

Thesis for the Degree of Doctor of Philosophy

Research on the correlation
between economic agglomeration,
technological innovation and
carbon emissions intensity across
provinces of China

by

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Pukyong National University

August 2025

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(중국 각 성의 경제집적과 기술혁신,
탄소 배출 강도의 상관관계에 관한
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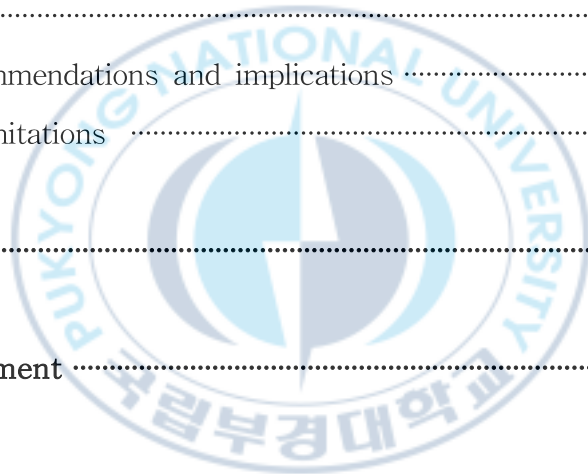
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Research on the correlation between economic agglomeration, technological innovation
and carbon emissions intensity across provinces of China

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Abstract

As industrialization and urbanization accelerate, population and industries concentrate, leading to economic agglomeration. This enhances resource efficiency and innovation through economies of scale and knowledge spillovers, promoting regional growth. However, it also has dual environmental effects—boosting efficiency while potentially increasing resource use and carbon emissions. Technological innovation helps reduce emissions by improving energy efficiency, advancing low-carbon products, and optimizing energy systems, though it may trigger a “rebound effect”, requiring institutional oversight. Research on the linkages between agglomeration, innovation, and carbon emission intensity supports precision emission-reduction policies, green development, and sustainable strategic planning.

This study uses panel data from 30 Chinese provinces (2003 - 2019) and applies spatial econometric methods—including the Spatial Durbin Model (SDM), Panel Threshold Model (PTM), and a modified Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model—to systematically

analyze the nonlinear relationship between economic agglomeration, regional technological innovation, and carbon emission intensity, along with their spatial spillover effects. Specifically, it investigates the nonlinear impact of economic agglomeration on regional technological innovation capacity and carbon emission intensity from two dimensions: industrial agglomeration and population agglomeration, and further explores the regulatory role of technological innovation in carbon emission intensity. The empirical results indicate that:

First, the impact of economic agglomeration on regional technological innovation capability is nonlinear. This capability exhibits significant spatial autocorrelation, with distinct agglomeration features and notable spatial spillover effects. The study finds that both industrial and population agglomeration exhibit a U-shaped relationship with regional innovation capability. When the logarithm of industrial agglomeration is below 5.969, it inhibits innovation capability; above this threshold, it promotes capability. When the logarithm of population agglomeration is below 3.872, it inhibits innovation capability; above this threshold, it promotes capability. Moreover, both types of agglomeration have significant direct effects.

Second, the impact of economic agglomeration on carbon emission intensity is nonlinear and exhibits significant spatial spillover effects. Industrial agglomeration shows an inverted U-shaped relationship with carbon emission intensity: initially promoting economic growth yet increasing energy consumption and emission intensity. However, once industrial agglomeration exceeds a logarithmic threshold of 6.197, economies of scale, environmental regulations, and technological spillovers take effect, reducing emission intensity. Conversely, population agglomeration exhibits a U-shaped relationship: moderate concentration optimizes resource allocation and energy efficiency, but exceeding a logarithmic threshold of 3.222 intensifies carbon-emission intensity due to urban traffic congestion and building energy demands.

Third, technological innovation exerts a nonlinear threshold effect on

carbon-emission intensity. When innovation capability is low, its inhibitory effect on emission intensity is limited. Once capability surpasses a specific threshold, the promotion and application of low-carbon technologies effectively reduce emission intensity. In regions with relatively higher emission intensity, enhanced innovation capability has a more pronounced inhibitory effect.

Finally, economic agglomeration fosters regional development and technological innovation, producing dual effects (inhibiting and promoting) on carbon-emission intensity. Such effects depend on the developmental stage of economic agglomeration and regional innovation capability. This study uncovers the nonlinear relationships and spatial spillover effects among economic agglomeration, regional innovation, and carbon-emission intensity, providing empirical evidence and policy insights. The findings inform the formulation of tailored low-carbon strategies, industrial structure optimization, and green economic transformation.

Keywords: Economic Agglomeration, Technological Innovation, Carbon Emission Intensity, Nonlinear Relationship, Spatial Interaction Effects, Regional Heterogeneity.

중국 각 성의 경제집적과 기술혁신, 탄소 배출 강도의 상관관계에 관한 연구

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요약

산업화와 도시화의 가속으로 인구와 산업이 집중되며 경제집적 현상이 나타났다. 이는 규모의 경제와 지식 확산을 통해 자원 효율과 기술혁신을 촉진하지만, 동시에 자원 소비와 탄소 배출 증가를 초래할 수 있다. 기술혁신은 에너지 효율 개선, 저탄소 제품 보급, 에너지 구조 최적화를 통해 탄소 저감에 이바지하지만, 반등 효과로 인해 제도적 지침이 요구된다. 경제집적, 기술혁신, 탄소 배출 강도 간의 비선형 관계에 관한 연구는 저탄소 정책과 지속 가능한 전략 수립에 중요한 기반이 된다.

이 논문은 2003년부터 2019년까지의 중국 30개 성의 패널 데이터를 사용하고, 공간 계량경제학 방법론인 공간 더빈 모델(SDM), 패널 임계값 모델(PTM)과 개선된 STIRPAT 모델을 적용하여 경제집적, 기술혁신 및 탄소 배출 강도 간의 비선형 관계와 그 공간적 파급 효과를 체계적으로 분석하였다. 연구는 경제집적이 지역 탄소 배출 강도와 기술혁신에 미치는 비선형 영향을 산업집적과 인구집적이라는 두 가지 차원에서 분석하며, 기술혁신이 탄소 배출 강도를 조절하는 역할을 추가로 살펴봤다. 실증 결과는 다음과 같다:

첫째, 경제집적이 지역 기술혁신에 미치는 영향은 비선형적이었다. 지역 기술혁신은 유의미한 공간적 상관관계를 나타내며 뚜렷한 공간 집적 특성과 주목할 만한 공간 파급 효과를 나타냈다. 연구에 따르면 산업집적과 인구집적은 모두 기술혁신과 U자형 관계를 보이는 것으로 나타났다. 산업집적 수준의 로그값이 5.969 미만이면 기술혁신에 억제 효과를 발휘하고, 로그값이 5.969를 초과하면 기술혁신을 촉진할 수 있었

다. 인구집적 수준의 로그값이 3.872 미만이면 기술혁신을 억제하고, 로그값이 3.872를 초과하면 기술혁신을 촉진하였다. 또한, 두 가지 모두 직접적인 효과가 유의미하였다.

둘째, 경제집적이 탄소 배출 강도에 미치는 영향은 비선형적이며 상당한 공간적 파급 효과를 나타냈다. 산업집적은 탄소 배출 강도와 역 U자형 관계를 보였다. 초기 단계에서는 산업집적이 경제 성장을 촉진하지만, 에너지 소비와 탄소 배출 강도를 증가시키기도 하였다. 그러나 산업집적 수준이 임계값 (로그값 약 6.197)을 초과하면 규모의 경제, 환경 규제 효과, 기술적 파급 효과가 나타나기 시작하여 탄소 배출 강도가 감소하였다. 반면 인구집적은 U자형 관계를 보이고, 적절한 정도의 인구집적은 자원 할당을 최적화하고 에너지 효율성을 향상시키는 데 도움이 되지만, 인구 밀도가 임계값 (로그값 약 3.222)을 초과하면 도시 교통 및 건물 에너지 소비와 같은 요인이 탄소 배출을 증가하였다.

셋째, 기술혁신이 탄소 배출 강도에 미치는 영향은 비선형적이었다. 기술혁신이 탄소 배출 강도에 미치는 영향은 임계값 효과를 나타냈다. 기술혁신이 낮을 때 탄소 배출 강도에 대한 억제 효과가 미미하지만, 기술혁신이 임계값을 초과하면 저탄소 기술의 홍보 및 적용을 통해 탄소 배출 강도를 효과적으로 억제할 수 있었다. 탄소 배출 강도가 높은 지역에서는 기술혁신의 개선이 탄소 배출 강도에 더 뚜렷한 억제 효과를 미쳤다.

마지막으로, 경제집적은 지역 발전과 기술혁신을 촉진하며, 탄소 배출 강도에 대해 촉진 효과와 억제 효과를 모두 가졌다. 이 효과는 경제집적의 발전단계와 기술혁신 수준에 영향을 받았다. 본 연구는 경제집적, 기술혁신, 탄소 배출 강도 간의 비선형적, 공간적 상호작용 효과를 밝혀내며, 차별화된 지역 저탄소 개발 전략 수립, 산업 구조 최적화, 녹색 경제 전환 촉진을 위한 실증적 증거와 정책적 시사점을 제공했다.

키워드: 경제집적, 기술혁신, 탄소 배출 강도, 비선형 관계, 공간적 파급 효과, 지역 이질성.

CHAPTER 1 Introduction

1. Research background and purpose

With the continuous advancement of industrialization and urbanization in China, population and economic activities have increasingly concentrated in city clusters and metropolitan areas, giving rise to a notable phenomenon of economic agglomeration. As a key concept in spatial economics, economic agglomeration primarily includes population agglomeration and industrial agglomeration. The former refers to the concentration of labor in major cities, forming high-density urban structures; the latter entails the clustering of related enterprises within specific regions, forming integrated industrial chains, supply chains, and innovation chains. The interaction between the two promotes urban expansion and enhances resource allocation efficiency.

From a theoretical perspective, Krugman (1991) and Glaeser et al. (1992) argued that agglomeration is influenced by factors such as market size, infrastructure, and public services, which help improve labor market matching and foster knowledge diffusion. Marshall (1890) proposed the “Marshallian externalities”—namely labor pooling, input sharing, and knowledge spillovers—as the fundamental mechanisms supporting industrial agglomeration. Fujita & Thisse (2002) further suggested that while moderate agglomeration enhances innovation efficiency, excessive concentration may lead to resource shortages,

environmental degradation, and other negative externalities.

Therefore, understanding the evolutionary logic and multidimensional impacts of economic agglomeration is essential for comprehending its profound implications for high-quality regional development.

Economic agglomeration provides institutional and resource support for innovation by fostering a high-density and diversified environment. Within agglomerated regions, frequent information exchange and close collaboration help enhance the dissemination of knowledge and diffusion of technology (Audretsch & Feldman, 1996; Duranton & Puga, 2004). Porter (1998) noted that clusters combining both competition and cooperation can drive technological upgrading and product innovation. High-tech clusters such as Silicon Valley and Zhongguancun serve as paradigmatic examples.

Data show that the technological innovation output in China is highly concentrated spatially, primarily in regions with high levels of economic agglomeration (CNIPA, 2023). Regions such as Beijing, Shanghai, and Guangdong exhibit robust technological innovation activity due to well-established industrial foundations, high talent concentration, and strong policy support. In contrast, central and western regions lag behind in innovation capacity due to less developed infrastructure (Mao, 2016). Against this backdrop, how to leverage economic agglomeration to promote technology diffusion and bridge regional innovation gaps has become a pressing issue for both academia and policymakers.

It should be emphasized that the promotion of innovation through agglomeration is not a linear process, rather it involves complex and stage-specific mechanisms. Notably, the impact of economic agglomeration on technological innovation is nonlinear. Although it promotes innovation in the early stages, excessive agglomeration may crowd out high-quality innovation through low-quality imitation, ultimately triggering the market for “lemons” effect. Therefore, identifying the nonlinear mechanisms at play carries significant theoretical and policy relevance.

Furthermore, the spatial unevenness in technological innovation capacity may exacerbate regional development disparities, posing new challenges for analyzing the interaction between economic agglomeration and technological innovation.

Economic agglomeration improves resource allocation efficiency on the one hand, but intensifies environmental pressure on the other. According to the Environmental Kuznets Curve (EKC) hypothesis, carbon emissions initially rise and then decline with economic development (Grossman & Krueger, 1995). Empirical evidence from Fan et al. (2021) indicates that in the early stages of agglomeration, carbon emissions increase, but begin to decline once a certain threshold is surpassed. Zhao et al. (2020) further demonstrate that rising traffic density and industrial concentration may lead to pollution spillovers, thereby hindering the green transition.

In addition, industrial agglomeration may trigger the “Pollution Haven Hypothesis (PHH)”¹⁾, whereby highly polluting industries relocate

to regions with weaker environmental regulations, thereby creating carbon emission hotspots. Such spatial heterogeneity implies that emission reduction policies must be region-specific. In China, the eastern region has achieved substantial emission reductions through technological advantages coupled with stringent environmental policies, whereas the central and western regions face elevated carbon pressure as recipients of relocated polluting industries (Chen et al., 2020).

These findings suggest that while economic agglomeration promotes economic efficiency, its environmental impact is characterized by both temporal complexity and spatial heterogeneity.

Technological innovation serves as the cornerstone for achieving reductions in carbon emissions and fostering a low carbon economy. It enhances energy efficiency, curbs carbon emissions, and catalyzes the development of green industries. As underscored by the OECD (2021), green technologies enable effective reductions in carbon emissions while maintaining economic growth. During the 13th Five Year Plan, China witnessed rapid expansion in green-technology patents, demonstrating that green innovation has risen to a national strategic priority.

Technological innovation affects carbon emissions through three main pathways: enhancing process efficiency to improve resource utilization, facilitating product substitution by promoting low-carbon alternatives (e.g., new energy vehicles), accelerating energy structure transition toward renewable sources (Zhou et al., 2021). Empirical

1) Pollution Haven Hypothesis (PHH) is an environmental economics theory suggesting that: companies in countries with strict environmental regulations tend to relocate their pollution-intensive production activities to countries with laxer regulations.

research by Wang et al. (2020) identified a significant negative correlation between R&D investment and carbon emissions, with particularly pronounced effects in technologically advanced urban centers. However, technological innovation also induces the “Rebound Effect”²⁾, whereby efficiency gains reduce usage costs, potentially increasing aggregate energy consumption (Gillingham et al., 2016). Consequently, policy incentives and market mechanisms must be synergistically aligned to maximize net environmental benefits.

In summary, whereas green technologies possess substantial emission reduction potential, their real-world efficacy is contingent upon the synergistic optimization of institutional frameworks and regional contexts. Economic agglomeration and technological innovation each influence carbon emission intensity in their own dimensions, and their interplay plays a crucial role in shaping regional pathways toward green development. However, existing studies have paid insufficient attention to the dynamic relationships, nonlinear mechanisms, and spatial heterogeneity among these three factors. Therefore, it is essential to further investigate the complex interactive mechanisms linking economic agglomeration, technological innovation, and carbon emissions from both theoretical and empirical perspectives.

Building upon this conceptual foundation, this study seeks to

2) “Rebound Effect” was first proposed in the 19th century by British economist William Stanley Jevons, and is known as the “Jevons Paradox.” Its core idea is that when technological progress improves energy efficiency, the unit cost of energy decreases, which in turn stimulates broader energy consumption, ultimately leading to an overall increase rather than a reduction in energy use.

systematically analyze the tripartite relationships among economic agglomeration, technological innovation, and carbon emission intensity in China. The specific objectives comprise:

To examine the mechanisms and nonlinear characteristics of the impact of economic agglomeration on regional technological innovation.

Guided by theories of knowledge spillovers and the spatial distribution of innovation, this study probes how technological innovation's inhibitory versus promotive effects evolve dynamically with population agglomeration and industrial agglomeration levels, while deciphering how economic agglomeration modulates the inflection point of the U-shaped relationship.

To examine the pathways and spatial heterogeneity in the impact of economic agglomeration on regional carbon emission intensity.

Based on the Environmental Kuznets Curve (EKC) framework, this study distinguishes between the effects of population agglomeration and industrial agglomeration, analyzes their exacerbating and mitigating effects at different stages of development, and identifies the inflection points in carbon emissions intensity. Spatial econometric models will be employed to uncover the spillover effects and regional disparities associated with agglomeration.

To analyze the mitigating effects of technological innovation on carbon emission intensity and its marginal effects across different levels of agglomeration.

A panel threshold regression model will be employed to establish a nonlinear framework using technological innovation level as the

threshold variable, examining how technological innovation's impact on carbon emissions intensity changes across agglomeration levels. Furthermore, a panel quantile regression model will be utilized to uncover heterogeneous innovation-driven emission reduction elasticity at varying carbon emission intensity levels.

This research seeks to offer theoretical foundations and evidence-based policy recommendations for formulating a regionally coordinated green low-carbon high-quality development pathway, making direct contributions toward fulfilling China's "3060 dual carbon" targets – carbon peak by 2030 and carbon neutrality by 2060.

2. Research methods

Literature research method. As the foundation and starting point of scientific research, the literature research method is widely used by scholars and is one of the most fundamental research approaches. The core task of this method is to organize and synthesize previous research findings, thereby summarizing the connections and differences between research phenomena and forming new research questions and perspectives. Its research steps generally include the following: collecting and reading existing literature, screening and integrating parts relevant to the research topic, and summarizing novel research viewpoints. Based on the research topic of this article, various literature databases were used for retrieval and downloading during the writing process, and literature on economic agglomeration, regional technological

innovation, and regional carbon emissions was collected, reviewed, and synthesized to clarify previous research results and the latest progress in this field.

Empirical Research Methods. Based on relevant mechanism analyses and theoretical assumptions, a quantitative analysis model is established. Through methods such as the entropy method, panel fixed effects model, spatial econometric model, and panel threshold model, the nonlinear effects of industrial agglomeration and population agglomeration on regional technological innovation capabilities and regional carbon emission intensity during the development of economic agglomeration are examined. Using spatial econometric techniques, this study analyzes the spatial autocorrelation and spillover effects of regional technological innovation capacity; examines the spatial spillover effects of industrial and population agglomeration on regional carbon emission intensity; and employs a panel threshold model to investigate the heterogeneous effects of regional technological innovation on carbon emission intensity at different agglomeration levels.

3. Paper structure

Chapter 1: Introduction

This chapter introduces the research background, objectives, methodology, and the structure of the thesis.

Chapter 2: The Impact of Economic Agglomeration on Regional Technological Innovation

Extending seminal work in innovation economics, this chapter is theoretically anchored in knowledge spillover theory and spatial innovation distribution frameworks. Investigate the dynamic evolution of innovation's dual effects (curbing versus enhancing impacts) across gradients of population agglomeration and industrial agglomeration, while elucidating how economic agglomeration governs the turning point in the U-shaped environmental innovation curve.

Chapter 3: The Impact of Economic Agglomeration on Regional Carbon Emission Intensity

Based on a review of existing literature and the Environmental Kuznets Curve (EKC) framework, this chapter constructs a spatial econometric model to explore the nonlinear relationship between economic agglomeration and regional carbon emission intensity from both industrial and population agglomeration perspectives. It also examines the spatial spillover effects of economic agglomeration on carbon emission intensity.

Chapter 4: The Impact of Technological Innovation on Regional Carbon Emission Intensity

This chapter constructs a comprehensive index system to measure technological innovation and employs panel threshold regression and panel quantile regression models to investigate the heterogeneous effects of technological innovation on regional carbon emission intensity.

Chapter 5: Conclusion and Policy Recommendations

This chapter summarizes the main findings of the study and proposes targeted policy recommendations based on the empirical results.

CHAPTER 2

The Impact of Economic Agglomeration on Regional Technological Innovation

1. Introduction

Innovation constitutes a fundamental driver of technological advancement and economic development (Schumpeter & Swedberg, 2021). Following China's national innovation strategy initiated in 2006, its gross domestic expenditure on R&D (GERD) grew at an annual average rate of 15.3%, elevating the country to the global leader in absolute R&D investment scale by 2018. In 2018, China's GERD reached 2.19% of GDP (exceeding the EU-15 average of 2.0%), while maintaining global leadership in full-time-equivalent R&D personnel (4.21 million) and invention patent grants (432,000) (NBS, 2019; WIPO, 2019). This generated significant endogenous growth momentum for sustainable development. Notwithstanding quantitative leadership, a substantial qualitative chasm persists, China's innovation efficiency index (0.38) trails the OECD average (0.72), indicating suboptimal knowledge translation (OECD, 2023). The 2023 Global Innovation Index (WIPO, 2023) positions China 12th globally, the sole upper-middle-income economy in the top 15, yet reveals critical

weaknesses in institutional quality (65th) and knowledge diffusion (42nd). This signifies subpar returns on innovation investment (ROI), with China's GERD-to-GDP ratio yielding only 0.78 units of innovation output per dollar versus 1.24 in the United States (NSF, 2023). China requires a fundamental transformation from input-driven to productivity-centered innovation.

Concurrently, industrial agglomeration occupies a central role in the development of regions across the globe. It effectively stimulates regional technological innovation by enabling the sharing of intermediate goods, spreading the risks associated with research and development, and improving the efficiency of labor allocation (Marshall & Marshall, 2023). From traditional industry clusters in Italy and manufacturing clusters in Germany to high-tech clusters like Silicon Valley, Scotland's Technology Parks, Bangalore in India, America's Route 128, and China's Zhongguancun high-tech industrial park, these clusters have substantially boosted innovation capacity in their regions (Filatotchev et al. 2011; Liu & Huang, 2001). Against this backdrop, China also places great emphasis on accelerating the implementation of innovation-driven development strategies, advancing the integrated development of strategic emerging industry clusters, and enhancing coordinated regional development (State Council, 2022).

Recently, the development of China's regional economy has exhibited significant spatial agglomeration characteristics, with the eastern coastal regions demonstrating a higher degree of economic concentration compared to the central and western regions (Zhang &

Wang, 2014). Additionally, regional innovative endeavors are predominantly located in the coastal areas of the east, with their innovation outputs markedly exceeding those of the central and western areas (Song & Zhao, 2018). The spatial distribution of economic agglomeration and regional technological innovation shows a high degree of consistency. This phenomenon is not exclusive to China, as global economic progress and regional technological innovation also exhibit similar spatial selectiveness and disparities (Giuliani, 2007). The notable disparities in innovation outputs among regions are primarily propelled by elements like natural resource endowments, human capital, fixed capital investments, and the extent of market openness (Andersson et al., 2005; Feldman & Audretsch, 1999; Paci & Usai, 1999).

