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Spatial Spillover Effect and Influencing Factors of Information Flow in Urban Agglomerations—Case Study of China Based on Baidu Search Index

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Abstract: Cities in an urban agglomeration closely interact with each other through various flows. Information flow, as one of the important forms of urban interactions, is now increasingly indispensable with the fast development of informatics technology. Thanks to its timely, convenient, and spatially unconstrained transmission ability, information flow has obvious spillover effects, which may strengthen urban interaction and further promote urban coordinated development. Therefore, it is crucial to quantify the spatial spillover effect and influencing factors of information flows, especially at the urban agglomeration scale. However, the academic research on this topic is insufficient. We, therefore, developed a spatial interaction model of information flow (SIM-IF) based on the Baidu Search Index and used it to analyze the spillover effects and influencing factors of information flow in the three major urban agglomerations in China, namely Beijing–Tianjin–Hebei (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD) in the period of 2014–2019. The results showed that the SIM-IF performed well in all three agglomerations. Quantitative analysis indicated that the BTH had the strongest spillover effect of information flow, followed by the YRD and the PRD. It was also found that the hierarchy of cities had the greatest impact on the spillover effects of information flow. This study may provide scientific basis for the information flow construction in urban agglomerations and benefit the coordinated development of cities.

Keywords: information flow; Baidu Index; spillover effect; China urban agglomerations; spatial econometric interaction model



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1. Introduction

Cities are in close contact with the outside through various flows, such as information, human migration, logistics, and capital flows [1]. Traditional urban interaction is dominated by tangible elements such as human migration and logistics, while information is comparatively less important. With the rapid development of information and communication technologies, society has marched into the information age. Information flow, due to its timely, convenient, and spatially unconstrained transmission, not only makes spatio-temporal interaction more flexible, frequent, and close [2], but also plays an important role in facilitating the generation and movement of other types of flow, such as innovation, industry, economy, and talents [3]. Through such close interaction, cities will gather together and become an indivisible and efficiently functioning spatial unit. Thus, information flow becomes increasingly important in urban interaction and regional integration promotion [4]. Undoubtedly, studying urban information flows is the foundation for analyzing complex city interaction patterns and also the key to the comprehensive understanding of the urban spatial structures.

Researchers have carefully studied the spatial patterns of information flows [5–7]. However, the mechanism of an information flow's formation have not been explored. As a matter of fact, since cities are communicating with each other, information flows are consequently in an interactive state as well, so that the formation of flow in a certain region is not only impacted by its internal factors, but also factors from its surrounding regions. Hence, it is necessary to analyze this spillover effect of information flows. Studies have already proved that elements such as economy, technology, and knowledge display strong spillover effects, which can significantly promote coordinated development in a region [8–10]. Compared to other elements, information has greater spreading and diffusion ability, which gives more reasons why its spillover effects and impacts cannot be ignored [11].

Moreover, China has been making great efforts to promote urbanization and regional integration. Building coordinated urban agglomerations and developing sustainably is now the new demand. Therefore, to study information spillover effects at an urban agglomeration scale, which is the most important basis for achieving these goals, deserves remarkable attention.

To sum up, the aim of this study was to research on the spillover effects and influencing factors of urban information flow in urban agglomerations, so as to provide a theoretical basis for sustainable urban growth.

The structure of this paper is organized as follows. Section 2 summarizes the related literature. Section 3 describes the methodology. Section 4 introduces the study area and data source. Section 5 analyzes the empirical results to reveal the spillover effects and influencing factors of information flows. Section 6 provides the discussion including policy implications. Section 7 sets out the conclusions.

2. Literature Review

Existing studies on urban information flows have mainly focused on depicting the structural characteristics of urban information networks, which help to analyze hierarchical structures of urban systems. The information network can be formed by different carriers, such as mail records [12], fixed-line telephone call durations [13], Weibo followers [14], Douban events [15], the Baidu Search Index [5,7,16], and so on. It can be found from these studies that the urban structural characteristics vary with different information flow carriers. Comparably, the Baidu Search Index is easier to access, meanwhile it has long time-series data and unified standards [17]. Therefore, it has greater potential of application in scientific researches. Moreover, these studies have suggested that the structures of information networks and cities are correlated at a certain level, although they are not completely the same. The above studies can help us better understand urban information flows and attach greater importance to information construction and development. However, spillover effects and influencing factors of urban information flow have not been studied.

The key to analyzing the spillover effects of information flows is finding an appropriate quantification method. Scholars have proposed various methods based on their different perceptions of spillover. Capello [18] and Yan and An [19] considered spillover as the extent to which the development of a region is influenced by other regions and constructed a spillover index to measure development intensity of spillover effects, based on the correlation between the development situations of regions. Carlino and Defina [20] and Gabauer and Gupta [21] interpreted spillover as a region's response to the change from another region. They first used the vector autoregressive model to simulate the urban development situation, and then analyzed the spillover effect through the generalized impulse response method. Although the above two methods are easy to implement, they ignore the spatial effects of spillover. Anselin [22] took spatial dependence and heterogeneity into account from the perspective of spillover externalities and put forward the spatial econometric model to analyze spillover effects. This model measures the spillover effects by calculating the partial regression coefficient, i.e., the partial derivative of the response variable on the explanatory variable. This coefficient is then decomposed

into direct and indirect effects, the latter of which is used to reflect the spillover effects. This spatial econometric model can not only quantify the spillover of flows, but also explore the potential factors affecting the flows to some extent, which may lead to further understandings of its nature. Therefore, this method has been widely used in studies of spillover effects. However, this model ignores the fact that flows are influenced by both their origin and destination characteristics at the same time, which is instead considered in the gravity model. Nevertheless, the gravity model assumes that all flows are mutually independent [23,24], which is, however, not applicable to the information flow with strong spatial dependence. To solve this problem, Lesage, the spatial econometrician, integrated the above two models and proposed the spatial econometric interaction model as a new method for analyzing the spillover effects of flows [25]. This model has already been applied to spillover effects of regional migration [26,27] and logistics flows [28] with reasonable results, but whether it is suitable for information flows has not yet been proved. Different from migration and logistics flows, the movement of information flows are not constrained by geographic space. Further research is thus needed to analyze the spillover effects of information flows using the spatial econometric interaction model.

