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Urban network externalities, agglomeration economies and urban economic growth

Yin Huang[a], Tao Hong[a], Tao Ma[a,b,*]

[a] School of Management, Harbin Institute of Technology, Harbin 150001, PR China
[b] State Key Laboratory of Urban Water Resource and Environment, Harbin 150001, PR China

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ABSTRACT

This study analyzes the effect of urban network externalities on urban growth and compares it with that of agglomeration economies from the perspective of the externality theory. Traditional regional and urban economic theories emphasize the role of agglomeration economies in promoting regional growth. However, urban networks have gradually become the main form of regional economic systems. Urban network externalities are also becoming increasingly critical with the dramatic development of infrastructure and information technology. This study identifies the national urban network and analyzes its structure and characteristics using complex network methods based on the data of train frequency among 273 municipal districts in China. Then, an urban growth model is constructed with Spatial Durbin Model specifications to examine the impact of urban network externalities on economic growth and compare it with that of agglomeration economies. The results show that the urban network externality has a significant effect on promoting urban economic development; cities with higher in-closeness centrality tend to enjoy higher economic growth due to their central position in the network. Moreover, compared with agglomeration economies, urban network externalities do not depend on the geographical proximity of cities but on the connections in the network, and can generate cross-spatial spillover effects.

1. Introduction

The linkages between cities are becoming increasingly close with the rapid development of transportation infrastructure and information technology that accompanies economic globalization and regional integration. Urban networks, centering on big cities and containing many small and medium-sized cities, have gradually formed with the accelerating flows of various material and non-material factors. The dominant urban form has also changed from "space of place" to "space of flow" (Batten, 1995; Camagni and Salone, 1993), where urban development depends more on the interaction and spatial spillover effects between cities than on their functions and characteristics. Since the proposition of urban networks, scholars (Glaeser et al., 2016; Johansson and Quigley, 2004; Meijers, 2005) have analyzed the mechanism and influence of urban network externalities on economic development, but relatively little is known about the extent to which urban network externalities affect urban growth or the empirical differences between urban network externalities and agglomeration economies. In this regard, the purpose of this study is to compare the two concepts of urban networks and agglomeration economies from the perspective of the externality theory, then examine empirically the effect of urban network externalities on urban performance to determine which types of cities would benefit more from urban network externalities.

In the field of urban and regional economies, the effect of agglomeration economy is regarded as a type of economic externality and is produced from the co-location of economic agents. However, the co-location is not the only source of economic externalities; the interaction of economic agents, which are not physically adjacent, can also produce externalities. Some scholars refer to this externality as "externality fields" (Phelps, 1992), "cluster economies" (Porter, 1996), or "complex economies" (Parr, 2002). Camagni and Salone (1993) define them as "urban network externalities" and consider them to be club goods, whereby only cities connected to the network are influenced by it. Capello (2000) further supplements Camagni's definition from the macro perspective of inter-city complementarity and synergistic relationships, and demonstrates that urban network externality is the essential element of urban networks. Compared to agglomeration externalities, urban network externalities increase the geographical scope and can also exert an influence when the agents are not physically adjacent (Boix and Trullén, 2007; Meijers, 2005).

* Corresponding author at: School of Management, Harbin Institute of Technology, No. 13 Fayuan Street, Harbin 150001, Heilongjiang Province, PR China.
E-mail addresses: hithuangyin@163.com (Y. Huang), hongtao@hit.edu.cn (T. Hong), matao@hit.edu.cn (T. Ma).

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Since the proposition of the conception of externality, a large body of literature, such as Henderson (1974), Jacobs (1969), and Sprague and Hoover (1937) have carried out theoretical research on the externalities of the urban economy. The Marshall-Arrow-Romer (MAR) externalities, regarding specialization effect, and Jacobs' externalities, regarding diversity effect, are the primary formation mechanisms of agglomeration economies. Glaeser et al. (1992) and Henderson et al. (1995) establish a dynamic urban growth model, which brings agglomeration externalities into the endogenous growth theory framework of Lucas (1988) and Romer (1986), and identify the differences between static and dynamic external economies. Many studies (Ellison et al., 2010; Faggio et al., 2017; Hanlon, 2012) also focus on the agglomeration economies from aspects such as input-output relations, regional heterogeneity, and industrial heterogeneity. However, most of these studies ignore the external relations of cities and are unable to explain the phenomenon of some small or medium-sized cities with high productivity, and the existence of a poverty belt around metropolitan areas. For these reasons, some studies use spatial econometrics methods to empirically examine the spillover effects between cities (Fingleton and López-Bazo, 2006; Sun, 2016). However, the traditional spatial weight matrix in spatial econometrics is based on geographic distance or adjacency, which ignores the complex linkages between cities, making it is impossible to identify the heterogeneity of urban network externalities in different cities.

Compared with agglomeration economic research, the absence of flow data and mature network analysis methods slow down the research on urban network and network externalities. In recent years, the significant progress in the field of big data, spatial econometrics, and network externality theory have created suitable conditions for such studies. From the 1990s, the development of polycentric regional spatial form has become increasingly important for manufacturing and advanced producer services (Batten, 1995; Hanssens et al., 2014). Moreover, the urban network has become an essential tool for urban spatial planning and regional policy, such as in the case of the European Spatial Development Perspective and Sustainable Management of European Polycentric Mega-City Regions. Research on the world-city network (Taylor et al., 2002; Taylor and Derudder, 2016) has also significantly promoted the development of urban network theories. Nonetheless, there are few empirical studies on the impact of urban network externalities on urban economic performance. Some scholars have studied the influence of spatial structure on regional economic growth by constructing polycentric morphological indicators (Lee and Gordon, 2011; Meijers and Burger, 2010), but have not examined the internal mechanism of the effects. Besides, whether the polycentric urban form can promote economic growth has not yet reached a unanimous conclusion because of the differences in research samples in terms of spatial scale, city size, and economic development levels.

In general, there are few empirical studies about the effects of urban network externalities on regional economic growth, and the internal formation mechanism remains unexplored. In this context, this study identifies a network of 273 cities across China based on the train frequency between cities, and applies complex network methods to characterize and measure the network. Then, a spatial econometric model is constructed to empirically examine the effects of urban network externalities on urban growth and to compare the network externalities with traditional agglomeration externalities.

Our research contributes to three broad literatures. Firstly, the study is related directly to the literature on the urban network, especially the discussion about the comparison of agglomeration economies and urban network externalities (e.g., Boix, 2003; Boix and Trullén, 2007; Burger and Meijers, 2016; Jiao et al., 2017; Johansson and Quigley, 2004; Meijers et al., 2016; van Meeteren et al., 2016). These studies mainly focus on the characterization and the empirical explanation of the urban network. On this basis, this study empirically examines the effect of urban network externalities and compares it with agglomeration economies using the complex network and spatial econometrics. The urban network and the coherent spatial weight matrix in the empirical model are constructed based on the train frequency data across cities, which is rarely studied in previous literature to the best of our knowledge.

Secondly, there are notable papers exploring the spillover effect of economic growth (e.g. Dall'erba and Le Gallo, 2008; Fingleton, 2001; Lesage and Fischer, 2008; Tian et al., 2010). The traditional spatial weight matrix in the spatial growth regression model is mostly based on spatial proximity, such as contiguity matrix and inverse distance matrix, while the counterpart in this research is constructed by integrating economic linkage strength across cities and spatial proximity. Moreover, this research compares the spillover effect of each of these separately, which could provide a new interpretation for the spillover process of economic growth and lead to novel results.

Finally, our work also relates to the large empirical literature on the relationship between economic development and transportation (e.g., Banerjee et al., 2012; Donaldson, 2018; Donaldson and Hornbeck, 2016; Duranton and Turner, 2012; Jiao et al., 2017; Li and Xu, 2018; Zhu et al., 2019). Based on these studies, we find that there is an increasing tendency to move from reduced form models (e.g., difference in difference, instrumental variable methods, and spatial econometrics) to structural model analysis (e.g., spatial computable general equilibrium model and quantitative general equilibrium model) in transportation and economies research. This study examines the impact of transportation on regional growth by focusing on network characteristics and the strength of connection of the transport network, rather than on whether a region has access to the network or road lengths, which is consistent with recent structural research including Allen and Arkolakis (2014) and Redding (2016).

The remainder of this paper is organized as follows. The second section theoretically compares urban network externalities and agglomeration economic effects under the theoretical framework of externalities, and proposes the research methodology of the study. Then, in Section 3, the urban network is identified based on the data of train frequencies between cities across China. Additionally, the study measures the characteristics and distribution of the urban network using complex network methods. Section 4 constructs the empirical model in spatial econometrics and analyzes the empirical results to examine the impact of urban network externalities on urban growth. Finally, Section 5 provides the conclusion and policy implications.