The spatial distribution theory of knowledge spillover and technological innovation indicates that the knowledge spillover effect diminishes with increasing distance, making distance a primary barrier to knowledge diffusion (Feldman & Audretsch, 1999; Von Hippel, 1994). Agglomeration can effectively mitigate this issue. However, when agglomeration reaches a certain scale, the "market for lemons" phenomenon (Akerlof, 1970) may emerge due to imitation cost advantages, where imitation displaces technological innovation, resulting in a crowding-out effect. Building on these theories, this paper empirically examines the nonlinear relationship between the spatial agglomeration of economic activities and regional technological innovation capabilities. By employing a spatial econometric model to

analyze potential spatial spillover effects, this study offers new insights into the complexity of regional technological innovation in China.

The remainder of this paper is structured as follows: Section 2 reviews prior literature. Section 3 establishes the theoretical model and describes the data sample. Section 4 presents and discusses empirical results. Section 5 provides a summary and policy recommendations.

2. Literature review

Currently, the academic community is discussing various factors affecting regional technological innovation capacity. Gössling & Rutten (2007) argue that issues related to regional economic development are closely related to the innovation capacity of organizations in that region. Based on data compiled by the European Union's Statistical Office and national regional data from all EU countries, using linear regression analysis, empirical studies have shown that per capita regional GDP, cultural diversity, the proportion of labor force with higher education, and the level of urbanization have a positive impact on innovation, while there is a strong negative correlation between total GDP and innovation. Wang et al. (2016) identified three main environmental factors influencing regional technological innovation capacity: economic infrastructure, the quality and composition of innovators, and regional openness. Their empirical analysis demonstrated that the quality and composition of innovators are direct factors affecting regional technological innovation capacity. Krakowiak-Bal & Ziemiańczyk (2017)

discovered through their research that GDP growth, an increase in employment opportunities in the technology sector, improved internet access, and higher levels of education can all enhance regional technological innovation capacity. Zemtsov & Kotsemir (2019) highlighted the impact of factors such as the quality of human capital, knowledge spillovers, and corporate R&D intensity on regional technological innovation, and noted that increasing R&D expenditure is a key factor in promoting the development of regional technological innovation.

Economic agglomeration plays a key role in influencing regional technological innovation capacity, and can be examined from two dimensions: industrial agglomeration and population agglomeration. Industrial agglomeration can significantly promote regional technological innovation by sharing resources, facilitating talent and information matching, and enhancing knowledge spillovers (Carlino & Kerr, 2015). Meyer-Stamer (2002) believes that industrial agglomeration helps establish innovation cooperation networks between enterprises, create an innovative environment, and thus promote corporate innovation output and enhance regional technological innovation capacity. Yang & Liu (2023) found that industrial specialization and related variety significantly promoted regional technological innovation, while the agglomeration of unrelated variety had a significant negative impact. Moreover, the effects of industrial agglomeration are not solely positive; excessive concentration of productive factors can lead to resource crowding and negative externalities, thereby adversely affecting innovation output (Boschma, 2005). Tao et al. (2017) found that different

types of manufacturing industries and agglomeration regions have significant differences in their impact on technological innovation. The increase in industrial agglomeration has a threshold effect on technological innovation, shifting from a positive to a negative impact.

Population agglomeration also affects regional technological innovation capacity. Zhao et al. (2019) found that the contribution of scientific and technological talent agglomeration to regional technological innovation capacity significantly exceeded that of industrial agglomeration, and it had a clear positive impact. Chen & Yang (2017) examined the impact of population agglomeration on regional technological innovation. They found a U-shaped relationship between general population agglomeration and regional technological innovation, while the agglomeration of talent significantly promotes regional technological innovation. Liu et al. (2023) showed that improving the regional allocation of talent can effectively promote high-quality economic development, mainly by enhancing regional technological innovation.

The literature review shows that there are an increasing number of studies on the impact of economic agglomeration on regional technological innovation capacity. However, few studies have examined the impact of economic agglomeration on regional technological innovation capacity from both industrial and population perspectives. In addition, few studies have investigated the nonlinear impacts and spatial spillover effects of this agglomeration pattern on regional technological innovation capacity. This study extends previous research by

incorporating population and industrial agglomeration, along with other relevant factors, into spatial econometric models to empirically examine their combined effects on regional technological innovation capacity across 30 provinces in China. This approach provides a more comprehensive analysis of the key factors influencing regional technological innovation capacity, thereby contributing to the development of more effective policies to promote regional technological innovation in China.

3. Methodology and data

3.1. Spatial autocorrelation test

Spatial dependence is a prerequisite for applying spatial econometric methods. In this study, we employ the global Moran's I test (Moran, 1948) to examine the spatial autocorrelation and spatial relationships of regional technological innovation capacity among regions in China. Equation (1.1) presents the test formula:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (1.1)$$

Where, W_{ij} is the spatial weight matrix, x_i and x_j respectively represent the technological innovation capabilities of the i th and j th

regions, n denotes the total number of regions, S^2 represents the variance of regional technological innovation capabilities, and \bar{x} represents the average value of regional technological innovation capabilities. The range of Moran's I is $[-1, 1]$. A positive value indicates positive correlation in technological innovation capabilities between regions, a negative value indicates negative correlation, and a value of zero indicates no correlation in technological innovation capabilities between regions.

The Local Moran's I index is used to detect the spatial correlation between each observation point or region in a spatial dataset and its surrounding neighbors, allowing for the identification of local spatial clustering patterns, such as high-high or low-low clusters, as shown in Equation (1.2):

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^n W_{ij} (x_j - \bar{x}) \quad (1.2)$$

In this formula, all variables have the same definitions as in the Global Moran's I index, but the Local Moran's I index calculates a value for each observation, thereby providing detailed information about the local characteristics of the spatial data distribution.

To determine the statistical significance of the calculated Moran's I index, the Z-value is commonly calculated to perform hypothesis testing. The Z-value measures the deviation of the observed Moran's I from its expected value under a random spatial distribution. Equation

(1.3) presents the test formula :

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}} \quad (1.3)$$

$E(I)$ and $VAR(I)$ represent Moran's I expectations and variance, respectively. When $|Z| > 1.96$, it means that there is significant spatial correlation in regional technological innovation capabilities at the 1% level.

3.2. Spatial weighting matrices

The fundamental difference between spatial econometrics and traditional econometrics lies in the application of spatial weight matrices. This article, based on existing matrix assumptions and integrating the characteristics of spatial geographical distance with factors related to economic distance, merges geographical distance weights with economic distance weights to construct a geoeconomic nested matrix. Moreover, leveraging the research achievements of Zhang & Hu (2020), this study effectively establishes a geoeconomic nested matrix. Equations (1.4) and (1.5) present the test formulas. Equation (1.4) is used for basic regression analysis, and Equation (1.5) is used for robustness testing.

$$W_{ij} = \begin{cases} \frac{GDP_i \times GDP_j}{d_{ij}^2} & i \neq j \\ 0 & i = j \end{cases} \quad (1.4)$$

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} \times \frac{1}{|GDP_i \times GDP_j|} & i \neq j \\ 0 & i = j \end{cases} \quad (1.5)$$

Where, d_{ij} refers to the actual geographical distance between two regional centers, GDP_i represents the average GDP of province i during the study period, and GDP_j represents the average GDP of province j during the same period.

3.3. Spatial regression model

In spatial regression, commonly used models include the Spatial Error Model (SEM), Spatial Autoregressive Model (SAR), and Spatial Durbin Model (SDM). The SDM model, which incorporates spatial lag terms of both the dependent and explanatory variables, allows researchers to simultaneously assess the spatial spillover effects of variables across regions. Considering the significant advantages of the SDM model, construct a two-way fixed-effects Spatial Durbin Model. Equation (1.6) presents the model specification:

$$Y_{it} = \beta_0 + \rho WY_{jt} + \beta X_{it} + \lambda WX_{jt} + \mu_i + \tau_t + \varepsilon_{it} \quad (1.6)$$

Where, Y_{it} represents the observed value of regional technological innovation in province i at time t . β_0 is constant term. ρ is represent the spatial lag term, capturing the impact of the neighboring region j 's Y value (regional technological innovation) on the local region i . W is the spatial weight matrix, used to describe the relationships between different provinces. β is the coefficient of the explanatory variable. X_{it} is the observed value of economic agglomeration and other control variables in province i at time t . λ captures the spatial spillover effect of the explanatory variables, indicating how the explanatory variables X in neighboring regions influence the dependent variable Y in the local region. WX_{jt} is the spatial lag of economic agglomeration and control variables. μ_i represents the spatial fixed effects. τ_t represents the temporal fixed effects. ϵ_{it} is the error term.

3.4. Entropy method

The National Innovation Capability Evaluation Index System assesses the innovation capabilities of major countries worldwide and reveals the characteristics and differences in innovation capabilities among countries. Published by the Ministry of Science and Technology of the People's Republic of China, this index system comprises 5 secondary indicators and 33 tertiary indicators, covering multiple dimensions such as innovation resources, knowledge creation, enterprise innovation, innovation performance, and the innovation environment. Due to data availability constraints, this study employs the indicators listed in Table 1.1 and applies the entropy method to evaluate the technological

innovation capabilities of 30 Chinese provinces from 2005 to 2019.

Table 1.1. Evaluation index system of regional technological innovation capability

Primary Indicator	Secondary Indicator	Tertiary Indicator	Characteristic
Scientific and technological innovation level	Innovation resources	Proportion of R&D investment to RGDP in various regions	+
		Number of R&D projects	+
		Full-time equivalent of R&D personnel	+
		Average number of college students per 100,000 people	+
	Innovation performance	Number of new product development projects in high-tech industries	+
		Number of patent grants to domestic applicants	+
		Technology market transaction volume	+
	Innovation environment	Number of research and development institutions	+
		Number of higher education institutions	+
		Proportion of science and technology expenditure in fiscal spending	+

The entropy method, an objective weighting approach, is employed to determine weights. Based on the properties of entropy, the dispersion degree of an indicator can be measured through entropy calculation. The higher the dispersion degree of an indicator, the greater its impact on comprehensive evaluation. Thus, using the information entropy tool, the weight of each indicator can be calculated based on its variation degree, serving as a foundation for multi-indicator comprehensive evaluation.

The specific steps are as follows: (1). Data standardization. Let x_{ij}

represent the data of the j th indicator in the i th region ($i=1, 2, \dots, m$; $j=1, 2, \dots, n$), where $m=30$ and $n=10$. The maximum value is x_{\max} and the minimum value is x_{\min} . The final standardized value is X_{ij} , as shown in equation (1.7).

$$X_{ij} = \begin{cases} \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}} & \text{Positive Indicator} \\ \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}} & \text{Negative Indicator} \end{cases} \quad (1.7)$$

(2). Calculate the weights of the indicators, denoted as W_j . The process begins by calculating the proportion Q_{ij} of the j th indicator for the i th region, as detailed in equation (1.8).

$$Q_{ij} = \frac{X_{ij}}{\sum_i^m X_{ij}} \quad (1.8)$$

(3). Calculate the entropy G_j of the j th indicator, which is presented in equation (1.9).

$$G_j = -(\ln m)^{-1} \sum_i^m Q_{ij} \ln Q_{ij} \quad (1.9)$$

(4). Determine the weight W_j of the j th indicator, as outlined in equation (1.10).

$$W_j = \frac{1 - G_j}{\sum_j^n (1 - G_j)} \quad (1.10)$$

(5). Calculate the level of technological innovation ($INNO_i$), as shown in equation (1.11).

$$INNO_i = \sum_j^n X_{ij} W_j \quad (1.11)$$

3.5. Data and variables

To ensure data consistency and continuity, 30 Chinese provinces (2005 - 2019) were selected as research subjects.³⁾ To maintain robustness and minimize noise, data after 2019 were excluded due to potential anomalies caused by COVID-19 disruptions.

Regional technological innovation capacity (as the dependent variable) was quantified via the entropy method using China's National Innovation Capability Evaluation Indicators (see Table 1.1 and Equations 1.7 - 1.11).

Urbanization rate serves as an effective measure of population agglomeration. Per China's National Bureau of Statistics, urbanization rate is defined as the proportion of urban permanent population to total permanent population in a region, reflecting urban-rural population

3) Due to limited data availability, this study covers 30 provinces excluding Tibet, Hong Kong, Macao, and Taiwan.

distribution.⁴⁾ Industrialization concentrates non-agricultural sectors in urban areas, prompting rural-to-urban migration and consequently increasing urbanization. Thus, urbanization rate effectively quantifies population agglomeration.

Industrial agglomeration is quantified through an agglomeration index. Standard metrics include location quotient and the Herfindahl index. Given data constraints, adopt Zhang et al. (2014) and Shao et al. (2019)'s method, utilizing industrial output density—defined as industrial value-added per unit administrative area—as an agglomeration proxy. Unlike alternative metrics, output density captures both the spatial distribution of economic activities and industrial carrying capacity per geographical unit, thus better aligning with industrial agglomeration's density attributes.

Building on previous research findings, identify several key factors influencing regional technological innovation (entropy method comprehensive scoring), including the level of informatization (proportion of postal and telecommunications services volume to regional GDP), financial level (proportion of financial industry value added in the tertiary industry value added), infrastructure construction level (length of long-distance fiber optic lines in various regions.), economic development level (per capita real GDP), and foreign investment (total foreign investment in each region) (Gao et al., 2024; Gössling & Rutten,

4) Under the standards for administrative divisions in China, administrative units at the town (鎮) level and above are collectively referred to as urban areas. In these areas, individuals residing for more than six months are referred to as the urban permanent population.

2007; Ma & Chen, 2019; Zhang et al., 2022). Table 1.2 provides a detailed explanation and clarification of these variables. All original data are sourced from the National Bureau of Statistics of China (NBS, 2023).

As empirical models employ natural logarithmic forms, all variables underwent log-transformation in descriptive analyses to maintain consistency and comparability. Log-transformation standardizes measurement scales, mitigates heteroscedasticity, and corrects distributional skewness—enhancing result reliability. This approach also enables elasticity-based interpretations of variable relationships, facilitating relative effect comparisons in regressions. Implementing log-transformation across modeling and descriptive stages ensures methodological consistency, strengthening scientific rigor and internal validity.

To support the analysis, a comprehensive descriptive statistics summary of key variables was compiled for the covered provinces. Presented in Table 1.3, these results establish an empirical foundation for later analyses.

Table 1.2. Description and sources of the variables

Type	Unit	Definition measuring method	Data source
Regional technological innovation (INNO)	/	entropy method comprehensive scoring	NBS
Industrial agglomeration (IA)	%	ratio of industrial value added to the area of regional administrative division	NBS
Urbanization rate (POPU)	%	proportion of the permanent population in the urban areas of a region to the total permanent population in that region	NBS
Informatization (INTE)	%	proportion of postal and telecommunications services volume to regional GDP	NBS
Financial development (FD)	%	proportion of financial industry value added in the tertiary industry value added	NBS
Infrastructure (INF)	10,000km	length of long-distance fiber optic lines in various regions.	NBS
Economic growth (perGDP)	CNY	per capita real GDP (constant ¥ 1992)	NBS
Foreign investment (FI)	100 million(¥)	total foreign investment in each region	NBS

Table1.3 Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Median	Max.
lnINNO	450	-2.061	0.850	-4.763	-2.126	0.356
lnIA	450	10.194	1.633	5.222	10.240	13.985
lnIA ²	450	106.581	32.735	27.271	104.855	195.588
lnPOPU	450	3.965	0.252	3.291	3.969	4.497
lnPOPU ²	450	15.786	2.001	10.831	15.752	20.226
lnINTE	450	-0.912	0.628	-2.371	-1.026	1.629
lnFD	450	-2.147	0.340	-3.323	-2.094	-1.444
lnINF	450	0.780	0.879	-2.746	1.069	2.504
lnperGDP	450	9.685	0.600	7.911	9.711	11.084
lnFI	450	3.295	0.857	1.555	3.075	6.347

4. Empirical analysis

4.1. Spatial autocorrelation analysis

To assess spatial dependence, the global Moran's I index for regional technological innovation capacity was calculated for Chinese provinces from 2005 to 2019. All values were statistically significant at the 1% level ($p < 0.01$), confirming strong positive spatial autocorrelation.

Table 1.4. Global Moran's I Index of regional technological innovation capabilities in 30 Chinese provinces (2005 – 2019)

Year	Moran's I	Z-value	P-value	Year	Moran's I	Z-value	p-value
2005	0.236	2.758	0.003	2013	0.274	3.111	0.001
2006	0.253	2.937	0.002	2014	0.279	3.153	0.001
2007	0.198	2.370	0.009	2015	0.252	2.882	0.002
2008	0.241	2.794	0.003	2016	0.267	3.025	0.001
2009	0.253	2.901	0.002	2017	0.257	2.927	0.002
2010	0.279	3.181	0.001	2018	0.273	3.077	0.001
2011	0.287	3.269	0.001	2019	0.295	3.294	0.000
2012	0.290	3.282	0.001	/	/	/	/

Note: When $|Z| > 1.96$, it indicates that there is significant spatial correlation at the 1% level.

This study examines spatial heterogeneity in regional technological innovation capacity through local Moran's I computations for 30 Chinese provinces (2005–2019). Focusing on benchmark years 2005 and 2019, provinces were classified into four quadrant-based clusters according to their innovation levels (Figures 1.1–1.2 for spatial clustering patterns).

Specifically, Quadrant I represents High-High (H-H) clustering, while Quadrant IV indicates High-Low (H-L) clustering. This implies that provinces with strong technological innovation capabilities may be adjacent to neighbors with either similarly high or relatively low capabilities. Quadrant II corresponds to Low-High (L-H) clustering, and Quadrant III to Low-Low (L-L) clustering, indicating that provinces with weaker capabilities may be surrounded by neighbors with higher or similarly low innovation levels. H-H and L-L clusters reflect smaller regional differences and positive spatial correlation, whereas H-L and L-H clusters suggest greater disparities and negative spatial correlation. These diagrams illustrate spatial patterns and fluctuations in regional technological innovation across provinces during the selected years, offering valuable insights into its geographic distribution.

Moran's I increased from 0.236 in 2005 to 0.295 in 2019, confirming significant positive spatial autocorrelation in regional innovation capacity – indicating that geographically proximate provinces tend to exhibit similar innovation levels. Figure 1.1 (2005) shows clear spatial clusters: coastal provinces such as Beijing, Shanghai, and Zhejiang formed High-High clusters (Quadrant I), while inland provinces like Guangxi, Xinjiang, and Hainan formed Low-Low clusters (Quadrant III). By 2019 (Figure 1.2), provinces in Quadrants II and IV shifted toward the cores of Quadrants I and III. This shift intensified spatial clustering and dependence. These patterns highlight spatial homogeneity, with high-capacity regions clustering together and low-capacity regions forming concentrated enclaves.

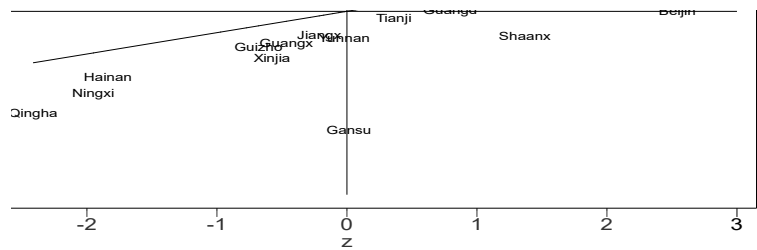


Fig. 1.1. Morgan scatter plot in 2005



Fig. 1.2. Morgan scatter plot in 2019

Fig. 1.1 - 1.2 Cluster distribution of regional technological innovation Capabilities in 30 Provinces of China

Note: The x-axis is the z-value and the y-axis is the spatial weight (Wz).



Fig. 1.3. The year of 2005

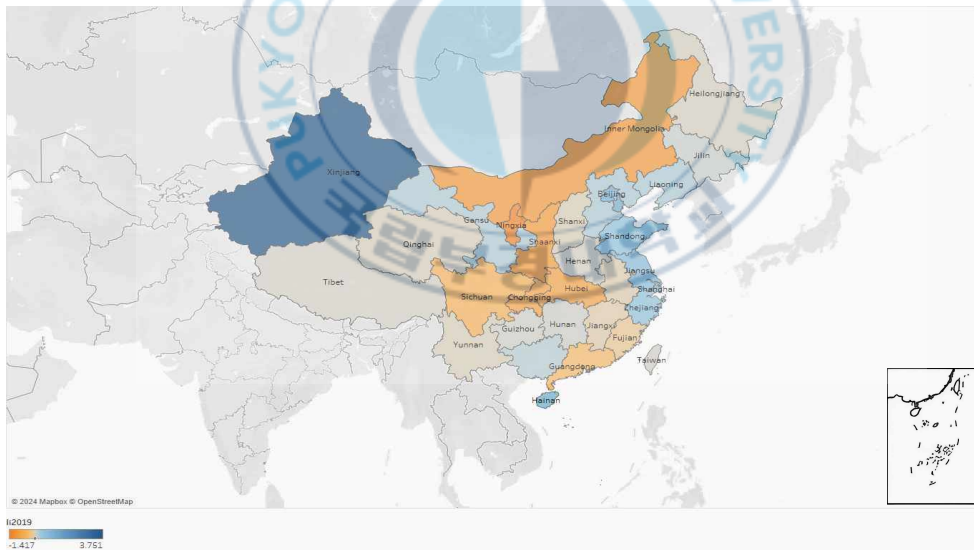


Fig. 1.4. The year of 2019

Fig. 1.3. - Fig. 1.4. Temporal and spatial evolution of regional technological innovation capabilities in each Chinese province

Figures 1.3 and 1.4, based on the Local Moran's I Index, present choropleth maps visually depicting the spatial distribution and trends of regional technological innovation capabilities across Chinese provinces from 2005 to 2019. These maps reveal clear spatial clustering patterns in regional technological innovation capabilities among China's provinces.

4.2. Selection of a spatial econometric model

This study, drawing upon the spatial diagnostic framework proposed by Elhorst (2014), systematically conducted a series of statistical tests, including LR tests, LM tests, and Hausman tests, with detailed results shown in Table 1.5. Specifically, Table 1.5 shows that all LM tests reject the null hypothesis, providing strong evidence for the coexistence of spatial lag and spatial error autocorrelation effects. Since the SDM effectively explains these phenomena, it is considered a reasonable choice. The LR test results confirm that the SDM should not be simplified to a Spatial Error Model (SEM) or Spatial Autoregressive Model (SAR). Meanwhile, the Hausman test strongly rejects the null hypothesis, supporting the use of a fixed effects model. Further LR test steps involved a detailed evaluation of the two-way fixed effects SDM, confirming its suitability. Based on this analysis, this study selects the two-way fixed effects SDM as the foundational model.

