

## Article

# How Do Urban Network Externalities Affect Regional Economic Growth? Evidence and Heterogeneity Analysis from China's Yangtze River Economic Belt

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## Abstract

Urban network externalities have emerged as a novel impetus for regional economic growth. However, the extent to which inter-urban network connections promote regional economic growth and the associated spatiotemporal heterogeneity remain underexplored. This study constructs a multi-dimensional urban network framework from the perspectives of enterprise linkages, infrastructure connectivity, and innovation collaborations, capturing the multifaceted nature of intercity relationships and their critical role in shaping regional development. Utilizing the Cobb–Douglas production function and the spatial Durbin model, the study quantitatively assesses the impact of urban network externalities on economic growth and examines the spatiotemporal heterogeneity of these impacts. The main findings are as follows: Urban network externalities generally exert a positive influence on regional economic growth, yet this effect exhibits significant regional and city-size heterogeneity. Regions with more developed networks experience stronger growth effects from these externalities. Moreover, large cities benefit more substantially from network integration compared to small and medium-sized cities. Spatial decomposition of effects further reveals that urban network externalities promote economic growth through both local direct effects and spillover effects to neighboring areas. Approximately 70% of the economic growth contribution originates from direct effects within the region, while nearly 30% stems from spillover effects from adjacent regions. Additionally, the spatial spillover effects display clear distance decay, following an inverted U-shaped pattern with a bimodal distribution. Significant spillover effects are observed within 380 km, peaking at 180 km and 340 km.

**Keywords:** urban network externalities; economic growth; spatial spillover; distance decay; Yangtze River Economic Belt (YREB)



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## 1. Introduction

Against the backdrop of rapid advancements in digital transformation, economic globalization, and regional integration, the flow of production factors—such as capital, labor, and population—between cities has intensified. This acceleration is driving a shift from a “space of places” to a “space of flows”, leading to a pronounced enhancement of intercity networking [1]. In this context, urban economic development no longer depends solely on local assets and resources but is increasingly influenced by spatial spillover effects arising

from external network connections [2,3]. By embedding themselves into multi-dimensional external networks—such as economic, transportation, and population flows—cities are reshaping the traditional Central Place Theory’s conception of place, which is primarily based on geographical proximity. These network connections reconfigure the spatial logic through which cities achieve economies of scale, enabling small and medium-sized cities to transcend the limitations of physical agglomeration. Through various network linkages, such cities can achieve specialized division of labor and expand their market reach even without a comparable population size, thus exhibiting the “borrowed size” effect. Moreover, this form of network embeddedness enhances the spatial transmission of knowledge spillovers. In contrast to the localized knowledge diffusion emphasized by traditional MAR externalities, urban networks facilitate long-distance, intercity knowledge transfer. Such transmission occurs via structured “pipeline spillovers” within corporate networks, strategic R&D alliances, and co-patenting activities, thereby supporting innovation diffusion across distances. Urban network externalities have emerged as a new driver of regional economic growth, surpassing agglomeration externalities in importance. Although existing studies have substantiated the benefits for cities embedded in various external networks [4,5], the spatial spillover effects of these externalities on economic growth and their heterogeneous impacts across different types of cities remain underexplored and warrant further in-depth investigation.

Scholars have extensively investigated various aspects of urban network externalities, including their measurement [4,6], their relative importance compared to agglomeration externalities in driving economic growth [4,7], spatial spillover effects [8,9], spatial heterogeneity of impacts [3,10,11], distance-decay characteristics of spillovers [12–14], and the underlying mechanisms through which such externalities promote economic development [15,16]. However, due to variations in network construction methods and models for measuring externalities, considerable academic debate persists regarding the magnitude of the impact of urban network externalities on economic growth, as well as the variation in these effects across different regions and tiers of cities. Some researchers argue that agglomeration externalities continue to be the primary driver of urban economic growth [7,17], while others maintain that urban network externalities exert a stronger influence on urban development than agglomeration effects [18,19]. A third perspective suggests a complementary relationship between the two, positing that network externalities do not merely substitute for agglomeration economies but enhance the fluidity of regional factor flows, thereby fostering synergistic development across spatial scales and functional hierarchies [20]. Furthermore, regarding the effects of urban network externalities, some scholars argue that they generate positive spillover effects on regional economic growth [4], while others contend that urban economic growth can produce adverse cross-regional spillover effects, potentially hindering development in neighboring cities [8]. Finally, existing studies also indicate that urban network externalities exhibit spatial heterogeneity. For instance, research on transportation networks has demonstrated that high-speed rail has a more substantial effect on enhancing innovation performance in large cities compared to small and medium-sized cities [18]. Similarly, analysis of knowledge diffusion across European regions by Bottazzi and Peri [13] revealed that significant spillovers occur only within a 300 km radius. These findings raise two critical yet underexplored questions: Which types of regions and cities are most likely to benefit from external network linkages? And does the spatial spillover effect of network externalities on economic growth exhibit a distance-decay pattern? Addressing these questions remains an urgent and pivotal task for future research.

Based on this, this study aims to address the following two research questions: (1) What is the impact of urban network externalities on economic growth? Does this

impact exhibit heterogeneity across different regions and cities? This study posits that integration into intercity networks plays a positive role in economic growth by expanding access to markets, capital, and knowledge. Recognizing the potential endogeneity of centrality metrics, the study employs an instrumental variable strategy and conducts robustness tests to ensure the reliability of the results. On this basis, subgroup regressions further demonstrate that the impact of urban network externalities on economic growth displays significant heterogeneity across cities of different sizes and in different regions. (2) Do urban network externalities generate spatial spillover effects? If so, do these spillover effects exhibit distance decay characteristics in space? To this end, this study constructs a spatial econometric model to decompose the impact of urban network externalities on economic growth into direct effects and indirect effects (i.e., spatial spillover effects). The findings reveal that urban network externalities promote economic growth through both endogenous drivers and spatial spillovers. Furthermore, by setting different geographic distance thresholds, the study finds that the spatial spillover effect exhibits distance decay. The robustness of these results is confirmed by expanding the distance thresholds between cities.

The structure of the paper is as follows. The literature review is presented in Section 2. An overview of the study area and the construction process of the urban network is provided in Section 3. Section 4 elaborates on the research methods, including social network analysis, the measurement of urban network externalities, and explanations of the main variables. The structural characteristics and evolution of the urban network in the YREB are analyzed in Section 5. Section 6 examines the impact of urban network externalities on economic growth and its heterogeneous characteristics. The spatial spillover effects of urban network externalities and their distance decay characteristics are investigated in Section 7. Finally, research conclusions, discussion, limitations, and directions for future research are presented in Section 8.

## 2. Literature Review

### 2.1. Agglomeration Externalities, Network Externalities, and Urban Economic Growth

Early scholarly work posited that economies of scale driven by agglomeration externalities—rooted in geographical proximity—constituted the primary engine of regional economic growth. These externalities were thought to function mainly within local boundaries through three core mechanisms: sharing, learning, and matching [21]. A key premise of this view was that economic activities in other regions exerted no meaningful influence on local economic dynamics [22]. Glaeser et al. further refined this framework by classifying agglomeration externalities into three types: MAR externalities, Jacobs externalities, and Porter externalities [23]. MAR externalities stem from specialization within a single industry and city, whereas Jacobs externalities arise from diversified industrial composition across sectors within an urban area [10]. Porter externalities, in turn, emphasize the role of competitive pressure within a specialized industrial cluster in stimulating efficiency and innovation [24]. A fundamental limitation shared by all three frameworks—MAR, Jacobs, and Porter—is their conception of urban development as a process constrained by geographical boundaries. Within this traditional paradigm, cities were largely treated as independent entities, with little recognition of meaningful spatial spillover effects between them. Beginning in the 1980s, substantial improvements in regional transportation infrastructure brought about a pronounced time-space compression effect. This transformation accelerated the flows of production factors between cities and intensified interregional interactions, prompting an evolution in urban structure. The conventional model, centered on a “space of places” founded on physical proximity, gradually yielded to a new organizational logic based on a “space of flows” and urban networks shaped by factor mobility.

Within this reconfigured setting, a growing body of scholars has come to acknowledge that a city's external network linkages—that is, its embeddedness in relational networks—play a critical role in shaping regional economic development [25].