The spillover effects show significant differences on different scales, such as at the prefectural level, provincial level, or urban agglomeration level [29–31]. Urban agglomeration is a highly developed spatial form of integrated cities and is one of the most important carriers for global economic development [32–34]. China has taken the urban agglomerations as the main body to build an urban pattern with the coordinated development of large and medium-sized cities and small towns in recent years. The Beijing–Tianjin–Hebei urban agglomeration (BTH), Yangtze River Delta urban agglomeration (YRD), and Pearl River Delta urban agglomeration (PRD) are the most developed urban agglomerations in China, which contribute up to 40% of the Chinese GDP. They have aggregated innovation factors, large population density, strong industrial competitiveness, and high economic efficiency. They are bearing the responsibility of building world-class urban agglomerations, as well as leading high-level urban agglomeration construction in China. These three are highly representative among all the urban agglomerations in China. Thereby, we conducted our study at the urban agglomeration scale and selected these three major urban agglomerations as our study area to study spillover effects of information flows and their causes.

The above-mentioned studies have not yet paid much attention to the information flows, let alone to exploring the mechanisms of their formation or to finding an appropriate method to quantify the effect from the spillover and influencing factors. To fill this gap in knowledge, this study contributes to the literature by proposing a new framework for studying the spillover effects and influencing factors of information flows. Using the Baidu Search Index to characterize information flow intensity among cities, we developed a spatial econometric interaction model and applied it to the three major urban agglomerations in China. This study has important implications on the coordinated and sustainable development of information flows in urban agglomerations.

3. Methodology

The spatial econometric interaction model, compared with the traditional spatial econometric model, is more suitable for analyzing the spillover effects of flows, since it considers the characteristics that flows are influenced by both their origins and the destinations. However, this model has not yet been applied to the study of information flows. Therefore, this study aimed to construct the spatial econometric interaction model of information flows (SIM-IF), and, based on this, analyze the spillover effect of information flows and its influencing factors. The method consisted of four main steps: (1) determining the spatial dependence mode of information flows, (2) testing spatial autocorrelation, (3) constructing the SIM-IF, and (4) analyzing spillover effects and influencing factors of information flow. The details are described in the following sections.

3.1. Spatial Dependence of Information Flow Determination

According to Chun’s [35] definition, there are three different specifications regarding spatial dependence of flows (Figure 1), namely origin-based dependence, destination-based dependence, and origin-destination-based dependence. When the flow from origin A to destination Z increases, there is origin-based dependence if the flow from the neighboring origins (B, C) to destination Z also increases; there is destination-based dependence if the flow from origin A to the neighboring destinations (X, Y) also increases; and there is origin-destination-based dependence if both the above situations occur. The information flow is generally affected by both the places where the information is sent and received; thereby, we applied the origin–destination-based dependence [36] (denoted as W_w) in this study. Its expression is given in Equation (1):

$$W_w = W_o + W_d = W \oplus W \tag{1}$$

where W is the spatial weight matrix of the region and \oplus is the Kronecker sum, and W_o and W_d denote the origin-based dependence and destination-based dependence of information flows, respectively. Their expressions are given in Equations (2) and (3):

$$W_o = W \otimes I_n \tag{2}$$

$$W_d = I_n \otimes W \tag{3}$$

where I_n is the $n \times n$ identity matrix, with n being the number of cities within the urban agglomerations and \otimes being the Kronecker product.

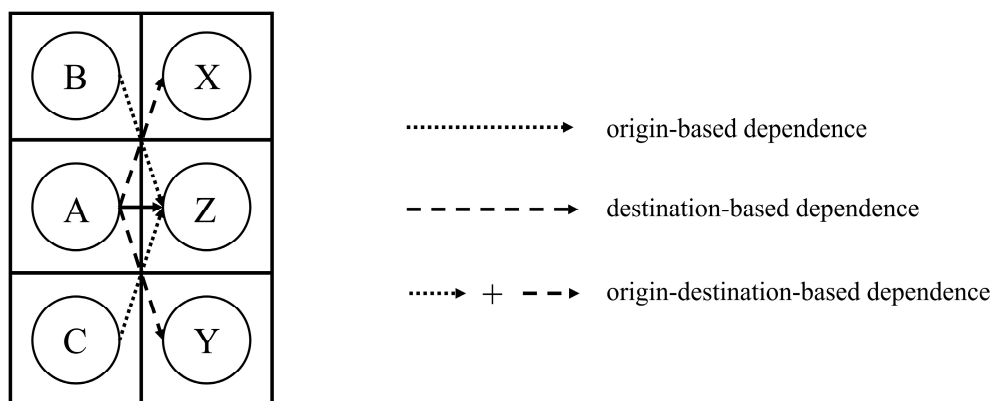


Figure 1. Spatial dependence of information flow.

In order to further quantify W_w , the spatial weight matrix W needed to be determined. However, whether information flow is constrained by the geographic space or not is still under debate. Some scholars have argued that information transmission is weakly restricted by geographic space and the spatial weight matrix for cyberspace needs to be considered [37]. In this study, we analyzed both types of spatial weight matrix. The geographic spatial weight matrix W^{geo} is constructed based on the geographic adjacency of two regions, with its element described in Equation (4), while the cyber spatial weight matrix W^{cyber} is constructed based on the hypothesis that regions with closer information amount interact more in the cyberspace [38], with its element described in Equation (6):

$$w_{ij}^{geo} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ is contiguous} \\ 0, & \text{else} \end{cases} \tag{4}$$

$$w_{ij}^{cyber} = \frac{\sum_{t=1}^T w_{ij,t}^{cyber}}{T} \tag{5}$$

$$w_{ij,t}^{cyber} = \begin{cases} 0, & i = j \\ 1/|F_{i,t} - F_{j,t}|, & i \neq j \end{cases} \quad (6)$$

where i and j represent different cities in the city agglomerations; $i, j = 1, 2, 3, \dots, n$; w_{ij}^{geo} and w_{ij}^{cyber} represent the impact of city i on city j in the geographic and cyber spatial weight matrix, respectively; $w_{ij,t}^{cyber}$ is the impact of city i on city j in year t in cyberspace; T is the period in our study; and $F_{i,t}$ and $F_{j,t}$ denote the total information amount in city i and city j in year t , respectively.

