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Specialized vs. Diversified Agglomeration: Which More Effectively Enhances Urban Comprehensive Carrying Capacity? Evidence from Chinese Cities

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Abstract

As the fundamental spatial carriers of population and economic activities, cities are central to advancing Chinese-style modernization, making the enhancement of their comprehensive carrying capacity (CCP) an essential pathway toward sustainable development. Drawing on panel data from 284 prefecture-level cities in China covering the period of 2005–2022, this study constructs a dynamic spatial Durbin model to examine how different forms of industrial agglomeration influence urban CCP. The results indicate the following: (1) Urban CCP demonstrates significant spatial dependence across cities. (2) Both specialization and diversification exert pronounced spatiotemporal lag effects. Specifically, specialized agglomeration tends to suppress the urban CCP of both local and neighboring cities, whereas diversified agglomeration generally contributes to its improvement. (3) The spatiotemporal effects of specialized agglomeration and diversified agglomeration on urban CCP exhibit heterogeneity across regions and economic development levels. Diversified agglomeration significantly enhances the CCP of cities in the central region and those with higher economic development levels, while the western region and cities with lower economic development levels are more suited for industrial specialized agglomeration. (4) Further research has found that specialized agglomeration and diversified agglomeration have heterogeneous spatiotemporal effects on different dimensions of urban CCP. These findings suggest that governments at all levels should formulate differentiated industrial agglomeration strategies that align with local resource endowments and industrial foundations, thereby fostering high-quality urban development tailored to local conditions.

Keywords: specialized agglomeration; diversified agglomeration; dynamic spatial panel model; urban comprehensive carrying capacity; China's cities

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Academic Editor: Gideon Baffoe

Received: 28 August 2025
Revised: 23 September 2025
Accepted: 10 October 2025
Published: 13 October 2025

Citation: Gao, M.; Lan, F. Specialized vs. Diversified Agglomeration: Which More Effectively Enhances Urban Comprehensive Carrying Capacity? Evidence from Chinese Cities. *Sustainability* **2025**, *17*, 9064. https://doi.org/10.3390/su17209064

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1. Introduction

The most recent projections of the United Nations Human Settlements Programme indicate that by 2050, the world's urban population will reach about 2.53 billion, representing nearly 64% of the global total, with the bulk of this increase anticipated to occur in developing regions [1,2]. This model will put tremendous pressure on the natural resources and environmental affordability of these countries. As the world's largest developing country, China's urban population has soared from 17.9% in 1987 to 65.2% in 2022, and its cities and urban agglomerations have become important platforms to participate in international

competition [3]. To a considerable degree, the growth of per capita income in China has been driven by urban development [4]. Currently, the national economy is transitioning from a phase of rapid expansion toward one that emphasizes high-quality and sustainable growth [5]. However, urbanization is often accompanied by the concentration of resources (e.g., population and enterprises), and lead to urban sprawl, increased resource consumption, and the risk of surpassing local carrying capacity, thereby constraining high-quality development. The continued deepening of industrialization has already given rise to a series of issues in China, including ecological and environmental degradation, inefficient use of urban land, shortages of key resources, and traffic congestion [6].

A comprehensive assessment of a city's carrying capacity is generally considered an effective way to improve its sustainability. Scholars believe that if the requirements for a city exceed its supporting systems, it will lead to a decline in urban sustainability [7]. Improving the CCP of cities is an important starting point to promote and achieve high-quality urban development, as well as a significant challenge for sustainable development [8]. Under the premise of accelerating global urbanization, addressing the tensions among resource availability, environmental sustainability, and economic growth has become a central challenge for sustainable development [9]. General Secretary Xi Jinping has underscored that urban development must be coordinated with regional economic growth and industrial distribution while remaining consistent with the carrying capacity of local resources and environmental conditions. Within this framework, a city's CCP serves as a critical metric for assessing the quality and sustainability of urban development. A rigorous and robust assessment of CCP, combined with a thorough analysis of how different patterns of industrial agglomeration affect CCP, is crucial for promoting Chinese-style modernization.

Both the New Economic Geography and the theory of agglomeration externalities focus on examining whether regional agglomeration promotes urban economic growth [10]. It is widely recognized that agglomeration externalities can promote economic development and improve enterprise efficiency. However, while the concentration of population, enterprises, and wealth contributes to urban economies, this also undermines the sustainable development of the city [11]. In recent years, the frequent occurrence of problems such as traffic congestion, shortage of educational resources, and haze pollution has brought the issue of urban CCP to the attention of both government and academia. As the structural foundation of urban economies, the spatial concentration of industries is a defining feature of the current stage of economic development. Following Marshall's initial articulation of industrial agglomeration, a substantial body of research has explored its influence on economic growth, technological innovation, energy efficiency, and environmental sustainability [12]. Most researchers maintain that industrial agglomeration contributes to economic growth and improves energy efficiency through factors such as economies of scale, knowledge spillover and resource sharing [13]. In addition, clustering manufacturing companies may alleviate the pollution-haven phenomenon [14].

The geographical concentration of economic activity and economic growth reinforce each other, and the link between this concentration and growth is determined by the flow of investment, labor, and physical inputs across regions [15]. Industrial agglomeration forms the foundation for urban development and constitutes an essential component of current strategies and plans for economic development in China [16,17]. Based on clustering characteristics, industrial agglomeration is generally divided into specialized and diversified forms [18], with markedly different impacts [19]. Marshall [20] argued that externalities arising from industrial specialization enhance knowledge diffusion among firms and improve urban economic efficiency. In contrast, Jacobs [21] emphasized that the externalities generated through diversified agglomeration are more effective in fostering knowledge spillovers and driving technological innovation. Some empirical studies show

that industrial specialization may hinder urban innovation, whereas diversification tends to promote it [22]. Both diversified and specialized agglomeration can significantly reduce carbon emissions in their own cities and surrounding regions through agglomeration externalities [23]. However, Van der Panne [24] used innovation data from the Netherlands and found the opposite—specialized agglomeration positively influences regional innovation, particularly in R&D-intensive and small enterprises. As urban networks and transportation systems become better and better, the connections between cities become closer. The influence of industrial clusters on the urbanization levels of surrounding cities is more conveyed through interactions between governments and the geographical flow of production factors [25]. Therefore, scholars began to focus their research on the spatial effects of different clustering patterns. For example, Lan et al. [26] reported that specialized manufacturing clusters tend to increase carbon emissions within the host city but exert little influence on emissions in adjacent regions. By contrast, diversified clusters do not significantly alter local emissions, yet they help reduce carbon output in neighboring areas. Likewise, Han et al. [23] observed that both specialized and diversified clustering patterns contribute to lower industrial energy efficiency in surrounding cities. These findings imply that, regarding energy outcomes, the negative "free-riding" spillover of agglomeration outweighs any positive demonstration or diffusion effects.

Research on industrial agglomeration and its spatial effects has been extensively conducted, yet most studies employ provincial panel data for empirical analysis. The literature examining the effects of industrial agglomeration externalities on urban CCP remains limited, particularly with respect to spatial spillover effects. Accordingly, this study addresses two fundamental questions within the context of China's urban development: first, which type of agglomeration—specialized or diversified—more effectively enhances urban CCP? Second, to what extent do spatial heterogeneity and spillover effects influence CCP across cities? To investigate these issues, this study employs panel data covering 284 prefecture-level Chinese cities from 2005 to 2022. After examining the mechanisms through which different forms of industrial agglomeration influence urban comprehensive carrying capacity, several research hypotheses are developed. Furthermore, a dynamic spatial Durbin model (SDM) is applied to assess the spatiotemporal impacts of agglomeration patterns on urban CCP.

This paper offers three main contributions. First, grounded in agglomeration economies and endogenous growth theory, it investigates the externalities of industrial agglomeration together with their spatial spillover effects. Second, by employing panel data for 284 prefecture-level cities in China over the period of 2005–2022, this study applies a dynamic spatial Durbin model (SDM) to capture these externalities while explicitly considering both spatial and temporal lags. Third, by integrating regional and economic heterogeneity into the analysis of agglomeration patterns, it identifies the direct and indirect influences of industrial agglomeration on urban comprehensive carrying capacity across space and time. The results yield solid empirical support and provide policy-relevant implications for improving urban carrying capacity and promoting balanced regional development.

The remainder of this article is structured as follows: Section 2 talks about research on targeted clustering, mixed clustering, and urban CCP, and puts forward some assumptions based on previous research. Section 3 explains the research methodology, detailing the sources of the data, how to measure variables, and how to build the model. Section 4 analyzes the results of spatial estimation. Section 5 explains the findings of dynamic spatial Durbin model (SDM). Section 6 gives conclusions and policy recommendations.

2. Literature Review

2.1. Specialized Agglomeration and Urban CCP

In recent years, traffic congestion, shortage of educational resources, haze pollution and other problems have occurred frequently, drawing increasing attention from both the government and academia. Since the 1980s, studies on carrying capacity have gradually broadened in scope and depth, with the concept commonly understood as the maximum population—human or animal—that a region can sustainably support [27]. Building on this foundation, related notions such as environmental carrying capacity, human carrying capacity, and urban carrying capacity have subsequently been developed [28–30]. Comprehensive carrying capacity is generally assumed to have a threshold beyond which damage to the urban environment is difficult to recover [28]. Oh et al. [31] defined the CCP of a city as follows: at different time scales, urban resource stocks can meet population growth, land use, economic development, and human activities without causing levels of severe degradation and damage that are difficult to recover from.

