0.0003	0.0005	0.64	0.525	-0.0007	0.0014
	<i>citylevel</i>	-0.0048	0.0084	-0.56	0.572	-0.0213	0.0118
	<i>k</i>	0.0039**	0.0013	3.14	0.002	0.0015	0.0064
<b>Total</b>	<i>ED</i>	-0.0001	0.0001	-1.85	0.065	-0.0003	0.0000
	<i>h</i>	-0.0009	0.0030	-0.30	0.766	-0.0068	0.0050
	<i>regu</i>	0.0004	0.0005	0.68	0.497	-0.0007	0.0014
	<i>citylevel</i>	-0.0669***	0.0070	-9.49	<0.001	-0.0807	-0.0531
	<i>k</i>	0.0046***	0.0013	3.52	<0.001	0.0020	0.0071

Notes: See Equation (3.12) for the specification of the model.

\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.0588 (P=0.674); All standard errors are robust standard errors.

Direct effect analysis revealed that the positive effects of Employment Density (ED) (0.0001,  $P=0.001$ ),  $h$  (0.0033,  $P<0.001$ ), and  $k$  (0.0006,  $P=0.001$ ) were sustained. In the indirect effects, the negative spillover of Employment Density (ED) (-0.0002,  $P=0.004$ ) contrasts sharply with the positive spillover of  $k$  (0.0039,  $P=0.002$ ). In terms of total effects, the impacts of  $citylevel$  (-0.0669,  $P<0.001$ ) and  $k$  (0.0046,  $P<0.001$ ) were the most prominent, while the total effect of Employment Density (ED) was marginally significant at the 10% level (-0.0001,  $P=0.065$ ). The model demonstrates adequate explanatory power ( $R^2=0.762$ ) and a satisfactory goodness of fit (Log-likelihood=2150.644). The variance component was found to be significant ( $\sigma^2=0.000004$ ,  $P<0.001$ ), indicating that the model setting is reasonable.

#### ***4.5.3.3 The Impact of Herfindahl-Hirschman Index on Environmental Performance***

The results in Table 4-34 indicate that the impact of the Herfindahl-Hirschman Index (HHI) demonstrates significant spatial heterogeneity. The main effect coefficient of 0.012 ( $P=0.012$ ) indicates that a 1-unit increase in the Herfindahl-Hirschman Index (HHI) directly promotes a 1.2% increase in the local dependent variable, with this positive effect being significant at the 1% level. However, the spatial lag term coefficient of -0.013 ( $P=0.137$ ) demonstrates a negative spatial spillover effect, although this did not pass the 10% significance test, thus suggesting the potential for competitive spatial interactions. The long-term direct effect remains significantly positive at 0.012 (95% CI [0.003, 0.021]), while the indirect effect and total effect do not reach significance. This indicates that the impact of Herfindahl-Hirschman Index is primarily confined to the local region. Interpretation-wise, the significant direct effect alongside insignificant indirect/total effects suggests that cross-province spillovers are not statistically supported for HHI in this specification. Contribution-wise, this SDM decomposition directly supports the study objective of separating within-province effects from cross-province spillovers and benchmarking HHI against LQ and ED in terms of spillover strength.

This finding supports the objective of study by distinguishing local (direct) effects from interregional (spillover) effects of industrial agglomeration using the SDM framework. Specifically, one objective is to test whether industrial concentration (HHI) generates measurable spillovers across provinces the insignificant indirect and total effects indicate that HHI mainly operates within the province rather than transmitting to neighbouring regions, thereby helping compare HHI with other agglomeration indicators (e.g., LQ and ED)

in terms of spillover strength. This also implies that policy interventions targeting industrial concentration may yield predominantly within-province innovation gains, while cross-provincial coordination may be less critical in the case of HHI-driven effects. In contrast, if other agglomeration measures exhibit significant indirect effects, they would call for stronger interprovincial policy alignment to manage spillover benefits and externalities.

**Table 4-34:**  
**Estimation Results of Spatial Durbin Model with Marginal Effects-Herfindahl-Hirschman Index**

Model Diagnostics: Panel structure: 30 provinces  $\times$  15 years (balanced); R<sup>2</sup>: Within=0.756, Between=0.352, Overall=0.372; Log-likelihood = 2144.997; Mean of fixed-effects=0.0403; Variance ( $\sigma^2$ ): 0.000004 \*\*\* (0.000000278)

Component	Variable	Coefficient	Std. Error	Z-value	P-value	[95% CI] Lower	[95% CI] Upper
Main Effects	<i>HHI</i>	0.012**	0.005	2.53	0.012	0.003	0.021
	<i>h</i>	0.003***	0	7.81	<0.001	0.002	0.004
	<i>regu</i>	0	0	-0.23	0.82	0	0
	<i>citylevel</i>	-0.058***	0.005	-10.99	<0.001	-0.068	-0.048
	<i>k</i>	0.001***	0	3.62	<0.001	0	0.001
Spatial Effects	<i>HHI</i>	-0.013	0.009	-1.49	0.137	-0.031	0.004
	<i>h</i>	-0.002	0.003	-0.62	0.539	-0.007	0.004
	<i>regu</i>	0	0	-0.45	0.649	-0.001	0.001
	<i>citylevel</i>	-0.005	0.011	-0.44	0.657	-0.027	0.017
	<i>k</i>	0.004***	0.001	3.28	0.001	0.002	0.006
Spatial Parameter	$\rho$	0.053	0.141	0.38	0.705	-0.223	0.33
<b>Long-Run Effect</b>							
Direct	<i>HHI</i>	0.012*	0.005	2.49	0.013	0.003	0.021
	<i>h</i>	0.003***	0	7.96	<0.001	0.002	0.004
	<i>regu</i>	0	0	-0.13	0.897	0	0
	<i>citylevel</i>	-0.058***	0.005	-11.23	<0.001	-0.068	-0.048
	<i>k</i>	0.001***	0	3.77	<0.001	0	0.001
Indirect	<i>HHI</i>	-0.013	0.009	-1.42	0.154	-0.031	0.005
	<i>h</i>	-0.002	0.003	-0.55	0.58	-0.007	0.004
	<i>regu</i>	0	0	-0.53	0.595	-0.001	0.001
	<i>citylevel</i>	-0.009	0.009	-0.93	0.35	-0.027	0.01
	<i>k</i>	0.004***	0.001	3.35	0.001	0.002	0.007
Total	<i>HHI</i>	-0.001	0.008	-0.16	0.87	-0.018	0.015
	<i>h</i>	0.002	0.003	0.55	0.585	-0.004	0.008
	<i>regu</i>	0	0	-0.6	0.551	-0.001	0.001
	<i>citylevel</i>	-0.067***	0.008	-8.08	<0.001	-0.083	-0.051
	<i>k</i>	0.005***	0.001	3.82	<0.001	0.002	0.008

Notes: See Equation (3.12) for the specification of the model.  
\*\*\* P<0.001, \*\* P<0.01, \* P<0.05; Confidence intervals reported at 95% level; Spatial autoregressive parameter (Verhoef & Nijkamp) = 0.0588 (P=0.674); All standard errors are robust standard errors.

Variable  $h$  exhibits a strong positive effect, with a main effect of 0.003 ( $p < 0.001$ ) and a stable, significant long-term direct effect. The coefficient for the spatial lag term for capital stock ( $k$ ) reached 0.004 ( $P=0.001$ ), with a total effect of 0.005 ( $P<0.001$ ), which is significant at the 1% level. The confidence interval [0.002, 0.008] excludes zero. This result validates the positive spillover effect of capital factors across regions. The main effect coefficient of -0.058 ( $P< 0.001$ ) indicates that the city level (city level) significantly inhibits the dependent variable. This pattern can be explained by the fact that more developed and highly urbanized areas tend to shift from labour-intensive manufacturing toward services and higher value-added, more automated manufacturing, so fewer manufacturing workers are concentrated in the same area. In addition, rising land and labour costs and stricter environmental and zoning constraints in developed cities often push manufacturing employment to surrounding or less-developed regions, which further reduces local employment density. However, this effect does not diffuse in the spatial dimension (spatial effect: -0.005,  $P=0.657$ ). Nevertheless, the total effect of -0.067 ( $P<0.001$ ) suggests that its negative impact has regional cumulative effects.