By applying the spatial weight matrices determined by Equations (4) and (5) to Equation (1), we could then obtain the spatial dependence expression under both circumstances, which is shown in Equation (7).

$$W_w = \begin{cases} W^{geo} \oplus W^{geo}, & \text{if geographic contiguous} \\ W^{cyber} \oplus W^{cyber}, & \text{if cyber contiguous} \end{cases} \quad (7)$$

3.2. Spatial Autocorrelation Tests

The Global Moran's I can measure spatial autocorrelation well and is easy to calculate. Therefore, we calculated the Global Moran's I [39] by Equation (8), with the spatial dependence determined by Equation (7), and further analyzed the spatial autocorrelation of information flows under different spatial dependence.

$$I = \frac{k}{\sum_{i,j=1}^n \sum_{u,v=1}^n W_{ij,uv}} \frac{\sum_{i,j=1}^n \sum_{u,v=1}^n W_{ij,uv} (x_{ij} - \bar{x})(x_{uv} - \bar{x})}{\sum_{i,j=1}^n (x_{ij} - \bar{x})^2} \quad (8)$$

$i \neq j, u \neq v$

where k denotes the number of information flows between cities ($k = n \times (n - 1)$); $W_{ij,uv}$ is the element in the matrix W_w and represents the impact of flow from city i to city j on flow from city u to city v under origin–destination-based dependence; x_{ij} and x_{uv} represent the amounts of these two flows reflected by the Baidu Search Index; and \bar{x} is the average amount of the information flows.

3.3. Construct Spatial Interaction Model for Information Flows (SIM-IF)

Since information flows are spatially autocorrelated, we used the extended panel data model [40] to construct the spatial econometric interaction model for information flows (SIM-IF) in this study, as shown in Equation (9):

$$Y_{o \rightarrow d,t} = \rho W_w Y_{o \rightarrow d,t} + \beta_o X_{ot} + \beta_d X_{dt} + \theta d_t + \varepsilon_{o \rightarrow d,t} \quad (9)$$

$\varepsilon_{o \rightarrow d,t} \sim N(0, \delta^2 I_k)$

where $Y_{o \rightarrow d,t}$ denotes the information flow from origin to destination in year t ; W_w denotes the spatial weight matrix of geographic or cyberspace under origin–destination-based dependence; ρ denotes the spatial dependence effect of information flows, i.e., the spillover effect on certain information flows from their neighboring information flows; X_{ot} and X_{dt} are the explanatory variables of the flow's origin and the destination in year t ; d_t is the geographic or information distance between the origin and destination of the flow in year t ; β_o , β_d , and θ are the coefficients of the corresponding explanatory variables; and $\varepsilon_{o \rightarrow d,t}$ is the error term following the standard normal distribution. The response and explanatory variables in the model are log-transformed according to Lesage [40].

The log-likelihood for the model was then calculated under both the geographic and cyberspace weight matrix. The matrix with a larger log-likelihood was then chosen for subsequent analysis. Based on the determined matrix, parameters of the SIM-IF were obtained through maximum likelihood estimation [40,41], since the commonly used least squares method is no longer applicable to models with spatial dependence.

3.4. Analyze Spatial Spillover Effects and Influencing Factors of Information Flows

According to the spatial econometric theory, there are two types of spillover effects of information flow in the SIM-IF constructed in Section 3.3. The first type is the spillover effect on a certain information flow from its neighboring flow, which can be represented by the coefficient ρ in Equation (9). The second type is the spillover effect on a certain information flow from the explanatory variables of its neighboring flow, which is estimated by calculating partial derivative of the information flow with respect to the explanatory variables. The total effect consequently obtained can then be decomposed into the direct effect and the indirect effect. The direct effect refers to the impact of the explanatory variables of a certain information flow on its own, which also reflects the influencing factors of the information flow. The indirect effect, which refers to the impact from the explanatory variables of a certain information flow on its neighboring information flows, is the second type of spillover effect [41]. Specific calculation steps for the second type of spillover effect and influencing factors of information flows are listed as follows.

Firstly, the explanatory variables of the information flow are denoted as $X_t = [X_{ot} \ X_{dt} \ d_t]$ for simplicity, and the information flow Y in year t can be expressed as:

$$Y_{o \rightarrow d, t} = \sum_{r=1}^n [(I_k - \rho W_w)^{-1} \beta_r] X_{t,r} + (I_k - \rho W_w)^{-1} \varepsilon_{o \rightarrow d, t} \quad (10)$$

where $X_{t,r}$ and β_r denote the explanatory variable r and its coefficient, respectively.

Secondly, the partial derivatives of the information flow with respect to each explanatory variable are calculated. Then, the partial derivative matrix of the information flow with respect to the explanatory variable r in year t is calculated, as shown in Equation (11):

$$\begin{bmatrix} S_{t,r}(W_w)_{1 \ 2,1 \ 2} & \cdots & S_{t,r}(W_w)_{1 \ 2,n \ n-1} \\ \vdots & \ddots & \vdots \\ S_{t,r}(W_w)_{n \ n-1,1 \ 2} & \cdots & S_{t,r}(W_w)_{n \ n-1, \ n \ n-1} \end{bmatrix} \quad (11)$$

where $S_{t,r}(W_w)_{ij,uv}$ denotes the impact of the explanatory variable r of the flow from city u to city v on the flow from city i to city j in year t . The non-diagonal elements of the matrix measure the spillover effects, and the diagonal elements measure the direct effects. Then, the spillover and direct effects of the information flow in the whole region can be obtained by averaging the non-diagonal and the diagonal elements in the $S_{t,r}(W_w)$ matrix, respectively.