Table 1.5 Diagnostic tests for spatial dependence

Diagnostic tests		Statistic	p-value
LM Test	Moran's I	17.178	0.000
	LM-Error	264.436	0.000
	Robust LM-Error	173.152	0.000
	LM-Lag	93.980	0.000
	Robust LM-Lag	2.696	0.101
LR Test	Assumption: SAR nested within SDM	35.340	0.000
	Assumption: SEM nested within SDM	30.280	0.000
Hausman Test	Ho: difference in coeffs not systematic	86.07	0.000
LR Test for SDM	Assumption: IND nested within Both	19.190	0.038
	Assumption: Time nested within Both	1062.650	0.000

4.3. Spatial econometric analysis

Table 1.6 presents the empirical results obtained using the spatial Durbin model, revealing the impact of economic agglomeration on regional technological innovation capabilities. Specifically: (1) The spatial autocorrelation coefficient ρ is significantly positive at the 1% level, indicating a significant spatial spillover effect in regional technological innovation capabilities. This means that a region's innovation capacity is influenced by that of neighboring regions and confirms the important role of spatial factors in studying regional technological innovation capacity.

(2) A U-shaped relationship exists between industrial agglomeration and regional technological innovation capabilities, where industrial agglomeration inhibits, then promotes regional technological innovation capabilities. This indicates that at the early stages of industrial agglomeration, the low agglomeration level results in insignificant

knowledge and technology spillover effects. However, over time, the increasing agglomeration level generates substantial agglomeration effects, significantly enhancing regional technological innovation capabilities.

(3) A U-shaped relationship also exists between population agglomeration and regional technological innovation capacity, meaning population agglomeration initially inhibits technological innovation capacity but later promotes it. In the early stage, the low level of population agglomeration causes knowledge and technology to be relatively dispersed, which hinders innovation capacity improvement. As population agglomeration increases and cities expand, it attracts labor, accelerates knowledge and technology accumulation, and helps enhance regional technological innovation capacity.

(4). According to the empirical results of the control variables, information technology, financial development, infrastructure, economic growth, and foreign direct investment significantly promote regional technological innovation at the 1% significance level. Information technology fosters innovation by accelerating information dissemination and enhancing research and development efficiency (Czarnitzki & Hottenrott, 2011). Financial development provides capital and risk mitigation for innovation (Levine, 1997). Improvements in infrastructure facilitate the flow of production factors and the diffusion of knowledge (Audretsch & Feldman, 1996). Economic development offers the material foundation and market demand necessary for innovation (Grossman & Helpman, 1991). Foreign direct investment brings about technological

spillover effects (Blomström & Kokko, 1998). Therefore, these factors jointly contribute to the formation of an ecosystem conducive to technological innovation, and policy formulation should take into account multidimensional factors to effectively promote regional innovation.

A key advantage of the Spatial Durbin Model (SDM) lies in its ability to decompose spatial effects, thereby capturing the influence of explanatory variables on the dependent variable through direct, indirect, and total effects. As shown in the right-hand column of Table 1.6, the direct effects of industrial agglomeration on regional technological innovation capacity reveal a U-shaped relationship: the first-order term is significantly negative, while the second-order term is significantly positive. Specifically, when the logarithm of industrial agglomeration is below 5.969, the effect on innovation capacity is inhibitory; once it exceeds 5.969, the effect turns positive and becomes promotional. In contrast, both the indirect and total effects of industrial agglomeration are statistically insignificant, suggesting the absence of meaningful spatial spillover effects on neighboring provinces or the broader region.

In addition, the direct effect of population agglomeration on regional technological innovation capacity also exhibits a U-shaped relationship. This indicates that when the logarithm of population agglomeration is below 3.872, it has an inhibitory effect on regional innovation capacity; once it exceeds 3.872, the effect becomes positive, promoting innovation. However, both the indirect and total effects are statistically insignificant, suggesting that population agglomeration does not generate meaningful spatial spillover effects on neighboring provinces or the region as a whole.

Table 1.6. Results of the spatial econometric model

Variables	Main	Wx	LR_Direct	LR_Indirect	LR_Total
lnIA	-0.382***	0.569*	-0.347**	0.645	0.298
	(-2.577)	(1.902)	(-2.255)	(1.473)	(0.616)
lnIA ²	0.032***	-0.027**	0.031***	-0.024	0.007
	(4.959)	(-1.983)	(4.527)	(-1.188)	(0.305)
lnPOPU	-7.799***	5.399	-7.481***	4.408	-3.073
	(-6.037)	(1.403)	(-5.495)	(0.722)	(-0.447)
lnPOPU ²	1.007***	-0.564	0.974***	-0.382	0.592
	(5.712)	(-1.124)	(5.282)	(-0.480)	(0.655)
lnINTE	0.226***	-0.082	0.227***	0.004	0.231**
	(8.497)	(-1.241)	(8.466)	(0.039)	(2.055)
lnFD	0.141***	0.006	0.147***	0.075	0.222
	(3.038)	(0.049)	(3.082)	(0.397)	(1.072)
lnINF	0.130***	0.072	0.138***	0.178	0.315
	(3.649)	(0.580)	(3.406)	(0.922)	(1.476)
lnperGDP	0.498***	-0.909***	0.450***	-1.027***	-0.577
	(3.451)	(-3.417)	(3.248)	(-2.842)	(-1.581)
lnFI	0.083***	-0.154***	0.076***	-0.186**	-0.110
	(3.812)	(-2.744)	(3.313)	(-2.049)	(-1.079)
Rho	0.342***				
	(4.537)				
sigma2_e	0.010***				
	(14.827)				
Obs.	450				
R-squared	0.646				
No. of province			30		

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

In terms of control variables, the direct effect and total effect of the level of informatization are significantly positive, indicating that it

has a significant positive impact on the output of the region's innovation capacity and has a significant spillover effect on the entire region. The direct effect of the level of financial development and the level of infrastructure is significantly positive, indicating a significant positive impact on the output of the region's innovation capacity. Although the indirect effect and the total effect are not significant, the coefficients are both positive, indicating that there is a positive impact on the adjacent regions and the entire region. The direct effect of the level of economic development and foreign investment is significantly positive, and the indirect effect is significantly negative, indicating that it will have a favorable impact on the innovation capacity of the region, but an adverse impact on the adjacent regions.

4.4. Robustness check

To further verify the robustness of the empirical findings, this study adopted a robustness check strategy by replacing the spatial weight matrix (Eq. 2.2) and comparing the regression results of the Spatial Durbin Model (SDM) with those of the SAR and the SEM. The SDM_1 model presents the estimation results after substituting the spatial weight matrix. The spatial autocorrelation coefficient (ρ) remains significantly positive at the 1% level, reaffirming the presence of a strong spatial spillover effect in regional technological innovation capacity.

Although the significance of the first-order term of industrial agglomeration slightly decreases, the second-order term remains

significant at the 1% level, confirming the persistence of the U-shaped relationship between industrial agglomeration and regional innovation capability. Similarly, the signs of both the first-order and second-order terms of population agglomeration are consistent with those in the baseline model, further validating the U-shaped relationship at the 1% significance level. Moreover, the coefficients of the control variables retain the same direction and significance as in the baseline regression.

Additional estimations using SAR and SEM models yield results broadly consistent with the baseline SDM, thereby reinforcing the robustness and reliability of the primary empirical conclusions.



Table 1.7. Robustness check

Variables	SDM	SDM_1	SAR	SEM
lnIA	-0.382***	-0.280*	0.131	-0.053
	(-2.58)	(-1.92)	(1.17)	(-0.44)
lnIA ²	0.032***	0.030***	0.014***	0.023***
	(4.96)	(4.54)	(2.63)	(4.14)
lnPOPU	-7.799***	-7.323***	-7.985***	-7.456***
	(-6.04)	(-5.92)	(-6.70)	(-6.59)
lnPOPU ²	1.007***	0.946***	1.068***	0.984***
	(5.71)	(5.61)	(6.57)	(6.40)
lnINTE	0.226***	0.235***	0.207***	0.212***
	(8.50)	(8.87)	(8.06)	(8.40)
lnFD	0.141***	0.146***	0.164***	0.161***
	(3.04)	(3.18)	(3.65)	(3.67)
lnINF	0.130***	0.115***	0.149***	0.143***
	(3.65)	(3.21)	(4.14)	(4.08)
lnperGDP	0.498***	0.379***	0.074	0.144
	(3.45)	(2.70)	(0.67)	(1.19)
lnFI	0.083***	0.087***	0.087***	0.095***
	(3.81)	(4.00)	(4.02)	(4.55)
Rho	0.342***	0.377***	0.350***	
	(4.54)	(4.99)	(5.09)	
lambda				0.408***
				(5.78)
sigma2_e	0.01***	0.01***	0.011***	0.011***
	(14.83)	(14.81)	(14.84)	(14.77)
Obs.	450			
No. of province	30			

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5. Brief summary and policy recommendations

5.1. Brief summary

This study is based on China's provincial panel data from 2005 to 2019, and uses the Spatial Durbin Model. Considering other factors that may affect regional technological innovation, this study employs industrial agglomeration and population agglomeration as core explanatory variables to examine the impact of economic agglomeration on regional technological innovation capabilities. The theoretical and empirical analyses demonstrate a significant influence of agglomeration on innovation. Unlike the linear assumptions found in most literature, this study identifies a nonlinear relationship between agglomeration and innovation. This finding broadens the understanding of the agglomeration - innovation nexus and provides both theoretical and practical insights for improving regional innovation policies. The research findings primarily include the following:

Firstly, the results of the Moran's I test confirm that regional technological innovation capabilities exhibit significant positive spatial autocorrelation, characterized by evident spatial clustering and strong spatial spillover effects.

Secondly, the analysis reveals a U-shaped relationship between both industrial agglomeration and population agglomeration and regional innovation capacity. Specifically, when the logarithm of industrial

agglomeration is below 5.969, it has an inhibitory effect on regional innovation capacity; when it exceeds 5.969, the effect becomes promotional. Similarly, when the logarithm of population agglomeration is below 3.872, it suppresses regional technological innovation; beyond 3.872, it enhances innovation capability. In both cases, the direct effects are statistically significant, indicating a strong localized influence of agglomeration on innovation performance.

Finally, advancements in informatization, financial development, infrastructure, economic growth, and foreign direct investment all exert significant positive impacts on regional technological innovation capacity. These factors collectively enhance the innovation environment by improving information flow, providing financial support, facilitating resource mobility, stimulating market demand, and enabling technology spillovers.

5.2. Policy recommendations

Based on the above findings, the following policy recommendations are proposed:

Firstly, efforts should be made to avoid local protectionism and facilitate the free flow of technological innovation outcomes across regions to maximize spatial spillover effects. Technological innovation has significant externalities, and its benefits often transcend administrative boundaries. However, in practice, local governments may impose technical barriers or restrict talent mobility due to concerns over tax revenues or political performance, thereby disrupting regional

innovation networks and reducing overall efficiency. To address this, administrative barriers should be dismantled, and cross-regional innovation cooperation platforms—such as the Yangtze River Delta G60 Science and Technology Innovation Corridor—should be further promoted. At the same time, institutional mechanisms should be established to ensure the rational distribution of intellectual property rights and to utilize market mechanisms for optimizing the allocation of innovation resources, achieving mutual benefit and shared growth. Additionally, the central government is encouraged to establish a Regional Coordinated Innovation Fund, which would provide targeted support for major cross-regional scientific and technological projects and promote the integrated development of regional innovation ecosystems.

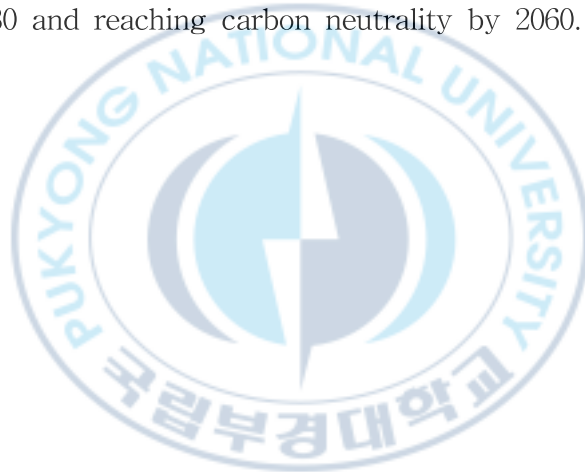
Secondly, concerted efforts should be made to systematically enhance the spatial agglomeration of the manufacturing sector, promote its transformation and upgrading toward high-end, intelligent, and green development, and fully leverage the catalytic effect of industrial agglomeration on technological innovation. A substantial body of research has demonstrated that manufacturing agglomeration facilitates knowledge spillovers, specialized division of labor, and collaborative supply chains, all of which contribute to enhancing firms' innovation efficiency. For instance, Guangdong Province has significantly strengthened its technological innovation capacity in the Pearl River Delta by establishing smart manufacturing industrial parks and high-tech development zones. In parallel, greater emphasis should be placed on the integration of

producer services with manufacturing, thereby enhancing the completeness, connectivity, and synergy of regional innovation chains. Regions should make full use of their comparative advantages to strategically plan and develop multi-tiered industrial spatial platforms, such as urban agglomerations, economic and technological development zones, and high-end industrial parks, thereby fostering regionally distinctive technological innovation hubs.

Finally, a scientifically managed, tiered population policy should be implemented to guide the rational flow and spatial redistribution of the population. Population agglomeration can enhance labor density, promote knowledge exchange and talent interaction, thereby accelerating the pace of technological innovation. However, when population concentration exceeds a city's carrying capacity, it can give rise to "urban diseases" such as traffic congestion, environmental degradation, and resource shortages. To mitigate these negative effects, population distribution must be optimized based on local conditions, encouraging the orderly relocation of population toward the peripheries of urban agglomerations. The central government can play a key role by improving the attractiveness and carrying capacity of small and medium-sized cities through fiscal incentives, talent settlement policies, and infrastructure investment. For instance, the Yangtze River Delta region has effectively eased population pressures in mega-cities like Shanghai by promoting integrated transportation systems and ensuring equitable access to public services, successfully guiding population inflows toward emerging hubs such as Hangzhou and Hefei metropolitan areas.

In summary, by dismantling local protectionism, fostering cross-regional collaboration, enhancing industrial agglomeration and structural upgrading, and guiding population mobility through scientific planning, China can effectively strengthen regional technological innovation capacity. These improvements will, in turn, contribute to green development and the realization of carbon reduction goals.

The coordinated implementation of these policy measures will offer robust support for China's pursuit of high-quality development and the successful achievement of its "dual carbon" targets—peaking carbon emissions by 2030 and reaching carbon neutrality by 2060.



CHAPTER 3

The Impact of Economic Agglomeration on Regional Carbon Emission Intensity

1. Introduction

High-speed economic growth and human activities have led to the over-consumption of fossil energy and the emission of greenhouse gases (GHGs), exacerbating climate and sustainability challenges. Fossil fuels are the primary driver of global climate change, accounting for over 75% of global greenhouse gas emissions and nearly 90% of all carbon dioxide emissions (United Nations Climate Action, 2023). According to the Energy Institute's (EI, 2023) 72nd edition of the Statistical Review of World Energy, published on June 26, 2023, global carbon emissions in 2022 reached 34.4 billion tonnes of carbon dioxide (CO₂), representing an increase of approximately 10% compared to 2010. Consequently, carbon emissions and their impact on climate change have remained a global focal point for several decades. The UN Climate Change Conference (COP26) held in Glasgow in 2021 emphasized the necessity of minimizing human-induced emissions to limit global warming to well below 2°C, preferably to 1.5°C. adjusting their levels of energy consumption and consumption structures in pursuit of

decarbonization goals. In recent years, countries worldwide have been adjusting their energy consumption patterns in pursuit of decarbonization goals.

Since the 1980s, rapid industrialization and urbanization have created favorable conditions for China's high-speed economic growth (Zheng & Walsh, 2019). However, as the economy developed and fossil fuel consumption increased, environmental pollution in China worsened (Dong et al., 2019). In 2005, China surpassed the United States to become the world's largest carbon dioxide emitter, accounting for more than a quarter of global emissions. Facing growing international pressure to curb emissions, the Chinese government announced its goals to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (3060 "dual carbon" targets). Given the tremendous pressure to reduce emissions, achieving energy conservation, promoting efficient energy use, and advancing low-carbon development are of great practical significance for China's sustainable development.

China's rapid economic development has led to the formation of economic agglomerations of various scales across regions, driven by urban expansion, rising population density, and growing industrial clusters. The expansion of economic activities typically increases resource consumption and waste generation, thereby escalating environmental stress. Technological advancements can enhance resource efficiency, reduce pollution emissions per unit of output, and help alleviate environmental stress. The Environmental Kuznets Curve (EKC) is a theoretical model describing the relationship between economic

development and environmental pollution. In the initial stages of economic growth, rapid industrialization and urbanization often prioritize development over environmental protection, leading to increased pollutant emissions and environmental degradation. As the economy grows and society becomes wealthier, public demand for environmental quality increases, prompting governments and businesses to invest more in environmental protection. At higher income levels, more advanced technologies are developed and applied, and environmentally friendly policies and technologies become widespread, resulting in reduced environmental pollution. Furthermore, structural changes in the economy, such as the shift from manufacturing to services, also influence pollution levels. The service sector is typically less pollution-intensive than the manufacturing sector. Therefore, a thorough analysis of the impact of economic agglomeration on carbon emissions is essential to promote low-carbon development.

This study employs a spatial econometric model to analyze the spatial effects of regional economic agglomeration on carbon emissions intensity. Furthermore, drawing on the theoretical framework of the Environmental Kuznets Curve (EKC), it empirically explores the dynamic relationship between economic agglomeration and carbon emissions. The goal is to provide strategic insights that support China's efforts in achieving energy conservation and emission reduction targets, advancing the green transformation of regional economies, and formulating data-driven, region-specific development policies.

This study is structured as follows: Section 2 reviews the relevant

literature. Section 3 constructs the theoretical framework and provides a detailed description of the data. Section 4 presents and analyzes the empirical results. Section 5 offers a brief summary and policy recommendations.

2. Literature review

Scholars around the world have demonstrated a keen interest in the issue of carbon emissions reduction. This research predominantly examines factors like economic growth, energy consumption structure, population structure, industrial structure, research and development investment, and technological innovation. Al-Mulali (2012) found that primary energy consumption and foreign direct investment (FDI) significantly influence carbon emissions intensity in 12 Middle Eastern countries. Cheng et al. (2014) used spatial panel econometric models to analyze the spatiotemporal dynamics of China's carbon emissions intensity, identifying key factors of mixed energy sources, energy intensity, urbanization, and industrial structure. Andreonia & Galmarini (2016) emphasized economic growth as a major driver of increasing carbon emissions intensity in 33 countries. Vujović et al. (2018) observed that an increase in renewable energy consumption effectively reduces carbon emissions. Wang et al. (2018) concluded from a variance decomposition analysis that urbanization, economic growth, and energy consumption are crucial determinants of carbon intensity across various income levels.

Dai et al. (2019) conducted a regression analysis on China's industrial air pollution using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model and panel data. They found that GDP growth, the proportion of secondary industry, and investment in the energy sector have a negative impact on China's environment. The authors also noted that advancements in the industrial structures of various regions in China would balance environmental inequalities. Rahman et al. (2022) used the autoregressive distributed lag (ARDL) model for the 25 largest emerging economies, showing that renewable energy reduced carbon emissions intensity between 1990 and 2018. Luo et al. (2023) analyzed the effects of aging and socioeconomic factors on carbon emissions in 30 Chinese provinces from 1997 to 2019 using a panel threshold model, noting that aging initially inhibited carbon emissions but this effect diminished over time. Petrović & Lobanov (2020) examined the impact of research and development (R&D) expenditures on carbon dioxide emissions in 16 OECD countries from 1981 to 2014, finding a generally negative effect, though with country-specific variations.

Early scholars paid significant attention to the environmental impact of population and industrial agglomeration. Yuan & Hwang (2023) observed that economic activities predominantly occur in major cities, resulting in relatively smaller populations in small and medium-sized cities. The rapid migration of populations from small and medium-sized cities to larger ones may significantly influence urban demographic changes and societal structures. At the national level, population

migration facilitates the recombination and diffusion of socio-economic elements. Shim et al. (2006) found a negative correlation between urban population density and per capita oil consumption in South Korea. Gaigné et al. (2012) suggested that compact, monocentric cities might generate more pollution than dispersed urban systems. Hu et al. (2018) indicated that an optimal urban population scale could enhance ecological health and sustainability. In contrast, Qin & Liao (2016) identified a negative relationship between urban population inflow and air quality in China, while Qin & Wu (2015) observed an initial increase and then a decrease in carbon dioxide emissions with urban population agglomeration.

In terms of the environmental impact of industrial agglomeration, Frank (2001) found a positive correlation between the scale of industrial agglomeration and atmospheric pollution in the European Union. Lin and Fang (2008) argued that advanced industrial clusters with strong enterprise cooperation can reduce emissions and improve ecological efficiency. Yan et al. (2011) showed that short-term industrial agglomeration reduces environmental pollution, but this effect does not necessarily persist in the long term. Yuan et al. (2019) reported that industrial agglomeration, influenced by foreign direct investment, increases carbon dioxide emissions. Xie and Xu (2019) found a U-shaped relationship between industrial agglomeration and carbon emissions in China, moderated by levels of foreign direct investment.

Our literature review reveals a growing body of research on the environmental impact of agglomeration. However, few studies have

examined how patterns of economic agglomeration affect carbon emissions from both population and industrial perspectives. Furthermore, research on the potential nonlinear effects and spatial spillovers of these agglomeration patterns on the environment is scarce. Building on previous research, this study incorporates population agglomeration, industrial agglomeration, and other major determinants of carbon emissions into a spatial econometric model to empirically examine their combined effects on regional carbon emission intensity across 30 provinces in China. This approach enables a more comprehensive analysis of the key factors influencing regional carbon emissions and, thus, helps in designing more effective policies to promote low carbon development in China.