The spatial autoregressive parameter  $\rho=0.053$  ( $P=0.705$ ) did not pass the significance test. When considered in conjunction with the high explanatory power of  $R^2=0.756$  within the group, this suggests that the model has effectively captured the primary source of spatial dependence through the explanatory variables. The variance,  $\sigma^2$ , was found to be 0.000004 ( $P<0.001$ ), and when combined with the maximum likelihood value of 2144.997, this indicates that the model specification has ideal statistical efficiency. The fixed-effect mean of 0.0403 indicates that individual heterogeneity has been effectively controlled. The  $R^2$  indicators across three dimensions (within-group 0.756, between-group 0.352, and overall, 0.372) collectively validate the model's explanatory power.

## 4.6 Discussion

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This thesis uses Spatial Durbin Model (SDM) to systematically compare three industrial agglomeration indicators—Location Quotient (LQ), Employment Density (ED), and the Herfindahl-Hirschman Index (HHI)—based on panel data from 30 provinces in China from 2008 to 2022—on the economic, technological, and environmental dimensions of regional economic performance, and decomposes direct effects and spatial spillover

effects, providing a unified framework for understanding industrial spatial linkages at the provincial level in China.

#### **4.6.1 The Impact of Manufacturing Industry Agglomeration on Economic Performance**

The global Moran's I results of this study indicate that the spatial distribution of China's regional economic performance underwent a transformation from random dispersion to significant clustering between 2008 and 2022. Between 2008 and 2011, Moran's I values were close to the expected value and not statistically significant, indicating relatively independent regional economic performance. However, starting from 2012, Moran's I values turned positive and gradually strengthened, with most years passing the significance test, revealing a stable spatial positive autocorrelation pattern. This trend aligns with recent research findings. For example, Shang et al. (2025) found that China's digital economy significantly promoted regional economic growth and exhibited notable spatial spillover effects between 2014 and 2022, particularly in eastern regions; Yin et al. (2024) confirmed that transportation infrastructure exhibits strong spatial positive spillover effects at the interprovincial level, driving regional economic coordination and development. Overall, these results provide direct evidence that provincial economic performance in China increasingly exhibits spatial dependence over time, which motivates the subsequent SDM decomposition of direct and spillover effects. These patterns may be associated with regional coordination policies, industrial relocation, and the deepening of market integration, which is consistent with the spatial spillover perspective adopted in this thesis.

Then, the Moran's I scatter plot visually reveals the dynamic evolution of China's regional economic performance spatial patterns. During the study period, the spatial distribution of economic performance shifted from random dispersion to significant clustering. In the early stages, spatial correlations were weak, with no significant clustering characteristics; in the later stages, a stable positive spatial correlation pattern gradually formed, with high-value regions adjacent to other high-value regions and low-value regions adjacent to other low-value regions, and the clustering phenomenon became increasingly prominent. This visual evidence complements the global Moran's I results by showing how the HH/LL clustering structure becomes more stable in the later period.

The results of this study indicate that the spatial correlation of provincial economic performance in China has undergone a gradual emergence and continuous strengthening

process, with regional development imbalances exhibiting new spatial characteristics. From the perspective of spatial agglomeration patterns, the high-value agglomeration effect in the eastern coastal regions has continued to strengthen, forming multiple economic growth poles centered on the Guangdong-Hong Kong-Macao Greater Bay Area, the Yangtze River Delta, and the Beijing-Tianjin-Hebei region. These regions not only maintain strong development momentum but also drive coordinated development in surrounding areas through spatial spillover effects (Li et al., 2023). Meanwhile, the low-value agglomeration phenomenon in western and northeastern regions exhibits trends of spatial solidification and expanding scope, highlighting the long-term and complex nature of regional development imbalances. This finding aligns with recent empirical studies, such as Yang et al. (2022) pointing out that China's regional economic growth exhibits significant spatial dependence, with the spillover effects in the eastern regions being significantly stronger than those in the central and western regions; further found that while regional coordination policies and industrial relocation have helped narrow the gap, they have also exacerbated spatial differentiation in some regions.

It is worth noting that the spatial structure of regional economies exhibits distinct hierarchical differentiation. On the one hand, the agglomeration effect in advantaged regions continues to strengthen, leading to a trend of “the strong getting stronger.” On the other hand, the spatial lock-in effect in underdeveloped regions has not been fundamentally altered, with some regions even facing a widening development gap. The evolution of this spatial differentiation pattern is closely related to the implementation of national regional development strategies, reflecting the regional development paths formed by the interaction of policy intervention and market forces. Recent studies also support this conclusion. For example, Yin et al. (2024) found that transportation infrastructure significantly exacerbates spatial disparities between regions while improving overall economic levels. Shang et al. (2025) found that the spatial spillover effects of the digital economy are most significant in eastern regions, further widening the gap with central and western regions. Taken together, the above Moran's I evidence establishes the spatial backdrop for interpreting subsequent SDM estimates as not purely local relationships, but relationships that may transmit across provinces.

The analysis results of the local Moran's I index provide important insights for policy-making. It not only confirms the significant spatial dependence in regional economic

development but also reveals the uneven distribution of this dependence, helping to identify regional growth poles and formulate differentiated coordination policies, which are conducive to promoting the convergence of the regional economic structure toward complementary advantages and high-quality development. Research over the past five years has shown that transportation infrastructure development has generated significant spatial spillover effects by enhancing regional accessibility, thereby exacerbating development gaps between regions (Yin et al., 2024); The development of the digital economy has not only promoted green transformation but also enhanced carbon emission reduction efficiency in adjacent regions through spatial diffusion (Zhou & Guo, 2024); regional economic integration strategies have strengthened cross-regional economic linkages and spillover effects (Zheng et al., 2025). These findings collectively emphasize that future regional development strategies should place greater emphasis on spatial spillover mechanisms and establish sound regional collaborative development mechanisms to facilitate the efficient flow and aggregation of resources, technology, and factors.

This thesis uses LM tests to find that the spatial dependence of economic performance exhibits significant heterogeneity. When analyzing location quotients (LQ) and Herfindahl–Hirschman Index (HHI), spatial lag effects dominate, indicating that direct economic interactions and industrial synergies between regions are the key channels driving spatial spillovers. This effect primarily stems from observable economic linkages such as the flow of production factors and technology diffusion. In contrast, when examining employment density factors, spatial error effects are more pronounced, reflecting the significant influence of unobservable factors such as infrastructure and institutional environments on regional economic differences. From a methodological perspective, these test results provide clear guidance for selecting spatial econometric models. Different modeling strategies should be adopted for different influencing factors: based on the results, the Spatial Durbin model is more appropriate for this study, thereby enhancing the scientific rigor of the model specification.

The results indicate that industrial agglomeration (Location Quotient, Employment Density, Herfindahl-Hirschman Index) has a significant positive impact on local economic performance, but their spatial spillover effects vary. Location Quotient (LQ) exhibits a significant positive spillover effect, while Employment Density (ED) shows a negative spillover effect. Additionally, the effects of human capital (h) and foreign direct investment

(fdi) exhibit strong spatial externalities across different models, while the impact of per capita GDP (pgdp) shows regional differentiation. These estimates distinguish the “local gain” of agglomeration from its “interprovincial externality,” showing that different agglomeration measures may transmit benefits or costs to neighboring provinces in different directions.

More developed cities may show lower employment density because manufacturing activities have increasingly decentralized from core cities to surrounding areas under high land and labour costs, tighter zoning and environmental constraints, and industrial upgrading policies. At the same time, developed cities shift toward services and knowledge-intensive functions, so the share of manufacturing employment within the city space declines, resulting in lower observed Employment Density (ED) despite stronger overall economic performance.

The results of this study show that location quotient has a significant positive direct effect and spatial spillover effect on economic performance, consistent with the findings of Hariyoko and Puspaningtyas (2020), indicating that location quotient can promote regional coordination and development. By developing competitive industries, it can promote sustainable economic development. Su (2024) found that the degree of coordination between the location quotient of the sports industry and the regional economy is relatively high in the Yangtze River Delta and Pearl River Delta agglomeration areas, and that the regional economy has achieved coordinated development, which is consistent with the results of this study.

Although employment density promotes the local economy, it also generates negative spatial spillover effects. This finding is consistent with the results of Shen et al. (2021) and reflects the regional competitive effects of agglomeration economies. Employment density has a significant threshold effect on economic development. Li and Pang (2022) based on panel data results, shows that when human capital levels exceed a certain threshold, the impact on the regional economy shifts from negative to positive. Consistent with the indirect effects of this study, this validates the externalities of talent agglomeration. Cheyuan and Maohua (2020) used the entropy weight method to calculate the Guangdong High-Quality Economic Development Index, pointing out that although FDI can significantly promote high-quality economic development in Guangdong, it may actually inhibit economic development as the economy matures. This is consistent with the findings in this thesis that

FDI has both promotional and inhibitory effects on economic development. The phenomenon of “local suppression and neighborhood promotion” of per capita GDP corresponds to Hu et al. (2021) observation in the Pearl River Delta that per capita GDP is significantly higher than that of surrounding cities, and that differences in per capita GDP reflect different agglomeration characteristics.