2. Theoretical framework and empirical strategy

The urban network is a spatial organization system that connects cities through various economic and social bonds, and provides externalities generated by complementary integration or synergies between connected cities' nodes (Boix and Trullén, 2007; Camagni and Salone, 1993). An urban network mainly has two meanings: one is the material connection, referring mainly to the infrastructure links including highways, railways, and communication networks. The second is the factor flows and non-material spatial links in economic, social, and cultural aspects, such as political and innovation cooperation in different cities. The micro-foundation of the urban network formation is the spatial selection of market agents including individuals and enterprises. The different behaviors of various economic agents, selected according to individual characteristics such as productivity, market demand, and economies of scale, have promoted the evolution of urban networks (Boschma and Martin, 2010). According to spatial forms, urban networks can be divided into vertical, horizontal, and multi-center networks. Particularly, the vertical network is the re-characterization of the single-center hierarchical system in Central Place Theory under the network paradigm. To date, research on urban networks mainly uses the data of the headquarters-branch distribution of advanced producer-service firms, infrastructure networks (such as airline-passenger and telecommunication flow), network of academic research and patent innovation cooperation, and transnational migration. Flow data is calculated to analyze the structure and evolution of the urban network, and is further used to study the issues in regional spatial planning, urban functional division, and regional economic imbalance. Despite extensive research on the urban network, the theoretical and empirical examination of its impact needs further development.

2.1. Theoretical framework of urban network externalities and agglomeration economies

Compared with traditional urban and regional economic studies, urban network externalities no longer regard cities as isolated units, but as nodes in urban network systems. The interaction between city nodes produces the network externalities, which does not depend on geographical proximity (Camagni and Salone, 1993). This means that urban network externalities are spatial dynamic effects between cities. The critical difference between spatial static and spatial dynamic externalities is the gap between the spatial extent of the externality and the size of the research objective. This standard can be used to compare the concepts of internal and external economies, and MAR, Jacobs', and urban network externalities. Boix (2003) summarized this in Table 1. The externality can be divided mainly into four categories based on the plant, firm, industry, and city criteria: internal economies is the externality internal to plants, MAR externality or the dynamic localized economy is external to the firm within the same industry and city, and Jacobs' externality or the dynamic urbanization economy exists between different industries within the same city (Glaeser et al., 1992; Henderson et al., 1995). Moreover, the externality between different cities is the urban network externality. Therefore, it can be regarded as the promotion of agglomeration economies in the larger spatial context. The difference between these two concepts is that agglomeration economies are spatially constrained and decay with distance while urban network externalities are not spatially constrained and depend on the strength of the functional relationship between cities rather than their proximity (Burger and Meijers, 2016). Additionally, there is no inherent mechanism that restricts the three sources of Marshall externalities, namely matching, sharing, and learning, to specific sectors or regions (van Meeteren et al., 2016). In other words, the three mechanisms are also the basic sources of urban network externalities and can exert impact at urban network scale. Such as in the transportation network we analyzed below, a variety of factors could flow and interact within a larger spatial scale through the transportation connection; therefore, cities in the network can benefit from the integration of labor market pooling, input sharing, and knowledge spillovers in different cities.

The micro-foundations of urban network formation are the spatial selection of economic agents; close connections between individuals and enterprises in the market have become an important source of network externalities. Given globalization and regional integration, transportation and communication costs are declining continuously. The innovation activities of transnational enterprises and transregional corporations can be conducted simultaneously in different cities, and particularly, are not limited to large cities. Additionally, the level of standardized production has also become significantly higher, which can reduce transaction costs and decrease the importance of trade partners' geographical proximity. Enterprises no longer rely on face-to-face communication and can choose sites in a larger space (Johansson and Quigley, 2004). Besides, the urban network is also the result of agglomeration diseconomies. The congestion effect and income gap caused by excessive agglomeration will promote the redistribution of enterprise location. In contrast to isolated enterprises, dispersed enterprises in the urban network establish cross-spatial links through cooperation and transactions with lower transaction costs, implying that urban network externalities can replace agglomeration economies to a certain degree (Meijers et al., 2016) and further expand the spatial extent of factors, commodity flows, and knowledge spillovers. Therefore, the reduction of transaction costs, globalization of enterprises, and spatial expansion of factor flows and knowledge spillovers enable the network externalities to break through the scope of agglomeration economies and expand their influence over a larger spatial scale.

Increasing returns to scale is an important mechanism for large cities to generate agglomeration economies and support advanced urban functions. Regarding the development of small cities, Alonso (1973) proposed the concept of "borrowed size" and claimed that a small city could "borrow" agglomeration economies from larger neighboring cities while simultaneously retaining the advantages of smaller scale (such as avoiding congestion effects) such that the cities around metropolises could also maintain high growth rate and productivity. Scholars, such as Burger et al. (2015), Hesse (2014), and Meijers and Burger (2017) further improved the concept and measuring methods of borrowed size and introduced it into studies on urban network externalities. They consider that what is important for an enterprise is access to the agglomeration advantages rather than proximity to the agglomeration area. Therefore, borrowed size should be interpreted as the network linkages across all cities, rather than limited to the cities within a small spatial scale. The network connection could provide a substitute for the benefits of geographical proximity to a certain degree. The borrowed size can be further divided into two parts: "function borrowing" and "performance borrowing." Function borrowing refers to expanding the scale of the city's factor and consumer market through connections with other cities, to host the functions that cannot be supported by its own scale. Performance borrowing occurs when a small city obtains the borrowed size from adjacent metropolises and can produce higher economic output through the network (Meijers and Burger, 2017). The borrowed size focuses on the positive spillover effect of the urban network externality while its negative counterpart is the agglomeration shadow, which depicts the phenomenon that some small cities around the metropolis have worse economic growth than would generally be the case due to competition effects (Burger and Meijers, 2016). Some studies have examined the existence of agglomeration shadows empirically (Burger et al., 2015; Partridge et al., 2009). In summary, urban network externalities influence urban economic growth through both borrowed size and agglomeration shadows. According to the position of cities in the network and their development stages, urban network externalities will have heterogeneous performance.

The overall theoretical framework of the study is shown in Fig. 1.

Table 1
Internal and external economies based on the spatial scale.

	Internal to the firm		External to the firm		
	Internal to the plant	External to the plant	Internal to the industry	External to the industry	
Internal to the city	Internal economies I1	I2	MAR externalities I3	Jacobs' externalities I4	Hoover's agglomeration economies (I1 + I3 + I4)
External to the city	E1	E2	E3	E4	Urban network externalities (E3 + E4)
	Hoover's internal economic	Network of firms			

Source: Boix (2003).

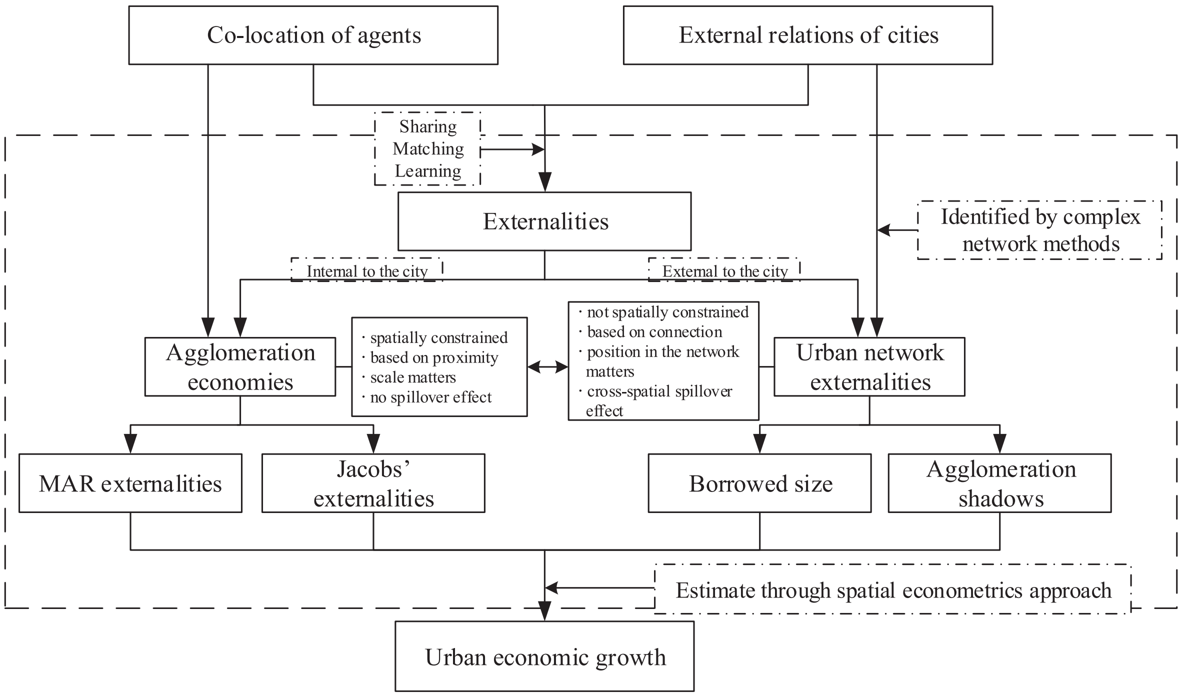

Fig. 1. The theoretical framework of the study.

We compare the notions of agglomeration economies and urban network externalities under the coherent theoretical framework of externalities, and explain the theoretical influence mechanism of urban network externalities on economic growth.