3. Methodology and data

3.1. Spatial autocorrelation test

Spatial correlation is fundamental in regional science, characterizing interdependent relationships among adjacent regions through economic activities, technology spillovers, and resource sharing. Accelerating globalization and regional integration intensify interregional economic linkages, thereby strengthening spatial correlation. Thus, provincial economic development in China exhibits spatial dependence, being contingent upon both local factors (policies/resources/markets) and neighboring provinces' economic conditions. Spatial autocorrelation

analysis quantifies correlation patterns in spatial datasets, serving as a core methodological tool in regional economics. This method identifies systematic spatial patterns, determining whether adjacent units exhibit similarity (positive autocorrelation) or dissimilarity (negative autocorrelation).

The global Moran's I index (Moran, 1948) evaluates overall spatial autocorrelation across the study area, quantifying its magnitude and direction (see equation 2.1)

$$I_i = \frac{n \sum_{i=1}^n \sum_{s=1}^n W_{is}^A (Z_i - \bar{Z})(Z_s - \bar{Z})}{(\sum_{i=1}^n \sum_{s=1}^n W_{is}^A) \sum_i (Z_i - \bar{Z})^2} \quad (2.1)$$

In this equation, Z_i signifies the observed carbon emission intensity for province i , while Z_s represents the observed carbon emission intensity for province s . The parameter n represents the total number of provinces under consideration, and W_{is}^A stands as the spatial weight matrix. The range of I varies from -1 to 1 . Positive values of I signify a positive spatial autocorrelation among neighboring areas. Conversely, negative I values indicate negative spatial autocorrelation. When I equals 0 , it denotes spatial independence, indicating that regions exhibit no discernible spatial relationship with one another. A smaller value of $1-I$ indicates a more concentrated spatial distribution of observations within the region.

To assess the overall spatial heterogeneity of carbon emission intensity across the entire study area, we employ the global Moran's I index. However, for a more granular examination of local spatial clustering intensity, our analysis incorporates the local Moran's I index method. Utilizing Moran's I scatter plots, we identify and visualize significant clustering patterns among provinces, as articulated in eq. (2.2).

$$I' = \frac{n(Z_i - \bar{Z}) \sum_{i \neq s}^n W_{is} (Z_s - \bar{Z})}{\left(\sum_{i=1}^n (Z_i - \bar{Z})^2 \right)} \quad (2.2)$$

In eq. (2.2), I' denotes the Local Moran's I index, a local metric of spatial autocorrelation. The interpretations of the other indicators align with the explanations provided in eq. (2.1).

3.2. Spatial weighting matrices

Spatial econometrics fundamentally differs from traditional approaches through its incorporation of spatial weight matrices. These matrices—including adjacency, inverse distance, and geographic-economic nested matrices—quantify spatial dependence structures. The adjacency matrix defines contiguity by shared borders, which may oversimplify emission-related spatial interactions. The inverse distance matrix assumes decaying socio-economic connectivity with increasing distance. The geographic-economic nested matrix integrates geographic proximity

and economic attributes, providing refined spatial interaction modeling. Consistent with Zhang & Hu (2020), this study employ a geographic-economic nested matrix that synthesizes spatial and economic dimensions for robust emission analysis.⁵⁾

$$W_{is}^{de} = \begin{cases} \frac{1}{|PGDP_i - PGDP_s| d_{is}} & i \neq s \\ 0 & i = s \end{cases} \quad (2.3)$$

Where $d_{i,s}$ refers to the actual geographical distance between the centroids of two provinces. And $PGDP_i$ represents the average per capita GDP of province i during the study period, and $PGDP_s$ represents the average per capita GDP of province s during the same period.

3.3. Traditional econometric models

This study applies the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model (Dietz & Rosa, 1994), an extension of the IPAT framework (Ehrlich & Holdren, 1971), to examine economic agglomeration's impact on carbon emission intensity across Chinese provinces. The STIRPAT model quantifies population, affluence, and technology effects on environmental outcomes

5) Present Moran scatter plots (Fig. 2.1-2.4) in Section 4 as a method for visualizing the spatial autocorrelation present in our data. The Moran scatter plots effectively shows the correlation of a variable with the spatially lagged value of itself, which indirectly incorporates the spatial weights into the visualization.

through stochastic regression. Natural logarithmic transformation is applied to mitigate heteroscedasticity and facilitate elasticity coefficient estimation. The final specification is presented in equation (2.4).

$$I = aP_i^b A_i^c T_i^d \theta_i \quad (2.4-1) \tag{2.4}$$

$$\text{Ln} I_{it} = a + b(\text{Ln} P_{it}) + c(\text{Ln} A_{it}) + d(\text{Ln} T_{it}) + \theta_i \quad (2.4-2)$$

$$\text{Ln} Y_{it} = \text{Ln} x'_{it} \beta + z'_{it} \delta + \gamma t + u_i + \epsilon_{it} \quad (2.4-3)$$

3.4. Spatial regression model

Methodologically, traditional econometrics often overlooks the impact of spatial factors, resulting in many previous studies failing to account for spatial correlations between geographical areas. However, as Anselin (2013) noted, “Almost all spatial data exhibit characteristics of spatial dependence or spatial autocorrelation”. Therefore, this study adopts spatial econometric methods to deeply explore the impact of economic agglomeration on regional carbon emission intensity.

Spatial econometric models integrate temporal features and spatial effects into panel data models. Three common types of spatial econometric models exist: Spatial Error Model (SEM), Spatial Autoregressive Models (SAR), and Spatial Durbin Model (SDM). SDM incorporates spatial lag factors for both dependent and explanatory variables, allowing concurrent examination of spatial spillover effects in a region for both the dependent and explanatory variables. Due to the

relative advantages of SDM, this study initially adopts it as the foundational model for empirical analysis. Subsequently, its suitability is evaluated through a spatial suitability test to determine its optimality. Therefore, based on equation (1.4-2), this paper introduces carbon emission intensity, spatial lag of carbon emission intensity, and spatial lag of explanatory variables to construct the SDM presented in eq. (2.5).

$$\text{Ln } Y_{it} = \beta_0 + \rho \sum_{j=1}^n W_{ij} \text{Ln } Y_{jt} + \beta \text{Ln } X_{it} + \theta \sum_{j=1}^n W_{ij} \text{Ln } X_{jt} + \mu_i + v_t + \varepsilon_{it} \quad (2.5)$$

Within eq. (2.5), $\text{Ln } Y_{it}$ is natural log of the dependent variable for unit i at time t . β_0 stands as the constant term, symbolizing the intercept. $\rho \sum_{j=1}^n W_{ij} \text{Ln } Y_{jt}$ is spatial lag of the dependent variables, weighted by the spatial weights matrix W_{ij} . This term represents the influence of neighboring units' dependent variables ($\text{Ln } Y_{jt}$) on unit i 's dependent variable ($\text{Ln } Y_{it}$). $\theta \sum_{j=1}^n W_{ij} \text{Ln } X_{jt}$ is spatial lag of the explanatory variable X_{jt} , weighted by the spatial weights matrix W_{ij} , capturing the influence of neighboring units' explanatory variables ($\text{Ln } X_{jt}$) on unit i .

3.5. Data and variables

This study encompasses an analysis of 30 provinces in China,

covering the years 2003 to 2019⁶). Due to the potential data anomalies caused by the external shocks of the COVID-19 pandemic after 2019, this study excludes post-2019 data to maintain research robustness and minimize noise.

We identified various factors that influence carbon emission intensity based on prior research, and Table 2.1 in this study provides detailed explanations of all the variables used. We sourced the explanatory variables from the National Bureau of Statistics of China (NBS, 2023) and obtained data on total carbon emissions from the China Stock Market and Accounting Research (CSMAR) database (CSMAR, 2023). A significant step in our empirical analysis was to transform all variables into logarithmic form, a key strategy to mitigate the issue of heteroscedasticity. Also, as the purpose of this study is to examine the potential nonlinear relationship between economic agglomeration and regional carbon emission intensity, the squared terms of the main explanatory variables (industrial agglomeration, population agglomeration) have been included in the analysis.

Carbon emission intensity serves as a crucial metric for quantifying greenhouse gas emissions, playing an increasingly significant role in climate change and environmental research.

The calculation of regional carbon intensity follows the methodologies established by Stern (2004) and He & Liu (2004). China's National Bureau of Statistics defines urbanization rate as the proportion

6) This study examines the 30 provincial-level administrative divisions of mainland China, excluding Hong Kong, Macau, Taiwan, and Tibet.

of urban permanent residents relative to total regional population. This metric effectively captures urban-rural population distribution patterns. Industrialization drives spatial clustering of non-agricultural sectors in urban areas, inducing rural-to-urban population migration. Such migration contributes to urban spatial expansion and elevated urbanization levels. Urbanization rate accurately reflects population concentration in urban areas, serving as an appropriate proxy for population agglomeration measurement.

Industrial agglomeration is analyzed through an agglomeration index measuring spatial concentration patterns. Standard measurement approaches encompass location quotient, Herfindahl index, and spatial Gini coefficient. Data limitations necessitate adoption of Zhang & Wang (2014) and Shao et al. (2019)'s output density methodology. Output density – calculated as industrial value-added per administrative unit area – functions as the primary agglomeration metric. Compared with spatial Gini coefficient, output density simultaneously captures economic activity density/distribution and per-unit-area carrying capacity. This alignment corresponds precisely with industrial agglomeration's density attributes.

To avoid estimation bias caused by omitted variables, and drawing on existing studies, this research controls as much as possible for other factors that may influence carbon emission intensity (total carbon emissions / RGDP), including technological investment (total R&D investment by region / RGDP), industrial structure upgrade (ratio of value added in the tertiary industry to value added in the secondary

industry), degree of trade openness (total exports and imports/RGDP), Working-age population (those aged between 15-64 years as a percentage of the total population), population aging (percentage of the population aged 65 and above in the total population), and the level of economic growth (per capita real GDP) (Dai et al., 2019; Luo et al., 2023; Wang et al., 2018; Yan et al., 2011; Yuan & Hwang , 2023).

All variables were log transformed for consistency and comparability. Table 2.2 presents summary statistics to support the analysis.



Table 2.1 Description and sources of the variables

Variables	Unit	Definition measuring method	Data source
Carbon emission intensity (CEI)	tons/10,000(¥)	total carbon emissions/RGDP	CSMAR, NBS
Industrial agglomeration (IA)	%	ratio of industrial value added to the area of regional administrative division	NBS
Technological investment (RND)	%	total R&D investment by region as a percentage of RGDP	NBS
Industrial structure upgrade (INDup)	/	ratio of value added in the tertiary industry to value added in the secondary industry	NBS
Trade openness (OPEN)	%	total exports and imports as a percentage of RGDP	NBS
Working-age population (LAB)	%	those aged between 15-64 years as a percentage of the total population	NBS
Population aging (AGING)	%	percentage of the population aged 65 and above in the total population	NBS
Urbanization rate (POPU)	%	proportion of the permanent population in the urban areas of a region to the total permanent population in that region	NBS
Economic growth (perGDP)	CNY	per capita real GDP (Constant ¥ 1992)	NBS

Table 2.2 Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Median	Max.
lnCEI	510	0.914	0.682	-1.120	0.908	2.853
lnIA	510	10.055	1.682	4.702	10.072	13.985
lnIA ²	510	103.933	33.239	22.105	101.451	195.588
lnPOPU	510	3.915	0.309	2.700	3.838	4.497
lnPOPU ²	510	15.423	2.358	7.292	15.511	20.226
lnRND	510	-6.950	1.045	-9.019	-7.207	-3.773
lnINDup	510	-0.060	0.376	-1.655	-0.021	0.640
lnOPEN	510	2.894	0.985	0.238	2.603	5.149
lnLAB	510	4.291	0.050	4.150	4.287	4.429
lnAGING	510	2.243	0.217	1.692	2.233	2.796
lnperGDP	510	9.580	0.660	7.686	9.621	11.084

4. Empirical analysis

4.1. Spatial autocorrelation analysis

Given evident spatial clustering characteristics, the global Moran's I index was computed to assess carbon emission intensity across Chinese provinces (2003–2019). As shown in Table 2.3, the Moran's I indices persistently exceed zero with mean values stabilizing around 0.25. Carbon emission intensity demonstrates stable spatial dependence patterns throughout the study period. The positive spatial autocorrelation remains robust, with statistical significance at the 5% level ($p < 0.05$).

Table 2.3 Global Moran's I index of carbon emission intensity of 30 provinces in China (2003 – 2019)

Year	Moran's I	Z-value	p-value	Year	Moran's I	Z-value	p-value
2003	0.182	1.976	0.024	2012	0.268	2.734	0.003
2004	0.210	2.215	0.013	2013	0.262	2.687	0.004
2005	0.221	2.309	0.010	2014	0.253	2.613	0.004
2006	0.249	2.558	0.005	2015	0.244	2.528	0.006
2007	0.278	2.822	0.002	2016	0.255	2.615	0.004
2008	0.289	2.913	0.002	2017	0.243	2.516	0.006
2009	0.286	2.882	0.002	2018	0.234	2.433	0.007
2010	0.272	2.765	0.003	2019	0.219	2.294	0.011
2011	0.260	2.672	0.004	/	/	/	/

Note: when $|Z| > 1.96$, it indicates that there is significant spatial correlation at the 1% level.

To explore regional disparities in carbon emission intensity across China, this study calculates the local Moran's I index for the period from 2003 to 2019. Specifically, four representative years (2003, 2008, 2013, and 2019) are selected for in-depth analysis. Based on the four quadrants of the local Moran's I scatter plots, Chinese regions are classified into four distinct spatial clustering types according to their carbon emission intensity. The detailed results are presented in Figures 2.1 and 2.4, which visually depict the spatial distribution patterns and temporal dynamics of carbon emission intensity across different regions throughout the study period.

Using the four quadrants of the local Moran's I scatter plots, China's regional carbon emission intensity is classified into three clustering types, as detailed in Figures 2.1 to 2.4. Specifically, quadrant I represents High-High (H-H), while quadrant IV represents High-Low (H-L). These signify that provinces with high carbon emission intensity are surrounded by neighboring provinces with either high or low values. Quadrant II corresponds to Low-High (L-H), and quadrant III corresponds to Low-Low (L-L). These indicate that provinces with low carbon emission intensity are encircled by neighboring provinces with either high or low values. High-High and Low-Low types denote smaller differences in carbon emission intensity between regions and a positive correlation, while High-Low and Low-High types signify greater differences in carbon emission intensity between regions and a negative correlation.

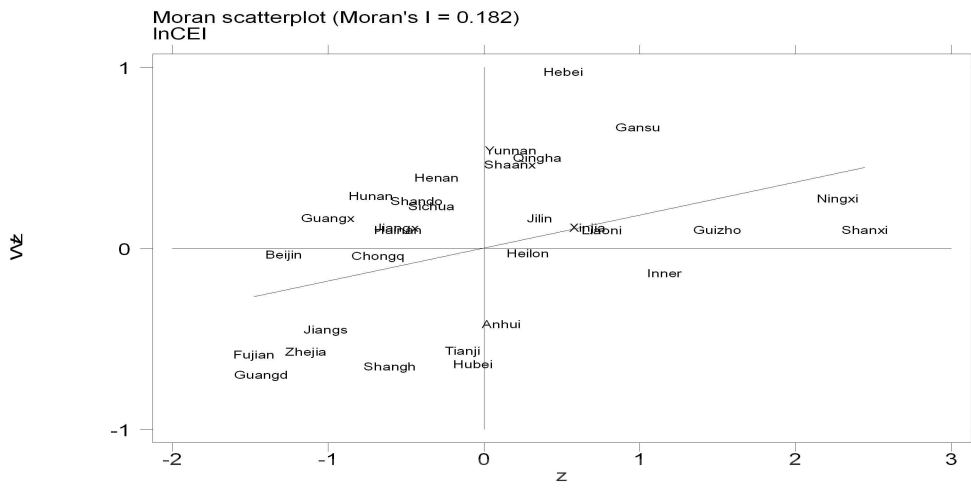


Fig. 2.1. Morgan scatter plot in 2003

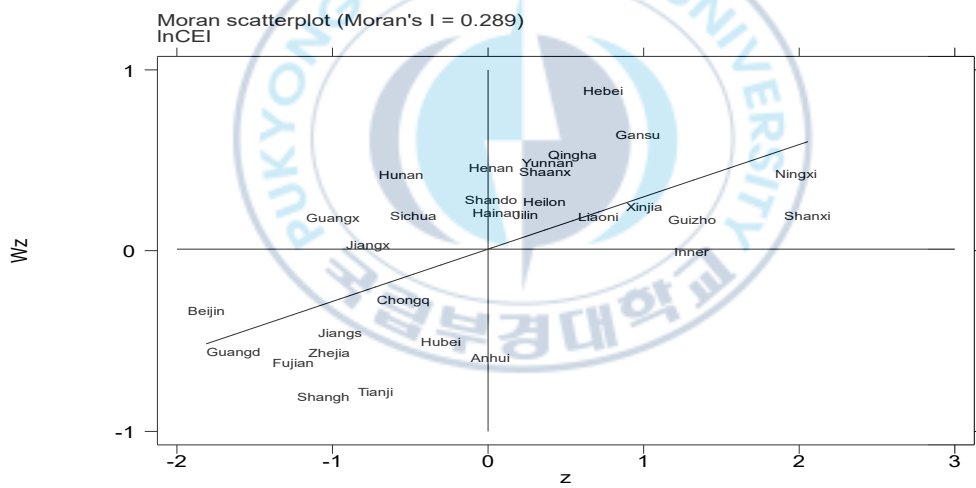


Fig. 2.2. Morgan scatter plot in 2008

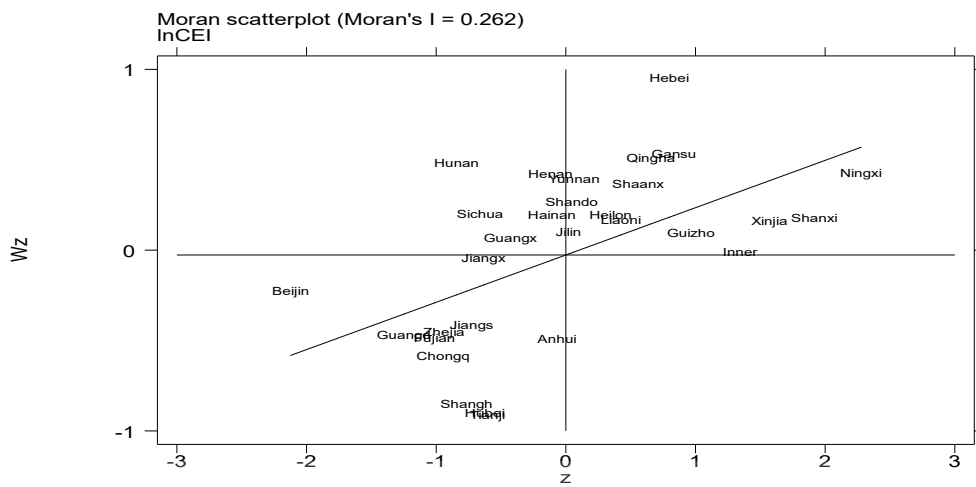


Fig. 2.3. Morgan scatter plot in 2013

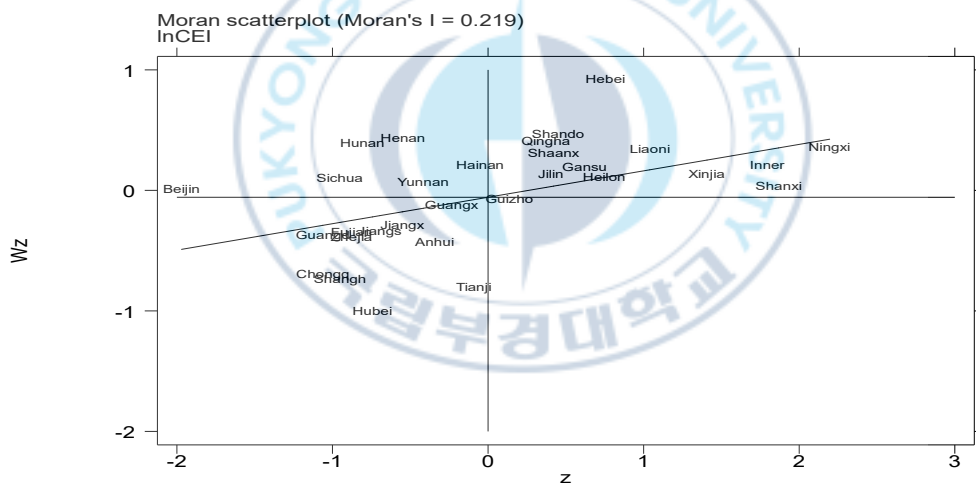


Fig. 2.4. Morgan scatter plot in 2019

Fig. 2.1. - 2.4. Cluster distribution of carbon emission intensity of 30 provinces in China

Note: The x-axis is the z-value and the y-axis is the spatial weight (Wz).

Figures 2.1 - 2.4 reveal three persistent spatial clustering patterns of China's provincial carbon emission intensity (2003, 2008, 2013, 2019): High-High (H-H), Low-Low (L-L), and Low-High (L-H) clusters. High-High clusters predominantly occur in northern and western provinces, including areas such as Shanxi, Inner Mongolia, Ningxia, Liaoning, and Gansu, characterized by resource abundance but economic underdevelopment, with energy-intensive industrial structures, limited high-tech sectors, low resource efficiency, and consequently high emission intensity. Low-Low clusters concentrate in coastal provinces like Fujian, Guangdong, Zhejiang, Shanghai, and Jiangsu, featuring developed economies dominated by technology- and capital-intensive industries, optimized energy structures, high efficiency, and thus low emission levels. Low-High clusters encompass provinces like Hunan, Sichuan, and Guangxi, represent spatial outliers where provinces with lower emission intensity significantly influence higher-emission neighbors.