The unexpected findings of this study offer important insights. The local promotion effect of the Herfindahl-Hirschman Index (HHI) without spatial spillover contradicts the predictions of standard agglomeration theory. As pointed out in the Qu et al. (2022) paper, in certain special circumstances, a low Herfindahl-Hirschman Index(HHI) may be more conducive to economic development. Ahmed et al. (2022) point out that institutional quality is a long-term driver of economic growth in South Asian countries, but the impact of institutional quality in this study is not significant, indicating that different countries yield different results. The study findings represent an important extension of regional development theory. The results of this study support the basic viewpoints of new economic geography and spatial economics. The geographical agglomeration of economic activities (such as LQ) improves efficiency through economies of scale and externalities(Chakraborty, 2025). In this sense, the economic-performance evidence contributes by showing that agglomeration can generate consistent local benefits while producing heterogeneous spillovers across different agglomeration indicators, which would be obscured in non-spatial models.

This study has several limitations: First, the global autoregressive coefficient ( $\rho$ ) of the Spatial Durbin Model is not significant, which may indicate that the spatial dependency setting needs further optimization (e.g., by adopting a dynamic SDM or considering nonlinear effects). Second, the measurement of variables (such as institutional quality and human capital) may be constrained by data limitations, and more granular proxy indicators could be introduced in future studies. Finally, the specification of the spatial weight matrix (such as geographic distance and economic distance) may affect the robustness of the results and should be tested in subsequent studies.

#### **4.6.2 The Impact of Manufacturing Industry Agglomeration on Technological Performance.**

Global Moran’s I analysis indicates that the spatial correlation of regional science and technology performance in China exhibited significant fluctuations between 2008 and

2022. In most years, Moran's I showed marginally significant or significant positive spatial autocorrelation, indicating spatial clustering of scientific and technological innovation—with spatial correlation being most significant during the period from 2010 to 2013, after which it tended to weaken, becoming nearly insignificant between 2017 and 2020, before slightly rebounding in 2021–2022. This fluctuation may reflect the dynamic adjustment of regional science and technology resource allocation patterns during the implementation of the national innovation-driven development strategy. Related studies also indicate, regional innovation talent agglomeration exhibits non-linear spatial spillover effects, significantly enhancing the innovation performance of neighboring regions within a certain scale (Yan et al., 2024); the digital economy also demonstrates clear positive spatial spillover effects by enhancing the efficiency of green innovation (Zhang et al., 2025).

The spatial autocorrelation characteristics of technological performance across regions in China from 2008 to 2022 were visually presented using Moran's I scatter plots, revealing the dynamic process of technological performance evolving from dispersed distribution to spatial aggregation. Analysis revealed that the Moran's I index remained positive throughout the study period, indicating that provinces with high technical performance tend to be adjacent to other high-performance provinces, while low-performance provinces also exhibit a clustering trend, confirming the significant spatial spillover effects in technological innovation activities. This spatial correlation aligns with recent research findings, such as in studies on the digital economy and regional innovation efficiency, where it was observed that the digital economy not only enhances local innovation efficiency but also drives the development of neighboring regions through spatial diffusion (Li & Li, 2018); simultaneously, technology transfer networks exhibit significant spatial dependence and spillover effects at both national and inter-city levels, thereby enhancing the innovation capabilities of surrounding cities (Wen & Shao, 2025). These studies collectively support the spatial aggregation and diffusion of technological performance and emphasize the necessity of considering the spatial dimension when examining regional innovation patterns.

From the perspective of dynamic evolution, the spatial pattern of China's regional technological performance has undergone four distinct phases. In 2008, a bipolar structure centered on Beijing and Guangdong began to emerge; by 2012, agglomeration intensity reached its peak, with the Yangtze River Delta region becoming increasingly prominent;

since 2016, a multi-center diffusion trend has emerged, with some central provinces gradually transitioning to higher-performance agglomeration types; by 2022, a multi-center innovation landscape had formed, with the Guangdong-Hong Kong-Macao Greater Bay Area, the Yangtze River Delta, the Beijing-Tianjin-Hebei region, and the Shandong Peninsula developing in synergy. This evolutionary trajectory is supported by recent research, which indicates that the cross-regional mobility of highly skilled talent significantly enhances the spatial spillover effects of high-tech industries, particularly within China's core urban agglomerations (Wang et al., 2021); Meanwhile, in terms of green innovation efficiency pathways, regions like the Yangtze River Delta have demonstrated stronger spatial diffusion capabilities (An et al., 2025). Related research has also found that the development of the digital economy has effectively enhanced the innovation performance of surrounding regions, resulting in noticeable spatial spillover effects (Xia et al., 2025). These findings collectively corroborate the spatial pattern of China's regional technological performance evolving from a single-center to a multi-center model. This evolutionary description further indicates that the spatial structure of technological performance is time-varying, which is consistent with the need to decompose direct and spillover effects in the SDM estimates.

Through LM test of the relationship between Location Quotient (LQ), Employment Density (ED) and Herfindahl–Hirschman Index (HHI) and technological performance, this study found that these indicators have significant spatial dependence. The test results of spatial error model and spatial lag model show that technological performance is affected by the spatial correlation of unobserved factors, and the spatial error term is more significant, which shows that these unobserved factors play a more critical role in technological performance. In addition, the intensity of spatial dependence varies among different indicators, but they all remain highly significant.

This study is based on 15 years of balanced panel data from 30 provinces, using a fixed-effects Spatial Durbin Model to systematically examine the spatial determinants of technological performance from three dimensions. Location Quotient (LQ), Employment Density (ED), and the Herfindahl-Hirschman Index (HHI). The results indicate that both the Location Quotient (LQ) and the Herfindahl-Hirschman Index (HHI) exert a “double inhibition” effect on technological performance, they not only significantly negatively impact local performance (direct effects of -0.276 and -1.606), but also reduce the performance of surrounding regions through strong negative spatial spillover effects (-2.504

and -6.014); while Employment Density (ED) has no statistically significant impact on technological performance. Meanwhile, R&D funding (fund) consistently exhibits a significant and robust local promotional effect (approximately 0.47–0.49), accompanied by positive or marginally significant spatial spillovers; government support (gov) only has a local effect, while research personnel (staff) exhibit a “local insignificance, neighboring negative” siphoning spatial pattern. In summary, regional technological performance exhibits strong spatial dependence, with innovation factors serving as the primary channel for negative spillovers.

This study supports the conclusions of some previous studies, such as During Du et al. (2022), who conducted an in-depth analysis of the current state of manufacturing innovation performance in the Wuhan urban agglomeration. The results indicate that the capital-driving effect of Wuhan's industrial agglomeration on surrounding cities is limited. This study supports the conclusions of some existing research, such as that excessive industrial concentration inhibits innovation performance Wang (2022), but it also provides new evidence that this inhibitory effect not only exists locally but also has a stronger negative impact on surrounding areas through spatial spillover, which differs from some predictions of traditional new economic geography (NEG) theory (Oláh & Alpek, 2021).

The Location Quotient (LQ) has no significant impact on technological performance, which is not entirely consistent with Qunshan (2024) research on the impact of agglomeration economies on technological innovation efficiency. The article shows that as the level of industrial agglomeration increases, the agglomeration of the traditional Chinese medicine industry has a significant promotional effect on technological innovation efficiency, but this may also be related to differences in the industries studied.

The negative spillover effect of scientific researchers (staff) contradicts the commonly held assumption that “talent promotes innovation” and may reflect the misallocation of resources caused by competition for talent between regions (Jin, 2024). This phenomenon is worth exploring in depth in the context of the recent “talent war.” The most unexpected result was the “negative spillover” rather than “positive sharing” of research staff. In the LQ, ED, and HHI models, the indirect effects of staff were all significantly negative at around -2.2, and the total effects were also negative. This is highly consistent with the recent findings of the Tsinghua University School of Economics and Management team that “the brain drain of scientific and technological talent leads to a net loss of innovation in

neighboring provinces.” The mechanism may be High-level talent flows unidirectionally across provinces, taking implicit knowledge with them; National major research facilities are spatially mismatched, preventing neighboring provinces from sharing them; The “talent war” driven by local government competition has raised labor costs in surrounding regions without bringing corresponding technological returns.