Prior research on the influence of specialized agglomeration on urban comprehensive carrying capacity (CCP) has mainly focused on its implications for environmental pollution [32], energy efficiency [33], and carbon reduction [34]. For instance, Pei et al. [35] examined the interaction between industrial agglomeration and the ecological environment, revealing a U-shaped association between specialization and pollution levels. Their results suggest that moderate clustering can mitigate environmental degradation, whereas excessive concentration tends to intensify it. Similarly, Shen N et al. [36] confirmed this U-shaped pattern, suggesting that specialized agglomeration initially mitigates but eventually exacerbates environmental pollution. Peng et al. [37] found an N-shape relationship between diversified agglomeration and the energy efficiency of all elements in China's digital economy, characterized by significant temporal snowball effects and spatial strategic competition. Boschma [38] showed that knowledge spillovers occur primarily among industries with similar technological bases, and that specialized agglomeration, along with its externalities, promotes regional economic development. Knowledge spillover is crucial to the formation of agglomeration economies, and these externalities contribute to regional economic development [24]. Moreover, agglomeration economies generate spatial externalities that vary according to city size [39].

Krugman's New Economic Geography theory [40] believes that industrial agglomeration promotes the flow of urban residents, businesses and other resources through knowledge spillover and sharing urban infrastructure. According to Marshall's theory of agglomeration economies, industrial clustering fosters population concentration and knowledge spillovers, reducing R&D costs and enhancing urban productivity. However, at higher levels of industrial development and maturity, specialized agglomeration may lead to monopolization, creating a monocultural industrial structure with closed boundaries that hinder efficient resource utilization. This can trigger destructive competition and imitation among regions and intensify resource conflicts among local firms. Studies have demonstrated that industrial agglomeration may bring about diseconomies of agglomeration, which inhibit productivity growth [41]. This effect likely arises because the competition and crowding associated with specialized agglomeration aggravate resource consumption and living costs, prompting firms and populations to relocate to peripheral areas. Moreover, excessive competition and monopolistic tendencies may inhibit local technological innovation and industrial development. Based on these insights, this paper proposes Hypothesis 1.

Hypothesis 1. *Specialized agglomeration intensifies the consumption and concentration of resources within a city, thereby constraining the improvement of its CCP and generating a "siphon effect" that draws resources away from neighboring cities.*

2.2. Diversified Agglomeration and Urban CCP

When different industries are gathered in one place, they allow knowledge from various fields to be shared and integrated. The impact of diversified agglomeration on a city's comprehensive carrying capacity is reflected in its ability to provide complementary resources, reduce path dependence, generate economies of scale, and create technology spillovers while also producing crowding effects. Localization, urbanization, and demand-driven economies of scale are considered the three basic sources of economic externalities [42]. Both Porter's and Jacobs' economic growth theories highlight the importance of knowledge spillovers in promoting economic development. Empirical evidence suggests that local competition and industrial diversity can significantly stimulate growth, with cross-industry interactions being particularly conducive to generating knowledge spillovers [38]. Researchers have investigated the economic and environmental effects of diversified agglomeration from various perspectives. Wang et al. [43] employed panel data from 30 Chinese provinces (2001–2011) and demonstrated that industrial diversification substantially strengthens regional innovation. By contrast, Gao [44] used provincial data from China's two-digit industrial classification (1985–1993) and found no significant correlation between diversified agglomeration and economic growth. Wei and Hou [45] analyzing panel data from Chinese provinces (2005–2017), reported that diversified agglomeration can inhibit regional green development. Similarly, Han et al. [23] combining panel data from 283 prefecture-level cities (2003–2010) with enterprise-level data and applying a dynamic spatial Durbin model, found that diversified agglomeration had no significant impact on a city's own energy efficiency but significantly reduced that of neighboring cities. Other studies indicate that economically diversified urban communities tend to experience lower rates of population loss and are less affected by urban shrinkage [46]. Furthermore, industrial diversification has been found to correlate positively with the emergence of new cities, while high levels of diversification and competition may correspond to weaker inter-city linkages [47].

In the study of the effects of diversified agglomeration spaces, diversified agglomeration is conducive to promoting the growth of industrial green total factor productivity [48]. Similarly, the neighboring cities' diversified agglomeration will lead to improvements of urban land use efficiency via the positive competition effect of local governments and the flow of production factors [17]. Moreover, the co-location of different industries within the same region incentivizes local governments to systematically improve infrastructure and public service provision to accommodate the diverse needs of these industries. Such measures improve the efficiency of inter-industry collaboration and strengthen the region's capacity to attract high-quality enterprises and skilled professionals. Importantly, the resulting infrastructure and services not only support local residents and industries but also extend benefits to nearby cities, enabling them to share regional resources, optimize cross-regional resource allocation, and enhance the overall carrying capacity and resilience of urban systems. Based on this, this paper proposes Hypothesis 2.

Hypothesis 2. *Diversified agglomeration enhances the CCP of the local city and generates spillover effects on neighboring cities.*

3. Methodology

3.1. Variable Measurement

3.1.1. Explained Variable: Urban CCP

1. Calculation of urban CCP

Urban CCP refers to the extent to which a city can sustain its population and socioeconomic activities, given the resource endowment, infrastructure, ecological environment, public education, and healthcare services. It describes a state in which the urban environment remains intact and free from irreversible degradation while supporting population growth and demands of land use [31]. Some scholars have used the ecological footprint [49] and the entropy method [8] to measure and evaluate the level of urban CCP. Based on existing studies and the rich connotation of urban CCP [50–52] and considering the availability of data, this study established an evaluation indicator system with five dimensions: socio-economic carrying capacity (CCP1), natural resource carrying capacity (CCP2), ecological environment carrying capacity (CCP3), public service carrying capacity (CCP4), and infrastructure carrying capacity (CCP5). To reduce the influence of subjective factors on the measurement and eliminate the dimensional differences among different indicators, we first standardized all the variables. Then, use the entropy method to assign weights to each indicator. Finally, by calculating the comprehensive evaluation values, the CCPs of 284 cities were obtained. The index weights calculated using the entropy method are shown in Table 1.

Table 1. Weights of each indicator.

Secondary Indicator	Weight	Tertiary Indicator	Weight
Socio-economic carrying capacity (CCP1)	0.3767	Retail sales of consumer goods	0.0981
		Actual utilized FDI	0.1871
		Secondary industry share of GDP	0.0140
		Natural population growth rate	0.0113
		GDP per capita	0.0410
		Average earnings of employed persons	0.0252
Natural resource carrying capacity (CCP2)	0.0949	Coverage rate of gas supply	0.0042
		Urban construction land area	0.0065
		Per capita green space	0.0606
		Population density	0.0131
		Per capita daily domestic water consumption	0.0106
Ecological environment carrying capacity (CCP3)	0.1386	Industrial sulfur dioxide emissions	0.0054
		Industrial smoke and dust emissions	0.0054
		Harmless treatment rate of domestic wastes	0.0056
		Green coverage rate of built-up areas	0.1117
		Centralized sewage treatment rate	0.0105

Table 1. *Cont.*

Secondary Indicator	Weight	Tertiary Indicator	Weight
Public service carrying capacity (CCP4)	0.2956	Number of hospital beds	0.0539
		Number of full-time primary and secondary school teachers per 10,000 students	0.0288
		Number of college students per 10,000 population	0.0627
		Library collection size	0.1274
		Per capita daily domestic water consumption	0.0228
Infrastructure carrying capacity (CCP5)	0.0942	Number of public buses and trolleybuses per 10,000 population	0.0386
		Paved road area per capita	0.0244
		Road freight volume	0.0052
		Drainage pipe density in built-up areas	0.0260

2. Temporal development characteristics of CCP

Using the entropy method with the indicators listed in Table 1, we measured the CCP of 284 prefecture-level cities in China from 2005 to 2022. Figure 1 reveals an inverted N-shaped trajectory, with CCP first declining, then rising, and finally declining again. Over this period, the highest value of CCP decreased from 0.2146 to 0.1134, indicating that rapid urbanization has placed severe pressure on cities' natural resources and ecological environment. This has intensified urban challenges such as environmental pollution, traffic congestion, and shortages of school placements and hospital beds, which in turn have hindered high-quality urban development. In addition, the average level of CCP declined significantly across the eastern, central, and western regions, i.e., from 0.2410, 0.1967, and 0.1882 in 2005 to 0.1226, 0.1003, and 0.1024 in 2022, representing decreases of 49.12%, 49.02%, and 45.60%, respectively. The trends in all three regions are largely consistent with the national pattern, with notable low points in 2009 and 2022. The western region reached its lowest point in 2009 and has shown a gradual recovery since then, surpassing the CCP of the central region in 2019, after which the central region remained the lowest among the three. Over the 18-year period, the level of CCP ranked consistently as follows: East > National Average > Central > West.

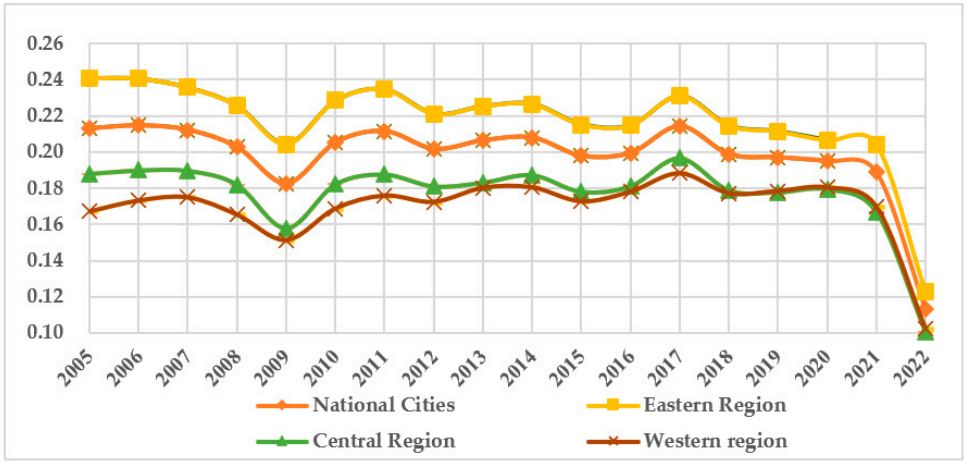


Figure 1. Levels of CCP across regions from 2005 to 2022.