Camagni and Salone pioneered the formal conceptualization of urban network externalities, defining them as external effects arising from the interconnection and cooperation among cities within a network [26]. These effects extend beyond individual urban boundaries and enable cities to capture additional advantages derived from their relational positioning. Capello later provided empirical support for this concept [27], solidifying its significance in the study of urban networks. Scholarly consensus highlights four core mechanisms through which these externalities operate: firstly, the synergistic effect, where cooperative and complementary interactions among cities produce outcomes greater than the sum of individual efforts [28], which suggests that the higher a city's centrality in the network system, the stronger its ability to access external resources and the better its economic growth performance; secondly, there is the integration effect: as cities become increasingly integrated across spatial, institutional, functional, and cultural dimensions, the externalities generated through intercity interactions are further enhanced [29,30]. Consequently, as cities become more integrated across multiple dimensions, network externalities are expected to intensify. It is anticipated that in a multi-dimensional integrated network combining corporate, innovation, and transportation linkages, a city's centrality level will have a significant promoting effect on economic growth. This promoting effect arises not only from connections in a single dimension but, more importantly, from the synergy of network linkages across different dimensions; thirdly, borrowed size, a phenomenon wherein smaller cities gain access to agglomeration benefits from larger neighboring cities without incurring the typical costs of size. This includes borrowing urban functions beyond their intrinsic scale and enhancing economic performance through metropolitan linkages [31,32]; and finally, agglomeration shadow, a negative externality wherein smaller cities experience inhibited growth due to the siphon effect of nearby larger cities, often resulting in poorer performance compared to similar cities not under such influence [25]. When the "borrowed size" effect outweighs the "agglomeration shadow" effect, urban network externalities can promote urban economic development. Conversely, when the "agglomeration shadow" effect outweighs the "borrowed size" effect, urban network externalities may inhibit urban economic growth. In summary, urban network externalities encompass the range of positive and negative consequences stemming from a city's embeddedness and connectivity within urban networks.

As summarized in Table 1, agglomeration externalities and network externalities differ fundamentally in their theoretical origins and spatial logic. Agglomeration externalities, derived from classical economic geography, arise from the geographic concentration of economic activities within a city and are primarily manifested as scale economies. Their influence is heavily constrained by physical distance and demonstrates evident decay with increasing geographical separation. In contrast, network externalities are grounded in the theoretical framework of network science, characterizing the external effects arising from interactions between cities. A defining feature of such externalities is their spatial independence; their magnitude depends primarily on the strength of intercity linkages rather than geographic proximity. As interurban connections strengthen, network externalities can overcome the limitations of physical space, thereby extending and enhancing the influence of agglomeration economies across wider spatial scales.



**Table 1.** Distinctions between agglomeration externalities and network externalities.

| Aspect of Comparison    | Agglomeration Externalities                                             | Network Externalities                                                                |
|-------------------------|-------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
| Theoretical comparison  | Neoclassical Location Theory, Urban Economics Theory, New Growth Theory | World Urban Network Theory, Global Production Network Theory, Complex Network Theory |
| Spatial scope           | Intra-city                                                              | Inter-city                                                                           |
| Spatial spillover range | Short-distance                                                          | Long-distance                                                                        |
| Spatial mechanism       | Geographic proximity                                                    | Network connectivity                                                                 |
| Determining factor      | Scale-dependent                                                         | Network position-dependent                                                           |

Source: Compiled from [4,10].

## 2.2. Construction of Urban Networks and Measurement of Network Externalities

The construction of urban networks is a foundational step in analyzing urban network externalities, as it directly shapes the accurate identification of a city's position and function within the network. Current research predominantly relies on single-dimensional approaches—such as enterprise linkages, infrastructure connectivity, factor flows, or socio-cultural ties—to model these networks. The enterprise-based approach measures inter-city economic connections through headquarters-branch relationships or corporate investment networks [33,34]. The infrastructure perspective constructs networks using transportation data, including air passenger flows, conventional rail, and high-speed rail services [8,35]. Factor flow models commonly utilize data on population movement, commuting patterns, or innovation diffusion (e.g., patent citations) to establish urban connections [4,9]. Meanwhile, the socio-cultural approach assesses inter-city ties through social media interactions, cultural industry collaborations, or other relational data [36]. However, since real-world urban interactions are inherently multi-dimensional, any single perspective offers only a partial representation of this complex, layered reality. Despite widespread recognition of this limitation, studies that integrate multi-source data to construct comprehensive and multi-dimensional urban networks remain relatively scarce.

In recent years, the measurement of urban network externalities has mainly followed two approaches. The first builds on the concept of borrowed size introduced by Meijers et al. to operationalize these externalities [2]. Second, urban network externalities are measured using social network analysis metrics, such as degree centrality and closeness centrality. For example, Huang et al. used a city's closeness centrality within a railway network to quantify these effects, revealing a significant positive impact on urban economic development [10]. This approach represents one of the most commonly adopted methods in current externality measurement. Moreover, when integrating spatial dimensions into econometric models to examine the spatial spillover effects of urban network externalities, commonly used methods include the spatial MRW model [37], the Geographically Weighted Regression (GWR) [38], and the spatial econometric model [34]. Empirically, studies such as that by Boix et al. have constructed spatial econometric models using network-derived spatial weights matrices to analyze spillover effects in urban economic growth factors [15]. Among these approaches, spatial econometric modeling has emerged as a standard tool for estimating spatial spillovers. By explicitly incorporating urban network structures into the model, this methodology captures spillover effects through the dynamics of “flow factors”, providing a robust and theoretically coherent framework for empirical analysis.

## 2.3. Literature Criticism

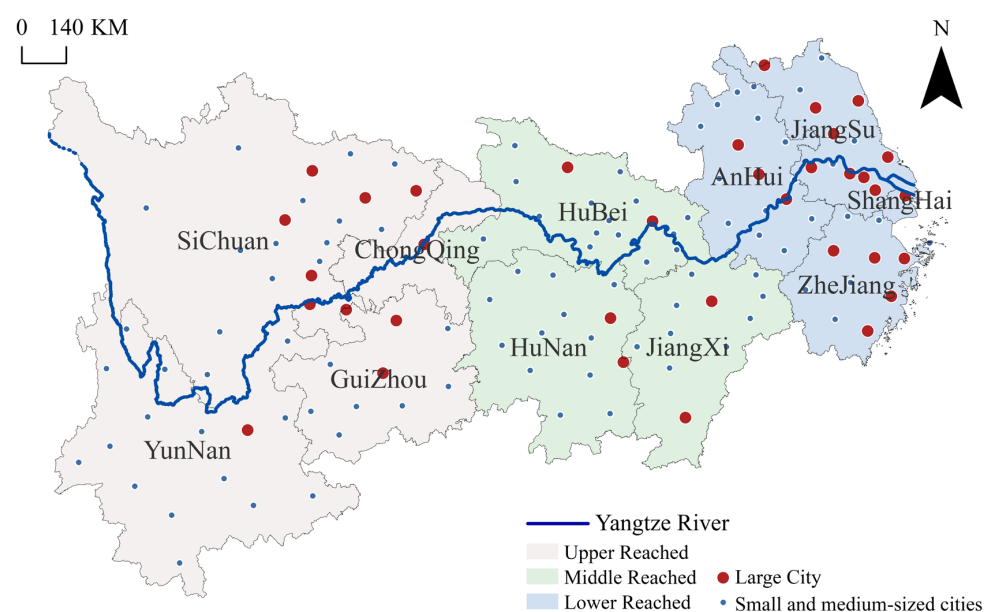
In summary, although scholars have conducted extensive research on the externalities of urban networks, the existing studies still have limitations: Firstly, the network

construction methods are single, and relying on a single element flow makes it difficult to comprehensively represent complex urban correlations; This article selects to integrate data from three parts: enterprise connections, train frequencies, and patent transfers, to construct a more comprehensive urban network from multiple dimensions such as economy, transportation, and innovation. Secondly, there is a lack of heterogeneity analysis of urban network externalities. This paper delves deeply into the differential impact of urban network externalities on different regions and urban types. Finally, there is insufficient research on whether urban network externalities have spatial spillover effects and their distance attenuation characteristics. This paper attempts to summarize the distance attenuation law of spatial spillover effects of urban network externalities.