In this study, technological performance was assessed solely based on patent data, failing to capture non-patent innovations. The industrial agglomeration index did not differentiate industry-specific technical interdependencies. Additionally, the use of provincial-level panel data may obscure city-level heterogeneity, and new spatial interdependencies such as high-speed rail networks were not considered. Although robust standard errors were employed, systematic sensitivity tests were not conducted for various spatial weights (economic, technical, transportation), and future research should explore Hausman-type optimal matrix selection. Future research could combine firm migration data and technological association matrices to further reveal the interactive effects of multidimensional proximity.

#### **4.6.3 The Impact of Manufacturing Industry Agglomeration on Environmental Performance**

The results of the analysis based on the global Moran’s I index indicate that the spatial clustering of China’s environmental performance gradually increased between 2008 and 2012, which may be closely related to the development of regional innovation systems and the promotion of green policies. During the period from 2013 to 2020, spatial clustering showed a fluctuating decline overall, possibly reflecting the impact of regional coordination strategies and the trend toward a multi-centered distribution of innovation resources. By 2021–2022, the spatial clustering of technological performance had once again increased, potentially signaling a spatial restructuring of new technology diffusion patterns and regional innovation networks in the post-pandemic era. Recent empirical studies support this evolutionary trend, Wu et al. (2022) found that environmental regulations have a significant spatial spillover effect on the total factor productivity of the pharmaceutical industry; Han et al. (2022) noted that green technology innovation in China is concentrated in southeastern coastal provinces and drives the development of surrounding regions through spatial diffusion. These studies collectively validate the close linkage between the phased changes in the spatial patterns of environmental and technological performance and policy impacts.

Analysis based on local Moran's I indicates that the spatial pattern of China's provincial environmental performance from 2008 to 2022 has undergone dynamic differentiation and evolution. Overall, it exhibits an "eastern lead, western differentiation, and central improvement" spatial pattern, reflecting regional disparities in environmental governance. Recent empirical studies have also confirmed this trend. For example, one study noted that China's green growth synergy levels have been steadily rising, with a spatial distribution characterized by "high in the east and low in the west," with the eastern regions showing a significant lead in improvement (Hu et al., 2023); another study based on prefecture-level cities found that China's urban green innovation efficiency exhibits significant spatial autocorrelation, with a clear trend toward the clustering of "low-low" type cities (Dong et al., 2022). These results support the long-standing imbalance in the spatial distribution of environmental performance and indicate that improvements in governance performance across regions are closely related to spatial diffusion effects.

From the perspective of temporal evolution, the spatial pattern of China's environmental performance exhibits distinct phased changes. In early 2008, the western region exhibited low-value aggregation and weak spatial dependence. Between 2012 and 2016, the northwestern region (such as Xinjiang) began to show a trend toward high-value aggregation, indicating the effectiveness of regional development strategies in enhancing local environmental governance. By 2022, the environmental performance of eastern developed cities had significantly consolidated, while the western region exhibited a divergent trend, with some provinces achieving significant improvements. This evolution reflects both the positive effects of policy initiatives and the structural imbalances in regional coordinated development. Recent studies have also validated this trend, Hu et al. (2023) found that China's ecological-economic-environmental coordination level exhibits an overall "east-high, west-low" spatial distribution pattern; Gong et al. (2024) emphasized that the clustering of productive services effectively promotes urban green development efficiency, with eastern cities holding a clear advantage. These empirical findings collectively indicate that China's environmental performance spatial pattern is undergoing a transition from a "west-low, east-high, central improvement" structure toward a multi-center evolution. Policy orientation, industrial clustering, and financial support play a crucial role in shaping regional differentiation.

This study systematically examined the influence mechanisms of multi-dimensional factors such as industrial agglomeration Location Quotient (LQ), Herfindahl-Hirschman Index (HHI), Employment Density (ED), human capital (h), city level (citylevel), and capital stock (k) on environmental performance through a spatial Durbin model. Location Quotient (LQ) and Herfindahl-Hirschman Index (HHI) both exhibit significant positive direct effects, but spatial spillover effects exhibit heterogeneity—Location Quotient (LQ) shows no significant spillover, while Herfindahl-Hirschman Index (HHI) exhibits potential negative spillover effects; Human capital (h) exhibits the most robust promotional effect; city level (citylevel) consistently demonstrates environmental pressure effects; capital stock exhibits a unique “local-neighborhood” dual positive impact; and Employment Density (ED) exhibits a subtle “local promotion, neighborhood inhibition” characteristic. These results distinguish local environmental gains from cross-regional externalities, which helps interpret why environmental outcomes may depend on interprovincial coordination.

This study found that Location Quotient (LQ) has a significant positive impact on environmental performance, which is consistent with the promotional effect of specialization on innovation and economic growth in some studies (Li , 2018). It also shows that under certain conditions, Herfindahl-Hirschman Index (HHI) can have a positive impact on environmental performance by improving resource allocation efficiency and technological innovation capabilities.

Many studies have emphasized the role of human capital in economic growth and innovation, and this study further confirms the positive impact of human capital on environmental performance (Cao , 2022). This is consistent with the theory that human capital promotes environmental governance by improving technical levels and management capabilities.

The negative effects of urban hierarchy align with findings from some studies highlighting the environmental pressures and governance challenges faced by large cities. This suggests that large cities often face more complex environmental issues during periods of rapid economic development and high population concentration, such as higher energy consumption, more severe pollution emissions, and greater ecosystem pressures (Weichen, 2022). Therefore, when formulating environmental policies, it is necessary to fully consider the differences in city size and hierarchy and develop more targeted environmental

governance measures for large cities to effectively address these challenges and achieve sustainable development.

In the results regarding the impact of employment density on environmental performance, the effect of environmental regulations (regu) was not significant, suggesting that current regulatory policies may suffer from poor enforcement or design flaws (Liu & Zhu, 2022). This finding differs from the conclusions reached in some studies regarding the effectiveness of environmental regulations, indicating a need for further review and optimization of environmental regulatory policies.

As a key player in environmental governance, the government's policy orientation and regulatory effectiveness significantly influence the environmental performance of heavily polluting industrial clusters (Wu et al., 2022). Through empirical analysis, this study finds that capital stock ( $k$ ) not only directly improves local environmental performance but also generates significant positive spatial spillover effects, indicating that cross-regional environmental investment coordination has an amplifying effect.

In terms of indicator construction, future studies may adopt a comprehensive environmental performance index to avoid the heterogeneous impact mechanisms of different pollutants. Secondly, in terms of spatial relationship settings, the current model only uses geographic proximity weights and ignores important economic linkages such as interregional industrial linkages and technology diffusion, which may affect the accurate estimation of spatial spillover effects. Third, the study fails to effectively address the potential bidirectional causal relationship between environmental regulatory policies and performance, leading to potential biases in the estimation of policy effects.

Finally, in terms of the temporal dimension, the static model framework struggles to capture the dynamic cumulative effects and long-term adjustment processes of environmental governance. These methodological limitations not only highlight the shortcomings of this study but also provide clear directions for future research. Future studies could focus on breakthroughs in pollutant segmentation, the construction of multi-dimensional spatial weights, the treatment of policy endogeneity, and the development of dynamic models.

To link these spatial results back to regional theory, the Moran's  $I$  clustering and the SDM decomposition largely confirm key regional-development arguments. Persistent HH

cores in coastal metropolitan belts and expanding LL areas are consistent with New Economic Geography and growth-pole/cumulative causation logic, where market access, increasing returns, and factor mobility reinforce a core–periphery structure. Meanwhile, the negative spillovers (e.g., siphoning effects) found for employment density and the technology dimension suggest that agglomeration does not automatically diffuse benefits, but can redistribute gains through interregional competition and factor reallocation. For environmental performance, spatial dependence reflects cross-border externalities and strategic interaction in regulation, implying that outcomes depend on industrial structure and the degree of interprovincial policy coordination. Overall, the spatial patterns do not contradict regional theories; rather, they extend them by clarifying when agglomeration yields local efficiency gains versus spatial redistribution or governance-driven divergence.

Accordingly, this subsection contributes by integrating Moran’s I evidence with SDM decomposition to clarify when environmental performance reflects local efficiency gains versus cross-regional externalities that require coordination.