4. Study Area and Data

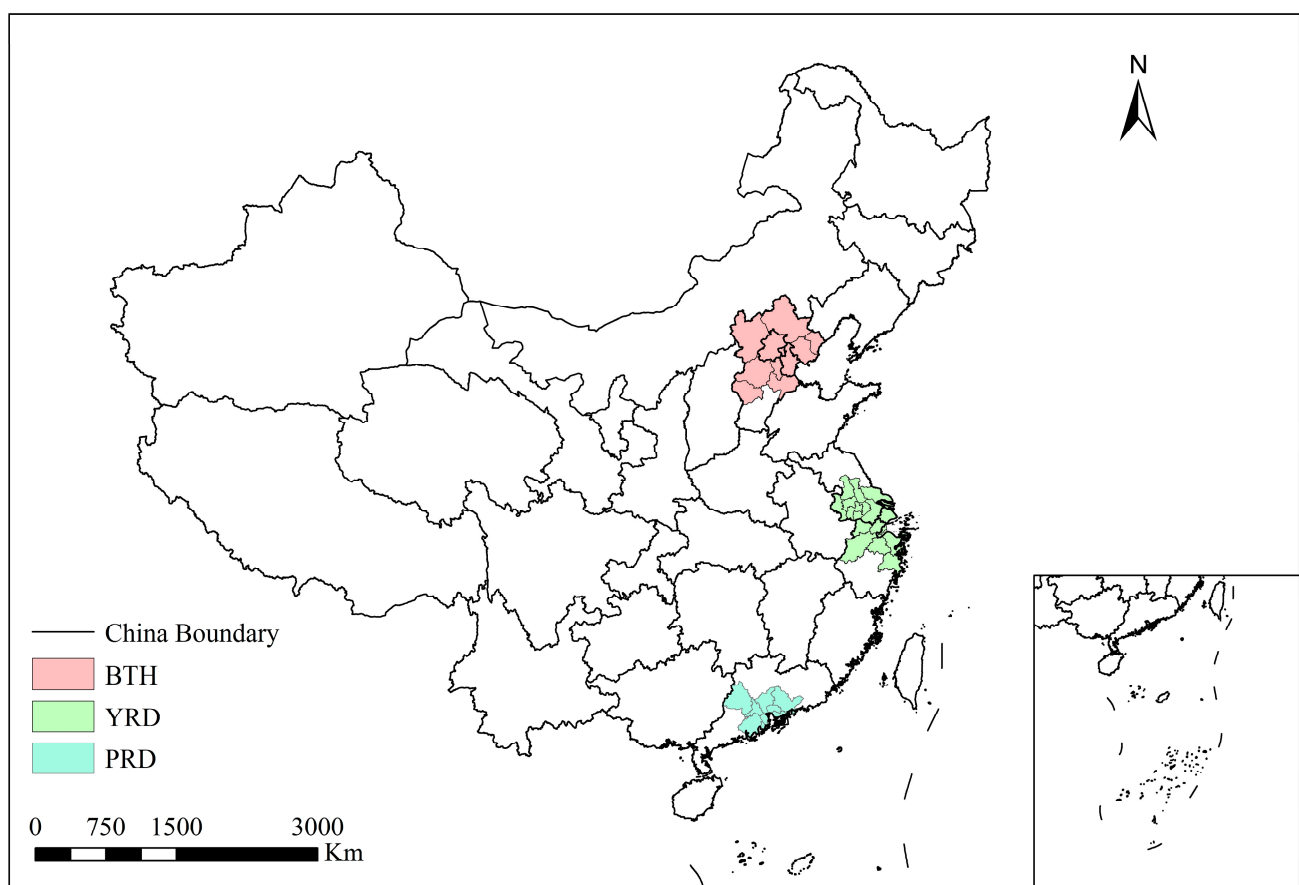
4.1. Study Area

As defined in the Beijing–Tianjin–Hebei Metropolitan Area Regional Plan, the Yangtze River Delta Regional Plan, and the Outline of the Plan for the Reform and Development of the Pearl River Delta (2008–2020), the BTH urban agglomeration is made up of 10 cities, including Beijing, Tianjin, and eight other cities located within Hebei province; the YRD urban agglomeration includes Shanghai, eight cities in Jiangsu Province, and seven cities in Zhejiang Province; the PRD urban agglomeration consists of nine cities in Guangdong Province. Detailed compositions and spatial distributions of each urban agglomeration are displayed in Table 1 and Figure 2, respectively.

Table 1. Composition of urban agglomerations.

Urban Agglomeration	Urban Area/ km ²	Population/ Million People	GDP/ Billion Yuan	Cities
BTH	22,280	89	7737	Beijing, Tianjin , Shijiazhuang, Tangshan, Qinhuangdao, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang
YRD	21,989	114	16,331	Shanghai, Nanjing , Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Taizhou (in Jiangsu province), Hangzhou , Ningbo, Jiaxing, Huzhou, Shaoxing, Zhoushan, Taizhou (in Zhejiang province)
PRD	10,400	64	8690	Guangzhou , Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, Zhongshan

Data updated in 2019. City name in bold is either provincial capital or municipality directly under the central government.

**Figure 2.** Study area.

4.2. Data Sources and Variable Selection

4.2.1. Dependent Variable

In this paper, we chose information flow constructed from the Baidu Search Index as the dependent variable. The Baidu Search Index, based on searches from Baidu users, sets keywords as the statistical objects and then calculates the weighted sum of the search frequency of each keyword in the search engine. It is divided into three categories including PC, mobile, and PC + mobile, according to the search devices used. The search index webpage provides three types of data, namely trend research, demand mapping, and crowd portraits for different applications. In trend research, users can set search time, search devices, and search location to obtain the amount of attention to the searched

keywords, which can reflect the popularity of different keywords in different areas to a certain extent. A greater index value indicates more attention to the searched keyword. If we set one city as the keyword and another city as the searching origin, the Baidu Search Index can then reflect the attention paid from the searching origin city to the keyword city. The size and the direction of the search index can thereby reflect the intensity and direction of information interaction between the two cities.

In this study, we set one city as the keyword, representing the place where the information was received (destination), and another city as the place where the information was sent from (origin). The search device was set to PC + Mobile. Then the search index between two cities in the three major urban agglomerations was obtained. To guarantee data integrity, the Chinese character “city” was not included in the keyword, for example, “Beijing” instead of “Beijing City” was used during the search process. The search period was set as 1 January 2014 to 31 December 2019. The constructed information network of the three major urban agglomerations based on the Baidu Search Index is shown in Figure 3, with the lines reflecting the Baidu Index between the cities.