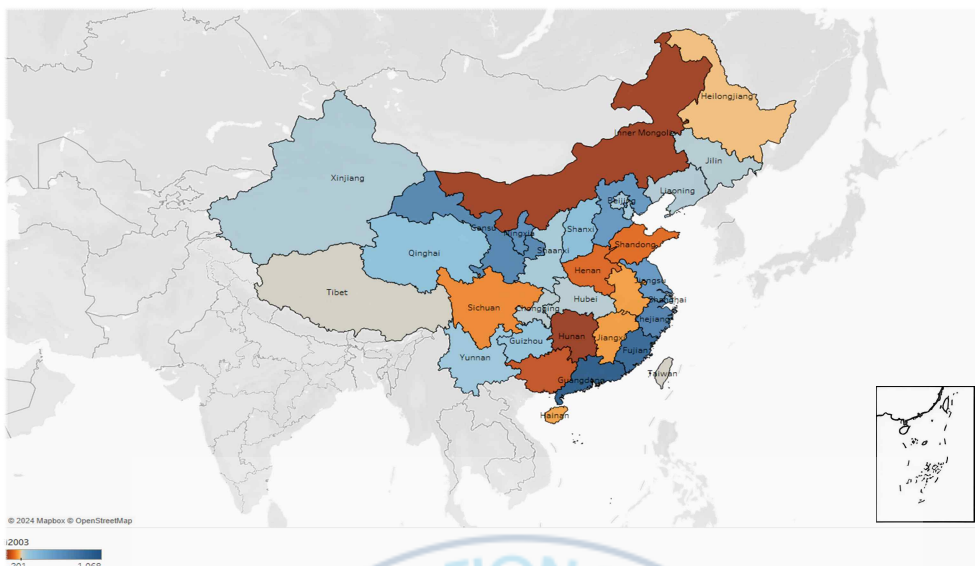


Fig. 2.5. The year of 2003

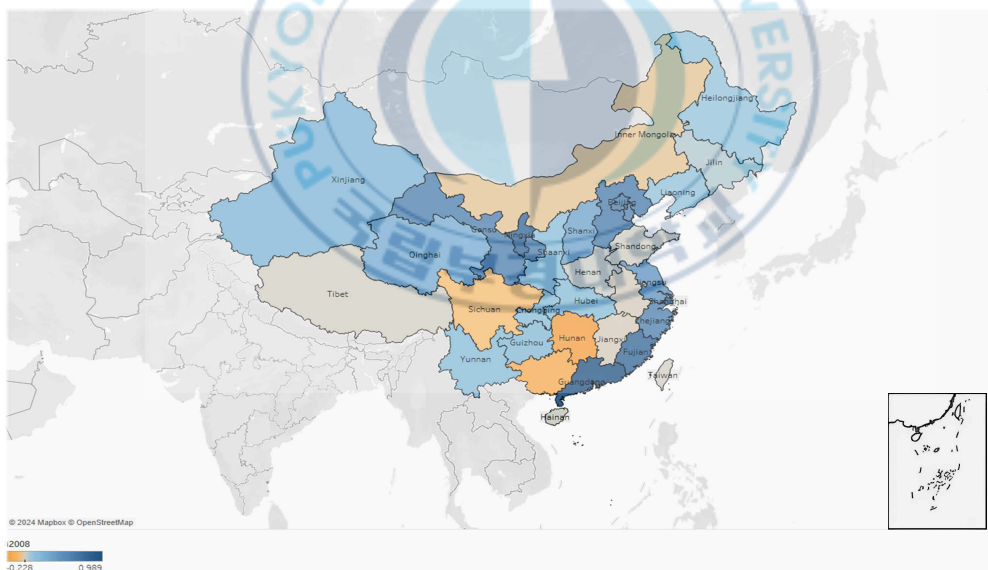


Fig. 2.6. The year of 2008



Fig. 2.7. The year of 2013

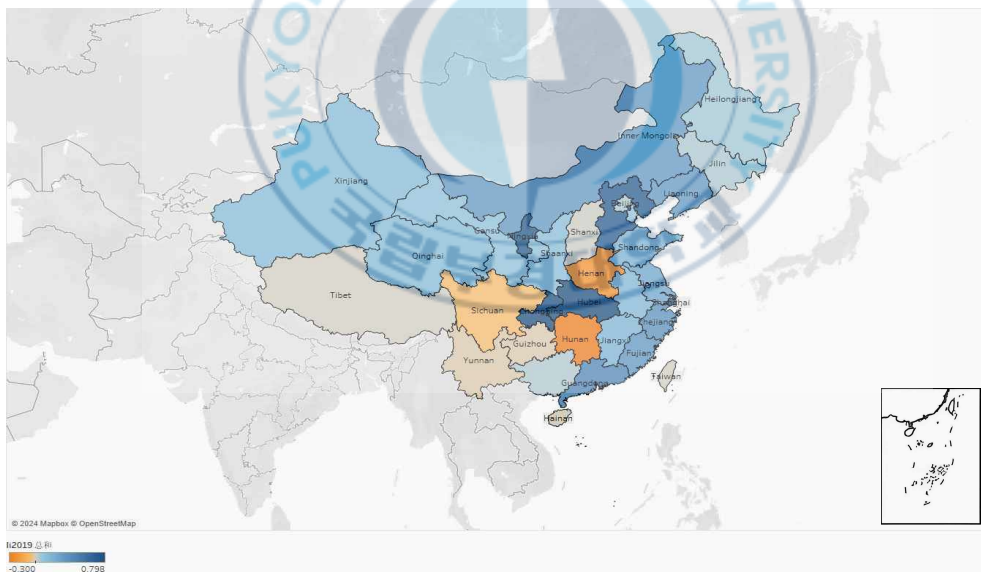


Fig. 2.8. The year of 2019

Fig. 2.5 - 2.8 Temporal and spatial evolution of carbon emission intensity in each province in China

Figures 2.5 to 2.8 is a color scale diagram drawn based on the local Moran I index, which intuitively shows the spatial distribution and changing trend of carbon emission intensity in each province in China. Overall, China's regional carbon emission intensity displays strong spatial clustering, significant spatial homogeneity, and relatively insignificant spatial heterogeneity. This suggests the presence of significant spillover effects in provincial carbon emission intensity, and this clustering trend remains relatively stable throughout the study period.

4.2. Selection of a spatial econometric model

Following Elhorst's (2014) spatial diagnostic framework, this study systematically implement Lagrange Multiplier (LM), Likelihood Ratio (LR), and Hausman tests. Table 2.4 demonstrates all LM tests significantly reject the null hypothesis ($p < 0.01$), confirming simultaneous spatial lag and error dependence. LR tests verify the spatial Durbin model (SDM) neither reduces to spatial error (SEM) nor autoregressive (SAR) models. The Hausman test strongly rejects randomness ($p < 0.01$), supporting fixed effects specification. Further LR tests on SDM constraints confirm two-way fixed effects appropriateness. Consequently, the two-way fixed effect SDM is selected as the primary specification.

Table 2.4 Diagnostic tests for spatial dependence

	Diagnostic tests	Statistic	p-value
LM Test	Moran's I	3.473	0.001
	LM-Error	10.551	0.001
	Robust LM-Error	6.353	0.012
	LM-Lag	26.347	0.000
	Robust LM-Lag	22.149	0.000
LR Test	Assumption: SAR nested within SDM	96.83	0.000
	Assumption: SEM nested within SDM	108.50	0.000
Hausman Test	Ho: difference in coeffs not systematic	44.74	0.000
LR Test for SDM	Assumption: IND nested within Both	89.44	0.000
	Assumption: Time nested within Both	1216.10	0.000

4.3. Spatial econometric analysis

Table 2.5 presents the spatial regression results, indicating a good model fit. The spatial autoregressive coefficient is significant at the 10% level, confirming the presence of spatial spillover effects in carbon emissions intensity across regions. However, the regression coefficients from the Spatial Durbin Model (SDM) do not fully capture the total impact of explanatory variables on the dependent variable. Therefore, it is necessary to examine the direct, indirect, and total effects, as shown in the right section of Table 2.5.

The analysis reveals an inverted U-shaped relationship between industrial agglomeration and carbon emissions intensity. Both the linear and quadratic terms of industrial agglomeration are significant at the 1% level. In the early stages, agglomeration increases energy consumption and carbon emissions intensity due to concentration of production activities. However, once the level of agglomeration

surpasses a threshold (log value of 6.197), scale and concentration advantages become dominant, reducing energy use per unit of output and lowering emissions intensity. This is further supported by the decomposition results: the linear component has a significantly positive direct effect, while the quadratic component has significantly negative direct, indirect, and total effects, reinforcing the inverted U-shape with substantial spatial spillovers.

In contrast, population agglomeration exhibits a U-shaped relationship with carbon emissions intensity. The linear coefficient is significantly negative and the quadratic coefficient is significantly positive. When the logarithm of population agglomeration is below 3.222, urban concentration improves energy efficiency through economies of scale and infrastructure utilization, leading to reduced carbon intensity. However, beyond this threshold, high density increases energy demand for urban services and infrastructure, often relying on less efficient energy systems. The direct, indirect, and total effects all remain significant at the 1% level, highlighting both local and spillover implications.

Turning to control variables, technological investment shows significantly positive direct, indirect, and total effects, implying that in the short term, such investments may not reduce emissions intensity. This may be due to R&D being in an energy-intensive phase or focused on improving productivity rather than environmental outcomes. If such investments prioritize upgrading traditional high-emission industries, they might trigger a rebound effect in carbon emissions

(Wang et al., 2024).

Similarly, the coefficient for trade openness is also significantly positive. This supports the pollution haven hypothesis: international trade activities may lead to increased emissions as polluting industries relocate to China, a global manufacturing hub (Antweiler et al., 2001; Lee & Min, 2015). Thus, trade liberalization should be paired with green standards and environmental thresholds to mitigate negative externalities.

Regarding population structure, the indirect and total effects of aging are significantly positive. An aging population can reduce labor force participation and shift consumption patterns, indirectly raising regional carbon emissions (Zhao et al., 2022). Conversely, the working-age population ratio has significantly negative indirect and total effects, reflecting the positive role of human capital in promoting green technologies and sustainable behaviors (Cole & Elliott, 2003).

As for industrial structure upgrading, although its local effect is insignificant, it may increase emissions in neighboring regions through industrial relocation, verifying the existence of structural spillover effects (Fang et al., 2020). This underscores the importance of coordinated regional industrial policies to avoid transferring pollution rather than reducing it.

In summary, the determinants of carbon emissions intensity exhibit clear spatial heterogeneity and nonlinear spillover effects. The interplay between industrial agglomeration, technological development, population dynamics, and trade openness is complex (Luo et al., 2023). Therefore,

policy design must be region-specific, emphasizing interregional coordination, differentiated strategies for green innovation, and population management to enhance the effectiveness of emission reduction efforts.

Table 2.5. Results of the spatial econometric model

Variables	Estimates	Wis	LR_Direct Effect	LR_Indirect Effect	LR_Total Effect
lnIA	0.471***	-0.259	0.469***	-0.247	0.222
	(0.00)	(0.45)	(0.00)	(0.51)	(0.58)
lnIA ²	-0.038***	-0.022*	-0.039***	-0.029*	-0.068***
	(0.00)	(0.08)	(0.00)	(0.05)	(0.00)
lnPOPU	-3.957***	-7.562***	-4.220***	-9.203***	-13.423***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnPOPU ²	0.614***	1.158***	0.655***	1.410***	2.066***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lnRND	0.105***	0.124**	0.111***	0.154**	0.266***
	(0.00)	(0.03)	(0.00)	(0.01)	(0.00)
lnINDup	0.046	1.291***	0.084	1.467***	1.551***
	(0.62)	(0.00)	(0.38)	(0.00)	(0.00)
lnOPEN	0.047*	0.131***	0.051**	0.154***	0.205***
	(0.05)	(0.01)	(0.03)	(0.01)	(0.00)
lnLAB	-0.167	-2.131**	-0.213	-2.404**	-2.618**
	(0.65)	(0.01)	(0.56)	(0.03)	(0.04)
lnAGING	-0.081	0.719***	-0.057	0.826***	0.770**
	(0.38)	(0.00)	(0.55)	(0.00)	(0.01)
lnperGDP	-0.346***	-0.958***	-0.374***	-1.144***	-1.518***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rho	0.137*				
	(0.05)				
Obs.	510				
R-squared	0.494				
No. of province			30		

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.4. Robustness check

To evaluate the robustness of the regression results, separate regressions are conducted for industrial agglomeration and population concentration based on Equation (2.5). The results are presented in the first and second columns of Table 2.6 (IA, POPU). Although the coefficient of the linear term for industrial agglomeration is not statistically significant, the squared term is significantly negative, indicating an inverted U-shaped relationship between industrial agglomeration and carbon emissions intensity. In contrast, for the model with population concentration as the sole regressor, both the linear and quadratic terms are highly significant, confirming the existence of a U-shaped relationship.

Secondly, to further test the robustness of the regression results, the spatial weight matrix is replaced. Specifically, the traditional gravity model matrix is used instead of the geographic-economic nested matrix in the regression analysis. The results, shown in the fourth column of Table 2.6 (SDM_1), similarly demonstrate significant effects of both industrial agglomeration and population agglomeration on carbon emissions intensity.

In addition, the Spatial Error Model (SEM) and Spatial Autoregressive Model (SAR) are applied, with findings consistent with the baseline regression, further confirming the robustness of the baseline results.

Table 2.6 Robustness check

Variables	IA	POPU	SDM	SDM_1	SAR	SEM
lnIA	0.233		0.471***	0.420**	0.463***	0.473***
	(1.74)		(3.76)	(3.07)	(3.79)	(3.77)
lnIA ²	-0.028***		-0.038***	-0.037***	-0.038***	-0.039***
	(-6.16)		(-8.48)	(-7.10)	(-9.77)	(-9.75)
lnPOPU		-7.562***	-3.957***	-4.235***	-4.284***	-4.265***
		(0.00)	(-6.63)	(-7.33)	(-7.33)	(-6.91)
lnPOPU ²		1.158***	0.614***	0.657***	0.665***	0.664***
		(0.00)	(7.01)	(7.74)	(7.66)	(7.23)
lnRND	0.0947***	0.149***	0.105***	0.103***	0.140***	0.137***
	(3.41)	(5.34)	(4.14)	(4.04)	(5.36)	(5.21)
lnINDup	0.086	-0.135*	0.046	0.133	0.093	0.086
	(0.82)	(-2.32)	(0.49)	(1.39)	(0.95)	(0.84)
lnOPEN	0.041	-0.029	0.047	0.058*	0.035	0.026
	(1.55)	(-1.13)	(1.93)	(2.34)	(1.48)	(1.08)
lnLAB	0.747	0.677	-0.167	-0.405	-0.343	-0.347
	(1.93)	(1.73)	(-0.46)	(-1.09)	(-0.90)	(-0.90)
lnAGING	-0.060	0.156	-0.081	-0.093	0.018	0.006
	(-0.59)	(1.61)	(-0.87)	(-1.01)	(0.20)	(0.07)
lnperGDP	-0.068	-0.310***	-0.346***	-0.341***	-0.329**	-0.314**
	(-0.67)	(-3.35)	(-3.65)	(-3.60)	(-3.26)	(-3.05)
Rho	0.281***	0.248***	0.137*	0.172**	0.270***	
	(4.10)	(3.59)	(1.95)	(2.71)	(4.24)	
Lambda						0.176*
						(2.22)

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5. Brief summary and policy recommendations

This study builds on the classical Environmental Kuznets Curve (EKC) theory by introducing nonlinear variables for agglomeration levels and applying spatial econometric methods. This approach enables a more effective identification of the staged impacts and spatial spillover effects of economic agglomeration on carbon emissions, thereby expanding the theoretical framework of how agglomeration affects emissions. Using panel data from 30 provinces in China for the period 2003 to 2019, this paper employs a spatial econometric model, SDM, to investigate the carbon emission intensity in China. Specifically, we examine the impact of industrial agglomeration and population agglomeration on carbon emission intensity and their spatial spillover effects.

The empirical analysis reveals that from 2003 to 2019, industrial and population agglomeration levels across Chinese provinces generally trended upward, albeit with regional variations. Carbon emission intensity among the 30 provinces exhibited a downward trend, accompanied by strong positive spatial autocorrelation and clustering effects. Within these regions, three agglomeration patterns (High-High, Low-Low, and Low-High) were identified. Furthermore, the empirical results indicate an inverted U-shaped relationship between industrial agglomeration and carbon emission intensity during this period, with notable spatial spillover effects. In contrast, population agglomeration

demonstrates a U-shaped relationship with carbon emission intensity, also accompanied by significant spatial spillovers. Additionally, increased international trade and technology investments in a region are found to elevate carbon emission intensity both locally and in neighboring regions.

This study underscores the need for a clear understanding of the complex interplay between industrial activities, population dynamics, and technological advancements in shaping carbon emission intensity. Based on the empirical findings, we suggest the following policy recommendations for China to help design more effective policies to attain the “3060 dual carbon” targets and advanced green and sustainable development.

First, the correlation between industrial agglomeration and carbon emission intensity manifests an inverted U-shaped trajectory. Initially, augmenting industrial agglomeration escalates carbon emission intensity. However, once economies of scale are achieved, further industrial agglomeration mitigates carbon emission intensity. Consequently, governmental policy should promote increasing agglomeration scale, fostering the holistic advancement of regional industrial clusters, guiding the flow, matching, and agglomeration of production factors, and stimulating cooperative development among regions to enhance the economies of scale stemming from industrial agglomeration.

Secondly, the connection between population agglomeration and carbon emission intensity delineates a U-shaped pattern. This implies that, in the short term, population agglomeration can constrain regional

carbon emission intensity. Nonetheless, with continued urban land expansion and the population mobility dynamics, excessive population agglomeration within urban areas can result in less efficient use of energy and unfavorable shifts in regional carbon emissions. Thus, during the urbanization process, the government should be involved in prudent urban planning, limiting undue concentration of population in certain areas and promoting the transition to eco-friendly and clean energy applications in the residential and transportation sectors. Furthermore, emphasis should be placed on the development and efficient use of low-carbon and clean energy, as well as the research and development of low-carbon and clean technologies to steer green urban development and address the root causes of high carbon emissions.

Overall, the research findings of this paper indicate that the impact of economic agglomeration, population agglomeration, and various social factors on carbon emission intensity in China is complex and exhibits spatiotemporal differences. Therefore, policymakers, in advancing the carbon peak and carbon neutrality goals, need to adopt flexible and effective policy measures based on the specific circumstances of different regions to promote green and sustainable development. This not only aligns with China's long-term development strategy but also contributes to addressing global climate change issues.

CHAPTER 4

The Impact of Technological Innovation on Regional Carbon Emission Intensity

1. Introduction

Since the industrial revolution, the global economy has experienced significant growth, with rapid industrialization and urbanization greatly promoting human survival and development. However, this extensive economic development model, relying on high energy consumption, has also exerted enormous pressure on the global ecological environment. Climate change, characterized by global warming, has posed a threat to ecosystems and human health (Li et al., 2016). Continuous greenhouse gas emissions further exacerbate these risks, potentially leading to economic stagnation, public health deterioration, food and water shortages, increased extreme weather events, and rising sea levels, especially in underdeveloped and ecologically fragile regions (Mora, 2018). Governments around the world are actively advancing energy-saving and emission-reduction policies to address the challenges posed by global warming. According to the assessment report of the Intergovernmental Panel on Climate Change (IPCC), human activities leading to massive fossil fuel consumption and CO₂ emissions are the

primary causes of global warming (Minx et al., 2011). To effectively control CO₂ emissions, the international community has signed the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Agreement, aiming to promote global cooperation on emissions reduction and sustainable development.

As the largest carbon emitter in the world, China submitted its Intended Nationally Determined Contributions (INDC) to the Secretariat of the United Nations Framework Convention on Climate Change in June 2015, clearly committing to peak carbon emissions around 2030 and increase the share of non-fossil energy in primary energy consumption to 20%. In September 2020, President Xi Jinping (2020) further proposed during the 75th United Nations General Assembly debate that “China will enhance its nationally determined contributions, implement more effective policies and measures, aim to peak carbon dioxide emissions before 2030, and strive to achieve carbon neutrality before 2060”. Against this backdrop, China faces increasing pressure to save energy and reduce emissions, with the key to achieving this goal lying in technological innovation and the decarbonization of the energy structure. Therefore, the impact of technological innovation on energy conservation and carbon reduction in China is worth further exploration.

Over the past 40 years since China’s reform and opening-up, the economy has continued to grow, making China the world’s second-largest economy. China’s economic development model has entered a transition phase from factor-driven and investment-driven to innovation-driven (Liu et al., 2017). Technological innovation is a crucial

factor in innovation-driven national development. It benefits the development and application of new environmental protection technologies in industrial enterprises, optimizes traditional industries, and promotes the progress of emerging industries. This will affect the efficiency of natural resource utilization (Miao et al., 2017). Additionally, technological innovation will help develop new energy sources, such as wind, solar, and tidal energy, to replace high-emission fossil fuels. However, if the goal of technological innovation is not energy conservation and carbon reduction but rather improving production efficiency and expanding production scale, it could lead to increased energy consumption and carbon emissions (Shao et al., 2013). China is vast, with significant regional development disparities, and regional technological innovation capabilities are also highly uneven. Therefore, the impact of regional technological innovation levels on carbon emission intensity deserves significant attention. Does technological innovation have a differential impact on carbon emission intensity at varying innovation levels? How does technological innovation affect carbon emission intensity at different quantiles? To explore these issues in depth, this study uses panel data from 30 Chinese provinces between 2005 and 2019, applies the entropy method to quantify regional technological innovation capabilities, and employs panel threshold regression and panel quantile regression models for analysis. The study aims to reveal the mechanism through which technological innovation levels affect regional carbon emission intensity and provide empirical support for promoting China's low-carbon sustainable development.

The structure of the remaining chapters is arranged as follows: Section 2 presents the preceding research in related fields. Section 3 constructs the theoretical model and describes the data sample. Section 4 discusses and analyzes the empirical test results. Section 5 brief summary and policy recommendations are provided.

2. Literature review

The factors influencing carbon emissions are complex and diverse, among which technological innovation is one of the key factors in addressing climate change and controlling carbon emissions (Xu et al., 2020). As a result, many scholars both domestically and internationally have conducted in-depth studies on the impact of technological innovation on carbon emissions. Existing literature generally believes that the impact of technological innovation on regional carbon emissions exhibits a dual effect.

On the one hand, technological innovation has a positive effect on emission reduction. This positive effect mainly stems from improvements in energy utilization efficiency, cost savings, and various technological spillover effects. Manne et al. (2004) pointed out that ignoring endogenous technological progress may lead to an overestimation of the negative impact of economic growth on the environment. Gerlagh (2007) further pointed out that the value of technological progress mainly lies in reducing carbon reduction costs and further promoting emission reductions through learning effects.

Additionally, Li & Li (2010) used a dynamic panel model to analyze the impact of population, economy, and technology on carbon dioxide emissions. The results showed that technological progress alleviated carbon emission pressure to some extent. Li & Niu (2014) used both static and dynamic panel models to further validate the significant inhibitory effect of technological progress on carbon emissions. Wei & Yang (2010) combined endogenous growth theory with environmental pollution models to analyze the impact of technological progress on carbon dioxide emissions. The study found that technological progress significantly promoted carbon reduction, but this effect exhibited noticeable regional differences.