### 3. Study Area, Network Construction, and Methodology

#### 3.1. Study Area

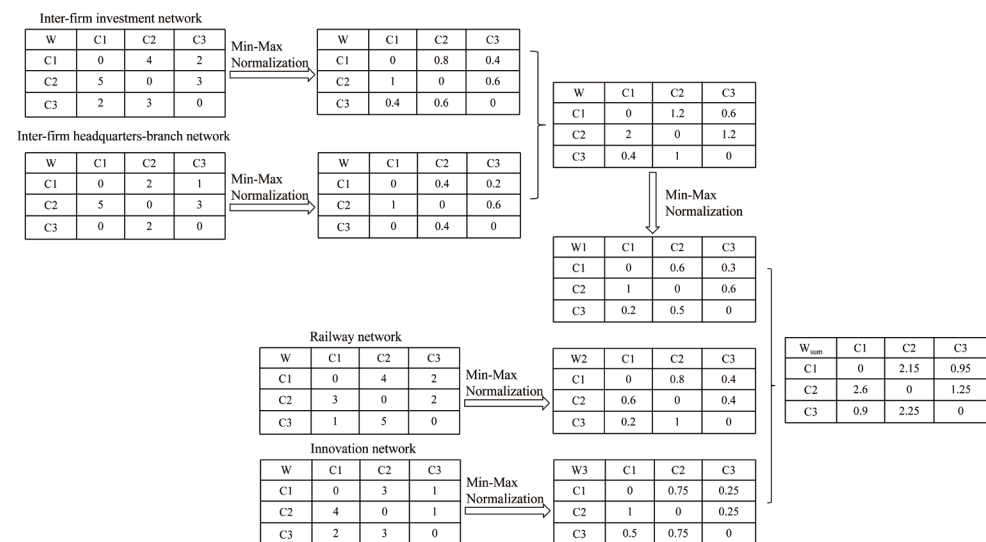
As illustrated in Figure 1, the YREB represents China's most pivotal inland economic corridor, featuring the country's largest river basin coverage and occupying a crucial socioeconomic position nationally. Encompassing 11 provinces and municipalities, the YREB includes 130 prefecture-level cities. By the end of 2022, it accounted for 21.4% of the nation's land area, 40.60% of its total population, and 46.3% of its GDP. The YREB is traditionally categorized into three major regions: the upstream region, which includes Chongqing, Sichuan, Guizhou, and Yunnan; the midstream region, covering Jiangxi, Hubei, and Hunan; and the downstream region, consisting of Shanghai, Jiangsu, Zhejiang, and Anhui. Among these, Shanghai, leveraging its locational advantages since its opening as a treaty port in 1843, rapidly emerged as the core gateway of modern China's regional networks. Following the reform and opening-up, Shanghai further integrated into the global urban network, becoming one of the world's most globally connected cities. Moreover, in Taylor's regional study of world city networks, Shanghai was identified as a critical global service node in the Asia-Pacific region [39]. This historical background has laid a profound foundation for its sustained dominant role in the YREB urban network. Within the study area, cities are classified according to their permanent urban population: those with a population exceeding 1 million are defined as large cities (35 cities), while those below this threshold are categorized as small and medium-sized cities (95 cities).



**Figure 1.** Regional map of the YREB.

### 3.2. Data Sources and Urban Network Construction

As illustrated in Figure 2, this study adopts a multidimensional approach to urban network analysis by focusing on three key dimensions critically linked to urban economic growth: enterprise linkages, infrastructure connectivity, and innovation flows. To operationalize this framework, we construct a composite urban network that integrates three representative subnetworks: an enterprise linkage network, a railway passenger transport network, and a patent transfer network, each corresponding to one of the three conceptual dimensions.



**Figure 2.** Schematic diagram of the multi-source data fusion process.

#### 3.2.1. Measuring Enterprise Linkages

The enterprise network was constructed using two types of data: headquarters-branch relationships and corporate investment linkages. Both datasets were obtained from the Qichacha Big Data Platform (<https://www.qcc.com/>, accessed on 10 May 2022). The construction process involved the following steps: First, we comprehensively collected companies operating within the study area that either have investment relationships or exhibit headquarters-subsidary structures. Second, by extracting the location information of both investing and invested enterprises, as well as the registered addresses of corporate headquarters and their branches, we derived city-level origin-destination (O-D) linkages for individual enterprises. This process resulted in a dataset comprising 225,421 headquarters and 847,326 branches forming the headquarters-branch relationship set, along with a corporate investment linkage dataset consisting of 652,055 investing firms and 1,534,038 invested enterprises. Subsequently, firm-level O-D linkages were aggregated to the city level, producing two  $130 \times 130$  inter-city matrices: an enterprise investment relationship matrix and a headquarters-branch relationship matrix. The strength of investment linkages between two cities is represented by the total amount of capital invested by firms located in each city pair. Similarly, the strength of headquarters-branch linkages is measured by a weighted index of connections between headquarters and their subsidiaries in the corresponding cities. Finally, under the premise that there is no a priori theory suggesting that one type of inter-firm linkage is more important than the other for urban network embeddedness, range normalization is applied to each of the two matrices separately, and they are then aggregated with equal weights to obtain a comprehensive inter-firm linkage matrix from an integrated perspective. The resulting values range between  $[0, 1]$ . This preprocessing ensures that the two types of linkages are numerically comparable; after

normalization, both measure the relative position of a city within that type of linkage on the same scale, with higher values indicating stronger inter-city enterprise connections.

### 3.2.2. Measuring Railway Passenger Transport Linkages

Railway passenger transport data from 2000 to 2020 were obtained from the official China Railway 12306 website (<http://www.12306.cn/index/>, accessed on 15 June 2022). The frequency of train services between stations was aggregated to the city level, forming a  $130 \times 130$  inter-city railway passenger transport matrix where each cell value represents the total number of train connections between a pair of cities. This matrix then underwent range standardization, rescaling all values to a  $[0, 1]$  interval to facilitate comparability and integration with other network layers.

### 3.2.3. Measuring Innovation Linkages

Patent transfer data were obtained from the China National Intellectual Property Administration (<https://www.cnipa.gov.cn/>, accessed on 9 August 2023), including address information such as the provinces and cities of patent applications. The number of inter-city patent transfers from 2000 to 2020 was collected and aggregated to obtain inter-city patent flow data for each year. An inter-city patent transfer matrix was then constructed and subjected to range normalization, scaling the values to fall within a  $[0, 1]$  interval.

### 3.2.4. Measuring Comprehensive Linkages

To comprehensively capture the multidimensional linkages between cities, this study constructs an urban network based on three core dimensions: economic capital, population mobility, and knowledge spillovers. These dimensions collectively reflect the actual spatial interaction patterns among cities, each playing a fundamental role in regional development and economic growth. Regarding the data fusion method, given that the weighting of multi-source data integration currently lacks sufficient reference literature and theoretical support, this study adopts the equal-weight summation method widely used in academic research to construct a comprehensive urban network [40,41]. Specifically, each sub-matrix is first subjected to range normalization to eliminate dimensional influences, after which they are summed with equal weights. This process ultimately yields a comprehensive inter-city linkage matrix with values ranging from 0 to 3. The original data for constructing the comprehensive urban network can be found in Data S1.

## 4. Urban Network Structure Analysis and Measurement of Network Externalities

### 4.1. Social Network Analysis Method

Social network analysis (SNA) is widely used in studies of urban network structure due to its ability to quantitatively examine relational patterns among actors, characterize network topology, and model dynamic evolution. In this study, we employ a suite of topological metrics to analyze the structural features of the urban network: network-wide cohesion and efficiency are measured using average degree, network density, average clustering coefficient, and average path length. The importance of individual nodes within the network is evaluated through degree centrality. The specific explanations of the network indicators are shown in Table 2.

**Table 2.** Description of social network indicators.

| Metric                         | Interpretation                                                                 | Formula                                                         | Explanation of the Formula                                                                      |
|--------------------------------|--------------------------------------------------------------------------------|-----------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| Degree centrality              | Indicates the importance of a node within the network.                         | $DC_i = \sum_{j=1}^n X_{ij} (i \neq j)$                         | The number of nodes directly connected to node $i$ .                                            |
| Average degree                 | Represents the average number of connections per node in the network.          | $K = \frac{DC_i}{n} = \frac{\sum_{j=1}^n X_{ij}}{n} (i \neq j)$ | The average number of connections incident to a node $i$ .                                      |
| Network density                | Measures the overall connectedness or sparsity of the network.                 | $D = \frac{\sum_{i=1}^n \sum_{j=1}^n X_{ij}}{n(n-1)}$           | The ratio of the actual number of links to the maximum possible number of links in the network. |
| Average clustering coefficient | Quantifies the tendency of nodes to form tightly connected groups or clusters. | $C = \frac{\sum_i \frac{2E_i}{k_i(k_i-1)}}{n}$                  | The average probability that two adjacent nodes of a node are also adjacent to each other.      |
| Average path length            | Measures the efficiency of information or flow propagation across the network. | $L = \frac{2}{n(n-1)} \sum_{i>j} d_{ij}$                        | The average number of steps along the shortest paths for all possible pairs of network nodes.   |

Note:  $i, j$  denote network nodes,  $n$  denotes the total number of network nodes;  $X_{ij}$  denotes the connection between nodes  $i$  and  $j$ ;  $d_{ij}$  denotes the distance between nodes  $i$  and  $j$ ;  $k_i$  denotes the number of nodes adjacent to node  $i$ ;  $E_i$  denotes the actual number of edges existing between the neighbors of node  $i$ .