2.2. Strategies and methodology for the empirical analysis

The main empirical challenge in examining the effect of urban network externalities is how to characterize them. Early studies in the field of urban and regional economies regarded agglomeration economies as being geographically constrained, with no spillover effect outside the agglomeration (Burger and Meijers, 2016; Rosenthal and Strange, 2004), and usually with the spatial scale of a city or industrial park. In other words, early studies ignored the interaction of cities. Since the early to mid-1990s, scholars led by Paul Krugman and Masahisa Fujita have introduced the spatial perspective to the economic theories, termed the “New Economic Geography,” and indicators such as market potential and accessibility have been proposed to represent the external relations of cities in this research paradigm (Duranton, 2016; Redding and Venables, 2004). This approach loses the information of the complex relationships between cities, though they take effect in some cases. Recent research on the world city network (Taylor and Derudder, 2016) and knowledge network (Giuliani, 2007) provides implications for the analysis of urban network externalities. The complex network is an ideal method to characterize the urban network. Moreover, spatial econometrics can examine the effect of urban network externalities directly, which could measure the external relations of cities by the spatial weight matrix rather than several indicators in the model. Therefore, this study combines the complex network and spatial econometrics approaches to analyze the extent to which urban network externalities influence urban economic growth.

Firstly, we need to identify and measure the urban network by complex network theory. To date, the method of identifying urban networks is mainly based on the data of the headquarters-branch distribution of advanced producer-service, infrastructure network, academic papers or patent cooperation, and transnational migration. The transportation infrastructure approach is a relatively direct measurement method, which could characterize the people and material flows much more realistically and effectively than others. Early studies based on traffic flow mainly use the data of the aviation network (Derudder and Witlox, 2008; Mahutga et al., 2010) because of its easier access. However, we take China's cities as the research samples; China' railway network, with its broader coverage area and higher traffic volume, has been the backbone of its transportation infrastructure compared to the aviation network. Moreover, China has built the largest high-speed railway network in the world, which has powerfully affected the spatial interactions between cities in China. Therefore, we choose the railway flow data to identify the urban network. Then, we use indicators including network density, degree centrality, closeness centrality, and block model approach to analyze and measure the China's urban network.

Based on the identification of China's urban network, the empirical model including urban network externalities and agglomeration economies could be constructed with spatial econometric specification. We firstly take the Cobb–Douglas production function as the benchmark model where the variables of network centralities as the indicators of urban network externalities are included. Then, the variables of specialization and diversification, as the indicators of agglomeration economies, are added to the benchmark model to reveal the difference between urban network externalities and agglomeration economies. We estimate the economic growth model with the Bayesian Monte Carlo estimation procedure to empirically examine the impact of these urban network externalities and agglomeration economies, as presented in Section 4.

3. Identification and measurement of urban network

3.1. Methodology and data

This study takes the municipal districts of prefecture-level cities in China's mainland (excluding Hong Kong, Macao, and Taiwan) as the research sample and there are 273 districts left after the data collection and cleaning. The urban network consists of nodes, edges, and edge weights, where the nodes are the 273 municipal districts in China's mainland and an edge represents whether there are trains plying between a particular node pair. As it is significantly much challenging to obtain the exact train passage numbers of all trains, we use the daily passenger train frequency between cities as an indicator of the edge weight (Jiao et al., 2017; Wei et al., 2015). We crawl the official train ticketing websites in China to obtain data on national passenger train schedule information. After appropriate data correction and cleaning,[1] we use Structured Query Language (SQL) to query the train frequencies between cities based on the passenger train schedule. The train is recorded when it passes by the municipal district's rail stations. To confirm the accuracy of the data to indicate urban network intensity, we merge the train records where one train passes different train stations in the same municipal district. In other words, each node in this study represents a city rather than a train station, and the weight of each edge ($w_{i,j}$) is set as the sum of the train frequencies from city i to city j.

The train frequency data used in this study is collected to indicate the strength of population flows between cities and further reveal the strength of economic linkages in the urban network. In this regard, the data should be collected to suitably measure the population flows, where the population mainly acts as the labor force during the movement, which, in itself, is the essential component of the economic linkages between cities. However, the movement of labor force is not consecutive and regular during the weekday. Therefore, we obtained one day's national train schedules in February 2016 as the train frequency sample, when is during the Chinese Spring Festival travel rush. The economic linkages become much more significant during this festival because of the large-scale population movements, thereby making it more suitable for this research.[2] The result of querying the train frequencies among cities is an asymmetric matrix with 273 rows and columns, and 74,529 elements. Finally, the urban network identified in this study is a directed weighted network.

3.2. Identification results of the urban network

Compared to previous researches, which measure the links between regions using the gravity model or static factor distribution, flow data can reflect the urban network characteristics more directly and dynamically. This study uses the geographic information system database provided by the Chinese Resource and Environment Data Cloud Platform Center[3] to map the urban network characterized by train frequencies among cities using ArcGIS Pro software. The visualization result is shown in Fig. 2.

Fig. 2 shows a strong spatial dependence and hierarchy of China's urban network, and is coherent with the structure of China's railway trunk lines, called "eight horizontal lines and eight vertical lines". The result indicates that the traffic infrastructure can apparently affect the formation of regional spatial links. Moreover, the train frequency distribution is much correlated with population density, consistent with the characterization of "Hu Huanyong Line" (Chen et al., 2016). High-intensity areas are mainly distributed in the central and southern regions of the Chinese mainland, especially in the economic areas such as Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta, with the top strong links between the Nanjing-Shanghai, Suzhou-Shanghai, Guangzhou-Shenzhen, and Nanjing-Suzhou pairs. Conversely, the northwest, southwest, and northeast regions have relatively low level of connectivity. The largest possible number of edges between 273 nodes is 74,529; there are actually 23,459 pairs with a total of 144,333 train frequencies. Hence, the network density (the actual number of edges/the maximum number of possible edges) is 0.315, indicating that the network's aggregation degree is not high and needs be strengthened. The overall network efficiency is 0.672, implying that there are many redundant links and obvious super-positions in the urban network, which could enhance its stability. In addition, the weighted aggregation coefficient of the network is 5.117 and the characteristic path length is 1.745, revealing a significant characteristic of "small world" network.

We further analyze the centrality of the urban network based on the train frequency and calculate the degree centrality and closeness centrality of each node. The blue circles in Fig. 2 depict the distribution of in-degree centrality of each city. Accordingly, the top five cities in terms of the index are Shanghai, Nanjing, Beijing, Wuhan, and Zhengzhou; these are also the top cities based on out-degree, showing that most trains pass through these cities. The top five cities based on closeness centrality are Beijing, Shanghai, Guangzhou, Wuhan, and Xuzhou, indicating the closest comprehensive length linked to other cities. Moreover, we find that the western region is at a weak position in China's urban network, while the central and eastern regions play an important role as the bridge and junction for various regions in China.

3.3. Block model analysis of China's urban network

The block model of complex networks was first proposed by Boorman and White (1976) to cluster the network based on the connecting intensities between nodes. Fig. 3 shows the clustering result of the urban network using the CONCOR algorithm. The network has eight partitions, and the number of nodes in each part is 31, 39, 48, 23, 41, 32, 32, and 27, in sequence. With an overall weighted density of the urban network of 1.937, we can obtain the image matrix of the block model based on the density matrix shown in Table 2. If the network density of one pair between partitions exceeds 1.937, then the corresponding element in the image matrix is set as 1, and is set as 0 otherwise. Due to space constraints, the image matrix, which can display the relationship between partitions, is provided in Appendix A.

The division of the block model for the urban network shows similar characteristics as the distribution of regional economic development levels, indicating the potential impact of urban network externality on economic growth to some extent. All diagonal figures in the image matrix are 1, revealing that the internal relations of each partition are stronger than the interrelations. Partition 4 has the highest density and includes mainly Shanghai, Jiangsu, and Anhui, which are among the most developed regions in China. Next, partition 6, including mainly Guangxi and the southern part of Guangdong, and partition 1, including mainly Beijing, Tianjin, and Shandong, also have high densities, indicating a strong correlation within the division. The regions with weak densities are the third and eighth divisions, which respectively include the regions of Shanxi northwest, Inner Mongolia, Ningxia, Gansu, and the areas along the Gui-Kun Railway and Xiang-Yu Railway, each of which is a relatively backward region. Moreover, partitions 3 and 8 have a weak correlation with others, indicating that they are relatively isolated compared to other regions. The image matrix figure shows that there are strong links within the pairs of partitions 1 and 2, 1 and 4, 4 and 7, and 5 and 6, indicating that the partitions 1 and 4 are the junctions of China's urban network. This is consistent with the role of Beijing-Tianjin and Yangtze River Delta regions in the national economic growth.

4. Empirical results

Based on the data of daily train frequencies within the 273 municipal districts of prefecture-level cities in 2016, this study identifies the urban network across the country and analyzes its structure and characteristics by complex network methods. On this basis, this section describes the results of our empirical study on the impact of urban

[1] We have deleted both the train stop records, which are outside the research sample, and duplicate data, where the same train has different train identification numbers at different running stages. Moreover, we manually verified the completeness and accuracy of the data.

[2] We have also tried to change another sample during the weekday. Because of the difficulties in accessing the historical national passenger train schedule information, we make another empirical analysis based on the latest train schedule data and former economic statistic data, and the estimate remains similar although understandably it cannot be the formal result

[3] The website of the Chinese Resource and Environment Data Cloud Platform Center is http://www.resdc.cn/.