In conclusion, although technological innovation shows positive effects in emission reduction, its impact exhibits certain heterogeneity due to regional and developmental differences. Therefore, further research on the specific effects of technological innovation across regions on carbon emissions is of significant theoretical and practical importance.

On the other hand, technological innovation may have a promoting effect on regional carbon emissions. Specifically, with the concentration of economic activities, the improvement in technological innovation levels may lead to an increase in carbon emissions, thereby exacerbating environmental pollution. Such studies emphasize the negative externalities brought about by technological innovation. Berkhout et al. (2000) analyzed and pointed out that this phenomenon is closely related to the “rebound effect” of energy. Although technological

innovation can improve energy efficiency and save resources, it may lead to a decrease in the production cost and price of each product, stimulating demand and consumption growth, ultimately offsetting the energy savings brought about by technological innovation through the additional energy consumption. Wu et al. (2018) found that the existence of the rebound effect makes the role of technological progress in improving carbon emission efficiency relatively limited compared to the scale of economic growth. Yang & Li (2017) concluded that technological progress, in the presence of rebound effects, may not effectively reduce carbon emissions. Cheng et al. (2018) further argued that when studying the impact of technological progress on carbon emissions, it is necessary to consider the indirect effects of industrial structure upgrade optimization and upgrading. Zhang et al. (2014) also pointed out that there are significant regional differences in the impact of technological innovation levels on carbon emissions, and in their empirical study, they found a significant positive correlation between the level of technological innovation and carbon emissions in central China. This difference mainly arises from the disparities in the economic foundation and technological development levels of different regions.

A review of existing research reveals that many scholars have focused on the impact of technological innovation on carbon emissions and conducted in-depth discussions, but there are still certain discrepancies in the research conclusions. As one of the key factors in addressing climate change and reducing carbon emissions, technological innovation remains an important area worthy of further study. China,

within the framework of its past extensive development model, is facing increasingly limited space, and the urgent need to transition to high-quality development is becoming more evident. In this process, innovation, as the core driving force of economic development and a key component of the new development concept, faces an increasingly sharp contradiction between technological innovation and environmental pollution. Especially in the context of achieving peak carbon emissions and carbon neutrality, promoting low-carbon innovation development has become urgent (Jing & Zhang, 2014). Given the differences in development levels across regions in China, this study uses panel threshold regression and panel quantile regression models, utilizing panel data from 30 Chinese provinces to analyze the impact of technological innovation on carbon emission intensity at different stages of development. It explores the potential non-linear relationship between technological innovation and carbon emission intensity, providing empirical support for the formulation of policies for China's low-carbon development.

3. Methodology and data

3.1. Methodology

In this study, we use the Population, Affluence, and Technology (STIRPAT) model with random effects to examine the impact of technological innovation on regional carbon emissions intensity in China. The STIRPAT model (Dietz & Rosa, 1994) is based on the premise that population, affluence, and technology are key determinants of environmental impact. The model provides a robust analytical framework that quantitatively evaluates how changes in these factors are associated with changes in carbon emissions intensity, thereby providing a detailed analysis of the specific contribution of technological progress to regional environmental impacts. The standard expression of the STIRPAT model is as follows:

$$I = aP_i^b A_i^c T_i^d \epsilon \quad (3.1)$$

Where, environmental impact (I) is the dependent variable, while the explanatory variables include population (P), affluence (A), and technology (T). The elasticity coefficients b, c, and d of these variables reflect their sensitivity to environmental impact. Additionally, the model includes a fixed effect (*a*) and a random error term (ϵ) to account for unobserved heterogeneity and potential random fluctuations.

This study places particular emphasis on the level of technological innovation which serves as the core explanatory variable. Other potential determinants are included as control variables to isolate the effect of innovation on the dependent outcome. To facilitate regression analysis and improve the interpretability of the estimated coefficients, the model is log-linearized by taking the natural logarithm of both sides of the equation. The resulting general linear form of the model is expressed as follows:

$$\ln I_i = a + b(\ln P_i) + c(\ln A_i) + d(\ln T_i) + \epsilon_i \quad (3.2)$$

3.2. Unit root test

To prevent the occurrence of spurious regression, it is essential to conduct unit root tests on each panel data series prior to model construction and parameter estimation. Unit root testing methods can be broadly classified into three generations: the initial first-generation method, the continuously developing second-generation method, and the advanced third-generation method.

Commonly used panel unit root tests include the Levin, Lin, and Chu (LLC) test; the Im, Pesaran, and Shin (IPS) test; the Breitung test; the Hadri-Tzavalis (HT) test; and the Fisher-type Augmented Dickey-Fuller (Fisher-ADF) test. Given the presence of cross-sectional dependence in the dataset examined in this study, it is necessary to

adopt unit root tests that explicitly account for such correlation. Accordingly, this study employs the IPS test proposed by Im et al. (2003), which allows for heterogeneity in the autoregressive coefficients across cross-sectional units and is suitable for panels with cross-sectional dependence.

The regression specification used for the IPS unit root test is as follows:

$$\Delta y_{i,t} = Z'_{i,t} \gamma_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p_i} \rho_{ij} \Delta y_{i,t-1} + \epsilon_{i,t}, \quad (3.3)$$

$$i = 1, \dots, N, t = 1, \dots, T,$$

where, $y_{i,t}$ represents the observation for region i at time t , and β_i represents the autoregressive parameter specific to region i . $Z'_{i,t} \gamma_i$ represents the individual fixed effect and the linear time trend. This representation accommodates the unique characteristics of each region in the dataset, while considering any linear trends over time. On the other hand, $\epsilon_{i,t}$ is characterized as a series of independently distributed normal variables, each with a mean of zero and finite variance, potentially exhibiting heterogeneity. When autocorrelation in the disturbance term $\epsilon_{i,t}$ exists, it can be effectively addressed by incorporating lagged differences into the model. The appropriate lag order is represented by p_i , which may differ across individuals in the dataset. The optimal lag order for each case can be precisely determined using information criteria, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), which

assess the trade-off between model fit and complexity.

3.3. Panel threshold model

Economic laws often exhibit nonlinearity, where the functional form may change with variations in specific variables. Therefore, nonlinear models are essential for studying such relationships. Integrating nonlinear characteristics with panel data models leads to the development of static panel threshold models. The static panel threshold model proposed by Hansen (1999) overcomes the linearity assumption of traditional panel models, effectively analyzing the nonlinear relationships between economic variables, which holds great significance for practical economic analysis.

Based on whether the threshold variable is endogenous, static panel threshold models can be categorized into exogenous threshold variable models and endogenous threshold variable models. Specifically, this study adopts a static panel threshold model based on exogenous threshold variables to empirically analyze the nonlinear relationship between regional technological innovation levels and carbon emission intensity in China.

The basic form of the panel data threshold model constructed by Hansen (1999) is as follows:

$$\begin{cases} \ln Y_{i,t} = \mu_i + \beta_1 \ln X_{i,t} + \epsilon_{i,t}, & (q_{i,t} \leq \gamma) \\ \ln Y_{i,t} = \mu_i + \beta_2 \ln X_{i,t} + \epsilon_{i,t}, & (q_{i,t} > \gamma) \end{cases} \quad (3.4)$$

The essence of the model is a piecewise function model. In eq. (3.4), Y represents the dependent variable, and X is the vector of explanatory variables. q_{it} denotes the threshold variable, and γ is the threshold to be estimated. When $q_{it} \leq \gamma$ the coefficient to be estimated is β_1 ; when $q_{it} > \gamma$, the coefficient to be estimated is β_2 , ϵ_{it} is the disturbance term, which is independently and identically distributed. By employing the indicator function $I(\cdot)$, the threshold model can be rewritten in a more concise form:

$$\text{Ln } Y_{i,t} = \mu_i + \beta_1 \text{Ln } X_{i,t} I(q_{i,t} \leq \gamma) + \beta_2 \text{Ln } X_{i,t} I(q_{i,t} > \gamma) + \epsilon_{i,t} \quad (3.5)$$

The indicator function takes values of 0 or 1. When the condition $q_{it} \leq \gamma$ is satisfied, the value of the indicator function is 1; otherwise, it is 0. When the condition $q_{it} > \gamma$ is satisfied, the value of the indicator function is 1; otherwise, it is 0. For panel data with a large sample size and T being relatively small compared to n , $X_{i,t}(\gamma)$ can be defined as follows:

$$\text{Ln } X_{i,t}(\gamma) = \begin{cases} \text{Ln } X_{i,t} I, & (q_{i,t} > \gamma) \\ \text{Ln } X_{i,t} I, & (q_{i,t} \leq \gamma) \end{cases} \quad (3.6)$$

Let $\beta = \begin{cases} \beta_1 \\ \beta_2 \end{cases}$, then the threshold model can be expressed in a more concise form as:

$$\text{Ln } Y_{i,t} = \mu_i + \beta \text{Ln } X_{i,t}(\gamma) + \epsilon_{i,t} \quad (3.7)$$

In this study, the data spans 15 years, covering 30 regions in China from 2005 to 2019. This temporal framework and geographic scope are represented as $i=1,2,\dots,30$ for regions and $t=1,2,\dots,15$ for years. The dependent variable $\text{Ln}Y_{i,t}$ represents the natural logarithm of carbon emission intensity in region i during year t , while $\text{Ln}X_{i,t}$ represents the explanatory variables. When $q_{it} \leq \gamma$ and $q_{it} > \gamma$, the influence coefficients of the explanatory variables on the dependent variable are represented by β_1 and β_2 , respectively. Individual fixed effects are denoted as μ_i , and the error term is denoted as ϵ_{it} . The threshold variable is represented by q_{it} , and the threshold value is represented by γ .

Based on the estimation of threshold values and variable coefficients, further tests of the empirical results are required. Threshold model testing primarily includes two components: (1) testing the significance of the threshold effect to determine whether it exists and (2) verifying the accuracy of the threshold estimate by constructing the asymptotic distribution and likelihood ratio (LR) statistics using the bootstrap method. The significance of the threshold effect is determined by examining whether there is a significant difference between β_1 and β_2 . If $H_0: \beta_1 = \beta_2$ is accepted, it indicates that no threshold effect exists. If H_0 is rejected, it indicates the presence of a threshold effect. This test is performed by constructing an F-statistic.

$$F = \frac{S_0 - S_1(\hat{\gamma})}{\sigma^2} \quad (3.8)$$

where, S_0 represents the sum of squared residuals under the null hypothesis, while S_1 represents the total sum of squared residuals when the threshold effect is present. Under the null hypothesis, γ is not specified, so the F-statistic does not follow a standard χ^2 distribution but rather a non-standard non-similar distribution, making it impossible to derive its critical value. Therefore, the bootstrap method proposed by Hansen (1996) is employed to simulate its asymptotic distribution and obtain the corresponding p-value for evaluation.

Once the existence of a threshold effect in the model is confirmed, the maximum likelihood method proposed by Hansen (1999) is applied to test the confidence interval of γ . To test the null hypothesis $H_0 : \gamma = \gamma_0$ the likelihood ratio test statistic is given by:

$$LR(\gamma) = \frac{S(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad (3.9)$$

The distribution of the LR statistic remains a non-standard normal distribution. However, Hansen calculated the critical value based on its cumulative distribution function to determine the rejection region. Specifically, the null hypothesis is rejected if $LR(\gamma) > -2\log(\sqrt{1-\alpha})$, where α represents the specified significance level. When the significance level is set at 95%, the corresponding critical value for LR (γ) is 7.35. Based on the magnitude of LR(γ), the confidence interval of the threshold estimate can be tested.

The panel threshold model not only reveals the nonlinear effects

between variables but also improves estimation accuracy and interpretability while controlling for heterogeneity. It is particularly suitable for analyzing structural relationships in complex economic and social issues.

3.4. Quantile regression

Quantile regression, originally introduced by Koenker and Bassett (1978), is a statistical technique that extends traditional regression analysis by estimating the conditional quantiles of the dependent variable, rather than solely focusing on the conditional mean as in ordinary least squares (OLS) regression. This approach enables researchers to capture the full distributional characteristics of the dependent variable, offering deeper insights into the nature of the relationships among variables – particularly in the presence of heterogeneity, non-linearity, or asymmetric distributions.

In the context of this study, building upon Equation (3.10), a panel quantile regression model is developed to investigate the heterogeneous effects of technological innovation on carbon emission intensity across different quantile levels. This model allows for a more nuanced understanding of how technological innovation influences regions with varying emission intensities. The formal specification of the panel quantile regression model is presented as follows:

$$\text{Ln } Y_{it} = \alpha_i + \beta_i \text{Ln } X_{it} + \epsilon_{it} \quad (3.10)$$

In this model, i and t represent the region and year, respectively; Y_{it} is the dependent variable; α_i denotes the individual fixed effects; β_i is the coefficient to be estimated; X_{it} represents the explanatory variables; and ϵ_{it} is the error term.

To simplify the model and reduce the number of parameters to be estimated, we assume that individual fixed effects do not vary across quantiles. The detailed formula of the overall quantile function is given by eq. (3.11):

$$QY_{it}(\tau|\alpha_i, X_{it}) = \alpha_i + \beta(\tau)X_{it} \quad (3.11)$$

where, $QY_{it}(\tau|\alpha_i, X_{it})$ represents the conditional expectation of the dependent variable Y_{it} at quantile τ , given the individual effect α_i and the explanatory variable X_{it} ; the parameter $\beta(\tau)$ denotes the coefficient to be estimated at quantile τ , reflecting the impact of the explanatory variable on the dependent variable at different quantile levels.

To estimate the parameters of the conditional distribution at quantile τ , the objective function is as follows:

$$\hat{\beta}(\tau) = \min_{\alpha, \beta} \sum_{j=1}^J \sum_{i=1}^N \sum_{t=1}^T \omega_j \rho_{\tau_j}(Y_{it} - \alpha_i - \beta(\tau)X_{it}) \quad (3.12)$$

$\hat{\beta}(\tau)$ represents the estimated value at quantile τ , ω_j denotes the weights that control the influence of different quantiles $\{\tau_1, \tau_2, \dots, \tau_j\}$

during the estimation process. ρ_{τ_j} is the control parameter of the objective function, reflecting the residual contributions at different quantile levels. The calculation of ρ_{τ_j} is given in eq (3.13):

$$\rho_{\tau_j} = \begin{cases} \tau_j - 1, & \text{if } Y_{it} < \alpha_i + \beta(\tau)X_{it} \\ \tau_j, & \text{if } Y_{it} \geq \alpha_i + \beta(\tau)X_{it} \end{cases} \quad (3.13)$$

This model facilitates the examination of how technological innovation influences carbon emission intensity across different points in its conditional distribution, thereby capturing the non-equilibrium effects of technological innovation. By employing a quantile regression approach, the analysis uncovers the heterogeneous mechanisms through which technological innovation affects regions with varying levels of carbon emission intensity—particularly distinguishing between high- and low-emission regions. Such insights contribute to a more nuanced understanding of policy needs and provide a scientific foundation for the formulation of region-specific environmental and innovation strategies.

Moreover, quantile regression is well-suited to address issues of heterogeneity and non-normality in the data distribution. Compared to conventional mean-based regression methods, it offers enhanced flexibility and robustness, making it a more appropriate tool for analyzing complex relationships in environmental and technological datasets.

3.5 Data description

In order to ensure the consistency and continuity of the data, 30 provinces in China from 2005 to 2019 were selected as research objects for analysis.⁷⁾ Due to the potential data anomalies caused by the external shocks of the COVID-19 pandemic after 2019, this study excludes post-2019 data to maintain research robustness and minimize noise.

To account for the multifaceted determinants of carbon emission intensity, the model incorporates a range of socio-economic variables identified in prior literature as key influencing factors. These include the level of technological innovation (measured through a composite index constructed via the entropy method), industrial structure upgrading (proxied by the ratio of value added in the tertiary sector to that in the secondary sector), trade openness (measured as the ratio of total imports and exports to regional GDP), the working-age population share (defined as the proportion of individuals aged 15-64 within the total population), population aging (the percentage of individuals aged 65 and above), and the level of economic development (measured by real per capita GDP) (Dai et al., 2019; Luo et al., 2023; Wang et al., 2018; Yan et al., 2011; Yuan & Hwang, 2023).

The dataset is compiled from authoritative sources: carbon emission data are obtained from the *China Stock Market and Accounting Research* (CSMAR) Database (2024); Technological innovation are

7) Due to limited data availability, this study selected 30 provinces excluding Hong Kong, Macao, Taiwan and Tibet as research objects.

derived from the *China Science and Technology Statistical Yearbook* and the *China Statistical Yearbook* (NBS, 2024); population and GDP statistics are sourced from the *China Statistical Yearbook*; energy-related data are drawn from the *China Energy Statistical Yearbook*; and industrial structure indicators are taken from the *China Industrial Statistical Yearbook*. All monetary variables have been deflated using 1992 as the base year to ensure consistency in real terms and eliminate the effects of inflation.

Table 3.1 presents detailed definitions and measurement methods for all variables employed in this study, thereby facilitating a clear understanding of their conceptual and empirical construction. Table 3.2 reports the descriptive statistics of these variables across the 30 sampled provinces over the study period.

It is noteworthy that, in alignment with the requirements of the STIRPAT modeling framework, all continuous variables were transformed using the natural logarithm prior to analysis. This transformation not only ensures consistency with the model's theoretical assumptions but also helps stabilize variance and mitigate potential skewness in the data distribution. Accordingly, the descriptive statistics presented in Table 3.2 reflect the logarithmically transformed values. All subsequent empirical estimations are likewise based on these log-transformed variables

Table 3.1. Description and source of variables

Variables	Unit	Definition measuring method	Data source
Carbon emission intensity (CEI)	tons/10,000 (¥)	total carbon emissions/RGDP	CSMAR, NBS
Technological innovation (INNO)	/	entropy method composite scores	NBS
Industrial structure upgrade (INDup)	/	ratio of value added in the tertiary industry to value added in the secondary industry	NBS
Industrial agglomeration (IA)	%	ratio of industrial value added to the area of regional administrative division	NBS
Trade openness (OPEN)	%	total exports and imports as a percentage of RGDP	NBS
Working-age population (LAB)	%	those aged between 15–64 years as a percentage of the total population	NBS
Population aging (AGING)	%	percentage of the population aged 65 and above in the total population	NBS
Urbanization rate (POPU)	%	proportion of the permanent population in the urban areas of a region to the total permanent population in that region	NBS
Economic growth (perGDP)	%	per capita real RGDP (constant ¥ 1992)	NBS

Table 3.2. Descriptive statistics

Variables	Obs.	Mean	Median	Std. Dev.	Min.	Max.
lnCEI	450	0.845	0.828	0.669	-1.121	2.586
lnINNO	450	-2.061	-2.126	0.850	-4.763	0.359
lnINDup	450	0.071	0.028	0.384	-0.640	1.655
lnIA	450	10.194	10.240	1.633	5.222	13.985
lnIA ²	450	106.582	104.855	32.735	27.271	195.588
lnOPEN	450	2.885	2.619	0.980	0.238	5.149
lnLAB	450	4.293	4.290	0.050	4.150	4.429
lnAGING	450	2.260	2.290	0.210	1.700	2.789
lnPOPU	450	3.965	3.969	0.252	3.291	4.497
lnPOPU ²	450	15.786	15.752	2.001	10.830	20.226
lnperGDP	450	9.685	9.711	0.600	7.911	11.084

4. Empirical analysis

4.1 Unit root test

To ensure the validity of the regression analysis and mitigate the risk of spurious regression, this study first conducted unit root tests on the panel data. Establishing the stationarity of the variables is a prerequisite for reliable econometric estimation, particularly in panel data models. Accordingly, unit root tests were performed to examine whether the data series are stationary over time. The results of these tests are summarized in Table 3.3.

Table 3.3. Unit root test results

Variables	IPS-ADF test statistic
	level
lnCEI	-2.332***
lnINNO	-2.415***
lnIA	-4.913***
lnPOPU	-6.670***
lnINDup	-5.634***
lnOPEN	-4.831***(First order difference)
lnLAB	-4.035***
lnAGING	-2.955***
lnperGDP	-10.560***

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The unit root test results indicate that all variables are stationary

at an acceptable significance level. Notably, the variable $\ln\text{OPEN}$ (trade openness) exhibited stationarity after first-differencing when assessed using the IPS test, demonstrating its robustness under this method. This outcome suggests that the applied data transformations effectively mitigated issues related to non-stationarity, thereby enhancing the reliability and validity of the subsequent econometric analyses.

4.2. Linear regression analysis using the panel threshold model

4.2.1. Threshold effect test

In order to further explore the relationship between regional technological innovation levels and carbon emission intensity, this section conducts an analysis based on the panel threshold model. The following results reveal the threshold effect characteristics at different innovation levels across regions, providing an in-depth perspective for understanding regional differences. Based on the nationwide, eastern, central and western regions.⁸⁾

8) Eastern Region: Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Anhui, Fujian, Shanghai, Guangdong, Guangxi, Hainan. Central Region: Heilongjing, Jilin, Shanxi, Henan, Hubei, Hunan, Jiangxi. Western Region: Inner Mongolia, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Xinjiang, Ningxia. (Excluding Tibet Autonomous Region, Taiwan, Hong Kong Special Administrative Region, Macau Special Administrative Region.)

Table 3.4. Threshold effect test results

Regions	Threshold number	F-value	Threshold estimated value	95% confidence interval
Nationwide	Single	44.35***	-0.427	(-0.531, -0.239)
	Double	33.34**	-3.336	(-3.386, -3.335)
	Triple	22.87	-2.760	(-2.776, -2.754)
Eastern region	Single	44.04***	-0.008	(-0.119, 0.027)
	Double	31.61**	-3.797	(-4.257, -3.323)
	Triple	16.88	-1.700	(-1.716, -1.681)
Central region	Single	8.13	-2.670	(-2.695, -2.647)
	Double	0.98	-2.585	(-2.585, -2.559)
	Triple	5.33	-2.280	(-2.290, -2.278)
Western region	Single	34.00***	-2.825	(-2.870, -2.814)
	Double	21.60***	-3.336	(-3.407, -3.335)
	Triple	10.04	-2.667	(-2.684, -2.658)

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

According to the analysis in Table 3.4, when regional technological innovation levels are used as threshold variables, all regions except for the central region exhibit threshold effects, and there is a dual threshold effect on the impact of carbon emission intensity. From a nationwide perspective, the regional technological innovation level shows a dual threshold effect on carbon emission intensity, which holds true at both the 1% and 5% significance levels, with thresholds of -0.427 and -3.336, respectively. When the regional technological innovation level reaches or exceeds 0.652 ($\ln 0.652 = -0.427$) and 0.036 ($\ln 0.036 = -3.336$), the estimated parameters in the model undergo significant changes.