#### 4.2. Measurement of Urban Network Externalities

The Cobb–Douglas production function is widely used to model the determinants of economic output by characterizing its constituent elements. Due to its analytical tractability, it is frequently adopted as the foundational specification in baseline economic growth regressions. Numerous studies have employed this functional form to analyze the mechanisms through which network externalities influence economic growth [10,42].

$$Y = A \cdot K^\alpha \cdot L^\beta \quad (1)$$

where:  $Y$  represents the output of the urban network;  $A$  denotes total factor productivity;  $K$  and  $L$  represent the fixed capital stock and effective human capital input of the urban network, respectively; and  $\alpha$  and  $\beta$  indicate the output elasticities of fixed capital and human capital, respectively. In accordance with the Cobb–Douglas production function framework, this study also adopts fixed capital stock and human capital as core variables to examine their influence on economic output.

Building on this foundation and following mainstream approaches to studying urban network externalities, this study incorporates structural metrics of the urban network to represent network externalities, while using industrial specialization and diversification to proxy agglomeration externalities, thereby extending the baseline Cobb–Douglas framework. To analyze the effect of urban network externalities on economic output and mitigate potential heteroscedasticity, a double-logarithmic form is adopted, resulting in the following econometric specification:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln NET_{it} + \beta_2 \ln SPE_{it} + \beta_3 \ln DIV_{it} + \beta_4 \ln FAI_{it} + \beta_5 \ln EDU_{it} + \varepsilon_{it} \quad (2)$$

where:  $i$  denotes individual cities;  $t$  denotes the year;  $\varepsilon_{it}$  is the random disturbance term;  $\beta$  represents the coefficients of the corresponding variables.

To further investigate the spatial spillover effects of urban network externalities on economic growth after incorporating spatial dependencies, a spatial weight matrix is



constructed to determine the spatial lag terms of the variables. The following panel spatial econometric model is established:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln NET_{it} + \beta_2 \ln SPE_{it} + \beta_3 \ln DIV_{it} + \beta_4 \ln FAI_{it} + \beta_5 \ln EDU_{it} + \rho_0 W \ln Y_{it} + \rho_1 W \ln NET_{it} + \rho_2 W \ln SPE_{it} + \rho_3 W \ln DIV_{it} + \rho_4 W \ln FAI_{it} + \rho_5 W \ln EDU_{it} + \varepsilon_{it} \quad (3)$$

where:  $\rho$  represents the spatial lag coefficient;  $W$  denotes the spatial weight matrix, which in this study is specified as a second-order contiguity matrix.

#### 4.3. Variable Selection and Description

**Dependent variable:** The level of economic growth is represented by the real GDP of each city within the YREB. To eliminate the impact of price fluctuations, nominal GDP was deflated to constant 2000 prices using the official GDP deflator, calculated as: Real GDP = (Nominal GDP / GDP Deflator)  $\times$  100.

**Independent variable:** Following existing methodologies [10], this study employs closeness centrality to assess urban network externalities. A city's closeness centrality reflects its overall advantage in efficiently accessing resources, technologies, and markets across the network. Thus, it serves as the core proxy variable for urban network externalities.

$$C_c(i) = \frac{1}{\sum_{j=1}^n d_{ij}} (i \neq j) \quad (4)$$

where:  $d_{ij}$  represents the shortest-path distance between node  $i$  and node  $j$ , and  $n$  is the total number of nodes in the network. A higher closeness centrality value indicates a shorter average distance from the node to all other nodes, signifying a more central position within the network.

**Control variables:** Considering data availability and potential multicollinearity, the following variables are selected as controls: Capital stock, a primary factor of production proxied by fixed asset investment. Human capital, representing both the size and quality of the labor force, is a core driver of sustained economic growth. This is measured by the number of individuals holding higher education diplomas (including college, undergraduate, and postgraduate degrees). Agglomeration externalities are a key determinant of regional economic growth. They are primarily captured through two mechanisms: specialization, which is quantified by the Location Quotient (LQ) [23] to measure the spatial concentration of a specific industry; and diversity, which is measured by the reciprocal of the Herfindahl-Hirschman Index (1/HHI) [43] to indicate a region's level of industrial diversification. The formulas for these measures are as follows:

$$LQ_{i,j} = (E_{ij}/E_i)/(E_j/E) \quad (5)$$

$$specialization_i = \max(LQ_{i,j}) \quad (6)$$

$$diversity_i = 1 / \left( \sum_j (E_{i,j}/E_i)^2 \right) \quad (7)$$

where:  $E_{ij}$  represents the number of employees in industry  $j$  in city  $i$ ;  $E_i$  denotes the total number of employees across all industries in city  $i$ ;  $E_j$  indicates the total number of employees in industry  $j$  across the entire study area;  $E$  is the total number of employees in all industries in the study area;  $LQ_{i,j}$  represents the location quotient; the degree of urban specialization is characterized by the maximum value of the location quotient across all industries within a city. Urban diversity is measured by the reciprocal of the Herfindahl-Hirschman Index (HHI).

To mitigate the effects of heteroscedasticity and reduce fluctuations in the variables, a logarithmic transformation was applied to all variables. The descriptive statistics of the transformed variables are presented in Table 3.

**Table 3.** Descriptive statistics of variables.

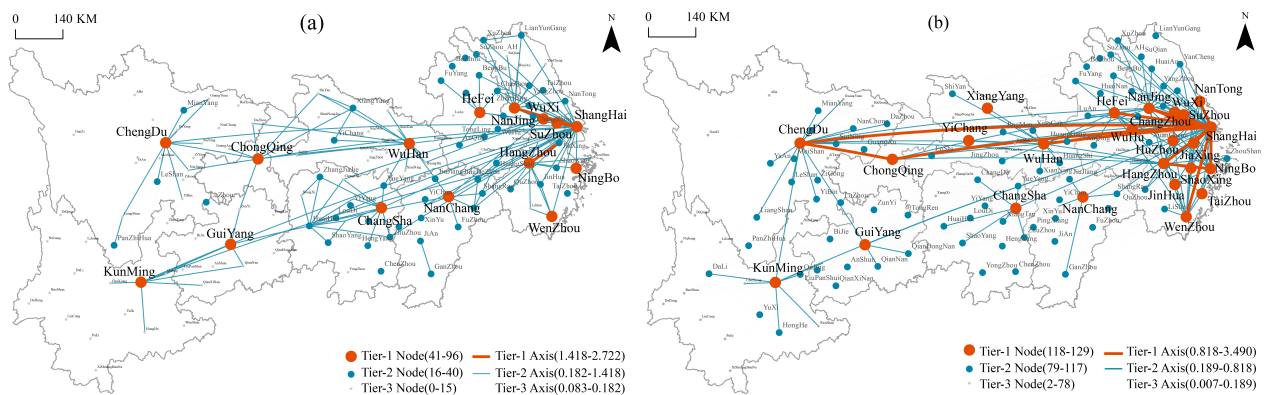
| Variable Name                               | Variable Symbol | Mean Value | Standard Deviation | Minimum Value | Maximum Value | Global Moran's I  |
|---------------------------------------------|-----------------|------------|--------------------|---------------|---------------|-------------------|
| Regional economic growth (CNY 100 million)  | lnRGDP          | 6.600      | 0.916              | 4.590         | 9.568         | 0.279 (6.459) *** |
| Closeness centrality                        | lnNET           | 3.874      | 0.042              | 3.801         | 4.015         | 0.142 (3.405) *** |
| Specialization                              | lnSPE           | 1.064      | 0.544              | 0.275         | 3.098         | 0.412 (3.409) *** |
| Diversification                             | lnDIV           | 1.810      | 0.288              | 0.726         | 2.250         | 0.213 (5.003) *** |
| Fixed asset investment (CNY 10,000)         | lnFAI           | 15.763     | 0.800              | 13.923        | 18.055        | 0.230 (5.351) *** |
| Highly educated population (10,000 persons) | lnEDU           | 2.932      | 0.806              | 1.435         | 5.229         | 0.091 (2.24) **   |

Note: Figures in parentheses for Global Moran's I are Z-statistic values. Significance levels: 1% (\*\*\*), 5% (\*\*).