## 4.7 Conclusion

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This study systematically examined the impact mechanisms of different dimensions of manufacturing industry agglomeration (Location Quotient, Employment Density, Herfindahl-Hirschman Index) on economic, technological, and environmental performance through a Spatial Durbin Model (SDM), and analyzed the spatial evolution characteristics of technological performance based on Moran's I.

The industrial agglomeration effect exhibits significant heterogeneity—both the Location Quotient (LQ) and the Herfindahl-Hirschman Index (HHI) demonstrate significant local promotion effects, but their spatial spillover directions are opposite, while Employment Density (ED) exhibits a “local promotion-peripheral inhibition” competitive effect; Human Capital (h) consistently exhibits the strongest local and spatial synergy effects, while Foreign Direct Investment (fdi) exhibits a unique “local inhibition-peripheral promotion” pattern; The spatial autocorrelation of technological performance exhibits an inverted U-shaped evolution (increasing from 2008 to 2012, decreasing from 2013 to 2020, and slightly recovering after 2021), with an average Moran's I of 0.0287, and its phased changes align with major policy cycles. These findings reveal a nonlinear relationship between industrial agglomeration and economic performance: Location Quotient (LQ) and Herfindahl-Hirschman Index (HHI) primarily promote development through local economies of scale,

while employment density may trigger regional competition. They also validate the spatial positive externalities of human capital as a core factor and the regulatory role of institutional factors in the technological spatial landscape, providing a theoretical basis for formulating differentiated regional policies.

The Location Quotient (LQ) and Herfindahl-Hirschman Index (HHI) both have a significant negative impact on technological performance and exhibit strong spatial spillover effects, indicating that excessive concentration inhibits technological innovation and creates a “siphoning effect” between regions. In contrast, research and development (fund) investment consistently demonstrates a significant positive promotional effect and exhibits cross-regional knowledge spillover characteristics. Notably, the allocation of research personnel (staff) exhibits a unique “local insignificance-peripheral negativity” pattern, reflecting issues related to talent mobility and regional coordination. Government support policies (gov) can enhance local technological performance but have limited cross-regional synergistic effects. The study also found that technological performance exhibits significant spatial dependence, indicating that innovation activities have distinct clustering characteristics. These findings provide important insights for optimizing regional innovation policies, when promoting industrial agglomeration, it is essential to balance specialization and diversification, strengthen R&D investment and rational talent allocation, while improving cross-regional policy coordination mechanisms.

The Location Quotient (LQ) and Herfindahl–Hirschman Index (HHI) both have a significant positive impact on environmental performance, indicating that industrial agglomeration contributes to environmental improvement. While Employment Density (ED) exhibits a weak positive local effect, it shows a negative spatial spillover, suggesting that there may be a “race to the bottom” in environmental governance between regions. Human capital (h) and capital stock (k) consistently exhibit significant promotional effects and positive spatial spillover characteristics. Notably, the negative impact of city level (citylevel) on environmental performance is prominent, reflecting the more severe environmental pressures faced by large cities. These findings provide important insights for environmental governance policy formulation, while promoting industrial agglomeration development, it is essential to strengthen regional collaborative governance mechanisms, prioritize increased environmental investment and human capital accumulation, and implement differentiated

environmental policies tailored to cities of different tiers to achieve synergistic development between economic benefits and environmental improvement.

CHAPTER 5:  
**CONCLUSION**

## **5.1 Conclusions**

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This study evaluates the impact of industrial agglomeration on the economic, technological, and environmental performance of China's manufacturing sector. The study has three objectives: to measure the local effects and spatial spillover effects of industrial agglomeration on the economic performance of manufacturing; to analyze the direct impact of industrial agglomeration on technological performance and its spatial spillover effects; and to assess the local and cross-regional impacts of industrial agglomeration on the environmental performance of manufacturing. This thesis is based on economic methods and employs spatial econometric theory to systematically examine the multidimensional impact mechanisms of industrial agglomeration on China's manufacturing sector from economic, technological, and environmental performance perspectives. A series of analytical methods, including the Moran's I analysis, LM test analysis, and Spatial Durbin Model, are employed to achieve the research objectives. Importantly, the Moran's I provides a policy-relevant spatial diagnosis, high-high (HH) hot spots and low-low (LL) cold spots reveal where performance is geographically self-reinforcing, while spatial outliers (HL/LH) flag potential cross-regional externalities.

The Spatial Durbin Model is used to measure the local effects and spatial spillover effects of industrial agglomeration on the economic performance of the manufacturing sector. This study finds that the impact of different production factors on economic performance exhibits significant spatial heterogeneity. Location quotient and Herfindahl–Hirschman Index primarily promote economic growth through direct effects on the local region, with the spatial spillover effects of location quotients being particularly prominent, indicating that industrial agglomeration not only benefits the local area but also drives the development of surrounding regions through regional linkage. However, although employment density has significantly improved local economic performance, it has had a competitive inhibitory

effect on neighboring areas, reflecting the possibility of a siphoning effect of labor factors between regions.

This study provides a scientific basis for the formulation of regional economic policies. Through an in-depth analysis of the mechanisms by which various factors influence regional economic development, the study identifies which factors can effectively promote regional economic growth and the roles these factors play in regional collaborative development. For example, while foreign direct investment (fdi) exhibits varying local effects, its spatial spillover effects are significant, indicating that guiding FDI flows and promoting regional collaborative cooperation can effectively enhance the overall economic level of a region. Notably, human capital exhibits strong direct effects and spatial spillover effects in all models, highlighting the central role of knowledge diffusion and technological spillovers in regional collaborative development. In summary, this study not only deepens our understanding of the factors that influence regional economic performance, but also provides strong support for the precise formulation of regional economic policies and the practice of regional coordinated development. It has important reference value for promoting high-quality regional economic development. In practical terms, these spatial “spots” can be translated into a targeting rule for government intervention: persistent LL cold spots identify priority areas for capacity-building to break low-performance lock-in; HH hot spots indicate areas where governance should focus on managing congestion/pressure and strengthening channels that diffuse positive spillovers to nearby regions; and HL/LH outliers suggest the need for cross-provincial coordination to mitigate siphoning effects and other spatial externalities.

These spatial clustering and spillover patterns are corroborated by recent evidence on interprovincial spillovers and regional polarization in China, including studies showing significant spatial spillovers from the digital economy (Shang et al., 2025) and transportation infrastructure (Yin et al., 2024), as well as work documenting stronger spillovers and growth pole formation in eastern regions (Yang et al., 2022; Li et al., 2023). Overall, the findings are broadly consistent with prior research and do not contradict the literature; any differences in the strength, timing, or spatial configuration of clustering across studies are likely attributable to variations in performance indicators, sample periods, spatial weight matrices, and sectoral focus.

The effects of Location Quotient (LQ), Employment Density (ED) and Herfindahl–Hirschman Index (HHI) on technological performance are analyzed in depth through the Spatial Durbin Model (SDM), which reveals the complex mechanism of industrial agglomeration's effect on technological performance. It is found that Location Quotient (LQ) has a significant negative effect on technological performance, indicating that increased industrial specialization may inhibit local technological performance and further exacerbate this inhibition through spatial spillover effects. This result suggests that excessive industrial specialization may lead to unidirectional flow of innovation factors and spatial mismatch of innovation resources, thus negatively affecting technological performance.

In contrast to the negative impact of Location Quotient (LQ), both R&D funding and government support show significant positive effects on technological performance. This indicates that R&D investment and government support play an important role in enhancing local technological performance, but their spatial spillover effects are not significant, suggesting that the impacts of these factors are mainly confined to the local area, with certain administrative boundary constraints. In addition, the statistically insignificant effect of Employment Density (ED) on technological performance suggests that simply increasing Employment Density (ED) is not effective in promoting technological performance, and more attention should be paid to the improvement of employment quality.

The analysis of the Herfindahl–Hirschman Index (HHI) further reveals the “double inhibition” effect of industrial concentration on technological performance, i.e., an increase in industrial concentration not only constrains local innovation, but also generates significant negative spillovers to neighboring regions. This finding emphasizes the potential risks of industrial concentration on technological performance, and suggests that policymakers need to carefully consider the potential negative impacts on innovation when promoting industrial agglomeration.

This study systematically examines the influence mechanism of Location Quotient (LQ), Employment Density (ED) and industrial concentration on environmental performance through the Spatial Durbin Model, and reveals the differentiated effects of different elements on environmental governance. It is found that both location quotient and Herfindahl–Hirschman Index significantly promote environmental performance, indicating that the scale effect brought by industrial concentration is favorable to the improvement of environmental governance efficiency. In contrast, the effect of employment density is

relatively limited, and there is a negative spatial spillover effect, reflecting the complex relationship between economic growth and environmental governance.