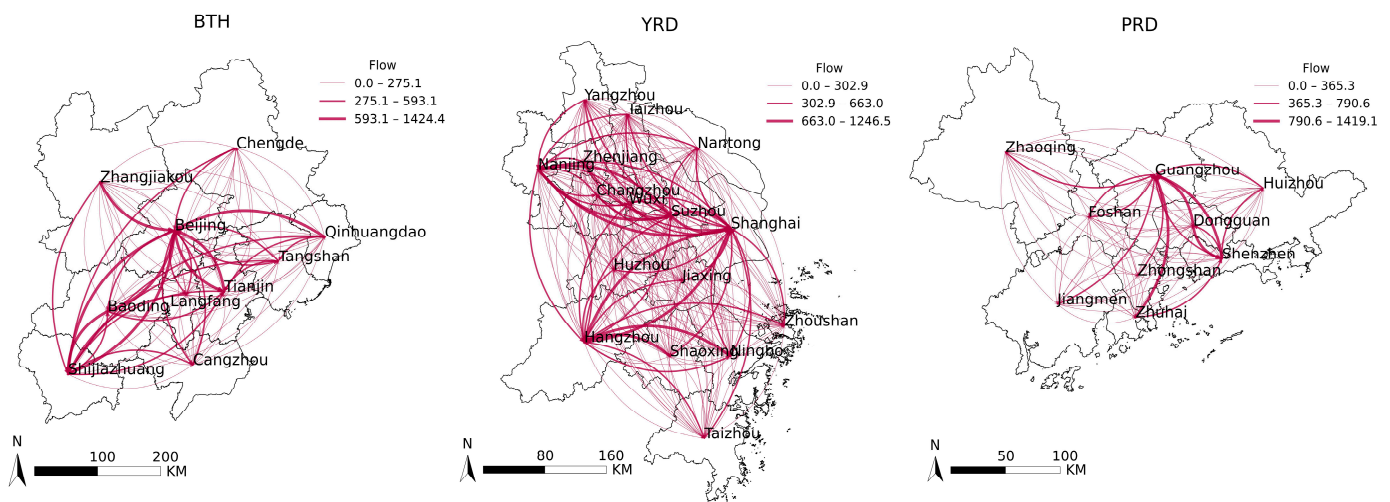


Figure 3. Information flows between cities of three agglomerations in 2014.

4.2.2. Independent Variables

Existing studies have usually indicated that information flow is primarily affected by four major factors, specifically, the status of cities' economic development, the effect of big events, the hierarchy of cities, and the distance between cities [7]. A city's economy supports its information infrastructure, and the status of its development largely determines the strength of information flows. Big events, such as conferences, exhibitions, and sports events, etc., have far-reaching impact on the city and will affect the information flows between the cities [42]. The hierarchy of cities, which is the rank of cities in the regional scales, will affect the information flows between the cities since it may reflect different attractions and appeal of cities [16].

Different studies may select different variables to characterize these factors. Based on comparative analysis results, we selected NPP-VIIRS nighttime light intensity (NTL), Baidu Media Index (event), weighted degree centrality (level), and geographic distance/information distance (distance) as explanatory variables to analyze the spillover effect of information flow and its influencing factors in our study. The same set of explanatory variables were chosen for both the “origin” and “destination” cities, otherwise, the estimation results would be biased [25]. To distinguish the variables from both cities, “O_” or “D_” prefix have been added, denoted as, for example, O_NTL and D_NTL. The following part of this section will introduce detailed meanings of the explanatory variables, reasons for selecting them, as well as the data processing methods.

Nighttime light (NTL) intensity is the radiation brightness of ground light sources obtained by remote sensing platforms, which has a significant positive correlation with GDP, population, and other socio-economic statistical indicators [43]. Unrestricted by administrative divisions, the NTL data can outperform traditional statistical data in various ways. This measure is often used to represent human socio-economic activity intensity at night and urban development situation. Compared with other NTL data products, the NPP-VIIRS product has comprehensive advantages in terms of spatial resolution, time series length, and radiation resolution. In this study, we selected the NPP-VIIRS monthly composite product for the same period as the Baidu Search Index (2014–2019). We removed outliers in the product by using Shi et al.'s method [44] and obtained the average annual light intensity of each city, which is denoted as Equation (12).

$$NTL = \{ntl_k^t \mid k = 1, 2, \dots, n; t = 2014, 2015, \dots, 2019\} \quad (12)$$

where n is the number of cities in the urban agglomeration.

Taking the year 2014 as an example, spatial distributions of the annual light intensity of the three major urban agglomerations are shown in Figure 4.

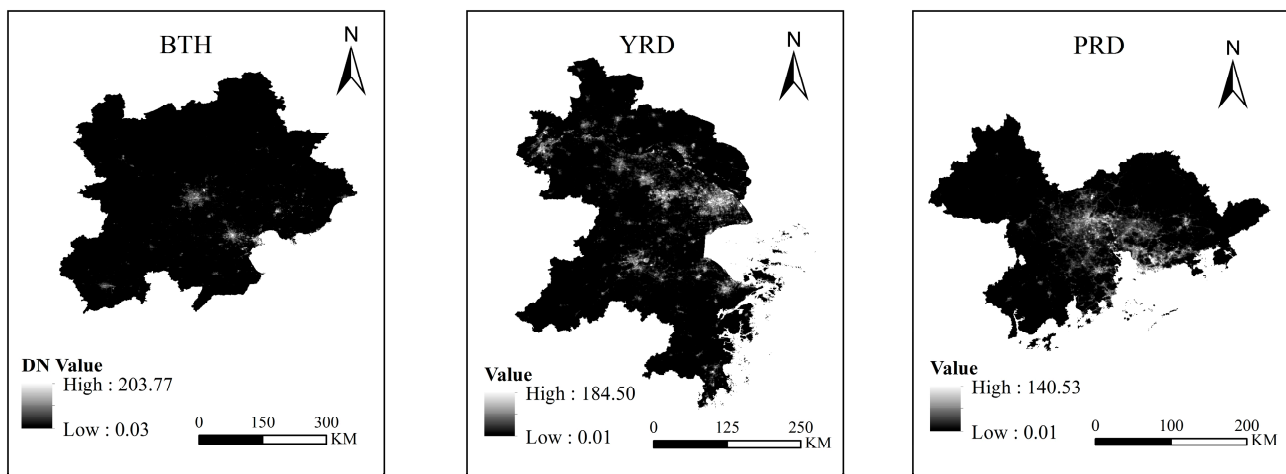


Figure 4. Spatial distribution of night time lights in 2014.

The Baidu Media Index reflects the number of reports including the keywords collected by the Baidu News Channel from major internet media [45]. It covers various major events such as sports events and cultural communication, and therefore is suitable for characterizing the effect of major events in cities. Since some outliers may lead to skewed data distribution, the annual median of the Baidu Media Index was adopted as the explanatory variable [16], denoted as event.