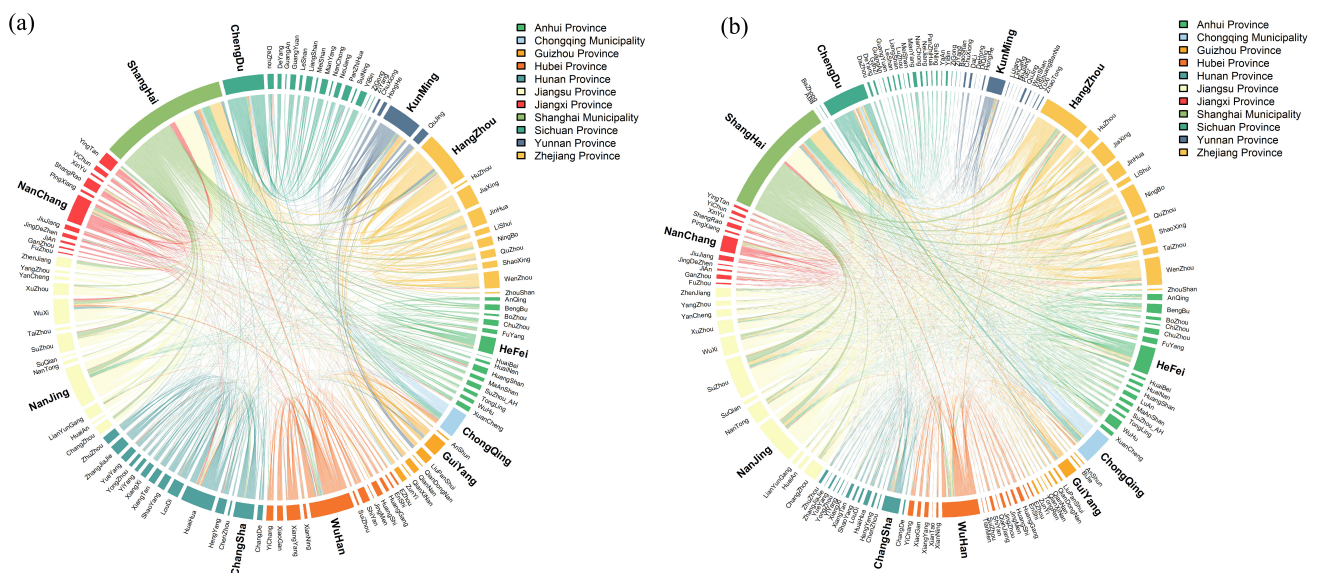
## 5. Structure and Evolution of the Urban Network in the YREB

Figure 3a,b visually demonstrate the spatial patterns of nodes and axes classified into three levels using the natural breakpoint method through Geographic Information System (GIS) visualization. Figure 4a,b use chord diagrams to represent node strength (arc length) and connection intensity (chord width). The analysis reveals the following key characteristics of the urban network in the YREB: Firstly, pronounced polycentric and networked development: The average degree increased from 20.78 to 94.91, and network density rose from 0.17 to 0.74, indicating a substantial expansion in node connectivity and overall network cohesion. Small-world properties became evident: the average path length decreased from 1.93 to 1.26, while the average clustering coefficient increased from 0.66 to 0.84, reflecting enhanced network efficiency and stronger local clustering. Secondly, the development of the urban network is highly uneven, exhibiting pronounced regional disparities. A distinct gradient pattern is observed, with the downstream region outperforming the midstream, which in turn exceeds the upstream region. Specifically, the density of primary and secondary nodes, the hierarchy of connectivity axes, and overall network connectivity in the downstream area are significantly higher than those in the midstream and upstream regions. Thirdly, the structure has evolved from a single-pole radiation pattern centered on Shanghai to a polycentric and collaborative network. High-level cities have formed new primary corridors, while linkages between first-tier nodes and secondary cities have been significantly strengthened. From 2000 to 2020, Shanghai maintained its position as a core hub in corporate linkage, transportation connectivity, and innovation networks, establishing connections with other cities through multiple pathways such as corporate linkages, railway passenger transport, and patent transfers. Through these diverse channels, it continuously exported capital, technology, and knowledge to the YREB. As the trend of network-oriented development gradually intensified, other central cities also significantly enhanced their positions within the network, while Shanghai's relative importance in the overall network structure experienced a certain degree of weakening. This evolution reflects a transition from a unipolar dominance structure toward a multi-polar coordinated development pattern. Fourthly, intercity linkages have intensified horizontally, with increasingly tight cross-regional interactions. In 2000, urban connections were

largely concentrated within provinces and between adjacent ones, with relatively limited long-distance inter-regional ties. By 2020, however, these networks had become notably more complex and extensive, transcending provincial boundaries and demonstrating a clear weakening of distance-based barriers.



**Figure 3.** Network node and axis hierarchical map of cities in the YREB from 2000 to 2020. (a) 2000 urban network node and axis hierarchical diagram. (b) 2020 urban network node and axis hierarchical diagram.



**Figure 4.** Chord diagram of urban networks in the YREB from 2000 to 2020. (a) 2000 urban network chord diagram. (b) 2020 urban network chord diagram.

## 6. The Impact of Urban Network Externalities on Economic Growth

### 6.1. Model Selection and Benchmark Regression

Table 4 reports the regression results for Model 1 (Pooled OLS), Model 2 (Fixed Effects), Model 3 (Random Effects), and Model 4 (Two-Way Fixed Effects). The regression data can be found in Data S2. Based on F-tests and the Hausman test results, the two-way fixed effects model was selected to analyze the impact of urban network externalities on economic growth. Therefore, the subsequent discussion focuses on the estimates derived from Model 4. The results indicate that urban closeness centrality, fixed capital stock, and human capital all significantly contribute to economic growth, while both industrial specialization and diversification exhibit inhibitory effects. The coefficient for  $\ln\text{NET}$  is 0.114, implying that a 1% increase in urban closeness centrality is associated with a 0.114% rise in real GDP. Similarly, a 1% increase in fixed capital stock and human capital leads to economic growth

of 0.080% and 0.262%, respectively. These findings underscore the importance of enhancing inter-city network connectivity, expanding fixed capital investment, and leveraging human capital endowments to foster sustained and high-quality regional economic development within the YREB. Conversely, the negative coefficients for both industrial specialization and diversification suggest a lack of effective synergistic dynamics among industries in stimulating regional economic growth. It is essential to optimize the industrial structure and promote a balanced approach between specialization and diversification to facilitate economic advancement.

**Table 4.** Comparison of benchmark regression models.

| Variables      | Model 1<br>(Pooled OLS) | Model 2<br>(Fixed Effects) | Model 3<br>(Random Effects) | Model 4<br>(Two-Way Fixed Effects) |
|----------------|-------------------------|----------------------------|-----------------------------|------------------------------------|
| lnNET          | 0.251 *** (0.030)       | 0.391 *** (0.017)          | 0.344 *** (0.015)           | 0.114 * (0.059)                    |
| lnSPE          | −0.035 (0.034)          | −0.014 (0.016)             | −0.019 (0.018)              | −0.011 (0.017)                     |
| lnDIV          | −0.496 *** (0.077)      | −0.122 *** (0.049)         | −0.227 *** (0.048)          | −0.083 ** (0.035)                  |
| lnFAI          | 0.257 *** (0.020)       | 0.234 *** (0.013)          | 0.211 *** (0.010)           | 0.080 *** (0.016)                  |
| lnEDU          | 0.777 *** (0.049)       | 0.536 *** (0.084)          | 0.768 *** (0.048)           | 0.262 *** (0.051)                  |
| Constant       | 0.282 (0.219)           | 0.034 (0.128)              | 0.116 (0.125)               | 3.532 *** (0.353)                  |
| R <sup>2</sup> | 0.945                   | 0.989                      | 0.988                       | 0.994                              |

Note: Standard errors are reported in parentheses. Significance levels: 1% (\*\*\*), 5% (\*\*), 10% (\*), same below.

As shown in the results of Table 5. To verify the robustness of the main findings, this study employs multiple validation approaches, including replacing the dependent variable, omitting control variables, and addressing potential endogeneity. Model 5 reports the results when using per capita GDP as the alternative dependent variable. Model 6 presents estimates after the removal of control variables. The results from both Model 5 and Model 6 show that the sign and statistical significance of the coefficient for the core explanatory variable (lnNET) remain consistent with those in the baseline model. These findings confirm the robustness of the regression results, as well as the appropriateness of the model specification and the selection of explanatory factors. Model 7 reports the results of the endogeneity test. One of the main sources of endogeneity stems from the causal relationship between the explanatory variables and the dependent variable. To address this issue, following existing studies, this paper employs the two-stage generalized method of moments (GMM) approach, using the spatial lag of the driving factors as instrumental variables. These instruments are correlated with the local driving factors while being exogenous to local economic growth shocks. The results show that the Kleibergen-Paap rk LM statistic is significant at the 1% level, rejecting the null hypothesis of underidentification. The Kleibergen-Paap rk Wald F statistic far exceeds the Stock-Yogo critical value for weak instruments at the 10% level, leading to rejection of the weak instrument hypothesis. The Hansen J statistic yields a *p*-value of 0.268 (>0.05), indicating that the null hypothesis of exogenous instruments cannot be rejected. This confirms that the selected instrumental variables satisfy the exogeneity requirement. In summary, these results support the appropriateness of the instrumental variable selection and the reliability of the model specification in mitigating endogeneity concerns. The signs and magnitudes of the coefficients for the key variables remain largely consistent, further affirming the robustness of the findings.