The results highlight the spatial heterogeneity of environmental governance factors. Human capital accumulation and environmental protection investment show significant positive effects, and environmental protection investment has obvious spatial spillover benefits; while city class shows a persistent negative effect, indicating that large cities face more severe environmental governance challenges. It is worth noting that the effect of environmental regulation is not significant, suggesting that existing policies may be poorly implemented or have design flaws.

The environmental governance advantages of industrial agglomeration should be fully utilized to improve the cross-regional environmental collaboration mechanism; environmental investment should be increased and its spatial spillover effect should be promoted; the environmental governance model of large cities should be optimized and the environmental regulation system should be reformed; and the training of environmental protection personnel and technological innovation should be strengthened. These findings provide a theoretical basis for the construction of a regionally coordinated environmental governance system, which is an important reference value for promoting the construction of ecological civilization.

## **5.2 Contribution of the Study**

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This study employs a Spatial Durbin Model (SDM) to systematically analyze the multidimensional impacts of industrial agglomeration on regional development, achieving three innovative outcomes. Methodologically, a comprehensive analytical framework incorporating locational quotient, employment density, and the Herfindahl–Hirschman Index was constructed, improving traditional spatial effect assessment methods; Theoretically, the double-edged sword effect of industrial agglomeration was revealed, the core driving role of human capital was validated, and new economic geography theory was expanded; In terms of policy, it proposes differentiated governance strategies, including developing specialized clusters, optimizing the allocation of innovation resources, and establishing a cross-regional environmental governance system, providing a scientific basis for regional coordinated development. More importantly, this thesis makes the “spatial” contribution explicit by linking (i) spatial dependence diagnosed from Moran’s I with (ii) causal-effect decomposition from the SDM (direct/indirect/total), thereby demonstrating not only whether

agglomeration matters, but also where and through which spatial channels the impacts are concentrated.

### **5.2.1 Methodological Implications**

This study systematically examined the impact of industrial agglomeration (location quotient, employment density, Herfindahl–Hirschman Index) on economic, technological, and environmental performance using a Spatial Durbin Model (SDM), while distinguishing between direct effects and spatial spillover effects, thereby addressing the limitations of traditional regression models that ignore spatial dependencies. This approach not only considers the direct impact of industrial agglomeration on local performance but also captures the spillover effects of industrial agglomeration on neighboring regions through spatial lag terms and spatial error terms (Jeleskovic & Loeber, 2023). By doing so, the empirical strategy directly matches the study objectives of separating “within-province effects” from “cross-province spillovers,” which cannot be identified by non-spatial panel models. Model fit ( $R^2$ ) and robustness tests (such as the significance of variance components  $\sigma^2$ ) validate the reliability of the method, providing methodological references for subsequent regional economic and environmental research. In summary, the Spatial Durbin Model can simultaneously estimate direct and indirect effects, thereby more comprehensively revealing the multidimensional effects of industrial agglomeration.

By comparing the differentiated effects of three types of agglomeration indicators—Location Quotient (LQ), Employment Density (ED), and the Herfindahl–Hirschman Index (HHI)—this study reveals the heterogeneity of the impact of different dimensions of industrial agglomeration on performance. For example, the Herfindahl–Hirschman Index exhibits a significant negative spillover effect on technological performance, while Location Quotient (LQ) demonstrates a prominent promotional effect on economic performance. This suggests that relying on a single indicator may obscure complex mechanisms, necessitating a comprehensive assessment. Specifically, the Spatial Durbin Model can simultaneously estimate direct and indirect effects, thereby more comprehensively revealing the multidimensional effects of industrial agglomeration. Additionally, this study introduces multiple indicators to measure the degree of industrial agglomeration, enriching the methods for measuring industrial agglomeration. Through this methodological innovation, this study can more comprehensively reveal the multidimensional effects of industrial agglomeration, providing a new analytical framework for subsequent research (Zhu et al., 2025). This

methodological innovation not only enhances the scientific rigor of the research but also provides other researchers with a valuable empirical analytical tool.

Finally, through dynamic decomposition of direct, indirect, and total effects, the spatio-temporal boundaries of industrial agglomeration effects were clarified. For example, the negative spatial spillover of Employment Density (-0.295) only became apparent in the medium to long term, while the positive spillover of human capital (e.g., 13.877) was sustained, providing quantitative evidence for the timing of policy intervention. Based on 15 years of data from 30 provinces, a two-way fixed effect model was used to control for provincial and annual heterogeneity and reduce omitted variable bias. All models used robust standard errors to mitigate heteroscedasticity and serial correlation issues, thereby enhancing the reliability of the results. In addition, this chapter combines global Moran's I and local LISA classifications to document the spatial clustering background against which the SDM effects are interpreted, ensuring that model-based spillovers are grounded in observed spatial dependence patterns rather than assumed.

### **5.2.2 Theoretical Implications**

This study enriches the theoretical understanding of the relationship between industrial agglomeration and regional performance. First, the results indicate that industrial agglomeration has a significant impact on economic, technological, and environmental performance. The study validates the significant promotional effects of Location Quotient (LQ) and Herfindahl-Hirschman Index (HHI) on the local economy, but also identifies the “siphoning effect” of employment density on surrounding regions, thereby enriching the discussion on agglomeration externalities in new economic geography. This provides direct empirical support for a spatially explicit “core–periphery” logic, core provinces can gain locally while generating adverse spillovers for nearby provinces through factor reallocation and competitive interactions.

Furthermore, this study found that Locational Quotient and Herfindahl-Hirschman Index have a significant positive impact on environmental performance, which is consistent with the theory of positive externalities of industrial agglomeration in new economic geography. It reveals that excessive Herfindahl-Hirschman Index (HHI) inhibits innovation, supporting the “competition inhibition hypothesis,” which suggests that high concentration may lead to misallocation of innovation resources. Meanwhile, the positive spillover of R&D

investment (fund) reinforces the “knowledge spillover theory.” Thus, the thesis clarifies a key theoretical tension, agglomeration can improve efficiency and environmental outcomes under upgrading, while over-concentration may reduce innovation dynamism and generate spatial inequality in technological gains.

In addition, human capital (h) was found to have a significant positive spillover effect on all three performance indicators, confirming the cross-sector consistency of “talent aggregation” as a core driving force. Talent aggregation refers to the spatial concentration of skilled labour and R&D personnel that enhances regional performance through (i) knowledge spillovers (learning-by-interacting), (ii) better firm–worker matching, and (iii) faster diffusion of managerial and green practices across neighbouring provinces via labour mobility and inter-firm networks. This helps explain why the spillover channel can be significant even when some local coefficients are modest, human capital generates benefits that extend beyond administrative boundaries. This reveals the “regional synergy paradox” of FDI, FDI has a significant spillover effect on economic performance, but the local effect is not significant in terms of technological performance, indicating that the role of foreign investment is highly dependent on regional absorption capacity. Specifically, FDI can raise economic performance locally through scale expansion, employment, and supply-chain upgrading, while technological upgrading is not automatic because technology transfer often requires local complementary assets (e.g., skilled engineers, R&D platforms, supplier capability, and innovation institutions). When these complements are weak, local “technology capture” is limited, and the technological benefits may appear mainly as spatial spillovers—e.g., neighbouring provinces with stronger innovation systems may absorb knowledge through supplier linkages, imitation, and talent flows. Hence, the paradox reflects “economic synergy without guaranteed technological synergy”, openness and factor inflows can boost output, but innovation gains depend on whether regions can internalise, adapt, and recombine external knowledge. This strengthens the theoretical message that factor mobility alone is insufficient; absorptive capacity determines whether external resources translate into local technological upgrading. Therefore, provinces that aim to convert FDI into technological performance need not only to attract investment, but also to strengthen absorptive capacity—particularly human capital accumulation, local R&D intensity, and innovation-network embeddedness—so that external knowledge becomes locally codified innovation rather than remaining an external (or neighbouring) benefit.

In addition, this study also revealed the negative effect of city level on environmental performance, suggesting that differences in city size and grade need to be considered in the process of industrial agglomeration. This result is consistent with the conclusions of existing studies on the environmental pressures and governance challenges faced by large cities, further enriching the application of industrial agglomeration theory in the field of environmental performance (Zhao et al., 2024).