The hierarchy of cities is often characterized by metrics describing the importance of nodes in a network, such as the degree centrality [46]. Considering that the information flow is directional, the degree centrality for directed weighted networks is used to represent the hierarchy of a city in an information network [47]. $Flow_{in}(i)$ and $Flow_{out}(i)$ are the total amount of information flow received and sent by city i , respectively, while n is the number of cities in the urban agglomeration. The weighted degree centrality of city i , denoted as $level_i$, can then be calculated using the following equations.

$$level_i = \sqrt[3]{Flow_{in}(i) \times Flow_{out}(i) \times \frac{1}{2}(Flow_{in}(i) + Flow_{out}(i))} \quad (13)$$

$$Flow_{in}(i) = \sum_{j=1, j \neq i}^n Flow_{ji} \quad (14)$$

$$Flow_{out}(i) = \sum_{j=1, j \neq i}^n Flow_{ij} \quad (15)$$

Distance is a common explanatory variable in flow research, with geographic distance being the most frequently used one. Some studies have used travel time, cost, economic distance, language distance, or cultural distance for different application problems [48–50]. To date, studies have not reached a consensus regarding the influence of geographic distance and information distance on information flow. Therefore, both distances were used as explanatory variables in this study to analyze their influence on information flow, denoted by d_{ij}^G and d_{ij}^I , respectively. The geographical distance was defined as the shortest distance between government offices of cities obtained from the Baidu map. The information distance was measured by the absolute difference between the total information amounts between cities, which was calculated as follows.

$$d_{ij}^I = |F_i - F_j| \quad (16)$$

$$F_i = Flow_{in}(i) + Flow_{out}(i) \quad (17)$$

where d_{ij}^I denotes the information distance between city i and city j , and F_i denotes the total information amount in city i .

After the selection of variables, the specific expression for the SIM-IF can be obtained by substituting these above explanatory variables into Equation (9), as shown in Equation (18).

$$Y_{o \rightarrow d, t} = \rho W_w Y_{o \rightarrow d, t} + \beta_{o1} O_DN_t + \beta_{o2} O_event_t + \beta_{o3} O_level_t + \beta_{d1} D_DN_t + \beta_{d2} D_event_t + \beta_{d3} D_level_t + \theta d_t + \varepsilon_{o \rightarrow d, t} \quad (18)$$

$$\varepsilon_{o \rightarrow d, t} \sim N(0, \delta^2 I_k)$$

5. Results

5.1. Spatial Autocorrelation Analysis

Using the method described in Section 3.1, we obtained the Global Moran's I for information flows in the three major urban agglomerations, namely the BTH, the YRD, and the PRD, from 2014–2019 under the geographic and cyber spatial weight matrices, as well as their significance test results, as shown in Table 2.

Table 2. Spatial autocorrelation results for different spatial weight matrices.

		BTH	YRD	PRD
	Year	Moran's I	Moran's I	Moran's I
Geographic space	2014	0.244 ***	0.323 ***	0.382 ***
	2015	0.196 ***	0.328 ***	0.407 ***
	2016	0.256 ***	0.337 ***	0.443 ***
	2017	0.260 ***	0.372 ***	0.423 ***
	2018	0.212 ***	0.365 ***	0.362 ***
	2019	0.245 ***	0.371 ***	0.421 ***
Cyberspace	2014	0.383 ***	0.457 ***	0.451 ***
	2015	0.339 ***	0.480 ***	0.461 ***
	2016	0.400 ***	0.487 ***	0.492 ***
	2017	0.420 ***	0.502 ***	0.490 ***
	2018	0.338 ***	0.530 ***	0.478 ***
	2019	0.416 ***	0.545 ***	0.515 ***

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

When analyzing the Moran's I, it was found that the information flows of the three major urban agglomerations showed significant aggregation under both spatial weight matrices, i.e., strong flows were closer to strong flows and low flows were closer to low

flows. In terms of the temporal dynamics of the spatial autocorrelation, information flows in the three major urban agglomerations were increasingly aggregated year by year, in general. For the information flow in the YRD, its spatial aggregation showed a steady upward trend, and the Moran's I under geographic space and cyberspace increased from 0.323 and 0.457 in 2014 to 0.371 and 0.545 in 2019, respectively. As for the information flows of BTH and PRD, though slight fluctuations in the spatial aggregation were observed, the Moran's I of both spatial weight matrices in 2019 were larger than those in 2014, indicating that the information flows were gradually forming a network of more aggregated connections. Among all the urban agglomerations, it was found that under the geographic space, information flows in the PRD were the most aggregated, while under the cyberspace, the flows in the YRD showed the most aggregation. This might show that information flows were more geographically related in the PRD, and were less spatially constrained in the YRD.

5.2. Application of SIM-IF

We applied the SIM-IF to the three major urban agglomerations and calculated the log-likelihood of the model under both the geographic and cyber weight matrix. The results are shown in Table 3. It was found that the SIM-IF obtained a higher maximum likelihood under the geographic weight matrix for all the three major urban agglomerations. This indicates that the geographic weight matrix was more appropriate in this model and the spillover effects of information were more obvious in geographic space.

Table 3. Log-likelihood of the SIM-IF under different spatial weight matrixes.

Distance	BTH	YRD	PRD
Geographic space	−50.778	360.465	−68.256
Cyberspace	−78.966	−64.728	−78.248

To further demonstrate the necessity for a spatial econometric interaction model, we estimated and tested the coefficients of both the non-spatial model ($\rho = 0$) and the spatial econometric interaction model based on the geographic weight matrix. When ρ equals 0, the constructed SIM-IF would degenerate into a simple linear regression model. In this case, the results obtained from either the maximum likelihood method or the least squares method would be the same. Hence, we used the least squares method to estimate the parameters of the non-spatial model.

The results (Table 4) show that the SIM-IF proposed in this paper provided obviously better fitting results for all three urban agglomerations. The r^2 for BTH, YRD, and PRD (0.815, 0.919, and 0.828, respectively) were significantly higher than those of the non-spatial model (0.764, 0.891, and 0.809, respectively). This indicates that the SIM-IF was more suitable for studying the information flow.

Table 4. Estimation results of the non-spatial model and the SIM-IF in three urban agglomerations.