**Table 5.** Robustness and endogeneity tests.

|                                     | <b>Model 5</b><br><b>(Replace Dependent Variable)</b> | <b>Model 6</b><br><b>(Remove Control Variables)</b> | <b>Model 7</b><br><b>(Endogeneity Test)</b> |
|-------------------------------------|-------------------------------------------------------|-----------------------------------------------------|---------------------------------------------|
| lnNET                               | 0.231 ** (0.112)                                      | 0.108 * (0.058)                                     | 0.421 * (0.247)                             |
| Control variables                   | Yes                                                   | Yes                                                 | Yes                                         |
| Individual fixed effects            | Yes                                                   | Yes                                                 | Yes                                         |
| Time fixed effects                  | Yes                                                   | Yes                                                 | Yes                                         |
| Kleibergen-Paap rk LM statistic     |                                                       |                                                     | 27.479 [0.0000]                             |
| Kleibergen-Paap rk Wald F statistic |                                                       |                                                     | 24.165 <19.93>                              |
| Hansen J statistic                  |                                                       |                                                     | 1.227 [0.268]                               |
| R2                                  | 0.989                                                 | 0.994                                               | 0.994                                       |

Note: Standard errors are reported in parentheses. Significance levels: 5% (\*\*), 10% (\*). Underidentification test uses the Kleibergen-Paap rk LM statistic; *p*-values are reported in square brackets [ ]. Weak instrument test uses the Kleibergen-Paap rk Wald F statistic; the critical value for the Stock-Yogo test at the 10% significance level is shown in angle brackets < >. Overidentification test uses the Hansen J statistic; *p*-values are reported in square brackets [ ].

## 6.2. Heterogeneity Analysis of the Economic Growth Effects of Urban Network Externalities

### 6.2.1. Regional Heterogeneity Analysis of Urban Network Externalities

Given the vast spatial extent of the YREB, subgroup regressions were conducted by partitioning the region into upstream (Model 8), midstream (Model 9), and downstream (Model 10) areas to examine whether urban networks exert differential impacts on economic growth across these subregions. Details of the heterogeneity analysis data can be found in Data S2. As shown in Table 6, the influence of urban network externalities on economic growth displays notable regional heterogeneity within the YREB. In the downstream region (Model 10), the effect of urban network externalities is statistically significant at the 10% level, indicating that enhanced network centrality contributes positively to economic growth in downstream cities. In the midstream region (Model 9), network centrality also exhibits a positive association with growth, though the result is not statistically significant. In terms of effect size, the downstream region (coefficient = 0.323) shows a stronger positive impact compared to the midstream region (coefficient = 0.217). Conversely, in the upstream region (Model 8), the coefficient for urban network externalities is negative, suggesting a suppressive effect on economic growth in this area. A potential explanation for the negative effect observed in the upper reaches lies in the interplay between network integration and industrial structure. Compared to the middle and lower reaches, cities in the upper reaches exhibit significantly lower strength and frequency of inter-urban network connections. This weak integration implies that even where industrial diversification exists locally, it may be predominantly composed of unrelated variety—diversification into technologically distant sectors that hedge against risk but do not facilitate knowledge spillovers [44]. In the absence of dense inter-urban linkages necessary to foster related variety and the associated knowledge externalities, the potential growth benefits of diversification are unlikely to be realized. Moreover, due to the relatively lagging economic development in the upper reaches, integration into the broader regional network may render limited local productive factors more susceptible to being siphoned toward core cities in the lower reaches. This agglomeration shadow effect, combined with the predominance of unrelated variety resulting from weak network integration, may collectively explain the negative coefficient observed in our model.



**Table 6.** Heterogeneity regression results.

|                          | Model 8<br>(Upstream) | Model 9<br>(Midstream) | Model 10<br>(Downstream) | Model 11<br>(Large Cities) | Model 12<br>(Small and<br>Medium-Sized Cities) |
|--------------------------|-----------------------|------------------------|--------------------------|----------------------------|------------------------------------------------|
| lnNET                    | −0.017 (0.071)        | 0.217 (0.156)          | 0.323 * (0.189)          | 0.492 * (0.285)            | 0.050 (0.93)                                   |
| Constant                 | 2.316 *** (0.818)     | 3.125 *** (0.555)      | 3.118 *** (0.874)        | 2.729 ** (1.090)           | 3.531 *** (0.419)                              |
| Control variables        | Yes                   | Yes                    | Yes                      | Yes                        | Yes                                            |
| Individual fixed effects | Yes                   | Yes                    | Yes                      | Yes                        | Yes                                            |
| Time fixed effects       | Yes                   | Yes                    | Yes                      | Yes                        | Yes                                            |
| R2                       | 0.996                 | 0.997                  | 0.997                    | 0.993                      | 0.993                                          |

Note: Standard errors are reported in parentheses. Significance levels: 1% (\*\*\*), 5% (\*\*), 10% (\*).

### 6.2.2. Heterogeneity Analysis by City Size

To assess whether urban networks exert differential effects on economic growth across cities of varying sizes, cities within the study area were classified into two categories—large cities (Model 11) and small and medium-sized cities (Model 12)—based on a threshold of one million permanent urban residents. Subgroup regressions were then conducted for each category. The results presented in Table 6 reveal significant city-size heterogeneity in the impact of urban network externalities on economic growth within the YREB. The influence of network externalities is strongly associated with urban scale: in large cities (Model 11), the coefficient for network centrality is positive and statistically significant at the 10% level, indicating that improved network connectivity meaningfully promotes economic growth. For small and medium-sized cities (Model 12), network externalities also show a positive association with growth, though the result is not statistically significant. A comparison of coefficient magnitudes further indicates that integration into urban networks contributes to economic growth substantially more in large cities than in small and medium-sized cities.

## 7. Spatial Spillover Effects of Urban Network Externalities

### 7.1. Decomposition of the Economic Growth Effects of Urban Network Externalities

This study further employs a spatial econometric model to examine the spatial spillover effects of urban network externalities on economic growth within the YREB. Drawing on the partial differential method proposed by LeSage and Pace [45], the spillover effects of the Spatial Durbin Model (SDM) are decomposed into three components: direct, indirect, and total effects. The direct effect measures the impact of a local independent variable on the dependent variable within the same city, capturing the purely local influence. The indirect effect (or spillover effect) represents the aggregate influence exerted by independent variables in neighboring regions on the local dependent variable. This effect operates through two main channels: first, changes in neighboring independent variables affect their own dependent variables, which subsequently propagate to the local dependent variable; second, changes in neighboring independent variables may also induce changes in local independent variables, thereby indirectly influencing the local outcome. The combination of these pathways constitutes the spillover effect. The total effect, defined as the sum of the direct and indirect effects, reflects the overall average impact transmitted throughout the interconnected urban network.

As shown in Table 7, both the direct and indirect effects of urban network externalities on economic growth are significantly positive, indicating that improvements in a city's own centrality and that of its neighboring cities contribute meaningfully to local economic growth. To accurately identify the respective contributions of local and neighboring influences, this study employs the partial differentiation method within the Spatial Durbin Model to decompose the effects. Specifically, a partial derivative matrix is constructed based on the matrix  $(1 - \rho W)^{-1}$  (where  $\rho$  represents the spatial autoregressive coefficient and  $W$  is the spatial weight matrix). This approach effectively accounts for spatial

feedback effects, thereby isolating the impact of changes in local variables on their own economic growth (direct effects) from their spillover effects on the economic growth of neighboring regions (indirect effects). Building on this, the relative proportion of direct effects is calculated as the ratio of the average direct effect to the average total effect, while the relative proportion of spillover effects is calculated as the ratio of the average indirect effect to the average total effect. The empirical results indicate that the direct effect of urban network externalities is 0.230, accounting for 70% of the total effect, while the indirect effect is 0.098, representing 30%. This suggests that for every unit of urban economic growth, approximately 70% is attributable to the city's own network externality, and 30% stems from the network externalities of neighboring cities. These results highlight that a city's endogenous development capacity serves as the foundational driver of its economic growth, while external network linkages enhance its nodal value through spatial spillover effects, thereby significantly boosting economic performance.