3. The spatial evolution pattern of CCP

Based on the calculation results, we use the natural break classification in ArcGIS to divide the CCP of China cities into five categories: high, higher-medium, medium, lower-medium, and low. Figure 2 presents the spatiotemporal distribution of urban CCP in China for 2005, 2010, 2015, and 2022. Overall, CCP levels remain relatively low, with most cities falling into medium or lower categories. Spatial patterns are evident: higher CCP is concentrated in eastern regions, lower in western regions, with marked north–south differences and a tendency toward multi-polar clustering. The largest capabilities are mainly concentrated in cities directly managed by the central government and provincial capitals.

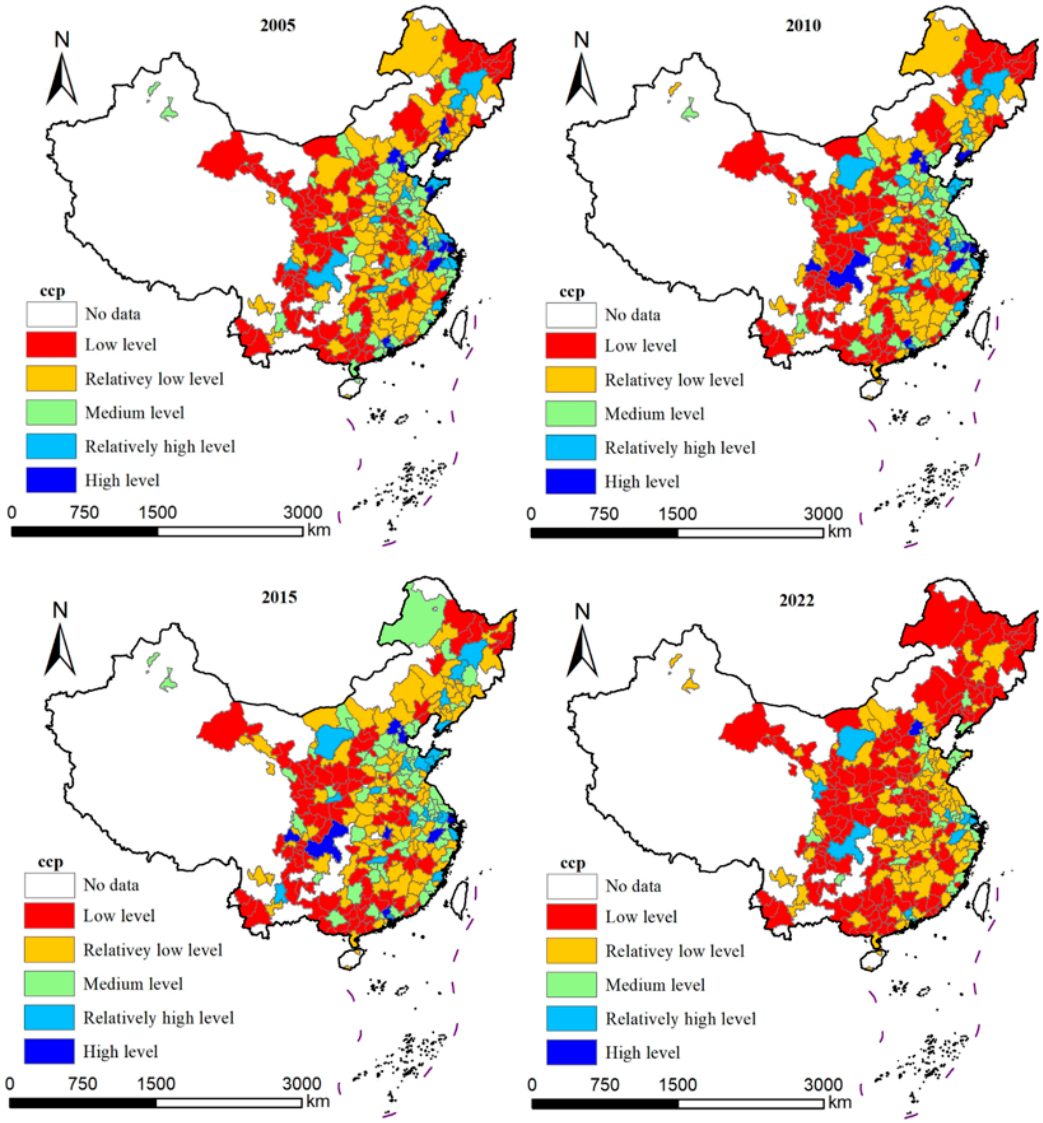


Figure 2. Spatial distribution pattern of CCP from 2005 to 2022. Note: These illustrations were produced using standard maps from the Map Technology Review Center Standard Map Service of the Ministry of Natural Resources (Map Review No.: GS (2023) 2762). The boundaries of the base map have not changed.

3.1.2. Explanatory Variable: Industrial Agglomeration

Based on the method of Duranton and Puga [22], each city's specialization and diversification are computed using the distribution of the employment across industries, as shown in Equations (1) and (2). Here, ris_i and rid_i represent the specialization and diversification

indices of city i, respectively, while s_{ij} and s_j denote the share of employment in industry j at the city and national levels.

$$ris_i = \max(s_{ij}/s_j) \quad (1)$$

$$rid_i = \frac{1}{\sum|s_{ij} - s_j|} \quad (2)$$

3.1.3. Control Variables

(1) Human capital (*edu*): In the global economy, competition among countries increasingly centers on attracting and keeping skilled workers. The enhancement of human capital can strengthen urban innovation capacity and optimize the industrial structure, thereby improving the total factor productivity (TFP) of cities [53]. Human capital, however, varies across cities of different sizes, with larger cities generally exhibiting higher educational attainment and wages [54]. In order to ensure analytical accuracy, this study incorporates urban human capital as a control variable, measured by the number of college students per 10,000 residents in municipal districts. (2) Population density (*pop*): Population density represents the intensity of human activities, which can impact urban resources and public infrastructure. Conversely, high-quality urban public services can also attract population migration and agglomeration, thereby enabling shared utilization of scarce infrastructure resources [55]. This study quantifies population density as the number of residents per square kilometer. (3) Foreign trade (*fdi*): According to the pollution haven hypothesis [14], pollution-intensive industries tend to build factories in cities with lower environmental standards. While an increase in actual utilized foreign direct investment can generate knowledge spillovers, it may also intensify industrial pollution. Consequently, this study controls for the level of foreign trade, measured by the amount of utilized foreign capital. (4) Transport infrastructure (*pbus*): Excessive dependence on private automobiles contributes to urban air pollution (e.g., haze) and resource consumption. In contrast, increased use of public transportation can mitigate these environmental pressures. Therefore, this study measures transport infrastructure by the number of public buses per 10,000 residents. (5) Economic development potential (*pgdp*): Economic development potential reflects a city's future vitality and its ability to sustain long-term growth in a competitive environment. In this study, it is represented by GDP per capita, adjusted to constant prices using 2005 as the base year.

3.2. Data Source

Owing to data availability, this study utilizes panel data covering 284 prefecture-level cities in China for the period of 2005–2022. Economic variables are mainly obtained from the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, and provincial and municipal statistical yearbooks. Geographic information is drawn from the standard maps released by the Map Technology Review Center of the Ministry of Natural Resources. For missing observations, interpolation techniques are employed. To address potential heteroscedasticity, dimensional variables are log-transformed, and all monetary indicators are converted into constant 2005 prices. The definitions of variables and their descriptive statistics are presented in Table 2.

Table 2. Definition of each variable and descriptive statistics.

Symbol	Variable Name	Definition	Mean	SD	min	max
ccp	Urban CCP	The comprehensive evaluation method is used for calculation according to the indicators in Table 1	0.1980	0.1010	0.0509	0.7890
ris	Specialized agglomeration	$ris_i = \max(s_{ij}/s_j)$	4.432	5.460	1.272	106.7
rid	Diversified agglomeration	$rid_i = \frac{1}{\sum\lvert s_{ij}-s_j\rvert}$	2.161	0.868	0.713	6.455
pgdp	Economic development level (yuan)	Regional GDP per capita	38,618	24,517	2662	321,557
edu	Human capital (measured by the number of people)	Number of college students per 10,000 residents	425	416	5	3189
pop	Population density (person per km2)	Population per square kilometer	3748	2706	27	20,093
pbus	Level of infrastructure (measured by the number of vehicles)	Number of public buses per 10,000 residents	8.202	7.049	0.320	225.50
fdi	Level of foreign trade ($10,000)	FDI	54,087	130,054	1.931	2,068,435.96

3.3. Model Building

3.3.1. Spatial Weight Matrix Setting

Before we can accurately measure the spatial correlation of urban CCP, we need to establish an appropriate spatial weight matrix. Based on existing studies [56,57], this research develops several different spatial weight matrices: the adjacency matrix (W_l), the geographic distance decay matrix (W_d), the economic distance matrix (W_e), and a nested matrix combining geographic and economic distances (W_{de}). These matrices are used to represent different mechanisms of spatial correlation and are expressed in Formulas (3)–(6):

$$W_l = \begin{cases} 1, (i \text{ was adjacent to } j) \\ 0, (i \text{ was not adjacent to } j) \end{cases} \tag{3}$$

$$W_d = \begin{cases} 1/d_{ij}^2, & i \neq j \\ 0, & i = j \end{cases} \tag{4}$$

$$W_e = \begin{cases} 1/|\overline{gdp_i} - \overline{gdp_j}|, & i \neq j \\ 0, & i = j \end{cases} \tag{5}$$

$$W_{de} = \alpha W_d + (1-\alpha) W_e \tag{6}$$

where d_{ij}^2 represents the squared geographic distance between cities i and j, calculated based on the latitude and longitude coordinates, while gdp_i and gdp_j denote the average per capita GDP of cities i and j from 2005 to 2022. Parameter α represents the weighting factor between W_d and W_e, α is set to 0.5.