Variables	BTH		YRD		PRD	
	Non-Spatial	SIM-IF	Non-Spatial	SIM-IF	Non-Spatial	SIM-IF
const	−7.895 ***	-	−6.437 ***	-	−7.482 ***	-
O_NTL	0.231 ***	0.039	−0.141 ***	−0.142 ***	−0.209 ***	−0.184 ***
D_NTL	−0.051	−0.120 ***	0.137 ***	0.05 ***	0.413 ***	0.322 ***
O_event	−0.004	0.045 *	0.013	0.003	−0.035	−0.030
D_event	−0.008	0.008	0.031 ***	0.034 ***	0.110 ***	0.097 ***
O_level	0.563 ***	0.574 ***	0.642 ***	0.619 ***	0.814 ***	0.676 ***
D_level	0.839 ***	0.733 ***	0.888 ***	0.825 ***	0.495 ***	0.331 ***
distance	−0.028	−0.029	−0.263 ***	−0.165 ***	−0.057 ***	−0.061 ***
ρ	-	0.475 ***	-	0.433 ***	-	0.345 ***
R-squared	0.764	0.815	0.891	0.919	0.809	0.828

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

5.3. Spillover Effects of Information Flows

Using the method described in Section 3.3, we obtained the spillover effects of neighboring information flow on the target information flow (Table 4) and the spillover effects of the explanatory variables of the neighboring information flow on the target information flow (indirect effect) (Table 5).

Table 5. Direct and spillover effects estimation of SIM-IF in three urban agglomerations.

Variables	BTH			YRD			PRD		
	Indirect	Direct	TOTAL	Indirect	Direct	Total	INDIRECT	Direct	Total
O_NTL	−0.106 ***	−0.125 ***	−0.230 ***	−0.037 ***	−0.053 ***	−0.089 ***	0.164 ***	0.331 ***	0.495 ***
D_NTL	0.031	0.039	0.070	−0.116 ***	−0.168 ***	−0.285 ***	−0.093 ***	−0.187 ***	−0.280 ***
O_event	0.007	0.008	0.014	0.008	0.011	0.019	0.050 ***	0.100 ***	0.150 ***
D_event	0.042 *	0.049 **	0.091 *	0.023 ***	0.033 ***	0.056 ***	−0.016	−0.031	−0.047
O_level	0.646 ***	0.759 ***	1.405 ***	0.574 ***	0.830 ***	1.404 ***	0.163 ***	0.334 ***	0.498 ***
D_level	0.511 ***	0.601 ***	1.112 ***	0.308 ***	0.446 ***	0.754 ***	0.343 ***	0.691 ***	1.034 ***
distance	−0.026	−0.030	−0.055	−0.115 ***	−0.166 ***	−0.281 ***	−0.032 ***	−0.063 ***	−0.095 ***

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

For the spillover effects of neighboring information flow on the target information flow, it was concluded from the spatial dependence (ρ in Table 4) that the first type of spillover effect in the three major urban agglomerations were all significantly positive, which means that if a certain information flow increased, its origin and destination also sent and received more information flow. Hence, information flows are mutually interactive. For three major agglomerations, the effects were the strongest in the BTH (0.475), followed by the YRD (0.433) and the PRD (0.345). This result is in accordance with the fact that the BTH contains the capital city in China, and the information flows have higher interaction intensity due to political bonds.

By further exploring spillover effects from the explanatory variables of neighboring information flows on the target information flow, we found the following characteristics for the second type of spillover effects (indirect effect in Table 5):

Firstly, the hierarchy of both origin and destination cities had significantly positive spillover effects on information flow in the three major urban agglomerations. The higher hierarchical position a city possessed, the more information was received and sent by its neighbors. Moreover, among all the influencing factors, city hierarchy had the strongest spillover effect on information flow, which indicates that improvement of cities' hierarchical position can most effectively help the development of information flows. This is possibly because higher hierarchical position is associated with more powerful government, and hence can affect and manage information flows more effectively. Among the three major urban agglomerations, the information flow in the BTH was the most affected one by the city hierarchy. This result also verified our above assumption to some extent. Specifically, if the hierarchical position of a certain city within BTH increased by 1%, the amount of information sent from and received by its neighbors would rise by 0.646% and 0.511%, respectively. It can, therefore, be concluded that enhancing the hierarchical position of cities is an effective way to promote the integrated development of information networks.

Secondly, the impact of the economic development level on information flow spillover effect varied greatly among different urban agglomerations. The flow origins of the PRD had the strongest positive impact. If the economic level of a certain city in the PRD grew by 1%, the amount of information sent from its neighbors would rise by 0.164%. However, the economic development levels of both flow origins and destinations in YRD showed significantly negative spillover effects. The neighbors of cities with the better economy would send and receive less information flow. This indicates the city's economic development level may impede the development of its neighbors' information flow in the YRD. The economic development level of flow origins in the BTH had no significant impact on information flows, i.e., information received by a city had little relationship with

the economic development level of its neighbors. It was concluded that the mechanism of economic development level on the information flow spillover effect is quite complicated and varies in different urban agglomerations. This might be due to the complex theory underlying economy, and how it affects information flows needs further microanalysis.

Thirdly, the effect of big events on the information flow was insignificant in the three major urban agglomerations. Only the origins in the BTH and the YRD, and the destinations in the PRD had significant spillover effects on the information flow. Specifically, if a city's big event effect increased by 1%, the amount of information received by its neighbors would increase by 0.042% and 0.023% in the BTH and the YRD, respectively, while the amount of information sent from its neighbors would increase by 0.050% in the PRD. These regression results are relatively small, which means holding big events may not be an effective way to promote information integration.

Fourthly, the distance factor had almost no spillover effect on information flows. Since distance is an inherent property, the information flow between any two cities is only affected by their distance between but not any other distances. It can also be seen that from Table 4 the estimated results of the distance factor for the three major urban agglomerations (-0.029 , -0.165 , and -0.061) were closer to the direct effects in Table 5 (-0.030 , -0.166 , and -0.063).

As can be concluded from the above, in these three urban agglomerations, the hierarchy of both origin and destination cities had the strongest spillover effects on information flow, while other factors had comparably weaker or insignificant spillover effects.