**Table 7.** Effect decomposition results of the SDM model.

|                 | lnNET             | lnSPE          | lnDIV              | lnEDU             | lnFAI             |
|-----------------|-------------------|----------------|--------------------|-------------------|-------------------|
| Direct effect   | 0.230 *** (0.052) | −0.005 (0.011) | −0.076 *** (0.025) | 0.238 *** (0.040) | 0.074 *** (0.013) |
| Indirect effect | 0.098 * (0.057)   | 0.056 (0.069)  | −0.298 *** (0.116) | 0.687 *** (0.211) | 0.111 *** (0.036) |
| Total effect    | 0.329 *** (0.038) | 0.051 (0.074)  | −0.374 *** (0.125) | 0.925 *** (0.224) | 0.185 *** (0.035) |

Note: Standard errors are reported in parentheses. Significance levels: 1% (\*\*\*), 10% (\*).

Similarly, both the direct effects and spillover effects of human capital and capital stock exert a significant positive influence on economic growth. Further analysis reveals that the spillover effect of highly skilled labor on urban economic growth accounts for approximately 74% of the total effect. Specifically, for every unit of growth in the urban economy, the city's own highly skilled talent contributes about 26%, while highly skilled talent from neighboring regions within the urban network contributes approximately 74% to the city's economic growth. This demonstrates the spillover value of talent in regional collaboration. Local capital stock contributes about 40% to regional economic growth, while neighboring regions account for approximately 60% of the impact, indicating that the networking of capital factors significantly promotes economic growth. Among agglomeration externalities, the degree of industrial specialization within a city has no significant effect on local economic growth, showing neither a significant promoting nor inhibiting effect in either direct or indirect terms. Meanwhile, the degree of industrial diversification within a city exerts a negative influence on economic growth. Specifically, a 1% increase in local industrial diversification leads to an approximate 0.076% decline in economic output. Moreover, the inhibitory effect of neighboring cities' industrial diversification on local economic growth far exceeds its direct effect. Both local and neighboring cities' industrial diversification suppresses economic growth.

To demonstrate the spatial spillover effect of urban network externalities, this paper uses the second-order adjacency matrix as the spatial weight matrix for the main regression analysis [46]. The selection basis is as follows: Firstly, the second-order adjacency matrix can illustrate the indirect paths of the spillover effect, and using only the first-order adjacency matrix would underestimate the spatial scope of the spillover; Secondly, the second-order adjacency matrix is completely constructed based on geographical relationships, avoiding the endogenous bias that might be introduced by the economic distance matrix.

To ensure the robustness of the findings, this study employs an alternative specification—the inverse squared geographical distance matrix—in the robustness tests. As shown in Table 8, both the significance and the sign of the spatial spillover effects remain consistent with those of the baseline regression.

**Table 8.** Robustness test.

|                 | lnNET            | lnSPE          | lnDIV              | lnEDU            | lnFAI            |
|-----------------|------------------|----------------|--------------------|------------------|------------------|
| Direct effect   | 0.182 *** (3.38) | −0.011 (−1.06) | −0.061 ** (−2.49)  | 0.225 *** (5.69) | 0.070 *** (5.29) |
| Indirect effect | 0.229 *** (2.78) | −0.007 (−0.06) | −0.528 *** (−2.15) | 0.259 *** (0.63) | 0.161 ** (2.43)  |
| Total effect    | 0.411 *** (5.93) | −0.018 (−0.14) | −0.374 *** (0.125) | 0.484 *** (1.13) | 0.231 *** (3.57) |

Note: Standard errors are reported in parentheses. Significance levels: 1% (\*\*\*), 5% (\*\*).

## 7.2. Distance-Decay Characteristics of the Economic Growth Effects of Urban Network Externalities

To examine the spatial extent of network linkage effects on economic growth and the distance-decay characteristics of their spillovers, this study constructs a series of spatial weight matrices under varying geographical distance thresholds  $d$ , with a starting point of 100 km and an incremental step of 20 km. For each threshold  $d$ , the spatial weight matrix  $W$  is defined as follows:

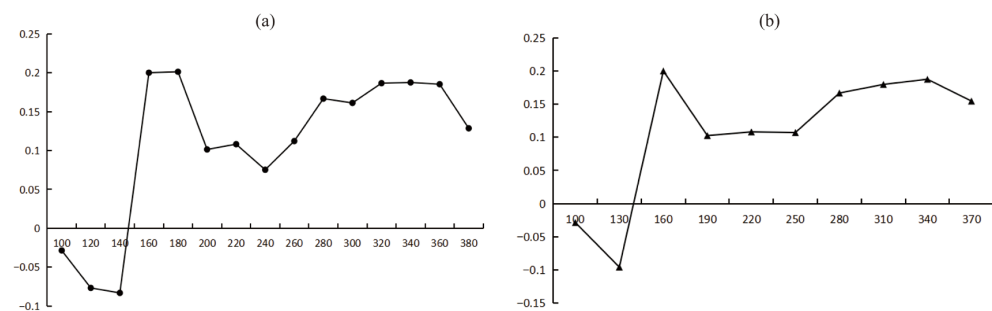
$$W_{ij} = \begin{cases} e^{-d_{ij}/d_{\max}} & d_{ij} \leq d \\ 0 & d_{ij} > d \end{cases} \quad (8)$$

where:  $d_{ij}$  represents the geographical distance between city  $i$  and city  $j$ ;  $d$  denotes the upper limit of the geographic distance threshold; and  $d_{\max}$  represents the maximum distance between any two cities within the study area.

This specification implies that when the geographical distance between two cities is less than or equal to the threshold  $d$ , their spatial weight follows a negative exponential decay as distance increases; when the distance exceeds the threshold, the weight is set to zero, indicating that no spatial association is assumed between city pairs beyond this threshold. Based on the spatial weight matrices constructed under these varying thresholds, this study estimates the Spatial Durbin Model separately for each threshold, obtaining the indirect effect coefficient (i.e., the spatial spillover effect of network externalities) corresponding to each distance threshold  $d$ .

As shown in Figure 5a, the spatial spillover effects of urban network externalities on economic growth exhibit clear distance-dependent characteristics within the YREB. As the geographical distance between cities changes, the spillover effects display a non-linear pattern with a notable inverted U-shaped trajectory featuring two distinct peaks, observed within the range of 100–380 km. Theoretically, the bimodal structure is a common phenomenon rooted in the polycentric nature of urban space. First, according to Central Place Theory, urban radiation is characterized by hierarchy, where spillover effects tend to skip lower-level centers and re-intensify at the next higher-order center, naturally giving rise to a bimodal pattern along the distance axis. Second, based on Spatial Interaction Theory, the breaking point between two major cities—where gravitational forces balance—becomes an active zone where factor flows seek equilibrium, often leading to localized peaks. Thus, the bimodal structure is essentially a spatial manifestation of polycentric urban network development. The spillover effects are analyzed by dividing the distance into the following intervals: Within the 100–140 km range, the economic spillover effect is significantly negative, suggesting that excessive proximity leads to inter-city resource competition and generates an agglomeration shadow effect. In the 160–180 km range, cities establish effective resource sharing and division of labor, resulting in a significantly positive economic spillover. The effect strengthens with increasing distance, reaching its first peak at 180 km. This indicates optimal resource allocation between core cities and secondary urban nodes within this radius. Within the 200–240 km range, the spatial spillover effect gradually weakens as distance continues to increase. In the 260–340 km range, the spillover effect intensifies again, reaching a second peak at 340 km. From the perspective of the

network structure, the emergence of the secondary peak is attributed to the transmission from secondary cities. The YREB has formed a network structure with multiple centers such as Shanghai, Wuhan, and Chongqing. This multi-center transmission mechanism has led to the formation of a secondary peak phenomenon in the distance attenuation curve. From the administrative boundary perspective, areas within 340 km mostly correspond to cross-provincial border areas (such as the adjacent regions of Shanghai, Jiangsu, and Zhejiang, and the border areas of Hubei, Hunan, and Jiangxi). With the advancement of regional integration, these areas have become active zones for factor flows, thereby strengthening the spatial spillover effect. Within the 360–380 km range, the economic spillover effect diminishes noticeably. Beyond 380 km, the spillover effect ceases to be statistically significant, demonstrating that increased distance attenuates inter-city connectivity and confirming a distinct geographical distance-decay pattern.



**Figure 5.** Changes in spillover effects at 20 km and 30 km regression distance thresholds. (a) The variation of spatial spillover effects with a distance threshold of 20 km. (b) The variation of spatial spillover effects with a distance threshold of 30 km.