3.3.2. Spatial Correlation Test

1. Global spatial correlation test

According to first law of geography in Tobler, economic and industrial development across regions does not occur in isolation [58]. To explore whether urban CCP exhibits spatial characteristics, *Moran's I* is applied to test for spatial autocorrelation. The corresponding formulas are presented in Equations (7) and (8):

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{7}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n} (x_i - \overline{x})^2 \tag{8}$$

where W_{ij} represents the spatial weight between cities i and j; x represents the CCP of each city; S^2 is the sample variance. The value of *Moran's I* index ranges from $[-1, 1]$. $I > 0$ indicates a positive spatial correlation, $I < 0$ indicates a negative spatial correlation, and $I = 0$ indicates no spatial correlation, and the larger the value, the stronger the correlation. The continuous spatial evolution of industries leads to disparities in the economic development of various cities, and variations in industrial agglomeration across different spatial regions inevitably generate interactive effects on CCP. Therefore, based on different spatial weight matrices, this paper employs Stata 16 to conduct a global spatial correlation test on the CCP of cities. The specific results are shown in Table 3.

Table 3. Moran's I for CCP under different spatial weight matrices.

Year	W_l	W_d	W_e	W_{de}
2005	0.2445 ***	0.1958 ***	0.3818 ***	0.2239 ***
2006	0.2319 ***	0.1886 ***	0.3678 ***	0.2163 ***
2007	0.2478 ***	0.2041 ***	0.3711 ***	0.2209 ***
2008	0.2374 ***	0.1988 ***	0.3456 ***	0.1903 ***
2009	0.1641 ***	0.1474 ***	0.3331 ***	0.2062 ***
2010	0.1939 ***	0.1739 ***	0.3551 ***	0.2023 ***
2011	0.1770 ***	0.1636 ***	0.3509 ***	0.2235 ***
2012	0.1818 ***	0.1649 ***	0.3906 ***	0.2036 ***
2013	0.1857 ***	0.1681 ***	0.3531 ***	0.1984 ***
2014	0.1613 ***	0.1482 ***	0.3510 ***	0.1768 ***
2015	0.1633 ***	0.1529 ***	0.3085 ***	0.1773 ***
2016	0.1599 ***	0.1439 ***	0.3136 ***	0.1773 ***
2017	0.1509 ***	0.1387 ***	0.3141 ***	0.1783 ***
2018	0.1231 ***	0.1213 ***	0.3167 ***	0.1746 ***
2019	0.1295 ***	0.1250 ***	0.2815 ***	0.1591 ***
2020	0.1196 ***	0.1172 ***	0.2515 ***	0.1428 ***
2021	0.1454 ***	0.1451 ***	0.2881 ***	0.1647 ***
2022	0.1404 ***	0.1218 ***	0.2280 ***	0.1336 ***

Note: *** indicates statistical significance at 1% level.

As shown in Table 3, regardless of whether the spatial weight matrix is defined as W_l, W_d, W_e, or W_{de}, the *Moran's I* statistics for urban CCP is significantly positive during the period from 2005 to 2022. Research shows there is a notable geographic correlation in the urban carrying capacity across China's municipal divisions. Since *Moran's I* index is

at its peak in matrix W_e, this matrix is used as the foundation for our upcoming spatial economic models.

2. Local spatial correlation test

The global Moran index results indicate that the overall urban CCP of China shows a significant spatial positive correlation feature. To further analyze the spatial heterogeneity of urban CCP, this study uses the local Moran index scatter plot to identify spatial clustering phenomena. The calculation method of the local Moran index is as shown in Formula (9).

$$I_i = \frac{x_i - \overline{x}}{S^2} \sum_{j=1}^{n} W_{ij}(x_i - \overline{x}) \tag{9}$$

Scatter plots of CCP for 2005 and 2022 were generated based on the local *Moran's I* using an economic distance matrix (Figure 3a,b). The plots are divided into four quadrants—high–high, low–high, high–low, and low–low—each representing distinct types of spatial association. Compared to 2005, spatial clustering in 2022 showed greater intensity, with an increased number of cities located in the first and third quadrants and a decrease in the second quadrant.

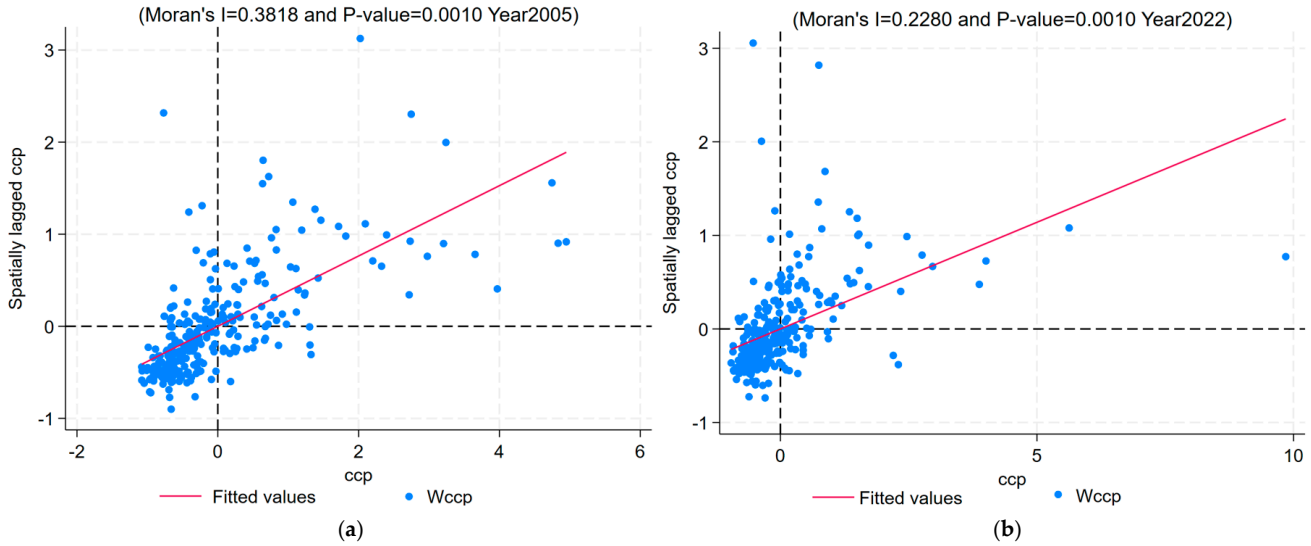


Figure 3. (**a**) Moran's I scatter plot of CCP in 2005; (**b**) Moran's I scatter plot of CCP in 2022.

3.3.3. Construction of Spatial Econometric Model

Knowledge spillovers and technology sharing from industrial agglomeration, along with the mobility of pollutants, create a strong spatial link between urban industrial concentration and CCP, which is supported by the results of spatial autocorrelation analysis. Spatial autocorrelation tests indicate significant spatial dependencies. While traditional spatial econometric models such as SAR and SEM account for spatial lags of the dependent variable or error term, they may overlook simultaneous dependencies in both. The spatial Durbin model (SDM) addresses this by including spatial lags of dependent and independent variables, capturing reciprocal spatial interactions and unobserved effects [59]. To identify the best-fitting model and assess derivations from SDM, SAR, and SEM models (Equations (10)–(15)) are constructed and tested accordingly.

In order to examine the spatial correlation between specialized agglomeration, diversified agglomeration, and CCP, the basic Spatial Durbin Model (SDM) specifications are defined in Equations (10) and (11):

$$ccp_{it} = \beta_0 + \rho_1 Wccp_{it} + \beta_1 ris_{it} + \beta_2 Xcontrol + \theta_1 Wris_{it} + \theta_2 WXcontrol + \mu_i + \lambda_t + \varepsilon_{it} \tag{10}$$

$$ccp_{it} = \beta_0 + \rho_1 Wccp_{it} + \beta_1 rid_{it} + \beta_2 Xcontrol + \theta_1 Wrid_{it} + \theta_2 WXcontrol + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

When the spatial effects of the independent variables in the SDM are absent—specifically, when $\theta_i = 0$ ($i = 1, 2$)—SDM simplifies to SAR, which captures only the spatial autocorrelation of the dependent variable, as shown in Equations (12) and (13):

$$ccp_{it} = \beta_0 + \rho_1 Wccp_{it} + \beta_1 ris_{it} + \beta_2 Xcontrol + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

$$ccp_{it} = \beta_0 + \rho_1 Wccp_{it} + \beta_1 rid_{it} + \beta_2 Xcontrol + \mu_i + \lambda_t + \varepsilon_{it} \quad (13)$$

When the spatial lag coefficient of the dependent variable (ρ), the regression coefficient (β_i), and the spatial interaction coefficients of the independent variables (θ_i) in the SDM satisfy the condition that $\theta_i + \rho\beta_i = 0$, the spatial lag model of SEM is obtained as in Equations (14) and (15):

$$ccp_{it} = \beta_0 + \rho_1 Wccp_{it} + \beta_1 ris_{it} + \beta_2 Xcontrol + \mu_i + \lambda_t + \varepsilon_{it} + \gamma W\varepsilon_{it} \quad (14)$$

$$ccp_{it} = \beta_0 + \rho_1 Wccp_{it} + \beta_1 rid_{it} + \beta_2 Xcontrol + \mu_i + \lambda_t + \varepsilon_{it} + \gamma W\varepsilon_{it} \quad (15)$$

where, i represents the specific city ($i = 1,\ldots,284$), t represents the specific year ($t = 2005, \ldots, 2022$), ccp_{it} represents the CCP of city i in year t, W represents spatial weight matrix, ris_{it} represents the urban industrial specialization index, rid_{it} represents urban industrial diversification index, *Xcontrol* represents control variables including economic development potential (*pgdp*), human capital (*edu*), population density (*pop*), transport infrastructure (*pbus*), and foreign trade (*fdi*). ρ denotes the spatial autoregressive coefficient, β represents the coefficient of the independent variable, θ captures the spatial interaction effect, and ε_{it} is the random error term, which is assumed to be independently and identically distributed. To mitigate the impact of extreme values, all variables measured on a scale are transformed using the natural logarithm.