5.4. Influencing Factors of Information Flows

Using the method described in Section 3.3, we also obtained the impact of various factors on the information flow (direct effect) (Table 5). According to the results, we found the following characteristics for the influencing factors of information flow.

Firstly, all the influencing factors had greater direct effects than the indirect effect, i.e., the second type of spillover effect on information flow. This indicates that these factors in a certain city have a greater impact on the information flow of itself, rather than on its neighboring information flows.

Secondly, the hierarchy of cities had a significant positive impact on information flow, which indicates that cities with higher hierarchy both send and receive more information. Among the three major urban agglomerations in China, this phenomenon was the most obvious in BTH. This may be because that agglomeration, with high hierarchical positions of its cities, attached more attention to long-term development and was more willing to facilitate technology development, which is the foundation for information flows. Specifically, when the centrality degree of a city in BTH increased by 1%, the amount of information sent from and received by it would rise by 0.795% and 0.601%, respectively.

Thirdly, the impact of economic development level on information flow varied in the three major urban agglomerations. Flow origins all showed significant impacts on information flow, while the PRD was the most significant one. When the economic development level of the cities in the PRD increased by 1%, 0.331% more information flow would be sent out. Direct effects in the other two urban agglomerations were, however, negative, indicating that cities with the weaker economy tended to send out more messages in the BTH and the YRD. Meanwhile, the effects of economic development level from flow destinations were significantly negative in the YRD and the PRD. This indicates that cities with weaker economy were more likely to receive information in these two urban agglomerations. The different results of the three major agglomerations may be due to the different economic development patterns underneath.

Fourthly, the influence of big events on information flow was insignificant in the three major urban agglomerations. Positive effects existed only in flow origins in the PRD, and flow destinations in the BTH and the YRD. This indicates that big events may have promoted the development of information flow to some extent. Among the three major urban agglomerations, the big event effect of information origins in the PRD had the largest

impact on information flow. When a city's big event effect increased 1% in the PRD, it would send out 0.1% more information flow. This might be credited to the plan for the Guangdong–Hong Kong–Macao Greater Bay Area. Many big events have been held in the PRD, which may have then impacted the information flow.

Fifth, the geographical distance may have influenced information flow to a certain extent. The impact was not significant in the BTH, but was negatively significant in the YRD and the PRD. The reason may be that the government played an important control role in the information construction in the BTH, so the flow between cities was less restricted by geographical location, while the information flows in the PRD and the YRD were mainly influenced by the market. In detail, if the distance between cities increased by 1%, the information flow in the YRD and the PRD would decrease by 0.166% and 0.063%, respectively. This indicates that the information interaction weakened as the distance between cities got longer. Geographic distance, therefore, remains an important constraint in the development of information flow. Among the three major urban agglomerations, the YRD had the strongest distance decay effect, followed by the PRD, while the information flow of BTH was the least affected. This means that the information transmission ability of the YRD was not as strong as that of the BTH or the PRD. The distance decay effect in our study was quite small, which may be ascribed to the fact that information flow has greater mobility and the fact that we have considered the spatial interactions in the model.

6. Discussion

Information flow is an important component in urban interaction. As the results show, the spillover effect can promote interactions between flows, and such information growth will facilitate more interaction within cities. With information as the carrier, elements such as innovation, industry, economy, and talents will flow and spread more smoothly, which leads to coordinated cooperation between cities. Accordingly, the development of the urban agglomerations will be more sustainable [51]. Hence, it is of great importance that the government make full use of the information flow.

Primarily, the government should reinforce the construction of information infrastructures, which is fundamental to the interconnection in urban agglomerations in the information era. Although the core cities within urban agglomerations have been highly informationized, the internet penetration rate is still low in some less developed areas. The government should take various measures, such as building more communication base stations, promoting broadband network constructions, and reducing internet fees, etc., to narrow the digital divide and develop a more equalized and interconnected communication system.

Furthermore, the government should also reinforce the intervention and management of information flow by adopting more proactive policies to strengthen intercity communication and connection, such as formulating reasonable development plans and outlines and actively undertaking coordinating efforts. As the results suggest, since the cities' hierarchy is the most important factor that contributes to the information flows, and also shows the strongest spillover effects for all the three urban agglomerations, the government can enhance the volume of information flows by raising the cities' hierarchical positions, such as by attracting more talents, increasing the number of culture sites, and appealing to more headquarters of major corporations and banking and financial institutions. For different urban agglomerations, the government may also raise their economic development levels, such as by improving GDP per capita or by making use of the effect of big events, including organizing more cultural or athletic events. With the consequent increase in information spillover effects, interaction within cities will also increase, which will make the urban agglomeration more unified and coordinated.

This study quantified the spillover effects and provides scientific basis for the information flow construction in urban agglomerations, which will benefit the coordinated development of cities. However, there are still some deficiencies in this study. Information flows' spillover effects are quite complex in their mechanisms and show spatial heterogene-

ity at the scale of urban agglomeration. Currently, we have only analyzed the spillover effects by considering the urban agglomeration as a whole and did not study the direction and the size of the spillover effects within the agglomerations. Future studies may focus on the spatial structure of information flows' spillover effects, which are likely to facilitate inter-city information interaction and resource sharing more effectively.

7. Conclusions

Information flows have obvious spillover effects, which may facilitate urban interaction and coordinated development. However, this topic has rarely been studied. To fill this gap, we quantified the spatial spillover effects and influencing factors of information flows in our study through a new framework. Specifically, we used the Baidu Search Index to characterize information flow intensity among cities and developed a spatial econometric interaction model of information flows (SIM-IF) to do the analysis. The model was then applied to the three major urban agglomerations in China in the period of 2014–2019 and the major findings are listed as follows:

- (1) The SIM-IF model performed well in the study area and revealed the mechanism of the formation of the information flows.
- (2) There were strong and spatially heterogeneous spillover effects between information flows, which were the strongest in the BTH and the weakest in the PRD.
- (3) Influencing factors, including the cities' economic development levels, the big events effect, the hierarchy of the cities, and the distance between cities, all have different spillover effects or direct effects on information flows in different urban agglomerations. Among them, the hierarchy of cities had the largest impact in the study area.

Our study offers a new perspective for studying information flows. The proposed method has great potential of application in different regions. This study may advance our understanding of information flows, provide suggestions for information construction in urban agglomerations, and furthermore facilitate the coordinated development of cities.

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