To test the robustness of the conclusions, the distance threshold increment was adjusted from 20 km to 30 km, and the analytical procedure was repeated. Detailed data on the distance decay effect analysis are available in Data S3. As shown in Figure 5b, a significantly negative spillover effect is observed within the 100–130 km range. The first peak occurs between 160 km and 190 km, followed by a fluctuating attenuation from 220 km to 250 km. Between 280 km and 340 km, the spillover effect intensifies again, forming a secondary peak in the 310–340 km interval. Beyond 340 km, the effect shows a clear decaying trend and becomes statistically insignificant after 370 km. These findings align closely with those derived using the 20 km interval, confirming the robustness of the distance-decay pattern in the economic spillover effects of urban network externalities.

## 8. Conclusions and Discussion

### 8.1. Conclusions

While exhibiting a polycentric-network spatial framework, the urban network of the YREB shows starkly uneven development. A clear maturity gradient is evident, descending from the downstream to the middle and upper reaches. Between 2000 and 2020, cross-regional horizontal linkages strengthened significantly, and interactions among higher-tier cities intensified. As a result, the urban network evolved from a unipolar structure centered on Shanghai to a polycentric and synergistically integrated development pattern. Existing empirical results indicate a significant positive association between network centrality and regional economic growth in the YREB, while also displaying significant heterogeneity. Compared to traditional growth drivers such as human capital and physical capital stock, inter-city connectivity through networks facilitates cross-regional resource sharing and knowledge spillovers, thereby contributing substantially to regional economic development. However, the influence of urban network externalities exhibits notable regional and city-size

variations. Regions with more developed networks experience stronger growth effects from network integration. Specifically, urban networks in the downstream region contribute more actively to economic growth than those in the midstream and upstream regions. Moreover, large cities benefit more significantly from urban network linkages in terms of economic growth compared to small and medium-sized cities.

Urban network externalities in the YREB exhibit significant spatial spillover effects that follow an inverted U-shaped pattern with increasing distance. The decomposition results indicate that the direct effect of local network externalities accounts for approximately 70% of the total effect, while the indirect effect stemming from network externalities in neighboring regions accounts for approximately 30%. Regarding the spatial behavior of these spillovers, significant effects are observed within a range of 100–380 km. Within the 100–140 km interval, a siphon effect dominates, resulting in negative spillovers. The economic spillover effect reaches its first peak between 160 km and 180 km, followed by a secondary peak between 320 km and 340 km, after which a clear distance-decay pattern emerges. The spillover effect ceases to be statistically significant beyond the critical threshold of 380 km.

### 8.2. Discussion

The potential research contributions of this study may be summarized as follows: First, it proposes a multidimensional framework for constructing urban networks by integrating economic, infrastructural, and innovation dimensions—specifically through enterprise linkages, railway passenger flows, and innovation cooperation networks. This comprehensive approach enables a more accurate and structurally refined representation of urban network connectivity. Second, the study systematically reveals the heterogeneous impacts of urban network externalities on economic growth across regions, city sizes, and spatial scales. It identifies the presence and spatial extent of agglomeration shadows within the network and delineates the characteristic distance-decay pattern of spatial spillover effects generated by urban network externalities.

Firstly, this study reveals that urban network embedding exerts significant heterogeneity on economic growth. Developed regions and large cities can benefit more significantly from external network connections compared to underdeveloped regions and small and medium-sized cities, confirming the established view that core cities and developed coastal areas have more advantages in the network [11]. The empirical results of the YREB further highlight regional differences: The downstream areas have formed a mature networked development model, and the improvement of urban network centrality has significantly promoted economic growth, verifying the conclusion that the network drives economic growth [10]; Although the midstream region shows a positive correlation, the network effect has not passed the significance test, indicating that it is still in the transitional stage from scale agglomeration to network collaborative development, and the degree of network correlation needs to be improved. The negative coefficient of the upstream region indicates that the impact of integrating into the external network on economic development is not always positive. At the same time, there are potential risks of factor outflow and inhibition of economic development. Therefore, cities of different scales and regions should implement differentiated development strategies based on their own positioning, and promote economic development by maximizing their advantages: core cities and developed areas should leverage network connections to overflow capital, factors, technology, etc., and drive the transformation of urban development from a single pole to a network-like outward radiation development. Small and medium-sized cities and underdeveloped regions should enhance their element connections with large cities and developed regions, expand



their own scale by leveraging larger platforms, and focus on their respective advantageous development fields, so as to avoid the emergence of agglomeration shadow effects.

In addition, this study demonstrates that the externalities of urban networks promote economic growth through a dual-path mechanism. The economic growth of cities in the YREB is characterized by 70% endogenous drive and 30% spillover effect. This finding supports the existing research conclusions: Regional economic growth mainly depends on the agglomeration of resources and elements within cities [47]. This also indicates that the development of a city must rely not only on its own accumulation of elements but also on external network connections. Both are indispensable and not contradictory to each other, but rather complement and enhance each other. In terms of agglomeration externalities, specialized agglomeration promotes urban economic spillover, while diversified agglomeration has a negative impact on the economic development of neighboring areas, confirming that agglomeration externalities have both positive and negative externalities on economic development [10].

In the research on the distance attenuation characteristics of the existing spatial spillover effect, the study by Moreno et al., based on 175 regional samples in Europe, shows that the spatial spillover effect presents significant distance attenuation characteristics [48]. When the geographical distance between regions exceeds 250 km, the spatial spillover effect generated by its economic and technological connections is no longer statistically significant. Fischer et al. found through total factor productivity analysis that the knowledge spillover effect in the European region is statistically significant only within a radius of 300 km [14]. The above-mentioned research provides important empirical evidence for studying the spatial attenuation boundary of urban network externalities. Based on the verification of the distance attenuation characteristic of the spatial spillover effect pointed out by previous studies, this paper further reveals that the distance between cities has a significant “double threshold” feature on economic spillover. This finding is in line with Martell’s strategic foresight perspective, which suggests that regional planning should consider the optimal connectivity threshold to avoid the clustering shadow caused by excessive short-distance integration, and build productive complementary relationships at the medium scale [49]. Specifically, when the distance is too short (in this paper, 100–140 km), cities are prone to have clustering shadows due to resource competition. Therefore, adjacent areas should subdivide industries and cultivate complementary industries to avoid homogeneous development. When the distance is within the moderate range (in this paper, 160–180 km, 320–340 km), cities can achieve synergy and reach the peak of positive spillover, confirming that medium distances are conducive to the formation of productive complementarity. Therefore, it is necessary to strengthen technological exchanges, talent cooperation, and resource sharing between cities. When the distance exceeds the spillover threshold (in this paper, >380 km), the correlation between cities weakens. In this case, it is necessary to rely on regional hub cities and adopt forms such as satellite cities and industrial clusters to break through the constraints of geographical attenuation through the “borrowed size” effect. In summary, this study identifies the double threshold spatial pattern of economic spillover and provides certain empirical evidence from the perspective of regional planning on how to avoid clustering shadows and strengthen synergy effects under different geographical distances.

### 8.3. Limitations and Future Research Directions

A variety of metrics are available to measure urban network externalities, including degree centrality (reflecting link frequency), PageRank centrality (capturing the quantity and quality of neighboring nodes), betweenness centrality (based on shortest-path intermediation), and closeness centrality (dependent on connectivity and shortest paths). Given

that the essence of a network lies in the interconnectivity among its elements, this study employed closeness centrality as the proxy for urban network externalities. While this metric effectively captures network structure from a connectivity-based perspective, it does not incorporate the complementary information offered by other centrality measures. Furthermore, as this research focuses primarily on the distance-decay pattern of spatial spillovers stemming from urban network externalities, the spatial weight matrices used to analyze these spillovers and their heterogeneity were constructed mainly based on geographical proximity. Future studies could adopt more diversified spatial weighting strategies—such as economic distance, network-based adjacency, or functional linkage matrices—to further elucidate the complex nature of spatial spillovers. Lastly, while this paper examines the aggregate effect of the composite multidimensional network on economic growth, the individual contributions of enterprise networks, passenger transport networks, and innovation networks remain to be disentangled. Analyzing the distinct mechanisms and effect sizes of these subnetworks represents a promising direction for future research.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/urbansci10030163/s1>, Data S1: Urban network construction data; Data S2: Baseline regression and heterogeneity analysis data.; Data S3: Distance-decay effect analysis data.

**Author Contributions:** S.Y.: Data curation, Writing—original draft. W.S.: Writing—review & editing. Y.L.: Software, Visualization, Formal analysis. S.H.: Conceptualization, Investigation, Supervision, Project administration, Funding acquisition. All authors have read and agreed to the published version of the manuscript.

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