3.3.4. Selection of Spatial Econometric Model

Given that the nature of spatial interactions is not known a priori, this study follows Anselin and employs LM, Wald, and LR tests to select the most appropriate spatial econometric model [60]. The test results for spatial model selection are shown in Table 4.

Table 4. Model selection test.

Test	Statistic	df	*p*-Value
LM-error	823.542 ***	1	0.000
Robust LM-error	131.448 ***	1	0.000
LM-lag	735.167 ***	1	0.000
Robust LM-lag	43.073 ***	1	0.000
Hausman test (χ^2)	257.22 ***	13	0.000
LR test for SAR (χ^2)	25.23 ***	8	0.000
Wald test for SAR (χ^2)	67.25 ***	6	0.000
LR test for SEM (χ^2)	42.31 ***	8	0.000

Table 4. *Cont.*

Test	Statistic	df	*p*-Value
Wald test for SEM (χ^2)	71.60 ***	6	0.000
LR test both ind (χ^2)	901.22 ***	14	0.000
LR test both time (χ^2)	10,800.89 ***	14	0.000

Note: *** indicates statistical significance at 1% level.

Based on the test results in Table 4, the individual-time fixed SDM is the most appropriate choice for modeling. The model specifications are as follows:

$$\begin{aligned} ccp_{it} = {} & \beta_0 + \rho_1 W ccp_{it} + \beta_1 ris_{it} + \beta_2 \ln pgdp_{it} + \beta_3 \ln pop_{it} + \beta_4 \ln fdi_{it} + \\ & \beta_5 \ln pbus + \beta_6 \ln edu + \theta_1 W ris_{it} + \theta_2 W \ln pgdp_{it} + \theta_3 W \ln pop_{it} + \\ & \theta_4 W \ln fdi_{it} + \theta_5 W \ln pbus_{it} + \theta_6 W \ln edu_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{16}$$

$$\begin{aligned} ccp_{it} = {} & \beta_0 + \rho_1 W ccp_{it} + \beta_1 rid_{it} + \beta_2 \ln pgdp_{it} + \beta_3 \ln pop_{it} + \beta_4 \ln fdi_{it} + \\ & \beta_5 \ln pbus + \beta_6 \ln edu + \theta_1 W rid_{it} + \theta_2 W \ln pgdp_{it} + \theta_3 W \ln pop_{it} + \\ & \theta_4 W \ln fdi_{it} + \theta_5 W \ln pbus_{it} + \theta_6 W \ln edu_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{17}$$

In practice, environmental pollution and economic growth often display path dependence and the Matthew effect due to the long-term cumulative influence of factors such as urban location, resource endowment, and industrial structure [61]. In addition, the CCP of a city is influenced not only by current factors but also by its past levels, reflecting a delayed or time-lagged effect. Factors such as industrial agglomeration, industrial structure characteristics, population density, and GDP per unit of fixed assets clearly exhibit lagged effects, which in turn may lead to delayed changes in CCP. Investigating this time-lag effect is therefore of great significance. Based on Elhorst [62], a dynamic spatial Durbin model (SDM) is constructed by incorporating the lagged term of CCP into the static SDM, as shown in Equations (18) and (19). Unlike the static SDM, the dynamic spatial Durbin model not only captures the spatial dependence of CCP but also mitigates endogeneity and potential biases arising from omitted variables, thereby improving the robustness and reliability of the estimation results.

$$\begin{aligned} ccp_{it} = {} & \psi \ln ccp_{it-1} + \beta_0 + \rho_1 W ccp_{it} + \beta_1 ris_{it} + \beta_2 \ln pgdp_{it} + \beta_3 \ln pop_{it} + \beta_4 \ln fdi_{it} + \\ & \beta_5 \ln pbus + \beta_6 \ln edu + \theta_1 W ris_{it} + \theta_2 W \ln pgdp_{it} + \theta_3 W \ln pop_{it} + \theta_4 W \ln fdi_{it} \\ & + \theta_5 W \ln pbus_{it} + \theta_6 W \ln edu_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{18}$$

$$\begin{aligned} ccp_{it} = {} & \psi \ln ccp_{it-1} + \beta_0 + \rho_1 W ccp_{it} + \beta_1 rid_{it} + \beta_2 \ln pgdp_{it} + \beta_3 \ln pop_{it} + \beta_4 \ln fdi_{it} + \\ & \beta_5 \ln pbus + \beta_6 \ln edu + \theta_1 W rid_{it} + \theta_2 W \ln pgdp_{it} + \theta_3 W \ln pop_{it} + \theta_4 W \ln fdi_{it} \\ & + \theta_5 W \ln pbus_{it} + \theta_6 W \ln edu_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{19}$$

In Equations (18) and (19), ψ represents the time lag coefficient, assessing the impact of the past epoch's CCP on its present status; definitions of the remaining variables align with the static spatial panel model.

4. Results

4.1. Analysis of Baseline Regression Result

Since the dynamic spatial Durbin model (SDM) includes both a first-order lag of the dependent variable and a spatial lag term, quasi-maximum likelihood estimation is used to address potential endogeneity and to test the impact of industrial agglomeration on CCP, following the approach of Lee and Yu [63]. To facilitate comparison and to evaluate the appropriateness of including a one-period lag of CCP, the findings for both the steady-state

Spatial Durability Model and the shifting SDM are detailed in Table 5. The analysis from Models 18 and 19 shows that the lag effect of CCP yields a positive value, and this is found to be statistically substantial at the 1% level. This holds true for models that account for either focused or varied clusters. This confirms that CCP exhibits a pronounced time-lag effect and path-dependent behavior. Specifically, improvements in CCP in the previous year significantly enhance the level in the current year, demonstrating a clear "snowball" effect. Therefore, omitting the time-lag effect of the dependent variable may lead to biased model estimates.

Table 5. The benchmark regression results of the SDM model.

Variables	Static SDM Model		Dynamic SDM Model	
	Model (16)	**Model (17)**	**Model (18)**	**Model (19)**
Main				
L.CCP			0.5310 ***	0.5310 ***
			(0.0411)	(0.0410)
ris	−0.00009		−0.00007	
	(0.0001)		(0.0001)	
rid		0.0005		0.0001
		(0.0006)		(0.0008)
lnpgdp	0.0252 ***	0.0251 ***	0.0138 ***	0.0137 ***
	(0.0015)	(0.0015)	(0.0017)	(0.0018)
lnpop	−0.0037 ***	−0.0038 ***	−0.0042 ***	−0.0043 ***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
lnfdi	0.0049 ***	0.0049 ***	0.0032 ***	0.0031 ***
	(0.0003)	(0.0003)	(0.0006)	(0.0006)
lnpbus	0.0136 ***	0.0136 ***	0.0105 ***	0.0105 ***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
lnedu	0.0150 ***	0.0150 ***	0.0122 ***	0.0122 ***
	(0.0006)	(0.0006)	(0.0011)	(0.0010)
Wx				
ris	−0.0004 *		−0.0003	
	(0.0002)		(0.0002)	
rid		0.0037 **		0.0030
		(0.0016)		(0.0019)
lnpgdp	0.0024	0.0017	0.0079	0.0073
	(0.0037)	(0.0037)	(0.0056)	(0.0057)
lnpop	0.0012	0.0010	−0.0003	−0.0004
	(0.0019)	(0.0019)	(0.0022)	(0.0022)
lnfdi	−0.0033 ***	−0.0034 ***	−0.0040 ***	−0.0041 ***
	(0.0008)	(0.0008)	(0.0011)	(0.0011)
lnpbus	0.0026	0.0020	0.0008	0.0005
	(0.0023)	(0.0023)	(0.0022)	(0.0021)
lnedu	0.0024	0.0023	0.0007	0.0006
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
rho	0.1980 ***	0.2000 ***	0.1610 ***	0.1630 ***
	(0.0228)	(0.0228)	(0.0447)	(0.0444)

Table 5. *Cont.*

Variables	Static SDM Model		Dynamic SDM Model	
	Model (16)	**Model (17)**	**Model (18)**	**Model (19)**
sigma2_e	0.0005 *** (0.000009)	0.0005 *** (0.000009)	0.0004 *** (0.000042)	0.0004 *** (0.000042)
N	5112	5112	4828	4828
R-sq	0.394	0.394	0.826	0.825

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Values in brackets represent robust standard errors. "L." denotes the one-period lag of the explanatory variable, applied consistently throughout the table.

Table 5's Models (16) and (18) reveal a noteworthy trend: the coefficients for specialized clustering and the spatial lag are negative, suggesting that specialized clustering hinders the boost in connectivity and collaboration (CCP) for local and nearby cities. However, a different picture emerges in Models (17) and (19), where the estimated coefficients for varied clustering and its spatial lag are positive, suggesting that diverse clustering helps to improve the CCP in both local and surrounding cities.