Finally, the environmental “boundary effects” of industrial agglomeration, such as the local environmental improvement effects of Location Quotient (LQ) and Herfindahl-Hirschman Index (HHI) and the cross-regional “race to the bottom” competition in employment density, complement the spatial dimension of the Environmental Kuznets Curve (EKC). These findings provide new theoretical perspectives for understanding the complex mechanisms of industrial agglomeration and lay a new theoretical foundation for future research. Overall, the thesis advances the theory by explicitly separating “local gains” from “spatial redistribution,” which helps explain why aggregate national upgrading may coexist with persistent regional divergence.

### **5.2.3 Policy Implications**

The findings of this study are highly aligned with China's national development strategies and policy directions in recent years. First, the results of industrial agglomeration reveal that excessive industrial agglomeration has an inhibitory effect on technological performance, a conclusion that resonates with the national strategic direction outlined in the 14th Five-Year Plan to “optimize industrial layout and promote the synergy between industrial chains and innovation chains.” Previous studies have pointed out that a single agglomeration model is detrimental to regional green transformation, while related diversification can better enhance regional development efficiency (Liu et al., 2024). This implies that future industrial policies need to be further integrated with the national innovation-driven development strategy, fostering strategic emerging industries, promoting regional industrial chain cooperation, and technological synergy to avoid path dependence and facilitate high-quality innovation development. Policy-wise, the results suggest that regions with strong local gains but weak spillovers should shift from “scale expansion” to “quality upgrading,” especially by preventing excessive concentration that may crowd out innovation dynamism.

This study found that human capital not only has a significant direct impact on economic and technological performance, but also generates spillover effects across regions. This is highly consistent with the implementation direction of the national “Science and Education for National Development Strategy” and “Talent-Driven National Development Strategy.” In recent years, China has been strengthening the formation of regional innovation hubs by increasing research and development investments, promoting the cultivation of high-level talent, and advancing the construction of research platforms. Empirical studies have also demonstrated that talent aggregation exhibits distinct spatial spillover effects, playing a crucial role in cross-regional technology diffusion and knowledge sharing (Wen et al., 2023; Yan et al., 2024). This suggests that when implementing national major strategies such as the “Beijing-Tianjin-Hebei Coordinated Development,” “Yangtze River Delta Integration Development,” and “Guangdong-Hong Kong-Macao Greater Bay Area Construction,” greater emphasis should be placed on building cross-regional scientific research cooperation networks and improving talent mobility systems, using institutional arrangements to promote knowledge diffusion and regional collaborative innovation. In addition, the spatial results imply differentiated intervention priorities: (i) HH cores should focus on coordinated spillovers (e.g., joint labs, inter-provincial R&D platforms), while (ii) LL areas require capacity-building (skills, infrastructure, and innovation services) to avoid long-term lock-in.

This study also reveals the cross-regional spillover effects of foreign direct investment (FDI) on manufacturing performance, which aligns closely with China's policy direction of maintaining high-level openness in recent years. As the “negative list for foreign investment access” is reduced and the development of free trade zones and free trade ports progresses, FDI is increasingly integrating into China's manufacturing value chain. Existing research indicates that FDI has a significant promotional effect on green innovation and industrial upgrading (Chen et al., 2024). Under the Belt and Road Initiative and the RCEP framework, further enhancing the depth of foreign investment participation in manufacturing and promoting the formation of cross-regional industrial collaboration networks will become an important lever for enhancing regional competitiveness and driving green transformation. The key policy implication here is to pair openness with absorptive-capacity policies (R&D support, supplier upgrading, talent programs), so that spillovers translate into local technological performance rather than remaining external.

In terms of environmental performance, this study found that environmental protection investments can generate significant positive spatial spillover effects, while large cities face greater pressure in environmental governance. This conclusion is highly consistent with the Chinese government's strategic goals of “carbon peaking and carbon neutrality” and the “Yangtze River Economic Belt Green Development Strategy.” Existing literature indicates that the development of the digital economy and the aggregation of productive services can effectively enhance regional green development efficiency and spread to surrounding areas through spillover effects (Xia et al., 2025). Therefore, advancing the “carbon peaking and carbon neutrality” process not only requires strengthening the driving role of environmental protection investment and green industries but also further improving cross-regional ecological compensation mechanisms and environmental governance systems, particularly by establishing new cooperative frameworks for cross-regional collaborative governance in key urban agglomerations such as the Beijing-Tianjin-Hebei region and the Yangtze River Delta. This also explains why “core cities” may appear as HL outliers, their governance and upgrading may outpace surrounding provinces, implying that policy should strengthen regional joint prevention-and-control mechanisms to convert local improvements into wider regional gains.

Finally, this study emphasizes the central role of spatial spillover effects in economic, technological, and environmental performance, which aligns closely with the overarching direction of the national “Regional Coordinated Development Strategy” and “New Urbanization Strategy.” Transportation and infrastructure development have been shown to have significant spillover effects on regional growth (Yin et al., 2024). Therefore, during the 14th Five-Year Plan period and beyond, policymakers should continue to promote interconnectivity of infrastructure and integrated governance of the ecological environment across regions, fostering a governance system centered on regional coordination and oriented toward high-quality development. This will not only deepen the positive interaction between industrial agglomeration and regional development but also provide a solid practical pathway for achieving Chinese-style modernization and a new development paradigm.

In summary, this study contributes a spatially explicit evidence base aligns closely with the strategic objectives of China's modernization. The research findings indicate that while industrial agglomeration drives economic growth, it is also necessary to coordinate technological progress and environmental governance to achieve high-quality development.

This aligns with the strategic requirements outlined at the 20th National Congress of the Communist Party of China to “accelerate the construction of a new development pattern and vigorously promote high-quality development.” By revealing the importance of spatial spillover effects, this thesis provides empirical evidence for promoting regional coordinated development, facilitating the free flow of factors of production, and optimizing resource allocation. This not only addresses the policy implementation needs of the “Regional Coordinated Development Strategy,” “Innovation-Driven Development Strategy,” and “Dual Carbon Goals,” but also provides scientific support for advancing China's path toward the coordinated development of economic prosperity, technological progress, and ecological civilization. In the future, the realization of Chinese-style modernization must place greater emphasis on the complementary advantages and collaborative win-win outcomes between regions to form a more balanced, inclusive, and sustainable spatial development pattern.

Relevant policy instruments that correspond to the empirical channels include the 14th Five-Year Plan, which emphasizes optimizing industrial layout and strengthening innovation-driven upgrading; the national advanced manufacturing cluster program led by the Ministry of Industry and Information Technology of the People’s Republic of China, which supports cluster-based upgrading and industrial-chain coordination; the Specialized and Sophisticated SME (Little Giant) program, which promotes capability building and niche innovation within clusters; and the 2024 Special Administrative Measures (Negative List) for Foreign Investment Access, which advances high-level opening-up by further easing foreign-investment access. Environmental spillover implications are also consistent with the Action Plan for Carbon Dioxide Peaking Before 2030 and the Yangtze River Protection Law, both of which institutionalize system-level and cross-jurisdiction ecological governance.

### **5.3 Limitations of the Study**

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Although this thesis has achieved certain results in terms of theory and empirical evidence, it inevitably has a number of limitations. These limitations are mainly reflected in the data level, indicator setting, spatial weight selection, and method application, and need to be further improved and expanded in subsequent research.

This study has certain limitations at the data level. Due to restrictions on official statistics, this thesis can only obtain panel data at the provincial level and cannot further delve into the micro-level mechanisms at the city, county, or even enterprise level. This may

underestimate the spatial heterogeneity of industrial agglomeration effects to some extent. In fact, agglomeration effects often exhibit more complex differences across regions at different levels, particularly within urban agglomerations or during the development of county-level economies, where their underlying mechanisms may differ significantly from those observed at the provincial level. Therefore, future research that incorporates statistical data or micro-level enterprise data from the municipal and county levels could help to more accurately reveal the diverse characteristics of agglomeration effects.

In terms of variable and indicator selection, this thesis primarily uses a single composite index to measure economic performance, technological performance, and environmental performance. While this approach provides an overall understanding of regional development levels, it inevitably overlooks differences between regions. This simplified treatment may lead to biases in the estimation of nonlinear characteristics. Future research could explore the use of a multidimensional performance indicator system to more comprehensively characterize regional differences.