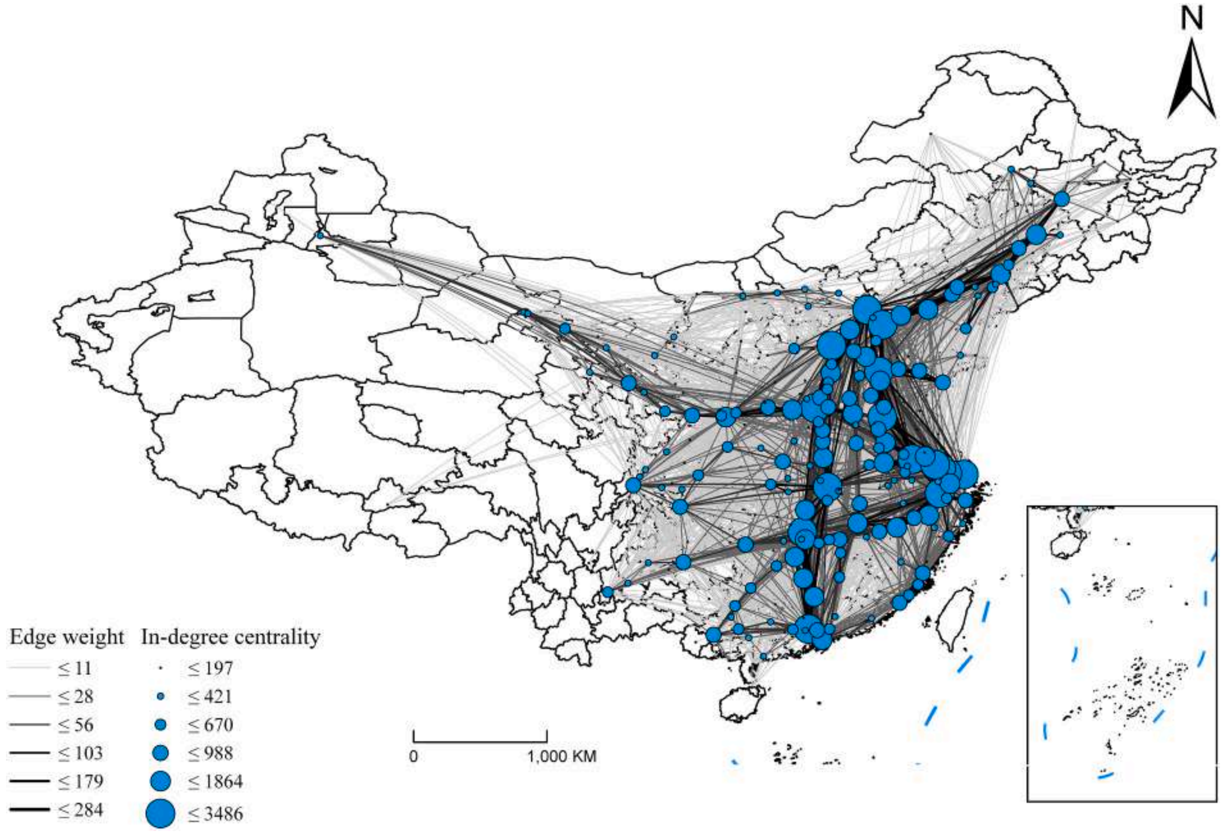

Fig. 2. Urban network based on train frequencies between cities in China.

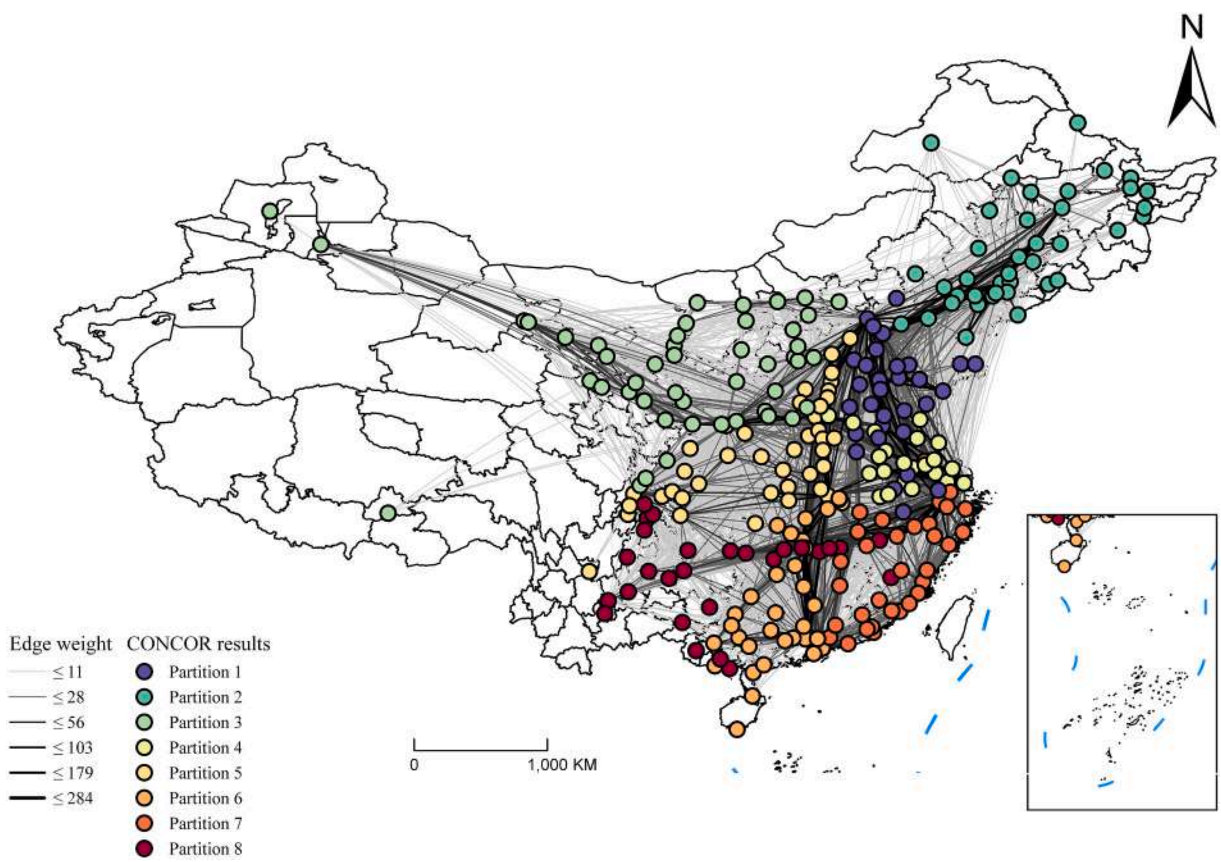

Fig. 3. Block model results for China's urban network.

Table 2
The density matrix of block model analysis.

	1	2	3	4	5	6	7	8
1	9.274	2.159	0.829	6.314	1.555	0.928	1.841	0.373
2	2.185	6.399	0.258	1.037	0.356	0.224	0.244	0.044
3	0.873	0.244	3.556	1.266	1.436	0.373	0.226	0.079
4	6.351	0.909	1.293	21.502	1.572	0.807	3.613	0.739
5	1.644	0.336	1.487	1.771	6.998	2.531	0.79	0.759
6	0.923	0.186	0.398	0.799	2.681	10.238	1.68	1.897
7	1.822	0.22	0.207	3.648	0.891	1.618	9.065	1.927
8	0.388	0.039	0.087	0.718	0.834	1.936	1.889	3.88

R-squared = 0.109.

network externalities and agglomeration economies on urban economic growth.

4.1. Empirical model and variables

Based on the Cobb–Douglas production function model, the benchmark model is set as follows:

$$\ln pergdp = \beta_0 + \beta_1 \times \ln perinvest + \beta_2 \times \ln employee + \beta_3 \times \ln perfisc + \beta_4 \times incloseness + \beta_5 \times outcloseness + \mu \quad (1)$$

The model takes the double-logarithmic form, where *pergdp* represents the per capita GDP, which measures the level of urban economic development; *perinvest* represents the per capita fixed asset investment; *employee* represents the number of employees at the end of the year; *perfisc* represents the per capita local fiscal general budget expenditure to measure the factor input of urban economic growth; and μ is the error term.[4] We omit the spatial lags of the interpreted or explanatory variables because of space limitations; these can be added according to the spatial model specification used. Additionally, the spatial econometric method could reduce the potential influence of omitted variable in the empirical model to some extent, especially the Spatial Dubin Model (SDM) used below (Lesage and Fischer, 2008). However, it cannot capture the heterogeneous impact of the urban network externalities in different cities; as such the closeness centralities, namely *incloseness* and *outcloseness*, are added to the model. The two variables indicate how close a city is to all other cities in the urban network based on the two different directions.

To further analyze the relationship between the urban network externalities and the agglomeration economies, specialization and diversification indicators are added to the benchmark model as follows, based on the methods used by Glaeser et al. (1992) and Henderson et al. (1995):

$$\ln pergdp = \beta_0 + \beta_1 \times \ln perinvest + \beta_2 \times \ln employee + \beta_3 \times \ln perfisc + \beta_4 \times incloseness + \beta_5 \times outcloseness + \beta_6 \times diversity + \beta_7 \times specialization + \mu \quad (2)$$

where *specialization* indicates the level of industrial specialization in the city, thereby measuring the effect of MAR externality, and *diversity* indicates the level of industrial diversification, measuring the effect of Jacobs' externality.

Given the challenges in obtaining the annual train frequency data and the complication of the estimation of the spatial dynamic panel data models with time-varying matrices, the cross-section data of 2016 is used to set the spatial econometric model. We take the same 273 municipal districts as the empirical research objects. The primary data source is China's City Statistical Yearbooks and the closeness centralities are calculated based on the urban network identified in Section 3. We impute missing data using STATA 15.0.