In the eastern region, the regional technological innovation levels

exhibit threshold effects on carbon emission intensity at values of -3.797 and -0.008. This suggests that when the technological innovation level reaches or exceeds 0.022 ($\ln 0.022 = -3.797$) and 0.992 ($\ln 0.992 = -0.008$), the impact of technological innovation on carbon emission intensity experiences significant shifts, leading to a notable change in the relationship.

In the western region, the dual threshold effect of regional technological innovation levels on carbon emission intensity is also significant at the 1% level, with thresholds of -3.336 and -2.825. When the regional technological innovation level reaches or exceeds 0.036 ($\ln 0.036 = -3.336$) and 0.06 ($\ln 0.06 = -2.825$), the effect on carbon emission intensity will also change.

After testing the thresholds, this study uses the likelihood ratio statistic as a benchmark to test the thresholds, with the formula $LR(\alpha) = -2 \ln [1 - (1 - \alpha)^{1/2}]$ where α represents the significance level. When $\alpha = 5\%$, $LR(\alpha) \approx 7.35$. All likelihood ratios less than 7.35, which is the critical value at the 5% significance level, form the 95% confidence interval for the regional technological innovation level threshold estimates, i.e., the region below the dashed line. The likelihood ratio functions related to the threshold test are shown in Fig. 3.1 - 3.3.

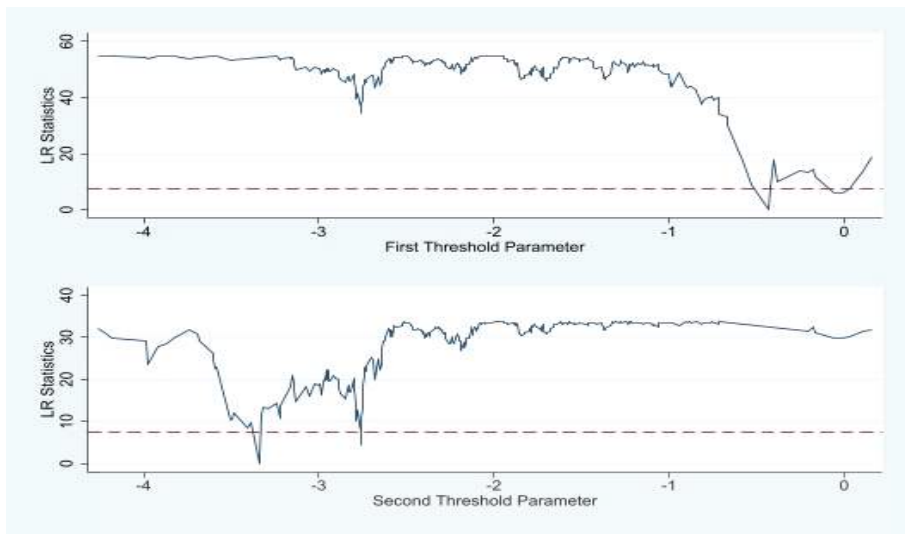


Fig. 3.1. LR diagram with the threshold variables (Nationwide)

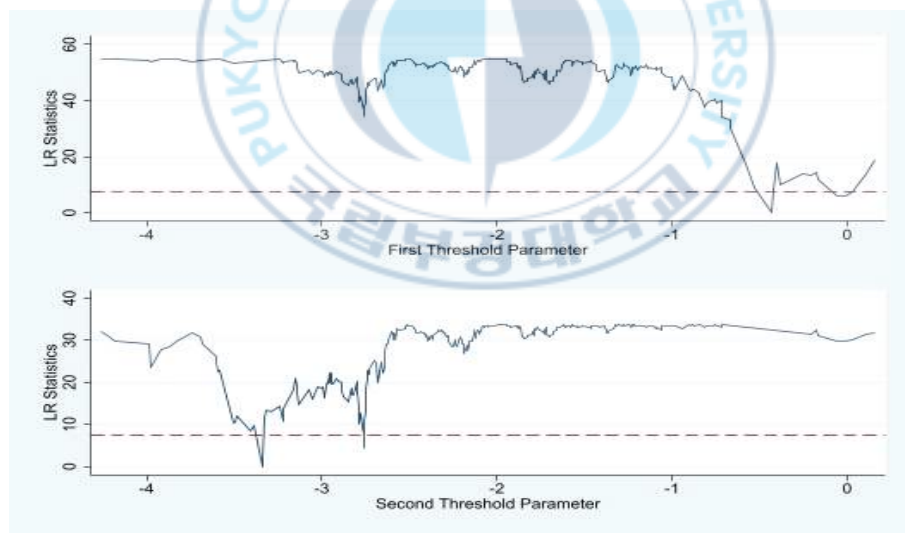


Fig. 3.2. LR diagram with the threshold variables (Eastern region)

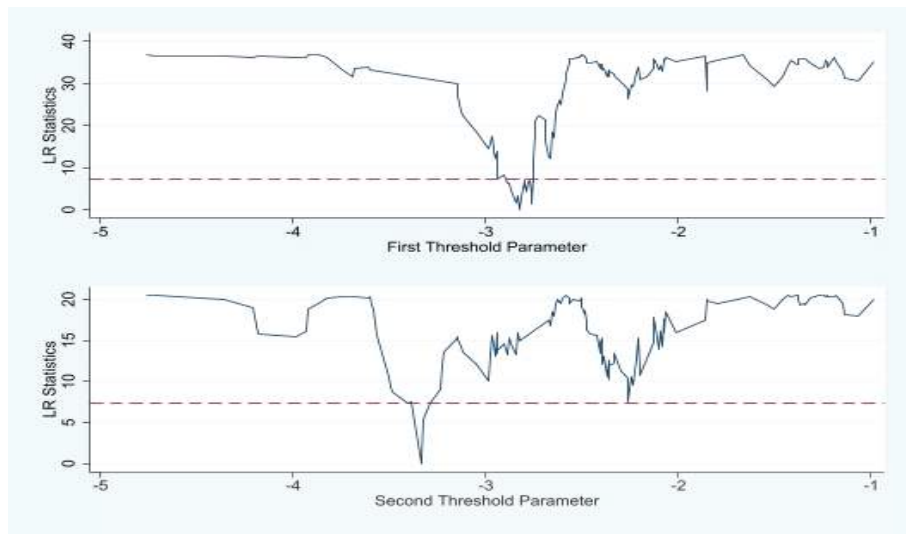


Fig. 3.3. LR diagram with the threshold variables (Western region)

4.2.2 Regression analysis of the threshold effect of regional technological innovation level

This study uses a panel threshold model to explore the impact of regional technological innovation levels on carbon emission intensity. The specific regression results are shown in Table 3.5. The analysis reveals that, after controlling for other variables. There is a threshold-related pattern in the relationship between regional technological innovation levels and carbon emission intensity. The specific analysis results are as follows:

(1) From a nationwide perspective, when regional technological innovation ≤ 0.356 , the correlation coefficient with carbon emission intensity is -0.049 (not statistically significant), indicating a weak

negative correlation between low-level technological innovation and emission reductions. As technological innovation levels increase from 0.036 to 0.652, the negative correlation with carbon emission intensity strengthens (coefficient = -0.129) but remains statistically insignificant, suggesting only a modest association in this range. When technological innovation > 0.652 , the correlation coefficient falls to -0.883 (significant at 5%), indicating that high level technological innovation is strongly correlated with systemic low-carbon performance and the adoption of energy-efficient and clean technologies.

(2). In the eastern region, technological innovation and carbon emission intensity exhibit a correlational pattern of initial positive association followed by negative association. When technological innovation ≤ 0.022 , the correlation coefficient with carbon emission intensity is +0.296, reflecting a positive association that may relate to higher resource and energy consumption at early stages. As technological innovation increases beyond 0.022, the positive correlation with emission intensity weakens (coefficient = +0.170), which may correlate with gradual adoption of energy-saving technologies and process optimizations. When technological innovation > 0.992 , the correlation coefficient becomes -1.379 (significant), indicating a strong negative association that may coincide with the adoption of advanced low-carbon technologies and energy management practices.

(3). In the western region, the negative correlation between technological innovation and carbon emission intensity strengthens as technological innovation levels increase. The correlation coefficient

becomes more negative—moving from -0.467 to -0.567 and -0.639 —with increasing statistical significance. At technological innovation ≤ 0.036 , the negative association with emission reductions is modest, which may reflect primarily local process optimizations. When technological innovation > 0.06 , the negative correlation with emissions (-0.639) becomes more pronounced, which may coincide with stronger efficiency gains.



Table 3.5. Regression analysis of threshold effects

Variables	Nationwide	Western region	Eastern region
$q_{i,t} \leq \gamma_0$	-0.049	-0.467**	0.296**
	(-0.54)	(-4.47)	(4.36)
$\gamma_0 < q_{i,t} \leq \gamma_1$	-0.129	-0.567***	0.170*
	(-1.49)	(-4.92)	(2.39)
$q_{i,t} > \gamma_1$	-0.883**	-0.639***	-1.379***
	(-3.15)	(-5.56)	(-5.53)
lnIA	0.822*	0.899***	-1.025
	(2.28)	(4.94)	(-1.33)
lnIA ²	-0.046**	-0.022	0.009
	(-3.10)	(-2.13)	(0.36)
lnPOPU	-10.25**	-9.756*	4.530
	(-3.52)	(-2.96)	(0.74)
lnPOPU ²	1.382**	1.141*	-0.512
	(3.57)	(2.40)	(-0.66)
lnINDup	-0.018	0.354	-0.608
	(-0.11)	(1.50)	(-2.17)
lnOPEN	0.039	-0.06	0.212*
	(0.95)	(-1.53)	(2.26)
lnLAB	0.632	-1.240	0.136
	(0.69)	(-0.70)	(0.15)
lnAGING	-0.089	-0.177	0.003
	(-0.50)	(-0.59)	(0.01)
lnperGDP	-0.715***	-0.687*	0.197
	(-4.00)	(-3.02)	(0.47)
_cons	20.19**	26.21**	-1.783
	(3.42)	(3.32)	(-0.16)
Obs.	450	165	165
R-squared	0.897	0.905	0.945

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3 Panel quantile model linear regression analysis

In this section, we build a panel quantile regression model to analyze the mechanism of technological innovation levels across different distributions of carbon emission intensity. Below are the specific estimation results of the model.

Technological innovation is significantly negatively correlated with carbon emission intensity across all quantiles, with a stronger negative correlation at higher quantiles (QR_70 to QR_90). For example, at the QR_90 quantile, the coefficient is -0.305 , reaching a 1% significance level. This suggests that in high-carbon emission intensity regions, the marginal effect of technological innovation on optimizing resource allocation and improving energy efficiency is more pronounced, further emphasizing the critical role of technological innovation in achieving low-carbon development.

Industry agglomeration and its square term exhibit a typical inverted U-shape relationship. In the early stages, industry agglomeration is positively correlated with carbon emission intensity, likely reflecting high energy consumption in concentrated industries; at later stages, deeper agglomeration shows a negative correlation with emission intensity, possibly via technological spillovers and economies of scale. This decreasing effect is particularly evident at higher quantiles (QR_80 to QR_90), indicating that industry agglomeration has a stronger carbon reduction effect in high-carbon emission intensity regions.

Table 3.6. Estimation results of the quantile regression model analyzing the impact of technological innovation on carbon emission intensity

Variables	QR_10	QR_20	QR_30	QR_40	QR_50	QR_60	QR_70	QR_80	QR_90
lnINNO	-0.212***	-0.194***	-0.182***	-0.172***	-0.178***	-0.254***	-0.259***	-0.280***	-0.305***
	-0.020	-0.032	-0.037	-0.039	-0.051	-0.069	-0.067	-0.042	-0.027
lnIA	-0.104	-0.102	-0.098	-0.062	0.058	-0.031	0.004	0.335**	0.480***
	-0.064	-0.101	-0.117	-0.126	-0.164	-0.221	-0.214	-0.135	-0.087
lnIA ²	0.007**	0.006	0.004	0.002	-0.005	0.000	-0.001	-0.019***	-0.028***
	-0.003	-0.005	-0.006	-0.007	-0.009	-0.012	-0.012	-0.007	-0.005
lnPOPU	-1.886	-2.215	-3.898	-5.302**	-7.357**	-7.943*	-5.21	-4.856*	-4.176**
	-1.307	-2.058	-2.387	-2.559	-3.334	-4.509	-4.352	-2.74	-1.771
lnPOPU ²	0.263	0.319	0.547*	0.732**	1.037**	1.173**	0.834	0.809**	0.772***
	-0.169	-0.266	-0.308	-0.33	-0.43	-0.582	-0.562	-0.354	-0.229
lnINDup	-0.248***	-0.283***	-0.337***	-0.407***	-0.493***	-0.503***	-0.558***	-0.481***	-0.444***
	-0.036	-0.057	-0.066	-0.071	-0.093	-0.125	-0.121	-0.076	-0.049
lnOPEN	-0.175***	-0.159***	-0.153***	-0.175***	-0.207***	-0.310***	-0.278***	-0.215***	-0.164***
	-0.015	-0.024	-0.028	-0.030	-0.039	-0.053	-0.051	-0.032	-0.021
lnLAB	3.813***	3.947***	3.157***	3.117***	2.456***	1.762*	0.0417	-1.383**	-2.301***
	-0.293	-0.460	-0.534	-0.573	-0.746	-1.009	-0.974	-0.613	-0.396
lnAGING	0.086	0.160	0.103	0.051	-0.017	-0.344	-0.889***	-0.978***	-0.928***
	-0.063	-0.100	-0.115	-0.124	-0.161	-0.218	-0.211	-0.133	-0.086
lnperGDP	0.521***	0.469***	0.445***	0.432***	0.459***	0.436***	0.593***	0.661***	0.576***
	-0.041	-0.065	-0.075	-0.081	-0.105	-0.142	-0.137	-0.086	-0.056
_cons	-16.33***	-15.96***	-8.936*	-5.854	-0.051	4.656	6.071	9.169	11.04***
	-2.840	-4.470	-5.185	-5.559	-7.244	-9.796	-9.454	-5.952	-3.847
Obs.	450	450	450	450	450	450	450	450	450

Notes: t statistics are in parentheses; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A significant non-linear relationship exists between the urbanization level and carbon emission intensity. Specifically, during the early stages of urbanization development, a stronger urbanization process is typically associated with lower carbon emission intensity. This phenomenon likely stems from the systematic optimization of infrastructure and significant improvements in energy utilization efficiency. However, it is noteworthy that when urbanization reaches a higher stage, its quadratic term exhibits a significant positive association. This suggests that excessive urbanization may lead to an upward rebound in carbon emission intensity.

Industrial structure upgrade exerts a significant effect on reducing carbon emission intensity across all quantile levels examined. Specifically, an increase in the proportion of the service sector and high-technology industries within the overall economic structure exhibits a significant negative correlation with carbon emission intensity (Zhang et al., 2019; Wang & Li, 2021). This finding robustly corroborates the existence of a close intrinsic link between industrial structural adjustment and improvements in carbon emission performance, further supporting the view that optimizing the industrial structure is a key pathway for achieving carbon reduction targets.

The degree of openness also demonstrates a significant negative association with carbon emission intensity, with this effect being particularly pronounced in the higher quantile intervals (QR₆₀ to QR₇₀). This trend likely stems from the positive effects of technology transfer fostered by an open economy, coupled with the generally

stricter environmental standards adhered to by foreign-invested enterprises (Chen et al., 2020; Liu & Chen, 2022). By facilitating the introduction of advanced production technologies and management expertise, the open economic model helps alleviate the environmental pressure faced by high-emission industrial sectors, thereby reducing their carbon emission intensity.

Regarding the impact of labor force size, the study found a significant positive correlation with carbon emission intensity at lower quantiles (QR₁₀, coefficient = 3.813, significant at the 1% level). This may reflect the stronger impetus provided by labor-intensive industries towards energy consumption during relatively early stages of economic development (Zhao & Huang, 2018). However, it is noteworthy that at higher quantiles (QR₉₀, coefficient = -2.301, significant at the 1% level), this positive correlation not only weakens but even reverses into a significant negative correlation. This shift clearly indicates that the contribution of industries with high labor intensity to carbon emissions is progressively diminishing alongside the ongoing upgrading and optimization of the industrial structure (Xu et al., 2021).

The phenomenon of population aging also exhibits a significant negative correlation with carbon emission intensity in higher quantile intervals (QR₈₀, coefficient = -0.978, significant at the 1% level). This relationship may reflect the relatively reduced demand for energy-intensive goods and services among the elderly population, alongside a trend towards lower-carbon consumption patterns within this demographic group (Fang & Wang, 2019; Li & Sun, 2020).

Finally, the level of economic development maintains a significant positive correlation with carbon emission intensity across all quantiles examined (Jiang et al., 2017), confirming the fundamental pattern that economic growth is often accompanied by an increase in total energy consumption. However, a noteworthy phenomenon is that the strength of this positive association exhibits a weakening trend as carbon emission intensity itself increases (Zhou & Ma, 2019). This suggests that in regions or developmental stages characterized by higher carbon emission intensity, there may be a tendency towards optimizing the energy structure and enhancing energy utilization efficiency, thereby partially offsetting the carbon emission pressure induced by economic growth.



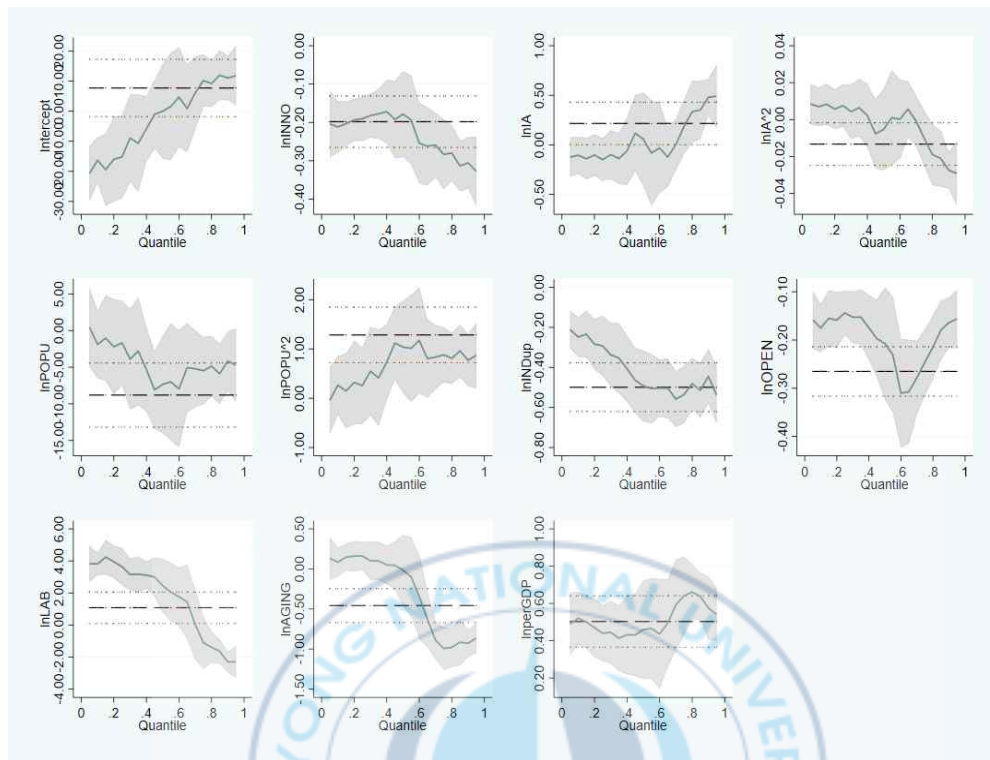


Fig. 3.4. Asymmetric impact diagrams.

Note: The x-axis represents the conditional quantiles of carbon emission intensity, and the y-axis denotes the coefficient values of various explanatory variables.

As shown in Fig. 3.4, the quantile regression coefficients exhibit significant heterogeneity, contrasting sharply with the constant-level OLS regression line. These coefficients show notable variation across different quantiles, highlighting the volatility of the explanatory variable's effect on the dependent variable. The step and fluctuating curves of these coefficients further emphasize the wide variation of these effects across different quantiles.

5. Brief summary and policy recommendations

Technological innovation is closely associated with the progress of low-carbon development. Unlike previous studies limited to linear models or single-path analyses, this research analyzes panel data from 30 Chinese provinces (2005 - 2019), examining the relationships among regional technological innovation, economic agglomeration, industrial structure, economic development, and population structure, and their correlation with carbon emission intensity. A more representative indicator system for technological innovation capacity is adopted, and panel threshold and quantile regression models are applied, allowing for an in-depth understanding of how technological innovation correlates with variations in emission intensity across regions and thresholds. The results offer valuable insights that may inform the formulation of region-specific and stage-sensitive low-carbon policies.

When using regional technological innovation levels as threshold variables, all regions—except the central region—exhibit noticeable threshold characteristics, indicating a dual-threshold relationship with carbon emission intensity.

(1). Dual threshold pattern at the nationwide

At the nationwide, carbon emission intensity is found to be closely associated with regional technological innovation levels through a statistically significant dual-threshold structure at the 1% and 5% levels. The estimated thresholds are approximately -0.427 and -3.336 , and

notable changes in model parameters are observed when technological innovation levels exceed 0.036 and 0.652, suggesting shifts in the strength or direction of this association.

When the technological innovation level is less than or equal to 0.356, the estimated coefficient is -0.049 . Although not statistically significant, this suggests a mild negative association with carbon emission intensity. In the range where the technological innovation level is greater than 0.036 but less than or equal to 0.652, the coefficient becomes -0.129 , indicating a stronger negative correlation. When the technological innovation level exceeds 0.652, the coefficient drops markedly to -0.883 and is statistically significant at the 5% level, implying that higher levels of technological innovation tend to be more strongly associated with reductions in carbon emission intensity.

(2). Threshold effect in the eastern region

In the eastern region, technological innovation levels are found to be associated with carbon emission intensity in a phased manner, based on threshold regression analysis. The identified thresholds are -3.797 and -0.008 . When the technological innovation level is less than or equal to 0.022, the estimated coefficient is 0.296 , suggesting a positive correlation with carbon emission intensity.