The regression data from Models (18) and (19) in Table 5 reveals that, no matter if local cities go for specialization or diversification in agglomeration strategies, three factors stand out: human capital, economic growth prospects, and transport links all contribute substantially to enhancing a city's competitive capacity, especially at the 1% significance threshold, but these benefits do not seem to cross city boundaries to impact neighboring locations. Population density, however, seems to hinder local cities' competitiveness significantly, at the 1% level, without influencing other nearby areas. Furthermore, a higher level of foreign trade has a marked positive impact on the competitive capacity of local cities at the 1% level, but conversely, it negatively affects that of surrounding cities at the same level of statistical significance.

4.2. Analysis of Spatial Effect

The dynamic spatial Durbin model (SDM) not only considers the spatial lag of the dependent variable and its prior periods, but also captures the broader, cross-regional spillover effects, which are distinct from localized impacts. To mitigate the risk of misinterpreting the estimated coefficients of the dynamic spatial Durbin model (SDM) as direct marginal effects on the dependent variable, this research employs the technique of partial differentiation [64]. This method allows for a dissection of how industrial clustering and urban expansion influence the CCP. Moreover, considering the ever-changing landscape of the Sustainable Development Model (SDM), it is crucial that the influence of every explanatory variable on the urban carrying capacity is assessed not just for immediate outcomes but also for the long-term repercussions that could arise from temporal delays. Using the model's estimates, the immediate and long-term impacts of each element on CCP have been broken down, and the findings are meticulously detailed in Table 6.

Table 6. The calculation method of long-term and short-term effects.

Direct Short-Term Effect	Indirect Short-Term Effect	Direct Long-Term Effect	Indirect Long-Term Effect
$[(I-\rho W)^{-1}(\beta_k I)]^{\overline{d}}$	$[(I-\rho W)^{-1}(\beta_K I)]^{\overline{rsum}}$	$\left\{\left[I(1-\psi)-(\rho+\varphi)^{-1}(\beta_K I)^{\overline{d}}\right]\right\}$	$\left\{\left[I(1-\psi)-(\rho+\varphi)^{-1}(\beta_K I)^{\overline{rsum}}\right]\right\}$

Note: I is the identity matrix; $\overline{d}$ represents the operator for computing the mean value of the diagonal elements of a matrix; $\overline{rsum}$ represents the operator for computing the row average of the non-diagonal elements of a matrix; β_k is the coefficient vector corresponding to each explanatory factor; φ, ψ and ρ represent the time-space-lag coefficient, time-lag coefficient, space-lag coefficient, respectively, which are set and estimated according to the model mentioned above. In this paper, $\varphi = 0$, $\psi = 0.531$, and ρ = 0.161, 0.163. The definitions of the remaining variables are consistent with previous definitions.

In Table 7, we can see the breakdown of the impact effects that stem from the models presented in Models (18) and (19). To sum it up, the immediate implications of both types of clustering—specialized and diversified—are on the smaller side compared to their long-term impacts. This implies that the lasting effect of industrial clustering on CCP is rather significant. Additionally, the direct, indirect, and overall effects of diversified clustering outstrip those of specialized clustering. Moreover, while specialized clustering exhibits negative indirect and total effects over both the short and long term, diversified clustering shows a bright side, with positive effects on all fronts.

Table 7. Effect decomposition of baseline regression.

Variable	Model (18)	Model (19)
	ris	*rid*
Direct short-term effect	−0.0001	0.0002
Indirect short-term effect	−0.0003	0.0036
Total short-term effect	−0.0004 *	0.0038
Direct long-term effect	−0.0002	0.0006
Indirect long-term effect	−0.0010	0.0100
Total long-term effect	−0.0012 *	0.0106

Note: * indicate statistical significance at 10% level.

In terms of direct effects, specialized agglomeration exerts an inhibitory effect on the CCP of local cities, while diversified agglomeration has a facilitative effect. While the effects maintain the same direction, their magnitude is larger in the long term than in the short term. Regarding indirect effects, diversified agglomeration generates positive spillover effects that enhance the CCP of neighboring cities, while specialized agglomeration produces a siphon effect that suppresses it. This implies that diversified agglomeration promotes, while specialized agglomeration inhibits, the improvement of CCP in neighboring cities. Over time, the effects of both types of agglomeration gradually intensify, providing support for Hypotheses 1 and 2. In terms of the total effects, it is clear that specialized agglomeration has a notably detrimental impact, reaching the 10% significance threshold, which shows it is a substantial drag on CCP improvement. On the flip side, diversified agglomeration yields a positively significant total effect, highlighting its supportive influence on CCP. Moreover, the total effects of both agglomeration types amplify over time, while their fundamental nature remains unchanged.

4.3. Analysis of Heterogeneity

4.3.1. Regional Heterogeneity Analysis

In accordance with the National Bureau of Statistics of China's "Fourth National Economic Census Bulletin" classification criteria, the 284 cities under scrutiny are segmented into three distinct zones: Eastern, Central, and Western China. Each of these zones was analyzed individually, using a dynamic spatial econometric model to probe into the regional disparities in how industrial clustering affects urban carrying capacity. As depicted in Table 8, when it comes to Eastern China's cities, the impacts of specialized clustering on comprehensive carrying capacity are uniformly negative, aligning with the findings from the initial regression analysis. Conversely, diversified clustering exhibits a positive short-term direct impact, but this shifts to a negative influence in both the long-term direct and indirect effects. In central China, a specialized agglomeration significantly inhibits the growth of local CCP at the 5% level. Its short-term indirect effect, however, significantly promotes the improvement of neighboring cities' CCP at the 1% level, while the long-term

indirect effect is positive but not statistically significant. Diversified agglomeration exerts a significant positive effect on both local and surrounding cities, with significance at the 10% level at least. For cities in western China, specialized agglomeration enhances the comprehensive carrying capacity of local cities and produces a positive spillover effect on neighboring cities. In contrast, diversified agglomeration inhibits the improvement of local CCP at the 10% level. Its short-term spillover effect on surrounding cities is positive, but over time, this effect evolves into a polarization effect. In every region, the lasting impact of both specialized and diversified agglomeration outweighs their immediate effects, underscoring the cumulative and sustained influence industrial clustering has on CCP over time.

Table 8. Effect decomposition of regional heterogeneity.

Variables	Eastern Area		Central Area		Western Area	
	ris	*rid*	*ris*	*rid*	*ris*	*rid*
Direct short-term effect	−0.00011	0.00008	−0.00028 **	0.00281 **	0.00004	−0.00263 *
Indirect short-term effect	−0.00002	−0.00019	0.00003 ***	0.00033 *	0.00025 **	0.00003
Total short-term effect	−0.00012	−0.00011	−0.00024 *	0.00313 **	0.00029	−0.00261 *
Direct long-term effect	−0.00023	−0.00378	−0.00045 **	0.00457 **	0.00019	−0.00691 *
Indirect long-term effect	−0.00008	−0.00543	0.00005	0.00056 *	0.00076	−0.00001
Total long-term effect	−0.00031	−0.00920	−0.00039 *	0.00513 **	0.00094	−0.00692 *

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

4.3.2. Analysis of Economic Development Heterogeneity

Industrial agglomeration has become a growth area for regions and cities [65], while the level of economic development also constrains the capacity for industrial agglomeration [66]. This research categorizes the 5112 cities analyzed during this study's timeframe by their median GDP per capita. Cities that boast a GDP per capita at or above the median threshold are deemed high-income, whereas those with a GDP per capita below the median are classified as low-income. A dynamic Spatial Durbin Model (SDM) is employed to conduct a heterogeneity analysis of cities at different income levels. In Table 9, we observe a telling pattern: for urban centers boasting robust economic growth, the impacts—both direct and indirect—of niche clustering on their competitive capabilities are predominantly negative, a stark contrast to the positive effects of a diversified clustering strategy. This aligns with the initial regression results, albeit with more pronounced effects and heightened statistical significance in the direct impacts. This suggests that cities with a strong economic pulse tend to be hubs for elite industries with robust outreach potential. Conversely, for those cities lagging in economic advancement, niche clustering tends to yield more favorable direct effects, but the indirect and overall effects of a diversified approach lean toward the negative.

Table 9. Effect decomposition of economic development level heterogeneity.

Variable	High Income		Low Income	
	ris	*rid*	*ris*	*rid*
Direct short-term effect	−0.00018 *	0.00024	0.00007	0.00004
Indirect short-term effect	−0.00057	0.00526 *	0.00010	−0.00067
Total short-term effect	−0.00075 *	0.00550	0.00017 *	−0.00062
Direct long-term effect	−0.00040 *	0.00074	0.00015	0.00008

Table 9. *Cont.*

Variable	High Income		Low Income	
	ris	***rid***	***ris***	***rid***
Indirect long-term effect	−0.00149	0.01340	0.00023	−0.00153
Total long-term effect	−0.00189 *	0.01410	0.00038	−0.00145

Note: * indicate statistical significance at 10% level.

4.4. Robustness Test

To bolster the credibility of the research findings, this investigation employs rigorous robustness checks, which involve swapping out the spatial weight matrix and altering the sample composition. The findings from the effect decomposition analysis are detailed in Table 10. In the case of specialized clustering, whether the adjacency, geographic distance, or nested matrices are utilized, both the immediate and long-term direct and indirect impacts on CCP are negative, aligning with the trends observed in the baseline regression outcomes. Upon omitting select city samples, like those governed directly by the central authority, the indirect influence of specialized clustering shifts from negative to positive, while the direct impact remains negative. For diversified clustering, the direct effect perseveres as positive when the adjacency or geographic distance matrices are employed, or when sample replacements are made. With the nested matrix, the short-term direct impact of diversified clustering is negative, but all other effects are positive. These effects' directions largely match those of the baseline regression, though their intensities are somewhat more pronounced. In conclusion, while there are slight variations in the values of certain variables when compared to the baseline estimates, the overarching impact patterns of both specialized and diversified clustering on CCP are steadfast. These outcomes validate the resilience of the effects of industrial clustering on CCP.