According to the theory of MAR externalities, regional specialization is the primary source of technological innovation. The upstream and downstream links across the industrial chain, labor market pooling, knowledge spillovers, and monopoly market structures in one industry are all conducive to innovation. We select the location quotient as the estimator of industrial specialization, which has been widely used as the MAR externalities indicator in relevant research (Beaudry and Schiffauerova, 2009), and calculate it as follows:

$$LQ_{i,j} = \frac{E_{i,j}/E_i}{E_j/E} \quad (3)$$

$$specialization_i = \max(LQ_{i,j}) \quad (4)$$

where $E_{i,j}$ represents the number of employees in the j-th industry of the i-th city, E_i represents the number of employees in the i-th city, E_j is the number of employees in the j-th industry across the entire research area, and $LQ_{i,j}$ indicates the location quotient, which is higher than 0 when the j-th industry is the specialized department of the i-th city. The specialization index of the city is set as the maximum industrial location quotient in the city.

Jacobs' externalities emphasize the role of industrial diversification in promoting innovation, where externalities' effects arise from the interaction between industries. The agglomeration of different industries is greatly conducive to the exchange and collision of knowledge. This study uses the reciprocal value of the Herfindahl-Hirschman Index as the estimator of industrial diversification, whereby the larger the index, the higher the degree of diversification. The formula is as follows.

$$diversity_i = 1/\left(\sum_j (E_{i,j}/E_i)^2\right) \quad (5)$$

Majority of the traditional spatial econometric models use either the adjacency, geographic distance, or economic geographic matrices as the spatial weight matrix. However, a matrix based on the geographical relations cannot reflect the economic interactions of the cities and there is no specific economic implication of the spillover progress of urban growth. In this regard, this study constructs the spatial weight matrix by multiplying the train frequency by the corresponding inverse distance between city pairs to derive the elements ($w_{i,j}$) in the spatial weight matrix W. Hence, the spillover effect in this study is due to the external relations of cities such as people, commodities, and knowledge flows, where there is a specific economic implication of the spillover progress which can alleviate the endogeneity of the spatial matrix to some extent.

4.2. Estimating the benchmark model

The main purpose of this study is to examine the influence of urban network externalities on regional economic growth. For this reason, the cross-sectional data of 273 municipal districts from 2016 is used to estimate the spatial econometric model.

Firstly, the spatial correlation of each variable is tested by Moran's I to judge its suitability for the spatial econometric specification. Table 3 presents the test results and descriptive statistics of each variable. The global Moran's I for each variable is positive at the corresponding significance level, indicating a significant positive spatial dependence. LeSage (2014) considers the SDM to be a better choice with global spatial effects, and the Bayesian Posterior Model Selection method to be more efficient than the likelihood ratio or Lagrange multiplier in

[4] We have considered other control variables, such as openness (with FDI as indicator) and infrastructure (with road area per capita as indicator). However, the estimates of these variables are not significant, which may be due to the inadequacy of the proxy indicators. Hence, we have removed these variables from the model and manuscript.

Table 3
Descriptive statistics and Moran's I test for each variable.

Variable	Obs	Mean	Std.Dev.	Min	Max	Moran's I
lnpergdp	273	10.954	0.587	8.327	12.993	0.104 (3.493)***
lnperinvest	273	10.804	0.677	8.437	12.194	0.065 (2.213)**
lnemployee	273	3.009	1.017	0.846	6.674	0.233 (7.656)***
lnperfisc	273	9.304	0.567	7.932	11.723	0.055 (1.892)*
diversity	273	7.937	1.437	3.935	11.321	0.225 (7.414)***
specialization	273	4.763	7.458	1.301	90.447	0.095 (3.701)***
incloseness	273	58.293	9.625	0.366	86.076	0.610 (19.997)***
outcloseness	273	36.785	3.549	27.255	46.024	0.751 (24.413)***

Notes: 1) Moran's I is a one-tailed test. Significance: 0.01 (***), 0.05(**), and 0.1 (*).
2) Z score of Moran's I is reported in parentheses following the corresponding statistic.

Table 4
Economic growth: estimates of urban network externalities.

Independent variables	OLS	SAR	SEM	SDM
	(1)	(2)	(3)	(4)
constant	5.042***	2.915***	4.920***	0.351
	(0.620)	(0.768)	(0.587)	(1.575)
lnperinvest	0.359***	0.422***	0.418***	0.470***
	(0.045)	(0.035)	(0.045)	(0.037)
lnemployee	0.134***	0.152***	0.142***	0.147***
	(0.033)	(0.023)	(0.031)	(0.024)
lnperfisc	0.224***	0.181***	0.184***	0.128***
	(0.054)	(0.037)	(0.050)	(0.041)
incloseness	0.011	0.011**	0.012*	0.011**
	(0.006)	(0.004)	(0.005)	(0.004)
outcloseness	−0.030	−0.040**	−0.036*	−0.034**
	(0.016)	(0.011)	(0.014)	(0.011)
*W*lnperinvest*				−0.149*
				(0.072)
*W*lnemployee*				0.052
				(0.050)
*W*lnperfisc*				0.118
				(0.086)
*W*incloseness*				−0.088**
				(0.033)
*W*outcloseness*				0.210**
				(0.087)
ρ		0.195**		0.207*
		(0.070)		(0.097)
lambda			0.294***	
			(0.117)	

Notes: 1) Significance: 0.001 (***), 0.01 (**), and 0.05 (*).
2) Standard errors of parameter estimates are reported in parentheses.

distinguishing the model specification. Referring to LeSage's approach, this study estimates the spatial autoregressive model (SAR), spatial error model (SEM), and SDM to analyze the impact of urban network externalities on economic growth, and then compares the models using Bayesian Posterior Model Selection approach. The estimate of the benchmark model is shown in Table 4 with the Bayesian Monte Carlo estimation procedure.

Column (1) in Table 4 presents the OLS estimation results followed by the results of SAR, SEM, and SDM, respectively. The posterior probability of the three spatial models is 0.0009, 0.00, and 0.9991, respectively. Therefore, it is reasonable to select the SDM as the basis for the conclusion. The direct and indirect averaged impact of SDM is provided in Table 5. Based on the estimates, we can conclude the following:

Table 5
Averaged impact of benchmark SDM.

	lnperinvest	*lnemployee*	*lnperfisc*	*incloseness*	*outcloseness*
Direct effect	0.470***	0.149***	0.132**	0.009*	−0.03*
	(12.868)	(6.264)	(3.254)	(2.179)	−(2.465)
Indirect effect	−0.057	0.106	0.183	−0.108*	0.255*
	−(0.554)	(1.519)	(1.652)	−(2.497)	(2.243)
Total effect	0.413***	0.255***	0.315**	−0.098*	0.225
	(4.011)	(3.607)	(2.811)	−(2.198)	(1.925)

Notes: 1) Significance: 0.001 (***), 0.01 (**), and 0.05 (*).
2) T-statistics are reported in parentheses.

1) There are significant urban network externalities among the municipal districts in China, which can significantly promote urban economic growth. The spatial lag coefficient ρ of the dependent variable is 0.207 at a 5% significance level, revealing that the economic growth of the linked cities will promote the city's economic development significantly. This is exactly the effect of urban network externalities; the SAR estimates also support this conclusion. Based on the SEM, the spatial error coefficient λ is significantly positive (0.294) at the 0.1% confidence level, indicating that the economic growth of each city is affected by some omitted variables of other cities in the urban network. Therefore, there is a significant spatial dependence in the urban network.
2) There is significant heterogeneity in the urban network externalities of different cities. Cities with higher in-closeness tend to achieve higher economic growth but, at the same time, the ones linked closely to them may be negatively influenced. Among the SAR, SEM, and SDM estimates, the coefficient and the average direct effects of *incloseness* are both positive and statistically significant at 5% levels, while those of *outcloseness* are both significantly negative at 5%, revealing that the economic performance of the cities will be negatively affected by high out-closeness. Cities with high out-closeness usually are the factor outflow regions in the network such that the economic growth tends to be lower, and the case of in-closeness is reverse. In the SDM estimate, the spatial lag coefficient (−0.088) and indirect effect (−0.108) of *incloseness* is significantly negative while the *outcloseness* (the coefficient and indirect effects are 0.210 and 0.255, respectively) is significantly positive, which is exactly opposite of each other. The results show that the cities are positively impacted by linked cities with high out-closeness and negatively impacted by those with high in-closeness in the network. This is consistent with the flow direction of economic factors in the urban network. Cities with high in-closeness will have higher economic development as the gathering place of various factors, but the growth of connected cities may be suppressed by the "agglomeration shadow" effects. It seems that the result is in conflict with the estimate of spatial lag coefficient ρ. It is because the former represents the strength of one city's linkage in the network, which may exert negative effect on the connected cities, while the latter stresses the spillover effect of the connection in the whole network.
3) Factor inputs, such as capital and labor, are still the primary driving force for urban economic growth. Among the OLS, SAR, SEM, and SDM estimates, the elastic coefficients of the fixed asset investment, employees, and per capita fiscal expenditure are always significantly positive at the 0.1% confidence level, and their degree of interpreting the dependent variable is also higher than others. Therefore, regional growth mainly depends on the local capital, labor, and other factor inputs. We notice that the coefficient of the spatial lag of *lnperinves* is negative (−0.149) at the 5% significance level while its indirect effect is not significant (0.183), revealing that there is no apparent spillover effect of fixed asset investment.