For technological innovation levels between 0.022 and 0.992, the coefficient decreases to 0.170 , implying a weakening of this positive association.

Once the technological innovation level surpasses 0.992, the coefficient turns negative at -1.379 , indicating a strong negative

correlation, potentially reflecting a shift toward emission reduction at higher technological innovation capacities.

(3). Dual threshold effect in the western region

In the western region, technological innovation levels show a statistically significant dual-threshold association with carbon emission intensity, with both thresholds significant at the 1% level. The estimated thresholds are -3.336 and -2.825.

When the level of technological innovation is less than or equal to 0.06, the corresponding regression coefficient is -0.467, which is statistically significant at the 5% level, indicating a notable negative correlation with carbon emission intensity in this range.

In the range where the technological innovation level is greater than 0.06 but less than or equal to 0.356, the estimated coefficient is -0.567, statistically significant at the 1% level. When the technological innovation level exceeds 0.356, the coefficient further decreases to -0.639, also significant at the 1% level. These findings suggest a progressively stronger negative correlation between technological innovation and carbon emission intensity in the western region as technological innovation levels rise.

(4). Special case of the central region

Unlike other regions, the central region does not show a significant threshold effect. This may be due to its lower technological innovation level or a more traditional economic development model.

Based on the panel quantile regression model, this study

comprehensively analyzes the multidimensional factors influencing regional carbon emission intensity, revealing significant nonlinear and heterogeneous characteristics.

(1). There is a significant negative correlation between technological innovation capability and carbon emission intensity, especially in higher quantiles. This pattern indicates that in regions with higher carbon emission intensity, stronger technological innovation capacity tends to be associated with lower emissions, possibly due to better resource allocation and improved energy efficiency.

(2). The nonlinear associations of industrial agglomeration and urbanization with carbon emission intensity exhibit distinct patterns.

Industrial agglomeration and its squared term display an inverted U-shaped correlation with carbon emission intensity. In the early stages, higher agglomeration levels are associated with increased emissions, while beyond a certain point, greater agglomeration tends to be linked to lower emissions, possibly due to technological spillovers and scale economies. This pattern appears more evident at higher quantiles.

Similarly, urbanization is negatively correlated with carbon emission intensity at lower levels, but its squared term is positively correlated, suggesting a potential rebound in emissions when urbanization becomes excessive, with stronger effects observed at the middle quantiles.

(3). The relationship between control variables and carbon emission intensity. Industrial structure upgrading is negatively correlated with carbon emission intensity across all quantiles, suggesting that regions with a shift from energy-intensive industries to service and high-tech

sectors tend to exhibit lower emissions.

A higher degree of openness is associated with reduced carbon emission intensity, especially at higher quantiles, which may relate to potential technology spillovers and alignment with stricter international environmental standards.

Labor force size shows a positive correlation with carbon emission intensity at lower quantiles, but this relationship weakens—and even turns negative—at higher quantiles.

The aging population is negatively associated with carbon emission intensity in higher quantiles.

Economic development level is positively correlated with carbon emission intensity throughout all quantiles, although its marginal correlation appears to weaken at higher quantiles.

Based on the empirical findings of this study, the following policy recommendations are proposed to provide theoretical support and practical guidance for the development of regional technological innovation systems, the optimization of industrial spatial structures, and the effective control of carbon emission intensity, thereby facilitating the coordinated advancement of green transformation and high-quality development..

(1). Emphasize the core role of technological innovation in emission reduction and systematically promote the research, development, and application of green and low-carbon technologies.

Technological innovation has long been regarded as a vital means

to achieve carbon reduction and sustainable development. The findings of this study further confirm its significant mitigating effect on carbon emission intensity, underscoring its leading role in driving the low-carbon transition. Regions should develop systematic policy frameworks to support technological innovation in alignment with green and low-carbon goals, in order to harness and unleash the potential of technological progress in reducing emissions. Governments can support enterprises, universities, and research institutions in collaborative R&D efforts by establishing dedicated research funds, high-level science and technology platforms, and application testing bases, with a focus on breakthroughs in critical green technologies. In terms of fiscal incentives, it is essential to improve policy instruments such as additional tax deductions for R&D expenses, subsidies for green technologies, and reward mechanisms for technology commercialization to stimulate sustained enterprise investment in green technological innovation. Meanwhile, the intellectual property protection system should be enhanced by establishing fast-track examination channels for green technology patents, strengthening patent enforcement and rights protection, and optimizing the technological innovation environment to promote the widespread dissemination and efficient commercialization of technological achievements.

(2). Enhance regional technological innovation capacity based on local conditions, with a focus on supporting technological upgrading in high carbon emission areas.

There are significant differences among China's regions in terms of

resource endowment, industrial structure, and stages of economic development, resulting in pronounced spatial heterogeneity in the impact of technological innovation on carbon emission intensity. Empirical analysis indicates that regions with higher carbon emission intensity experience more pronounced marginal emission reduction effects from technological advancement. Therefore, at the nationwide a regional collaborative technological innovation mechanism should be established to promote the flow and agglomeration of scientific and technological resources toward central and western regions with high emissions and weak technological foundations. For example, pilot zones for green and low-carbon technologies can be established in these regions, and high-tech enterprises from the more developed eastern areas can be encouraged to set up R&D institutions or technological innovation centers in central and western China, facilitating interregional flow of technology and complementary resource allocation. In policy design, differences in industrial base, technological level, and environmental carrying capacity across regions should be carefully considered to formulate differentiated and targeted support measures that enhance overall emission reduction efficiency and technological advancement capacity.

(3). Promote the green transformation of new urbanization and industrial agglomeration, and establish institutional mechanisms for coordinated economic and ecological development.

As key drivers of regional economic growth, urbanization and industrial agglomeration bring benefits such as economies of scale and

optimized resource allocation, but may also lead to increased carbon emission intensity. Therefore, it is essential to optimize urbanization pathways at the source, prevent unregulated urban sprawl and excessive population concentration, and reduce the resulting environmental pressure. In densely populated areas, measures such as optimizing land-use structures, improving public transportation systems, and raising building energy efficiency standards should be implemented to effectively curb increases in carbon emission intensity.

In terms of industrial spatial layout, efforts should be made to promote the agglomeration of industries toward green, low-carbon, and high value-added sectors, forming a modern industrial system centered on technological innovation. Governments should support the green transformation and technological upgrading of traditional high-energy-consuming industries, while increasing policy support for emerging sectors such as new energy, intelligent manufacturing, and green finance to foster new momentum for green industrial development. Notably, the risk of “pollution transfer” should be effectively mitigated during the process of industrial agglomeration to avoid development models that sacrifice environmental quality for agglomeration advantages, thereby forging a green development path that balances resource efficiency, environmental friendliness, and economic benefits.

In summary, technological innovation is not only the key engine driving regional low-carbon transitions, but also a strategic lever for achieving coordinated emission reductions across regions. Future policy design should focus on three aspects: strengthening the supply of green

technologies, optimizing regional collaborative technological innovation mechanisms, and advancing the green transformation of industrial agglomeration. These coordinated efforts will promote high-quality green economic development and effectively achieve the dual goals of sustained reductions in carbon emission intensity and continuous improvement of the ecological environment.



CHAPTER 5 Conclusions

This research utilizes panel data from 30 provinces in China between 2005 and 2019 (with some models covering 2003 - 2019). It investigates the relationship between economic agglomeration, regional technological innovation, and carbon emission intensity from various angles. The main findings can be summarized in the following three areas: 1) The connection between economic agglomeration and regional technological innovation capacity. Using the spatial Durbin model, the study examines the relationship between economic agglomeration and regional technological innovation capacity, considering industrial and population agglomeration while controlling for other factors. 2) The influence of economic agglomeration on carbon emission intensity and its spatial spillover effects. Using a spatial econometric model (SDM), the study investigates the effects of industrial and population agglomeration on carbon emission intensity, along with their spatial spillover effects. 3) The heterogeneity analysis of how technological innovation affects carbon emission intensity. By developing a technological innovation index system and applying panel threshold regression and panel quantile regression models, the study analyzes the heterogeneous effects of technological innovation on regional carbon emission intensity.

1. Summation

The Moran's I test reveals that regional technological innovation capacity has significant spatial autocorrelation and exhibits a clear spatial clustering pattern. Additionally, the spatial autocorrelation coefficient ρ is significantly positive at the 1% level, suggesting that the technological innovation capacity of a region is influenced by its neighboring regions. The study further shows a U-shaped relationship between industrial agglomeration and regional technological innovation capacity. In the initial stage of industrial agglomeration, due to low levels and insignificant knowledge and technology spillover effects, it has a suppressive impact. As agglomeration increases, however, agglomeration effects intensify, promoting regional technological innovation capacity.

Similarly, population agglomeration exhibits a U-shaped relationship with regional technological innovation capacity: initially, population concentration helps attract labor and accumulate knowledge and technology, thereby enhancing technological innovation capacity. However, as population increases and congestion effects develop, it weakens the region's innovation capacity.

Moreover, the control variables, such as informatization level, financial development, infrastructure, economic development, and foreign investment, are all significantly positive at the 1% level, indicating their significant promoting effect on regional technological innovation capacity.

The Spatial Durbin Model further allows for the decomposition of spatial effects, breaking down the influence of explanatory variables on the dependent variable into direct, indirect, and total effects. Empirical results indicate that the direct effect of industrial agglomeration on regional technological innovation capacity exhibits a U-shaped relationship, where the first-order coefficient is significantly negative and the second-order coefficient is significantly positive. When the logarithm of industrial agglomeration is below 5.969, it exerts a suppressive effect, but after surpassing this threshold, it becomes a promoting factor. However, both the indirect and total effects are not significant, and no clear spatial spillover effects are observed. Similarly, the direct effect of population agglomeration on regional technological innovation capacity also shows a U-shaped relationship. When the logarithm of population agglomeration is less than 3.872, it suppresses innovation capacity, but beyond this threshold, it promotes it. Both its indirect and total effects are also not significant. On the other hand, the level of informatization not only has a significant positive direct impact on regional technological innovation capacity but also exhibits a significantly positive total effect, indicating a clear spillover effect. Financial development level and infrastructure level, while only showing significant direct positive effects, both have positive impacts on adjacent regions and the overall region. In contrast, although economic development level and foreign investment can promote innovation within the region, their indirect effects are significantly negative, indicating potential negative impacts on neighboring regions.

From 2003 to 2019, industrial and population agglomeration levels in China's 30 provinces generally increased, although there were regional differences. At the same time, carbon emission intensity decreased, showing significant positive spatial autocorrelation and agglomeration effects, with High-High, Low-Low, and Low-High clustering types observed. The spatial autoregressive coefficient is significant at the 10% level, suggesting the presence of spatial spillover effects in carbon emission intensity between regions. The analysis shows an inverted U-shaped relationship between industrial agglomeration and carbon emission intensity: in the early stage, industrial agglomeration increases energy consumption, leading to a rise in carbon emission intensity. As scale and concentration benefits emerge, energy consumption per unit of output decreases, and carbon emission intensity declines. Both the linear and quadratic terms of industrial agglomeration are significant at the 1% level.

Population agglomeration shows a U-shaped relationship with carbon emission intensity: in the early stages, population concentration in urban areas improves regional energy efficiency, lowers per capita energy consumption, and reduces carbon emission intensity. However, as population agglomeration and urban development progress, energy efficiency declines, and energy consumption for urban services such as transportation, heating, and cooling increases, resulting in a rise in carbon emission intensity.

Furthermore, the coefficient for economic development in the control variables is significantly negative, indicating that China's carbon

emission intensity has decoupled from economic growth. The effects of industrial restructuring and regional population structure (the share of working-age population and aging) on carbon emission intensity are not significant. However, the coefficients for international trade and R&D investment are significantly positive, supporting the pollution haven hypothesis in China, which posits that international trade and technological investments focused on improving production levels have contributed to an increase in carbon emission intensity.

The Spatial Durbin Model's advantage lies in its ability to decompose the effects of explanatory variables on the dependent variable into direct, indirect, and total effects, thus comprehensively reflecting the influence of each factor. Empirical results show that in the direct effect of industrial agglomeration, the coefficient of the first-order term is significantly positive and the second-order term's coefficient is significantly negative, indicating that when the logarithm of industrial agglomeration is below 6.197, it increases regional carbon emission intensity. However, when the logarithm exceeds 6.197, it suppresses carbon emission intensity and is associated with significant spatial spillover effects. Similarly, the direct effect of population agglomeration exhibits a significant negative first-order term and a positive second-order term, revealing a U-shaped relationship: when the logarithm of population agglomeration is less than 3.222, it reduces regional carbon emission intensity; but when the logarithm exceeds this threshold, it increases carbon emission intensity and has significant spatial spillover effects. For control variables, the direct, indirect, and

total effects of technological investment are all significant, indicating a significant negative impact on both local and overall carbon emission intensity. International trade shows a similar trend to technological investment. Although the direct effect of aging speed is not significant, both its indirect and total effects are positive, indicating that an increase in the elderly population has an adverse effect on nearby areas and the overall carbon emission intensity. The direct effect of industrial added value is significantly greater than the effect of population agglomeration.

Analysis employing regional technological innovation level as the threshold variable reveals a significant double-threshold effect at the nationwide, with precise threshold values of -0.427 and -3.336 . When the technological innovation level reaches or exceeds 0.036 and 0.652 respectively, its suppressive effect on carbon emission intensity is markedly enhanced. In the western region, a comparable double-threshold effect is detected (with threshold values of -3.336 and -2.825), suggesting that as technological innovation intensifies, the suppressive impact on carbon emission intensity is progressively strengthened. Conversely, in the eastern region, the effect of technological innovation on carbon emission intensity is stage-dependent: in the initial phase, it may even promote carbon emission intensity, but after a significant increase in technological innovation, it transitions to a marked inhibitory effect. Meanwhile, in the central region, no obvious threshold effect emerges, which could be attributed to its relatively low level of technological innovation or a more conventional economic development paradigm.

The analysis employing a panel quantile regression model demonstrates that regional carbon emission intensity is affected by various factors in a nonlinear and heterogeneous way. The findings suggest that both innovation capacity and technological advancement can significantly lower carbon emission intensity, with an even more pronounced effect in high carbon emission intensity regions. The effect of industrial agglomeration follows an inverted U-shape: initially, it elevates carbon emission intensity; however, as agglomeration intensifies, technological spillovers and scale economies lead to a significant reduction in carbon emission intensity. While urbanization initially lowers carbon emission intensity, excessive urbanization may lead to a rebound in carbon emission intensity levels. While urbanization initially lowers carbon emission intensity, excessive urbanization may lead to a rebound in carbon emission intensity levels. Labor force size has a positive effect on carbon emission intensity at lower quantiles, but its influence weakens or even reverses at higher quantiles. In high quantile regions, the aging effect helps to lower carbon emission intensity. Economic development level is found to significantly elevate carbon emission intensity at all quantiles, albeit with a reduced marginal effect at higher quantiles.

While economic agglomeration promotes regional development and technological innovation, it exerts both promoting and inhibiting effects on carbon emission intensity, with outcomes influenced by the stage of agglomeration development and the degree of synergy with technological innovation capacity.

Economic agglomeration enhances regional technological innovation by strengthening knowledge spillovers, promoting resource sharing, and optimizing factor allocation, thereby facilitating industrial upgrading and the adoption of green technologies, which offer an effective pathway to carbon emission reduction. However, in the early stages of agglomeration, increased industrial concentration and higher resource consumption often lead to rising carbon emission intensity, exhibiting a “pollution-first” characteristic. As agglomeration deepens and technological accumulation grows, innovation-driven effects begin to emerge, promoting cleaner production, energy conservation, and green transformation, thus forming a positive feedback mechanism of “innovation-led emission reduction.” Therefore, the effectiveness of economic agglomeration in achieving carbon reduction critically depends on its interaction with technological innovation.

Therefore, policy formulation should strengthen regional technological innovation systems and guide industrial agglomeration toward a transformation that is efficient, green, and intelligent, thereby establishing a sustainable development path centered on “agglomeration driven innovation and innovation-driven emission reduction”.

2. Policy recommendations and implications

This study examines the complex impacts of industrial activities, population dynamics, and technological progress on carbon emission intensity, and, based on empirical findings, puts forward corresponding policy recommendations to help China achieve its “3060 dual carbon” targets and promote green, sustainable development. The study finds that industrial agglomeration exhibits an inverted U-shaped relationship with carbon emission intensity. Initially, an increase in industrial agglomeration raises carbon emission intensity; however, as economies of scale are achieved, further agglomeration leads to a reduction in carbon emissions. This is primarily because, in the initial phase of industrial agglomeration, high energy consumption and the predominance of heavily polluting industries drive up carbon emission intensity. However, as industrial upgrading and technological progress occur, firms gradually adopt energy-saving and emission-reduction technologies, enhance production efficiency, and benefit from economies of scale, thereby reducing carbon emission intensity. Therefore, the government should guide industrial agglomeration in a rational manner, promote coordinated regional industrial development, optimize the allocation of production factors, and foster cross-regional cooperation, so as to fully leverage economies of scale to reduce carbon emission intensity. At the same time, environmental regulation should be strengthened, and efforts should be made to drive high-polluting enterprises toward green,

low-carbon industries, enhance industrial chain synergy, and promote the development of green industries. In addition, the government can implement differentiated carbon tax policies, imposing varying carbon taxes on different industries and regions to offer incentives to enterprises to reduce carbon emissions and promote the development of low-carbon industries.

The relationship between population concentration and carbon emission intensity is U-shaped. In the short term, concentrating the population can improve energy utilization efficiency and lower carbon emissions. On one hand, population concentration aids in optimizing public resource allocation, boosts the efficiency of infrastructure usage, and lowers unit carbon emissions via economies of scale. However, as urban areas expand and excessive population concentration occurs, energy demand rises, placing additional strain on city infrastructure and transit systems—potentially increasing carbon emission intensity. In the urbanization process, a significant influx of people can cause traffic jams, an increase in housing demand, and intensified energy consumption, which in turn elevates carbon emissions. Therefore, government authorities should enhance urban planning, appropriately regulate population density, encourage the adoption of green and clean energy in both residential and transportation sectors, and bolster the research and application of low-carbon technologies, optimize city infrastructure, and elevate sustainable development levels. Additionally, efforts should be made to fortify public transit infrastructure, promote new energy vehicles, and advocate for green building technologies to

reduce the carbon emission burden caused by high population concentration. The government may also adopt smart city development strategies, employing big data, IoT, and artificial intelligence to optimize the distribution of urban resources, boost energy efficiency, and cut down on superfluous carbon emissions. Concurrently, policymakers could introduce green consumption incentive measures, for instance by implementing a carbon credit scheme, to motivate residents to adopt energy-efficient appliances and reduce high-carbon commuting, ultimately cultivating a sustainable, low-carbon way of life.

The research further revealed that current regional investments in technology are mainly aimed at boosting production efficiency rather than ensuring environmental sustainability, which results in higher carbon emission intensity. This phenomenon demonstrates that, despite the significant role of technological advancement in spurring economic growth, its impact on reducing carbon emissions is still limited. Many companies and local authorities prefer to focus on increasing production capabilities rather than mitigating environmental pollution when making technology investments. Therefore, the government should encourage enterprises to align their technology investments with green development goals, promote innovation in environmental protection technologies, and improve the research, development, and application of low carbon technologies. In addition, it is important to avoid local protectionism, promote the diffusion of innovation, strengthen regional cooperation, build a high end industrial chain, and enhance the agglomeration effect of productive services to improve industrial diversity and boost

enterprise innovation capability. At the same time, the government should optimize population mobility policies, strengthen the supply of infrastructure and public services, and increase urban carrying capacity to mitigate the negative impacts of excessive population concentration. In terms of policy, a green innovation fund could be established to support the research, development, and application of low carbon technologies, and to encourage collaboration among universities, research institutions, and enterprises in developing new energy technologies. Furthermore, the government should work to improve the carbon trading market by using market based mechanisms to offer incentives to enterprises to reduce carbon emissions and reward companies that achieve emissions reductions beyond targets, thereby promoting the research, development, and application of low carbon technologies.

Based on provincial panel data from China spanning 2005 to 2019, this study systematically examines the relationship between economic agglomeration, technological innovation, and carbon emission intensity by employing spatial Durbin models, panel threshold models, and quantile regression techniques. From multiple analytical dimensions, it explores the effects of industrial and population agglomeration on regional innovation capacity and carbon emission intensity, including their spatial spillover effects.

First, the study finds that economic agglomeration significantly influences regional technological innovation, and this relationship is nonlinear. This finding goes beyond the linear assumptions commonly adopted in the literature, offering a richer theoretical perspective on the

role of agglomeration in promoting innovation and providing a theoretical basis for optimizing regional innovation policies.

Second, under the framework of the Environmental Kuznets Curve (EKC), the study incorporates nonlinear agglomeration variables and adopts spatial econometric approaches to identify the phased effects and spatial spillovers of economic agglomeration on carbon emission intensity, thereby extending the theoretical framework for analyzing the impact of agglomeration on environmental outcomes.

Furthermore, the study constructs a more representative indicator system for technological innovation and systematically analyzes the influence pathways of innovation, economic agglomeration, industrial structure, economic development, and demographic structure on carbon emission intensity. It reveals the nonlinear characteristics and regional heterogeneity of technological innovation in advancing low-carbon transitions.

In summary, the findings provide robust empirical support for formulating region-specific and stage-based low-carbon development policies. The results highlight the importance of coordinating agglomeration characteristics and regional innovation capacity in policy design to achieve synergies between economic efficiency and environmental sustainability during the green transition.

3. Research limitations

The present research concentrates on the regional effects of

economic agglomeration on carbon emission intensity at the provincial level in China, and underscores the need for future studies to utilize more accurate data to explore the potential impact mechanisms of carbon emissions, regional spillover effects, and the function of specific economic clusters, thereby offering more reliable policy guidance. Moreover, optimizing data quality and research methods will further improve the precision of the analysis. Nonetheless, the study faces several limitations, including a restricted time period, the intricate nature of the relationships among economic agglomeration, regional technological innovation, and carbon emission intensity, as well as constraints in data quality that may affect the findings. Therefore, future research could expand the data scope to include municipal and county-level data, and incorporate mediating variables such as policy interventions, market mechanisms, and energy structure transitions, in order to thoroughly analyze the pathways through which economic agglomeration and technological innovation contribute to low-carbon development. With advancements in statistical data and research methods, the use of spatial econometric models and machine learning tools can further reveal the complex effects of various factors on carbon emissions, thereby providing scientific support for the government to formulate precise green development policies.

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