Table 10. Effect decomposition of the robustness test.

Variable	Effect Decomposition	W_1	W_d	W_{de}	After Sample Replacement
ris	Direct short-term effect	−0.00011	−0.00010	−0.00008	−0.00009
	Indirect short-term effect	−0.00011	−0.00042	−0.00079	0.000004
	Total short-term effect	−0.00022	−0.00052	−0.00087	−0.000086
	Direct long-term effect	−0.00024	−0.00025	−0.00021	−0.00017
	Indirect long-term effect	−0.00030	−0.00278	−0.00637	0.00001
	Total long-term effect	−0.00054	−0.00303	−0.00658	−0.00016
rid	Direct short-term effect	0.00014	0.00003	−0.00011	0.00007
	Indirect short-term effect	−0.00075	−0.00088	0.00491	−0.00009
	Total short-term effect	−0.00061	−0.00085	0.00480	−0.00002
	Direct long-term effect	0.00027	0.00004	0.00005	0.00010
	Indirect long-term effect	−0.00173	−0.00102	0.04380	−0.00013
	Total long-term effect	−0.00146	−0.00098	0.04390	−0.00003

4.5. Further Analysis

Urban comprehensive carrying capacity is like a multifaceted puzzle, integrating economic and social (CCP1), natural resource (CCP2), ecological environment (CCP3), public service (CCP4), and infrastructure (CCP5) factors. To delve deeper into how specific

kinds of urban clustering, like specialized and diverse agglomeration, impact these different aspects of carrying capacity, we employ the models detailed in Equations (18) and (19). Their direct and indirect influences are then dissected with the techniques outlined in Table 6. All the nitty-gritty details can be found in Table 11.

Table 11. Effect decomposition of regression results across different dimensions.

Variable	Effect Decomposition	CCP1	CCP2	CCP3	CCP4	CCP5
ris	Direct short-term effect	−0.00004	0.00002	−0.00003	0.00001	−0.00006 ***
	Indirect short-term effect	−0.00007	0.00004	−0.00007	−0.00026 ***	0.00000
	Total short-term effect	−0.00011	0.00005 *	−0.00010 *	−0.00025 ***	−0.00005
	Direct long-term effect	−0.00012	0.00004	−0.00005	0.00001	−0.00010 ***
	Indirect long-term effect	−0.00030	0.00010	−0.00011	−0.00034 ***	−0.00000
	Total long-term effect	−0.00042	0.00014 *	−0.00016 *	−0.00033 ***	−0.00010
rid	Direct short-term effect	−0.00037	−0.00008	0.00003	0.00095 ***	−0.00017
	Indirect short-term effect	0.00145	−0.00023	0.00020	0.00108	0.00050
	Total short-term effect	0.00108	−0.00031	0.00023	0.00203 **	0.00033
	Direct long-term effect	−0.00098	−0.00022	0.00005	0.00125 ***	−0.00030
	Indirect long-term effect	0.00518	−0.00061	0.00035	0.00148	0.00095
	Total long-term effect	0.00420	−0.00083	0.00040	0.00273 **	0.00065

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 11 reveals divergence in how specialized and diversified agglomeration impacts various aspects of CCP. Specialized clustering removes both CCP1 and CCP3, with lasting adverse effects, although CCP2 sees the benefits. With CCP4, specialized agglomeration delivers a 1% positive direct hit, yet the 1% negative ripple and total effect paint a different picture for CCP5. On the other hand, diversified clustering paints a different story—its direct punch at CCP1 and CCP5 is less than kind, while its supportive indirect strike gives the overall effect a fighting chance. For CCP2, the direct, indirect, and total effects of diversified agglomeration are all negative. For CCP3, all three direct, indirect, and total are positive, which is a stark contrast. CCP4 takes the cake with diversified agglomeration's 1% direct win and an indistinct yet optimistic indirect boost, leading to a 5% positive finish.

5. Discussion

5.1. Regional Disparities in CCP

The evolution of China's urban comprehensive carrying capacity (CCP) from 2005 to 2022 presents a distinct inverted "N-shaped" trajectory, reflecting the dynamic interaction between regional economic growth, resource constraints, and policy interventions. The observed trend, characterized by an initial decline, subsequent rebound, and eventual decrease, is consistent with the transitional patterns reported in previous research on urban sustainability and carrying capacity dynamics [67,68]. The regional heterogeneity—namely "high in the east, low in the west," coupled with "north–south disparities" and "multi-polar agglomeration"—underscores the long-standing imbalance in China's spatial development. Similar findings have been documented in ecological and resource-based assessments of regional carrying capacity, which emphasize the uneven distribution of resources and infrastructure across provinces [52].

5.2. Specialized Agglomeration and CCP

According to the estimation results and effect decomposition from SDM, specialization agglomeration shows a more complex and often inhibitory relationship with CCP. The analysis indicates that specialization suppresses the enhancement of overall CCP, particularly in terms of economic–social (CCP1) and infrastructure (CCP5) capacities. It also restrains the development of surrounding cities' CCP4, although it positively contributes to the host city's CCP4 and neighboring cities' CCP5. These asymmetric spillover effects suggest that specialization may create localized efficiency gains at the cost of regional balance. A possible explanation is that the "scale effect" and "agglomeration effect" generated by specialized agglomeration are weaker than the "competition effect" and "crowding effect" on resources within the same region, thereby constraining local carrying capacity. These asymmetric spillover effects suggest that specialization may create localized efficiency gains at the cost of regional balance.

This model aligns with the viewpoints presented in the existing literature, which warn of the risks associated with excessive reliance on specialization, including the risks of inhibiting innovation, generating diseconomies of scale, and causing environmental degradation [27,31,41]. Nonetheless, specialization remains beneficial in specific contexts: in western and less-developed cities, it enhances both local and neighboring CCP, confirming its role as a catalyst for catch-up development. Such outcomes are aligned with system dynamics models showing that specialization can accelerate growth when infrastructural and technological bases are underdeveloped, albeit with potential sustainability trade-offs [69].

The analysis of heterogeneity reveals unique regional impacts of specialized clustering on urban CCP in China. In the eastern region, specialization consistently suppresses the improvement of both local and neighboring cities' CCP, creating a "double loss" effect. This inhibitory role may arise from energy-intensive production, resource depletion, environmental degradation, and congestion externalities, which not only constrain local development but also spill over into adjacent areas [70]. In the central region, specialized agglomeration significantly reduces local CCP, while generating positive short-term spillover effects on neighboring cities through shared infrastructure and labor migration; however, its long-term spillover benefits are weaker and statistically insignificant. This reflects the dual mechanism in which resource misallocation and environmental costs coexist with inter-city spillovers that enhance productivity and reduce costs. By contrast, in the western region, specialization exerts positive short- and long-term direct and indirect effects, with significant short-term spillovers, suggesting that resource-based advantages and focused industrial development can enhance both local and regional CCP. These findings confirm that the impact of specialization is highly context-dependent, shaped by levels of economic maturity, industrial structure, and regional development stage, and they underscore the need for differentiated industrial clustering strategies [70].

The results of robustness testing indicate that, irrespective of whether W_1, W_d, or W_{de} is employed, specialized agglomeration exerts an inhibitory effect on the enhancement of CCP. After sample replacement, specialized agglomeration continues to hinder the CCP of local cities while promoting the improvement of that of neighboring cities. Moreover, when W_d is used, the inhibitory effect of specialized agglomeration becomes more pronounced. This may be attributed to the fact that with economic development and the enhancement of transportation infrastructure, intercity connectivity within the region has become increasingly strong [38]. Under such conditions, specialized agglomeration accelerates the depletion and competition for urban resources both within and across regions, thereby constraining the improvement of CCP. Overreliance on a solitary industry diminishes a city's CCP diversity through inefficient resource distribution and skewed functionality. Even when regional economic complementarity exists, the "local factor accumulation"

and "neighboring resource siphoning" effects of specialized agglomeration remain dominant. However, the negative impacts exhibit a spatial attenuation pattern with increasing distance. In the original sample—which included megacities such as provincial capitals and sub-provincial cities—the excessive congestion induced by specialized agglomeration exceeded the threshold of local CCP. This not only impaired local CCP but also suppressed improvements in neighboring cities through a siphoning effect. After replacing the sample, the excessive concentration of a single industry still hindered the enhancement of local CCP; however, neighboring cities benefited from absorbing supporting industries that spilled over from the core area. At this stage, the diffusion effects of specialized agglomeration began to emerge.

5.3. Diversified Agglomeration and CCP

The findings reveal that diversification agglomeration exerts a generally positive influence on urban comprehensive carrying capacity (CCP), particularly in enhancing natural resource (CCP2), ecological environment (CCP3), and public service (CCP4) dimensions. However, its effects are heterogeneous across different components; while diversification promotes CCP1 and CCP5 in neighboring cities, it tends to suppress these capacities in the host cities themselves. This duality reflects the complexity of resource allocation and infrastructure sharing under diversified industrial clusters.

The heterogeneity analysis shows that diversification agglomeration exerts regionally differentiated impacts on urban CCP. In eastern China, it enhances local CCP in the short term through cross-sector integration, but long-term effects turn negative as resource mismatches, factor siphoning, and congestion pressures emerge, also constraining neighboring cities [71]. In contrast, the central region benefits significantly, as industrial transfer and diversified clustering promote knowledge recombination, technological exchange, and lower transaction costs, improving both local and neighboring CCP [72]. In the west, diversification reduces local CCP due to increased energy use, environmental degradation, and congestion, yet generates positive spillovers for surrounding cities as population and enterprises relocate, transferring resources and innovation. Over time, however, excessive diversification produces environmental stress, congestion, and over competition, ultimately inhibiting sustainable improvements in CCP. Meanwhile, the heterogeneity analysis of economic development reveals that developed cities benefit more from diversification, which enhances their comprehensive carrying capacity through innovation and resource integration.