4.3. Urban network externalities and agglomeration economies

Based on the basic model, we further add the diversity and specialization variables, which indicate the agglomeration economies, to compare the effect of urban network externalities and agglomeration economies. The estimation results are shown in Table 6.

Table 6
Economic growth: estimates of urban network externalities and agglomeration economies.

Independent variables	OLS	SAR	SEM	SDM
	(1)	(2)	(3)	(4)
Constant	5.184***	2.938***	5.094***	0.929
	(0.632)	(0.794)	(0.604)	(1.614)
lnperinvest	0.339***	0.399***	0.398***	0.440***
	(0.047)	(0.037)	(0.046)	(0.038)
lnemployee	0.098**	0.122***	0.114**	0.123***
	(0.038)	(0.026)	(0.035)	(0.026)
lnperfisc	0.214***	0.166***	0.175***	0.117**
	(0.055)	(0.037)	(0.049)	(0.041)
incloseness	0.011	0.011*	0.012*	0.011**
	(0.006)	(0.004)	(0.006)	(0.004)
outcloseness	−0.033*	−0.043**	−0.039*	−0.036**
	(0.016)	(0.011)	(0.015)	(0.012)
diversity	0.049	0.046**	0.042**	0.038*
	(0.027)	(0.019)	(0.024)	(0.019)
specialization	−0.000	0.001	0.000	−0.000
	(0.004)	(0.003)	(0.003)	(0.002)
*W*lnperinvest*				−0.173*
				(0.074)
*W*lnemployee*				0.005
				(0.062)
*W*lnperfisc*				0.126
				(0.086)
*W*incloseness*				−0.078**
				(0.034)
*W*outcloseness*				0.184*
				(0.089)
*W*diversity*				0.034
				(0.047)
*W*specialization*				−0.010
				(0.009)
ρ		0.211**		0.228**
		(0.071)		(0.098)
lambda			0.293**	
			(0.115)	

Notes: 1) Significance: 0.001 (***), 0.01 (**), and 0.05 (*).
2) Standard errors of parameter estimates are reported in parentheses.

The posterior probabilities of SAR, SEM, and SDM are 0.2038, 0.00, and 0.7962, respectively, using the Bayesian Posterior Model Selection approach. Therefore, it is still reasonable to select SDM as the correct model specification. Table 7 provides the direct and indirect average impact of SDM. The SDM estimates in Table 6 are similar to those in Table 4, proving the reliability and robustness of the study's results to some extent. The coefficient of *diversity* is 0.038 and is significant at the 5% confidence level, while the *specialization* variable is not significant. Hence, the result supports Jacobs' externalities theory and is consistent with the results provided by Glaeser et al. (1992). The indicator of MAR externalities, the maximum value of location quotient in the city, may reduce the differences between cities, which may be one of the reasons why MAR externalities are not significant. For this reason, we choose another indicator of MAR externalities to examine the result and the estimates are consistent.[5] Beaudry and Schiffauerova (2009) reviewed the literature and found that the studies supporting Jacobs' externalities are mostly conducted at the regional level while the studies supporting MAR externalities are at the enterprise level. Therefore, it is believed that the research scale and the measurement approach of agglomeration will lead to differences in relevant research findings regarding MAR externalities and Jacobs' externalities.

Based on the SDM estimates, the indirect effects of *diversity* and *specialization* are not statistically significant, implying that there is no spillover effect of agglomeration economies; the effects are limited to within the region, which is consistent with the theoretical analysis described in Section 2. Compared to agglomeration economies, the urban network externalities effects have a larger spatial scope. To further examine this result, we add the interaction terms of *diversity/specialization* and *incloseness/outcloseness* in the SDM to explore the relationship between agglomeration economies and urban network externalities. The results are shown in Appendix C; the interaction terms are all not statistically significant, revealing the lack of interaction effects between them.

4.4. Robustness tests of the results

The empirical analysis in Sections 4.2 and 4.3 uses the composite matrix obtained by multiplying the corresponding elements of the train frequency matrix and the inverse distance matrix. To further demonstrate the conclusions of this study, we estimate the SDM based on the train frequency matrix or inverse distance matrix, as the spatial weight matrix. The former reveals the spatial effect across the urban network and the latter shows the spatial effect based on the geographic proximity. The corresponding estimates are shown in columns (1) and (2) of Table 8.

Column (1) of Table 8 shows that the coefficient ρ of spatial lag of the dependent variable is positive (0.365) at the 1% significance level, while the ρ in column (2) is not significant, indicating that the spillover effect of economic growth in this study is based on the urban network linkages rather than the geographic proximity. That is, it is the interactions among cities that promote the formation of urban network externalities. The estimated difference in the indirect effects of both *incloseness* and *outcloseness* between columns (1) and (2) in Table 8 also supports this conclusion. It is important to note that many previous studies provided evidence about spillover effects based on the geographic proximity while it was also concluded that the spatial effect would rapidly decay with distance (Baldwin et al., 2008; van Soest et al., 2006; Wenqing, 2013). The research sample of the study comprises municipal district units rather than whole prefecture-level cities across China, which differs from most of the previous studies. There are few direct borders among the units, which are also far apart from each other. This may be the reason why the spatial spillover effects of capital, labor, and agglomeration economies are not significant. Therefore, the contradiction between this study and the previous studies about the spillover effect of agglomeration economies can be explained. Besides, we notice that the coefficients of spatial lags of *diversity* and *specialization* are statistically significant in column (2), while the indirect effects are not significant (shown in Appendix D). Therefore, there is no spatial effect of agglomeration economies, consistent with the previous analysis.

Additionally, we check the robustness of these results in several ways. Firstly, above analyses are all based on the train frequencies between cities, however there are large distinctions in the speed of different types of trains, such as the high-speed rail (the train number begin with "G") is over three times faster than the local train (the train number begin with "K"). The ignorance of train type heterogeneity may influence the result to some extent although the strength of urban network linkage is our research priority. Therefore, we classify the train records into four types according to their average speed and assign them weights of 0.8:1:1.2:1.5 respectively. Then we reconstsruct the spatial weight matrix and estimate the model again as shown in column (3) of Table 8. We find that the result is robust, and the estimates of the main variables remain stable. Secondly, we re-estimate SDM using full lndet computation and spline lndet approximation, as shown in columns (4) and (5) of Table 8, respectively. The results are similar to those outlined in column (4) of Table 6, indicating that the model optimization method does not affect the main results of this study.

[5] We construct 3 new indicators of MAR externalities: 1) the sum of top five industries' location quotient in the city. 2) the total size of the city's top five industries' employment. 3) Herfindahl-Hirschman Index of the city's industries. The estimates are shown in Appendix B and are consistent with the SDM results in Table 6.

Table 7
The average impact of SDM with agglomeration economies.

	lnperinvest	*lnemployee*	*lnperfisc*	*incloseness*	*outcloseness*	*diversity*	*specialization*
Direct effect	0.439***	0.124***	0.121**	0.009*	−0.031*	0.039*	−0.0003
	(11.504)	(4.822)	(2.989)	(2.025)	−(2.554)	(2.048)	−(0.121)
Indirect effect	−0.087	0.045	0.199	−0.098*	0.226	0.056	−0.013
	−(0.839)	(0.549)	(1.718)	−(2.175)	(1.906)	(0.892)	−(1.056)
Total effect	0.352***	0.169*	0.320**	−0.089	0.194	0.095	−0.013
	(3.327)	(1.975)	(2.698)	−(1.906)	(1.591)	(1.384)	−(1.027)

Notes: 1) Significance: 0.001 (***), 0.01 (**), and 0.05 (*).
2) T-statistics are reported in parentheses.

Table 8
Estimates of robustness tests.

Independent variables	Based on train frequency matrix	Based on inverse distance matrix	Based on the speed-weighted matrix	Full lndet computation	Spline approximation	Average wage as dependent variable
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−3.284	3.489	0.854	0.602	0.548	3.638***
	(2.723)	(5.832)	(1.623)	(1.624)	(1.565)	(1.100)
lnperinvest	0.442***	0.455***	0.44***	0.440***	0.441***	−0.005
	(0.038)	(0.038)	(0.039)	(0.039)	(0.038)	(0.017)
lnemployee	0.138***	0.108***	0.123***	0.122***	0.123***	0.024*
	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)	(0.012)
lnperfisc	0.125***	0.130***	0.119***	0.117**	0.117**	0.063**
	(0.039)	(0.039)	(0.04)	(0.041)	(0.040)	(0.022)
incloseness	0.009*	0.010**	0.011**	0.010**	0.011*	0.003*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
outcloseness	−0.034**	−0.033**	−0.036**	−0.036**	−0.036**	−0.0003
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.006)
diversity	0.041*	0.038*	0.039*	0.038*	0.037*	0.024**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.009)
specialization	−0.0004	−0.0006	0	0.000	−0.000	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
*W*lnperinvest*	−0.168	−0.622*	−0.163*	−0.183**	−0.188**	0.065*
	(0.108)	(0.309)	(0.076)	(0.075)	(0.075)	(0.033)
*W*lnemployee*	0.064	−0.094	0.002	−0.006	−0.0002	0.023
	(0.101)	(0.303)	(0.062)	(0.063)	(0.064)	(0.030)
*W*lnperfisc*	0.088	0.638	0.116	0.118	0.117	0.000
	(0.136)	(0.412)	(0.087)	(0.088)	(0.088)	(0.041)
*W*incloseness*	−0.167**	−0.037	−0.079*	−0.079*	−0.080**	−0.014
	(0.057)	(0.078)	(0.034)	(0.034)	(0.033)	(0.015)
*W*outcloseness*	0.412*	−0.039	0.185*	0.186*	0.189*	0.023
	(0.159)	(0.207)	(0.091)	(0.090)	(0.088)	(0.041)
*W*diversity*	−0.0303	0.424*	0.037	0.036	0.033	−0.048*
	(0.076)	(0.234)	(0.048)	(0.047)	(0.049)	(0.023)
*W*specialization*	−0.005	−0.049*	−0.008	−0.010	−0.010	0.002
	(0.011)	(0.028)	(0.009)	(0.009)	(0.009)	(0.003)
ρ	0.365**	0.262	0.225*	0.268***	0.272**	0.546***
	(0.155)	(0.372)	(0.098)	(0.106)	(0.106)	(0.091)

Notes: 1) Significance: 0.001 (***), 0.01 (**), and 0.05 (*).
2) Standard errors of parameter estimates are reported in parentheses.