The setting of the spatial weighting matrix also has limitations. The main method used in this thesis is a weighting matrix based on geographical distance, which can reflect the spatial connections between neighboring regions but fails to incorporate economic variables. As a result, some spatial correlations may be incorrectly classified as random errors, leading to an underestimation or overestimation of the true spatial spillover effects. Future research should aim to upgrade the existing single geographic distance matrix to a “comprehensive economic-geographic matrix,” incorporating multidimensional information such as economic scale, industrial structure, transportation accessibility, and institutional differences when constructing spatial weights. This approach would achieve a more reasonable balance between “economic logic” and “geographic reality.”

Additionally, this study has certain limitations in terms of methodological choices. Although the spatial Durbin model (SDM) can simultaneously capture the effects of spatial lag and error terms, it fails to adequately account for nonlinear features such as threshold effects, quantile differences, or spatiotemporal interactions. This may lead to an underestimation of the heterogeneity of policy effects. Future research could explore more flexible modeling approaches, such as spatial quantile regression or spatio-temporal geogewicht regression, to validate the robustness of the findings and further elucidate the differences in policy responses across regions in both temporal and spatial dimensions.

In summary, this thesis still has certain limitations in terms of data hierarchy, variable measurement, spatial weighting, and method selection. These shortcomings lead to certain biases in the identification and interpretation of industrial agglomeration effects, especially in terms of spatial heterogeneity and the nonlinear characteristics of policy effects. Future research that combines more detailed county-level and enterprise microdata, constructs a multi-dimensional performance indicator system, incorporates multiple factors such as economic, transportation, and institutional factors into spatial weighting settings, and employs more flexible spatial quantile regression or spatiotemporal geographic weighting regression methods will help to more deeply reveal the true mechanisms through which industrial agglomeration influences economic, technological, and environmental performance. This not only addresses the shortcomings of existing research but also provides more targeted and effective policy recommendations for optimizing industrial layout and promoting regional coordinated development.

#### **5.4 Suggestions for Future Research**

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Future research can build on the existing foundation to further deepen and expand, continuously driving the development of the regional industrial economy. This study uses provincial panel data to reveal the spatial effects of industrial agglomeration, but there are significant inter-city and county differences in China's regional development. It is recommended that future studies use more granular prefecture-level city or county data and combine multi-scale spatial models (such as cross-level Spatial Durbin Model) to reveal the spatial effects of industrial agglomeration, with a particular focus on the heterogeneous characteristics of new spatial units such as metropolitan areas and urban agglomerations. Future research can be further expanded to other industries to validate and supplement the findings of this study. Cross-industry comparative studies (such as manufacturing vs. finance, retail, etc.) can help identify universal patterns or industry-specific factors, providing a basis for developing more targeted policies and management practices. At the same time, developing a more general analytical framework based on data from multiple industries will further enhance the theoretical value and practical application potential of the research.

The current model primarily analyzes static spatial relationships, while the impact of industrial agglomeration on manufacturing performance may involve lag effects and path dependence. Future research is recommended to construct dynamic spatial panel models (such as the spatiotemporal double fixed-effects Spatial Durbin Model), introduce time

weight matrices, and quantify the dynamic cumulative mechanisms of agglomeration effects and spatial spillover cycles. Additionally, by incorporating China's unique institutional context, such as the five-year planning cycle, dynamic spatial panel models that include policy lag effects can be constructed to better align with China's specific circumstances.

It is necessary to shift away from single economic, technological, and environmental performance indicators and establish a multidimensional evaluation system incorporating new metrics such as green total factor productivity and supply chain security indices. Subsequent research should focus on exploring the economic-environmental synergies of industrial agglomeration under the constraints of the “dual carbon” goals, using spatial simultaneous equation models to identify optimal agglomeration intensity thresholds for different regions, thereby providing scientific basis for differentiated environmental regulatory policies.

Future research could delve into the micro level, such as integrating multi-source information including corporate data, patent citation networks, and talent mobility trajectories, and employing spatial econometric microanalysis methods to systematically analyze the spatio-temporal transmission pathways of the “brain drain effect,” particularly distinguishing the differentiated roles of different enterprises in spatial knowledge spillovers.

Finally, the economic impact of industrial agglomeration often extends beyond the local area and “spills over” to surrounding regions, but the extent of this spillover effect varies significantly between different regions. To better understand these differences, future research could focus on developing a spatially computable general equilibrium model system tailored to China's unique circumstances. By conducting multi-scenario policy simulations, this model could provide precise decision-making support for regional collaborative governance. This research direction could more directly serve the implementation of the national strategy for coordinated regional development.

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# APPENDICES

**Appendix Table 1:  
Industrial Classification of the National Economy – Manufacturing Segment**

<b>Mark</b>	<b>Industry Name</b>
C1	Agricultural and Food Processing Industry
C2	Food Manufacturing
C3	Alcohol, Beverage and Refined Tea Manufacturing
C4	Tobacco Products
C5	Textile Industry
C6	Textile clothing and apparel industry
C7	Leather, Fur, Feather and their products and
C8	Wood processing and wood, bamboo, rattan, palm and grass
C9	Furniture Manufacturing
C10	Paper and paper products industry
C11	Printing and recording media reproduction industry
C12	Literary, educational, industrial, sports and recreational goods
C13	Petroleum, coal and other fuel processing industry
C14	Chemical raw materials and chemical products manufacturing
C15	Pharmaceutical Manufacturing
C16	Chemical Fiber Manufacturing
C17	Rubber and plastic products industry
C18	Non-metallic mineral products industry
C19	Ferrous metal smelting and rolling processing industry
C20	Non-ferrous metal smelting and rolling processing industry
C21	Metal Products Industry
C22	General Equipment Manufacturing
C23	Specialty Equipment Manufacturing
C24	Automobile Manufacturing
C25	Railroad, ship, aerospace and other
C26	Electrical machinery and equipment manufacturing
C27	Computer, communication and other electronic equipment
C28	Instrumentation Manufacturing
C29	Other manufacturing industries
C30	Comprehensive utilization of waste resources industry

Source: China Statistical Yearbook (2017).

**Appendix Table 2:  
Descriptive Statistics of Manufacturing Industry by Province (2022)**

<b>Province</b>	<b>No. of manufacturing legal entities (units)</b>	<b>Manufacturing average wage (RMB)</b>	<b>Manufacturing fixed-asset investment growth (%)</b>
<b>Beijing</b>	26482	147872	18.4
<b>Tianjin</b>	48214	91425.5	-1.2
<b>Hebei</b>	310895	68254	13.4
<b>Shanxi</b>	48278	64536.5	6.8
<b>Inner Mongolia</b>	34049	82767	42.6
<b>Liaoning</b>	107050	72595	1
<b>Jilin</b>	32419	72250	5.2
<b>Heilongjiang</b>	39224	68228	10.2
<b>Shanghai</b>	58167	129209	2.1
<b>Jiangsu</b>	641215	93669	8.8
<b>Zhejiang</b>	564339	85979	17
<b>Anhui</b>	171586	74785	21.5
<b>Fujian</b>	192832	80251.5	19.7
<b>Jiangxi</b>	131457	65721	6.5
<b>Shandong</b>	473971	73083	11.2
<b>Henan</b>	205705	58741.5	29.7
<b>Hubei</b>	137732	73595	23.2
<b>Hunan</b>	101083	73358	14.6
<b>Guangdong</b>	708572	87071	12.2
<b>Guangxi</b>	64915	65609.5	26.2
<b>Hainan</b>	6274	76896	21.1
<b>Chongqing</b>	68144	81935.5	8.8
<b>Sichuan</b>	97886	78097.5	10.2
<b>Guizhou</b>	67048	74583.5	28
<b>Yunnan</b>	47602	72518.5	40.3
<b>Shaanxi</b>	64222	75633.5	6.6
<b>Gansu</b>	22363	70822	46.9
<b>Qinghai</b>	6663	79483.5	41
<b>Ningxia</b>	11211	81262.5	26.6
<b>Xinjiang</b>	35395	75534.5	15

Data Sources: All data are compiled from the China Statistical Yearbook (2022) and the China Industrial Statistical Yearbook (2022).

Manufacturing Average Wage: This figure represents the average wage of employees in the manufacturing sector for each province in 2022.

Manufacturing Fixed-asset Investment Growth: This refers to the year-on-year percentage change in fixed-asset investment (excluding rural households) within the manufacturing industry.

Scope: The table covers 30 provincial-level administrative divisions in mainland China (excluding Tibet due to data availability).

Legal Entities: This refers to organizations with independent legal status operating in the manufacturing sector at the end of 2022.