The robustness tests reveal that diversification agglomeration has context-dependent effects on urban CCP. In the context of adjacency and geographic distance matrices, we observe a favorable direct impact, whereas indirect and cumulative effects are adverse. Core cities reap the rewards of knowledge diffusion and infrastructure growth, yet they inadvertently drain resources from their surrounding areas, leading to traffic jams and pollution, aligning with the coreperiphery theory [52]. By contrast, under the economic–geographic nested matrix, short-term local effects are negative due to inefficient investment-driven expansion, yet long-term direct, indirect, and total effects turn positive as regional linkages strengthen, enabling infrastructure integration and ecological compensation. Excluding higher-tier cities further underscores the role of administrative hierarchy: in smaller cities, diversification improves the alignment of public service supply and demand, but a convergence of industrial structures can lead to redundant construction and wasted resources, while stronger cities intensify factor extraction from weaker ones, reinforcing negative spillovers.

Furthermore, the long-term impacts of both forms of agglomeration surpass their short-term effects, which aligns with the system dynamics perspective that urban sustain-

ability evolves through cumulative interactions between innovation, resource allocation, and policy feedback loops. Importantly, regional heterogeneity plays a decisive role in shaping outcomes. In the eastern region, specialization is consistently inhibitory, while diversification shows only temporary benefits. In the central and western regions, specialization demonstrates positive spillovers, particularly in less developed areas, where industrial clustering still drives capacity enhancement. This supports the argument that the economic development stage moderates the relationship between agglomeration and urban sustainability [69,73].

6. Conclusions and Implications

6.1. Main Conclusions

Drawing on theories such as New Economic Geography and Spatial Economics, this study begins by theoretically unpacking how different patterns of industrial agglomeration influence the comprehensive development level (CCP). It then builds an indicator framework and uses the entropy method to compute CCP values for the period of 2005–2022, examining their spatiotemporal evolution. Finally, a dynamic spatial Durbin model is employed to evaluate the effects of different agglomeration patterns on carbon emission performance. The main findings are summarized as follows.

First, between 2005 and 2022, the CCP in Chinese cities followed a distinctive inverted "N" pattern: it dipped at first, then climbed, only to drop once more. During this timeframe, the peak CCP value fell from 0.2146 down to 0.1134. The average level of CCP followed the regional feature of eastern region > national average > central region > western region. From a spatial differentiation perspective, CCP demonstrates clear patterns of "higher in the east and lower in the west," "north-south disparities," and "multi-polar agglomeration." Higher concentrations of these areas are situated in cities that fall under direct central or provincial administration, while those with fewer such areas are predominantly located in northeastern cities and those in the central and western regions.

Second, the long-term effects of specialization and diversification agglomeration on the urban comprehensive carrying capacity (CCP) are more pronounced than the short-term effects, though their impacts vary. Concentrations of specialization limit enhancements in CCP, CCP1, and CCP3 across both local and adjacent urban areas while enhancing CCP2 within these same regions. Moreover, it suppresses the development of CCP4 in surrounding cities and CCP5 in local cities while fostering the improvement of CCP4 in local cities and CCP5 in neighboring cities. In contrast, diversification agglomeration has positive effects on CCP, CCP2, CCP3, and CCP4 in both local and adjacent cities. However, it inhibits local CCP1 and CCP5 while promoting the enhancement of CCP1 and CCP5 in neighboring cities.

Third, the spatiotemporal effects of industrial agglomeration on urban CCP demonstrate significant heterogeneity across regions and varying levels of urban economic development. In the eastern part of China, there is a unique cluster that hampers the economic growth of both local and nearby cities. On the other hand, a more varied cluster may give a short-term boost to the local economy, but in the long run, it ends up slowing down both local and neighboring areas. In central China, specialized agglomeration suppresses local CCP while promoting it in neighboring cities. In western China, specialized agglomeration facilitates the improvement of CCP in both local and neighboring cities, whereas diversified agglomeration inhibits local CCP, and its spillover effect on surrounding cities gradually shifts from positive to negative over time, with the effects being most pronounced in the central region. In cities with advanced economic development, diversified agglomeration contributes to an enhancement in CCP, whereas specialized agglomeration tends to suppress it. Conversely, in less economically developed cities, specialized agglomeration

boosts the CCP both locally and in surrounding areas, while diversified agglomeration improves local capacity but inhibits that of neighboring cities.

6.2. Policy Recommendations

(1) Enhance equitable regional growth and refine the spatial layout of urban Communist Party branches. The characteristics of urban comprehensive carrying capacity—such as the "east-high, west-low" gradient, north–south disparities, and multi-tiered agglomeration patterns—highlight the persistent issue of regional development imbalance in China. It is imperative to improve top-level design, strengthen inter-city and inter-regional coordination capabilities [74], enhance cross-regional coordination mechanisms, and narrow the carrying capacity gaps between different areas. Eastern cities can sustain a high level of carrying capacity by upgrading their industrial structures, fostering innovation in the service sector, and promoting intensive land use. Central and western areas must aggressively push for industrial focus, cultivate unique sectors that capitalize on their local strengths, and refine the distribution of urban resources as well as enhance the quality of public services. Given the "inverted N-shaped" fluctuation pattern observed during the study period, a real-time monitoring platform should be established to implement tiered and city-specific early warning management.

(2) Reasonably guide the types of industrial agglomeration and leverage the differential roles of specialization and diversification. Specialized clustering enhances economic efficiency by deepening the division of labor and knowledge spillover, but it may also bring about environmental pressure and path dependence. Traffic congestion reduces the carrying capacity of urban infrastructure, intensifies the plundering of public service facilities in surrounding cities, and thereby lowers the economic efficiency of cities. Hence, in championing specialized clustering, the government needs to prioritize the eco-friendly and smart evolution of the industrial chain. To mitigate its downsides, they should embrace clean production and leverage digital oversight. Compared to other approaches, varied clustering typically improves the region's total support capacity, yet it exerts limitations on the local expression of CCP1 and CCP5. Therefore, while promoting industrial diversification, more investment should be made in transportation, communication, energy, and public service facility construction to improve the city's supporting capabilities. This will efficiently encourage a blend of diverse clustering towards integration with eco-friendly and carbon-neutral practices, alongside the development of intelligent urban infrastructure. This approach aims to boost the efficiency of energy usage and enhance the intelligence of societal governance, while sidestepping the pitfalls of resource mismanagement and spiraling administrative expenses that often accompany over-dispersal.

(3) Adopt differentiated industrial policies tailored to local conditions, as the effects of agglomeration on urban carrying capacity vary across development levels. In the east, excessive specialization may cause congestion [40], making diversification and service upgrading more effective in easing spatial and environmental constraints. In the central region, specialization has negative direct but positive spillover effects, while diversification enhances both local and neighboring capacities; thus, building core–periphery cooperation platforms and strengthening hubs such as Zhengzhou and Wuhan is crucial. In the west, specialization benefits local and regional capacity, whereas diversification imposes short-term pressures but yields long-term gains through regional linkages; policies should therefore reinforce specialized clusters while improving infrastructure and guiding diversified industries toward coordinated growth. Overall, diversification is more suitable for advanced cities, while specialization remains a viable path for less-developed areas, provided that inter-city collaboration mitigates potential negative spillovers.

(4) A dual approach integrating regional coordination and dynamic monitoring is essential to enhance the adaptability of industrial and urban policies. Cross-regional platforms for resource sharing and joint infrastructure development can reinforce complementarities and optimize industrial division among eastern, central, and western regions. Eastern cities should leverage their technological and human capital advantages to facilitate diversified collaborative development in central areas, while western regions should consolidate specialized industrial clusters. Ecological compensation and strengthened public services can mitigate local carrying capacity constraints. Concurrently, a dynamic cross-regional evaluation system employing big data analytics and spatial econometric methods can identify critical thresholds and inflection points of agglomeration patterns. Tailoring policies to regional development stages and resource endowments, rather than adopting uniform measures, improves policy precision and adaptability, thereby promoting coordinated and sustainable regional development.

6.3. Limitations and Future Directions

After completing the empirical examination, we believe that this study still has certain limitations. Presently, accessing aggregate statistics for the producer service sector in 2023–2024 is challenging. In the future, we will continue to search for the aforementioned data to enhance the scientific rigor of this study. Additionally, some studies indicate that diversified agglomeration and specialized agglomeration can influence urban resilience and urban innovation through technological progress [74,75]. This provides a direction for future research, and we will further explore how industrial agglomeration patterns affect the comprehensive carrying capacity of cities through technological innovation.

Author Contributions: Conceptualization, F.L. and M.G.; methodology, M.G.; software, M.G.; vali dation, F.L. and M.G.; formal analysis, M.G.; investigation, F.L.; resources, F.L.; data curation, M.G.; writing—original draft preparation, M.G.; writing—review and editing, F.L. and M.G.; visualization, F.L. and M.G.; supervision, F.L.; project administration, F.L. and M.G.; funding acquisition, F.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. 72174162), the Soft Science Project of Henan Provincial Department of Science and Technology (Grant No. 252400410382), and the Key Scientific Research Project of Henan Higher Education Institutions (Grant No. 26A790016).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The urban data can be obtained at https://data.stats.gov.cn/ and https://cnki.net/ (accessed on 1 January 2024).

Acknowledgments: The authors are grateful to the editor and the anonymous reviewers of this paper.

Conflicts of Interest: The authors declare no conflicts of interest.

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