Thirdly, referring to the method of Glaeser et al. (1992), we replace the dependent variable with the average wage of employees as the measurement of economic development. The result is presented in column (6) of Table 8. Compared to the result in column (4) of Table 6, the coefficient of fixed asset investment and the spatial lags of in-closeness and out-closeness are not significant, and the spatial lag of diversity is negative while the spatial lag of the dependent variable remains positive at the 5% significance level. Therefore, there exist positive urban network externalities on economic growth, ensuring the robustness of our conclusions.

4.5. Further discussion and policy implications

This study aims to determine whether the urban network externalities affect urban growth and what are the relationships and differences between agglomeration economies and network externalities. The results show that the urban network externalities can promote urban growth significantly and the structural position of cities within the urban network could affect their performance. Moreover, the urban network externalities break through the geographical proximity limitation and can generate cross-spatial spillover effects, which is the primary distinction to agglomeration economies.

Based on the results, we find that the urban network is an effective policy instrument for regional economic growth. There is a significant global spillover effect through urban network linkages, and it is consistent with the development of Chinese regional policy. The Chinese government used to stress on the role of varieties of industrial parks in regional growth, which mainly promote the effect of agglomeration economies, while the development of urban agglomerations, such as the Yangtze River Delta and Guangdong-Hong Kong-Macao Greater Bay Area, have become the priority in recent years. The economic integration and rapid growth in these two regions demonstrate the effect of urban network externalities. Though agglomeration shadow effects may exist around mega-cities and the economic factors might flow from less developed to developed areas, the key point is that all cities could embed in a much larger and specialized division of labor through urban networks, and thereby compete both nationally and globally as a dynamic system. Although the urban network in this study is constructed based on the transportation linkage, we believe that the theoretical analysis and the main mechanisms would hold in other cases. Moreover, we conclude that the global economic growth could benefit from urban networks, but the effect on regional disparity remains to be explored.

Another important aspect of urban network externality is that it provides evidence and support for the rise of mega-regions (Florida et al., 2008; Lin, 2013; Taubenböck et al., 2014). With the development of globalization and regional integration, political borders no longer define economies. Instead, the mega-region has become the new “natural” economic unit worldwide where the firms and agents compete, representatively the Greater Tokyo, Boston-New York-Washington corridor, and Chicago-Pittsburgh mega-region. On a far larger spatial scale, the urban network could better promote the mega-region to perform functions that the great cities did in the past—massing together innovation, production, and consumer markets. Besides, mega-regions are more than just a bigger version of the city or metropolitan region, they are a new “emergent” economic unit with characteristics that are quite different from those of cities (Florida et al., 2008). The previous notions and approaches of spatial planning might not be able to meet the demand of the new stage. The rise of mega-regions presents both challenges and chances for strategic spatial planning. How to maintain the economic competitiveness and regional coordination on a larger spatial extent is the primary question for future spatial planning. Meanwhile, urban planning should also consider the change and focus more on the connection and structure position in the urban network. The city could develop more through the full embeddedness in the national even global markets and supply chains.

Besides, the urban network externalities provide a new implication for the economic development of the developing countries. We usually regard cities as the central engines of economic growth and development (Jacobs, 1969, 1984). Hence, countries tended to give priority to developing large cities during the urbanization process in the past. However, many problems stemming from mega-cities in terms of congestion, poverty, and diseases limit the further development of the cities, especially in the developing countries (Daniels, 2004; Van der Ploeg and Poelhekke, 2008). The attraction for transnational enterprises and competitiveness of a single city are both declining nowadays. Accordingly, the development of the city depends more on the region it belongs to. There is a debate about whether the urban network or larger mega-cities would increase the national economic growth (Glaeser et al., 2016). Camagni et al. (2016) argued that in recent years the further urbanization of large mega-cities is not the key to economic growth while the factors such as the external linkages and co-operation networks are. Additionally, many developing countries, such as South Africa and Kenya, are undergoing rapid development through the construction of their respective transportation networks, which is similar to the case of China. Therefore, developing countries could focus more on the connecting all the cities rather than relying only on large cities. The city-region could be the new engine of economic development in developing countries.

5. Conclusions and future directions

As an important policy tool and development direction of China's regional and urban spatial planning, urban networks have become increasingly prominent in their theoretical significance and practical value. Based on the externality theory perspective, this study demonstrates the mechanism of urban network externalities on urban economic growth, and the relationship with agglomeration economies. Moreover, we empirically examine the impact of urban network externalities and agglomeration economies on regional growth using a spatial econometric model based on the urban network identified by the train frequency data across 273 municipal districts in China. The conclusions of this study are as follows:

(1) There are significant urban network externalities between the municipal districts in China, which can promote urban economic growth significantly. The urban network identified in this study mainly represents the inter-cities transportation network linkage. Its externality effect can accelerate the economic growth of the city by reducing the transaction cost and expanding the spatial scope of the flows and knowledge spillovers of economic factors. This has also been examined empirically. The estimated coefficient of the spatial lag of the dependent variable is positive at least at the 5% confidence level, which indicates a positive externality impact in the urban network.
(2) There is significant heterogeneity in the urban network externalities across different cities. Borrowing size and agglomeration shadows are the main sources of urban network externalities. A city's impact from urban networks externalities differs according to its development stage and position in the network. Districts with high in-closeness centrality tend to achieve higher economic growth benefiting from the central position in the network. However, they may depress the performance of linked cities.
(3) Jacobs' externalities are the primary source of the agglomeration economies at the municipal districts and mainly take effects within the city. The discussion about whether Marshall externalities or Jacobs' externalities best promote growth has not yet reached a consistent conclusion. The results of this study support the view that Jacobs' externalities are the primary source of the agglomeration economies at the municipal districts and that the impact of MAR externalities is not significant. Moreover, there is no spillover effect of agglomeration economies at the municipal district level.
(4) Compared to agglomeration economies, the urban network externalities break through the geographical proximity limitation and can generate cross-spatial spillover effects. Indeed, unlike agglomeration economies, there is a significant spillover effect of network externalities. This implies that the urban network externalities can take effects on a larger spatial scale. Moreover, based on the estimates using different spatial weight matrices, we can conclude that the urban network externalities are not based on geographical proximity, but on network linkages; as such, they can generate a cross-spatial spillover effect.

This study empirically examines the impact of urban network externalities on economic growth through spatial econometric models. Although the empirical analysis is based on a Chinese sample, the theoretical analysis and the main conclusion of this research are general and applicable worldwide. The rise of urban networks and mega-regions has become an important phenomenon both in developed and developing countries, and they are confronted with the similar development opportunity and challenge as in China. Thus, the research based on the Chinese case is also implicational for the development of other countries. Additionally, the analysis has some shortcomings. First, due to the difficulty in accessing historical train frequency data and the complication of estimating spatial dynamic panel data models with a time-varying matrix, the study constructed a cross-sectional spatial econometric model, as a result of which the conclusions of this study may not be applicable to a larger sample size and sample period. With the development of spatial econometrics, spatial dynamic models with a time-varying matrix could be constructed. Second, the spatial weight matrix in the empirical model is constructed by multiplying the train frequency and inverse distance between cities to reduce endogeneity. However, we should emphasize that there still exists an endogeneity concern based on the composite spatial weight matrix. The causal relationship between transportation infrastructure and economic growth needs to be further explored. Third, although traffic flow data is one of the most intuitive and representative ways to portray urban networks, it can only reflect one dimension of the same. The integration of multi-source data, such as population migration, communication, and capital flow, to identify a more comprehensive network may be helpful to conduct a more systematic and in-depth research of urban network externalities.

CRediT authorship contribution statement

Yin Huang: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Tao Hong:** Conceptualization, Data curation, Investigation, Methodology, Supervision, Validation, Writing - original draft, Writing - review & editing. **Tao Ma:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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Appendix A. Image matrix of China's urban network

	1	2	3	4	5	6	7	8
1	1	1	0	1	0	0	0	0
2	1	1	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0
4	1	0	0	1	0	0	1	0
5	0	0	0	0	1	1	0	0
6	0	0	0	0	1	1	0	0
7	0	0	0	1	0	0	1	0
8	0	0	0	0	0	0	0	1

Appendix B. Estimates with different indicators of MAR externalities

MAR externalities indicator	Sum of top five industries' LQ	Total size of city's top five industries' employment	Herfindahl-Hirschman Index
	(1)	(2)	(3)
Constant	1.031	0.319	0.573
	(1.674)	(1.629)	(1.609)
lnperinvest	0.437***	0.44***	0.444***
	(0.038)	(0.041)	(0.038)
lnemployee	0.12***	0.128***	0.114***
	(0.027)	(0.032)	(0.027)
lnperfisc	0.124***	0.12**	0.116**
	(0.041)	(0.044)	(0.041)
incloseness	0.011*	0.011*	0.011**
	(0.004)	(0.004)	(0.004)
outcloseness	−0.036**	−0.038**	−0.036**
	(0.012)	(0.012)	(0.012)
diversity	0.037*	0.039*	0.043*
	(0.019)	(0.019)	(0.019)
specialization	−0.002	0	0.228
	(0.002)	(0)	(0.234)
*W*lnperinvest*	−0.193**	−0.165*	−0.155*
	(0.079)	(0.071)	(0.076)
*W*lnemployee*	−0.009	0.065	−0.009
	(0.065)	(0.073)	(0.069)
*W*lnperfisc*	0.135	0.169*	0.102
	(0.087)	(0.095)	(0.091)
*W*incloseness*	−0.081*	−0.075*	−0.08**
	(0.034)	(0.034)	(0.034)
*W*outcloseness*	0.193*	0.182*	0.196*
	(0.092)	(0.09)	(0.09)
*W*diversity*	0.038	0.027	0.04
	(0.049)	(0.048)	(0.052)
*W*specialization*	−0.009	0	0.219
	(0.007)	(0)	(0.468)
ρ	0.222**	0.211*	0.215*
	(0.097)	(0.1)	(0.096)

Notes: 1) Significance: 0.001 (***), 0.01 (**), and 0.05 (*).
2) Standard errors of parameter estimates are reported in parentheses.

Appendix C. Estimates with interaction terms of *diversity/specialization* and centrality

Independent variables	(1)	(2)	(3)	(4)	(5)
Constant	0.849	0.924	1.164	1.587	5.969
	(1.646)	(1.758)	(2.577)	(3.303)	(9.255)
lnperinvest	0.442***	0.44***	0.436***	0.437***	0.443***
	(0.038)	(0.041)	(0.04)	(0.037)	(0.039)
lnemployee	0.123***	0.124***	0.128***	0.129***	0.135***
	(0.025)	(0.025)	(0.027)	(0.027)	(0.029)
lnperfisc	0.114***	0.116**	0.125**	0.123**	0.112**
	(0.04)	(0.04)	(0.043)	(0.042)	(0.041)
diversity	0.037*	0.037*	0.093	0.138	0.53
	(0.019)	(0.019)	(0.08)	(0.13)	(0.401)
speciality	0.012	0.018	−0.0003	−0.0001	0.028
	(0.025)	(0.038)	(0.002)	(0.002)	(0.101)
incloseness	0.012**	0.011**	0.018*	0.011**	−0.052
	(0.004)	(0.004)	(0.011)	(0.004)	(0.075)
outcloseness	−0.036**	−0.034**	−0.034**	−0.012	0.167
	(0.012)	(0.012)	(0.012)	(0.03)	(0.199)
*speciality*incloseness*	−0.0002				−0.0003
	(0.0005)				(0.0032)
*speciality*outcloseness*		−0.0005			−0.0003
		(0.0011)			(0.008)
*diversity*incloseness*			−0.001		0.009
			(0.0013)		(0.01)
*diversity*outcloseness*				−0.0028	−0.027
				(0.0035)	(0.026)
*W*lnperinvest*	−0.165*	−0.17*	−0.16*	−0.157*	−0.162*
	(0.075)	(0.08)	(0.079)	(0.074)	(0.08)
*W*lnemployee*	0.002	−0.002	−0.006	−0.004	−0.027
	(0.062)	(0.063)	(0.064)	(0.062)	(0.067)
*W*lnperfisc*	0.138	0.136	0.12	0.116	0.177*
	(0.091)	(0.09)	(0.09)	(0.089)	(0.098)
*W*diversity*	0.034	0.039	−0.082	−0.177	−1.441
	(0.048)	(0.048)	(0.233)	(0.365)	(1.065)
*W*speciality*	−0.052	−0.071	−0.009	−0.009	0.63
	(0.097)	(0.154)	(0.01)	(0.009)	(0.564)
*W*incloseness*	−0.08*	−0.077*	−0.1*	−0.086**	0.075
	(0.034)	(0.036)	(0.05)	(0.035)	(0.231)
*W*outcloseness*	0.181*	0.176*	0.196**	0.155	−0.312
	(0.092)	(0.099)	(0.09)	(0.107)	(0.598)
*W*speciality*incloseness*	0.001				0.025
	(0.002)				(0.018)
*W*speciality*outcloseness*		0.002			−0.057
		(0.004)			(0.044)
*W*diversity*incloseness*			0.002		−0.029
			(0.004)		(0.026)
*W*diversity*outcloseness*				0.006	0.086
				(0.01)	(0.069)
ρ	0.226*	0.228**	0.225*	0.222**	0.223*
	(0.096)	(0.099)	(0.1)	(0.1)	(0.097)

Notes: 1) Significance: 0.001 (***); 0.01 (**); 0.05 (*).
2) Standard errors of parameter estimates are reported in parentheses.

Appendix D. Average impact of robustness tests

		lnperinvest	*lnemployee*	*lnperfisc*	*incloseness*	*outcloseness*	*diversity*	*specialization*
Based on train frequency matrix	Direct effect	0.443***	0.140***	0.127 **	0.007	−0.029*	0.041*	0.000
		(11.751)	(5.399)	(3.211)	(1.550)	(−2.390)	(2.131)	(−0.177)
	Indirect effect	0.021	0.200	0.234	−0.274*	0.667	−0.020	−0.009
		(0.089)	(0.964)	(0.871)	(−2.066)	(1.924)	(−0.140)	(−0.410)
	Total effect	0.464	0.340	0.360	−0.267*	0.638	0.022	−0.009
		(1.926)	(1.611)	(1.320)	(−1.984)	(1.819)	(0.148)	(−0.420)
Based on inverse distance matrix	Direct effect	0.454***	0.108***	0.134***	0.010*	−0.033**	0.041*	−0.001
		(11.933)	(4.116)	(3.373)	(2.396)	(−2.799)	(1.990)	(−0.352)
	Indirect effect	−0.793	−0.097	1.463	−0.068	−0.122	0.971	−0.104
		(−0.769)	(−0.100)	(0.636)	(−0.260)	(−0.174)	(0.578)	(−0.652)
	Total effect	−0.340	0.011	1.597	−0.058	−0.155	1.012	−0.105
		(−0.329)	(0.011)	(0.692)	(−0.220)	(−0.220)	(0.599)	(−0.654)

Based on the speed-weighted matrix	Direct effect	0.439***	0.124***	0.123**	0.009*	−0.031*	0.04*	0
		(11.412)	(4.857)	(3.115)	(1.965)	(−2.534)	(2.087)	(−0.083)
	Indirect effect	−0.075	0.04	0.185	−0.098*	0.227	0.06	−0.011
		(−0.722)	(0.484)	(1.641)	(−2.142)	(1.881)	(0.938)	(−0.914)
	Total effect	0.364***	0.164	0.307**	−0.089	0.196	0.1	−0.011
		(3.441)	(1.887)	(2.725)	(−1.884)	(1.576)	(1.418)	(−0.885)
Full lndet computation	Direct effect	0.439***	0.123 ***	0.122**	0.009*	−0.030*	0.040*	0.000
		(11.442)	(4.704)	(2.984)	(1.944)	(−2.497)	(2.081)	(−0.085)
	Indirect effect	−0.079	0.038	0.206	−0.104*	0.240	0.064	−0.013
		(−0.705)	(0.433)	(1.662)	(−2.154)	(1.894)	(0.931)	(−1.056)
	Total effect	0.360**	0.161	0.328**	−0.095	0.209	0.104	−0.014
		(3.137)	(1.729)	(2.564)	(−1.903)	(1.600)	(1.381)	(−1.012)
Spline approximation	Direct effect	0.440***	0.124***	0.122**	0.008	−0.030*	0.039*	0.000
		(11.481)	(4.875)	(3.089)	(1.866)	(−2.382)	(1.964)	(−0.093)
	Indirect effect	−0.078	0.045	0.206	−0.107*	0.247	0.061	−0.013
		(−0.687)	(0.500)	(1.649)	(−2.189)	(1.951)	(0.859)	(−1.052)
	Total effect	0.362**	0.169	0.328*	−0.098	0.217	0.100	−0.014
		(3.099)	(1.758)	(2.577)	(−1.947)	(1.656)	(1.277)	(−1.013)
Average wage as dependent variable	Direct effect	0.000	0.026*	0.065**	0.002	0.001	0.022**	−0.002
		(−0.009)	(2.072)	(2.983)	(0.870)	(0.206)	(2.349)	(−1.533)
	Indirect effect	0.139	0.082	0.079	−0.028	0.050	−0.076	0.002
		(1.822)	(1.146)	(0.869)	(−0.775)	(0.534)	(−1.400)	(0.258)
	Total effect	0.138	0.108	0.144	−0.026	0.052	−0.054	0.000
		(1.792)	(1.429)	(1.501)	(−0.687)	(0.530)	(−0.926)	(−0.038)

Notes: 1) Significance: 0.001 (***); 0.01 (**); 0.05 (*).
2) T-statistics are reported in parentheses.

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